Does Fund Size Affect Private Equity Performance? Evidence from Donations to Private Universities

Abhishek Bhardwaj Abhinav Gupta Sabrina T. Howell
Kyle E. Zimmerschied*

June 2026

Abstract

Do private equity (PE) returns rise or fall with fund scale? Since better managers can raise larger funds, a causal effect is difficult to identify. We develop an instrument using donations to universities. Donations affect fund size because endowments are sensitive to donation income, have sticky relationships with PE managers, and signal fund quality to other Limited Partners. We find decreasing returns to scale: a 1% instrumented increase in fund size reduces net IRR by 0.1 percentage points. Larger funds do larger deals, which underperform. We find no change in risk, in part because additional deals are more levered.

Keywords: Private Equity, Performance, Returns to Fund Size, University Endowments

*Abhishek Bhardwaj (abhardwaj@tulane.edu) is at the Tulane University A.B. Freeman School of Business. Abhinav Gupta (abhinav_gupta@kenan-flagler.unc.edu) is at the University of North Carolina, Kenan-Flagler School of Business. Sabrina Howell (showell@hbs.edu) is at Harvard Business School. Kyle E. Zimmerschied (kylez@uark.edu) is at the University of Arkansas, Sam M. Walton College of Business. We are grateful to Matteo Binfaré, Greg Brown, Jun Chen, Arthur Korteweg, Josh Lerner, Vladimir Mukharlyamov, and Emil Siriwardane for comments, as well as to participants at the University of Midwest Finance Association 2026, Toronto Rotman School, the UNC Institute for Private Capital, Boston Symposium, the MSCI SQA Conference, 21st Annual Olin Finance Conference, and NBER SI Corporate Finance. We thank the Private Equity Research Consortium (PERC), the Institute for Private Capital, and MSCI for access to the MSCI-Burgiss data and Wendy Hu for research support.

1 Introduction

Private equity (PE) has grown dramatically as an asset class, with fundraising reaching over 3% of GDP in recent years. Alongside this growth, the average fund size has grown as well, especially within the larger and more experienced firms (Figure 1). Harris et al. (2023) show that while poor performance is persistent across funds within a firm, good performance is no longer persistent in the post-2000 era. One potential culprit is larger fund size: Do firms sacrifice returns when they raise larger funds?

This question is an urgent one amid new retail access to PE, including through 401(k) retirement plans. PE has historically been restricted to highly sophisticated investors, specifically institutions and the ultra-wealthy. By providing new capital, retail investors may enable fund sizes to continue to grow even as institutional demand appears saturated. In addition, retail investments are likely to concentrate in brand names, which will benefit the large PE houses and their megafunds.[1] Finally, retail funds typically have evergreen structures, which have no ex-ante caps to size and thus can grow without limit. These semi-liquid funds have high fixed costs, requiring larger scale to run profitably (Ewens and Faber, 2026).[2] By exploring the causal effect of size increases on returns, we begin to shed some light on the question of what types of opportunities retail investors will have access to and how they may be different from previous generations of PE funds.

In most studies of the PE buyout industry—including our own—there is no significant relationship between fund size and returns (see Figure 2, Panel A, and Harris et al. (2014); Johnson (2026); Kaplan and Schoar (2005); Robinson and Sensoy (2013)). To explore how Limited Partners (LPs)—who are the primary consumers of PE—perceive the issue, we conducted a survey. Among 81 institutional allocator respondents, 80% reported that they believe small funds perform better. What might explain the discrepancy between average statistics and LP beliefs? While there are multiple possible reasons, including LP biases, risk preferences, and the choice of performance metric, one answer lies in the endogeneity of fund size. Higher quality managers (General Partners or GPs) will enjoy greater demand from LPs. Since fee structures create a strong incentive to raise larger funds, higher quality GPs are likely to sort into larger funds (Johnson, 2026), leading to

[1] Indeed, it is the largest firms that have launched 401(k) partnerships so far, such as Blackstone, KKR, and Apollo. See https://montaka.com/alt-asset-401k/.

[2] In analyzing Pitchbook data from 2000 to 2025, we find that funds with retail-oriented structures can be much larger, with mean size of about $1.1 billion, vs. about $600 million for a comparable group of drawdown PE funds.

upward bias in descriptive analysis of the correlation between fund size and returns.

If we can address the selection problem, it is not obvious how fund size—holding all else constant—should affect returns. On the one hand, if good managers have unconstrained access to good deals or advantageous relationships with creditors, they might enjoy economies of scale. On the other hand, a larger fund might force managers to do worse deals. Also, more fee income might encourage "quiet life" behavior, where managers put less effort into performance.

To identify a causal relationship, we use donations to private university endowments. When a university receives more donations, its endowment has more money to invest, and a portion of this additional capital is allocated to GPs with whom the endowment has a pre-existing relationship. This commitment also has a signaling effect, certifying the fund as higher quality to other LPs. As a result, the connected GP can raise a larger fund, for reasons unrelated to his own prior performance. We document each step of this logical chain and show evidence to support the validity of the exclusion restriction.

Our analysis relies on a novel database with information on university donations, university-GP linkages, and buyout fund returns. We collect donation data from IRS Form 990 and investment data from IRS Form 990-T, which private universities must file to maintain nonprofit status and report unrelated business taxable income. While prior research has primarily relied on commercial sources such as Preqin to document university-GP relationships, our use of investment commitment data from Form 990-T enhances coverage of private university investments by more than 50%. The resulting dataset of 95 universities provides a valuable resource for future research. We gather fund and deal information from Preqin, Pitchbook, and a large fund of funds firm.[3]

There are three key elements that make our identification strategy possible. First, private university endowment investment is sensitive to donations (Binfarè and Zimmerschied, 2024; Dimmock, 2012; Rosen and Sappington, 2016). Donations are an important source of non-financial income, accounting for about 20% of total revenue during our sample. Second, university LP-GP relationships are sticky; for example, we show that universities are nearly 25 times more likely to invest in a GPs follow-on fund, conditional on investing in the prior fund. This is consistent with evidence from pension plans of sticky, continuing relationships that materially affect returns Korteweg et al. (2024).

[3]This is a large fund of funds and advisory services firm, which has built a private market database since 2006. This firm wishes to be anonymous.

Third, private university commitments can significantly affect fund size because they serve a certification (i.e., signaling) function for other potential investors. Private universities are considered prestigious investors who cultivate long-term, stable relationships with—and thus good information about—their PE managers (Gilbert and Hrdlicka, 2015; Lerner et al., 2008, 2007). When a private university that previously invested in a GP commits to the follow-on fund, it serves as a credible signal of GP quality to other potential investors. Our survey of LPs offers support for such certification. Sixty percent of LPs reported that it would increase their chances of investing in a fund if they learned that a private university endowment had already committed. This informativeness is greater than that of pension funds, which are traditionally the largest source of capital for the industry but which have struggled to invest in the best managers (Hochberg and Rauh, 2013). Indeed, only 33% of the LP survey respondents reported that learning about a government pension commitment would positively influence their decision.

The first stage estimates indicate that university donations explain a substantial portion of the variation in connected GPs' subsequent fund size. The baseline first-stage F-statistic is approximately 30, comfortably exceeding the standard thresholds for instrument relevance. Consistent with certification, the instrument predicts a larger number of pension and other non-university LPs in the fund, but does not affect private university LPs. We find that the donation-induced increase in funding from relationship universities and from less sophisticated LPs via signaling roughly balance, resulting in a larger fund without a significantly shift in the composition of the LP base.

Our identification strategy relies on the exclusion restriction that donations influence fund returns solely through their effect on endowment allocations. Several compelling tests suggest that this is satisfied. We find that endowment donations affect the size of the fund only for established university-GP relationships. When we randomize these relationships, the effect disappears, suggesting that the observed impact is driven by specific relationship ties rather than a correlation between donor behavior and asset allocation. We also show that university donations exhibit wide year-to-year dispersion and minimal correlation with each other or market returns. More broadly, our instrument is uncorrelated with key GP characteristics, such as prior performance, number of past funds, time since last fund, and fee structure. Also, we show that the results do not reflect donations from individuals or firms in the PE or broader financial sector, so it is not the case that the same individuals who are raising larger funds are also donating. Last, our models include fixed effects for year $\times$ GP region and year $\times$ fund industry, which absorb time-varying shocks across geographies and industries that could affect fund performance.

In the causal analysis, we show that there is a large, negative effect of fund size on performance. Our estimates imply that a 1% increase in fund size (an increase of \$15.1 million relative to the mean) reduces a fund's net internal rate of return (IRR) by 0.1 percentage points (pp). For funds with top quartile growth—whose next fund is on average \$600 million larger—our estimates suggest that such an increase in size would reduce returns by 3.2 pp. Since the typical fund's net IRR is 18% in our sample, this result implies a significant decline in performance as funds grow larger.[4] We confirm that our results are robust to alternative performance measures, including the Direct Alpha method from Gredil et al. (2023), the Public Market Equivalent (PME) from Kaplan and Schoar (2005), and the α measure from Korteweg and Nagel (2024), which account for the timing of cash flows and, in the case of Korteweg and Nagel (2024), explicitly adjust for systematic risk. The causal effect does not appear to reflect a reduction in risk. While larger funds might be less risky on average, we see a causal leftward shift in the entire return distribution as the fund grows. Also, we ensure the main result holds using various sample periods, including controls such as various linear trends, and after restrictions such as excluding the largest GPs, the largest funds, or the smallest funds. We also find similar results in alternative models, such as one that instruments using only large gifts above \$1 million.

When a fund scales up, it must either do more deals or larger deals. Our data suggest that larger deals, which tend to underperform, are an important driver of lower returns. First, we show that instrumented increases in fund size lead to larger deals; a 1% increase in fund size increases the average deal size by about \$0.4 million (0.4% relative to the mean). Next, we show that larger deals have lower returns, both in OLS and IV models. In a deal-level IV model, where we instrument for deal size using the endowment gifts measure, a 1% increase in deal size (\$1.41 million) reduces a deal's gross IRR by 0.18 pp. The larger deals induced by exogenously larger funds can account for more than 60% of the decline in fund-level returns stemming from larger fund size. This finding aligns with industry reports suggesting that as the PE industry has matured, it has become more difficult to create value in big deals (Pitchbook, 2024). In the words of one middle market investor, smaller deals have "more room for growth" (Shi, 2025).

Indeed, we show in instrumented, deal-level regressions that at the time of deal entry (immediately post-LBO), larger targets are more profitable and more leveraged. As a result, they may have less scope for operational improvement and a larger debt service burden. Supporting this idea, we find that following the LBO, instrumented increases in deal size reduce profitability growth and do not

[4]We find similar results using the net multiple on invested capital (MOIC) as a performance measure.

affect leverage. Like the fund-level results, there is no effect on deal risk; while on average large deals tend to be less risky (Brown et al., 2023), the effect of larger funds on deal size does not come with a commensurate decline in deal riskiness. Overall, our results on deal size—where larger funds lead managers to invest in larger deals with less scope for operational engineering—suggest that larger funds lead GPs to enjoy a "quieter life," possibly because they earn more fees independent of performance.

Another mechanism might be human capital capacity constraints, where GPs are stretched too thin when they execute more deals. We find a causal effect of larger funds on the number of deals, but we also find that larger funds hire more partners to compensate, and additional partners are not less experienced. We also find no evidence that larger funds have more sectoral or geographical diversification. Overall, the results are not especially consistent with human capital constraints explaining lower returns at larger funds, though we cannot rule out that they play a role.

Our results highlight a trade-off for LPs: While larger funds enable more capital deployment, they reduce returns. This is an important concern for LPs seeking to expand PE allocations despite the limited availability of high-performing funds. To quantify the tradeoff, we use the causal estimates from our empirical analysis to model the net present value (NPV) implications of fund size in a stylized calculation based on the average fund in our sample. For LPs, the NPV increases in a concave manner until reaching a maximum at a fund size of $1.13 billion fund (the 67th percentile). Beyond this threshold, declining net IRRs outweigh scale benefits, driving NPV downward and eventually turning it negative at $2.63 billion (the 82nd percentile). For GPs, the management fee scales linearly with fund size, leading to a monotonically positive, albeit concave, relationship between fund size and NPV over the relevant fund size range. The key takeaway is that the diseconomies of scale affect LPs and GPs differently; GPs always benefit from larger funds while LPs do not.

Our results offer useful benchmarks for LPs to evaluate their investments and their relationships with the GPs, showing that when GPs raise larger follow-on funds, with all else held constant, they may sacrifice returns. However, the implication is not that funds above our thresholds for negative NPV should be avoided. There are many reasons larger funds can perform well, such as high-quality managers and good investment opportunities. Indeed, the contrast between the null OLS results and negative IV estimates indicate strong positive selection, where the highest-quality funds attract the largest inflows. Our results are also relevant to the broader industry and policymakers. As more money flows into the sector—for example from retail investors—and funds become larger, the causal effect should dominate unless the industry can compensate with better investment opportunities or managerial talent.

In the model of Berk and Green (2004), highly skilled mutual fund managers attract inflows to the point where they no longer outperform a passive benchmark, because of decreasing returns to scale. Correspondingly, decreasing returns to scale are well-documented in the mutual fund industry due to public market liquidity frictions (Chen et al., 2004; Pástor et al., 2015). However, it is not obvious that these findings extend to PE, where funds buy illiquid, controlling stakes rather than liquid, passive ones. Our primary contribution is to offer the first causal analysis of the effect of fund size on performance in the PE industry.

We build on previous studies that correlate fund size with performance. One strand of this literature studies performance persistence, which has declined over time (Braun et al., 2017; Harris et al., 2023; Kaplan and Schoar, 2005; Sensoy et al., 2014). Braun et al. (2024) measure performance at the individual GP level, focusing on the role of internal capital allocation within PE firms. Other related work on GP manager skill includes Korteweg and Sorensen (2017) and Cavagnaro et al. (2019). Our results speak to the agency problems inherent in the PE model, which Robinson and Sensoy (2013) and Begenau and Siriwardane (2024) document in their work on fees in PE. Closely related to our paper is Lopez-de Silanes et al. (2015), who study the organizational implications of scale in PE. Using fundraising prospectuses provided to LPs, they show that when PE firms have more simultaneous investments (a proxy for scale), they tend to perform worse. We contribute by offering causal evidence for decreasing returns to scale among PE funds and by documenting that one reason is larger deals, in which GPs have less ability to create value for LPs.

2 Fund Size, Returns, and LP Relationships

In this section we first explain our data sources. Next, we present three types of descriptive evidence. First, we provide summary statistics about our sample. Second, we describe our survey of LPs. Third, we present OLS regression analysis, which draws from and confirms previous work. A key takeaway is that while small funds do not outperform large funds on average, LPs think that they do.

2.1 Data Sources on Private Equity

We source fund-level data from Preqin, a leading provider of private capital data widely used in academic research (Begenau and Siriwardane, 2024; Harris et al., 2014; Sensoy et al., 2014). Our initial sample includes all Preqin funds within the asset class grouping "Private Equity" with vintage years between 2000 and 2017. We further restrict to funds with committed capital of at least $100 million, because private universities typically do not invest in funds beneath this threshold. Our two primary performance metrics are the net IRR and the MOIC. We exclude funds with missing returns in Preqin. Next, we require PE firms to have a relationship with one or more private university endowments, because our empirical strategy relies on GP exposure to university gifts. (The relationship variable is defined using university tax filings, which are introduced below.) After applying these filters, our final Preqin sample comprises 1,231 funds managed by 193 unique PE firms.

To track partners affiliated with these funds and to increase coverage of deal-level information, we incorporate data from PitchBook. We first match PE firms, which we interchangeably call "GPs", using name and address, and then match funds using name and vintage years. The merged Preqin-PitchBook dataset covers 1,115 unique funds, representing a 91% match rate. Information on fund managers is available for 725 of these funds. PitchBook's person-level records enables us to measure partners' number of prior deal and fund affiliations, as well as fund characteristics such as deals per partner and AUM per partner.

We augment the fund-level data with granular information about PE deals from a large US-based fund of funds and advisory firm. We retrieve deal-level information for 581 funds in our sample. We restrict the sample to deals with non-missing return information and an associated prior fund in order to compare deal characteristics, leaving 466 funds with 8,748 deals. The fund of funds database contains information on the size of the deal and the target company's sector and location. Further, it provides detailed financial information, including debt, profitability, and size of the target company at deal entry and exit. This granular information permits us to trace how PE ownership relates to company fundamentals and to fund-level returns.[5]

While IRR and MOIC represent the standard metrics by which the industry evaluates itself

[5]In our main analysis, we use deal information across the Fund of Funds, Pitchbook, and Preqin. We prioritize deal-level information from the fund of funds when available. If fund of funds data is missing, we supplement it with data from Pitchbook. Finally, if both fund of funds and Pitchbook deal-level information are missing, we supplement it with data from Preqin.

(Gompers et al., 2016, 2020)—perhaps reflecting LP preference for simplicity—they have well-known limitations, including their sensitivity to cash flow timing and their inability to account for illiquidity. To ensure our results do not spuriously reflect features of these measures, we also measure performance using the α measure from Korteweg and Nagel (2024), the Direct Alpha method from Gredil et al. (2023), and PME from Kaplan and Schoar (2005). All three methods rely on cash flow level data to benchmark fund performance against similarly timed public market returns, but differ in how they account for risk. The Direct Alpha and PME measures discount cash flows using realized returns on a public market benchmark and implicitly assume a fund's risk aligns with market risk ($\beta = 1$). In contrast, Korteweg and Nagel (2024) estimate a stochastic discount factor that allows for flexible risk exposures to systematic risk factors. To obtain fund-level cash flow data for this analysis, we match our sample to MSCI Burgiss, yielding a subsample of approximately 530 funds.

2.2 Summary Statistics

We present fund-level statistics in Table 1 Panel A. The average fund is \$1.5 billion, though the median is much smaller at \$0.64 billion. The average IRR and multiple are 18% and 1.9x, respectively. The average fund with cash flow level data in Burgiss performs well with a median PME of 1.12 and a median α of 0.19. The average fund does 19 deals with an average deal size of about \$98 million. Based on fund employment data from Pitchbook, the average fund in our sample has seven partners.[6] In Table 1 Panel B, we present deal-level summary statistics. The first two variables, IRR and MOIC, are measured at the end of the deal lifecycle and have average values of 21% and 2x, respectively. The subsequent variables—from Deal Size to Debt relative to Enterprise Value—are measured at the time of entry, immediately following the LBO. Lastly, we measure changes in operating performance and leverage by comparing these ratios at deal exit versus entry. On average, EBITDA relative to enterprise value declines by 2 pp, while debt relative to enterprise value drops by 5 pp.

Sample Representativeness. Our sample contains 1,231 PE funds with vintage years from 2000 to 2017 with an average fund size of about \$1.5 billion and a net IRR of 18%. Korteweg

[6] We follow industry convention in referring to these fund employees as "partners". The lowest rank reported in Pitchbook is principal or director, implying that all employees in our count are senior employees.

and Nagel (2024) use a sample of 1,073 U.S. buyout funds from MSCI-Burgiss, with vintage years between 1978 and 2016. They have an average size of about \$1.1 billion and a net IRR of 16%. Harris et al. (2023) use data on 929 funds between 1987 and 2015, which have an average size of \$1.1 billion and a net IRR of 14% on average. Differences in vintage, along with our requirement that funds have at least \$100 million in committed capital and maintain relationships with one or more private university endowments, result in our sample being modestly tilted toward larger funds.

2.3 Survey of LPs

LPs are the consumers of PE, so it is useful to explore what they think about the relationship between fund size and return. Their views may reflect lived experience, research they've read or undertaken, or rules of thumb inherited from a previous manager. We conducted a survey in May 2025 of 1,129 institutional LPs, based on LP data from Pitchbook. The survey was sent by email, and its content as viewed by respondents is shown in Appendix C.1. We sent only one round of emails, and obtained a response rate of 7.2% (81 responses across 74 institutions). Over half the responses are from pension funds, which is appropriate since they provide the majority of capital to the industry. There are also foundations, sovereign wealth funds, family offices, and insurance companies.[7] Appendix Figures IA.C.1 Panels A and B show that relative to the emailed sample, respondents have more assets under management and are somewhat more likely to be U.S.-based. Overall, the sample contains a significant group of LPs, whose opinions are likely reasonably representative.

The first substantive question in the survey is: "If you could hold all other factors about the fund fixed (such as the quality of the manager), do you believe that smaller or larger funds tend to perform better?" We did not define "small" explicitly in the question, allowing respondents to interpret it relative to their own investment universe. This flexibility may reduce internal comparability, but better captures decision-making heuristics. The results are reported in Figure 2 Panel B; remarkably, 80% of respondents believe that smaller funds perform better. This contrasts with Panel A, which shows that there is no observable difference across fund terciles (this remains true if we alternatively consider fund quartiles or quintiles).[8] The share is relatively consistent across institution types,

[7]See Appendix Table IA.C.1, which collapses to the unique institution and reports by institution type.

[8]Recall from earlier that as in our sample, substantial previous work also shows no descriptive relationship between fund size and performance (Harris et al., 2014; Kaplan and Schoar, 2005; Robinson and Sensoy, 2013).

as shown in Appendix Figure IA.C.2. Note that this survey finding might reflect frictions in LP learning or salient past experiences; for example, LPs could perceive higher dispersion among small funds, and overweight top performers.

2.4 Descriptive Analysis

We present OLS estimates of the relationship between fund size and performance to set the stage for the causal analysis and to connect to prior literature. We use the following model:

$$\text{Return}_{f,p,t} = \beta \text{ Fund Size}_{f,p,t} + \delta_1 \text{ Prior Return}_{p,t} + \delta_2 \text{ Controls}_{p,t-1} + \alpha_p + \alpha_r + \alpha_i + \alpha_{l,t} + \varepsilon_f \tag{1}$$

Here, $\text{Return}_{f,p,t}$ is the net-of-fee return of a fund f of GP p with the vintage year of t. Fund $\text{Size}_{f,p,t}$ is the total capital committed to the fund in \$ Billions. GP fixed effects (α_p) address the concern that larger GPs might have the ability to raise larger funds or better access to endowments. We control for the region of the world targeted by the fund's investment strategy (α_r), as well as the targeted industry (α_i). We employ GP Region $\times$ Vintage Year fixed effects ($\alpha_{l,t}$) to ensure that regional trends in local capital supply or investment opportunities do not drive our results.[9]

We also control for time-varying factors at the GP level. First, we control for the GP's past performance using Prior $\text{Return}_{p,t}$. This is the average return of the GP's previous funds raised before year $t-5$. It is important because there is a positive flow-performance relationship in PE (Metrick and Yasuda, 2010). We use a five-year lag to avoid noisy interim performance measures for recently-raised funds (Korteweg and Nagel (2024)). We further control for the number and value of funds raised in year $t-1$ and earlier, the average size of funds raised prior during the year $t-1$ and before, and the number of years since the last fund was raised. We two-way cluster the standard errors at the GP and vintage year level.

The results are presented in Table 2, with IRR in Panel A and MOIC in Panel B. Across columns 1 to 5, the relationship between fund size and performance is negative but statistically insignificant.[10] These results are consistent with Kaplan and Schoar (2005), Robinson and Sensoy

[9]We define GP region into 4 U.S. regions (Northeast, South, North Central, and West) following the U.S. Census Bureau's classification and 1 broad international region, based on the state headquarter location of the GP.

[10]We find similar effect sizes using the broader sample of all funds—including those without any relationship

(2013), and Harris et al. (2014), who do not find a statistically significant correlation between PE buyout fund size and returns. However, they contrast with investor perceptions from our survey. This discrepancy between descriptive patterns and investor beliefs underscores the need for causal identification to assess whether observed performance is driven by the selection bias of higher-quality managers sorting into larger funds.

3 University Endowments: Context for Causal Analysis

This paper is motivated by the challenge to interpreting descriptive relationships between fund size and returns. As explained above, well-performing managers can raise larger funds, reflecting the importance of track record in fundraising (Howell et al., 2024). Therefore, unobservable manager skill might drive both fund size and performance. To establish the effect of scale, we must isolate variation in fund size that is orthogonal to other determinants of fund performance. We propose a new instrument for fund size: gifts to private universities, which the university endowment then allocates in part to PE managers with whom it has pre-existing relationships. The instrument must satisfy two conditions. First, to be relevant, donations must affect fund size, meeting standard thresholds for instrument strength. Second, donations must affect fund returns only through fund size. While this exclusion restriction cannot be directly tested, we offer three distinct pieces of institutional and empirical evidence that lend credibility to it.

In this section, we present institutional evidence motivating our instrument and supporting the exclusion restriction. Specifically, we argue that: (i) donations represent significant income variation for university endowments uncorrelated with fund or overall market performance; (ii) universities channel endowment funds to their relationship PE funds; and (iii) when a private university with a pre-existing relationship with a GP invests in a follow-on fund, it acts as a positive signal to other LPs about the quality of the fund.

to endowment funds—as reported in Table IA.1.

3.1 Donations and Endowment Investments

There is reason to think that endowment investments will shift with donations.[11] Jonathon King, who is the President & CEO of the UNC Management Company and was formerly the Chief Investment Officer for Dartmouth College, explained that:

> "When a donor establishes, for example, an endowed scholarship or professorship, that money goes into our long term investment fund. Every month the university sends us the cumulative gifts for that month. Over the course of the year, we receive typically between $100 and $300 million in gifts for our fund."[12]

A significant portion of private universities' funding comes from external donations, which in 2017 amounted to nearly $15 billion, representing approximately 20% of their total revenue. These donations are often large and right-skewed. For instance, in 2015, more than 13% (approximately $2 billion) of all donations came from large gifts exceeding $50 million while gifts above $1 million comprised about 20% of overall giving (see Figure IA.1). Therefore, a few, unpredictable large gifts can have an outsized impact on endowment investment capacity. In Table IA.2, we provide some examples of large gifts to university endowments, such as a single donation of $400 million made by John A. Paulson to Harvard University in 2015.

Rosen and Sappington (2016) show that "background income," defined as non-financial university income from sources such as donations, tuition, and public grants, have significant effects on endowment investment activity. They conclude that "universities that expect higher levels of background income: (i) are more likely to invest in alternative assets; and (ii) allocate a larger percentage of their endowments to alternative assets." Dimmock (2012) examines how university income risk affects endowment investment choices. He shows that non-financial university income has large effects on investment decisions; for example, lower variation in non-financial income leads to more risk-taking at the endowment.

Variation in university income is likely to flow to relationship GPs. This is because relationships between university endowments and GPs are "sticky." University LPs are 25 times more likely to invest in follow-on funds raised by GPs with whom they have previously invested, relative to a random GP who is fundraising, as shown in Figure 3. Consistent with these data, Tim Sullivan, the

[11] Using data from IRS Form 990 schedule D available from 2008 onward, we find that ≈ 90 percent of gifts to university endowments are cash gifts (rather than non-cash or other financial assets) and ≈ 50 percent of total gifts are contributed to the endowment rather than directly spent.

[12] One of the authors spoke with Mr. King in May 2025. Mr. King has managed the UNC Investment Fund, which invests UNC endowment assets, since 2005. Before that, he was the CIO for Dartmouth College.

longtime head of PE investment at the Yale Endowment, explained that endowments invest in the same GPs repeatedly in part because:

> "If you know the people and strategy and have seen their performance up close, the risk of a bad outcome is lower, even if you might worry that their performance might not be as good as in the past. Also, as practical matter, people don't want too many managers or relationships."[13]

Therefore, more donations to a university are likely to increase capital supply for GPs who (a) have pre-existing relationships with that university; and (b) are fundraising. The GP can leverage this commitment to raise a substantially larger fund.

3.2 The Signal of a University Endowment Commitment

University endowments have historically played an important role in the PE industry. A long-standing literature has focused on the essentially infinite investing horizon of university endowments and their ability to serve as consistently liquid, long-term allocators in relatively high-risk assets (Gilbert and Hrdlicka, 2015; Hansmann, 1990; Tobin, 1974). Starting in the early 2000s, large university endowments ramped up their allocations to alternative assets, of which PE is by far the largest portion (Lerner et al., 2008). Today, large university endowments typically allocate about 35% of their assets to PE, and even more for the most elite universities (Unglesbee, 2024).[14] We hypothesize that when an endowment which has a pre-existing relationship with a GP invests in a follow-on fund, it will serve as a positive signal to other LPs, leading to an overall substantially larger fund. One mechanism for this is the inside information that comes from any pre-existing relationship between an LP and a GP. Once an LP invests in a fund, it observes much more information about the GPs performance than can be gleaned from an initial pitch. For example, LPs typically receive regular reports on how portfolio companies are doing, how the fund's strategy is evolving, and what is and is not working well. The decision of the LP about whether or not to invest in the follow-on fund serves as a credible signal about the GPs quality.

In addition, university endowments are often considered "smart money" by significant institutional LPs, in a setting characterized by much larger information asymmetries than in public markets. Conversations with industry practitioners suggest that when a GP has a commitment

[13]One of the authors spoke with Mr. Sullivan in January, 2025, when he was the Senior Director of Private Equity. Mr. Sullivan has been investing in PE on Yale's behalf since 1986.

[14]See https://www.highereddive.com/news/private-equity-university-endowments-harvard-yale/721514/.

from a university LP, it is considered a credible, positive signal to other investors. For example, Will McLean, the CIO for Spider Management, noted that “for good or bad, LPs tend to follow investors they respect, and university signaling does happen.”[15] As a second example, Rick Slocum, the CIO of the Harvard Management Company, said that “If we enter a fund, it’s usually a positive signal for other LPs. And we do typically put our money to work with relationship GPs. If they are doing a good job, we continue to invest.”[16] Cole et al. (2020) survey anchor investors and conclude that there is “a catalytic ‘halo’ effect for funds receiving anchor investments, as funds benefit from an early endorsement by a respected investor.”

To examine the views of LPs broadly, we asked the following question in our LP survey (which was introduced in Section 2.3): “Suppose you were considering investing in a fund and you were informed that a large private university endowment had already committed to that fund. Would this increase your chances of investing?” The results are reported in Figure 4. We see that 8.6% reported it would be very important, and 50.6% reported it would be somewhat important. The remaining 40% reported that it would not influence them. Appendix Figure IA.C.3 shows that the share saying it would be at least somewhat important is spread fairly evenly across institution types. Thus, a majority of LPs responding to our survey would update their beliefs about a fund positively after learning about a university. Note that our mechanism requires *some* other LPs to respond to the university commitment, not all of them. Also, recall that our surveyed sample is positively selected on larger LPs, suggesting that the certification effect might be even stronger for an average LP.

The perception of university endowments as strong allocators contrasts with that of pension funds. Pension funds have struggled to retain strong managers and face political pressures on investment decisions, causing their returns to suffer (Andonov et al., 2018; Andonov and Rauh, 2022; Lerner et al., 2007). Consistent with this, Figure IA.C.4 shows that the distribution of responses is very different when we ask about the signal value of government pension commitments. A majority (59%) of respondents would not be influenced at all by learning about such a commitment, and 7.4% would view it as a negative signal.

[15] One of the authors spoke to Will McLean in June, 2025. Spider Management manages the University of Richmond and other endowments. Mr. McLean was formerly the CIO of the Northwestern University endowment.

[16] One of the authors spoke to Rick Slocum in January, 2026.

3.3 Data Sources on University Endowments

We focus on private rather than public universities because private universities hold the majority of endowment assets,[17] are more reliant on gifts,[18] and explicitly report the amount of gifts from outside donors on Part VIII, Line 1F.[19] Private universities report these gifts on Form 990, which is required to maintain their nonprofit status under Section 501(c)(3) of the IRS code. In contrast, public universities aggregate gifts, grants, and government contracts in their IPEDS reporting (Association of American Universities, 2024).

We measure university-linked donations to a fund as follows. For a fund f of a GP p with the vintage year t (defined in Preqin as the year of the fund's first investment), we construct the linked donations (*Raw Gifts*) as the sum of gifts the GP's university LP base received in year *t-2*. We lag gifts by two years to ensure these donations occur before or during fundraising, which typically lasts 12-18 months. The university LP base includes all universities that have invested in the GP's funds from years *t-7* to *t-3*. This five-year interval follows Hochberg et al. (2007) and is intended to capture actively maintained relationships between universities and GPs. We illustrate how this measure works for the case of Emory University and Yorktown Energy Partners in Figure IA.2. For analysis, we standardize *Raw Gifts* to construct $\text{Gifts}_{p,t-2}$.[20]

To capture linkages across private universities and GPs, we use data from Preqin about university investments, which we augment with novel data from IRS Form 990-T. Private universities file IRS Form 990-T to report unrelated business taxable income (UBIT) from activities that are unrelated to their tax-exempt educational and charitable purposes which primarily stems from their investments. Form 990-T requires universities to disclose total UBIT each year, and in many cases includes an itemized breakdown that lists specific PE funds.[21,22]

[17] 80% of the $450 billion in university endowments as of 2017 were held by private universities. The top 10 private university endowments accounted for 55% of all private university endowment assets.

[18] Donations account for 20% of annual revenues for private schools, compared to 3% for public universities (Binfarè and Zimmerschied, 2024)

[19] Reported gifts are measured on an accrual basis and include both realized cash inflows and the present value of pledged contributions that might be realized in future years following an unconditional promise to give. In Appendix D, we construct a cash-flow-based measure that nets out changes in pledges receivable and show that our results are robust to this adjustment. This is consistent with realized cash inflows accounting for the majority (typically over $>$ 80%) of reported gifts in most university-years.

[20] We standardize Raw Gifts by subtracting the sample mean and dividing by the standard deviation across funds, so that regression coefficients represent the effect of a one-standard-deviation change.

[21] See Figure IA.3 for a sample 990-T form from Baylor University for the 2005 academic year.

[22] Disclosure of private equity partnerships on Form 990-T is typically contingent on the investment

We scrape Form 990-T from ProPublica for the largest 110 private universities (based on endowment assets), and we find that about 40% of university-year observations contain an itemized breakdown of partnerships, a group that includes elite endowments such as Harvard, Yale, and Princeton. We convert these PDFs into text using an OCR-reader and hand-match listed funds to their Preqin Fund IDs.[23] Although we only observe itemized breakdowns for a subset of university-year observations, we benefit from the fact that the average PE fund life is 10 years. Moreover, our measure of university-GP linkage requires only one investment during a five-year window. In total, Figure IA.5 shows that relative to using only Preqin data, we increase the coverage of private university investments by about 50%.

Table 3 Panel A presents statistics on gifts, endowments, and investments at private universities. The average university receives \$110 million in gifts from outside donors, with a maximum of nearly \$1.7 billion. Average endowment assets total nearly \$2.5 billion. The average private university has about two relationship GPs with which it has invested in the last five years, or 3.84 when weighted by endowment size. [24] The average fund is linked to over \$220 million in donations across its private university LP base. $Gifts_{GP}$ has a mean near zero by construction. The average GP is linked to about two universities and these linkages tend to be quite persistent. Private university endowments account for a meaningful share of capital commitments in private equity. Conditional on a fund having at least one private university LP, such endowments comprise approximately 12% of the LP base in a typical fund.

4 First Stage Estimates and Validation

In this section, we present the first stage estimates of our 2SLS specification and conduct tests of the instrument's validity. The first stage regresses fund size on GP-level gifts to relationship

generating non-zero UBIT as only around 4% of disclosures report UBIT values of \$0. Figure IA.4 plots the distribution of raw UBIT in Panel A and the disclosed UBIT relative to a private university's estimated commitment size in Panel B. Disclosed annual UBIT values are small in absolute magnitude with a mean (median) of -\$24,970 (-\$253) and are concentrated near zero when scaled by commitment size. These magnitudes are consistent with residual UBIT exposure flowing through to universities even in the presence of blocker corporations, which might reduce UBIT without completely eliminating it.

[23]We plan to make the list of fund investments by private universities publicly available for future research.

[24]For this summary table, we construct a balanced university $\times$ year level which results in ≈ 30 percent of observations, primarily among smaller private universities, having no relationship GPs mechanically lowering the average.

universities using the following equation:

$$\text{Fund Size}_{f,p,t} = \gamma\ \text{Gifts}_{p,t-2} + \delta_1 \text{Prior Return}_{p,t} + \delta_2 \text{Controls}_{p,t-1} + \alpha_p + \alpha_r + \alpha_i + \alpha_{l,t} + \varepsilon_f \quad (2)$$

We condition on the GP raising a subsequent fund, focusing on the intensive margin. The outcome variable, Fund Size$_{f,p,t}$, is measured in billions of dollars. The instrument, described in Section 3.3, is Gifts$_{p,t-2}$. The controls in this baseline model are the same as in Equation 1, though we conduct many robustness tests to ensure that particular specification choices do not drive our results. We double cluster standard errors at the GP and vintage year level.

The first stage results are reported in Table 4 Panel A. Our preferred estimate in column 5 shows that a one standard deviation increase in the GP-level gifts ($390 million) measure is associated with a $322 million increase in fund size.[25] The effect is statistically and economically significant, implying that a $1 increase in donations leading to a $0.83 increase in fund size.[26] The first stage F-statistic is 30.7, which shows that our instrument is sufficiently strong. Figure 5 graphically illustrates this relationship, and also suggests declining sensitivity in fund size as gifts approach the right tail of their distribution.

We can use a back-of-the-envelope calculation to interpret the magnitude. First, note that approximately 87% of university gifts are in cash, and about 47% of that is allocated to the endowment. Thus, a $390 million increase in gifts translates into roughly $159 million in additional endowment contributions ($390 × 0.87 × 0.47). Assuming a 37% allocation to private equity (Unglesbee, 2024), this corresponds to approximately $59 million flowing into the private equity investments. Endowments are typically connected to multiple GPs, but only a subset raise funds in a given year. The endowment size-weighted average number of connected GPs is 3.84, while the average number of new funds raised annually by these GPs is 0.35. This implies that, on average, a university allocates approximately $44 million ($59 ÷ [3.84 × 0.35]) of incremental capital to each new fund to which it is connected. Our first-stage estimates indicate that fund size increases by $322 million in response to these donations. Taken together, this implies that $44 million in direct university capital is associated with a $278 million increase in other fund-raising ($322 − $44), suggesting a multiplier of 6.3x, i.e. each $1 of university LP capital crowds in approximately $6.3 of committed capital ($278 ÷ $44).

[25] A one unit increase in Gifts$_{GP}$ corresponds to a one standard deviation increase in Raw Gifts.

[26] This estimate is obtained by dividing the expected increase in fund size ($322 million) with a one standard deviation change in *Raw Gifts* ($390 million).

This amplification is consistent with a certification effect, where endowment investments in connected GPs based on pre-existing relationships and informational advantages serve as a positive signal to other LPs, who subsequently contribute the majority of the additional capital. Supporting this interpretation, we show that greater exposure to our instrument predicts a larger number of other LPs in the fund (Appendix Table IA.5). For example, Column 1 shows that a one standard deviation increase in GP-level gifts is associated with approximately five additional LPs, relative to a mean of about 24. Columns 2 and 3 indicate that this increase is driven by pension funds and other institutional investors (e.g., insurance companies and corporate pensions), with a modest increase in private foundations.

Despite the increase in fund size, LP composition remains stable. Given that each dollar of gifts crowds in \$6.3 in committed capital, direct university donations account for 13.7% of the total new fund-raising (\$1 ÷ (\$1+\$6.3)). This figure is close to the baseline share of university endowments in the LP base (around 12%), implying that fund expansion occurs without a meaningful shift in the relative importance of university investors. Consistent with the calculation, we find no statistically significant change in the share of AUM from pension funds, a large LP group for which dollar commitment data are available (Column 5). Overall, the evidence suggests that capital inflows from relationship universities crowd in additional investment from other LPs, leaving the composition of the investor base broadly unchanged.

In Table IA.3, we repeat these estimates for the slightly larger sample in which we observe the MOIC, and find similar results. In Table IA.4, we show that the first stage result holds for both small and large university endowments, though it is stronger for the larger ones, consistent with them sending a stronger certification signal. Overall, these results show that GPs raise larger funds (relative to their average fund size) when their related universities receive more gifts compared to other GPs raising funds within the same year and geographic region.

We further test if there is any impact of these donations on the extensive margin, by changing the probability of new fund formation. Table IA.6 shows that our results are driven by increasing fund size rather than any increase in the number of funds launched. These results are consistent with our focus on the intensive margin effects of exposure to university donations for GPs *conditional* on raising a fund.

Exclusion Restriction Tests. Conditional on controls included in the IV regression, university donations should affect connected GP fund returns only through their effect on fund size. Our most compelling evidence for the exclusion restriction is a placebo test that randomizes GP-university connections while preserving vintage-year structure. In column 1 of Table 4, Panel B, we randomize LP commitments at the vintage-year level—assigning universities to random GPs with funds in the same vintage year—while holding the instrument and specification otherwise identical to Equation 2. The results show that private university donations not connected to a focal GP do not predict fund size in the first stage. Figure IA.6 further illustrates this by comparing a bootstrapped distribution of first-stage *F-statistics* from the placebo setup in Table 4, column 1 (with randomized university × year connections), to our main first-stage estimate from Panel A, column 5 (with observed connections). None of the placebo estimates surpass the conventional threshold for instrument relevance (Bound et al., 1995).[27] These results support the interpretation that our identification is driven by university-GP relationships rather than by spurious aggregate time trends.

We also test whether the gifts instrument is correlated with GP- and fund-level characteristics that are observable ex-ante and might affect fund returns. The results are displayed in columns 2 to 6 of Table 4 Panel B. We do not find a statistically significant relationship between a GPs prior IRR (column 2), number of funds raised in the past (column 3), and time since the last fund closed (column 4), indicating that the gift inflow is not driven by the past performance and fundraising activity of the GP. Furthermore, we do not find that donations are correlated with the level of carried interest or the management fee (columns 5-6).

Although the placebo test addresses concerns that macroeconomic factors such as market cycles or overall capital supply might simultaneously drive both donations and fund returns, we also directly test this hypothesis by comparing market returns with university donations. In Figure 6, we plot S&P 500 returns alongside university donation patterns: each gray line represents an individual university, and the red line shows the total value of large gifts (above $1 million). The figure reveals little correlation between market performance and donation flows, with substantial idiosyncratic variation across universities in a given year. A similar pattern emerges at the GP level in Figure 7, where the red line shows average aggregate gifts across GPs, and the gray lines represent individual GPs. Again, we observe no relationship between stock market returns and donations, and substantial heterogeneity across GPs. Together, these findings provide both institutional and

[27] We find similar results when constructing the placebo instrument using donations received by universities to which a GP is *never* connected.

empirical support for the validity of the exclusion restriction.

A final concern is that our results may be confounded by individuals who both benefit from PE returns and make donations to universities, thereby creating a spurious correlation between PE performance and donation levels. To address this, we exclude all donations from individuals affiliated with PE, the broader finance industry, or within the same state as the university. Our results remain robust to these exclusions. We provide a detailed discussion of this and other robustness checks following the description of our main specification.

5 Effect of Fund Size on Returns

To estimate the causal effect of fund size on returns, we use the following second stage equation:

$$\text{Return}_{f,p,t} = \beta \; \widehat{\text{Fund Size}}_{f,p,t} + \delta_1 \text{ Prior Return}_{p,t-1} + \delta_2 \text{ Controls}_{p,t-1} + \alpha_p + \alpha_r + \alpha_i + \alpha_{l,t} + \varepsilon_f \tag{3}$$

The outcome variable, $\text{Return}_{f,p,t}$ is again the net-of-fee return of fund f of the GP p that has a vintage year t. The key independent variable, $\widehat{\text{Fund Size}}_{f,p,t}$, is the predicted value of fund size from the first stage in Equation 2. The set of fixed effects and controls are same as in the first stage.

The main estimates are reported in Table 5. To interpret the effects, we focus on the most tightly specified model in column 5. The effect of -0.053 on IRR in Panel A implies that a 1% increase in fund size (an increase of \$15.1 million) reduces a fund's net IRR by 0.1 percentage point (0.0151×0.053). Alternatively, experiencing top-quartile growth in fund size (approximately \$600 million) reduces a fund's net IRR by 3.2 percentage points (0.6×0.053). These results are economically meaningful, since the average net IRR in our sample is 18%. In Panel B, we consider the MOIC. The coefficient in column 5 indicates that a 1% increase in fund size reduces fund net MOIC by 0.4 percentage points (0.0151×0.252), which is 0.21% of the mean in the sample.[28] In sum, there is a large decline in performance as funds scale up.

There are two other takeaways from the table. First, the results are similar across specifications, suggesting that region, industry, and time do not play a major role. This offers comfort that the

[28] Regressions that use net multiple as the dependent variable have slightly more observations (1,306 versus 1,231) as Preqin has more available data for this measure than IRR.

IV is identifying exogenous variation. Second, there is a negative coefficient on prior performance (columns 4 and 5 of both panels), indicating that there is mean reversion in fund returns.

As noted earlier, IRR and MOIC are widely used in industry (Gompers et al., 2016) and are highly correlated with more sophisticated cash-flow-based risk-adjusted performance measures (Brown et al., 2025). However, a potential concern is that unadjusted measures of performance such as net IRR or multiples may not fully account for the timing of cash flows or differences in risk exposures. In Table 6 we re-estimate our results using cash-flow based performance measures using Direct Alpha (Gredil et al., 2023), PME (Kaplan and Schoar, 2005), and α (Korteweg and Nagel, 2024), which benchmark fund performance against public markets and, in the latter case, explicitly adjust for systematic risk. These measures are constructed using cash flow level data from MSCI-Burgiss for the subset of funds with available data.[29] Panel A of Table 6 replicates our baseline IRR results in this restricted sample and finds coefficient magnitudes similar to those in the baseline specification. Panels B and C of Table 6 show that increases in fund size lead to statistically and economically significant declines in Direct Alpha and PME, respectively. These results are robust to alternative benchmark choices, such as the Russell 3000 in place of the S&P 500 (Brown et al., 2025). Panel D of Table 6 examines the impact on a fund's α and shows that increases in fund size lead to declines in risk-adjusted performance even while allowing for private equity funds' market exposure to vary from one.[30] Overall, these results indicate that larger funds underperform.[31]

Risk-Return Trade-off Lower fund returns might not necessarily indicate worse performance if increasing the fund size leads to lower risk. To investigate the effect on return dispersion, we divide the funds in our sample into quartiles by net IRR. Then we examine if larger values of predicted fund size increases the likelihood that the fund is in 2nd or 3rd quartiles, which implies it is less risky (i.e., not in the tails of the distribution). In Table 7, we present the IV results using these binary outcome variables representing indicators for the fund falling in one of the four net return quartiles, with IRR in Panel A and multiple in Panel B. Column 1 of Panel A shows that a one

[29] Requiring cash flow level data reduces our sample from 1,231 funds to $\approx$ 530 funds across more than 140 GPs. Due to the smaller sample, we exclude Year $\times$ GP Region fixed effects while all other controls and fixed effects mirror our main specification.

[30] In our sample of PE funds, we estimate a β of 0.77 and average α of 0.27. These estimated parameters are of comparable magnitude to Korteweg and Nagel (2024) which estimates a mean α of 0.19 and β of 0.91.

[31] Table IA.7 shows the OLS relationship between fund performance and fund size with increases in fund size being linked to a decline in fund performance.

percent increase in fund size (about \$15.1 million) increases the likelihood of a fund's return falling into the bottom quartile by 0.25 percent (0.0151×0.169). On the other hand, such an increase results in a 0.26 percent (0.0151×-0.175) decline in the probability of a fund achieving very higher returns. There is a similar pattern for the MOIC in Panel B. In sum, we find a leftward shift in the overall distribution as funds grow in size. We present this graphically in Figure IA.7. These results suggest that larger funds are not necessarily safer and their lower average returns indeed signify worse performance outcomes.

External Validity. The variation driving our IV estimate comes from GPs who raise more money when exposed to more university donations. A question is whether these GPs are similar to the typical GP, and thus whether our results could reasonably be expected to generalize. Although we cannot affirmatively test for external validity, we compare funds launched by GPs with university connections and other funds which meet our sampling restrictions, but whose GPs lack connection to a private university LP in Table IA.8. Overall, funds launched by university-connected GPs tend to be slightly larger on average and these GPs more frequently fundraise. However, the median across most of the fund comparison measures is quite similar. While our results may be more applicable to more established GPs, this is also the most relevant subset: larger funds are disproportionately concentrated among these GPs, and are likely to grow further as they lead the expansion into retail investor capital.

Robustness Tests. We also conducted many robustness tests related to sampling choices and variable construction. The results are reported in Table 8, with the baseline main result in the top row for easy comparison. The first group of tests adjusts the sample. In row 2A, we add funds from the 1990 to 1999 vintages to our baseline sample which originally only includes funds from 2000 to 2017 to allow for a better capturing of university $\times$ GP relationships. The effect is very close to our baseline result. Next in row 2B, we include GPs with and without relationships to private universities, which expands our sample but results in nearly identical effect sizes. In row 2C, we include funds from the full sample (2A + 2B) while removing fund of funds and find similar results. In row 2D, we exclude the 10 largest GPs from our sample to demonstrate that our results are not driven exclusively by funds raised by a subset of the largest GPs. In row 2E, we exclude funds above the 90th percentile value in terms of the number of investments and we find similar results. In rows 2F and 2G, we exclude funds in the bottom and top deciles of fund size, respectively.

Overall, we find evidence of a negative relationship between fund size and performance throughout the distribution of fund size.

In row 2H, we include the number of universities that a GP is related to as the control variable. This ensures that the variation in our instrument is primarily coming from the change in gifts to the universities that the GP is already connected to, instead of coming from the formation and termination of GP-endowment relationships. The results are consistent with our baseline analysis, and the first-stage F-statistic increases, indicating that changing relationships do not explain the results. In rows 2I and 2J, we find that our results are robust to including controls for the performance of recent funds (between years [*t-5*,*t-1*]) and funds regardless of their size, respectively.

Next, we use alternative definitions of our key variables. In row 3A, we report results using *Raw Gifts*, defined as the non-standardized level of gifts (in billions of dollars), and find estimates comparable to those in our baseline specification. In row 3B, we use gifts data from an alternative source to create our instrument. Instead of using the 990-T filings, we use the IPEDS data on gifts, grants, and contracts to construct our instrument which documents a similar effect across a broader measure of gifts. In row 3C, we construct the instrument using only large gifts (those above $1 million), which have a more fat-tailed distribution and thus might contribute more variation to the instrument. The coefficient is similar to the main result. In row 3D, we exclude large gifts from in-state donors to address concerns that local conditions might drive both gifts and the PE fund industry and our effect size remains largely unchanged.[32] In row 3E, we instrument for the logarithm of fund size rather than continuous fund size to minimize the effect of outliers and we find an economically similar effect size.[33] In row 3F, we net out changes in pledges receivables from reported gifts to approximate a cash-flow based measure. The coefficient is unchanged relative to the baseline, reflecting the high correlation between the two measures ($\rho \approx 0.99$) while the first-stage F-statistic increases, consistent with cash-flow based gifts more closely capturing LP investment

[32]When aggregating the large gifts at the university $\times$ year level, we include only donations denoted as gifts (rather than pledges) and we also set an upper-bound for large gifts at 90% of the gifts a university received in a given fiscal year to better capture when these large gifts reach the university. Our results are robust to removing this upper-bound in comparing large gifts to the university's reported donation inflows.

[33]Our coefficient of -0.108 implies that a 1% increase in fund size leads to a decline in net IRR of 0.108%, which closely matches our baseline economic effect: a 0.1% decrease in returns for every 1% increase in fund size. The first-stage coefficient is 0.157, indicating that a one-unit increase in Gifts-GP (equivalent to $390 million) raises fund size by 15.7% relative to the average fund size of $241.60 million. Put differently, each additional $1 in donations is associated with a $0.62 increase in fund size ($241.60 divided by $390), again closely aligning with our baseline estimate.

decisions.[34] In row 3G, we expand our instrument to include gifts received from *t-4* to *t-2* to account for the gradual conversion of pledges into cash, and find economically similar results.

Our last set of tests adjust the way that we control for time and the inclusion of other controls. In rows 4A-4F, we exclude year fixed effects. Instead, we include a linear time trend (row 4B), include annual controls for total PE fund raising (row 4C), and control for year fixed effects rather than year × location fixed effects (row 4D). The effect becomes slightly larger and remains highly significant. In row 4E, we add GP state × vintage year fixed effects to our baseline specification and find consistent results which shows that more fine-grained location × year effects are unlikely to drive our results. In row 4F, we include fund industry × year fixed effects to account for time-varying differences in investment opportunities across fund types and find comparable results to our baseline specification. Overall, these tests show that the negative relationship between fund size and net IRR is a robust finding. In row 4G, we include controls for the average company age and leverage within a given fund, and we find our results are largely unchanged.[35] Table IA.10 repeats these tests using net multiple as the performance outcome.

A final concern is reverse causality, where GPs with higher returns might donate to universities, thereby increasing fund size. Table IA.9 shows that our results remain consistent after excluding university donors affiliated with PE or the broader finance industry.[36] These tests help rule out the possibility that the ability of PE firms to generate returns and the philanthropic behavior of wealthy individuals are endogenously linked in a way that would bias our estimates.

6 Why Do Larger Funds Have Worse Performance?

To understand why a larger fund size attenuates performance, we first examine how larger funds differ from smaller ones in terms of their investment strategy. To do so, we employ deal-level information to identify investment characteristics that differ across small and large funds and study which of these differences drive the negative size-performance relationship. Overall, the data point

[34] See Appendix D for additional details and validation of the reconciliation used to construct this cash-flow based measure.

[35] We interpolate age and deal leverage to the average and including an indicator variable when a fund is missing deal-level information.

[36] Appendix F provides additional details on the prompt used with OpenAI's API to classify donor affiliations and the share of gifts originating from private equity and finance-related sources of wealth.

to larger deals as the primary culprit: In causal analysis, larger funds make larger investments, and these larger deals perform worse.

In Panel A of Table 9, we present the causal effect of fund size on portfolio strategy.[37] The first outcome is the fund's average deal size, in millions of dollars. The coefficient in column 1 is large and significant at the 1% level. It implies that a 1% increase in fund size increases the average deal size by about \$0.4 million (.0151 $\times$ 23.88), which is 0.4% relative to the sample mean (\$98.47 million). Alternatively, top-quartile growth in fund size (approximately \$600 million), increases the average fund's deal size by \$14.3 million (0.6 $\times$ 23.88), which is 14% of the mean deal size in the sample. This result does not reflect the portfolio company's sector, age, or deal leverage, which might be correlated with fund size.[38]

Next, we examine the number of deals in column 2. The coefficient is also large and robust; it implies that a 1% increase in fund size leads to 0.1 more deals or a 0.5% increase relative to the mean ($\frac{0.015\times7.02}{19.15}$). If larger funds do more deals, they may take longer to execute all LBO transactions. Consistent with this, column 3 shows that a larger fund size causes a longer investment period, with the last deal executed about two months later for a 1% increase in fund size. In descriptive analysis, we do not find that later deals tend to have lower returns. Last, we find no measurable effect on diversification across industries or geographies in columns 4-6.

If the increase in number of deals drives the effect of fund size on performance, it would likely reflect managers becoming stretched too thin. In turn, this implies they are doing more deals without scaling the investment team. To test this, we collect information on the number of partners managing the fund from Pitchbook. The results are reported in Panel B of Table 9. The number of partners increases by 0.5% relative to the mean ($\frac{0.015\times2.36}{7.33}$) in response to a 1% increase in fund size (column 1). Therefore, the growth in the number of investments is proportional to the growth in team size suggesting that additional deals are offset with new hires. This is formalized in columns 2 and 3, where we show null effects on the number of deals per partner and AUM per partner. Another possibility is that larger funds hire relatively inexperienced managers, leading the team to be less sophisticated and skilled. We study this in column 4, where the dependent variable is the number of prior funds that the GPs have managed, averaged across the focal fund's managers.

[37]We interpolate missing fund-level characteristics to the sample mean and include missing-value indicators for all average deal-level characteristics when the number of deals is observed but the deal characteristic is missing. This ensures a consistent sample across specifications.

[38]These results and further robustness tests are available on request.

We find no evidence that manager experience declines. In sum, stretched or lower quality human capital does not seem to be a primary driver, though we cannot rule out that it plays a role.

Our evidence thus far suggests that larger deal size is an important—if not the main—driver of lower returns from larger funds. We explore this further by using our instrument at the deal level to predict deal size.[39] The first stage results are reported in Table IA.11. The instrument has strong predictive power over deal size, consistent with a causal channel for larger deals at larger funds.[40] We turn to the second stage in Table 10, where the outcome variable is deal-level IRR. Column 1 shows that a 1% increase in deal size ($1.41 million) reduces a deal's gross IRR by 0.18 percentage points (.0141 $\times$ 0.13). This is a significant decline in returns given that the gross IRR of an average deal is 21 percent. How much of the decline in fund returns is explained by the decline in deal-level returns? Mapping this effect onto the earlier results on deal size suggests that the increase in deal size induced by exogenously larger funds can explain more than 60% of the total decline in fund-level returns.[41]

Brown et al. (2023) show in descriptive analysis that larger deals have lower returns, but that they are also less risky. We examine whether there is a causal effect of larger deal size (induced by a larger fund) on risk. As in the fund-level analysis, we divide the deals into four equal groups on the basis of their gross IRR. Then, we study whether deal size affects the probability of the deal falling within each of the four buckets. Columns 2-5 of Table 10 document that larger deals are more likely to be in the lower return quartiles and less likely to be in the higher return quartiles. For example, column 2 shows that a 1% increase in deal size increases the probability of a deal falling in the bottom quartile by 0.2 percentage points (0.15 $\times$ 0.0141) while columns 4 and 5 show a decline in the chance of being in the top two quartiles. In other words, the distribution of returns does not compress, but instead, shifts leftwards with the increase in deal size as shown graphically

[39] The endogenous variable is now Deal Size$_{d,f,p,t}$, which is the size of deal d in fund f, expressed in $100 millions. Fund f belongs to the GP p and has the vintage year t. The instrument is Gifts$_{p,t-2}$, which is the sum of gifts that all private universities related to the GP p received in the year $t-2$.

[40] The results in column 5 show that the expected increase in fund size stemming from a 1 standard deviation increase in the GP-level gifts increases average deal size by $14 million. Relative to the average deal size of $141 million this increase represents about a 10% increase.

[41] In Panel A of Table 9 we showed that a 1% increase in fund size ($15.1 million) increases deal size by $0.4 million (.0151 $\times$ 23.88). Plugging in this estimated increase in deal size to column 1 of Table 10, a 1% increase in fund size reduces deal returns by 0.05 percentage points (0.004 $\times$ 0.13). Table 5 shows that 1% in fund size reduces fund net IRR by 0.08 percentage points (0.0151 $\times$ 0.053). Accounting for the fact our estimated deal-level declines use gross IRRs while our fund-level results use net IRRs, suggests our estimates provide a lower bound of the true proportion of the role increasing deal size plays in reducing returns.

in Figure IA.8.[42] Similar results using the multiple are in Table IA.13. In sum, there appear to be diseconomies of scale at the deal level.

In our final analysis, we use the deal-level IV specification to explore channels that might explain the negative effect of deal size on performance. We focus on the three dimensions of PE performance: selection, financial engineering, and operational engineering (Gompers and Kaplan, 2022). The results are in Table 11, with selection variables measured at the time of entry (but post-LBO) in columns 1-2 and engineering variables representing change between deal entry and exit in columns 3-4. First, instrumented larger deals are more profitable relative to the mean, with a $100 million increase in instrumented deal size associated with 30% higher entry profitability (column 1). This suggests less scope for improvement. Column 2 shows that instrumented deal size is associated with 39% more indebtedness post-LBO. This could reflect more use of debt in the LBO, or it may reflect buying companies that are more ex-ante indebted. Either way, it suggests that larger deals have larger debt service burdens and less ability to take on new debt over the course of the deal.

We proxy for operational engineering with the change in the ratio of EBITDA to enterprise value from entry to exit. Column 3 of Table 11 shows that a $100 million increase in deal size reduces profitability growth by 0.02 pp, which is 100% of the mean. We also examine if managers increase the indebtedness (measured as the change in the ratio of a company's debt to enterprise value from entry to exit) of their targets but do not find a statistically significant effect (column 4). Overall, these results are consistent with larger funds incentivizing "quiet life" behavior, in which the GPs invest in more profitable, larger companies. They then seem to do less operational engineering post-LBO, which leads to lower deal-level returns. As a result, larger deals drag down the average returns of the entire fund.

Our survey of LPs and interviews with endowment executives support this interpretation. First, in the survey, we asked respondents to explain their preference for larger or smaller funds.[43] Figure 8 presents word clouds summarizing their responses, separately for those who reported that smaller funds perform better (Panel A) and those who reported that larger funds perform better (Panel B).[44]

[42]This causal result contrasts with the OLS results in Table IA.12 which finds that increasing deal size compresses the expected deal return to the middle of the distribution.

[43]Specifically, we asked: "Why did you answer that one type performs better than the other?"

[44]To build word clouds, we first extracted from each response the two most relevant phrases using ChatGPT and excluded common or generic terms. Excluded common words include large, larger, small, smaller, fund, size, etc., question, answer, invest, better, outperform, outperformance, performance, lower, less, higher, underperform, market, options, and outcome.

Respondents who prefer smaller funds explain their outperformance through better opportunities to reduce inefficiency through operational improvements, better incentive alignment with LPs, and better exit value. In contrast, those who prefer larger funds do so because they believe they offer diversification as well as manager access and negotiating power.

Second, four interviews with top endowment executives offer anecdotal evidence. Tim Sullivan, longtime head of PE investments for the Yale endowment, told us that:

> "For PE managers, big companies feel better; they have deeper management, are easier to finance, and are easier to buy and sell. But it means there is less you can do to make them a better company, and fewer people who want to buy it in the first place. Then you wake up and wonder why you're not generating the returns that you used to."[45]

As a second example, Jonathon King, President of UNC Management Company and CIO of the UNC Investment Fund, told us that:

> "We strongly prefer small size funds...We think smaller funds can bring more operational enhancements to smaller companies than larger funds can with larger companies."[46]

Third, Rick Slocum, CIO for the Harvard Management Company, explained that

> If you're good at identifying excellent first-time GPs, who typically have spun out of other buyout firms, have the expertise, but have something to prove – you have the opportunity to generate much higher returns than with established, institutional quality funds, that are much larger in size. A lot less has to go right if you pay 5x EBITDA for a company than if you pay 15x.

And finally, Will McLean, CIO for Spider Management, noted that:

> "While small size funds have better return opportunities, their distribution of returns is wider. There is certainly more ability for the manager to add value, but more problems can develop with small businesses. The best funds can exhibit persistent returns if they maintain discipline around fund size. That is difficult to do, and many do not have the courage to remain true to the part of the market where they generated great returns. If fund size doubles for each successive fund, it is usually a sign to move on as future returns will likely be lower."[47]

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[45] One of the authors spoke with Mr. Sullivan in January 2025, when he was the Senior Director of Private Equity. Mr. Sullivan has been investing in PE on Yale's behalf since 1986.

[46] As noted above, one of the authors spoke with Mr. King in May 2025.

[47] One of the authors spoke with Mr. McLean in June 2025. Mr. McLean is the CIO for Spider Management Co. which manages the Univ. of Richmond endowment and OCIO services for other endowments. Before that, he spent 19 years as the CIO for Northwestern University.

These quotes support our key finding: In a causal sense, small funds perform better because they invest in smaller deals with more scope for operational improvement. They also highlight the challenges facing LPs when relationship GPs look to raise larger funds.

7 Implications for Discounted Cash Flows

Thus far, we have shown that increasing fund size leads to a decline in returns driven by GPs doing larger deals that perform worse. In this section, we calculate the net present value (NPV) implications of our results for LPs and GPs. LPs, such as university endowments, are better off allocating an additional dollar to the same fund as long as the marginal rate of return exceeds their opportunity cost (i.e., discount rate). GPs considering raising an additional dollar must balance the increase in fixed fee collection with the decline in variable carried interest.

To understand how fund size affects these tradeoffs for LPs and GPs, we apply our causal estimates to a stylized calculation. Our first step is to construct a waterfall of cash flows to LPs and GPs. We assume an 8% annual hurdle rate, 20% carried interest, and immediate capital deployment net of an annual fee, which is 2% of committed capital. To account for the time value of money, we use a 12% discount rate for both LP and GP carry (Andonov and Rauh, 2022), and a 4% risk-free rate for GP fees, which are contracted and predictable. In Figure IA.9, we plot the payoff for LPs and GPs as a function of the gross exit value, using the average fund in our sample (which has committed capital of \$1.51 billion and a net IRR of 18%). The model estimates an NPV of \$0.62 billion for GPs and \$1.02 billion for LPs. The details of this exercise are in Appendix F.

Next, in Figure 9 we repeat this exercise for alternative fund sizes, allowing us to trace out the implications of our findings across the fund size distribution. Specifically, we repeat the above exercise for funds ranging from \$0.1 billion to \$3.0 billion in size. The net IRR, derived from regression coefficients and sample moments, is plotted on the right axis. On the left axis, we overlay the NPVs of LPs (in red) and GPs (in blue). The figure shows that for LPs, the NPV curve is concave with fund size initially increasing the NPV, as they earn net IRRs exceeding their 12% required rate of return on a larger capital base. NPV grows with fund size up to the optimal size of \$1.13 billion (at the 67th percentile). Beyond this, net IRR erosion offsets gains, causing LP NPV to decline. Both the average fund (\$1.51 billion) and the 75th percentile fund (\$1.64 billion) reside in this diminishing-return region, where NPV remains positive but decreases with size. Further increases push net IRR below the 12% hurdle, turning LP NPV negative at \$2.63 billion (at the 82nd percentile) fund size. For GPs, larger fund sizes increase NPV primarily through the linearly-scaling fixed management fee revenue, as evidenced by the upward-sloping GP curve. However, beyond very large fund sizes, declining IRRs reduce carried interest sufficiently to flatten the GP NPV curve.

Last, we conduct sensitivity tests to see how these thresholds vary if we shift the relationship between fund size and net IRR. If there is no performance drag from increasing fund size (i.e., a zero IV coefficient), the NPV for LPs increases linearly with fund size, as LPs earn an 18% net IRR on an expanding capital base, exceeding their required rate of return of 12%. A coefficient half the magnitude of our IV estimate implies an optimal fund size of \$1.69 billion (76th percentile), while a coefficient twice the magnitude of our IV estimate implies an optimal fund size of \$0.8 billion (58th percentile). Overall, this analysis serves to illustrate the diseconomies of scale implied by our estimates, where poor returns on larger deals drive down the returns of large funds.

What are the takeaways for LP allocators? The implication of our results is that if the average fund in the sample were to grow beyond about \$2.63 billion, with all other factors held constant, the causal effect would drive the NPV below zero. This does not imply that funds at the 82nd percentile will necessarily underperform. Large funds may differ from the average in ways that mitigate the negative effects of scale, such as superior deal access or management. This helps explain why the OLS relationship is attenuated relative to our IV estimate.

8 Conclusion

This paper studies the effect of PE fund size on performance. This question has become increasingly important as more capital flows into the industry and fund sizes increase at the top firms. We show that exogenous increases in fund size lead to lower performance. While there are likely multiple drivers, we find strong evidence that larger deals play an important role: Larger funds do larger deals, which at the time of the LBO are more indebted and more profitable, leaving less scope for subsequent operational and financial engineering. The larger deals perform worse; indeed, their under-performance can explain a majority of the overall negative effect of fund size on fund performance.

To quantify the implications of our causal analysis, we calculate the NPV for LPs and GPs across PE funds with varying sizes. As fund size grows, LPs benefit as they earn a return exceeding their cost of capital on an expanding capital base. However, deteriorating fund performance dominates the scale effect after a certain size threshold. In our sample, the optimal investment for LPs is characterized by the fund size of $1.13 billion. GPs, by contrast, earn fixed fees that scale with fund size. This causes their NPV to increase almost linearly with fund size, even though declining performance reduces carry after a certain point. These results help explain why, in the presence of sticky LP-GP relationships that in part reflect information frictions in the LP-GP market, the industry has become more concentrated despite a negative relationship between fund size and performance.

Finally, our paper sheds light on the investment strategies and long-term sustainability of university endowments. Campbell et al. (2024) emphasize the critical role of endowments in the research university enterprise, and the importance of generating sustainable long-horizon returns. There are many avenues for future research. For example, would a significant endowment tax affect the allocation of alternatives and the role of universities in the PE ecosystem? Another question is whether sophisticated LPs—such as private university endowments—adjust their strategy in response to the negative fund size-performance relationship, which our survey suggests is a widely held belief. A third avenue for study is whether GPs trade off current and future fundraising ability, and whether that is mediated by macroeconomic capital supply. Our novel dataset on university donations and investments could be useful for these and other questions.

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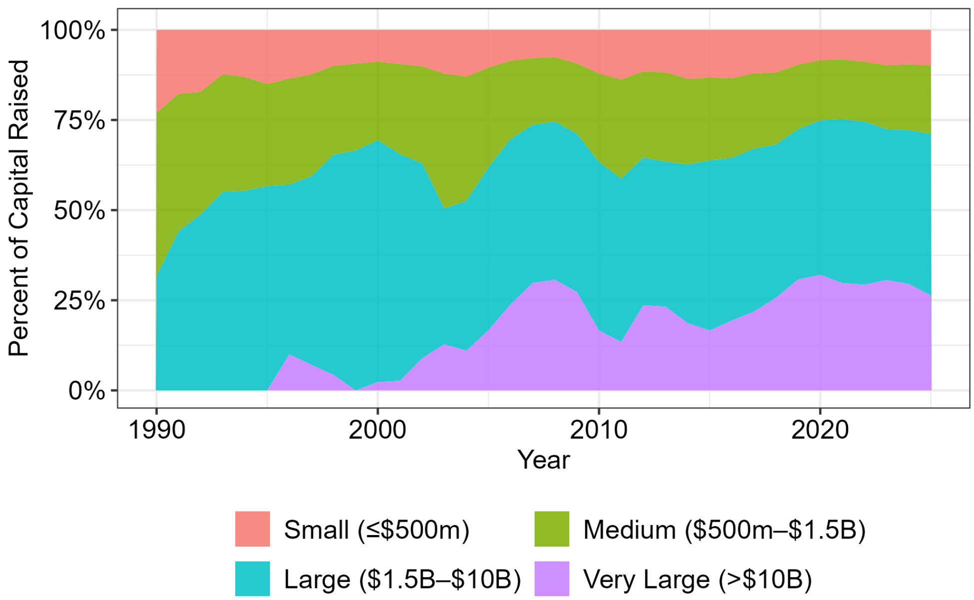
Figure 1: Size Composition of U.S. Private Equity Fund Raising

Notes: This figure shows the composition of U.S. private equity fundraising across inflation-adjusted fund size bins (2025 dollars) over time. Panel A includes all GPs while Panel B restricts to the top 15 GPs, ranked by cumulative capital raised through 2004. The underlying data are from Pitchbook and include private equity funds (including real estate and infrastructure funds).

Panel A. Allocation Across Fund Sizes Over Time (All GPs)



Panel B. Allocation Across Fund Sizes Over Time (Top 15 GPs)

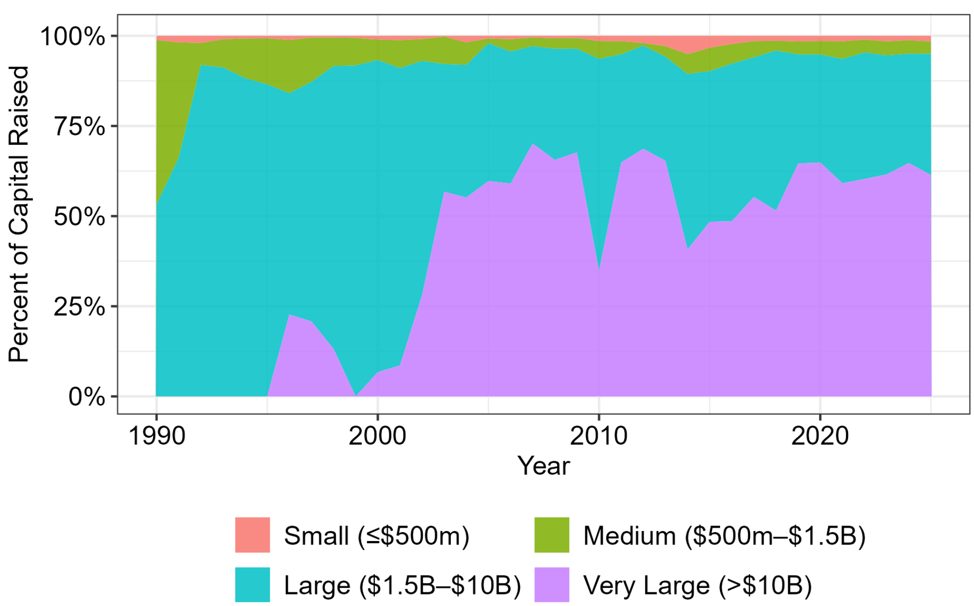
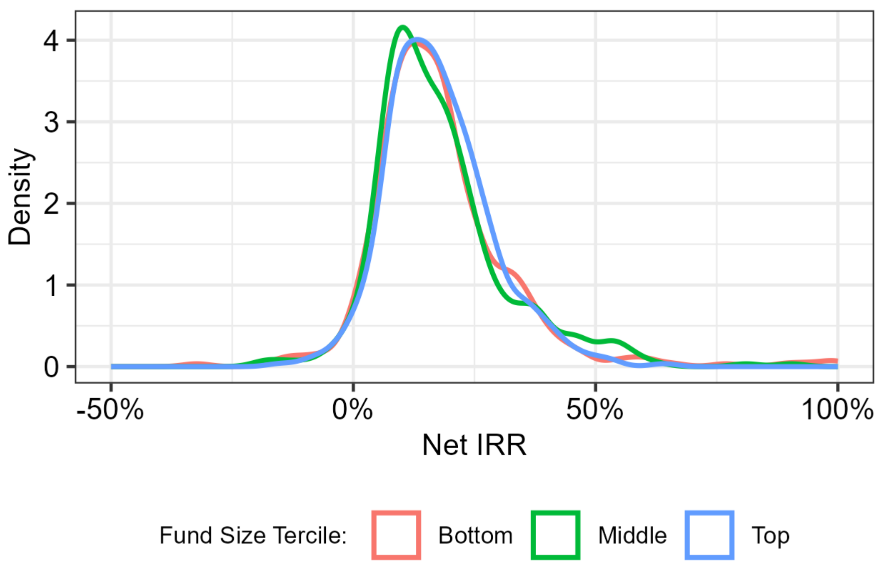


Figure 2: Actual Average Returns vs. LP Beliefs about Returns by Fund Size

Notes: Panel A of this figure shows the distribution of fund returns across fund size terciles. It includes all Preqin private equity funds with a fund size greater than $100 million in AUM, the general partner is linked to a private university at some point, and the fund has a vintage year between 2000 and 2017. Net IRRs in the figure are truncated between -50% and 100%. Panel B reports shows results from the survey of LPs (see Section 2.3 and Appendix C for details). The prompt was "If you could hold all other factors about the fund fixed (such as the quality of the manager), do you believe that smaller or larger funds tend to perform better?" The total number of responses is 81.

Panel A. Actual Returns by Fund Size



Panel B. Limited Partner Survey Responses

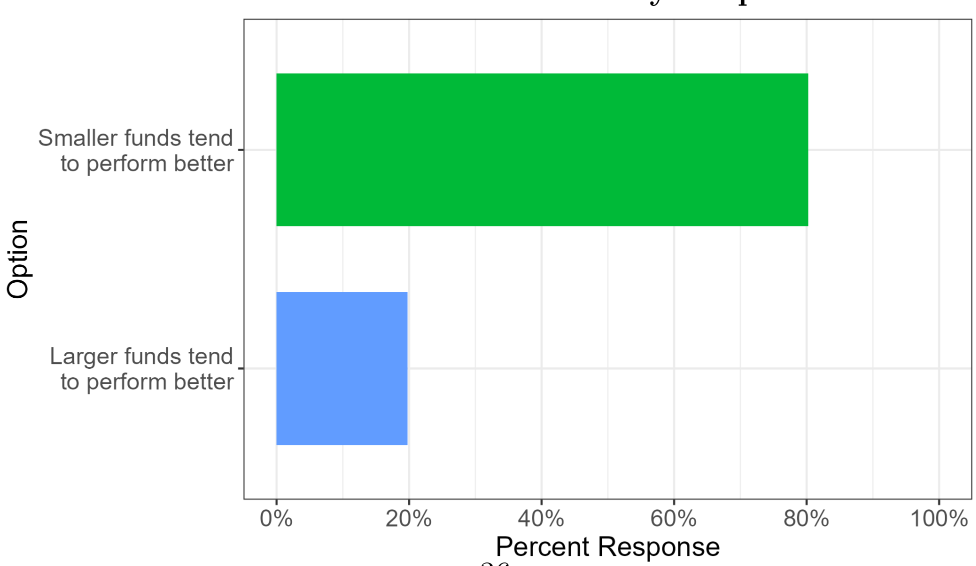


Figure 3: LP-GP Relationships are Sticky

Notes: This figure shows the likelihood a university LP invests in a given private equity fund. *P(Invest Fund)* represents the probability a given university LP invests in a private equity fund *unconditionally*. For example, the likelihood Yale invests in Bain Capital Fund IX (2006 vintage) is 1.38%. *P(Invest Fund|Invest Last Fund)* represents the probability a given university LP invests in a private equity fund conditional on investing in a general partner's prior private equity fund. For example, conditional on Yale investing in Madison Dearborn Capital Partners IV, the likelihood they invest in Madison Dearborn Capital Partners V (2006 vintage) is 31.56%.

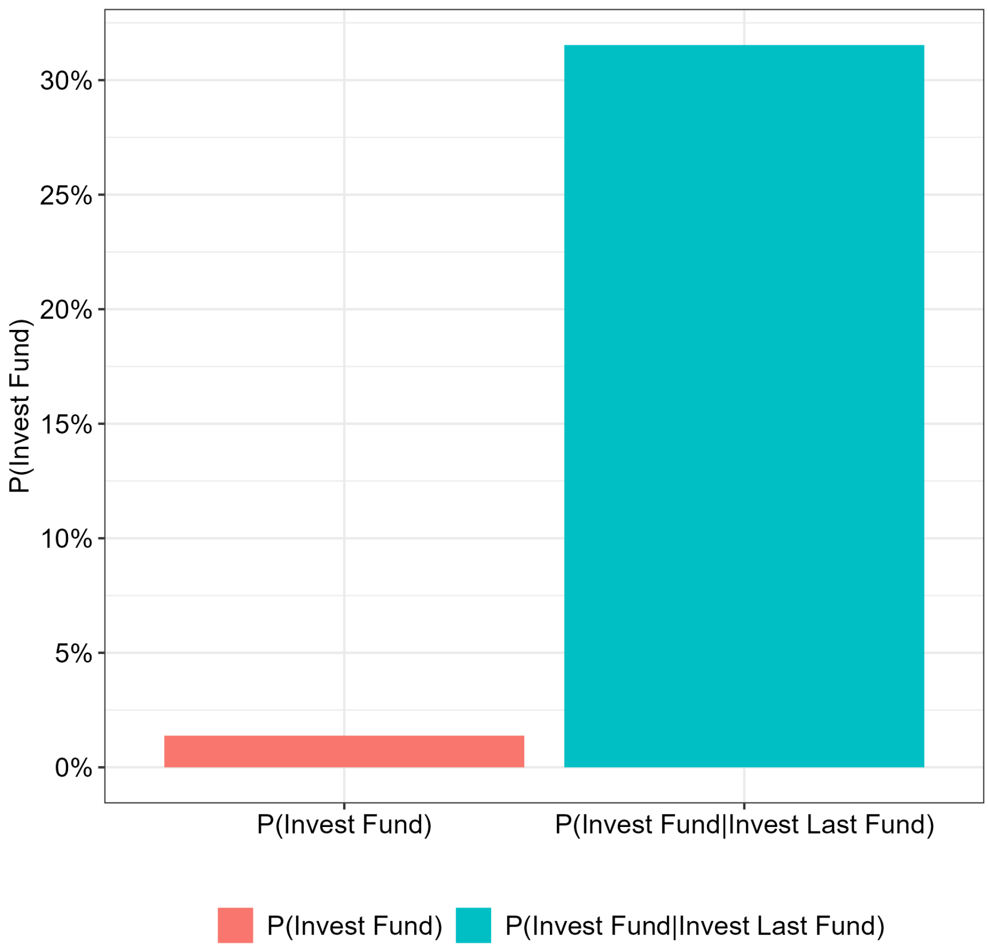


Figure 4: Signaling Power of Private University Commitments

Notes: This figure shows results from the survey of LPs (see Section 2.3 and Appendix C for details). The prompt for the responses was "Suppose you were considering investing in a fund and you were informed that a large private university endowment had already committed to that fund. Would this increase your chances of investing?" The total number of responses is 81.

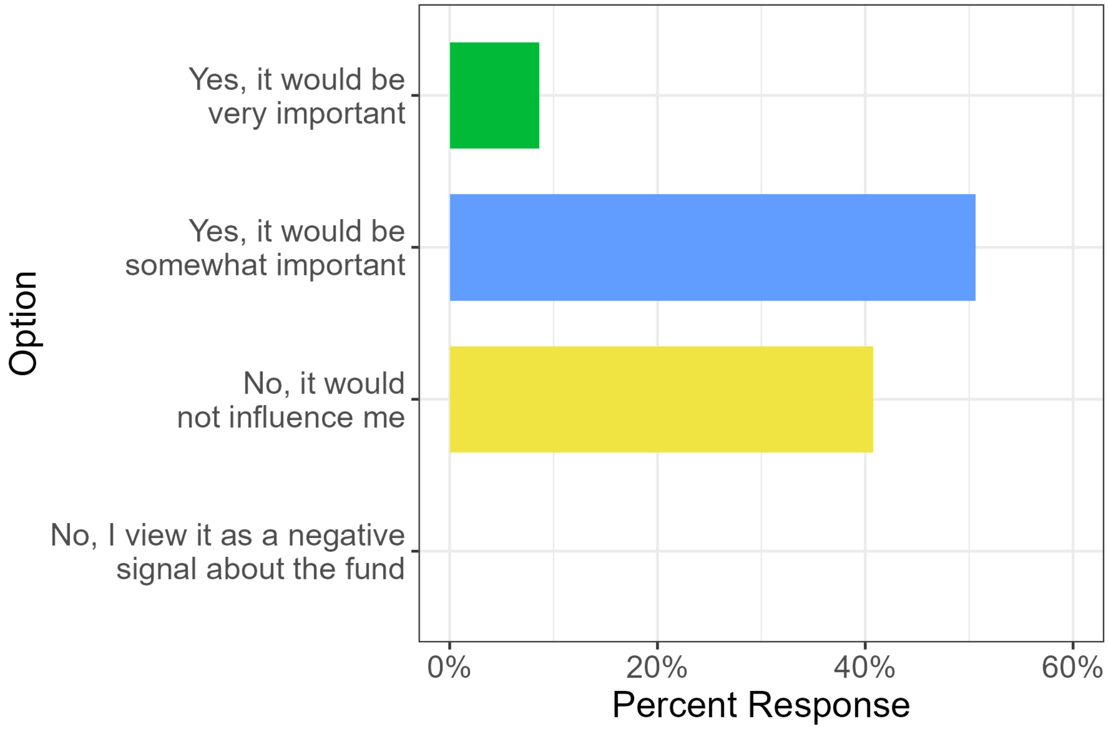


Figure 5: First Stage Relationship between Donations and Fund Size

Notes: This figure shows the binscatter plot between fund size and donations that the general partner is exposed to via connected endowments. Both fund size and gifts are residualized on General Partner, Region & Industry, Year × GP Region fixed effects, and GP controls (prior IRR, log of number and average size of funds raised in the last 5 years, log of total proceeds raised, and log of years since the last fund was raised). *Fund Size* is the total amount of committed capital to the fund (in $ Billions). *Gifts* is the standardized sum of gifts received by related universities, where the relationships are defined if a private university had invested in a general partner's fund from years *t-7* to *t-3*.

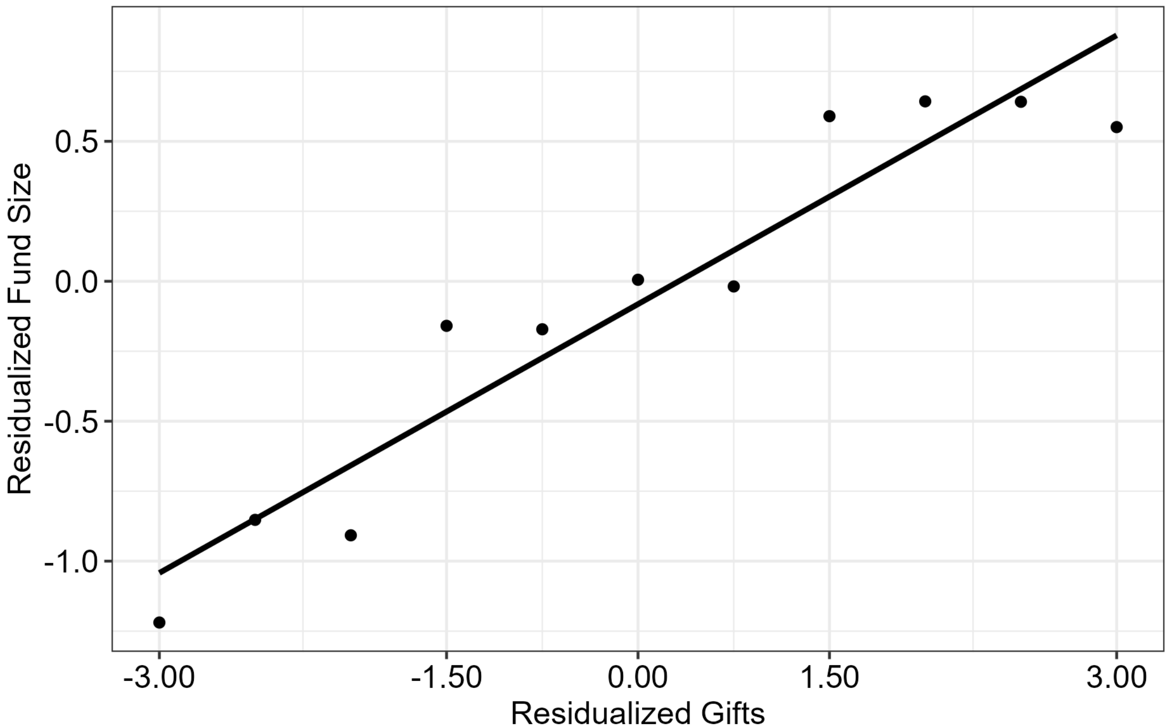


Figure 6: University Donations and Market Return

Notes: This figure shows the gifts at the university level versus the annual, value-weighted stock market return from CRSP for the 30 largest private university endowments. *Stock Return %* is the annual return on the stock market. *University Gift Growth %* is the percent change in gifts within *individual* universities, and *Total Large Gifts* are the total, gifts above $1 million reported as gifts to 990-filing universities from Indiana University Indianapolis' Million Dollar List and The Chronicle of Philanthropy Big Charitable Gifts List. Years are based on academic years with 2000 coinciding to the period from July 2000 to June of 2001.

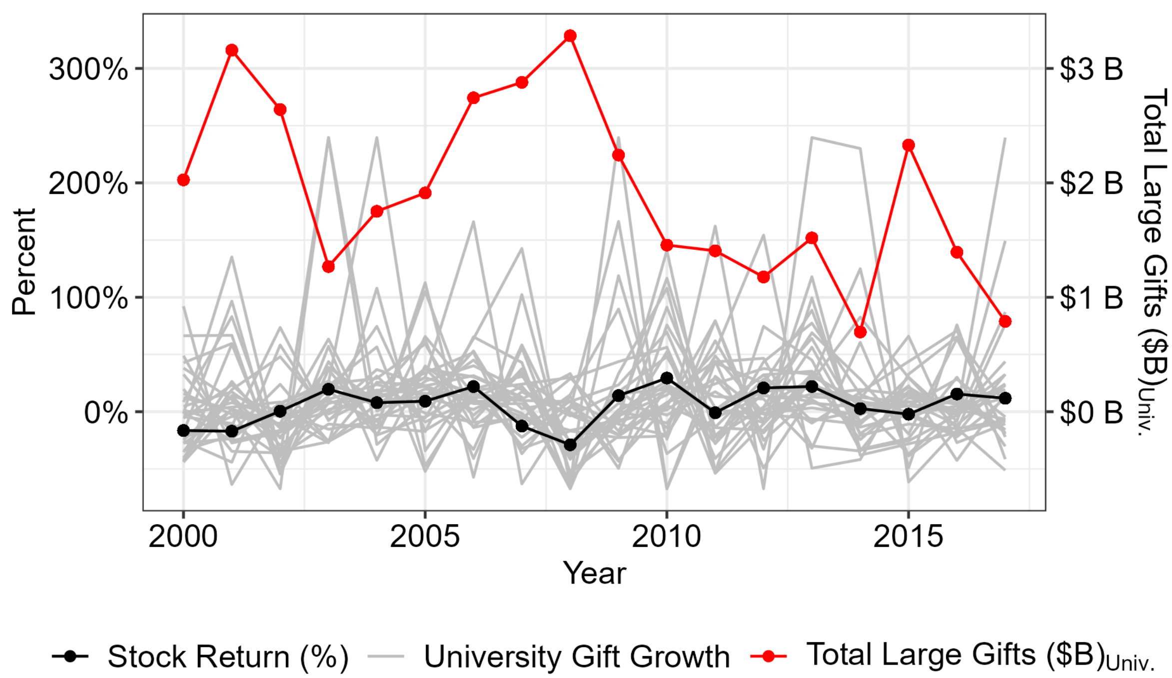


Figure 7: General Partner-Level Connected University Donations and Market Return

Notes: This figure shows the gifts at the general partner level versus the annual, value-weighted stock market return from CRSP. *Stock Return %* is the annual return on the stock market. $Gifts_{GP}$ is the standardized sum of gifts from universities an *individual* General Partner is linked to in a given year, and *Average* $Gifts_{GP}$ is the average of $Gifts_{GP}$ across all General Partners within a given vintage year. Years are based on academic years with 2000 coinciding to the period from July 2000 to June of 2001.

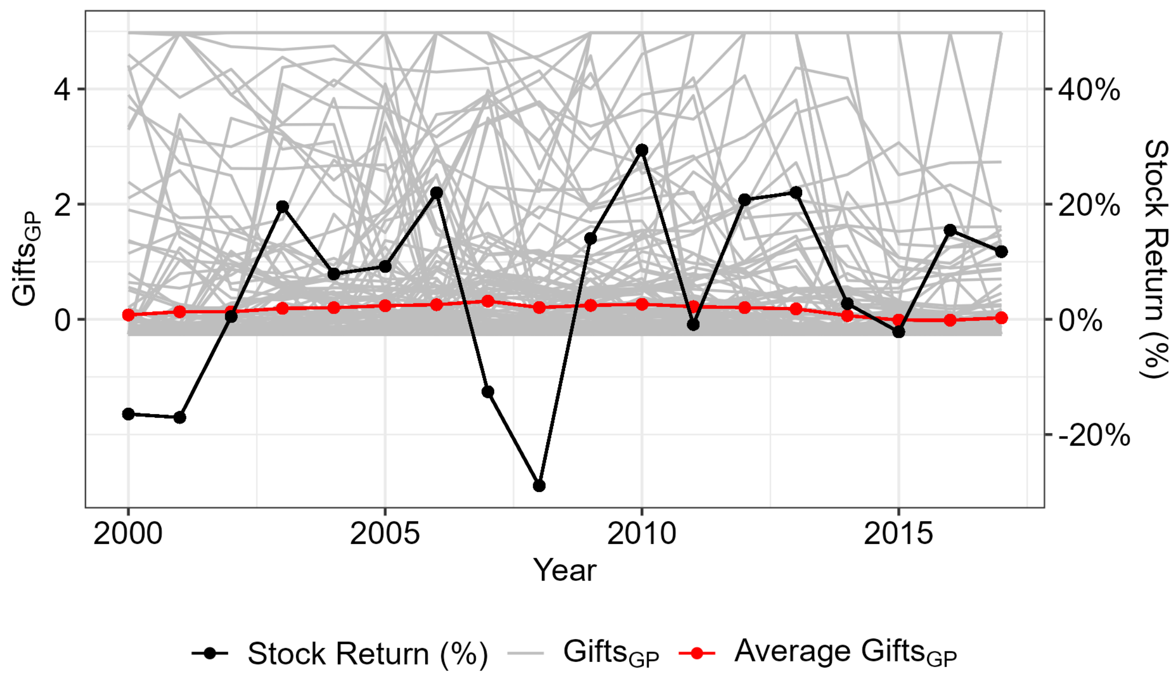


Figure 8: Reasons LPs Believe Smaller or Larger Funds Perform Better

Notes: This figure presents results from a survey of limited partners (see Section 2.3 and Appendix C for details). We analyzed responses to the question: *Why did you answer that one type performs better than the other?* using ChatGPT to extract the two most relevant phrases from each response. To focus on meaningful content, we excluded the following generic words: *large*, *larger*, *small*, *smaller*, *fund*, *size*, *etc*, *question*, *answer*, *invest*, *better*, *outperform*, *outperformance*, *performance*, *lower*, *less*, *higher*, *underperform*, *market*, *options*, and *outcome*. Based on the cleaned text, we generated word clouds separately for those respondents who believed that larger firms perform better (Panel A) and those who believed smaller firms perform better (Panel B). The total number of responses analyzed is 81.

Panel A. Responses from participants who believe smaller funds outperform

Panel B. Responses from participants who believe larger funds outperform

Figure 9: Calibrated Relationship Between Fund Size and NPV for GPs and LPs

Notes: This figure shows how the net present value (NPV) for LPs and GPs (left axis) varies with the fund size, as implied by our IV regression estimates for IRR and sample moments. Detailed calculations of net IRR and the NPVs are described in Appendix E.

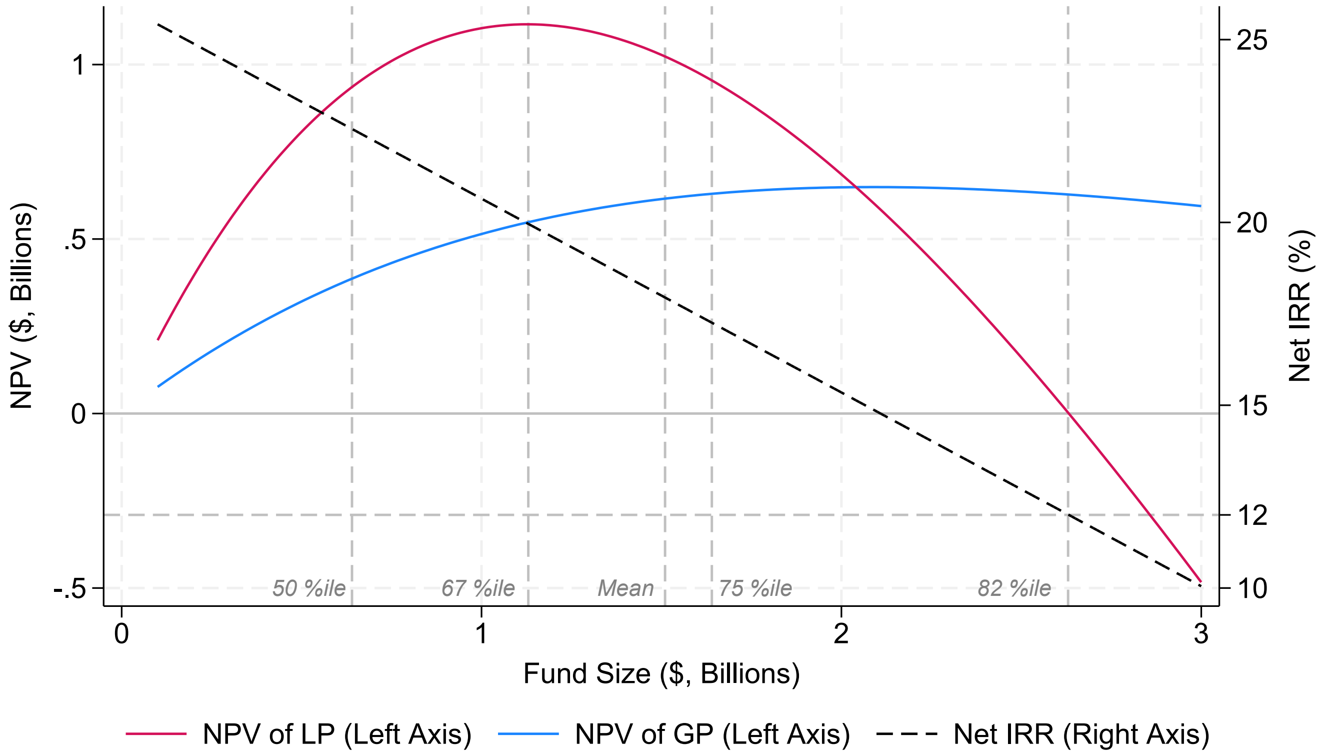


Table 1: Fund and Deal-Level Summary Statistics

Notes: This table presents the summary statistics at the fund-level and deal level. Panel A presents measures at the fund-level and deal-level measures aggregated to the fund level. Fund-level measures include measures of size (absolute and relative to the prior fund), performance, and details on fund team employment. Deal-level measures aggregated to the fund level include characteristics such as size, number of deals, and location of deals. Panel B presents the financials (deal size, enterprise value, etc.) of the portfolio company at the time of the private equity investment measured post-buyout. Deal-level measures also include the change in EBITDA and debt (as a fraction of enterprise value) between deal entry and deal exit. All continuous, non-logged variables are winsorized at the 1st and 99th percentile. The sample includes private equity funds with greater than $100 million in AUM, with vintage years between 2000 and 2017, and the general partner is linked to at least one private university. See the variable definitions in the Appendix for additional details.

	Panel A: Fund-Level Statistics							
	N	Mean	SD	p1	p25	Median	p75	p99
Fund Characteristics								
Fund Size ($ Billions)	1231	1.51	2.06	0.10	0.30	0.64	1.64	8.50
Net IRR	1231	0.18	0.13	-0.26	0.09	0.16	0.23	1.06
Net Multiple	1180	1.91	0.70	0.21	1.49	1.76	2.17	6.87
Prior IRR	1231	0.15	0.10	-0.10	0.10	0.13	0.20	0.67
Burgiss Return Measures								
Net IRR	528	0.16	0.11	-0.10	0.09	0.16	0.22	0.58
Direct Alpha	528	0.05	0.11	-0.19	-0.02	0.03	0.09	0.54
Public Market Equivalent	528	1.20	0.43	0.35	0.93	1.12	1.40	2.80
α	514	0.27	0.40	-0.54	0.02	0.19	0.45	1.61
Comparison with Prior Fund								
Δ Fund Size ($ Billions)	1094	0.18	1.92	-8.37	-0.28	0.08	0.61	8.37
Deal Characteristics								
Average Deal Size ($ Millions)	837	98.47	112.17	0.34	21.16	55.42	124.94	490.66
Number of Deals	837	19.15	19.42	1.00	8.00	14.00	23.00	131.00
Number of Sub-Sectors	837	8.72	7.40	0.00	1.00	8.00	13.00	29.00
Number of States	837	9.39	8.43	1.00	2.00	7.00	16.00	27.00
Number of Regions	837	1.90	1.04	1.00	1.00	2.00	2.00	5.00
Time Last Deal (Years)	837	4.57	2.55	0.00	3.00	4.00	6.00	13.00
Fund Team Data								
Partners	837	7.33	5.22	1.00	4.00	7.33	9.00	26.00
$\frac{Deals}{Partners}$	837	4.33	6.18	0.14	1.67	3.00	4.33	79.00
$\frac{\text{Fund Size (\$ Billions)}}{Partners}$	837	0.44	0.69	0.00	0.13	0.32	0.44	10.80
	Panel B: Deal-Level Statistics							
Deal Performance Characteristics								
Gross IRR	8748	0.21	0.40	-0.64	0.01	0.19	0.40	1.24
Net Multiple	8531	2.04	0.63	0.63	1.61	1.91	2.35	3.59
Deal Characteristics at Entry								
Deal Size ($ Millions)	8748	141.02	163.12	0.11	30.16	75.97	191.38	743.84
Time to Entry	8748	2.12	1.64	0.00	1.00	2.00	3.00	7.00
Age	8522	25.09	28.30	0.00	7.00	16.00	32.00	138.00
Enterprise Value ($ Millions)	5107	792.80	1,046.83	14.60	115.00	321.12	967.98	3,669.79
$\frac{EBITDA}{\text{Enterprise Value}}$	4850	0.10	0.07	-0.19	0.07	0.10	0.13	0.37
$\frac{Debt}{EBITDA}$	4675	3.59	4.65	-16.00	1.66	4.01	5.81	22.36
$\frac{Debt}{\text{Enterprise Value}}$	4784	0.33	0.33	-0.71	0.10	0.41	0.57	0.88
Entry-to-Exit Deal Changes								
$\Delta\frac{EBITDA}{\text{Enterprise Value}}$	4320	-0.02	0.08	-0.37	-0.04	-0.02	0.01	0.34
$\Delta\frac{Debt}{\text{Enterprise Value}}$	4361	-0.05	0.31	-0.76	-0.23	-0.08	0.08	1.33

Table 2: Relationship between Fund Size and Performance (OLS)

Notes: This table presents estimates of the relationship between fund size and performance, using data on funds with vintage years from 2000 to 2017. The table displays the OLS results from regressing Net IRR on Fund Size in Panel A and the OLS results from regressing Net Multiple on Fund Size in Panel B. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund. *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Net IRR				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.001	-0.002	-0.004	-0.004	-0.003
	[0.004]	[0.005]	[0.003]	[0.003]	[0.002]
Prior IRR				-0.210**	-0.258***
				[0.087]	[0.088]
Observations	1231	1231	1231	1231	1231
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes
Y-mean	0.18	0.18	0.18	0.18	0.18

	Panel B: Net Multiple				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.002	-0.007	0.005	0.007	0.010
	[0.015]	[0.015]	[0.012]	[0.012]	[0.012]
Prior Multiple				-0.111*	-0.127**
				[0.053]	[0.060]
Observations	1306	1306	1306	1306	1306
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes
Y-mean	1.88	1.88	1.88	1.88	1.88

Table 3: University Donations, Endowment, and Related GP Summary Statistics

Notes: This table presents the summary statistics at the fund-level and deal level. Panel A presents measures at the university × year level including gifts received, endowment size, and details on investments and the number of connected GPs within the last five years and overall. Panel B presents measures at the fund-level based on gifts aggregated to the GP × fund level and investor compositions for universities (public and private) and public pension LPs. The data in Panel A are presented across 95 universities from 1998 to 2017 which file IRS, Form 990-T with at least one observed investment in a private equity fund during the sample. The sample in Panel B includes private equity funds with greater than $100 million in AUM, with vintage years between 2000 and 2017, and the general partner is linked to at least one private university. See the variable definitions in the Appendix for additional details.

	Panel A: University Panel							
	N	Mean	SD	p1	p25	Median	p75	p99
University Gifts & Endowments								
Raw Gifts ($ Billions)	1887	0.11	0.17	0.00	0.02	0.04	0.12	1.69
Endowment ($ Billions)	1479	2.32	4.52	0.02	0.55	0.87	1.79	25.54
Relationship GPs	1887	2.02	2.40	0.00	0.00	1.00	3.00	11.00
	Panel B: Fund-Level Statistics							
Gift Exposure and Connections								
Raw Gifts ($ Billions)	1231	0.22	0.39	0.00	0.00	0.03	0.24	1.75
Gifts_{GP}	1231	-0.02	0.90	-0.50	-0.50	-0.43	0.02	4.05
Linked Private Universities	1231	1.56	2.31	0.00	0.00	1.00	2.00	9.00
Δ Linked Private Universities	1231	0.03	0.74	-2.00	0.00	0.00	0.00	2.00
Investor Composition								
Pension & Other LPs	1074	19.99	22.72	0.00	4.00	12.00	27.00	96.00
Public University & Private Foundations	1074	3.01	4.08	0.00	0.00	1.00	4.00	16.00
Private University LPs	1074	0.78	1.58	0.00	0.00	0.00	1.00	8.00
Total LPs	1074	24.14	25.56	1.00	6.00	15.00	32.00	107.00
Private University LPs (Proportion)	1074	0.04	0.12	0.00	0.00	0.00	0.04	1.00

Table 4: First Stage Estimates and Exclusion Restriction Tests

This table presents estimates of the relationship between gifts and fund size and fund characteristics, using data on funds with vintage years from 2000 to 2017. Panel A presents IV first stage estimates that regress fund size on the sum of gifts received by private universities to which a general partner is connected. The gifts measure is standardized so that a one unit increase represents a standard deviation. Panel B presents a placebo first-stage, regressing Fund Size ($ Billions) onto a placebo instrument, Gifts_{GP} which randomizes university × year connections in column 1 and OLS estimates of the relationship between the gifts measure and and various *ex-ante* characteristics of the GP: *Prior IRR*, which is the average IRR of a general partner's funds raised at least five years before the current fund; *Log(# of Funds Raised)*, which is the logarithm of the number of funds a GP has raised before; *Time Since Last Fund*, which is the number of years since a general partner's last fund; the *Carried Interest* for the current fund; and the *Management Fee* for the current fund. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: First Stage Fund Size ($ Billions)				
	(1)	(2)	(3)	(4)	(5)
Gifts_{GP}	0.425***	0.416***	0.328***	0.329***	0.322***
	[0.092]	[0.085]	[0.074]	[0.074]	[0.058]
Prior IRR				0.232	0.246
				[0.648]	[0.708]
F-Statistic	21.32	23.94	36.48	36.65	30.73
Observations	1231	1231	1231	1231	1231
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes

	Panel B: Exclusion Restriction					
	Randomize Connections	Prior IRR	Log(# of Funds Raised)	Time Since Last Fund	Carried Interest	Mgmt. Fee
	(1)	(2)	(3)	(4)	(5)	(6)
Gifts_{GP}	0.105	-0.001	0.006	-0.034	-0.001	0.040
	[0.080]	[0.005]	[0.004]	[0.039]	[0.002]	[0.041]
Prior IRR			-0.022	0.142	-0.039	0.139
			[0.022]	[0.215]	[0.035]	[0.254]
Observations	1231	1231	1231	1231	269	149
General Partner F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes	Yes	Yes
Y-mean	1.51	0.15	2.23	2.30	0.17	1.78

Table 5: Effect of Fund Size on Performance (IV)

Notes: This table reports IV estimates of how fund size, instrumented with university endowment gifts, affects fund performance. We use data on funds with vintage years from 2000 to 2017. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund. *GP Controls* includes controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively. Robustness to design choices is shown in Table 8 for net IRR and Table IA.10 for net multiple.

	Panel A: Net IRR				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billion)	-0.070**	-0.063*	-0.059**	-0.062**	-0.053**
	[0.032]	[0.032]	[0.022]	[0.022]	[0.024]
Prior IRR				-0.202**	-0.247**
				[0.093]	[0.090]
F-Statistic	21.32	23.94	36.48	36.65	30.73
Observations	1231	1231	1231	1231	1231
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes
Y-mean	0.18	0.18	0.18	0.18	0.18

	Panel B: Net Multiple				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.227***	-0.179***	-0.281***	-0.291***	-0.252**
	[0.077]	[0.060]	[0.082]	[0.081]	[0.089]
Prior Multiple				-0.078	-0.093
				[0.049]	[0.054]
F-Statistic	19.28	23.29	50.33	48.86	34.21
Observations	1306	1306	1306	1306	1306
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes
Y-mean	1.88	1.88	1.88	1.88	1.88

Table 6: Effect of Fund Size on Performance (IV): Cash Flow Level Analysis

Notes: This table reports IV estimates of how fund size, instrumented with university endowment gifts, affects fund performance. We use data on funds with vintage years from 2000 to 2017 with cash flow level data in Burgiss. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund. *GP Controls* includes controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Net IRR				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.033**	-0.028**	-0.031**	-0.041**	-0.042**
	[0.013]	[0.013]	[0.013]	[0.019]	[0.019]
F-Statistic	60.57	36.58	35.48	15.30	15.39
Observations	528	528	528	528	528
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Prior IRR Control	No	No	Yes	No	Yes
GP Controls	No	No	No	Yes	Yes
Y-mean	0.16	0.16	0.16	0.16	0.16

	Panel B: Gredil et al. (2023) Direct Alpha				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.051***	-0.047***	-0.050***	-0.041*	-0.042*
	[0.014]	[0.014]	[0.015]	[0.020]	[0.020]
F-Statistic	60.57	36.58	35.48	15.30	15.39
Observations	528	528	528	528	528
Panel A F.E. & Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	0.05	0.05	0.05	0.05	0.05

	Panel C: Kaplan and Schoar (2005) PME				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.209***	-0.192***	-0.197***	-0.177*	-0.180*
	[0.063]	[0.060]	[0.063]	[0.089]	[0.090]
F-Statistic	60.57	36.58	35.48	15.30	15.39
Observations	528	528	528	528	528
Panel A F.E. & Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	1.20	1.20	1.20	1.20	1.20

	Panel D: Korteweg and Nagel (2024) α				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.188***	-0.167***	-0.170***	-0.146*	-0.148*
	[0.054]	[0.048]	[0.050]	[0.070]	[0.071]
F-Statistic	58.77	40.47	38.94	16.63	16.77
Observations	514	514	514	514	514
Panel A F.E. & Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	0.27	0.27	0.27	0.27	0.27

Table 7: Effects of Increases in Fund Size on Fund Return Distribution (IV)

Notes: This table reports IV estimates of how fund size, instrumented with university endowment gifts, affects the fund performance distribution. We use data on funds with vintage years from 2000 to 2017. The dependent variable is an indicator variable for the quartile a given fund's return falls into with Panel A displaying *Net IRR* and Panel B displaying *Net Multiple*. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund. *GP Controls* includes controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Net IRR			
	Bottom Quartile	2^{nd} Quartile	3^{rd} Quartile	Top Quartile
	(1)	(2)	(3)	(4)
Fund Size ($ Billions)	0.169**	0.161*	-0.155**	-0.175*
	[0.066]	[0.092]	[0.073]	[0.085]
Prior IRR	0.745**	-0.048	-0.086	-0.610***
	[0.275]	[0.240]	[0.187]	[0.201]
F-Statistic	30.73	30.73	30.73	30.73
Observations	1231	1231	1231	1231
General Partner F.E.	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes
Y-mean	0.25	0.25	0.25	0.25

	Panel B: Net Multiple			
	Bottom Quartile	2^{nd} Quartile	3^{rd} Quartile	Top Quartile
	(1)	(2)	(3)	(4)
Fund Size ($ Billions)	0.097*	0.165*	-0.092	-0.170**
	[0.054]	[0.082]	[0.087]	[0.074]
Prior Multiple	0.038	-0.007	-0.012	-0.019
	[0.029]	[0.027]	[0.034]	[0.032]
F-Statistic	34.21	34.21	34.21	34.21
Observations	1306	1306	1306	1306
General Partner F.E.	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes
Y-mean	0.25	0.26	0.24	0.24

Table 8: Effect of Fund Size on Fund IRR Robustness Tests (IV)

Notes: This table reports alternative versions of the IV results from Table 5 Panel A. The first panel repeats the model in column 5 of Table 5. The second panel presents variants on this model as follows: Row 2A expands the sample period from 1990-2017, row 2B includes all private equity funds from 2000-2017 without requiring a GP is linked to a private university, row 2C includes funds from the full sample (2A + 2B) and excludes fund of funds, row 2D excludes the 10 largest GPs by proceeds raised during the sample, row 2E excludes funds above the 90th percentile in the number of deals, row 2F excludes funds below the 10th percentile of fund size, row 2G excludes funds above the 90th percentile of fund size, row 2H includes relationship controls for the number of linked universities and changes in linkages, row 2I includes an additional control for the weighted-average IRR for funds launched within the last 5 years, and row 2J includes funds regardless of their size removing the $100 million fund size filter. The third panel presents results from alterations of the instrument: Row 3A uses $Raw\ Gifts_{GP}$ the non-standardized measure of gifts as the instrumental variable, row 3B uses an alternative measure of university gifts defined as *Gifts, Grants, and Contracts* as reported to the Integrated Postsecondary Education Data System (IPEDS) as the instrumental variable and includes both public and private universities, row 3C uses only million dollar gifts or bequests reported to Indiana University Indianapolis' Million Dollar List or the Chronicle of Philanthropy as the instrumental variable, row 3D subsets the million dollar gifts result from 3C but excludes gifts from in-state donors, row 3E uses the logarithm of fund size as the endogenous variable, row 3F nets out changes in pledges receivable to approximate a cash-flow based measure rather than an accrual-based measure, and row 3G expands the gift exposure window from *t-2* to *t-2 to t-4*. The fourth panel presents results from varying the fixed effects: Row 4A excludes *Year* fixed effects, row 4B includes a linear time trend, row 4C includes annual PE fundraising, row 4D includes *year* fixed effects, and row 4E includes *GP State* × *Year* fixed effects based on the location of a general partner's headquarter state in place of *GP Region* × *Year* fixed effects. Row 4F includes *Industry* × *Year* fixed effects while Row 4G includes average deal leverage and age controls which are interpolated to the average when missing. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Net IRR			
Instrument Variable	Coefficient	Standard Error	F-Statistic	Observations
1. Base Specification				
Fund Size ($ Billions)	-0.053**	0.024	30.74	1231
2. Sampling Choices				
A. 1990-2017				
Fund Size ($ Billions)	-0.058**	0.027	21.49	1372
B. Include GP's With and Without Relationships				
Fund Size ($ Billions)	-0.057**	0.021	32.38	1758
C. Without Fund of Funds				
Fund Size ($ Billions)	-0.038*	0.019	35.28	1372
D. Exclude 10 Largest GP's				
Fund Size ($ Billions)	-0.060*	0.029	21.84	1106
E. Exclude Funds ≥ 90th Percentile of # Deals				
Fund Size ($ Billions)	-0.042*	0.020	17.91	743
F. Exclude Funds ≤ 10th Percentile of Fund Size				
Fund Size ($ Billions)	-0.049*	0.024	42.69	1105

(Continued on next page)

Table (*continued*)

	Net IRR			
Instrument Variable	Coefficient	Standard Error	F-Statistic	Observations
G. Exclude Funds ≥ 90th Percentile of Fund Size				
Fund Size ($ Billions)	-0.091**	0.043	20.57	1094
H. Include Relationship Controls				
Fund Size ($ Billions)	-0.046*	0.025	42.40	1231
I. Include Recent IRR Control				
Fund Size ($ Billions)	-0.055**	0.024	31.66	1231
J. Include Funds Regardless of Size				
Fund Size ($ Billions)	-0.047*	0.023	30.02	1403
3. Instrument and Dependent Variable Choices				
A. Use *Raw Gifts*				
Fund Size ($ Billions)	-0.052**	0.024	33.43	1231
B. Use IPEDs' Measure of Gifts, Grants, and Contracts				
Fund Size ($ Billions)	-0.055*	0.028	18.83	1231
C. Use Million Dollar Gifts				
Fund Size ($ Billions)	-0.048*	0.023	20.90	1231
D. Exclude In-State Million Dollar Gifts				
Fund Size ($ Billions)	-0.048*	0.026	14.46	1231
E. Instrument for Log(Fund Size)				
Fund Size ($ Billions)	-0.108**	0.039	32.98	1231
F. Instrument for Cash-Based Proxy				
Fund Size ($ Billions)	-0.053**	0.023	42.49	1231
G. Instrument Using Rolling Gifts				
Fund Size ($ Billions)	-0.052**	0.022	38.25	1231
4. Adjust Fixed Effects & Controls				
A. Exclude Year F.E.'s				
Fund Size ($ Billions)	-0.102***	0.027	34.26	1231
B. Include Linear Time Trend				
Fund Size ($ Billions)	-0.069***	0.022	20.68	1231
C. Include PE Annual Funds Raised				
Fund Size ($ Billions)	-0.094***	0.025	33.47	1231
D. Include Year Fixed Effects				
Fund Size ($ Billions)	-0.057**	0.023	27.25	1231
E. Include GP State × Year F.E.'s				
Fund Size ($ Billions)	-0.058**	0.024	17.09	1184
F. Include Industry × Year F.E.'s				
Fund Size ($ Billions)	-0.071***	0.022	17.62	1177
G. Include Average Deal Leverage and Age				
Fund Size ($ Billions)	-0.053**	0.024	23.90	1231

Table 9: Effect of Fund Size on Deal Characteristics and Human Capital (IV)

Notes: This table reports IV estimates of how fund size, instrumented with university endowment gifts, affects average deal characteristics (Panel A) and human capital aggregated to the fund-level (Panel B). We use data on funds with vintage years from 2000 to 2017. The dependent variables in Panel A are interpolated between the Fund of Funds database, Preqin, and Pitchbook while Panel B is based on fund manager employment data from Pitchbook. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund, *Fund Controls* which control for the average company's age and leverage,and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Both Panels A and B include the controls listed at the bottom of the table. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Deal Characteristics					
	Deal Size	# Deals	Time to Last Deal	# Sub Sectors	# States	# Regions
	(1)	(2)	(3)	(4)	(5)	(6)
Fund Size ($ Billions)	23.88***	7.02***	1.08***	0.36	0.72	0.26
	[6.86]	[1.89]	[0.28]	[0.77]	[1.60]	[0.16]
Prior IRR	-4.17	-1.59	-0.73	-1.83	-0.32	0.35
	[29.36]	[7.39]	[1.24]	[2.32]	[2.64]	[0.34]
F-Statistic	29.39	29.39	29.39	29.39	29.39	29.39
Observations	837	837	837	837	837	837
General Partner F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes	Yes	Yes
Y-mean	98.47	19.15	4.57	8.72	9.39	1.90

	Panel B: Human Capital			
	# Partners	$\frac{\#Deals}{Partner}$	$\frac{AUM}{Partner}$	Prior Fund Exp.
	(1)	(2)	(3)	(4)
Fund Size ($ Billions)	2.36***	0.15	0.12	-0.11
	[0.80]	[1.00]	[0.17]	[0.12]
Prior IRR	0.53	3.76	-0.12	-0.50
	[2.14]	[3.69]	[0.27]	[0.37]
F-Statistic	29.39	29.39	29.39	29.39
Observations	837	837	837	837
General Partner F.E.	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes
Y-mean	7.33	4.33	0.44	1.55

Table 10: Effects of Increases in Deal Size on Deal Return Distribution (IV)
This table reports IV estimates of how deal size, instrumented with university endowment gifts, affects the deal performance distribution. We use data on funds with vintage years from 2000 to 2017. The dependent variable in column 1 is a continuous measure of IRR while columns 2 to 5 are indicators if IRR falls within a given quartile. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the deal entry year and fund level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Gross IRR	Bottom Quartile	2^{nd} Quartile	3^{rd} Quartile	Top Quartile
	(1)	(2)	(3)	(4)	(5)
Deal Size ($100 Millions)	-0.13**	0.15***	0.03	-0.16**	-0.03
	[0.06]	[0.05]	[0.06]	[0.06]	[0.06]
F-Statistic	25.80	25.80	25.80	25.80	25.80
Observations	8748	8748	8748	8748	8748
Deal Sector F.E.	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	0.21	0.25	0.25	0.25	0.25

Table 11: Effects of Deal Size on Deal Selection and Subsequent Engineering (IV)

Notes: This table reports IV estimates of how deal size, instrumented with university endowment gifts, affects the deal characteristics related to selection and subsequent operational and financial engineering. We use data on funds with vintage years from 2000 to 2017. The dependent variable in column 1 *EBITDA/Enterprise Value* is the ratio of the company's EBITDA scaled by its enterprise value at the time of entry, 2 *Debt/Enterprise Value* is the entry ratio of the company's debt scaled by its enterprise value, 3 Δ *EBITDA/Enterprise Value* is the change in the ratio of the company's EBITDA scaled by its enterprise value at deal exit versus entry, and 4 Δ *Debt/Enterprise Value* is the change in the ratio of the company's debt scaled by its enterprise value at deal exit versus entry. The independent variable is instrumented *Deal Size*, a continuous measure (in $100 millions) of the amount a general partner invests in a given deal. Standard errors are clustered at the deal entry year and fund level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Deal Selection		Operational vs Financial Engineering	
	EBITDA/ Ent. Value	Debt/ Ent. Value	Δ EBITDA/ Ent. Value	Δ Debt/ Ent. Value
	(1)	(2)	(3)	(4)
Deal Size ($100 Millions)	0.03***	0.13**	-0.02**	0.01
	[0.01]	[0.05]	[0.01]	[0.05]
F-Statistic	32.09	38.29	24.77	33.78
Observations	4850	4784	4320	4361
Year × GP Region F.E.	Yes	Yes	Yes	Yes
General Partner F.E.	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes
Y-mean	0.10	0.33	-0.02	-0.05

Appendix A: Additional Figures and Tables

Figure IA.1: Large Gifts and Total Gifts Received by Private Universities

Notes: This figure shows the magnitude of large gifts (those above $1 million) and total gifts received by all private universities. We use data from the Indiana University Indianapolis' Million Dollar List from 2000 to 2013 (coverage ends in 2014) and data from the Chronicle of Philanthropy from 2014 onward to construct the series of large gifts. Data on total gifts comes from IRS Form 990.

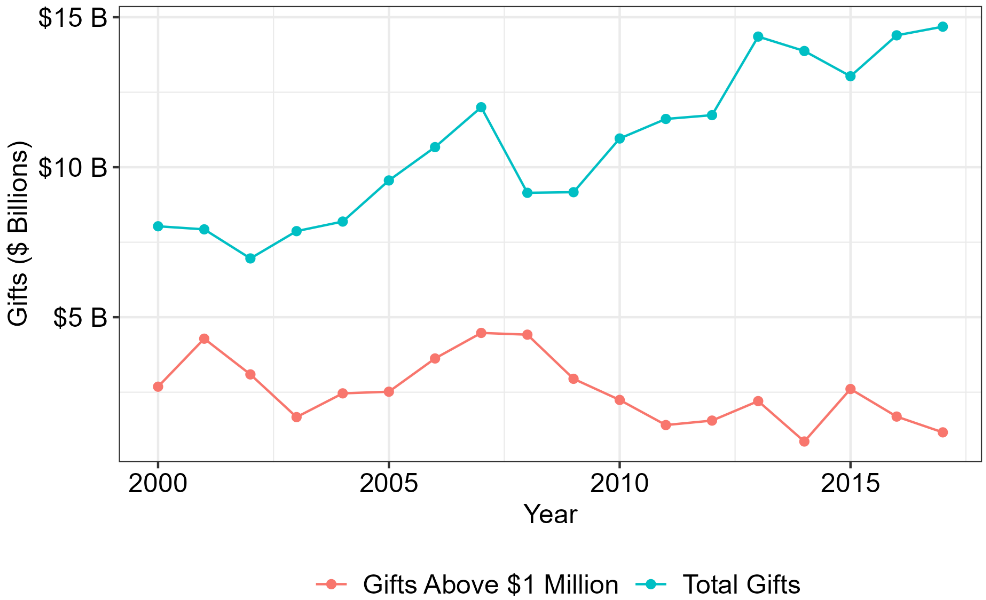
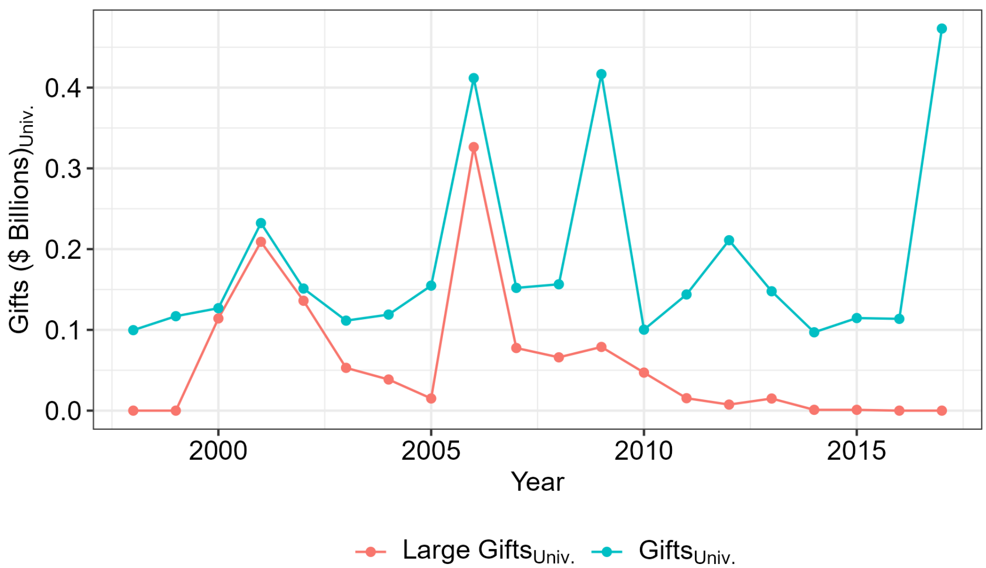


Figure IA.2: Case Study: Large Gifts and Total Gifts to Emory University

Notes: This figure shows the large gifts and total gifts to Emory University over time. *Total Large Gifts* are the total, gifts above $1 million reported as gifts to 990-filing universities from Indiana University Indianapolis' Million Dollar List and The Chronicle of Philanthropy Big Charitable Gifts List. We include only gifts denoted as gifts or bequests (excluding pledges and gifts over time), and bound this at 90 percent of total gifts in cases which *Total Large Gifts* exceeds *Total Gifts*. Data are reported based on the academic year with 2000 coinciding to July 2000 to June of 2001.



<u>Case Study Example: Emory University</u>

YEP VII	YEP VIII	YEP IX	YEP X
2006	2008	2010	2013

- Emory University first invests in Yorkstone Energy Partners (YEP) in 2006
- Our measure requires a university to be linked to a general partner from *t-7* to *t-3* implying that YEP IX and YEP X will both be linked to donations to Emory University
  - Preqin has comprehensive coverage of vintage years (while data on fund launch dates is sparse) so we lag gifts by $\approx$ 2 years to assure these donations occur *prior to or during* the fund raising stage which takes on average 12-18 months
  - YEP VII and YEP VIII both occur before Emory University has been *previously* linked to Yorktown Energy Partners
- Our estimand regresses the fund performance of YEP IX on a fund's size instrumented by the donations to Emory University (and all other linked universities to Yorktown Energy Partners) on the donations to these universities in 2008 while controlling for rich fixed effects at the following levels: year $\times$ general partner location, general partner, fund region, fund industry levels, and other general partner controls.

Figure IA.3: Sample 990-T Form

Notes: This figure shows a 990-T form filed by Baylor University for the 2005 academic year. The figure displays the name of the private partnership, Employer Identification Number (EIN), and unrelated business income tax (UBIT) to provide a reconciliation of *Income (Loss) From Partnerships* required for Part I, Line 5 of IRS, Form 990-T. 990-T forms are available after 2001 and are available on ProPublica.com.

FORM 990-T (2005/2006) Baylor University #74-1159753 May 31, 2006

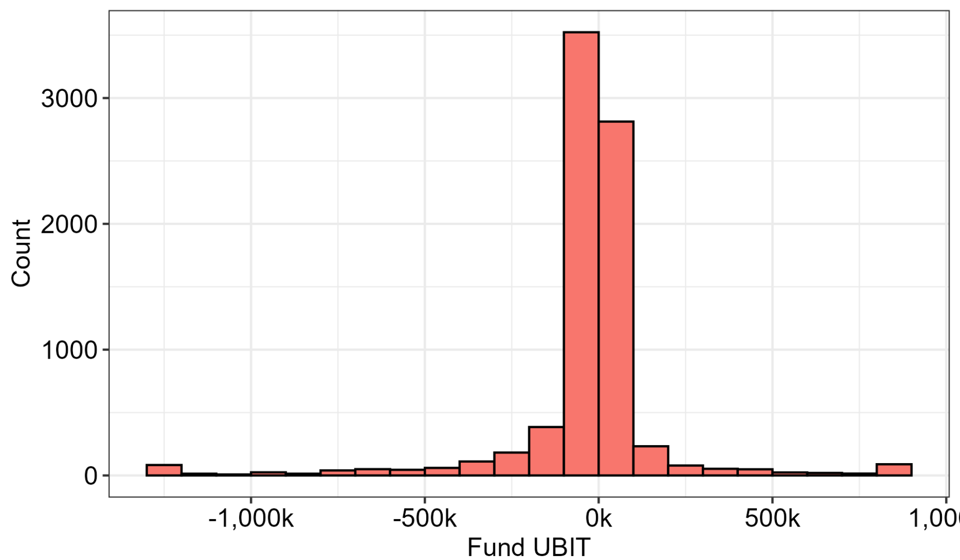
Part I, Line 5 Income (Loss) From Partnerships

Name	EIN	UBIT Amount
AG Private Equity Partners II	05-0538891	74,354
American Private Equity Partners, L.P.	75-2906244	(31,747)
BIV Capital Partners, L.P.	71-0882125	(20,322)
HRJ Capital Real Estate II, L.P.	01-0823703	7,492
Chase Capital Partners Private Equity Fund of Funds II, Ltd.	98-0227519	5,288
Kayne Anderson Energy Fund III (Q.P.) L.P.	83-0407922	21,664
Midmark Equity Partners II, L.P.	22-3687123	(230,473)
Midstate Bancorp, Inc.	73-0736860	164
OCM Principal Opportunities Fund III, L.P.	20-0679312	(37,252)
Permal Private Equity Opportunities II, L.P.	51-0507610	(133)
Private Advisors Small Company Buyout Fund, L.P.	54-2025625	8,290
Reservoir Capital Investment Partners, L.P.	72-1599720	(358)
Southport Energy Plus Partners, L.P.	06-1531979	(54,256)
	Total	(257,289)

Figure IA.4: Distribution of Disclosed Unrelated Business Income Tax (UBIT)

Notes: This figure shows the distribution of the disclosed UBIT for private partnerships disclosed by private universities on Form 990-T. Panel A shows the raw values for UBIT while Panel B shows the raw values for UBIT scaled by an investor's estimated commitment size. Commitment size is estimated by scaling a fund's size by the number of observed public pension investors and university investors based on data from Preqin and IRS, form 990-T. UBIT and scaled UBIT as a fraction of estimated commitment size values are winsorized at the 1st and 99th percentiles.

Panel A. Distribution of Annual UBIT



Panel B. Distribution of Scaled Annual UBIT

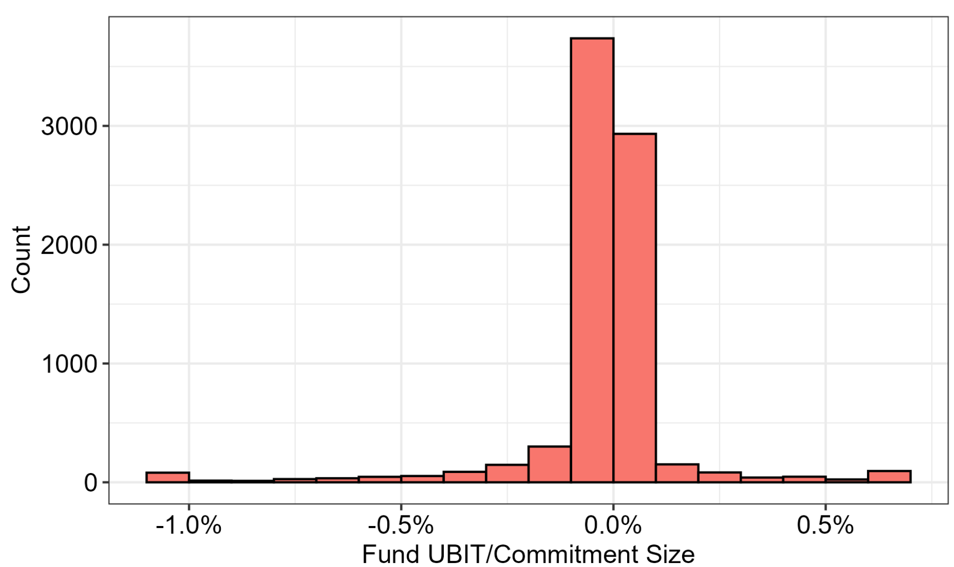


Figure IA.5: Preqin vs. 990-T Coverage for Private Universities by Vintage Year

Notes: This figure shows the total number of university × fund combinations by vintage year covered by Preqin data versus Preqin data augmented with data from the 990-T across all private universities. The sample of funds includes only private equity funds above $100 million in AUM, with non-missing returns, and requires the general partner to be linked to at least one private university during the sample to be included.

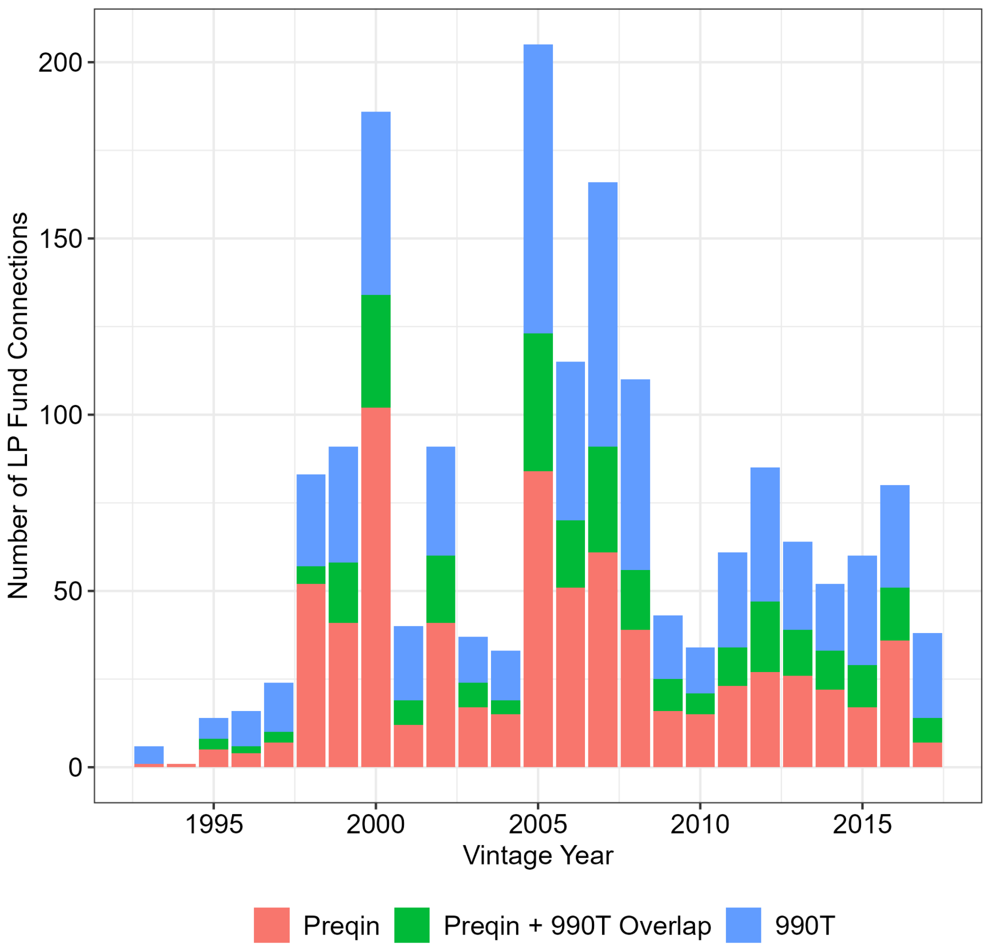


Figure IA.6: Bootstrapped First-Stage F-statistics from Randomized Connections

Notes: This figure shows the bootstrapped first-stage *F-statistics* from Table 4 Panel B column 1 where university $\times$ GP connections are randomized. The histogram (pink bars) shows the distribution across 250 iterations while the black, dotted vertical line plots the *F-statistic* from Table 4 Panel A column 5 based on the observed university $\times$ GP connections.

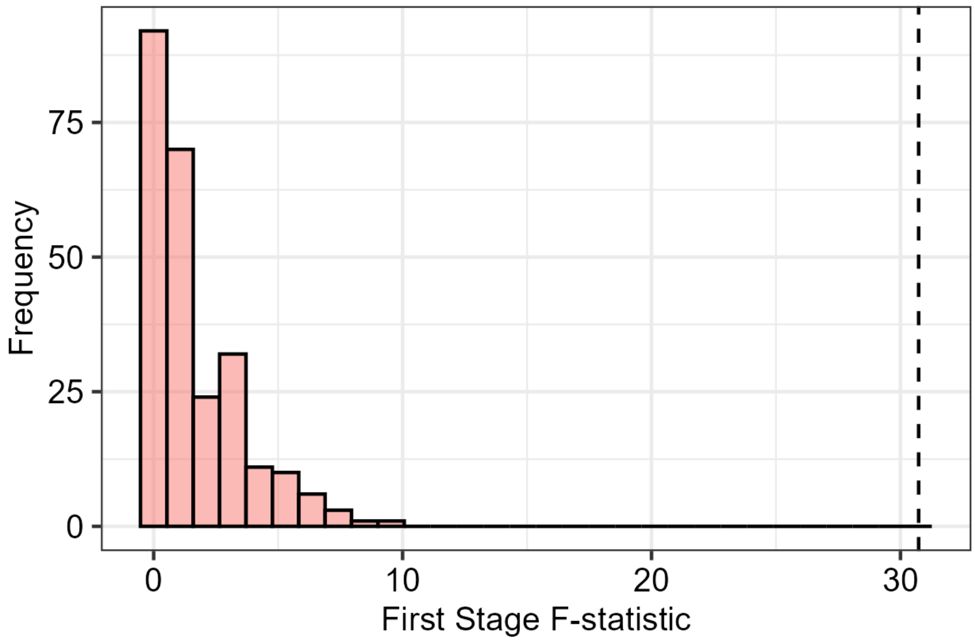


Figure IA.7: IV Effect of Increases in Fund Size on Fund Return Distribution

Notes: This figure displays the IV-regression coefficients from regressing the likelihood of fund IRR performance falling within a given quartile onto the fund's size which is instrumented by $Gifts_{GP}$ which is the standardized sum of gifts received by private universities a general partner is connected to. Regressions include controls for *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Regressions include deal sector, general partner, fund region, fund industry, and vintage year × general partner headquarter region fixed effects (9 different geographic regions). Standard errors are clustered at the year and general partner level. Regressions require that the fund size is greater than $100 million in AUM, the general partner is linked to a private university at some point, and the fund has a vintage year between 2000 and 2017.

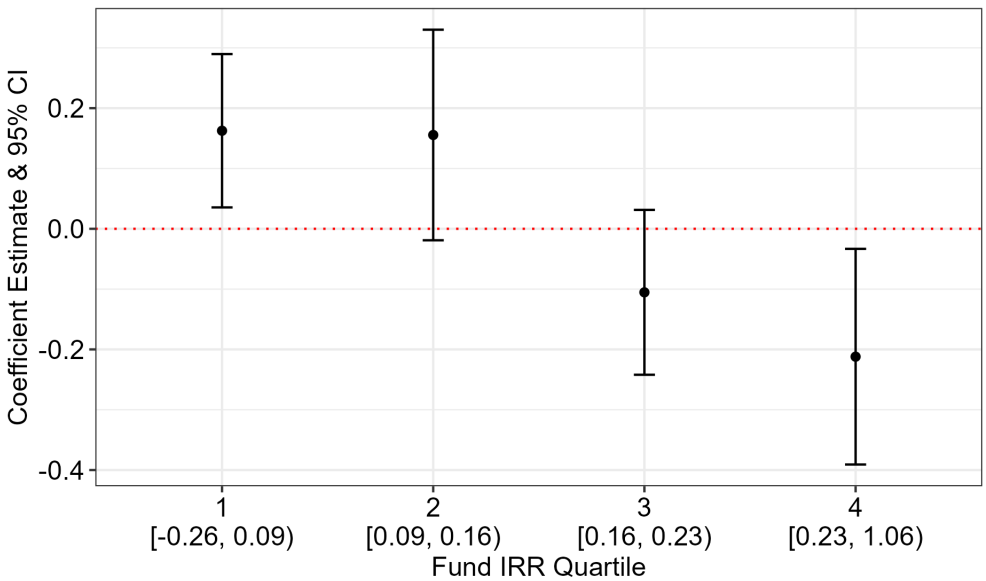


Figure IA.8: IV Effect of Increases in Deal Size on Deal Return Distribution

Notes: This figure displays the IV-regression coefficients from regressing the likelihood of deal IRR performance falling within a given quartile onto the deal's size which is instrumented by $Gifts_{GP}$ which is the standardized sum of gifts received by private universities a general partner is connected to. Regressions include controls for *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Regressions include deal sector, general partner, fund region, fund industry, and vintage year × general partner headquarter region fixed effects (9 different geographic regions). Standard errors are clustered at the year and general partner level. Regressions require that the fund size is greater than $100 million in AUM, the general partner is linked to a private university at some point, and the fund has a vintage year between 2000 and 2017.

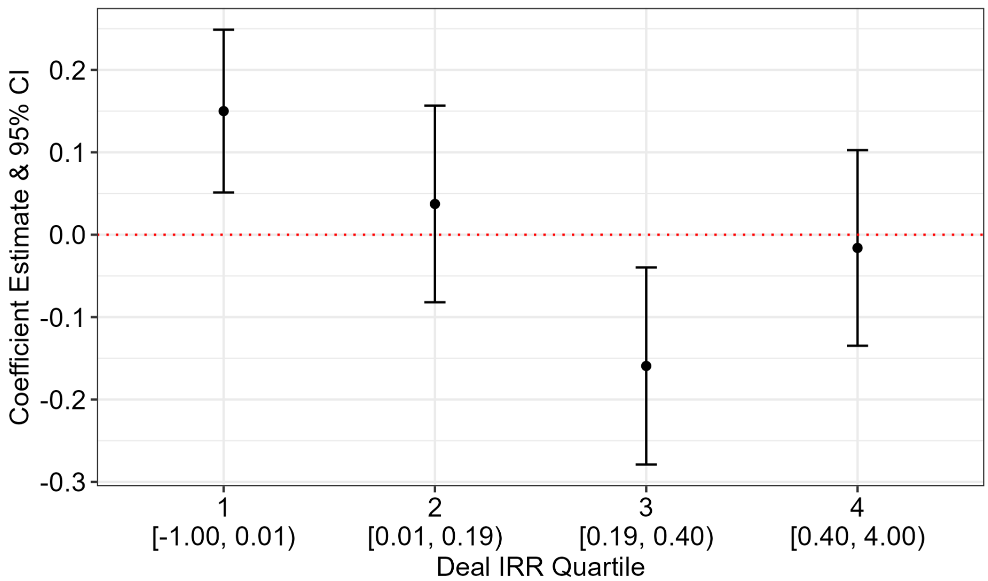


Figure IA.9: PE Waterfall and LP/GP Payoff Diagram

Notes: This figure shows the relationship between the payoffs received by LPs (blue line) and GPs (red line) and the gross exit value of the fund. The gross exit value is calculated as the total capital deployed compounded for 10 years of fund life at the gross IRR rate. The total capital deployed is measured as committed capital net of the present value of annual fixed management fee paid to the GPs.

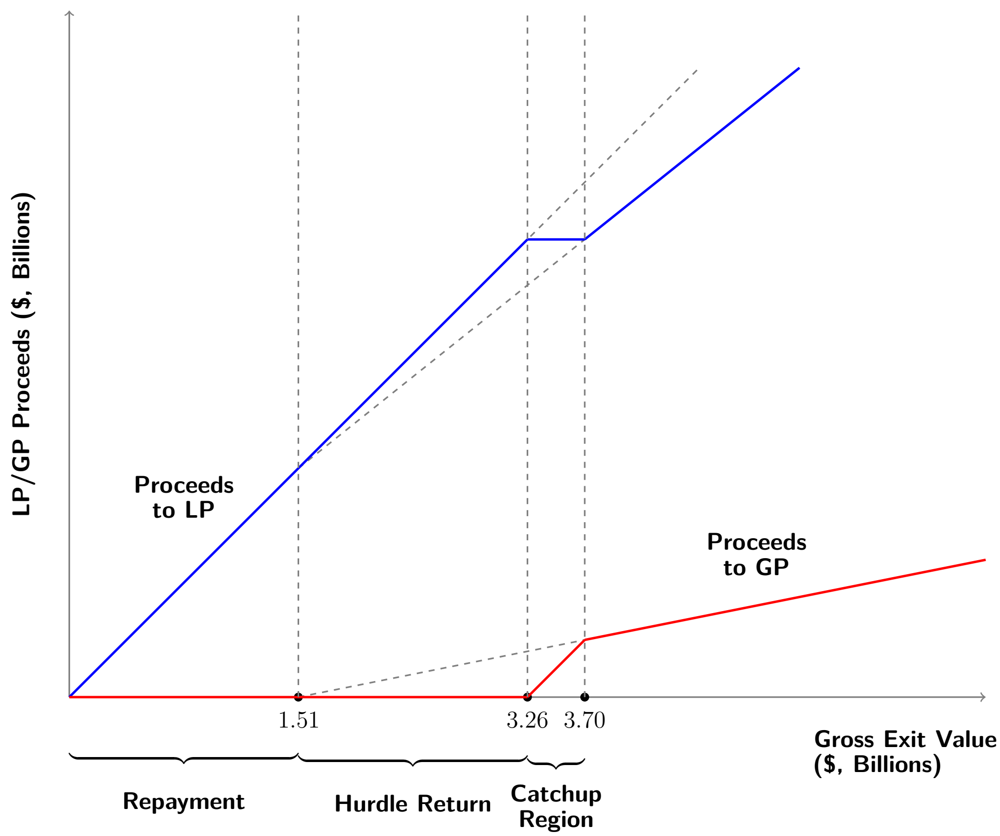


Table IA.1: Relationship between Fund Size and Performance (OLS)

Notes: This table presents estimates of the relationship between fund size and performance, using data on funds with vintage years from 2000 to 2017 without conditioning on the GP being connected to a private university. The table displays the OLS results from regressing Net IRR onto *Fund Size* in Panel A and the OLS results from regressing Net Multiple onto *Fund Size* in Panel B. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund. *GP Controls* include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Net IRR				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.002	-0.002	-0.005*	-0.006*	-0.005*
	[0.004]	[0.005]	[0.003]	[0.003]	[0.002]
Prior IRR				-0.215**	-0.253***
				[0.079]	[0.081]
Observations	1758	1758	1758	1758	1758
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes
Y-mean	0.18	0.18	0.18	0.18	0.18

	Panel B: Net Multiple				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.010	-0.015	-0.006	-0.005	-0.002
	[0.014]	[0.013]	[0.011]	[0.011]	[0.011]
Prior Multiple				-0.118***	-0.131***
				[0.028]	[0.035]
Observations	1890	1890	1890	1890	1890
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes
Y-mean	1.87	1.87	1.87	1.87	1.87

Table IA.2: Examples of Large Gifts

Notes: This table presents examples of large gifts to universities displaying the donor name, university recipient, year of the gifts, amount of the gift, and the gift's purpose. Information on large gifts comes from Indiana University Indianapolis' Million Dollar List and The Chronicle of Philanthropy Big Charitable Gifts List.

Donor	Recipient	Year	Amount ($M)	Purpose
Helen Diller	UC San Francisco	2017	$500	Research
John W. Kluge	Columbia University	2007	$400	Financial Aid
William & Flora Hewlett Foundation	Stanford University	2001	$400	Endowment
Philip Knight	Stanford University	2016	$400	Graduate Program
John A. Paulson	Harvard University	2015	$400	Endowment
Michael Bloomberg	Johns Hopkins University	2013	$350	Research and Financial Aid
Gerald & Ronald Chan	Harvard University	2014	$350	School of Public Health
Stephen Schwarzman	MIT	2018	$350	College of Computing
Gordon & Betty Moore Foundation	Caltech	2001	$300	Research

Table IA.3: First Stage Estimates Controlling for Prior MOIC

Notes: This table presents estimates of the relationship between gifts and fund size and fund characteristics, using data on funds with vintage years from 2000 to 2017. We regress fund size on the sum of gifts received by private universities to which a general partner is connected. The gifts measure is standardized so that a one unit increase represents a standard deviation. Control variables include *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Fund Size ($ Billion)				
	(1)	(2)	(3)	(4)	(5)
Gifts_{GP}	0.408***	0.398***	0.319***	0.324***	0.309***
	[0.093]	[0.082]	[0.066]	[0.066]	[0.053]
Prior Multiple				0.123*	0.135
				[0.066]	[0.093]
F-Statistic	19.28	23.27	23.53	23.79	34.18
Observations	1306	1306	1306	1306	1306
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes

Table IA.4: First Stage Estimates by Endowment Size

Notes: This table presents estimates of the relationship between gifts and fund size and fund characteristics, using data on funds with vintage years from 2000 to 2017. We regress fund size on the sum of gifts received by private universities to which a general partner is connected. The gifts measure is standardized so that a one unit increase represents a standard deviation. $\text{Gifts}_{GP:SmallLP}$ restricts the set of university endowments to those that are not in the top 15 by size. Similarly, $\text{Gifts}_{GP:LargeLP}$ includes only the 15 largest university endowments. $\text{Gifts}_{GP:SmallLP}$ and $\text{Gifts}_{GP:LargeLP}$ are constructed to be of similar magnitudes so an $\approx$ \$275 million increase in gifts results in a one standard deviation increase in gifts to a GP. *Prior IRR* represents the average IRR of a general partner's funds raised at least five years before the current fund. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Fund Size ($ Billion)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gifts_{GP}	0.329***	0.322***						
	[0.074]	[0.058]						
$\text{Gifts}_{GP:SmallLP}$			0.221**	0.205**			0.132	0.132
			[0.095]	[0.084]			[0.115]	[0.115]
$\text{Gifts}_{GP:LargeLP}$					0.296***	0.288***	0.252***	0.252***
					[0.072]	[0.070]	[0.090]	[0.090]
Prior IRR	0.232	0.246	0.248	0.284	0.155	0.204	0.223	0.223
	[0.648]	[0.708]	[0.671]	[0.718]	[0.649]	[0.716]	[0.636]	[0.636]
F-Statistic	19.86	30.71	5.39	5.88	16.76	17.04	11.90	11.90
Observations	1231	1231	1231	1231	1231	1231	1231	1231
General Partner F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GP Controls	No	Yes	No	Yes	No	Yes	No	Yes

Table IA.5: Spillover Effects of University Gifts on Number of LPs & Composition

Notes: This table reports the effects of university donation gift exposure on the number and composition of LPs. This table displays the reduced form effect where the dependent variable is the count or proportion of a given LP type and the independent variable is our instrument $Gifts_{GP}$. The most common LP types include public pension funds, corporate pensions, university endowments, insurance companies, foundations, and corporations. *Pension & Other LPs* includes all LP types besides university endowments and private foundations. LP commitment data is sourced from Preqin, Form 990-T, and Pitchbook. University endowment data is sourced from Form 990-T and Preqin while all other LP commitment data is sourced from Pitchbook. Funds are included in the sample estimation conditional on at least one LP commitment being observed. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Number of LPs				LP Composition
	Total LPs	Pension & Other LPs	Private Foundations	Private Univ.	% Pension AUM
	(1)	(2)	(3)	(4)	(5)
Gifts_{GP}	5.54***	4.19***	0.46***	0.03	0.00
	[0.89]	[1.00]	[0.10]	[0.16]	[0.01]
Prior IRR	1.52	-0.84	0.34	0.66	-0.01
	[12.53]	[11.09]	[1.16]	[0.63]	[0.06]
Observations	1074	1074	1074	1074	1074
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	24.14	19.99	2.47	0.78	0.22

Table IA.6: Extensive Margin Effects

Notes: This table reports reduced-form extensive margin effects of a GP's exposure to university inflows and its fund launch and fund size decision. $\mathbb{I}$*(Raise Fund)* is an indicator variable if a GP raised at least one fund in a given vintage year, *# Funds Raised* represents the number of funds a GP raised in a given vintage year, *Log(Funds Raised)* represents the logarithm of total proceeds raised by a GP in a given vintage year conditional on a GP launching at least one fund in that vintage year, and $\overline{\textit{Log(Fund Size)}}$ represents the average of the logarithm of fund size in a given year conditional on a GP launching at least one fund in that vintage year. *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Funds Launched		Proceeds Raised	
	$\mathbb{I}$(Raise Fund)	# Total Proceeds	Log(Proceeds Raised)	$\overline{\text{Log(Fund Size)}}$
	(1)	(2)	(3)	(4)
Gifts_{GP}	-0.00	-0.01	0.10^{***}	0.11^{**}
	[0.01]	[0.02]	[0.03]	[0.04]
Observations	3202	3202	917	917
General Partner F.E.	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes
Y-mean	0.29	0.37	6.97	6.78

Table IA.7: Effect of Fund Size on Performance (OLS): Cash Flow Level Analysis

Notes: This table reports OLS estimates of how fund size affects fund performance. We use data on funds with vintage years from 2000 to 2017 with cash flow level data in Burgiss. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund. *GP Controls* includes controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Net IRR				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.010*	-0.015***	-0.015***	-0.015***	-0.015***
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]
Observations	528	528	528	528	528
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Prior IRR Control	No	No	Yes	No	Yes
GP Controls	No	No	No	Yes	Yes
Y-mean	0.16	0.16	0.16	0.16	0.16

	Panel B: Gredil et al. (2023) Direct Alpha				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.016***	-0.021***	-0.022***	-0.015***	-0.014***
	[0.005]	[0.005]	[0.005]	[0.003]	[0.003]
Observations	528	528	528	528	528
Panel A F.E. & Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	0.05	0.05	0.05	0.05	0.05

	Panel C: Kaplan and Schoar (2005) PME				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.061***	-0.079***	-0.079***	-0.054***	-0.053***
	[0.018]	[0.017]	[0.017]	[0.010]	[0.010]
Observations	528	528	528	528	528
Panel A F.E. & Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	1.20	1.20	1.20	1.20	1.20

	Panel D: Korteweg and Nagel (2024) α				
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.059***	-0.075***	-0.075***	-0.052***	-0.050***
	[0.018]	[0.017]	[0.017]	[0.010]	[0.010]
Observations	514	514	514	514	514
Panel A F.E. & Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	0.27	0.27	0.27	0.27	0.27

Table IA.8: Comparison of Funds by Presence of University Connection

Notes: This table reports the mean, median, and standard deviation across private equity general partner and fund characteristics across funds launched by GPs with and without connections to private universities. We employ data on funds with vintage years from 2000 to 2017. *Univ. GPs* are defined as private equity funds with GPs with at least one observed connection to a private university while *Non-Univ. GPs* have no observed connection to a private university. *Prior Fund Level* contains characteristics at the fund-level for the first private equity fund launched in a vintage year preceding the focal fund while *Prior Aggregate Funds* contains characteristics based on funds launched by a GP within the last 5 years. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively. See the variable definitions in the Appendix for additional details.

	Univ. GPs (N = 1231)			Non-Univ. GPs (N = 527)			Diff. (N = 1,758)
	Mean	Median	SD	Mean	Median	SD	Mean
Prior Fund Level							
Net IRR	0.16	0.15	0.11	0.15	0.14	0.12	0.02*
Fund Size ($ Billions)	1.38	0.56	1.93	0.67	0.42	0.79	0.71***
Carried Interest	0.17	0.20	0.06	0.20	0.20	0.03	-0.02***
Management Fee	1.71	2.00	0.48	1.84	2.00	0.33	-0.13*
Prior Aggregate Funds							
Prior IRR	0.15	0.13	0.10	0.15	0.13	0.13	0.00
Time Since Last Fund	2.30	1.00	1.75	3.66	4.00	2.07	-1.37***

Table IA.9:

Effect of Fund Size on Performance (IV) after Excluding Financial and PE Donors

Notes: This table reports IV estimates of how fund size, instrumented with university endowment gifts, affects fund performance. We use data on funds with vintage years from 2000 to 2017. The instrumental variable is comprised of the sum of gifts received by a given university minus the large gifts it receives from donors either in the financial or private equity sector. *Large Gifts* data comes from million dollar gifts or bequests reported to Indiana University Indianapolis' Million Dollar List or the Chronicle of Philanthropy. Donor's sector of employment is identified using OpenAI's API. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund. *GP Controls* includes controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and GP level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Net IRR					
Exclude Gifts From:	PE Donors			Finance-Related Donors		
	(1)	(2)	(3)	(4)	(5)	(6)
Fund Size ($ Billion)	-0.07**	-0.07**	-0.06**	-0.06**	-0.06**	-0.05*
	[0.02]	[0.02]	[0.03]	[0.02]	[0.02]	[0.03]
Prior IRR		-0.20**	-0.25**		-0.20**	-0.25**
		[0.09]	[0.09]		[0.09]	[0.09]
F-Statistic	28.06	28.21	24.25	29.56	29.67	25.38
Observations	1231	1231	1231	1231	1231	1231
General Partner F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
GP Controls	No	No	Yes	No	No	Yes
Y-mean	0.18	0.18	0.18	0.18	0.18	0.18

Table IA.10: Effect of Fund Size on Fund MOIC Robustness Tests (IV)

Notes: This table reports alternative versions of the main IV results from Table 5 Panel B. The first panel repeats the model in column 5 of Table 5. The second panel presents variants on this model as follows: Row 2A expands the sample period from 1990-2017, row 2B includes all private equity funds from 2000-2017 without requiring a GP is linked to a private university, row 2C includes funds from the full sample (2A + 2B) and excludes fund of funds, row 2D excludes the 10 largest GPs by proceeds raised from the sample, row 2E excludes funds above the 90th percentile in the number of deals, row 2F excludes funds below the 10th percentile of fund size, row 2G excludes funds above the 90th percentile of fund size, row 2H includes relationship controls for the number of linked universities and changes in linkages, row 2I includes an additional control for the weighted-average IRR for funds launched within the last 5 years, and row 2J includes funds regardless of their size removing the $100 million fund size filter. The third panel presents results from alterations of the instrument: Row 3A uses $\textit{Raw Gifts}_{GP}$ the non-standardized measure of gifts as the instrumental variable, row 3B uses an alternative measure of university gifts defined as *Gifts, Grants, and Contracts* as reported to the Integrated Postsecondary Education Data System (IPEDS) as the instrumental variable and includes both public and private universities, row 3C uses only million dollar gifts or bequests reported to Indiana University Indianapolis' Million Dollar List or the Chronicle of Philanthropy as the instrumental variable, row 3D subsets the million dollar gifts result from 3C but excludes gifts from in-state donors, row 3E uses the logarithm of fund size as the endogenous variable, row 3F nets out changes in pledges receivable to approximate a cash-flow based measure rather than an accrual-based measure, and row 3G expands the gift exposure window from *t-2* to *t-2 to t-4*. The fourth panel presents results from varying the fixed effects: Row 4A excludes *Year* fixed effects, row 4B includes a linear time trend, row 4C includes annual PE fundraising, row 4D includes *year* fixed effects, and row 4E includes *GP State* × *Year* fixed effects based on the location of a general partner's headquarter state in place of *GP Region* × *Year* fixed effects. Row 4F includes *Industry* × *Year* fixed effects while Row 4G includes average deal leverage and age controls which are interpolated to the average when missing. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Net Multiple			
Instrument Variable	Coefficient	Standard Error	F-Statistic	Observations
1. Base Specification				
Fund Size ($ Billions)	-0.251**	0.089	34.21	1306
2. Sampling Choices				
A. 1990-2017				
Fund Size ($ Billions)	-0.339***	0.114	22.50	1460
B. Include GP's With and Without Relationships				
Fund Size ($ Billions)	-0.239***	0.079	42.27	1671
C. Without Fund of Funds				
Fund Size ($ Billions)	-0.234**	0.11	24.71	1482
D. Exclude 10 Largest GP's				
Fund Size ($ Billions)	-0.257**	0.109	23.45	1045
E. Exclude Funds ≥ 90th Percentile of # Deals				
Fund Size ($ Billions)	-0.128	0.111	17.17	771
F. Exclude Funds ≤ 10th Percentile of Fund Size				
Fund Size ($ Billions)	-0.241**	0.085	49.01	1170

(Continued on next page)

Table (*continued*)

	Net IRR			
Instrument Variable	Coefficient	Standard Error	F-Statistic	Observations
G. Exclude Funds ≥ 90th Percentile of Fund Size				
Fund Size ($ Billions)	-0.618*	0.315	10.12	1159
H. Include Relationship Controls				
Fund Size ($ Billions)	-0.232*	0.131	54.10	1306
I. Include Recent IRR Control				
Fund Size ($ Billions)	-0.281***	0.091	32.54	1306
J. Include Funds Regardless of Size				
Fund Size ($ Billions)	-0.193**	0.084	36.75	1331
3. Instrument and Dependent Variable Choices				
A. Use *Raw Gifts*				
Fund Size ($ Billions)	-0.241**	0.091	38.65	1306
B. Use IPEDs' Measure of Gifts, Grants, and Contracts				
Fund Size ($ Billions)	-0.262**	0.110	24.33	1306
C. Use Million Dollar Gifts				
Fund Size ($ Billions)	-0.227*	0.111	18.77	1306
D. Exclude In-State Million Dollar Gifts				
Fund Size ($ Billions)	-0.339**	0.153	13.78	1306
E. Instrument for Log(Fund Size)				
Fund Size ($ Billions)	-0.507**	0.191	25.04	1306
F. Instrument for Cash-Based Proxy				
Fund Size ($ Billions)	-0.261**	0.095	48.98	1306
G. Instrument Using Rolling Gifts				
Fund Size ($ Billions)	-0.250**	0.090	41.71	1306
4. Tighter Fixed Effects				
A. Exclude Year F.E.'s				
Fund Size ($ Billions)	-0.286***	0.083	31.41	1306
B. Include Linear Time Trend				
Fund Size ($ Billions)	-0.256***	0.085	20.98	1306
C. Include PE Annual Funds Raised				
Fund Size ($ Billions)	-0.307***	0.080	32.05	1306
D. Include Year Fixed Effects				
Fund Size ($ Billions)	-0.267**	0.098	25.13	1306
E. Include GP State × Year F.E.'s				
Fund Size ($ Billions)	-0.263**	0.100	18.05	1253
F. Include Industry × Year F.E.'s				
Fund Size ($ Billions)	-0.373***	0.121	12.50	1251
G. Include Average Deal Leverage and Age				
Fund Size ($ Billions)	-0.233**	0.087	31.52	1306

Table IA.11: First Stage Estimates at Deal Level

Notes: This table reports first stage estimates using gifts to predict deal size, with deal-level data from funds with vintage years from 2000 to 2017. The dependent variable is Deal Size and the instrumental variable is $Gifts_{GP}$ which is the standardized sum of gifts received by private universities a general partner is connected to along with a variation of fixed effects and controls. Control variables include *Prior IRR* which is the average net IRR of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Regressions include general partner, fund region, fund industry, vintage year × general partner headquarter region fixed effects (9 different geographic regions), and deal sector fixed effects. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Deal Size ($100 Millions)				
	(1)	(2)	(3)	(4)	(5)
Gifts_{GP}	0.225***	0.229***	0.146***	0.147***	0.140***
	[0.042]	[0.039]	[0.029]	[0.029]	[0.028]
Prior IRR				-0.176	-0.060
				[0.282]	[0.271]
F-Statistic	28.46	33.95	25.09	25.87	25.80
Observations	8748	8748	8748	8748	8748
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	No	Yes	Yes	Yes	Yes
Year × GP Region F.E.	No	No	Yes	Yes	Yes
Deal Sector F.E.	Yes	Yes	Yes	Yes	Yes
GP Controls	No	No	No	No	Yes

Table IA.12: Relationship between Deal Size and Deal Return Distribution (OLS)

Notes: This table reports the OLS estimates of the relationship between deal performance and deal size, using data on funds with vintage years from 2000 to 2017. The dependent variable in column 1 is a continuous measure of IRR while columns 2 to 5 are indicators if IRR falls within a given quartile. Control variables include *Prior IRR* which is the average IRR of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last fund. Standard errors are clustered at the deal entry year and fund level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Gross IRR	Bottom Quartile	2^{nd} Quartile	3^{rd} Quartile	Top Quartile
	(1)	(2)	(3)	(4)	(5)
Deal Size ($100 Millions)	-0.05***	-0.00	0.02***	0.01**	-0.04***
	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]
Prior IRR	-0.26***	0.09	0.07	0.06	-0.23***
	[0.09]	[0.07]	[0.05]	[0.07]	[0.06]
Observations	8748	8748	8748	8748	8748
Deal Sector F.E.	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes
Y-mean	0.24	0.25	0.25	0.25	0.25

Table IA.13:

Effects of Increases in Size on Fund and Deal MOIC Return Distribution (IV)

Notes: This table reports IV estimates of how fund size affects the performance distribution, using MOIC as the measure of performance rather than IRR. We employ data on funds with vintage years from 2000 to 2017. Panel A uses fund-level data while Panel B uses deal-level data. Control variables include *Prior Multiple* which is the average net multiple of a general partner's funds raised at least five years before the current fund and *GP Controls* which include controls for the prior number of funds raised, total funds raised, average fund size, and the time since the last private equity fund raised. Standard errors are clustered at the year and general partner level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: IV: Fund-Level Multiple Distribution				
	Net Multiple	Bottom Quartile	2^{nd} Quartile	3^{rd} Quartile	Top Quartile
	(1)	(2)	(3)	(4)	(5)
Fund Size ($ Billions)	-0.252**	0.097*	0.165*	-0.092	-0.170**
	[0.089]	[0.054]	[0.082]	[0.087]	[0.074]
Prior Multiple	-0.093	0.038	-0.007	-0.012	-0.019
	[0.054]	[0.029]	[0.027]	[0.034]	[0.032]
F-Statistic	34.21	34.21	34.21	34.21	34.21
Observations	1306	1306	1306	1306	1306
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	1.88	0.25	0.26	0.24	0.24

	Panel B: IV: Deal-Level Multiple Distribution				
	Net Multiple	Bottom Quartile	2^{nd} Quartile	3^{rd} Quartile	Top Quartile
	(1)	(2)	(3)	(4)	(5)
Deal Size ($100 Millions)	-0.43	0.15**	-0.01	-0.13	-0.01
	[0.27]	[0.06]	[0.05]	[0.08]	[0.07]
Prior Multiple	-0.01	0.00	-0.01	0.01	-0.01
	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]
F-Statistic	18.40	18.40	18.40	18.40	18.40
Observations	9490	9490	9490	9490	9490
Deal Sector F.E.	Yes	Yes	Yes	Yes	Yes
Year × GP Region F.E.	Yes	Yes	Yes	Yes	Yes
General Partner F.E.	Yes	Yes	Yes	Yes	Yes
Region & Industry F.E.	Yes	Yes	Yes	Yes	Yes
GP Controls	Yes	Yes	Yes	Yes	Yes
Y-mean	2.26	0.28	0.24	0.24	0.24

Appendix B: Variable Definitions

B.1 Fund-Level Statistics

Preqin Measures

Fund Size ($ Billions) is the total amount of capital committed by investors to a specific fund. Source: Preqin.

Net IRR is the fund's internal rate of return (IRR) after accounting for fees. Source: Preqin.

Net Multiple is the fund's multiple on invested capital after accounting for fees. Source: Preqin.

Prior IRR is the fund's weighted-average internal rate of return (IRR) after accounting for fees on all funds with vintage years at least five years before the focal fund. Source: Preqin.

Burgiss Measures

Net IRR is the fund's internal rate of return (IRR) after accounting for fees using cash flow level data. Source: Burgiss.

Direct Alpha is the fund's Direct Alpha computed by Burgiss based on Gredil et al. (2023) using cash flow level data and discounted using the S&P 500 index. Source: Burgiss.

Kaplan and Scholar Public Market Equivalent is the fund's public market equivalent computed by Burgiss based on Kaplan and Schoar (2005) using cash flow level data and discounted using the S&P 500 index. Source: Burgiss.

$\boldsymbol{\alpha}$ is the fund's measure of risk-adjusted performance computed following Korteweg and Nagel (2024) using cash flow level data and the market risk premium from Ken French's website. Source: Burgiss.

Raw Gifts$_{GP}$ **($ Billions)** The sum of gifts received by linked universities in academic year *t-2* where gifts are aggregated to the GP $\times$ year level for academic year *t-2* and relationships are defined if a private university had invested in a general partner's fund from academic years *t-7* to *t-3*. Source: IRS Form 990-T.

Gifts$_{GP}$

- The standardized sum of gifts received by linked universities in academic year *t-2* where gifts are aggregated to the GP $\times$ year level for academic year *t-2* and relationships are defined if a private university had invested in a general partner's fund from academic years *t-7* to *t-3*.
  - Standardized by subtracting a GPs inflows by the average across all GPs during the entire sample and dividing by the standard deviation of all gifts across the entire sample
- Preqin has comprehensive coverage of vintage years (while data on fund launch dates is sparse) so we lag donations by two years and relationships by three years to assure these donations occur *prior to or during* the fund raising stage
  - Fund launch to a fund making its first investment (its vintage year) takes about 12-18 months for the average fund in Preqin
- Relationships are allowed to form and break over time (e.g. if a private university starts or stops investing in a given general partner in the last five years).

Linked Universities The number of universities a given general partner is linked to at time *t-3* used to calculate its gift exposure. Source: Preqin and IRS Form 990-T.

Δ Linked Universities The change in the number of universities a given general partner is linked to from time *t-4* to time *t-3*. Source: Preqin and IRS Form 990-T.

Δ Fund Size The change in fund size relative to the last private equity fund launched by a given GP. Source: Preqin.

% Δ Fund Size The percent change in fund size relative to the last private equity fund launched by a given GP. Source: Preqin.

Partners is the number of senior employees within a given private equity fund. Source: Pitchbook.

Average Deal Size is the average deal size across private equity deals within a given private equity fund. Source: Fund of Funds, Pitchbook, Preqin.

Number of Deals is the average number of deals within a given private equity fund. Source: Fund of Funds, Pitchbook, Preqin.

Number of Sub-Sectors is the average number of sub-sector deals within a given private equity fund occur. Source: Fund of Funds, Pitchbook, Preqin.

Number of States is the average number of states deals within a given private equity fund occur. Source: Fund of Funds, Pitchbook, Preqin.

Number of Regions is the average number of global geographic region deals within a given private equity fund occur. Source: Fund of Funds, Pitchbook, Preqin.

Time Last Deal is the average fund's length from its vintage year to its last completed deal. Source: Fund of Funds, Pitchbook, Preqin.

B.2 Deal-Level Statistics

Gross IRR is the gross internal rate of return (IRR) for a given deal. Source: Fund of Funds.

Net Multiple is the multiple on invested capital for a given deal after deducting fees. Source: Fund of Funds.

Deal Size ($ Millions) is the amount of equity committed to a given private equity deal. Source: Fund of Funds.

Debt is the amount of debt committed to a given private equity deal. Source: Fund of Funds.

Age is the age of a portfolio company for a given private equity deal. Source: Fund of Funds.

Enterprise Value ($ Millions) is the total value of the company (debt + equity) in a given private equity deal. Source: Fund of Funds.

EBITDA is the earnings before interest, taxes, and depreciation for a given company in a given private equity deal. Source: Fund of Funds.

B.3 University Statistics

Raw Gifts ($ Billions) is the sum of gifts a university receives in a given fiscal year reported as direct public support on IRS, Form 990. Source: IRS Form 990.

Large Gifts ($ Billions) is the sum of million dollar gifts or bequests reported to Indiana University Indianapolis' Million Dollar List and The Chronicle of Philanthropy Big Charitable Gifts List. The series is interpolated across the two sources with gifts prior to 2014 being sourced from Indiana University Indianapolis' Million Dollar List and donations from 2014 onward sourced from The Chronicle of Philanthropy. We include only gifts denoted as gifts or bequests (excluding pledges and gifts over time), and bound this at 90 percent of *Raw Gifts* in cases which Large Gifts exceeds

Raw Gifts for illustration purposes. Our results are robust to including an unbounded measure of *Large Gifts*. Source: Indiana University Indianapolis' Million Dollar List and The Chronicle of Philanthropy Big Charitable Gifts List.

Endowment ($ Billions) is the size of a university's endowment at the end of the fiscal year as reported to the integration postsecondary education data system (IPEDS). Source: Integrated Postsecondary Education Data System (IPEDS).

Relationship GPs The number of unique GPs a 990-filing university invests in within the last 5 years across its private equity investments for 990-filing universities in our sample for investments reported across Preqin and IRS, Form 990-T. Source: Preqin and IRS Form 990-T.

Pension & Other LPs The number of public pension, insurance companies, and corporate pension LPs within a given private equity fund (excludes university and private foundation LPs). Source: Pitchbook.

Public University & Private Foundation LPs The number of public university & private foundation LPs within a given private equity fund. Source: Pitchbook, Preqin, and IRS Form 990-T.

Private University LPs The number of private university LPs within a given private equity fund. Source: Preqin and IRS Form 990-T.

Total LPs The number of public pension LPs and university investors within a given private equity fund. Source: Pitchbook, Preqin, and IRS Form 990-T.

Appendix C: Survey

C.1 Survey Content

Survey on Allocator Beliefs Regarding Private Equity

Introduction

We are working on a research project about the relationship between fund size and returns in private equity. An important part concerns the beliefs of allocators. If you work with PE investments, it would be enormously helpful if you could respond to this short survey. If you don't, please forward this to an investment officer who does work with PE.

We are developing a causal estimate of the impact of larger funds on net returns (holding all other factors fixed), which we will be happy to share with you when the paper is finished if you respond to the survey.

This research is academic in nature. We will not share any non-aggregated data from this survey with anyone outside of our research team.

Questions

* 1. Your Name (so we can send you the finished paper):

* 2. What is the approximate size (AUM) of your institution's investment portfolio (including all assets)?

* 3. If you could hold all other factors about the fund fixed (such as the quality of the manager), do you believe that smaller or larger funds tend to perform better?

- ○ Smaller funds tend to perform better
- ○ Larger funds tend to perform better

* 4. Considering your answer to the previous question, why did you answer that one type performs better than the other?

* 5. Suppose you were considering investing in a fund and you were informed that a large private university endowment had already committed to that fund. Would this increase your chances of investing?

- ◯ Yes, it would be very important
- ◯ Yes, it would be somewhat important
- ◯ No, it would not influence me
- ◯ No, I view it as a negative signal about the fund

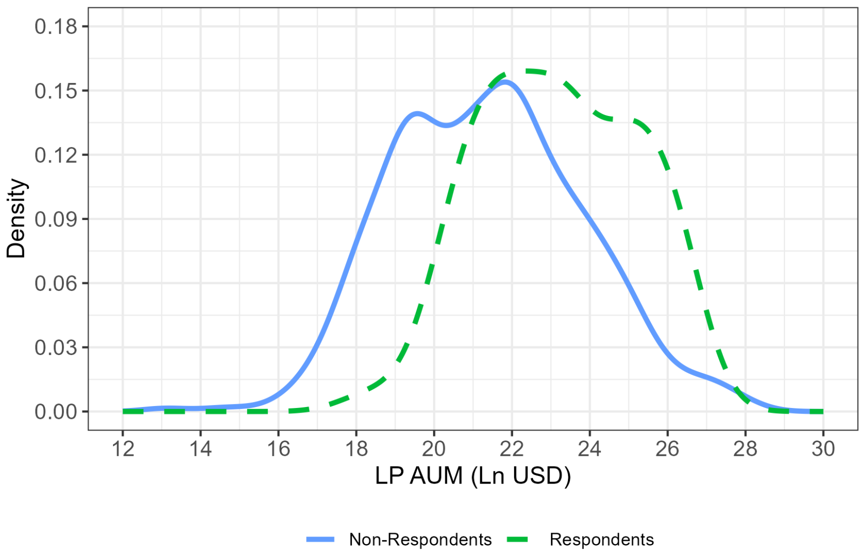
* 6. Suppose you were considering investing in a fund and you were informed that a government pension fund had already committed to that fund. Would this increase your chances of investing?

- ◯ Yes, it would be very important
- ◯ Yes, it would be somewhat important
- ◯ No, it would not influence me
- ◯ No, I view it as a negative signal about the fund

Figure IA.C.1: Selection of LP Respondents by AUM and Location

Notes: This figure shows results from the survey of LPs (see Section 2.3 and Appendix C for details). Panel A shows the distribution of respondents and non-respondents by assets under management (AUM). Panel B shows the U.S.-based share of each group. The total number of responses is 81.

Panel A. Distribution of AUM



Panel B. Location

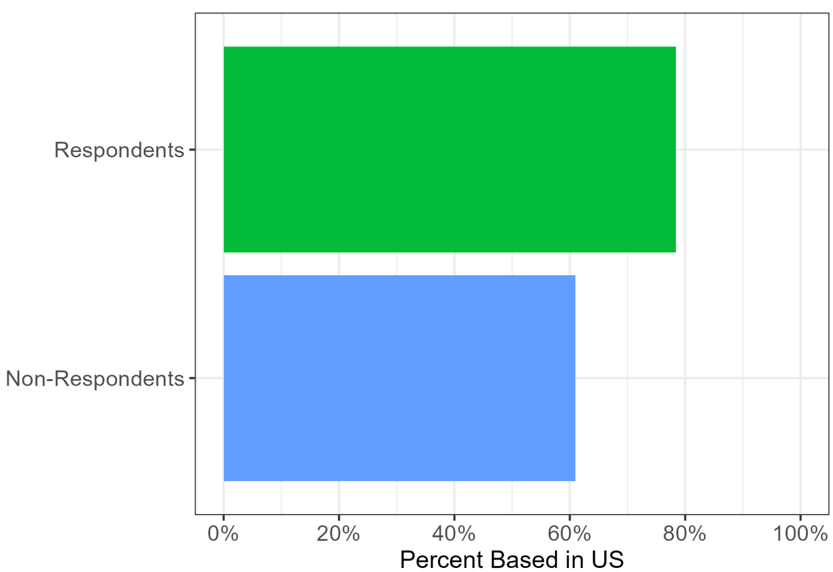


Figure IA.C.2: LP Beliefs about Returns by Fund Size Across Institution Type

Notes: This figure shows results from the survey of LPs (see Section 2.3 for details), breaking down the result from Figure 2 Panel B by institution type. We show the share of each institution type reporting that they believe small funds perform better. The total number of responses is 81.

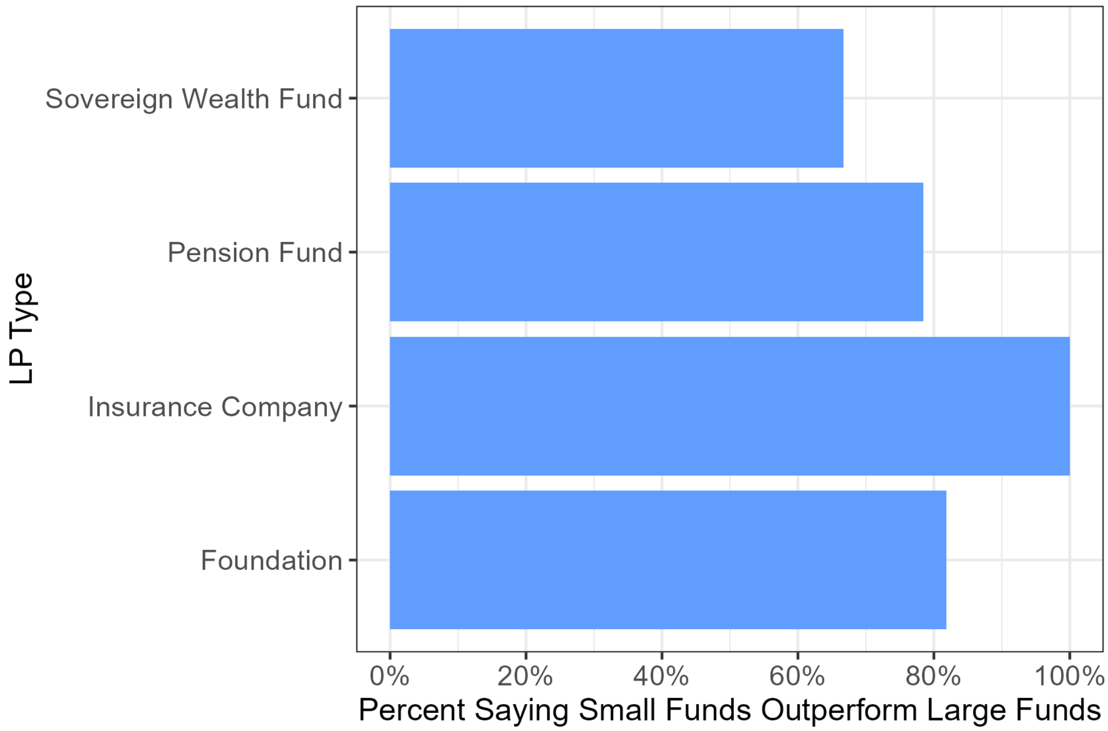


Figure IA.C.3: Signaling Power of University Commitments by Institution Type

Notes: This figure shows results from the survey of LPs (see Section 2.3 and Appendix C for details), breaking down the result from Figure 4 by institution type. We group respondents who reported that university commitments would be somewhat or very important into a single category, and then show the share of each institution type with this response. The total number of responses is 81.

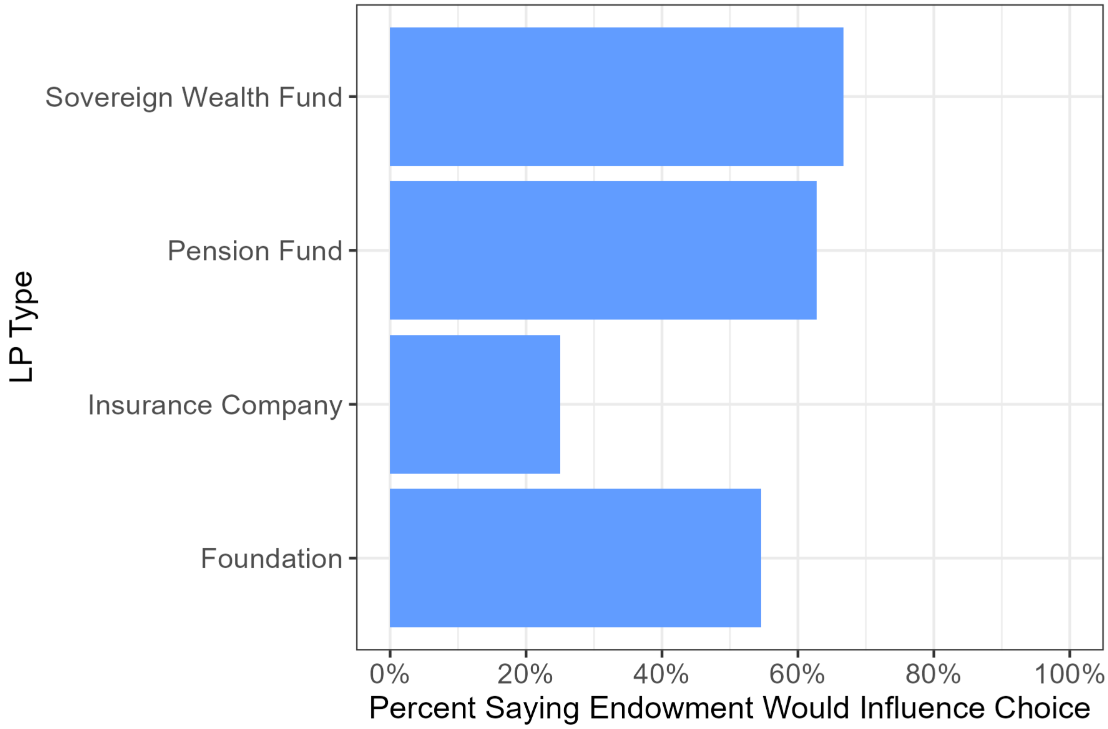


Figure IA.C.4: Signaling Power of Government Pension Commitments

Notes: This figure shows results from the survey of LPs (see Section 2.3 and Appendix C for details). The prompt for the responses was "Suppose you were considering investing in a fund and you were informed that a government pension fund had already committed to that fund. Would this increase your chances of investing?". The total number of responses is 81.

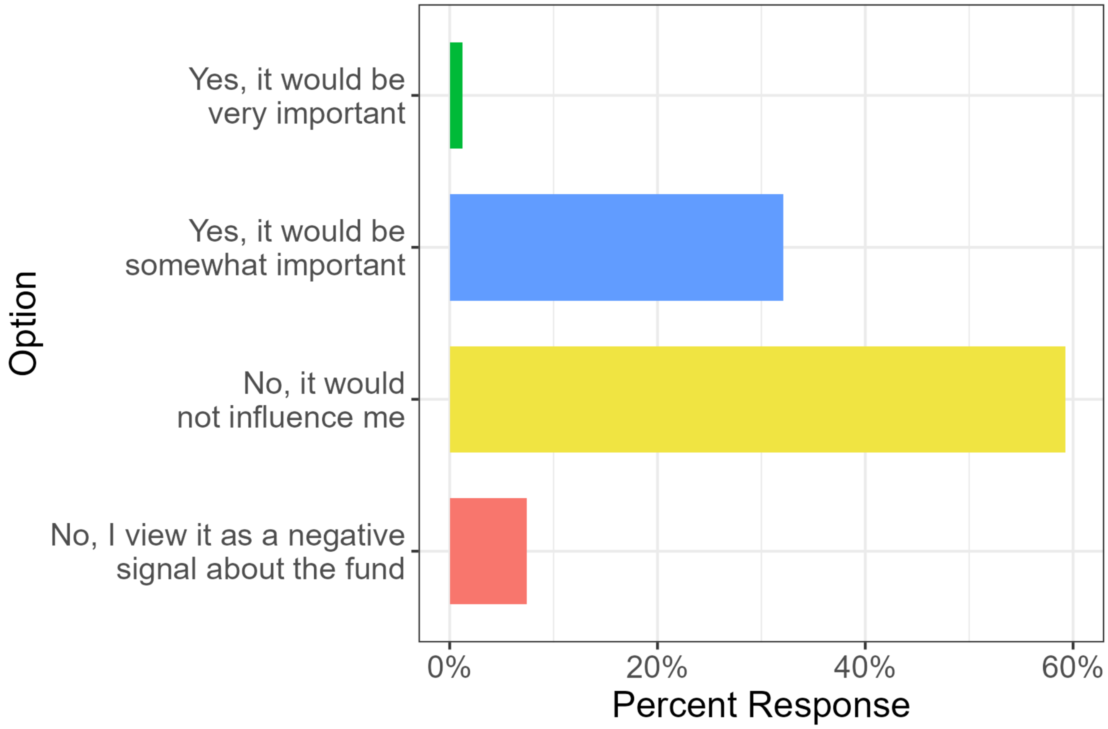


Table IA.C.1: Selection of Survey Respondents by Institution Type

Notes: This table reports response rates to the LP survey by LP type, as classified by Pitchbook along with the total across all LP types. *# Contacted* denotes the number of institutions within a given type we contacted in our survey, *# Responded* denotes the number of surveyed institutions which responded. *% Responded* represents the proportion of surveyed institutions which responded.

LP Type	# Contacted	# Responded	% Responded
Pension Fund	571	44	8%
Foundation	395	22	6%
Insurance Company	117	4	3%
Sovereign Wealth Fund	22	3	14%
Family Office	19	1	5%
Other	5	0	0%
Total	1,129	74	7%

Appendix D: Constructing Cash-Flow Based Measure of Gifts

D.1 Form 990 Gift Reporting & Revenue Recognition

Our measure of *Raw Gifts* is reported on a university's form 990 Part VIII line 1F ("All Other contributions, gifts, grants, and similar amounts not included above"). We use this line item of gifts in our analysis as it cleanly captures financial support from non-governmental, private entities.[48]

These *Raw Gifts* are an accrual-based measure which includes both contemporaneous gifts (those occurring in the given fiscal year) and the discounted present value of future gifts (i.e., pledges) as shown in Equation 1.

$$\text{Raw Gifts}_{\text{i},t} = \underbrace{\text{Gifts Received}_{\text{i},t}}_{\text{Contemporaneous Gift Inflows}} + \underbrace{\sum_{s=1}^{\infty} \frac{\text{Expected Cash Receipts}_{\text{i},t+s}}{(1+r)^s}}_{\text{Pledges}} \tag{1}$$

Cornell University describes this practice of revenue recognition: "A distinction is made between an intention to give and an unconditional promise to give (pledges); intentions to give are non-binding and not recorded as assets; unconditional promises to give are considered binding, and therefore, are recorded. If it is clear that a communication from a donor is clearly an unconditional promise to give, then it would be recorded as a receivable and contribution revenue, regardless of whether or not it is legally enforceable."[49] This decomposition highlights that reported gifts (*Raw Gifts*) combine contemporaneous cash inflows with accrual-based recognition of pledges, motivating a cash-flow-based adjustment.

D.2 Disentangling Gifts and Pledges

While we are unable to observe these two components of "Contemporaneous Gift Inflows" and "Pledges" directly, when universities receive "Pledges" they must report the stock of the discounted present value of future pledges on their balance sheet on Part X line 3 ("Pledges and grants receivable,

[48]Within the reporting for the Integrated Postsecondary Education Data System (IPEDS), revenues from gifts, grants, and contracts are reported jointly.

[49]See https://finance.cornell.edu/sites/default/files/revenue-classification.pdf

net"). This reporting practice of a university increasing "Pledges and grants receivable, net" as "Pledges" are received provides a way to disentangle the magnitude of each component of *Raw Gifts* which we detail below.

By accounting definition:

$$
\begin{aligned}
\underbrace{\text{Pledges Receivable}_{\text{i},t}}_{\text{Current Stock Pledges}} = {} & \underbrace{\text{Pledges Receivable}_{\text{i},t-1}}_{\text{Previous Stock Pledges}} \\
& + \underbrace{\sum_{s=1}^{\infty} \frac{\text{Expected Cash Receipts}_{\text{i},t+s}}{(1+r)^s}}_{\text{New Pledges}} \\
& - \underbrace{\text{Realized Cash Pledges}_{\text{i},t}}_{\text{Realized Pledges}}
\end{aligned}
\tag{2}
$$

Moving terms we can show that:

$$
\begin{aligned}
\underbrace{\text{Pledges Receivable}_{i,t} - \text{Pledges Receivable}_{i,t-1}}_{\Delta\text{Pledges}_{i,t}} = {} & \underbrace{\sum_{s=1}^{\infty} \frac{\text{Expected Cash Receipts}_{\text{i},t+s}}{(1+r)^s}}_{\text{New Pledges}} \\
& - \underbrace{\text{Realized Cash Pledges}_{\text{i},t}}_{\text{Realized Pledges}}
\end{aligned}
\tag{3}
$$

While Δ *Pledges Receivable*$_{i,t}$ is not a direct measure of new pledges, Equations 2 and 3 show that it captures the net effect of new pledges and realized pledge payments. Increases in pledges receivable reflect periods in which new pledges exceed realized payments, while decreases reflect the opposite. As a result, changes in pledges receivable provide a tractable proxy for the accrual component embedded in *Raw Gifts*.

To convert our accrual-based measure of gifts closer to the true, cash-flow based measure *Cash-Based Raw Gifts*, we subtract out these changes in Δ *Pledges Receivable*$_{i,t}$ = Pledges Receivable$_{\text{i},t}$ − Pledges Receivable$_{\text{i},t-1}$ from our accrual-based measure *Raw Gifts*$_{i,t}$ as shown in Equation 4.

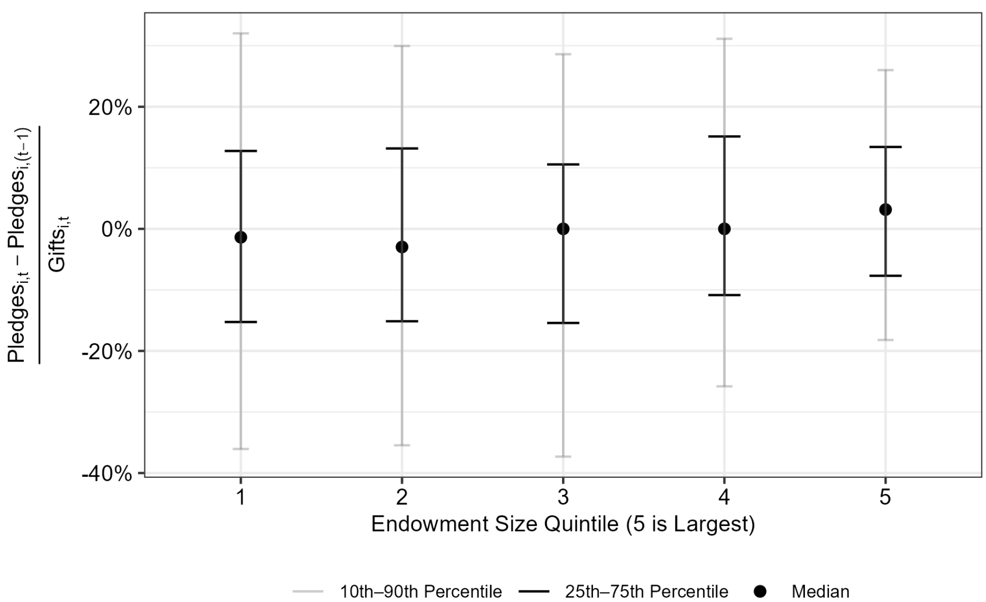
$$
\text{Cash-Based Raw Gifts}_{i,t} = \text{Raw Gifts}_{i,t} - (\text{Pledges Receivable}_{i,t} - \text{Pledges Receivable}_{i,t-1}) \tag{4}
$$

D.3 Magnitude of Gifts and Pledges

To get an idea on the importance of this adjustment and the magnitude of *Pledges* relative to *Contemporaneous Gift Inflows*, we create $\frac{\Delta\text{Pledges Receivable}_{i,t}}{\text{Raw Gifts}_{i,t}}$ which scales Δ *Pledges Receivables* by *Raw Gifts*. The magnitude of this estimate indicates the share of reported gifts (*Raw Gifts*) attributable to accrual adjustments from pledges. Figure IA.D.1 shows the Δ *Pledges Receivables* scaled by *Raw Gifts* across different university endowment size groupings. Overall, scaling Δ *Pledges Receivables* by a university's *Raw Gifts* has a median around 4%, a 25th percentile around -10%, and a 75th percentile around 10% with dispersion declining as endowment size increases. These results indicate that for the typical university-year, reported gifts are largely driven by contemporaneous cash inflows, with accrual adjustments from pledges contributing a smaller but non-trivial share. In the next section, we provide an understanding of the correlation of *Raw Gifts* and our proxy for Pledges (Δ Pledges Receivables) along with how our results compare when using *Cash-Based Raw Gifts*.

Figure IA.D.1: Δ Pledges Receivables Scaled by *Raw Gifts* By Endowment Size

Notes: This figure shows the proportion of *Raw Gifts* that accounted for by changes in pledges receivable for universities by endowment size. The x-axis splits universities into 5 groups based on their average endowment size with endowment size increasing in group number. The median is shown within each distribution as a point, p25 and p75 as a dark confidence band, and p10 and p90 as a light confidence band.



In Table IA.D.1 we detail the correlation structure between *Raw Gifts*$_{i,t}$, the accrual-based measure of gifts reported on form 990, Δ Pledges Receivable (Pledges Receivable$_{i,t}$- Pledges Receivable$_{i,t-1}$), and *Raw Gifts* net of Δ Pledges Receivable. As detailed above in Equation 1, *Raw Gifts* and *Pledges* are connected resulting in a correlation of 0.60 when estimated on *Raw Gifts* and our proxy for *Pledges*. When netting *Raw Gifts* less Δ Pledges Receivables we find a very strong correlation of 0.99. In Row 3F. of Table 8, we construct our instrument using *Raw Gifts* less Δ Pledges Receivables and find a nearly identical coefficient estimate while the first-stage F-statistic increases, consistent with cash-flow based gifts more closely capturing LP investment decisions. As a placebo test, we run our first-stage using Δ Pledges Receivables as the instrument, which results in a first-stage F-statistic below 1. Reassuringly, this test along with our prior analysis indicates that contemporaneous gifts drive variation in our instrument rather than pledges.

Table IA.D.1: Correlation Matrix

	(1)	(2)	(3)
(1) Raw Gifts$_{i,t}$	1.00		
(2) ΔPledges$_{i,t}$	0.60	1.00	
(3) Cash-Based Raw Gifts$_{i,t}$	0.99	0.49	1.00

Appendix E: Numerical Example of PE Waterfall

E.1 Introduction

Private equity (PE) funds distribute proceeds through a hierarchical mechanism known as a "waterfall," which prioritizes cash flows to Limited Partners (LPs) and General Partners (GPs) in a defined sequence. This case study examines an average fund in our sample having a fund size of \$1.51 Billion, structured under the following assumptions:

- **Cash Flow Timing**: All cash flows, except for fixed fees, occur at fund liquidation happening 10 years after the vintage.
- **Immediate Capital Deployment**: The entire committed capital is called upfront, net of a 2% annual fixed management fee deducted at inception.
- **Hurdle Rate**: LPs are entitled to an 8% preferred return (compounded annually) on their initial investment before GP participation.
- **Catch-Up Provision**: After the hurdle is met, GPs receive 100% of profits until achieving 20% of total profits.
- **Carried Interest**: Post-catch-up, profits are split 80% to LPs and 20% to GPs.

E.2 Key Calculations

The waterfall mechanism involves four sequential stages. First, the fixed annual management fee is calculated as a percentage of committed capital, and its present value (considering a risk-free rate of return of 4%) deducted from the committed capital to get the amount available for deployment. The deployed capital is compounded at the fund's gross internal rate of return (IRR) over its life to determine the gross exit value, using the formula:

$$\text{Gross Exit Value} = \text{Capital Deployed} \times (1 + \text{Gross IRR})^{\text{Fund Life}} \tag{5}$$

Proceeds are allocated hierarchically. LPs first recover their initial committed capital. Thereafter, they receive a preferred return calculated by compounding the hurdle rate over the fund's life. If gross profits exceed the hurdle return, GPs enter a catch-up phase, receiving 100% of subsequent profits until achieving 20% of total profits. The maximum catch-up amount is derived by applying the carry rate to the hurdle return and adjusting for the profit-sharing ratio:

$$\text{Maximum Catch-Up Amount} = \frac{\text{Hurdle Return} \times \text{Carry}}{1 - \text{Carry}}. \tag{6}$$

Residual profits are split between LPs (80%) and GPs (20%). Net present value (NPV) for LPs and GPs is computed by discounting their respective cash flows at the PE's required rate of return, which we assume is 12% (Andonov and Rauh, 2022).

E.3 Numerical Example

The average fund in our sample has \$1.51 Billion in committed capital (AUM), a 22.3% gross IRR, and a 10-year life.[50] After deducting the present value of the 2% fixed annual fee amounting to \$0.24 Billion, \$1.27 Billion is deployed. This capital compounds at the gross IRR to generate a gross exit value of \$1.27 Billion $\times (1 + 0.223)^{10} =$ \$9.46 Billion. LPs first receive their initial investment of \$1.51 Billion, leaving gross profits of \$7.95 Billion to be distributed between LPs and GPs. The hurdle return, calculated as the initial investment of \$1.51 Billion compounded at 8% annually for 10 years, amounts to \$1.75 Billion. Gross profits after repayment and hurdle return total \$6.2 Billion. From this, GPs claim a catch-up amount of $\frac{\$1.75\text{ Billion}\times 0.2}{1-0.2} = \$0.44$ Billion. Finally, the residual \$5.76 Billion is split 80% to LPs (\$4.6 Billion) and 20% to GPs (\$1.15 Billion).

In total, LPs receive \$7.87 Billion (initial capital + hurdle return + post-hurdle split), yielding a net IRR of $\left(\frac{\$7.87\text{ Billion}}{\$1.51\text{ Billion}}\right)^{1/10} - 1 = 18.0\%$, consistent with the average net IRR reported in Table 1. Discounting LP cash flows at the 12% required rate results in an NPV of $\frac{\$7.87\text{ Billion}}{(1+0.12)^{10}} - \$1.51\text{ Billion} =$ \$1.02 Billion. GPs earn \$1.83 Billion in total, out of which \$0.24 Billion in fixed fee is earned at inception and \$0.37 Billion in catch-up and carry is earned at liquidation. At a required rate of return of 12%, this yields a GP NPV of \$0.62 Billion.

Figure IA.9 depicts the private equity waterfall structure through a payoff diagram delineating allocations to LPs and GPs. Following the deduction of the fixed management fee from committed capital, LPs receive distributions from the gross exit value until they fully recoup their initial investment of \$1.51 Billion. Subsequently, LPs continue to receive proceeds until they achieve their 8% preferred return (hurdle rate), realized when the gross exit value reaches \$3.26 Billion. Beyond

[50] Since Preqin fund return data only contains net IRR, we set the gross IRR such that the post-waterfall net IRR comes out to be equal to the 18% that we observe for such a fund in our estimation sample.

this threshold, GPs claim 100% of subsequent proceeds until they ”catch up” to their 20% carried interest split in total profits, which is attained at a gross exit value of $3.70 Billion. Thereafter, any remaining proceeds are split between LPs and GPs at an 80/20 ratio, reflecting the carry structure.

Appendix F: OpenAI's API to Identify Donor's Source of Wealth for Large Gifts

F.1 Donation Data on Large Gifts

We collect data on large gifts (those above $1 million) to private universities to understand the sources of wealth for large donors. Identifying the donor's source of wealth also allows us to exclude gifts from donors who experience wealth shocks that are informative to subsequent private equity returns. We use data from the Indiana University Indianapolis' Million Dollar List from 2000 to 2013 (coverage ends in 2014) and data from the Chronicle of Philanthropy from 2014 onward to construct the series of large gifts which also includes information about the donor's identity, recipient of the gift, amount of the gift, and the type of the gift. To ensure that we capture gifts when they are likely to end up in the endowment, we keep only gifts that are denoted as "Bequests" or "Gifts" and exclude gifts that are denoted as "Payment over Time" or "Pledges". Additionally, we bound large gifts at 90% of the reported total gifts for a given university $\times$ year observation from IRS Form 990 as reported large gifts in excess of total gifts are likely to reflect gifts paid over time. We hand-match donation data recipients to a university's unitid identifier from the Integrated Postsecondary Education Data System (IPEDs).

F.2 OpenAI's API to Classify Sources of Donor Wealth

To classify the sources of donor's wealth we use information on the donor's name, location, recipient of the gift, amount and timing of the gift, and additional details of the gift when available. We classify these entries using OpenAI's API in `R`, specifying a fixed model version and setting the temperature parameter to zero to ensure reproducible results. The classification process consumes approximately 4 million tokens, incurring a cost of around $50 using the `gpt-4-0125-preview` model, which provides a practical balance between accuracy and processing speed.

We use the following prompt to classify a donor's source of wealth:

```
classify_asset_type_batch <- function(classify_string, max_retries = 3) {
  prompt <- paste0(
    "You are a financial researcher analyzing large philanthropic gifts.\n",
    "Based on the donor name, location, recipient, gift amount, date, and description,
    classify the **most likely source of wealth**.\n\n",

```

```
 "Classify each of the following prompts into exactly one of the wealth categories listed below, using your best judgment based on:\n",

 "Guidelines:\n",
 "- Use known donor names and locations to inform your classification along with information on the description of the gift from news articles.\n",
 "- Use institutional naming patterns (e.g., 'Family Foundation') and the donation purpose to support your reasoning.\n",
 "- For each donor, ONLY return the classification label from the list below (e.g., 'Private Equity/Venture Capital').\n",
 "- DO NOT repeat the donor name or number.\n",
 "- Return exactly one line per donor, and only the classification label.\n",

 "Examples:\n",
 "1. Donor: 'Bill & Melinda Gates Foundation' â  Category: Public Company Executive / CEO\n",
 "2. Donor: 'Pershing Square Foundation' â  Category: Hedge Fund\n",
 "3. Donor: 'Kresge Foundation' â  Category: Inherited Wealth\n",
 "4. Donor: 'Thiel Foundation' â  Category: Venture Capital\n\n",

 "Use the following categories:\n",
 "1. Private Equity/Venture Capital - Donor name or foundation has worked for a private equity or venture capital fund\n",
 "2. Hedge Fund - Donor name or foundation has worked for a private equity fund\n",
 "4. Investment Banking - Donor name or foundation has worked in investment banking\n",
 "5. Real Estate - Donor name or foundation has worked in real estate\n",
 "6. Finance (General) - Donor name or foundation has worked in non-PE/HF/IB finance people (e.g., asset managers, CPAs, wealth advisors, insurance execs)\n",
 "7. Technology Executive / Founder - Donor name or foundation is a tech company leader or founder\n",
 "8. Entrepreneur / Business Owner (Not Tech) - Donor name or foundation is a non-tech company leader or founder\n",
 "9. Public Company Executive / CEO - Donor name or foundation has worked as executive\n",
 "10. Inherited Wealth Donor name or foundation has inherited wealth\n",
 "11. Energy / Natural Resources - Donor name or foundation has worked in energy sector or natural resources.\n",
 "12. Retail / Consumer Products - Donor name or foundation has worked in retail or consumer prodcuts\n",
 "13. Legal Profession - Donor name or foundation has worked in the legal profession\n",
 "14. Medical Profession / Healthcare Executive - Donor name or foundation has worked in the medical profession\n",
 "15. Unknown / Other - Donor name of foundation is unable to be classified to any of the above fields\n\n",

 "Here are the funds to classify:\n\n",
 paste0(seq_along(classify_string), ". ",classify_string, collapse = "\n")
)
```

We classify 12,570 gifts to private universities in our sample (with observed connections to private equity investments) from 2000-2017. Overall, we find that approximately 13% of gifts (1,592) to private universities come from finance-related donors while 2% of gifts (304) comes from private-equity related donors. On an asset-weighted basis we find these proportions are slightly larger due to finance-related donors making larger donations, with 19% of gifts to private universities coming from finance-related donors while 5% of gifts comes from private-equity related donors. Using OpenAI's API significantly improves upon direct name matching from Pitchbook's people data which finds only 8 exact matches due to the unstructured nature of the text, that donors often include spouses or multiple individuals, and donors can also include foundations.

Accuracy We sample from the classifications of OpenAI's donor source of wealth to verify the accuracy of OpenAI's classifications.[51] Across donors that OpenAI classifies as connected to private equity we find that fewer than 10 percent of classified donors are not affiliated with private equity directly with all but one of these donors connected to finance (e.g., hedge funds, investment banking, or private equity like deal making). Across donors that OpenAI classifies as finance we find fewer than 5 percent of classified donors are not finance related. In our subset of non-finance related entities, we find OpenAI's API correctly classifies 92 percent of entries with the remaining 8 percent being connected to broader finance or private equity. Overall, our work validates the classifications of OpenAI's API and allows us to correctly identify and exclude gifts from donors connected to the private equity or broader finance related sectors.

Replicability To assess classification consistency, we randomly sample 1,000 unique entries from the list of large donations and re-query them through OpenAI's API 10 additional times. Using the above prompt, the model first classifies each donor's source of wealth into detailed sub-wealth sources (e.g., public company executive, private equity/venture capital, and investment banking) and then we aggregate these classifications into two broader categories: "Non-finance Related," and "Finance Related." Overall, we find a 96 percent match rate of additional classifications that match OpenAI's baseline classification into "Finance Related" and a 98.75 percent match rate of additional classifications that match OpenAI's baseline classification into the sub-category "Private Equity Related."

[51]We select the sampling size to verify for private equity and finance classifications based on a power calculation test that assumes an 80 percent correct classification likelihood for OpenAI's API, a 95% confidence interval, and a 5% margin of error. We verify 149 private equity classifications, 169 finance classifications, and also select 100 non-finance related classifications.