Democratizing Private Markets? Private Equity Performance of Individual Investors

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Abstract

Using novel data on U.S. households, we provide the first systematic study of private equity performance by individual investors. On average, individual investments in private equity perform similarly to institutions. However, the most affluent investors outperform the least affluent by 9 percentage points in public market equivalent. Advisor fixed effects explain two-thirds of the variation in private equity performance and 75% of the wealth performance gap, as wealthier investors have better advisors that deliver persistently higher returns. Intermediary fees impose a sizable drag on performance, especially for less affluent investors.

JEL Classification: G11, G24, D14

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Individual investors now account for a substantial share of private equity (PE) capital, with recent estimates placing their holdings at roughly $1 trillion of the $8 trillion in PE assets under management. Industry analyses further project that individual investors will account for a disproportionately large fraction of future growth in PE, providing 30-50% of capital raised in the near future.[1] Some of this growth reflects the ongoing "democratization" of private markets—the expansion of access beyond institutions and high-net-worth investors (Ivashina and Mylavarapu, 2024). This increasing importance of individual investors represents a significant shift for an asset class historically structured around institutional investors.

Yet, surprisingly little is known about individuals' actual investments in this market. How do households perform in private equity, and how does performance vary across individual investors? In particular, do they earn returns comparable to institutional benchmarks, and are differences in outcomes systematically related to observable characteristics such as wealth? Finance theory highlights a range of intermediation frictions that may shape household performance, including limited access to top funds, heterogeneity in fund selection skill, and multi-layer fee structures. Moreover, most households invest through intermediaries rather than directly: advisors and wealth managers often influence which funds clients invest in and at what cost. How do intermediaries then shape households' private equity outcomes? These questions are important to household finance and first-order for evaluating the consequences of democratizing private markets, but credible answers require data that are rarely available.

To study individual investors' private equity portfolios, we would ideally have data with at least four characteristics. First, the data should cover a broad and relevant sample of investors, spanning the wealth distribution and the intermediation channels through which households typically access PE. Second, the data must be reported at the investor level, so that we can measure cross-sectional heterogeneity in performance and relate it to observable investor characteristics. Third, the data should include complete net-of-fees cash-flows for each fund investment so that performance can be measured using standard metrics. Finally, the data should identify intermediaries involved in each investment, which is essential for assessing how intermediation shapes outcomes.

In this paper, we leverage novel microdata from Addepar, a wealth and asset management

[1]To calculate the size of PE market invested by individuals, one approach combines McKinsey & Company (2024)'s estimate of $8.2 trillion in PE AUM with Bain & Company (2023) finding that individuals hold 16% of alternative assets ($8.2 \times 0.16 = \$1.3$ trillion). Alternatively, Adams Street (2025) reports that individuals account for $2.7 trillion in private markets overall. Scaling this figure by McKinsey & Company (2024)'s estimate of equity's share of total private markets AUM produces a similar estimate ($2.7 \times \frac{8.2}{13.1} = \$1.6$ trillion). KKR expects between 30% and 50% of the capital raised over the next few years to come from private wealth (Bain & Company, 2023).

platform, to provide the first systematic study of individual investors' PE performance. The data originate from financial advisors who use the Addepar platform to manage client portfolios and produce detailed investment reports. The anonymized portfolio data are reported at the individual investor and fund level and include a quarterly breakdown of capital calls, distributions, and valuations. Our sample includes a broad range of investors, from those near the accredited investor threshold of $1 million in AUM to billionaires, and covers investments made through multiple intermediary channels that capture the dominant pathways through which households access PE: registered investment advisers (RIAs), broker-dealers, and family offices, representing $340 billion in PE assets as of 2024. The data thus provide a unique window into the performance of individual PE portfolios and the role of intermediaries in shaping that performance.

We use these detailed cash flows to measure fund-level performance for more than 4,500 closed-end PE funds between 2000 and 2020, spanning buyout, venture capital, and fund-of-funds categories. As our primary performance metric, we use a beta-adjusted public market equivalent (PME), which compares PE returns to a public market benchmark while adjusting for systematic risk differences across fund categories following Brown, Lundblad, and Volckmann (2025). For robustness, we also report results using standard performance metrics—Total Value to Paid-In (TVPI), Internal Rate of Return (IRR), Kaplan and Schoar (2005) PME—as well as Korteweg and Nagel (2024) alphas. In our baseline analysis, all performance metrics are net of general partner (GP) fees.

We obtain four main results. First, funds held by individual investors perform similarly to institutional benchmarks on average. Matching on fund vintage and category against two institutional benchmarks—Preqin and the MSCI Private Capital Universe—allows for a direct comparison between individual and institutional investors. Using the Kaplan–Schoar PME (here not adjusted for risk due to data availability for institutional benchmarks), we find that individual investors achieve a value-weighted PME of 1.19, falling between the two institutional benchmarks. Thus, frictions in access or fund-selection skill do not, on average, prevent individuals from achieving performance similar to institutional benchmarks and from outperforming public markets before adjusting for risk. This similarity in performance is not mechanical as individuals access a different fund universe: roughly 2,000 funds in our data are absent from Preqin and at least 1,000 from MSCI. The same conclusion obtains using alternative performance metrics (IRR and TVPI), and when we restrict attention to the median wealth group ($10–$30 million) to limit the influence of ultra-high-net-worth investors.

Second, this average performance masks substantial heterogeneity in returns that strongly

correlate with wealth. Our sample spans a wide range of investor financial wealth: from 3,500 investors with less than $3 million to 2,700 with more than $100 million, including 230 billionaires. The most affluent investors substantially outperform the least affluent by 9 percentage points in risk-adjusted PME (1.12 versus 1.03). This wealth gradient is concentrated in venture capital and fund-of-funds, rather than buyout funds, and is not explained by differences in vintage timing or category composition. These patterns suggest that less affluent households are worse positioned to benefit from access to private markets, even within the high-net-worth segment.

Third, financial advisors explain most of the cross-sectional variation in individual PE performance. The wealth-performance gap largely disappears among investors served by the same advisor, indicating that performance heterogeneity operates primarily at the intermediary level. Furthermore, advisor fixed effects account for a striking two-thirds of the residual dispersion in PE performance within category and vintage (partial $R^2 = 0.643$). One interpretation is that advisors allocate identical funds to most clients due to fixed costs of due diligence or access frictions. An alternative is that investors with common unobserved preferences sort into the same advisor. To test this alternative hypothesis, we study the role of advisors in public equity. We find an advisor partial R^2 of only 0.272 in public equity, implying that the 0.643 partial R^2 in PE is hard to explain with preferences alone. Advisors thus exert disproportionate influence on PE portfolios, consistent with clients delegating fund selection to advisors who then make largely uniform investment choices across their client base.

If advisors drive investor performance, what advisor characteristics are associated with better performance? We find evidence consistent with persistent differences in advisor quality. Advisors with more experience and advisors whose investments performed better in the past are associated with significantly better future PE performance. This heterogeneity is more consistent with differences in skill than differences in access alone: the performance advantage of more experienced and previously top-performing advisors persists even within subsamples of funds that are plausibly easier to access, such as first-round funds and low-commitment funds. While more affluent investors appear to sort into better-performing advisors, the strength of this sorting is relatively weak: even among the most affluent investors (>$100m), more than one third are matched to advisors in the bottom two performance quartiles.

Fourth, intermediation fees amplify the wealth gradient in net performance. We estimate performance net of three additional sources of fee variation beyond typical GP fees: (i) within-fund differences in net performance that arise from investor-specific GP terms (LP tiers), such as fee rebates offered to selected investors, (ii) access fees such as platform or

feeder-fund fees, and (iii) simulated advisory fees based on standard AUM-based pricing schedules. The combined fee drag increases the performance gap by more than 50% and fully offsets outperformance relative to public markets for the least affluent investors.

Our findings relate to the current policy debate about expanding retail access to private equity. Regulators could broaden access by lowering the income and wealth thresholds that define accredited investors or by permitting private equity allocations in mainstream products such as ETFs or target-date funds offered in retirement plans (Morningstar, 2025). Our results speak to both the promises and the risks of such reforms. On the positive side, we find no evidence that funds available to individuals underperform on average, suggesting that greater private equity exposure could improve outcomes for some investors. On the other hand, our analysis highlights frictions that erode net returns for less affluent households: greater reliance on worse-performing advisors and materially higher fees tend to offset outperformance relative to public markets. These findings imply that whether through retail products or by lowering accredited investors thresholds, expanding access without addressing the higher intermediation costs faced by smaller investors may yield little benefit relative to liquid alternatives.

Our results contribute to the literature on household finance and household portfolio choice (Campbell, 2006; Gomes et al., 2021; Campbell and Ramadorai, 2026). Much of this literature relies on account-level data from brokerage houses (e.g., Barber and Odean, 2000), administrative records from Nordic countries (e.g., Grinblatt and Keloharju, 2000; Calvet, Campbell, and Sodini, 2007; Fagereng, Gottlieb, and Guiso, 2017), or survey data (e.g., Cocco, Gomes, and Maenhout, 2005). These data sources have limited coverage of high-net-worth investors and, importantly for our question, do not observe individual households' investments in private equity funds and their associated performance. By contrast, the Addepar data cover a large sample of high-net-worth households at the investor and investment level and report granular net-of-fees cash flows, allowing us to provide the first systematic study of individual investor performance in private equity. Our results complement the growing literature on household performance in alternative asset classes (Moskowitz and Vissing-Jørgensen, 2002; Célérier and Vallée, 2017; Vokata, 2021, 2025; Karlsen, Kisseleva, Mjøs, and Robinson, 2024). Our results on the wealth-performance gradient also connect to recent evidence that returns are correlated with wealth in other asset classes (Bach, Calvet, and Sodini, 2020; Fagereng, Guiso, Malacrino, and Pistaferri, 2020). We document the correlation of returns with wealth in a new asset class and, unlike previous work, link it to the role of intermediaries.

Our findings also expand the literature on private equity performance by studying a new class of investors (e.g., Kaplan and Schoar, 2005; Harris, Jenkinson, and Kaplan,

2014).[2] Existing work largely draws on datasets sourced primarily from institutional investors including commercial databases such as Preqin and MSCI (previously Burgiss). As we show, these databases are ill-suited for studying individual investors because they miss a sizable number of funds in which individuals invest. We introduce a new dataset covering previously unexplored investors and funds. Existing work finds evidence of skill for general partners, institutional limited partners, and entrepreneurs (Lerner, Schoar, and Wongsunwai, 2007; Gompers, Kovner, Lerner, and Scharfstein, 2010; Korteweg and Sorensen, 2017). We complement this literature by providing evidence consistent with differences in advisor skill among the intermediaries serving high-net-worth households.

Finally, our results contribute to the literature on financial intermediaries and financial advice. Existing research has primarily focused on advisors and brokers serving retail investors in public equity (Foerster, Linnainmaa, Melzer, and Previtero, 2017; Linnainmaa, Melzer, and Previtero, 2021). We extend this work by studying advisors to high-net-worth investors in an asset class with unique intermediation frictions. Consistent with intermediaries playing a first-order role in this market, advisor fixed effects explain most of the cross-sectional variation in private equity performance, more than double the corresponding role in public equity.

Two contemporaneous papers use other data together with imputation or proxy approaches to study high-net-worth investors in private equity. Miller et al. (2024) conduct a survey experiment of professional and individual investors and use investor counts disclosed in Form D filings to proxy for fund participation by individuals. Gocmen et al. (2025) focus on a smaller sample of individual investors covered by Pitchbook and compute performance from imputed deal-level valuations. The Addepar data have significant advantages for studying individual investors in PE: we observe a large sample of investors at the individual level, their actual private equity fund holdings, and granular net-of-fees cash flows. As a result, we can measure performance directly without relying on assumptions required by these proxy-based approaches. Outside of the U.S., Lerner, Li, and Liu (2026) use data on individual investors in China to study entrepreneurial spillovers.

The remainder of the paper is structured as follows. Section 1 describes the data and characterizes the types of private equity investments made by individual investors. Section 2

[2]See surveys by Kaplan and Sensoy (2015), Korteweg and Westerfield (2022), and Korteweg (2023). An active literature studies the performance of different categories of private equity (e.g., Phalippou and Gottschalg, 2009; Franzoni, Nowak, and Phalippou, 2012; Gupta and Van Nieuwerburgh, 2021; Barber, Morse, and Yasuda, 2021; Andonov, Kräussl, and Rauh, 2021; Brown, Ghysels, and Gredil, 2023). Another line of the literature examines the performance of different types of investors (e.g., Hochberg and Rauh, 2013; Sensoy, Wang, and Weisbach, 2014; Andonov, Hochberg, and Rauh, 2018).

measures raw and risk-adjusted private equity performance among individual investors and compares performance to institutional investors and across the wealth distribution. Section 3 analyzes the drivers of performance heterogeneity. Section 4 assesses the impact of fees, and the final section concludes.

1 Data and Institutional Background

This section presents institutional background on individual investors in private equity, describes our data sources, and reports summary statistics.

1.1 Institutional Background

We start by summarizing the institutional features of individual investors' access to private equity that are most relevant for understanding performance heterogeneity.

Private equity funds are typically organized as closed-end limited partnerships in which general partners (GP) manage capital provided by limited partners (LP). Fund lifecycles often span ten to fifteen years. GP fees traditionally follow a 2-and-20 structure, with 2% annual management fees and 20% carried interest on profits above a hurdle rate (typically 8%). However, terms can vary substantially not only across funds (Gompers and Lerner, 1999; Metrick and Yasuda, 2010; Robinson and Sensoy, 2013) but also across investors within the same fund (Begenau and Siriwardane, 2024). GPs commonly use tiered fee schedules and side letters to modify management fees, carry, or expense allocations.

In the U.S., investments in PE funds are generally restricted to accredited investors—individuals meeting income and wealth thresholds, or holding specific professional licenses.[3] These investors access private equity through two primary channels. First, they invest directly in funds that accept individual LPs, including ultra-high-net-worth focused funds and low-minimum funds designed to broaden access. Second, they invest through pooled vehicles—such as feeder funds, platforms, or capital pooling arrangements managed by wealth managers—which aggregate commitments to meet fund minimums. While traditional

[3]Prior to 2020, accredited investor status required annual income of at least $200,000 ($300,000 with spouse) for the prior two years or net worth of at least $1 million excluding primary residence. The SEC's 2020 amendments expanded eligibility to include holders of Series 7, 65, or 82 licenses and certain family office clients. Entities may also qualify, including those with investments exceeding $5 million. While Rule 506(b) of Regulation D generally requires accredited investor status, issuers may sell to up to 35 non-accredited investors if they avoid general solicitation.

institutional funds often require minimum commitments of $5–10 million, funds targeting individuals may accept commitments as low as $100,000–250,000, with some platforms enabling even lower thresholds.

Individual investors typically access private equity through financial intermediaries, including registered investment advisors (RIAs), family offices, broker-dealers, and private banks. These advisors source investment opportunities, conduct due diligence, and monitor portfolios. In addition to GP fees, individuals may incur additional intermediation costs. Platforms and feeder funds may charge access fees, and wealth managers typically charge advisory fees based on assets under management. These costs can materially reduce net returns, particularly for smaller investors who face higher percentage-based fees and have limited bargaining power.

1.2 Data

We next describe the individual investor data, discuss coverage and potential selection into our sample, and introduce the institutional benchmarks used in the analysis.

1.2.1 Individual Investor Data

Our main data come from Addepar, a technology and data platform providing analytics and reporting for investment managers and financial advisors whose clients hold complex portfolios spanning public and private assets. Advisors use Addepar to track holdings, monitor performance, and report investor activity, including for tax purposes, making the underlying data highly scrutinized and reliable. Addepar data have been used in prior research by Balloch and Richers (2023), Gabaix et al. (2024), Gabaix et al. (2025), and Mainardi (2025).[4] We use a novel version of the data designed specifically to study private equity investments.

Investor Holdings. We observe comprehensive quarterly holdings at the account level across liquid and illiquid assets managed by advisors.[5] We focus on investors with at least one position in a PE fund raised between 2000 and 2020. We identify PE holdings and compute total assets under management (AUM), which we use to assign investors to five wealth groups:

[4] In related work, Balloch and Peng (2025) use surveys to study advisors' subjective beliefs and portfolios.

[5] The data are fully anonymized, with Addepar applying strict confidentiality procedures prior to researcher access.

<$3 million, $3–10 million, $10–30 million, $30–100 million, and >$100 million.[6]

Fund Cash Flows. For each investor-fund position, we observe quarterly valuations and cash flows, including commitments. All cash flows and valuations are reported net of management fees and carried interest, allowing measurement of realized investor returns. The data span 2000 Q1 to 2024 Q3.

To ensure accurate performance measurement, we retain only investor–fund observations with consistent valuation reporting and complete cash flow histories, and we exclude observations with data quality issues. Unless otherwise specified, we compute fund-level performance as the median across investors with complete cash flows: $PME_i = \text{median}(PME_{ij})$ for fund i and investor j. This approach allows performance assignment even when cash flows are incomplete for a particular investor-fund observation. For a small number of funds with no complete cash flow histories in Addepar, we supplement with Preqin-reported performance (available for IRR and TVPI) as of 2024 Q3.

Access Fees. We additionally observe intermediary access fees paid to participate in specific funds, including fees charged by feeder funds, platforms, investment consultants, and specialized advisors.

Advisors. We observe anonymized links between investors and advisory firms, along with broad advisor categories (RIAs, broker-dealers, family offices). We refer to these entities collectively as advisors and construct advisor-level characteristics such as total AUM, past performance, and the number of PE funds invested in.

Sample definition. We focus on North American PE funds categorized as buyout, venture capital, and funds of funds.[7] We limit our attention on the dominant forms of individual participation and exclude direct stakes in private companies, crowdfunding investments, co-investments (Fang, Ivashina, and Lerner, 2015; Lerner, Mao, Schoar, and Zhang, 2022), and a small number of evergreen and semi-liquid interval funds (Pegoraro, Shive, and Zambrana, 2025). Following a standard practice in the literature (see, e.g., Cavagnaro et al., 2019) we exclude funds raised after 2020 to allow time for fund returns to be realized.

[6]One potential concern is that platform assets may not capture investors' full portfolios. We find evidence of incomplete portfolios for a small fraction of our sample (1,352 investors, who correspond to 4.0 percent of all investor-fund observations). For these cases, we impute total wealth as described in Appendix A.2.1. Our results on the wealth performance gap are qualitatively and quantitatively unchanged if we exclude these investors from the sample.

[7]Following Harris et al. (2014), buyout includes balanced, buyout, and growth strategies; venture capital includes seed, early-stage, expansion/late stage, general venture, and venture debt; funds of funds include traditional fund of funds, secondaries, and direct secondaries. Table A1 provides a description of fund strategies within each category.

Because our data include investors whose advisors use Addepar, we assess representativeness along two dimensions: coverage of wealthy U.S. households and potential platform-specific selection.

First, we benchmark the Addepar sample against external evidence on the U.S. wealth distribution and portfolio composition. Addepar primarily covers wealthy households, where taxable financial assets are concentrated, including 729 investors with wealth exceeding $1 billion at some point in the sample.[8] Importantly, the sample is not narrowly confined to the ultra-wealthy. Mainardi (2025) shows that average wealth in Addepar aligns closely with capitalization-based estimates for the top 10% of U.S. households (Saez and Zucman, 2016, 2020; Smith et al., 2023).Portfolio allocations in Addepar are also broadly consistent with external benchmarks. For investors with less than $3 million in direct equity holdings, allocations to cash, public equity, and fixed income closely match those observed in the Survey of Consumer Finances (SCF) (Gabaix et al., 2024). For wealthier investors, Addepar exhibits higher liquid asset holdings and lower public-equity shares than the SCF, consistent with well-known SCF limitations at the extreme right tail (Bricker et al., 2019, 2020; Kennickell, 2017). Allocations to pass-through businesses—the standard PE and VC structure—also closely match those implied by the capitalization method (Balloch and Richers, 2023). Overall, these comparisons indicate that Addepar offers reliable and representative coverage of the top 10% of U.S. households by wealth.

Second, a natural question is the extent to which the Addepar data are representative of the market for individual-investor PE. Because our sample consists of investors whose advisors use Addepar, advisors that adopt the platform may differ systematically from those that do not. One way to assess this concern is to examine advisor performance by the year the advisor joined Addepar. If platform adoption is correlated with advisor performance, we would expect systematic differences in performance across joining cohorts. We observe advisors joining the platform between 2013 and 2024. Figure B8 shows stable performance across joining cohorts, suggesting that platform-specific selection is unlikely to drive our results.

1.2.2 Institutional Investor Data

We benchmark individual investor performance against institutional data from Preqin and MSCI Private Capital Universe data (previously Burgiss). Preqin primarily relies on Freedom of Information Act (FOIA) requests and voluntary disclosures, while MSCI uses confidential,

[8]As a point of reference, Forbes estimates that there were 813 billionaires in the U.S. in 2024.

verified cash flow data from institutional investors.

From Preqin, we obtain fund characteristics (e.g., vintage, category, region, fund number) and classify funds as oversubscribed when reported size exceeds target size. We use the latest IRR or TVPI reported on or before 2024 Q3 as institutional performance proxies. Because the Kaplan and Schoar (2005) PME is not available via WRDS, we compute it directly from Preqin cash flows. We also collect fund minimum commitments from Preqin for approximately two-thirds of the funds in our sample. We complement Preqin with data from MSCI, which provide aggregate performance statistics by vintage and category through 2024 Q3.

1.3 Summary Statistics

Table 1 reports summary statistics for 4,593 funds invested by 17,886 individual investors via 745 advisors.

1.3.1 Fund Universe

Panel A of Table 1 reports fund-level statistics. The sample includes 1,672 buyout funds, 2,210 venture capital funds, and 711 funds of funds. Funds are held by an average of 17, 13, and 23 individual investors in buyout, venture capital, and funds of funds, respectively (medians: 8, 6, and 8). Between 20 and 30 percent of funds are oversubscribed. On average, investors hold the third or fourth fund in a series and between the fifth and fourteenth fund raised by a GP.

Figure 1 compares the number of funds in Addepar with the number of funds in Preqin with available performance data. While Preqin covers more funds in early vintages, Addepar coverage exceeds Preqin starting in 2011. By the end of the sample, the number of funds held by individuals is more than double that in Preqin. Furthermore, these new funds are not parallel "twin" vehicles issued in parallel with institutional offerings by the same GPs.

Instead, 84% are the sole fund issued by the GP within a given vintage-category.[9] For MSCI, we do not observe fund names and therefore cannot directly compare fund universes. We can, however, construct a lower bound on the number of newly covered funds in Addepar by comparing fund counts by vintage and category. By this measure, Addepar includes at least 1,136 funds not covered in MSCI.[10]

These comparisons suggest that existing private equity datasets—sourced primarily from institutional investors—are unlikely to provide comprehensive coverage of the funds accessed by individual investors, underscoring the need for new data that directly measure individuals' private equity holdings and their performance.

1.3.2 Individual Investors

Returning to Table 1, Panel B summarizes investor characteristics by wealth. The sample includes 3,541 investors with less than $3 million in AUM and 2,720 with more than $100 million. Private equity accounts for a meaningful portfolio share: the average PE share is 13%, and average PE assets are $0.2 million for the lowest wealth group and $107.8 million for the highest. Overall, more affluent investors allocate more to buyout and venture capital, hold more funds, and make larger commitments, while allocations to funds of funds decline. These patterns are consistent with less affluent investors facing diversification frictions.

Observed commitments are an order of magnitude smaller than typical institutional minimums. While Korteweg and Westerfield (2022) report $5 million as a typical institutional minimum, median commitments in our data range from $0.1 to $1.5 million across wealth groups, indicating distinct access mechanisms for individuals.

[9] We also observe that 92% of the new funds are managed by GPs that rarely report to Preqin. As shown in Table A4, those GPs include prominent VC firms, consistent with Abuzov, Gornall, and Strebulaev (2025), GPs affiliated with family offices and wealth managers, and GPs targeting high-net-worth investors. Table A3 compares fund characteristics for newly covered Addepar funds with funds covered in both datasets and funds covered only in Preqin. Relative to Preqin, new Addepar funds are more concentrated in venture capital, recent vintages, and early-sequence funds, and include substantial shares of both top- (24%) and bottom-quartile (35%) funds based on TVPI and MSCI benchmarks. Funds covered in both datasets are larger (mean $1.1 billion), while funds covered exclusively in Addepar or Preqin are smaller ($216 million and $332 million, respectively). Oversubscription rates are similar across groups. The largest difference across datasets is instead minimum commitments. Average minimums are $1.4 million for newly covered funds, $4.2 million for funds in both datasets, and $8.6 million for funds covered only in Preqin.

[10] Table A2 reports fund counts by vintage and category for all datasets.

1.3.3 Advisors

Panel C of Table 1 reports advisor characteristics. More than 12,000 investors are advised by RIAs, over 3,000 by family offices, and 2,000 by broker-dealers. Family offices tend to have both fewer investor and fewer PE funds. Median investor counts are 15, 20, and 3 for advisors, broker-dealers, and family offices, respectively. Median PE fund counts are 11, 27, and 9. There is also substantial dispersion in advisor AUM. While average PE AUM is largest for advisors and broker-dealers, median PE AUM is highest for broker-dealers, and PE represents the largest share of total AUM for family offices.

2 PE Performance of Individual Investors

In this section, we provide the first comprehensive analysis of individual investors' performance in private equity. We begin by describing how we measure performance, followed by an analysis of aggregate performance and comparison to the performance of institutional investors. We also examine performance after adjusting for systematic risk and its variation across the wealth distribution.

2.1 Performance Measurement

We use several metrics to evaluate individual PE performance. Our primary performance metric is risk-adjusted PME following Brown et al. (2025), using the CRSP value-weighted market index as a benchmark. Standard PME metrics implicitly assume a market beta of one, which accurately adjust for risk only if the risk of private equity investments is identical to the risk of the public benchmark. To account for differences in systematic risk across fund categories, we estimate category-specific betas using Dimson (1979) regressions, which account for potential biases arising from smoothed reported valuations common in PE. The estimated betas, reported in Table B7, are 0.93, 1.37, and 1.00, for buyout, venture capital, and funds of funds, respectively.[11] We then use the beta estimates to generate a

[11] For the baseline risk-adjustment, we use the category specific betas reported in the columns labeled "All" in Table B7. We also estimate and report betas for different buyout fund sizes, and different VC strategies, for reference. Our estimated betas are consistent with the literature (Korteweg, 2023)—buyout funds exhibit betas close to unity, while venture capital funds display higher betas. Fund of funds have intermediate beta values, lying between buyouts and venture capital. The benchmark used for these estimations is the CRSP value-weighted index. As a robustness check of the Dimson (1979) betas, we also estimate betas following the methodology of Korteweg and Nagel (2024), and find similar estimates. Further details are provided in Appendix B.

"beta-adjusted" PME—which discounts cashflows using the public market index multiplied by the beta point estimate—and a "high beta" PME which uses the point estimate plus two standard errors. These two levels span a plausible range of systematic risk exposure, reflecting both the point estimates and conservative upper bounds.[12]

We complement the risk-adjusted PMEs with three standard metrics that account for different aspects of investment returns: (i) TVPI, (ii) IRR, and (iii) PME. TVPI calculates the total value return on investment by dividing the sum of the ending value and distributions by the sum of all contributions. While TVPI provides a straightforward measure of profitability, it does not account for the time value of money. IRR addresses this limitation by representing the annualized effective compounded rate of return, taking into account the timing of cash flows. The Kaplan and Schoar (2005) PME compares private investment performance to public market indices. PME discounts both distributions and contributions using the return of the chosen public market index, allowing for a direct comparison between private equity investments and public markets. We use the Russell 3000 as the benchmark index in the Kaplan and Schoar (2005) PME computation, to align our benchmark with the one used in MSCI.[13]

Table 2 reports summary statistics for each of performance metric across the three categories. For buyout funds, we find the strongest overall performance with a mean beta-adjusted PME of 1.21 (1.12 for the high-beta PME), indicating outperformance relative to public markets. The distribution of performance is positively skewed, with a median beta-adjusted PME of 1.13 and an interquartile range of 0.91–1.38. The Kaplan and Schoar (2005) PME (not risk-adjusted) is 1.25, reflecting the fact that buyout funds exhibit market exposure close to one.[14] TVPI and IRR average 1.83 and 16.81%, respectively.

Venture capital funds show weaker risk-adjusted performance with a mean beta-adjusted PME of 1.01 (0.87 for the high-beta PME). This reflects, in large part, their higher systematic risk, as measures of absolute performance before risk-adjustment are not dramatically worse relative to buyout funds. The mean TVPI is 2.08 and the mean IRR is 12.0%, with wide variation. The mean PME is 1.23, but the standard deviation is substantially higher than in buyouts, at 1.12. The distribution is also more skewed with a median PME of 0.98 and an interquartile range of 0.73–1.37.

Funds of funds in our sample display the lowest dispersion but also the lowest absolute performance across all three categories. The mean TVPI is 1.77 and the mean IRR is 13.3%.

[12]We adopt the terminology of "high beta" from Brown et al. (2025).
[13]Our preferred benchmark, the CRSP value-weighted index, is not available in MSCI.
[14]Table B19 provides the breakdown of PME by strategy.

The mean PME is 1.07, with relatively low dispersion (standard deviation of 0.29). Risk adjustment slightly weakens performance, with a mean beta-adjusted PME of 1.07 (0.97 for the high-beta PME).

Overall, many of the patterns in Table 2—including the strong performance of buyout funds, the greater dispersion among venture capital funds, and positively skewed performance—echo previous evidence from institutional funds. The universe of funds invested in by individual investors thus displays market characteristics similar to those of institutional funds.

The last column of Table 2, "% of investments", displays the fraction of all investor-fund observations covered by funds with available performance metrics. The coverage exceeds 90% for buyout and venture capital funds, indicating excellent coverage.

2.2 Comparison with Institutional Investors

We next compare the performance of individual investors' funds with institutional benchmarks from Preqin and MSCI. We begin by examining performance by vintage in Figure 2. The figure displays the median fund PME for each vintage year and category, separately for individual investors, Preqin, and MSCI. The results show that the performance of funds held by individual investors largely tracks the median performance in Preqin and MSCI across all three categories.[15] We observe somewhat greater discrepancy between Preqin and MSCI in the latter half of our sample period, with individual investors' funds generally falling between the two institutional benchmarks. Overall, these patterns provide little evidence of systematic differences in the performance of individual investors' funds.[16]

The preceding analysis in Figure 2 and Table 2 treats each fund equally, which accurately describes the investment opportunity set but may not reflect realized investor outcomes if capital is allocated unevenly across funds. Individual investors may tilt their portfolios toward funds they perceive as higher quality, or conversely, constraints on access may concentrate capital in lower-performing funds. To assess whether allocation patterns systematically differ from equal-weighted benchmarks and to benchmark aggregate individual performance against institutions, Table 3 reports commitment-weighted performance alongside equal-weighted averages and compares both to institutional benchmarks from Preqin and MSCI.

[15] For funds of funds, MSCI reports buyout fund of funds and venture capital fund of funds performance separately; we use their average as the benchmark for funds of funds in our sample.

[16] Figures B4 and B5 in the appendix show the corresponding patterns for TVPI and IRR, which reinforce this conclusion. The full distributions, including interquartile ranges and extreme percentiles, are shown in Figures B6 and B7 in the appendix and confirm that performance dispersion is also similar across datasets.

The first row of each panel compares equal-weighted (EW) and value-weighted (VW) averages across individual investors. While aggregate value-weighted performance does not differ dramatically from equal-weighted averages, important differences emerge across fund categories. In particular, we find higher value-weighted performance for venture capital funds. For example, the equal-weighted average IRR is 12.0% for venture capital funds, whereas the value-weighted average is 14.3%. In contrast, the value-weighted performance of buyout funds is weaker compared to equal-weighted performance. For funds of funds, the value-weighted and equal-weighted performances are more similar. These patterns hint at superior performance of more affluent investors in venture capital, a point to which we return in Section 2.3.

The second and third rows of each panel present excess performance relative to institutional benchmarks, defined as the difference between each fund's performance and the average performance in Preqin or MSCI for the same vintage and category. We do not find robust evidence of excess performance by individual investors relative to institutional benchmarks. While some excess performance metrics are statistically significant, they do not reveal a consistent pattern, as the direction of excess performance largely depends on the choice of performance metric and the institutional benchmark. For example, the value-weighted excess IRR is -1.8% compared to Preqin but virtually zero and not statistically significant compared to MSCI. At the same time, the value-weighted excess TVPI is 0.14 compared to Preqin and 0.06 relative to MSCI, both statistically significant. For PME, individual investors' value-weighted performance is 0.04 lower than Preqin, and 0.13 higher than MSCI.

Across categories, venture capital most consistently exhibits excess value-weighted performance. For buyouts, we find weak evidence of underperformance. The excess performance of fund of funds falls between Preqin and MSCI; excess performance metrics are mostly negative when compared to Preqin, but turn positive when compared to MSCI.[17]

Importantly, the economic magnitude of these differences is substantially smaller than performance differences across institutional investor types documented in prior literature. For example, Lerner et al. (2007) document average differences in IRR between endowments and public pension funds of more than 20 percentage points, whereas our largest excess performance measures are under 5 percentage points.

[17]Two potential concerns might affect the interpretation of these results. First, our sample spans the wealth distribution and may therefore overweight ultra-high-net-worth investors. In Table B17, we thus restrict the sample to our median wealth group ($10–30 million AUM) and confirm similar patterns. Second, recent vintages contain unrealized investments whose interim valuations may be biased (Barber and Yasuda, 2017; Brown, Gredil, and Kaplan, 2019) or stale. Table B18 excludes vintages after 2015 and again finds comparable results, suggesting our conclusions are not driven by unrealistic valuations in young funds.

2.3 Performance Across Wealth Distribution

Having established that individual investors perform comparably to institutions on average, we next examine whether this result masks important variation across the wealth distribution. Several factors might cause less affluent investors have lower PE performance. First, GPs may view smaller investors as less attractive LPs due to lower capital commitments, higher administrative costs per dollar, and greater liquidity pressures leading to early exit requests. Second, informational asymmetries may create adverse selection, with lower-quality funds disproportionately marketed to less sophisticated or poorly connected investors unable to assess fund quality (Calvet et al., 2007; Grinblatt et al., 2011). Finally, since meaningful diversification across PE funds requires substantial capital (Brown et al., 2024), less wealthy investors may more often rely on fund-of-funds structures that provide diversification at the cost of an additional fee layer (Harris et al., 2018).

We explore the role of investor wealth for performance in Table 4, which presents the beta-adjusted PME—our preferred risk-adjusted measure—on an equal-weighted (by investor-fund) and value-weighted (by commitment) basis, for each wealth group. Panel A reveals a clear performance gradient across the wealth distribution. The least affluent investors earn an average equal-weighted PME of 1.03, while the most affluent achieve 1.12—a difference of 9 percentage points that is both statistically (p-value < 0.01) and economically significant. This wealth-performance gradient is most pronounced in venture capital, where the most affluent investors outperform the least affluent by 6 percentage points (1.03 vs. 0.97). The gradient is more modest in buyout funds and in funds of funds.

Panel B of Table 4 reports the number of distinct funds held by investors in each wealth group and reveals large differences in the set of funds across wealth groups. As a group, the least affluent investors access only about a fourth of the funds invested in by the most affluent investors across all three categories. In contrast, the universe of funds invested in by the most affluent investors largely overlaps with the full universe of funds we study, encompassing 3,403 out of the total 4,593 funds. Overall, the results in Table 4 suggest an economically strong performance gradient in returns across the wealth distribution, particularly for VC funds.

3 Drivers of Performance Heterogeneity

In this section, we consider several drivers of the wealth performance gap described earlier. We begin by assessing the robustness of the gap to controlling for vintage timing. We then turn to quantifying the role of advisors in driving the outperformance of wealthier investors and variation in performance. We also present evidence of persistent heterogeneity in advisor performance and advisor skill. In the last part of the section, we assess the strength of investor sorting into better-performing advisors.

3.1 Performance Regressions

A natural question to ask is whether the wealth performance gap can be explained by vintage timing, as different wealth groups may have entered private equity at different times (Brown, Harris, Hu, Jenkinson, Kaplan, and Robinson, 2021). To test this hypothesis, we estimate performance regressions where the unit of observation is investor by fund. We regress the beta-adjusted PME of fund i held by investor j, $PME_{i(j)}$, on a set of indicators for investor wealth groups $InvestorWealth_{m(j)}$ and category-by-vintage fixed effects, λ_{ct}:

$$PME_{i(j)} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{ct} + \epsilon_{i(j)}. \quad (1)$$

Our empirical design assigns a single, median-investor performance value to each fund. Hence, our focus is on the cross-sectional variation *across* funds—examining whether different types of investors systematically invest in funds with different performance—rather than *within*-fund variation, which can arise due to differences in fees, which we analyze in Section 4. In addition, this design allows us to analyze the most comprehensive sample of investments, even those for which $PME_{i(j)}$ is not available for investor j. In doing so, we follow the empirical designs of Lerner et al. (2007) and Sensoy et al. (2014), which also assign fund-level performance to all LPs in a fund and compare outcomes across investor types. We control for the fact that we have multiple observations per fund or investor by double clustering the standard errors at the fund level and at the investor level. To limit the impact of extreme observations, we winsorize PME at the 1% and 99% level.

In Table 5, column (1) presents the results without category-by-vintage fixed effects and shows that the wealth performance gap is highly statistically significant. Relative to the omitted category of the most affluent investors (>$100m in AUM), the least affluent investors (<$3m) underperform by 7.5 percentage points of PME (p-value <0.01). Column

(2) shows that, once we control for category-by-vintage fixed effects, the wealth performance gap narrows to 5.2 percentage points, but remains economically and statistically significant. Hence, the gap is largely not driven by the timing of investments.

Columns (3) through (5) report the results separately for each fund category: buyout, venture capital, and funds of funds. The wealth gradient is strongest in venture capital, where the least affluent investors underperform the wealthiest by 12 percentage points of PME. The pattern is somewhat weaker for funds of funds with a 5 percentage point difference, and is not statistically significant for buyout funds. These findings confirm the earlier results that the performance gap is most pronounced in venture capital and funds of funds, even after controlling for the timing of the investment.[18]

3.2 Role of Advisors

To analyze the role of advisors in the wealth performance gap, in column (6) of Table 5, we add advisor fixed effects. Recall that an "advisor" in our data is defined at the level of the advisory firm for all the wealth managers in our data (RIAs, broker-dealers, and family offices) as we do not observe individual advisors serving different clients within the same firm. Hence, our analyses with advisor fixed effects provide a conservative estimate of the role of individual advisors.

We find that with advisor fixed effects, the coefficient on the lowest wealth group in column (6) falls to –0.012, about 15% of the initial gap in column (1), and becomes statistically insignificant. This implies that most of the wealth performance gap is driven by differences between advisors, rather than by within-advisor differences in investor performance across the wealth distribution.

Identification in this specification comes only from advisors who serve clients in multiple wealth categories; advisors without such within-advisor variation do not contribute to the estimate. To ensure that our results are not driven by limited within-advisor variation, we re-estimate the specification in Table 5 on the subset of advisors who span all wealth categories in Appendix Table B16. There are 135 advisors whose clients span all five wealth groups, with the average (median) advisor in this subset managing 99 (45) individuals. The results remain virtually unchanged, confirming that the attenuation of the wealth–performance gap with advisor fixed effects is not an artifact of insufficient within-advisor variation.

[18]These results are robust to including strategy×vintage fixed effects, as shown in Appendix Table B20; the results are therefore not driven by the wealthiest investors predominantly investing in early-stage venture capital, for example.

3.2.1 Variance Decomposition

The regression results above show that conditioning on the advisor largely eliminates the wealth–performance gradient. To understand the influence of advisors on investor portfolios in more detail, we next perform a decomposition of the overall variation in performance to differences *between* advisors, as opposed to heterogeneity *within* advisors.

Specifically, we implement a variance decomposition analysis. In this subsection, we standardize performance within each category-by-vintage cell (mean zero, variance one). This normalization puts outcomes on a common scale, so fixed-effect magnitudes can be interpreted consistently and compared to the public equity benchmarks we introduce below. Let $PME^z_{i(j)}$ denote a standardized PME of fund i held by investor j, and let λ_{ct} denote category-by-vintage fixed effects. We first estimate the restricted specification

$$PME^z_{i(j)} = \lambda_{ct} + \epsilon_{i(j)}, \tag{2}$$

and then augment it with advisor-by-category-by-vintage fixed effects, γ_{act}:

$$PME^z_{i(j)} = \gamma_{act} + \nu_{i(j)}. \tag{3}$$

We summarize the incremental explanatory power of the advisor component using the standard partial R^2 from the nested specifications:

$$\text{Partial } R^2_{\text{advisor}} = \frac{R^2_{\text{full}} - R^2_{\text{restricted}}}{1 - R^2_{\text{restricted}}}. \tag{4}$$

This statistic therefore answers: of the performance variation not explained by category-by-vintage differences, what fraction is captured by between-advisor differences in average performance within the same category and vintage?

Figure 3 visualizes the decomposition. The left histogram in Panel (a) shows the total variation in standardized performance ("total" variation). The middle histogram shows the distribution of advisor-by-category-by-vintage mean performance ("between-advisor" variation). The right histogram shows the residual dispersion after absorbing advisor-by-category-by-vintage fixed effects ("within-advisor" variation). Two patterns stand out. First, the between-advisor distribution closely tracks the dispersion of total performance, implying that most of the variation in performance is associated with differences in advisor-level average performance. The between-advisor variation is also economically large: Moving from the 25th to the 75th percentile corresponds to a two-standard-deviation improvement in performance.

Second, the within-advisor distribution is much more concentrated, with a pronounced spike at zero. To accommodate this spike, the within-advisor histogram is plotted on a different (higher) y-axis scale. A striking 72% of observations coincide with the within-advisor mean performance. This pattern implies comparatively little remaining dispersion among investors served by the same advisor within the same category and vintage. Consistent with this visual evidence, the partial R^2 of advisor fixed effects in private equity is 0.643.

One interpretation of this finding is that advisors allocate identical private equity investments to most of their clients because of the fixed costs of due diligence or access frictions that are particularly pronounced in private markets. An alternative interpretation of advisor fixed effects considered in the literature is that investors with common preferences sort into the same advisor (Foerster et al., 2017). We test this alternative by examining another segment of the portfolio where client preferences should play a role.[19]

Specifically, we focus on the public equity share of investor portfolios, consisting of direct stocks, mutual funds, and ETFs. Panel (b) of Figure 3 reports the results of a similar variance decomposition for public equities. We use the same sample of investors and advisors as in Panel (a), but replace private equity performance with the returns of equity positions initiated by each investor in a given month. We again standardize performance within each month so that the total variation in the leftmost panel has the same mean and variance as for private equity. We then estimate regressions similar to Equations (2) and (3) with year-month fixed effects and advisor-by-year-month fixed effects, respectively.[20]

In contrast to the equivalent histogram for private equity, public equities display substantially more dispersed within-advisor variation: The zero bin in Panel (c) peaks below 30% and the corresponding partial R^2 is only 0.272. This comparison highlights that the portion of performance dispersion associated with advisor-level differences is markedly larger in private equity than in liquid public equities. The pivotal influence of advisor fixed effects in private equity is striking also compared to the literature. For example, Foerster et al. (2017) find an R^2 of 22% for advisor fixed effects in the allocation to risky assets in Canadian mutual funds. We conclude that advisors exert a disproportionately large role in shaping investor outcomes in private equity and that the role of advisor fixed effects in private equity is not simply an artifact of unobserved investor preferences shared by clients of the same advisor. This finding is also consistent with accounts from advisory firms that clients often

[19] A different approach to assessing the role of unobserved investor preferences is to use advisor switches (Foerster et al., 2017). We do not observe investors across multiple advisors (investor identifiers are advisor specific) and therefore cannot use this approach.

[20] The construction of this public equity sample and return measure is described in Appendix A.3.

delegate fund choice to advisors, who perform due diligence on their behalf and then allocate the same investments across most clients.

3.3 Heterogeneity Across Advisors

We next examine which advisor characteristics predict fund performance. Existing work on institutional investors finds that, consistent with the role of investor skill, some investors perform persistently better than others (Lerner et al., 2007; Hochberg and Rauh, 2013; Cavagnaro et al., 2019), although this relationship has become weaker over time (Sensoy et al., 2014). More recently, Begenau and Siriwardane (2024) find that larger, more experienced, and better-performing institutions receive more advantageous fee arrangements. Motivated by this literature, we next examine whether advisor characteristics capturing past performance, experience, and size are associated with better subsequent performance.

We estimate versions of the following regression:

$$PME_{i(j)} = \gamma_0 + \mathbf{Z}'_{k(j)}\gamma + \lambda_{m(j)} + \lambda_{ct} + \epsilon_{i(j)}, \tag{5}$$

where the dependent variable is the β-adjusted PME, $\mathbf{Z}_{k(j)}$ denotes the vector of advisor characteristics for advisor k serving investor j, $\lambda_{m(j)}$ are investor-wealth-group fixed effects, and λ_{ct} are category×vintage fixed effects. The sample is identical to the one in Table 5, subject to the availability of advisor characteristics, and standard errors are double-clustered at the fund and advisor level.

We consider five advisor characteristics. The first, *advisor category*, consists of indicator variables for broker-dealers and family offices, with RIAs as the omitted category. The second, *past performance quartile*, proxies for demonstrated skill in fund selection. We compute this measure by first defining excess PME as PME relative to the vintage×category average. For each advisor and vintage, we then calculate the advisor's average excess PME over funds from the prior four vintages, rank advisors by this trailing average, and assign them to quartiles (1 = lowest, 4 = highest). The third characteristic, *experience*, is the count of distinct funds the advisor has invested in previously, scaled in hundreds. The fourth and fifth characteristics proxy for *advisor size*: total commitments in a given vintage and average AUM over the sample period. Both size measures are in logs and winsorized at the 2.5th and 97.5th percentiles.

Table 6 reports the results. Column (1) shows that advisor categories are not systematically

related to performance: broker-dealers and family offices perform similarly to RIAs (omitted category) on average. In contrast, both past advisor performance and experience are positively associated with performance. A one-quartile increase in past performance is associated with 4.8 percentage points higher PME. This coefficient implies that the top quarter of advisors in the past continue to outperform bottom-quarter advisors by roughly 14.4 percentage points ($\approx 3 \times 0.048$). The magnitude is economically large: it is more than double the wealth performance gap estimated in Table 5, suggesting that matching with advisors is a more important determinant of performance than investor wealth. Furthermore, advisor experience is also positively related to performance. The coefficient in column (1) implies that having experience with additional 100 funds (corresponding to the standard deviation of experience in the sample of RIAs) is associated with 2.5 percentage points better future performance. Column (2) adds two size proxies to the regression and shows that neither size measure is statistically significant, with coefficients on past performance and experience remaining virtually unchanged. This result suggests that the significant association of past performance and experience is not merely an artifact of scale effects.

One concern with interpreting columns (1) and (2) is that advisor characteristics may proxy for investor characteristics rather than capturing independent advisor effects. Experienced advisors tend to serve experienced investors—both accumulate track records over time—making it difficult to separate the two channels. Column (3) addresses this by restricting the sample to investors making their first private equity investment. These investors are less likely to have established GP relationships or to have superior skill in selecting well-performing funds. By construction, they have also no experience with private equity investments. If our advisor proxies primarily capture investor-specific characteristics, their association with performance should disappear in this new-investor subsample. However, this is not what we find: we document an economically stronger effect of advisor experience and muted effect of past performance.

In columns (4) through (6) we explore the role of advisor characteristics within each fund category. Similar to the wealth performance gap, the role of past advisor quartile is most significant in venture capital (10 percentage points per quartile, column (5)), which is the category with the largest performance dispersion (Kaplan and Schoar, 2005; Harris et al., 2014). The role of advisor performance is weaker and significant only at the 10% level for buyouts (0.016 per quartile, column (4)), and insignificant for fund of funds. Overall, the evidence suggests persistent differences in advisor performance, consistent with heterogeneity in advisor quality.

3.3.1 Role of Advisor Skill

The persistent differences in advisor performance documented in Table 6 could reflect differences in advisor *skill* in fund selection or differences in *access* to constrained funds. For example, advisor quartile can be capturing the effect of differential access to top GPs who persistently perform better (Kaplan and Schoar, 2005; Korteweg and Sorensen, 2017; Harris et al., 2023). Alternatively, some advisors may have superior skill in fund selection, which has been documented in the literature on institutional investors (Lerner et al., 2007; Hochberg and Rauh, 2013; Cavagnaro et al., 2019).

We explore these hypotheses in Table 7 by focusing on the subsamples where access frictions should be weaker. The common approach in the literature to distinguish between skill and access is to focus on early (Lerner et al., 2007) or first-time funds (Sensoy et al., 2014) which have arguably less developed LP networks (Howell et al., 2024) and as a result are less likely to limit access. In column (2) we therefore estimate Equation (5) in the subsample of first-time funds. For ease of comparison, column (1) repeats the baseline specification from Table 6. If advisor experience or performance were primarily driven by access, we would expect the coefficients to be weaker in this subsample. Instead, we find that the coefficients are similar to the full sample reported in column (1). This result suggests that advisor experience and performance quartile primarily reflect skill in fund selection rather than differential access.

The results in column (2) also rule out a mechanical explanation: that high-quartile advisors simply invest repeatedly with the same successful GPs (i.e., investing in follow-on funds from existing relationships). This is because advisor performance quartile is constructed using only investments with GPs that existed *before* the first vintage of the new GPs in the first-time-fund sample. Column (2) therefore implies that higher-quartile advisors invest in better-performing funds even across different GPs.

Beyond access frictions to constrained funds, advisors serving individual investors may face barriers stemming from minimum commitments. Commitments of institutional investors typically exceed $5 million (Korteweg and Westerfield, 2022), while the median commitment of individual investors ranges from $0.1–1.5 million, as shown in Table 1. If fund managers screen on commitment size, either through stated minimums or informal preferences for larger LPs, smaller investors may be excluded from the highest-quality funds regardless of their advisor's skill or relationships. We examine this channel by examining two subsamples where commitment-size barriers should be attenuated: funds with stated minimum investments below $1 million in column (4) and investments where realized commitments fall below $0.1

million in column (5). Again, we find that the coefficients are similar to or stronger than in the full sample reported in column (1).

Finally, in column (5), we test whether our results are driven by access to oversubscribed funds, which are more likely to impose capacity constraints. If advisor experience and past performance primarily captured differential access to sought-after funds, we would expect these effects to be concentrated among over-subscribed funds. Instead, we find that the coefficients on advisor experience and performance quartile are statistically insignificant for over-subscribed funds. Overall, the patterns suggest that the role of advisors that we document reflects differences in selection skill rather than differential access.

3.4 Sorting of Investors Across Advisors

The preceding results raise a natural question: if advisor quality varies substantially, do wealthier investors sort into relationships with better-performing advisors? Such sorting would provide a direct link between advisor characteristics and the wealth-performance gradient that we have documented earlier. To make progress on this question, Figure 4 plots the regression coefficients (dots, left axis) and 95-percent confidence intervals (in grey) from a regression of advisor performance quartile on investor wealth-group indicators, weighted by the number of investments in each wealth group. These coefficients can be interpreted as the estimated mean advisor-performance quartile for each wealth group. Moreover, we plot the portfolio share advised by advisors in each performance quartile (stacked bars, right axis).

We begin with Panel (a), which reports results for the full sample of investors. We find a clear positive pattern: wealthier investors are more likely to be advised by better-performing advisors. Moving from the least-wealthy to the wealthiest investor group, the average advisor performance quartile increases from 2.6 to 2.9, or about 10% of the full quartile span (from 1 to 4). Overall, these patterns are consistent with positive but modest investor sorting. However, the distribution of advisor quality remains dispersed even among the wealthiest investors.

In Panel (b), we provide further evidence of sorting by focusing on new investors—those who have not yet established a relationship with an advisor—and by using only performance information available at the time of the investor's first private equity investment with that advisor. Specifically, we restrict the sample to investments in each investor's first vintage with the advisor. We compute advisor performance quartiles using interim PMEs calculated from cash flows available prior to the investor's first private equity investment with the advisor.

We also exclude funds with fewer than five years of cash flow data, for which interim PMEs are only weakly correlated with final PMEs (Hochberg et al., 2014). We find a similar positive pattern: the average advisor performance quartile increases from 2.4 to 2.8. Moreover, the portfolio share advised by advisors in the top performance quartiles increases monotonically from the least-wealthy to the wealthiest investor group.

While more affluent investors appear to sort into better-performing advisors, the strength of sorting is relatively weak: even among the most affluent investors, more than one third are matched to advisors in the bottom two performance quartiles. This dispersion suggests that even ultra-high-net-worth investors face meaningful search frictions when selecting an advisor. A key barrier is that advisor track records in private equity are not easily observed or benchmarked ex-ante, and meaningful performance information tends to arrive with a substantial lag, sometimes only years after the initial investment.

Taken together, the results in this section point to financial advisors as a primary mechanism driving individual investors' performance dispersion in private equity. Vintage timing or category selection explain little of the performance gradient across wealth. In contrast, advisory firm fixed effects account for roughly two-thirds of the variation in fund performance within vintage-category, far in excess of advisors' explanatory power for investors' public equity returns. Among advisor characteristics, past performance and experience emerge as predictors of fund performance, unlike advisor type and size. Finally, wealthier investors are more likely to be advised by better-performing advisors.

4 Fees

The performance measures thus far are computed net of standard GP fees (management fees and carried interest), following convention in the literature and allowing for direct comparison with institutional benchmarks. In this section, we estimate the impact of additional fee layers on net-of-fee performance across the wealth distribution. We refer to this performance net of all fees as net-net performance (Fang et al., 2015).

4.1 Types of Fees in PE

There are several ways in which individual investors in private equity may be charged fees on their investments. First, different LPs may be charged different fees by their GP, either as a different management fee or a different percentage of carry (Begenau and Siriwardane,

2024). Following this earlier literature, we refer to these differences in GP terms as "LP tiers". Second, advisors may use platforms, feeder funds, or investment consultants and other specialized advisors to gain access to a broad menu of private equity investments, and these intermediaries may charge a fee for providing this access. We refer to this fee as "access fee". Third, advisors provide investment advice in exchange for fees, which are typically charged as a percentage of wealth managed or invested based on a fee schedule which is decreasing in wealth. We refer to this fee as "advisor fee."

While these fees can have a material impact on the net-net performance of investors, data on private equity fees are scarce in most datasets.[21] To make progress in evaluating the impact of fees, we next leverage the fact that we observe the impact of LP tiers and access fees on performance for the investors in our data with complete cash flows. We then augment our analyses by simulating the impact of advisor fees based on disclosed fee schedules.[22]

4.2 Estimated Net-Net Performance

For fund i, investor j in wealth group m, and advisor k, we model net-net performance PME^N_{ijk} as:

$$PME^N_{ijk} = PME_i - \hat{f}^{Tier}_{m(j)} - \hat{f}^{Access}_{ik} - \tilde{f}^{Advisor}_{i,m(j)}, \tag{6}$$

where PME_i is the baseline risk-adjusted PME measured from the median-investor cash flows in fund i as described in Section 2, $\hat{f}^{Tier}_{m(j)}$ is the performance drag or lift associated with differential terms imposed by GPs, $\hat{f}^{Access}_{ik}$ are intermediary fees paid to access fund i by advisor k, $\tilde{f}^{Advisor}_{i,m(j)}$ are fees charged by the advisor as a percentage of investor's AUM. We can measure terms $f^{Tier}_{m(j)}$ and f^{Access}_{ik} while the advisor fees $\tilde{f}^{Advisor}_{i,m(j)}$ are unobserved.

To estimate each fee component for all investor-fund observations, we proceed in the following steps. First, we use observed variation across the performance of investors in the same fund i to estimate $\hat{f}^{Tier}_{m(j)}$. For investor-fund observations where we observe full cash flows, we can calculate this term exactly using the following identity:

$$f^{Tier}_{ij} = PME_{ij} - PME_i, \tag{7}$$

where PME_{ij} is the risk-adjusted PME of investor j in fund i. Table B21 presents results

[21] The vast majority of the PE literature reports performance net of GP fees, but offers limited evidence on other fees. One exception is Fang et al. (2015), who impute net-net performance based on internal cost data estimates from four institutional investors.

[22] Fee structures are disclosed in reports made by investment professionals called Form ADVs.

from the regressions of f_{ij}^{Tier} on investor wealth groups and fund-by-advisor fixed effects. Consistent with more affluent investors receiving better terms from the GPs, we find that f_{ij}^{Tier} is positive and statistically significant for the wealthiest investor group. The average LP tier difference between the most and the least affluent group is 3–4 percentage points. For observations where we do not observe full cash flow data, we set $\hat{f}_{m(j)}^{Tier}$ equal to the average values implied from Table B21, thereby assuming that tier adjustments are constant within wealth groups.

Second, to estimate the fee drag from access fees, we leverage the fact we observe both the value and timing of access fees in the cash flow data. For investor-fund observations in the cash flow data we can calculate the access fee drag as

$$f_{ij}^{Access} = PME_{ij} - PME_{ij}^{Access}, \tag{8}$$

where PME_{ij}^{Access} is the risk-adjusted PME calculated net of access fees. Approximately 20% of the investments in the cash flow data incur access charges and the median access charge is 1.9% of total contributions. Whether an investment incurred an access charge varies by advisors and funds, where buyout funds and high minimum commitment funds are significantly more likely to be associated with access charges. To extrapolate access fee drag to the full sample, we set $\hat{f}_{ik}^{Access} = \bar{f}_{ij(k)}^{Access}$.

Finally, to estimate the fee drag from advisors, we resort to a simulation using a typical fee schedule charged by financial advisors as we do not observe fees charged by advisors in our dataset. This fee starts at 1.75%, and declines to 0.50% for wealthier investors.[23] Using this fee schedule, we simulate dollar fees paid by individual investors in each quarter by multiplying the percentage fee by the initial market value of individuals' positions. We then compute the drag from advisory fees as

$$f_{ij}^{Advisor} = PME_{ij}^{Access} - PME_{ij}^{Advisor}, \tag{9}$$

where $PME_{ij}^{Advisor}$ is the risk-adjusted PME of investor j in fund i net of both access and simulated advisory fees. To extrapolate advisory fee drags to the full sample, we set $\hat{f}_{im}^{Advisor} = \bar{f}_{i,m(j)}^{Advisor}$, where the latter denotes the average advisory fee drag across investors by

[23] Specifically, we assume that assets from \$0 to \$400,000 are charged a 1.75% annual fee, followed by an annual fee of 1.25% on the next \$350,000 (up to \$750,000), 1.00% annual fee on the next \$250,000 (up to \$1,000,000), 0.75% annual fee on the next \$2,000,000 (up to \$3,000,001), 0.60% annual fee on the next \$7,000,000 (up to \$10,000,000), and 0.50% annual fee on the next \$15,000,000 and assets above \$25,000,000. This fee schedule is based on the public disclosures in Form ADV of a large advisor that manages private equity investments.

fund and wealth group.

Figure 5 illustrates how different types of fees impact the baseline performance advantage of wealthier investors. Specifically, the figure decomposes the impact of fees on risk-adjusted PME across our five wealth categories, showing both baseline performance and the cumulative effect of three distinct fee drags. The baseline bars (in dark blue) represent the raw performance differences across wealth groups that we documented earlier, which are driven by fund selection rather than fees. This baseline performance already nets out standard GP management fees and carry, but does not account for the variation in these terms across different investor tiers or the additional costs of accessing private equity, via a platform, feeder fund, consultant, or advisor charging additional fees.

The LP tier adjustments (in red) capture how general partners offer different fee terms to different classes of investors within the same fund. Consistent with our earlier findings, wealthier investors receive modestly better terms, with the most affluent group benefiting from a small performance lift while other groups face modest drags. Furthermore, the access fee drag (in green), reflecting the platform and intermediary costs that some investors pay to gain entry to specific funds, are relatively uniform across wealth groups and impose a modest but consistent drag on net performance.

The advisor fee drag (in orange) represents the most substantial cost, reflecting the asset-under-management fees that advisors may charge for portfolio management and private equity selection. This fee component has the largest and most regressive impact across the wealth distribution, as in our simulation less affluent investors are charged higher percentage fees. Together, the fees increase the performance gap between the least and most wealthy investors by more than 50% (in light blue). For the least affluent investors, the combined fee burden absorbs their outperformance relative to public markets, reducing their net-net PME below one, on average. Overall, our results suggest that while individual investors can successfully access high-quality private equity funds, fees create a meaningful barrier to realizing these returns, particularly for less affluent investors.

5 Conclusion

This paper provides the first systematic analysis of private equity performance among individual investors using comprehensive cash flow data. We document that the closed-end PE funds individual investors invested over two decades performed similarly to institutional benchmarks on average. This indicates that the universe of funds accessed by individual

investors does not seem restricted due to access frictions or fund-selection skill. However, this finding masks important heterogeneity across investors, with in particular a significant wealth gradient: the most affluent investors substantially outperform the least affluent. This is not driven by the timing of investments in specific vintages within categories. Financial advisors account for a considerable share of the dispersion in performance across individuals within category and vintage, which is consistent with individuals delegating fund selection to advisors. Advisor experience and past performance are associated with better fund selection, and more affluent investors are more likely to have better-performing advisors. We show that fees, particularly advisor fees, appear to substantially reduce performance in ways that disproportionately affect less wealthy investors.

Our evidence has implications for how regulators and policymakers assess expanding household access to private equity. First, at the asset class level, we do not find that the funds reaching affluent households are systematically of lower quality: conditional on investing, realized performance is broadly comparable to institutional benchmarks. This result makes it difficult to justify blanket prohibitions that rest purely on claims that the funds offered to individual investors are adversely selected. The key policy question is therefore less about whether private equity, as an asset class, is unsuitable for households, and more about how access is structured.

Shifting attention from the asset class to the intermediation layer, a different set of concerns emerges. We document sizable wealth gradients in realized PE performance and show that advisor quality and fees explain a large share of these gaps. Our findings suggest that policies that broaden the set of private investments available to households, while leaving fee structures, compensation schemes, and advisory practices unchanged, may widen performance dispersion across the wealth distribution instead of narrowing it.

At the same time, we acknowledge that our results are specific to closed-end funds accessed through professionalized channels. Evergreen, interval, and semi-liquid structures differ in their liquidity provisions and fee arrangements. While evaluating the risk-return tradeoffs of these vehicles require longer return histories as these markets evolve, we anticipate that the several mechanisms we highlight—the role of advisor quality in fund selection and the compounding effect of fee layers—are likely to remain relevant.

Taken together, our results suggest that any serious assessment of democratizing private equity must move beyond the binary question of whether households should be allowed into the asset class and toward the more granular design problem of how they are brought in. For regulators and plan sponsors, the key margins are the architecture of fees and advice

and the criteria used to define eligible investors. For researchers, our findings underscore the importance of measuring realized outcomes net of all fees across the wealth distribution and of modeling the joint behavior of households, intermediaries, and private-market funds as access expands. We view the evidence in this paper as a first step in that direction and as a foundation for future work that quantifies welfare and distributional effects under alternative regulatory designs.

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Table 1. Descriptive Statistics

This table presents descriptive statistics for the sample of 4,593 funds raised between 2000 and 2020 and 17,886 individual investors who invested in these funds. Panel A presents fund characteristics. Size is the fund size reported in Preqin. Oversubscribed is an indicator variable for funds where the size exceeds the target size. Minimum commitment is hand-collected from Preqin. Panel B summarizes investor characteristics. Total AUM and Private Equity AUM are measured as of the end of the sample period. Panel C summarizes advisor characteristics. Number of investors is the total number of advised investors with at least one private equity investment.

Panel A: Descriptive Statistics—Funds

	Buyout						Venture Capital						Fund of Funds					
	N	Mean	Std.Dev.	Min.	Med.	Max.	N	Mean	Std.Dev.	Min.	Med.	Max.	N	Mean	Std.Dev.	Min.	Med.	Max.
Vintage	1,672	2014	5	2000	2015	2020	2,210	2015	5	2000	2017	2020	711	2012	6	2000	2013	2020
Size (m)	1,581	1,438	2,730	3	485	24,714	1,918	219	357	0	100	3,750	651	629	1,323	1	269	14,000
N. of individual investors	1,672	17	28	1	8	583	2,210	13	24	1	6	360	711	23	55	1	8	768
Oversubscribed	1,310	0.2	0.4	0.0	0.0	1.0	1,477	0.3	0.5	0.0	0.0	1.0	418	0.3	0.5	0.0	0.0	1.0
Fund number overall	1,672	5.1	6.5	1.0	3.0	59.0	2,206	4.7	6.9	1.0	3.0	102.0	706	13.6	16.2	1.0	8.0	98.0
Fund number series	1,659	3.3	2.4	1.0	3.0	14.0	2,165	2.9	2.7	1.0	2.0	27.0	691	4.2	3.0	1.0	3.0	15.0
Min commitment (m)	1,276	5.2	8.5	0.0	3.0	100.0	1,250	1.0	5.2	0.0	0.1	100.0	405	2.5	8.5	0.0	0.5	100.0

Panel B: Descriptive Statistics—Investors

				PE portfolio share				
Wealth group	Number of investors	Total AUM (m)	Private Equity AUM (m)	Buyout	Venture Capital	Fund of Funds	Number of funds	Median commitment
<3m	3,541	1.7	0.2	29.1	30.3	40.6	1.9	0.1
3m–10m	3,682	8.3	1.0	30.4	25.6	44.0	2.3	0.3
10m–30m	4,308	24.7	3.2	34.5	25.1	40.4	3.4	0.4
30m–100m	3,635	71.4	9.3	35.9	29.2	34.9	5.6	0.6
>100m	2,720	615.3	107.8	39.6	33.2	27.1	10.7	1.5

Table 1. Descriptive Statistics (continued)

Panel C: Descriptive Statistics—Advisors

	RIAs					Broker Dealers					Family Offices				
	Mean	Std.Dev.	Min.	Med.	Max.	Mean	Std.Dev.	Min.	Med.	Max.	Mean	Std.Dev.	Min.	Med.	Max.
Total AUM	4,088	19,181	0	540	253,524	6,366	14,054	1	2,110	90,456	1,722	3,878	1	693	52,170
Private Equity AUM	710	4,087	0	36	48,032	538	953	0	204	5,059	325	2,171	0	62	44,624
First Vintage	2007	6	2000	2007	2020	2005	6	2000	2004	2019	2009	6	2000	2009	2020
Number of Investors	50	116	1	15	814	48	73	1	20	351	8	28	1	3	520
Number of Funds	43	101	1	11	985	55	73	1	27	345	17	25	1	9	276
Number of Advisory Firms	241					48					456				

Table 2. Performance of Individual Investors

This table presents summary statistics of performance metrics for 4,593 funds closed between 2000 and 2020. For each fund, we first compute performance measures (TVPI, IRR, PME) using investor-level cash flow data, then take the median across investors to obtain fund-level metrics. We complement the calculated performance metrics with TVPI and IRR reported in Preqin. TVPI is the multiple of invested capital, calculated as the ratio of total value (distributions plus NAV) to total capital invested. IRR is the internal rate of return that equates the present value of distributions and NAV to capital contributions. PME is the Kaplan and Schoar (2005) public market equivalent, calculated using the Russell 3000 as the benchmark index for comparison to institutional benchmarks, to align with the data provided by MSCI. Risk-adjusted PMEs are estimated using Dimson regressions reported in Table B7 for each fund category, and the CRSP value-weighted index as the benchmark. *% of investments* is the fraction of all individual investors investments with available performance metrics.

Panel A: Buyout									
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N	% of investments
TVPI	1.83	0.89	0.51	1.31	1.65	2.15	4.97	1,672	0.97
IRR	16.81	19.80	-21.84	8.38	15.00	22.51	74.50	1,670	0.96
PME	1.25	0.65	0.26	0.92	1.15	1.43	3.65	1,534	0.95
PME (β-adjusted)	1.21	0.58	0.26	0.91	1.13	1.38	3.02	1,376	0.93
PME (High β)	1.12	0.55	0.24	0.85	1.05	1.30	2.79	1,376	0.93
Panel B: Venture Capital									
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N	% of investments
TVPI	2.08	2.11	0.26	1.06	1.50	2.29	10.94	2,210	0.94
IRR	11.99	17.45	-23.51	1.49	10.16	19.43	71.11	2,196	0.94
PME	1.23	1.12	0.13	0.73	0.98	1.37	5.43	2,071	0.92
PME (β-adjusted)	1.01	0.93	0.11	0.61	0.82	1.12	4.54	1,963	0.91
PME (High β)	0.87	0.81	0.08	0.52	0.71	0.96	3.78	1,963	0.91
Panel C: Fund of Funds									
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N	% of investments
TVPI	1.77	0.72	0.71	1.37	1.62	2.01	4.50	711	0.80
IRR	13.27	8.97	-8.25	8.09	13.13	17.80	37.08	705	0.80
PME	1.13	0.35	0.39	0.93	1.09	1.27	2.27	613	0.78
PME (β-adjusted)	1.07	0.29	0.36	0.91	1.04	1.20	1.90	544	0.77
PME (High β)	0.97	0.27	0.32	0.82	0.95	1.10	1.73	544	0.77

Table 3. Excess Performance of Individual Investors

This table presents the excess performance of individual investors. For each performance metric, we report the equal-weighted (on fund level) average and value-weighted average based on committed capital. Excess performance of each fund is calculated by deducting the average performance in the Preqin/MSCI database for funds of the same vintage and category (buyout/venture capital/funds of funds). We use the Russell 3000 as the benchmark index in PME calculations to align our benchmark with the one used in the data provided by MSCI. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: TVPI								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
TVPI	1.94	1.82	1.83	1.68	2.08	2.10	1.77	1.72
Excess $TVPI_{Preqin}$	0.08***	0.14***	-0.05**	-0.05***	0.23***	0.49***	-0.06**	0.03
Excess $TVPI_{MSCI\text{-}Burgiss}$	0.02	0.06***	0.03	-0.07***	-0.04	0.20***	0.17***	0.13***
Observations	4,593		1,672		2,210		711	
Panel B: IRR								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
IRR	13.9	14.5	16.8	15.1	12.0	14.3	13.3	13.6
Excess IRR_{Preqin}	-2.9***	-1.8**	-1.7**	-1.5***	-3.7***	-0.5	-2.8***	-4.4**
Excess $IRR_{MSCI\text{-}Burgiss}$	-1.2**	-0.3	0.6	-0.9**	-3.3***	0.6	0.8	-0.3
Observations	4,571		1,670		2,196		705	
Panel C: PME								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
PME	1.22	1.19	1.25	1.15	1.23	1.31	1.13	1.09
Excess PME_{Preqin}	-0.04***	-0.04***	-0.10***	-0.14***	0.04	0.19***	-0.12***	-0.18***
Excess $PME_{MSCI\text{-}Burgiss}$	0.12***	0.13***	0.14***	0.06***	0.11***	0.25***	0.14***	0.09***
Observations	4,218		1,534		2,071		613	

Table 4. Performance Across Wealth Distribution

This table presents average performance by investor wealth group. Investors are assigned to wealth groups using the average observed wealth. In Panel A, we report the equal-weighted average PME over investments and the value-weighted average using committed capital. This PME is the beta-adjusted PME, which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. Panel B reports the total number of funds held by any investor in the wealth group.

Panel A: PME								
	All Funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
<3 m	1.03	1.05	1.18	1.15	0.97	1.00	1.04	1.02
3-10 m	1.06	1.03	1.19	1.06	0.97	1.04	1.06	0.99
10-30 m	1.10	1.08	1.19	1.14	1.04	1.09	1.04	1.02
30-100 m	1.11	1.07	1.21	1.15	1.05	1.03	1.04	1.01
>100 m	1.12	1.11	1.21	1.13	1.03	1.12	1.07	1.06

Panel B: Number of Funds				
	All Funds	Buyout	Venture Capital	Fund of Funds
<3 m	1,043	418	441	184
3-10 m	1,514	546	675	293
10-30 m	2,296	840	1,076	380
30-100 m	2,797	992	1,385	420
> 100 m	3,403	1,232	1,700	471

Table 5. Investor Wealth and Fund Performance

The table reports results from OLS regressions of fund performance on investor characteristics. All columns report versions of the following regression:

$$PME_{i(j)} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{ct} + \lambda_{k(j)} + \epsilon_{i(j)}.$$

$PME_{i(j)}$ is the beta-adjusted PME of fund i held by investor j, which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are the investor wealth groups. The omitted category is investors with >100 million of AUM. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{k(j)}$ are fixed effects for advisor k. The samples consist of all investor-fund observations over 2000-2020 vintages. Standard errors are double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: PME						
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.075***	-0.052***	0.001	-0.115***	-0.049**	-0.012
	(0.022)	(0.017)	(0.021)	(0.037)	(0.023)	(0.013)
3–10m	-0.045***	-0.032**	0.016	-0.066**	-0.053***	-0.007
	(0.017)	(0.015)	(0.021)	(0.031)	(0.018)	(0.013)
10–30m	-0.025**	-0.021*	0.011	-0.044*	-0.035**	0.004
	(0.013)	(0.012)	(0.015)	(0.024)	(0.014)	(0.011)
30–100m	-0.016	-0.015	0.018	-0.035*	-0.037***	-0.007
	(0.011)	(0.010)	(0.013)	(0.020)	(0.010)	(0.007)
Constant	1.104***	1.100***	1.156***	1.068***	1.056***	1.088***
	(0.016)	(0.013)	(0.013)	(0.028)	(0.020)	(0.010)
Category × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	65,449	65,449	25,386	26,111	13,952	65,393
R^2	0.002	0.126	0.089	0.118	0.131	0.191

Table 6. Advisor Characteristics and Fund Performance

The table reports results from OLS regressions of fund performance on advisor characteristics. The samples consist of investor-fund observations over 2000-2020 vintages. All columns report versions of the following regression:

$$PME_{i(j)} = \beta_0 + \sum_k \beta_{1k} AdvisorCharacteristics_{k(j)} + \lambda_{ct} + \lambda_{m(j)} + \epsilon_{i(j)}.$$

$PME_{i(j)}$ is the beta-adjusted PME of fund i held by investor j , which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are advisor characteristics: *categories*, i.e. broker-dealer or family office, with RIA as the omitted category, *past performance quartile* defined using average PME in excess of vintage-category averages over the past four vintages, *experience* measured using the count of funds previously invested, divided by 100, and two measures of *size*: total commitments in a given vintage, and average AUM over the sample period, in logs and winsorized at the 2.5th and 97.5th percentiles. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{m(j)}$ are fixed effects for investor wealth group m. In column (3), the sample consists only of the investments in the first vintage an investor makes a PE investment. Standard errors are double clustered at the fund and the advisor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: PME						
Investors:	All	All	New	All		
				Buyout	Venture	FoF
	(1)	(2)	(3)	(4)	(5)	(6)
Advisor category						
Broker Dealer	-0.012	-0.013	0.011	-0.038	-0.005	0.040
	(0.021)	(0.021)	(0.032)	(0.033)	(0.034)	(0.025)
Family Office	0.017	0.008	0.030	0.036	-0.039	0.068**
	(0.019)	(0.019)	(0.034)	(0.023)	(0.034)	(0.029)
Performance quartile	0.048***	0.048***	0.023	0.016*	0.101***	0.002
	(0.014)	(0.014)	(0.016)	(0.008)	(0.029)	(0.014)
Experience (number of past funds)	0.025***	0.024***	0.034***	0.053*	-0.002	-0.024
	(0.005)	(0.008)	(0.011)	(0.029)	(0.013)	(0.115)
Ln(Total commitments)		-0.002	-0.002	-0.006	0.007	0.001
		(0.005)	(0.008)	(0.007)	(0.011)	(0.009)
Ln(Advisor mean aum)		0.009	0.013	-0.009	0.032**	-0.002
		(0.007)	(0.013)	(0.007)	(0.013)	(0.010)
Constant	0.932***	0.902***	0.943***	1.148***	0.569***	1.043***
	(0.032)	(0.055)	(0.076)	(0.039)	(0.120)	(0.057)
Category × vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor Wealth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,904	61,904	12,297	23,727	24,960	13,217
R^2	0.140	0.141	0.215	0.102	0.154	0.144

Table 7. Advisor Characteristics and Fund Performance: Access Subsamples

The table reports results from OLS regressions of fund performance on advisor characteristics. The samples consist of investor-fund observations over 2000-2020 vintages. All columns report versions of the following regression:

$$PME_{i(j)} = \beta_0 + \sum_k \beta_{1k} AdvisorCharacteristics_{k(j)} + \lambda_{ct} + \lambda_{m(j)} + \epsilon_{i(j)}.$$

$PME_{i(j)}$ is the beta-adjusted PME of fund i held by investor j , which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are advisor *categories*, i.e. broker-dealer or family office, with RIA as the omitted category, *past performance quartile* defined using average PME in excess of vintage-category averages over the past four vintages), and *experience* measured using the count of funds previously invested, divided by 100. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{m(j)}$ are fixed effects for investor wealth group m. Standard errors double clustered at the fund and the advisor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: PME					
Sample	All	First Fund	Minimum < 1m	Commitment <0.1m	Over-subscribed
	(1)	(2)	(3)	(4)	(5)
Advisor category					
Broker Dealer	-0.012	0.012	-0.041	-0.032	-0.035
	(0.021)	(0.041)	(0.036)	(0.034)	(0.037)
Family Office	0.017	0.069	-0.014	-0.002	-0.040
	(0.019)	(0.045)	(0.030)	(0.032)	(0.034)
Performance quartile	0.048***	0.041**	0.049**	0.072***	0.025
	(0.014)	(0.018)	(0.021)	(0.021)	(0.015)
Experience (number of past funds)	0.025***	0.033**	0.033***	0.027**	0.044
	(0.005)	(0.015)	(0.007)	(0.013)	(0.042)
Constant	0.932***	0.941***	0.934***	0.958***	0.989***
	(0.032)	(0.061)	(0.055)	(0.065)	(0.058)
Category × vintage FE	Yes	Yes	Yes	Yes	Yes
Investor Wealth FE	Yes	Yes	Yes	Yes	Yes
Observations	61,904	8,507	20,569	8,769	7,126
R^2	0.140	0.139	0.249	0.168	0.154

Figure 1. Fund Universe Overlap Between Individual and Institutional Investors

This figure plots for each fund vintage the number of funds held by individual investors and the number of funds with performance data available in Preqin. The blue area marks the number of funds that overlap between individual investors and Preqin performance data.

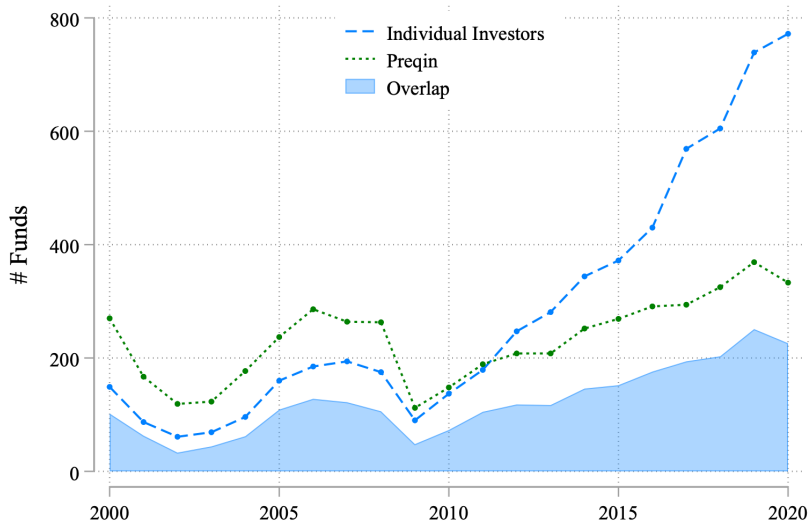
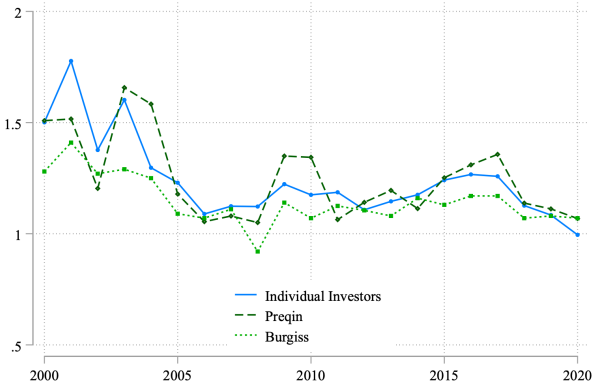


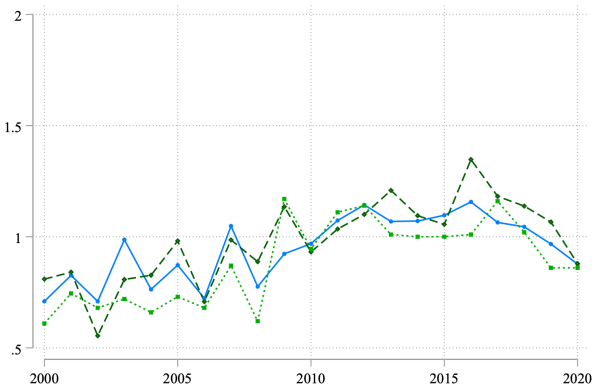
Figure 2. Comparison of Performance Metrics to Institutional Investors

This figure compares the performance of private equity investments across the Addepar, MSCI, and Preqin datasets for (a) Buyout, (b) Venture Capital, and (c) Fund of Funds. For each dataset and vintage year, we report the median fund PME for each fund category.

(a) Buyout



(b) Venture Capital



(c) Fund of Funds

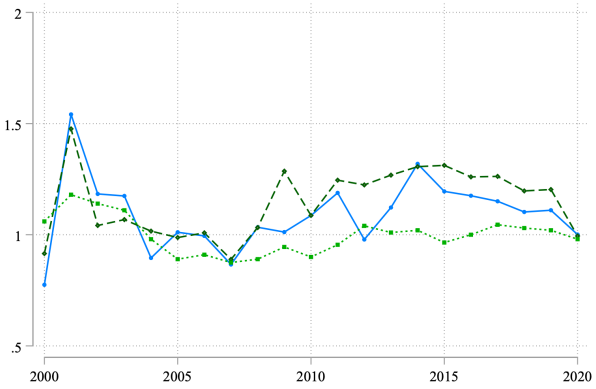
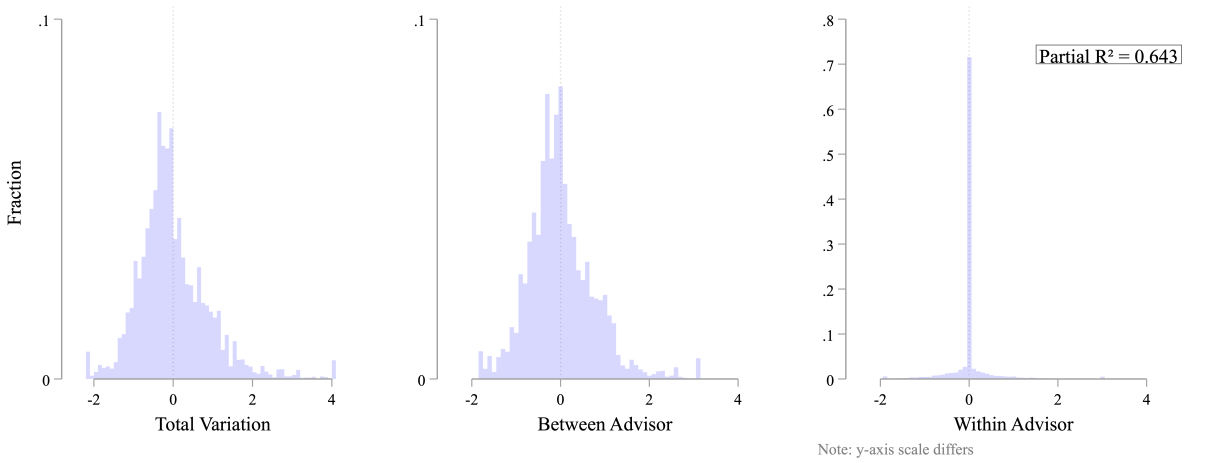


Figure 3. Dispersion in Performance

This figure decomposes performance variation into between-advisor and within-advisor components for private equity in Panel (a) and public equity in Panel (b), for an identical set of investors and advisors. For private equity, we first residualize beta-adjusted PME by category-by-vintage fixed effects, and then standardize to mean zero and unit variance. The left histogram shows the distribution of these standardized residuals across all investor-fund observations. The middle histogram plots the distribution of advisor-by-category-by-vintage mean performance, capturing systematic differences across advisors. The right histogram shows residuals after absorbing advisor-by-category-by-vintage fixed effects, capturing variation among investors served by the same advisor in the same category and vintage. For public equity, we apply an analogous procedure to value-weighted returns on new equity positions initiated by each investor in a given month, with year-month fixed effects replacing category-by-vintage fixed effects.

(a) Private equity



(b) Public equity

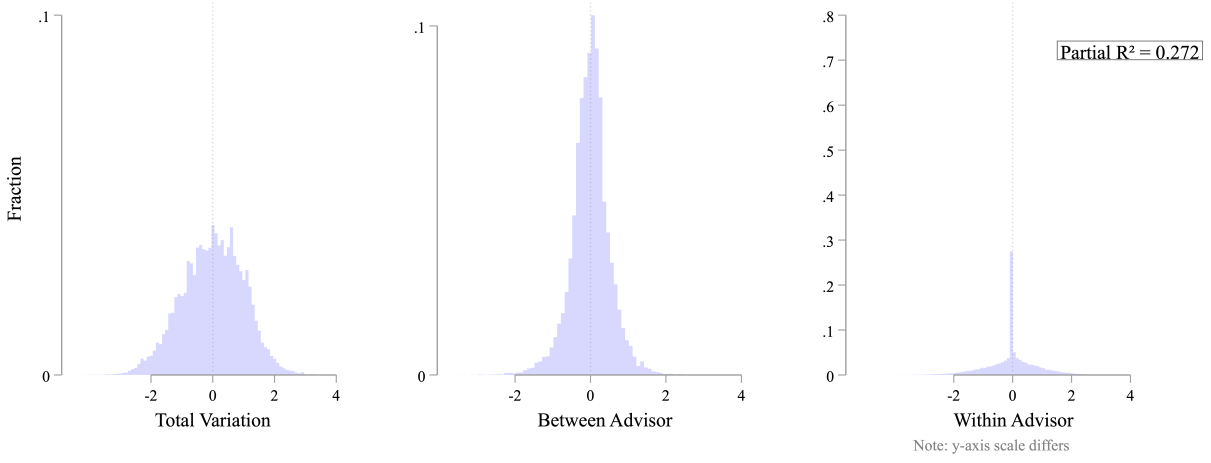
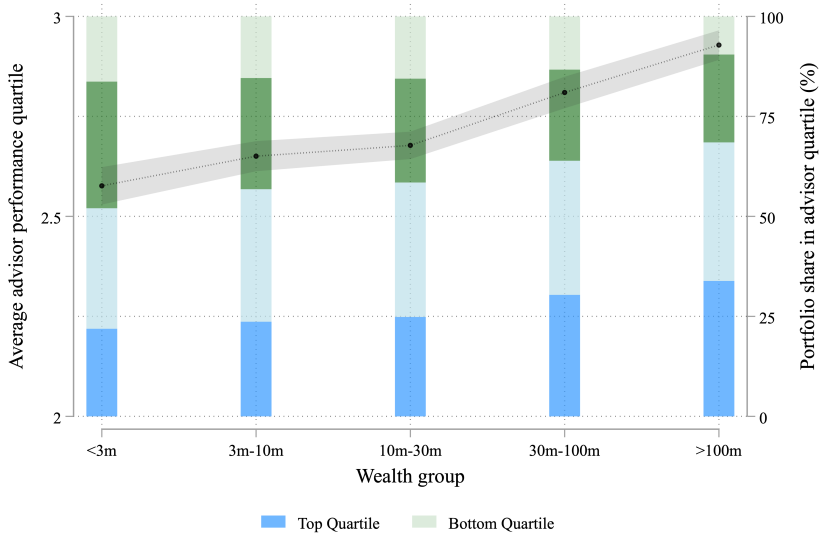


Figure 4. Investor Sorting by Advisor Performance Quartiles

This figure displays the relationship between investor wealth and advisor quality. Each panel plots regression coefficients and 95% confidence intervals (gray bands) from a regression of advisor performance quartile (1 = lowest, 4 = highest) on investor wealth-group indicators, weighted by the number of investments in each wealth group. Dots indicate the estimated mean advisor-performance quartile for each wealth group (left axis). Stacked bars show the portfolio share advised by advisors in each performance quartile (right axis). Panel (a) uses the full sample of investors. Panel (b) restricts to new investor-advisor relationships: investments in each investor's first vintage with a given advisor. For Panel (b), advisor performance quartiles are computed using interim PMEs based only on cash flows available prior to the investor's first private equity investment with that advisor; funds with fewer than five years of cash flow data are excluded, as interim PMEs for younger funds are only weakly correlated with final PMEs (Hochberg et al., 2014).

(a) All investors, final PMEs



(b) New investors, interim PMEs

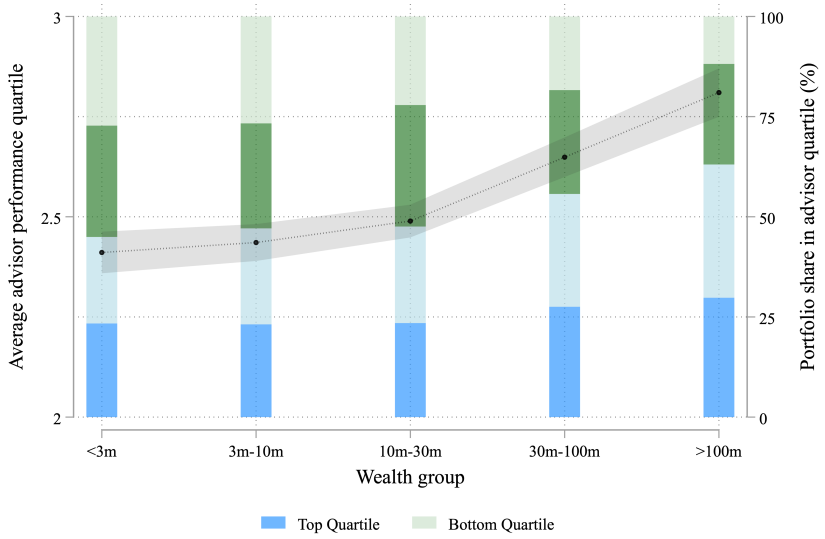
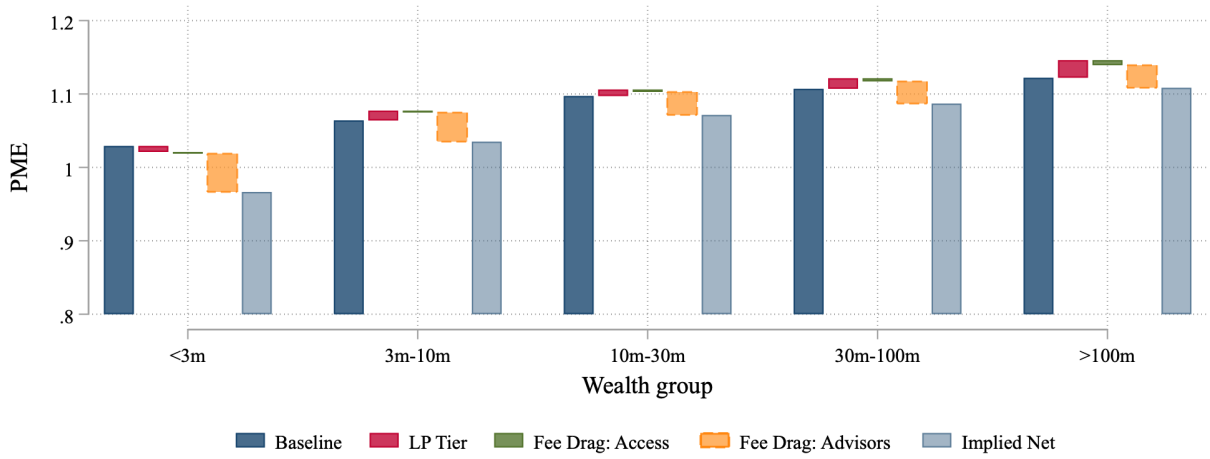


Figure 5. Estimated Net-of-Fees Performance

This figure plots the estimated net-of-fees PME by investor wealth category. Baseline corresponds to the median-β PME obtained from median-investor cash flows as described in Section 2. *LP Tier* corresponds to the performance drag or lift associated with differential terms, such as different management fees or carry charges by the GP, experienced by investors in the same fund. *Fee Drag: Access* measures the decline in net performance associated with paying intermediary fees for accessing specific funds. *Fee Drag: Advisors* simulates the impact of typical fees charged by advisors. *Implied Net* is the PME net of all drags. The bars plot equal-weighted averages based on 64,736 investments in funds closed between 2000-2020.



Internet Appendix for "Democratizing Private Markets? Private Equity Performance of Individual Investors"

Cynthia Balloch Federico Mainardi Sangmin S. Oh Petra Vokata

February 2026

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A Data Appendix

A.1 Data Sources and Sample Construction

A.1.1 Fund Category and Fund Strategy Definitions

Table A1. Fund Category and Fund Strategy

This table lists the fund categories and fund strategies used for the analyses in this paper. We use this categorization for both Addepar and Preqin datasets. The definition of each fund strategy is taken from Preqin.

Category	Strategy	Definition
Buyout	Balanced	Invests in companies at all stages of development, from early stage to buyout.
Buyout	Buyout	Invests in established companies, often with the intention of improving operations and/or financials. Investment often involves the use of leverage.
Buyout	Growth	Typically takes significant minority positions in companies without the use of leverage. Targets profitable, but still maturing, investee companies with significant scope for growth.
Venture Capital	Early Stage	Type of venture fund that invests only in the early stage of a company life. Can be either Seed or Start-up.
Venture Capital	Early Stage: Seed	Allows a business concept to be developed, perhaps involving the production of a business plan, prototypes and additional research, prior to bringing a product to market and commencing large-scale manufacturing.
Venture Capital	Early Stage: Start-up	Supports a non-commercial company's product development and marketing.
Venture Capital	Expansion/Late Stage	Invests in companies towards the end of the venture stage cycle. Provides capital injections for expansion into a position of stable profit streams.
Venture Capital	Venture (General)	Provides capital to new or growing businesses with perceived, long-term growth potential.
Venture Capital	Venture Debt	A type of debt financing provided to venture capital-backed companies by a specialized financier to fund-working capital or capital expenses.
Fund of Funds	Direct Secondaries	The sale of an interest in a direct private equity investment or a portfolio of direct private equity investments to a new third-party investor. The buyer either manages the investment/portfolio or appoints a manager, typically a direct secondaries manager, to do so.
Fund of Funds	Fund of Funds	Invests in a number of private equity partnerships.
Fund of Funds	Secondaries	Acquires stakes in private equity funds from existing limited partners.

A.1.2 Comparison of Number of Funds Across Datasets

This appendix describes how the investor-level private equity data from Addepar for Buyout, Venture Capital, and Funds of Funds compares to benchmarks in Preqin and Burgiss. Buyout and Venture Capital are the categories typically focused on in the academic literature, for which performance metrics can be more reliably computed and compared across datasets.

Table A2. Comparison of Datasets: Number of Funds

This table compares the number of unique funds across three datasets—Addepar, Preqin, and MSCI. For all datasets we report the number of funds with available IRR metric.

	Buyout			Venture Capital			Fund of Funds		
Vintage	Addepar	Preqin	MSCI-Burgiss	Addepar	Preqin	MSCI-Burgiss	Addepar	Preqin	MSCI-Burgiss
2000	17	86	53	44	123	133	10	37	41
2001	7	48	31	19	69	68	8	35	27
2002	6	35	21	8	48	23	4	27	35
2003	10	34	26	11	45	27	8	37	40
2004	15	55	48	17	61	47	7	45	58
2005	38	89	57	22	61	66	21	74	59
2006	44	100	75	26	84	89	21	86	85
2007	44	99	70	35	77	81	19	75	76
2008	36	87	70	45	65	63	22	95	75
2009	17	37	22	17	30	28	6	35	38
2010	32	51	30	31	38	36	17	47	36
2011	46	67	50	43	50	49	22	65	46
2012	61	85	54	73	50	61	29	61	42
2013	71	76	48	87	57	59	38	60	59
2014	92	89	79	106	75	97	30	68	55
2015	90	101	58	141	79	113	32	67	56
2016	115	111	84	148	74	88	46	87	65
2017	140	100	65	233	90	114	56	73	62
2018	137	128	89	235	94	132	51	70	65
2019	192	167	112	335	99	140	61	68	58
2020	189	151	87	341	90	177	68	65	66

A.1.3 New Fund Universe

Table A3. Comparison of Fund Characteristics Across Data Sources

This table reports the fund characteristics for the sample of funds held by individual investors with no performance data in Preqin (Only Addepar), the sample of funds held by individual investors with performance data in Preqin (Both Datasets), and the sample of funds not held by individual investors with performance data in Preqin (Only Preqin). Performance quartiles are based on TVPI and MSCI vintage by category cutoffs. The samples cover North American funds closed between 2000 and 2020.

	Only Addepar ($N = 2,077$)		Both Datasets ($N = 2,494$)		Only Preqin ($N = 2,204$)	
	Mean	SD	Mean	SD	Mean	SD
Category						
Buyout	0.23	0.42	0.48	0.50	0.30	0.46
Venture Capital	0.67	0.47	0.32	0.47	0.34	0.47
Fund of Funds	0.10	0.30	0.20	0.40	0.36	0.48
Vintage	2016.1	4.2	2012.5	6.0	2009.8	6.2
Size (m)	215.7	499.6	1,128.6	2,336.2	332.0	578.0
N. of individual investors	15.4	29.6	16.3	34.7	–	–
Oversubscribed	0.30	0.46	0.24	0.43	0.42	0.49
Fund number overall	4.7	7.4	7.6	10.6	8.3	14.6
Fund number series	2.5	2.3	3.9	2.8	3.3	2.7
Minimum commitment	1.4	6.3	4.2	8.4	8.6	20.6
Performance quartile						
Top	0.25	0.43	0.26	0.44	0.28	0.45
2	0.18	0.39	0.24	0.43	0.23	0.42
3	0.22	0.41	0.23	0.42	0.20	0.40
Bottom	0.35	0.48	0.26	0.44	0.26	0.44

Figure A1. Fund Size Distribution Across Data Sources

This figure shows histograms of the fund size distribution for funds where performance is calculated only in Addepar data (top panel), funds covered in both datasets (middle panel), and funds where performance is available in Preqin but not Addepar (bottom panel).

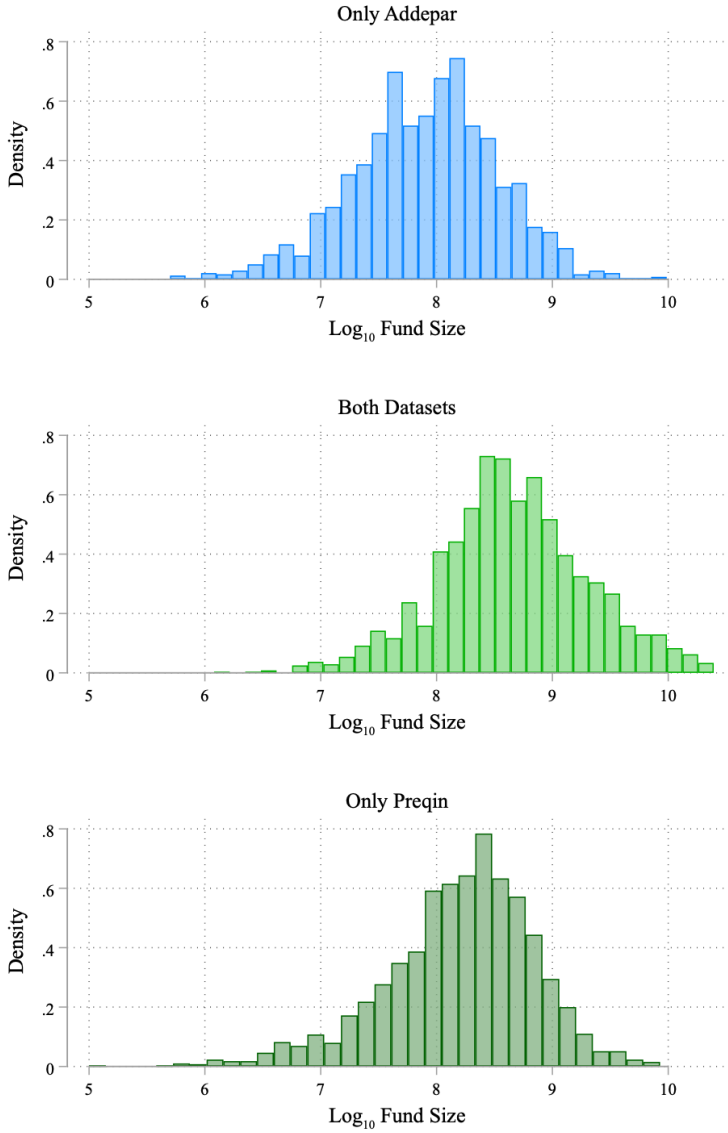


Figure A2. Fund Size and Minimum Commitment Across Data Sources

This figure plots a scatterplot of the log of fund size against the log of fund minimum commitment, for funds where performance is calculated only in Addepar data, funds in both datasets, and funds where performance is available in Preqin but not in Addepar. Funds covered in both datasets tend to be larger and have higher minimum commitments. Funds only in the Preqin data tend to have higher minimum commitments, but also include some smaller funds.

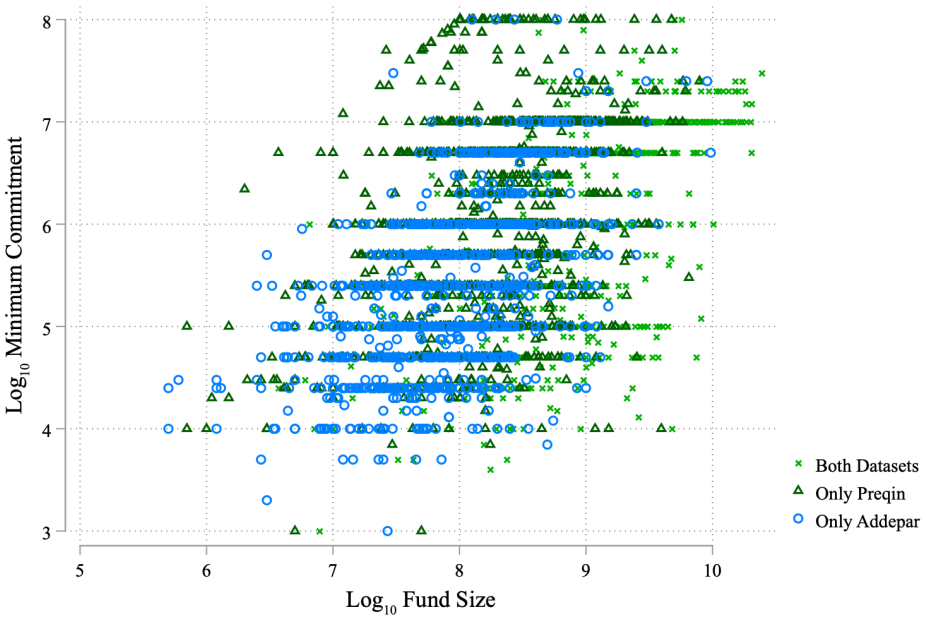
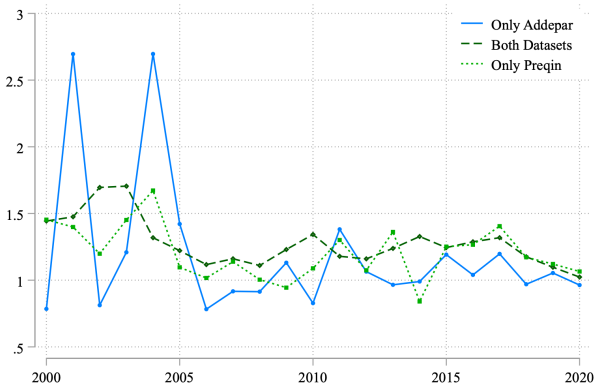


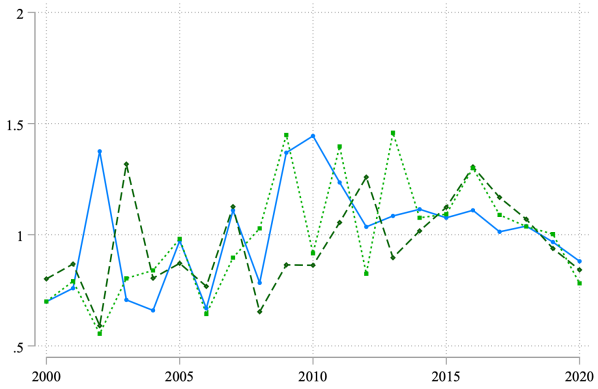
Figure A3. Comparison of Performance Across Data Sources

This figure compares the performance of private equity investments for funds with performance that is newly covered in the Addepar data, funds in both Addepar and Preqin, and funds where performance is available in Preqin but not in Addepar. For each data source and vintage year, we report the median PME across funds. For funds in both datasets, the median PME reported is calculated using individual investor cash flows.

(a) Buyout



(b) Venture Capital



(c) Fund of Funds

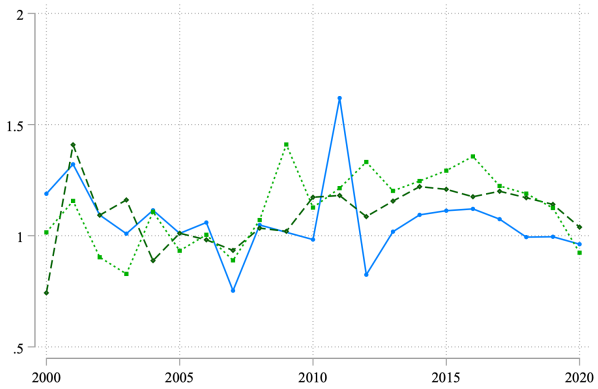


Table A4. Firms by Performance Reporting Rate in Preqin

This table lists firms in Preqin along with their performance reporting rate in Preqin—the fraction of funds with reported performance. Only firms with at least 15 funds are included. This analysis uses only Preqin data and is independent of our main Addepar dataset.

Fund Manager	**Reporting Rate**	**Fund Manager**	**Reporting Rate**
Alumni Ventures Group	0	AlpInvest Partners	61
Bluestem Capital Company	0	Lightspeed Venture Partners	62
NextGen Venture Partners	0	HQ Capital	63
Andreessen Horowitz	0	Grove Street Advisors	63
West River Group	0	Greenspring Associates	66
Capital Integration Systems	0	abrdn	68
Certuity	0	Northgate Capital	68
Prime Movers Lab	0	Top Tier Capital Partners	72
Crestone Asset Management	0	SVB Capital	72
Brown Advisory	0	Carlyle Group	74
HOF Capital	0	Ares Management	74
Plum Alley	0	PineBridge Investments	76
Alliance Consumer Growth	0	General Catalyst Partners	78
Promus Ventures	0	New Science Ventures	79
Florida Funders	0	50 South Capital Advisors	81
ICONIQ Capital	4	TrueBridge Capital Partners	81
Caffeinated Capital	4	TPG	82
Venrock	5	HarbourVest Partners	82
Kleiner Perkins	6	Portfolio Advisors	83
Lerer Hippeau Ventures	6	Apogem Capital	84
Glade Brook Capital Partners	8	CF Private Equity	85
Fifth Wall Ventures	8	Bain Capital	86
Accel	18	HighVista Strategies	87
Sequoia Capital Global Equities	27	Pantheon	88
Sapphire Ventures	29	Neuberger Berman	88
Quilvest Capital Partners	40	Industry Ventures	95
GCM Grosvenor	41	RCP Advisors	96
JP Morgan Asset Management	44	Pathway Capital Management	97
Capital Dynamics	45	Adams Street Partners	97
Foundry Group	47	Franklin Park	100
StepStone	47	Schroders Capital	100
BlackRock Private Equity Partners	52	Park Street Capital	100
TIFF	52	Fairview Capital Partners	100
Hamilton Lane	57	Abbott Capital Management	100
Union Square Ventures	59		
Blackstone Group	59		
Goldman Sachs XIG	60		
Hirtle, Callaghan & Co.	60		

A.1.4 Minimum Commitments

Table A5. Minimum Commitments For All Preqin Funds

This table reports summary statistics of fund minimum commitment in $ million for all North American funds in Preqin with available minimum commitment data. The sample covers funds closed between 2000 and 2024.

	N	Mean	SD	p1	p25	p50	p75	p99
Buyout	3,760	3.30	4.78	0.002	0.100	1.000	5.000	20.000
Venture Capital	6,203	0.84	2.48	0.001	0.025	0.100	0.500	11.150
Fund of Funds	1,831	3.27	5.68	0.010	0.100	0.500	5.000	20.000

A.2 Investor-Level Variables

A.2.1 Wealth Imputation

To classify investors into wealth categories, we use the average total assets managed on the platform. This approach may lead to measurement error if an investor holds only a fraction of their wealth with an advisor. Conditioning on having assets in PE, Investors with lower observed wealth on the platform tend to have higher portfolio shares allocated to PE, consistent with incomplete portfolios for this segment. To correct for the possible miscategorization of investors with lower wealth, we impute wealth for investors with wealth below \$7 million and with PE share above 35%, which represents the 75th percentile for investors with observed wealth above \$7 million. We calculate imputed wealth as

$$\text{Imputed Wealth} = \frac{\text{Observed PE Holdings}}{\text{Average PE Share}}, \tag{A.1}$$

where Average PE Share is the mean PE portfolio share for investors with observed wealth above \$7 million (10.35% in our sample).

A.2.2 Portfolio Shares Compared to Institutions

As an alternative way to assess the funds that individual investors are able to access, we compare their portfolio shares across characteristics relevant for access to institutional shares. Specifically, we compare the commitment-weighted shares across various fund characteristics to the shares observed in the aggregate market, which are weighted by the total size of each fund. The aggregate market is largely dominated by institutional investors, so these market shares serve as a good proxy for institutional portfolio allocations.

Comparing individual and institutional portfolio shares reveals three key insights challenging the idea that individual investors cannot access funds with similar characteristics to institutional investors. First, as reported in Table A6, individual investors' private equity investments are not limited to small funds or firms: 72% of their portfolio is in top-quartile funds by size (vs. 81% for institutions) and 74% is in top-quartile firms (vs. 85% for institutions). Second, individual investors invest primarily in established entities: only 10% of their funds are first-time or new firms (vs. 11% for institutions), though they invest slightly more in new fund series (20% vs. 17%). Third, individual investors access funds with similar levels of demand: 12% of their funds are oversubscribed compared to 17% for institutions.

Table A6. Individual Portfolio Shares Compared to Institutional Shares

The table reports portfolio shares (in percent) by fund characteristics. Institutional shares are based on fund size reported in Preqin. Individual shares are based total committed capital. Fund size quartiles and firm size quartiles are measured based on vintage and category specific cutoffs. For firm size quartiles we only include firms with non-missing fund size for at least half of their funds. The sample consists of North American funds of 2000–2020 vintages.

Panel (a): Category		
	Inst.	Ind.
Buyout	67	42
Venture Capital	17	31
Fund of Funds	16	26

Panel (b): Fund-Size Quartile								
	All Funds		Buyout		Venture Capital		Funds of Funds	
	Inst.	Ind.	Inst.	Ind.	Inst.	Ind.	Inst.	Ind.
1 (smallest)	1	2	1	1	1	1	2	7
2	5	8	4	7	5	5	7	14
3	13	17	12	19	17	18	17	12
4 (largest)	81	72	84	73	76	76	74	67
Panel (c): Firm-Size Quartile								
1 (smallest)	1	2	0	0	3	4	1	2
2	4	8	1	3	11	14	4	12
3	11	16	6	9	29	33	13	13
4 (largest)	85	74	92	88	57	49	83	73
Panel (d): Fund-Number Overall								
1	11	10	11	10	17	14	5	6
2	9	11	8	13	15	13	5	5
3	9	12	9	15	11	9	4	10
4	8	7	9	9	8	5	4	7
5 +	63	60	63	53	49	59	81	72
Panel (e): Fund-Number Series								
1	17	20	16	16	23	28	14	16
2	12	18	11	14	18	30	11	8
3	11	13	11	16	12	14	10	6
4	10	11	10	13	8	7	10	13
5 +	51	39	53	41	38	21	55	57
Panel (f): Oversubscribed								
No	83	88	83	89	82	85	85	89
Yes	17	12	17	11	18	15	15	11
Panel (g): Minimum Commitment								
<1 m	21	44	13	18	56	75	33	70
1–5 m	12	14	9	12	21	13	17	20
>5 m	67	42	78	71	23	12	49	10

A.3 Public Equity Sample and Return Measure

This appendix describes the construction of the public equity returns sample used in Section 3.

A.3.1 Sample Construction

Public equity returns are constructed from the Addepar holdings dataset, which reports investor–security positions and returns at monthly frequency and spans the period from January 2000 through December 2024. To ensure consistency with the private market analysis in Section 3, we restrict the public equity sample to the same set of investors (and their associated advisors) with available private equity performance. This restriction aligns the sample of investors used to evaluate performance in private and public markets, and ensures that any advisor-level comparisons are not driven by differences in coverage across datasets.

A.3.2 Return Measure

For each investor and month, we compute a public equity return as the value-weighted average of returns across all securities classified by Addepar under the asset class U.S. Equity. Portfolio weights are proportional to the dollar value of each security held at the beginning of the month. The asset class U.S. Equity includes both direct holdings (e.g., individual stocks) and indirect holdings through pooled vehicles such as mutual funds and exchange-traded funds (ETFs). To isolate variation that is plausibly attributable to active advisor decisions, for each investor-month we restrict the attention to newly initiated positions, defined as securities that entered the portfolio during the previous month. This approach limits the influence of long-lived "stale" positions whose month-to-month variation is primarily driven by broad market movements rather than advisor actions.

B Performance Measurement and Robustness

B.1 Risk Adjustment

B.1.1 Dimson Betas

To estimate category-specific betas, we construct quarterly value-weighted performance indices separately for buyout, venture capital, and fund of funds portfolios. Each fund's quarterly return is weighted by its invested capital at the beginning of the quarter, with capital calls and distributions assumed to occur at quarter-end. Following Dimson (1979), we regress these portfolio returns on the contemporaneous market return (CRSP value-weighted index) and five lags to account for staleness in reported valuations. We choose five lags to minimize the Akaike Information Criterion (AIC). The total beta exposure is then calculated as the sum of contemporaneous and lagged market factor coefficients.

We further estimate betas within subsamples to capture heterogeneity inside each asset class. This addresses the possibility that beta varies systematically across fund types, which could lead to overstated performance for some segments. For buyouts, we sort funds into firm–vintage size terciles as a proxy for GP scale and reputation. For venture capital, we estimate separate betas for early-stage, late-stage, and general VC to reflect differences in portfolio maturity and risk profiles.[24] The full set of Dimson regression estimates for all categories and subcategories is reported in Table B7.

Table B7. Dimson Betas

The table reports results from quarterly time-series regressions of commitment-weighted portfolio returns that include both contemporaneous and lagged factors to account for stale pricing in reported fund valuations (Dimson, 1979). We report total factor exposures (sum of contemporaneous and lagged coefficients) for both the CAPM model with 5 lags. Standard errors are Newey-West standard errors with automatic bandwidth selection. High beta is calculated as Beta plus two standard errors.

	Buyout				Venture Capital				Funds of Funds
	All	Large	Medium	Small	All	Early	Late	General	All
Beta	0.93	0.93	0.83	0.97	1.37	1.30	0.96	1.44	1.00
SE	0.11	0.11	0.14	0.26	0.23	0.23	0.25	0.26	0.12
2×SE	0.21	0.21	0.27	0.51	0.47	0.46	0.50	0.51	0.25
Quarters	97	97	97	95	98	98	98	98	98
R^2	0.71	0.71	0.32	0.18	0.48	0.38	0.32	0.45	0.65

[24] There is one venture debt fund with 14 quarters of cash flows. For this exercise, we assign this fund to Venture (General).

B.1.2 Korteweg and Nagel (2024) Estimation

We implement the Korteweg and Nagel (2024) framework directly on the Addepar cash flow data. This approach constructs a benchmark portfolio that matches the systematic risk of PE cash flows, then measures abnormal performance (α) as the difference between realized fund payoffs and what a levered public market investment would have delivered over the same horizon. The method delivers asset-class beta and fund-level α which are jointly estimated, which are identified by requiring that the benchmark portfolio produce the same average abnormal payoff as the SDF-based GPME while minimizing cross-sectional variance across funds.

To make our analysis fully comparable to the methodology in the original paper, we replicate their estimation environment with one adaptation. Specifically, as our data are investor-specific rather than fund-aggregate, many funds exhibit two median investors. To match the construction in the main analysis of the paper which uses the median investor performance within the fund, we run two versions of the dataset: a higher version (where ties in median wealth are resolved in favor of the higher-performance investor) and a lower version (ties resolved toward the lower-performance investor). These two samples bracket the plausible range of cash-flow paths for the representative median LP.[25]

Table B8. Korteweg and Nagel (2024) Betas

This table reports SDF parameters and market betas estimated using the method of Korteweg and Nagel (2024). We estimate the exponential-affine SDF separately for buyout, venture capital, and fund-of-funds (FoF) using two constructions of the representative median investor: a higher version (breaking median ties toward the higher-wealth investor) and a lower version (breaking ties toward the lower-wealth investor).

	Buyout		Venture Capital		Funds of Funds	
	Higher	Lower	Higher	Lower	Higher	Lower
Panel A. SDF Parameters						
b_0	0.5018	0.4620	0.4111	0.4245	0.6289	0.6044
b_m	-6.2913	-5.9411	-5.5755	-5.7186	-6.5541	-6.4810
Panel B. Beta Estimates						
Beta	0.98	1.00	1.36	1.38	1.22	1.34

[25] We exclude fund-of-funds with 2000 vintage from the estimation, as the estimation is excessively sensitive to a small number of influential observations from this vintage.

Table B9. Korteweg and Nagel (2024) Alphas

This table reports fund-level abnormal performance (α) estimated using the method of Korteweg and Nagel (2024). Alpha measures the difference between realized fund payoffs and what a levered public market investment would have delivered over the same horizon. We report the mean, standard deviation, and percentiles of the alpha distribution separately for buyout, venture capital, and fund-of-funds (FoF).

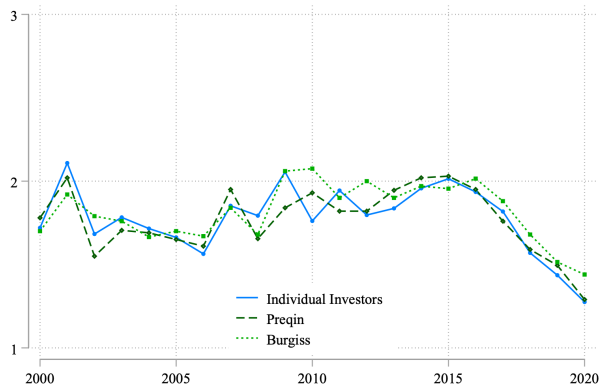
	Buyout	Venture Capital	Fund of Funds
Mean	0.11	−0.06	−0.08
Std.Dev.	0.80	0.79	0.24
25th	−0.13	−0.35	−0.20
50th	0.06	−0.18	−0.07
75th	0.27	0.05	0.04
N	1,376	1,963	535

B.2 Comparison to Institutional Investors

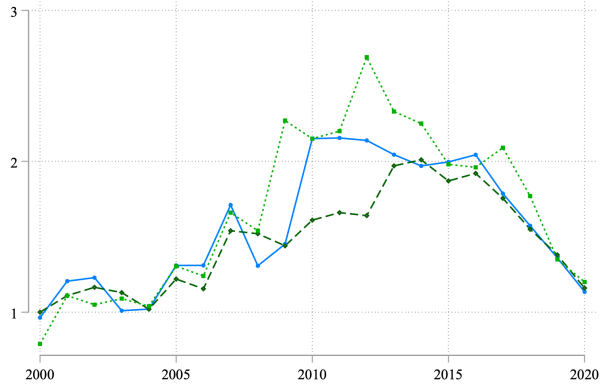
Figure B4. Comparison of Performance Metrics to Institutional Investors: TVPI

This figure compares the performance of private equity investments across individual investors, MSCI, and Preqin datasets for (a) Buyout, (b) Venture Capital, and (c) Fund of Funds. For each dataset and vintage year, we report the median TVPI across funds.

(a) Buyout



(b) Venture Capital



(c) Fund of Funds

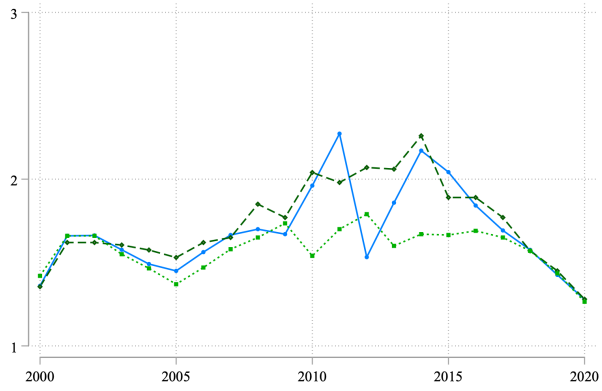
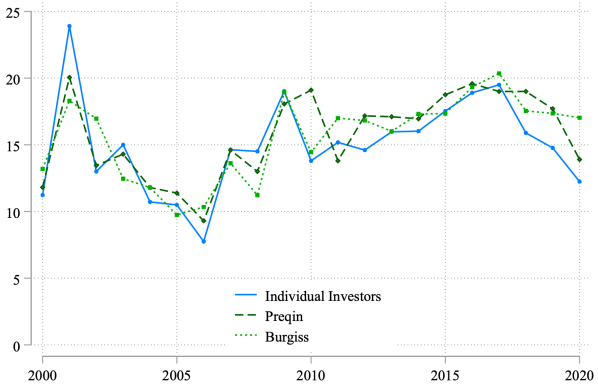


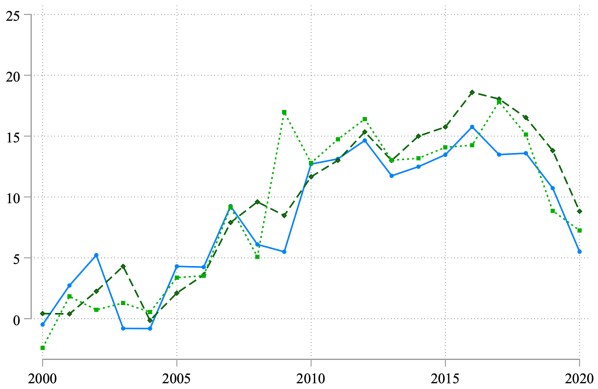
Figure B5. Comparison of Performance Metrics to Institutional Investors: IRR

This figure compares the performance of private equity investments across individual investors, MSCI, and Preqin datasets for (a) Buyout, (b) Venture Capital, and (c) Fund of Funds. For each dataset and vintage year, we report the median IRR across funds.

(a) Buyout



(b) Venture Capital



(c) Fund of Funds

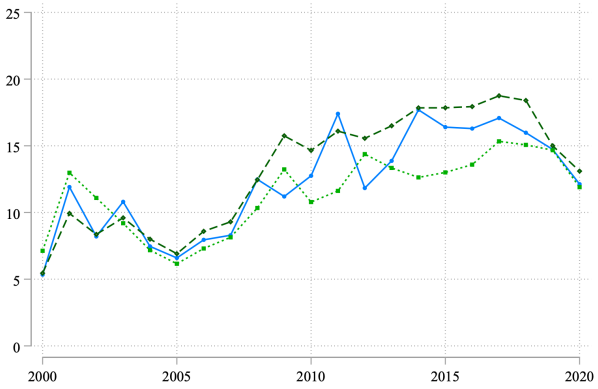
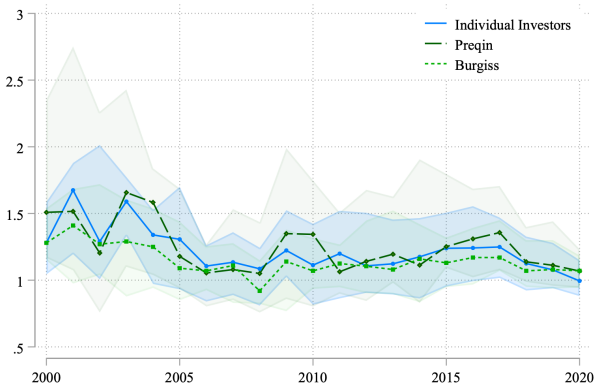


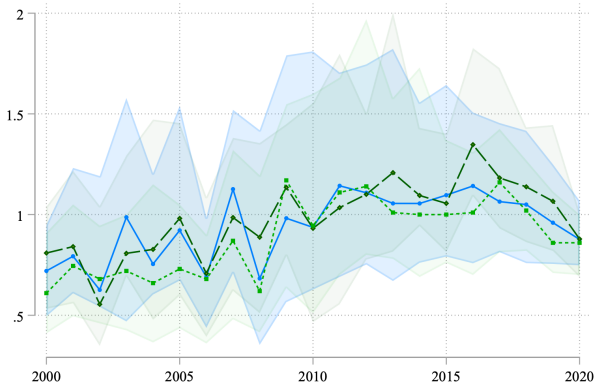
Figure B6. Comparison of Performance Metrics to Institutional Investors: PME (with IQR)

This figure compares the performance of private equity investments across individual investors, MSCI, and Preqin datasets for (a) Buyout, (b) Venture Capital, and (c) Fund of Funds. For each dataset and vintage year, we report the median PME and IQR across funds.

(a) Buyout



(b) Venture Capital



(c) Fund of Funds

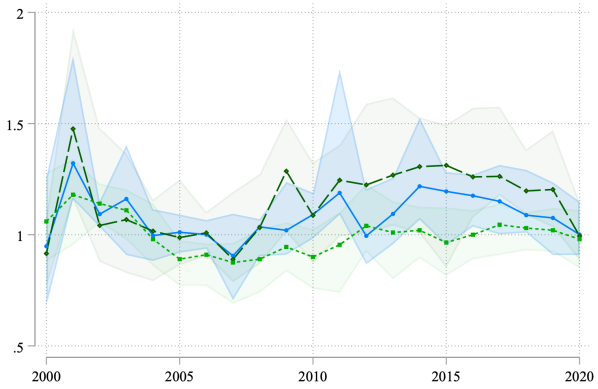
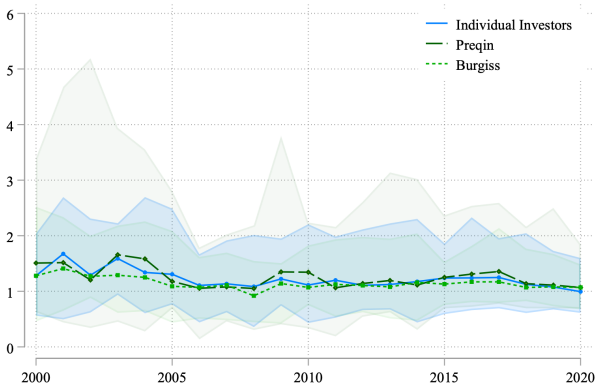


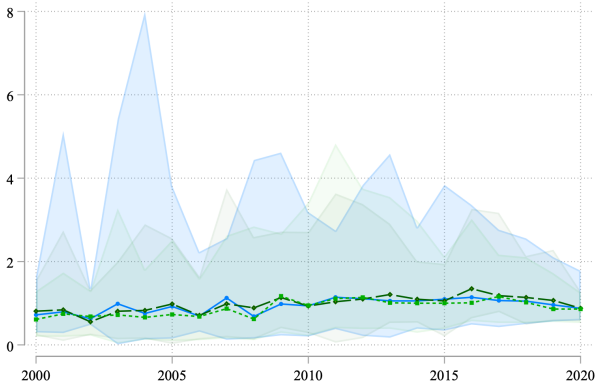
Figure B7. Comparison of Performance Metrics to Institutional Investors: PME (with 5th and 95th percentiles)

This figure compares the performance of private equity investments across individual investors, MSCI, and Preqin datasets for (a) Buyout, (b) Venture Capital, and (c) Fund of Funds. For each dataset and vintage year, we report the median PME and 5th and 95th percentiles across funds.

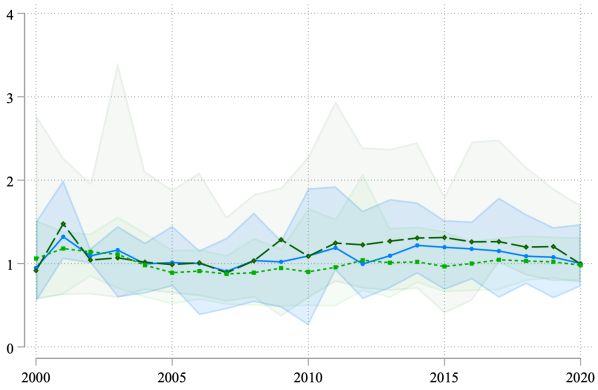
(a) Buyout



(b) Venture Capital



(c) Fund of Funds



B.3 Robustness: Alternative Performance Metrics

B.3.1 TVPI

Table B10. Investor Wealth and Fund Performance: TVPI

The table reports results from OLS regressions of fund performance on investor characteristics. All columns report versions of the following regression:

$$TVPI_{i(j)} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{ct} + \lambda_{k(j)} + \epsilon_{i(j)}.$$

$TVPI_{i(j)}$ is the TVPI of fund i held by investor j. The independent variables are the investor wealth groups. The omitted category is investors with >100 million of AUM. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{k(j)}$ are fixed effects for advisor k. The samples consist of all investor-fund observations over 2000-2020 vintages. Standard errors are double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: TVPI						
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.183***	-0.105***	0.027	-0.320***	-0.021	-0.004
	(0.060)	(0.037)	(0.043)	(0.086)	(0.044)	(0.029)
3m-10m	-0.134***	-0.084***	0.027	-0.206***	-0.061*	-0.002
	(0.048)	(0.030)	(0.034)	(0.072)	(0.035)	(0.026)
10m-30m	-0.113***	-0.055**	0.024	-0.133**	-0.042*	0.012
	(0.033)	(0.024)	(0.026)	(0.053)	(0.025)	(0.022)
30m-100m	-0.084***	-0.046**	0.037*	-0.117**	-0.050**	-0.010
	(0.028)	(0.022)	(0.020)	(0.046)	(0.021)	(0.016)
Constant	1.972***	1.941***	1.740***	2.221***	1.784***	1.903***
	(0.040)	(0.027)	(0.021)	(0.060)	(0.036)	(0.021)
Category × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	70,126	70,126	27,222	27,211	15,693	70,079
R^2	0.003	0.262	0.164	0.252	0.324	0.317

Table B11. Advisor Characteristics and Fund Performance: TVPI

The table reports results from OLS regressions of fund performance on advisor characteristics. The samples consist of investor-fund observations over 2000-2020 vintages. All columns report versions of the following regression:

$$TVPI_{i(j)} = \beta_0 + \sum_k \beta_{1k} AdvisorCharacteristics_{k(j)} + \lambda_{ct} + \lambda_{m(j)} + \epsilon_{i(j)}.$$

$TVPI_{i(j)}$ is the TVPI of fund i held by investor j. The independent variables are advisor characteristics: *categories*, i.e. broker-dealer or family office, with RIA as the omitted category, *past performance quartile* defined using average PME in excess of vintage-category averages over the past four vintages, *experience* measured using the count of funds previously invested, divided by 100, and two measures of *size*: total commitments in a given vintage, and average AUM over the sample period, in logs and winsorized at the 2.5th and 97.5th percentiles. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{m(j)}$ are fixed effects for investor wealth group m. In column (3), the sample consists only of the investments in the first vintage an investor makes a PE investment. Standard errors are double clustered at the fund and the advisor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: TVPI						
Investors:	All	All	New		All	
				Buyout	Venture	FoF
	(1)	(2)	(3)	(4)	(5)	(6)
Advisor category						
Broker Dealer	-0.040	-0.036	-0.021	-0.052	-0.047	0.086
	(0.054)	(0.053)	(0.069)	(0.047)	(0.093)	(0.055)
Family Office	-0.023	-0.037	-0.062	0.042	-0.171**	0.131**
	(0.042)	(0.045)	(0.066)	(0.040)	(0.076)	(0.067)
Performance quartile	0.099***	0.096***	0.053*	0.032**	0.223***	-0.026
	(0.030)	(0.029)	(0.032)	(0.014)	(0.063)	(0.029)
Experience (number of past funds)	0.047***	0.034**	0.045**	0.119***	-0.034	0.152
	(0.014)	(0.017)	(0.022)	(0.044)	(0.026)	(0.219)
Ln(Total commitments)		0.007	0.008	-0.020	0.028	0.014
		(0.012)	(0.018)	(0.013)	(0.023)	(0.020)
Ln(Advisor mean aum)		0.032**	0.043*	-0.007	0.097***	-0.017
		(0.014)	(0.025)	(0.013)	(0.029)	(0.014)
Constant	1.633***	1.460***	1.542***	1.724***	0.994***	1.753***
	(0.070)	(0.108)	(0.144)	(0.066)	(0.249)	(0.085)
Category × vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor Wealth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,640	65,640	13,544	25,236	25,807	14,597
R^2	0.277	0.279	0.340	0.175	0.285	0.323

B.3.2 High-beta PME

Table B12. Investor Wealth and Fund Performance: High-beta PME

The table reports results from OLS regressions of fund performance on investor characteristics. All columns report versions of the following regression:

$$PME_{i(j)}^{High\,\beta} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{ct} + \lambda_{k(j)} + \epsilon_{i(j)}.$$

$PME_{i(j)}^{High\,\beta}$ is the high-beta PME of fund i held by investor j, which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are the investor wealth groups. The omitted category is investors with >100 million of AUM. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{k(j)}$ are fixed effects for advisor k. The samples consist of all investor-fund observations over 2000-2020 vintages. Standard errors are double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: High-beta PME						
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.056***	-0.043***	0.003	-0.090***	-0.052**	-0.012
	(0.020)	(0.015)	(0.020)	(0.030)	(0.022)	(0.012)
3m-10m	-0.033**	-0.027**	0.015	-0.054**	-0.051***	-0.009
	(0.016)	(0.013)	(0.019)	(0.026)	(0.017)	(0.011)
10m-30m	-0.014	-0.017*	0.010	-0.036*	-0.033**	0.002
	(0.011)	(0.010)	(0.014)	(0.020)	(0.013)	(0.009)
30m-100m	-0.008	-0.012	0.015	-0.027	-0.035***	-0.006
	(0.009)	(0.009)	(0.012)	(0.017)	(0.010)	(0.006)
Constant	0.985***	0.985***	1.076***	0.910***	0.960***	0.976***
	(0.014)	(0.011)	(0.012)	(0.024)	(0.019)	(0.009)
Category × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	65,449	65,449	25,386	26,111	13,952	65,393
R^2	0.001	0.135	0.083	0.093	0.142	0.199

Table B13. Advisor Characteristics and Fund Performance: High-beta PME

The table reports results from OLS regressions of fund performance on advisor characteristics. The samples consist of investor-fund observations over 2000-2020 vintages. All columns report versions of the following regression:

$$PME_{i(j)}^{High\,\beta} = \beta_0 + \sum_k \beta_{1k} AdvisorCharacteristics_{k(j)} + \lambda_{ct} + \lambda_{m(j)} + \epsilon_{i(j)}.$$

$PME_{i(j)}^{High\,\beta}$ is the beta-adjusted PME of fund i held by investor j , which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are advisor characteristics: *categories*, i.e. broker-dealer or family office, with RIA as the omitted category, *past performance quartile* defined using average PME in excess of vintage-category averages over the past four vintages, *experience* measured using the count of funds previously invested, divided by 100, and two measures of *size*: total commitments in a given vintage, and average AUM over the sample period, in logs and winsorized at the 2.5th and 97.5th percentiles. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{m(j)}$ are fixed effects for investor wealth group m. In column (3), the sample consists only of the investments in the first vintage an investor makes a PE investment. Standard errors are double clustered at the fund and the advisor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: High-beta PME						
Investors:	All	All	New		All	
				Buyout	Venture	FoF
	(1)	(2)	(3)	(4)	(5)	(6)
Advisor category						
Broker Dealer	-0.009	-0.010	0.011	-0.038	0.001	0.037
	(0.018)	(0.018)	(0.027)	(0.029)	(0.027)	(0.024)
Family Office	0.020	0.012	0.038	0.033	-0.028	0.064**
	(0.016)	(0.016)	(0.030)	(0.020)	(0.029)	(0.028)
Performance quartile	0.043***	0.043***	0.021	0.016**	0.087***	0.004
	(0.012)	(0.012)	(0.014)	(0.008)	(0.025)	(0.013)
Experience (number of past funds)	0.022***	0.023***	0.031***	0.044	0.001	-0.041
	(0.004)	(0.007)	(0.010)	(0.027)	(0.012)	(0.107)
Ln(Total commitments)		-0.003	-0.003	-0.005	0.004	-0.001
		(0.005)	(0.007)	(0.006)	(0.010)	(0.008)
Ln(Advisor mean aum)		0.007	0.009	-0.009	0.025**	-0.001
		(0.006)	(0.011)	(0.006)	(0.011)	(0.010)
Constant	0.834***	0.822***	0.862***	1.067***	0.498***	0.951***
	(0.028)	(0.048)	(0.066)	(0.036)	(0.103)	(0.056)
Category × vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor Wealth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,904	61,904	12,297	23,727	24,960	13,217
R^2	0.150	0.150	0.217	0.096	0.132	0.163

B.3.3 Alpha

Table B14. Investor Wealth and Fund Performance: Korteweg and Nagel (2024) alpha

The table reports results from OLS regressions of fund performance on investor characteristics. All columns report versions of the following regression:

$$\alpha^{KN}_{i(j)} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{ct} + \lambda_{k(j)} + \epsilon_{i(j)}.$$

$\alpha^{KN}_{i(j)}$ is the Korteweg and Nagel (2024) alpha of fund i held by investor j. The independent variables are the investor wealth groups. The omitted category is investors with >100 million of AUM. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{k(j)}$ are fixed effects for advisor k. The samples consist of all investor-fund observations over 2000-2020 vintages. Standard errors double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: Korteweg and Nagel (2024) alpha						
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.085***	-0.052***	0.001	-0.110***	-0.053**	-0.018
	(0.023)	(0.015)	(0.019)	(0.031)	(0.021)	(0.011)
3–10m	-0.058***	-0.029**	0.014	-0.060**	-0.048***	-0.010
	(0.019)	(0.013)	(0.020)	(0.025)	(0.016)	(0.010)
10m-30m	-0.035***	-0.019*	0.005	-0.038*	-0.028**	0.000
	(0.012)	(0.010)	(0.014)	(0.019)	(0.011)	(0.008)
30m-100m	-0.017*	-0.011	0.016	-0.027	-0.030***	-0.005
	(0.009)	(0.009)	(0.012)	(0.017)	(0.008)	(0.006)
Constant	0.030**	0.020*	0.091***	0.008	-0.088***	0.011
	(0.013)	(0.011)	(0.013)	(0.022)	(0.016)	(0.009)
Category × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	65,366	65,366	25,386	26,111	13,869	65,310
R^2	0.004	0.129	0.062	0.099	0.242	0.187

Table B15. Advisor Characteristics and Fund Performance: Korteweg and Nagel (2024) alpha

The table reports results from OLS regressions of fund performance on advisor characteristics. The samples consist of investor-fund observations over 2000-2020 vintages. All columns report versions of the following regression:

$$\alpha^{KN}_{i(j)} = \beta_0 + \sum_k \beta_{1k} AdvisorCharacteristics_{k(j)} + \lambda_{ct} + \lambda_{m(j)} + \epsilon_{i(j)}.$$

$\alpha^{KN}_{i(j)}$ is the Korteweg and Nagel (2024) alpha of fund i held by investor j. The independent variables are five advisor characteristics: *categories*, i.e. broker-dealer or family office, with RIA as the omitted category, *past performance quartile* defined using average PME in excess of vintage-category averages over the past four vintages, *experience* measured using the count of funds previously invested, divided by 100, and two measures of *size*: total commitments in a given vintage, and average AUM over the sample period, in logs and winsorized at the 2.5th and 97.5th percentiles. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{m(j)}$ are fixed effects for investor wealth group m. In column (3), the sample consists only of the investments in the first vintage an investor makes a PE investment. Standard errors are double clustered at the fund and the advisor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: Korteweg and Nagel (2024) alpha						
Investors:	All	All	New		All	
				Buyout	Venture	FoF
	(1)	(2)	(3)	(4)	(5)	(6)
Advisor category						
Broker Dealer	0.002	0.002	0.025	-0.005	-0.000	0.028
	(0.017)	(0.016)	(0.025)	(0.031)	(0.026)	(0.020)
Family Office	0.020	0.015	0.049*	0.042**	-0.024	0.052**
	(0.015)	(0.015)	(0.028)	(0.018)	(0.028)	(0.025)
Performance quartile	0.041***	0.041***	0.019	0.013*	0.084***	0.008
	(0.011)	(0.011)	(0.013)	(0.007)	(0.023)	(0.010)
Experience (number of past funds)	0.020***	0.019***	0.028***	0.035	-0.002	-0.039
	(0.004)	(0.007)	(0.009)	(0.026)	(0.011)	(0.088)
Ln(Total commitments)		-0.001	0.001	-0.001	0.006	-0.001
		(0.004)	(0.006)	(0.005)	(0.009)	(0.007)
Ln(Advisor mean aum)		0.006	0.010	-0.013**	0.024**	0.003
		(0.005)	(0.010)	(0.006)	(0.011)	(0.010)
Constant	-0.124***	-0.143***	-0.146**	0.083**	-0.391***	-0.123**
	(0.024)	(0.044)	(0.061)	(0.034)	(0.095)	(0.049)
Category × vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor Wealth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,897	61,897	12,295	23,727	24,960	13,210
R^2	0.139	0.139	0.253	0.067	0.129	0.264

B.4 Robustness: Alternative Samples

B.4.1 Advisors with all Five Wealth Groups

Table B16. Investor Wealth and Fund Performance: Advisors with all Five Wealth Groups

The table reports results from OLS regressions of fund performance on investor characteristics, for investors whose advisors span all five wealth groups and that are not family offices. All columns report versions of the following regression:

$$PME_{i(j)} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{ct} + \lambda_{k(j)} + \epsilon_{i(j)}.$$

$PME_{i(j)}$ is the medium beta PME of fund i held by investor j, which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are the investor wealth groups. The omitted category is investors with >100 million of AUM. λ_{ct} are fixed effects for fund category c by vintage t, and $\lambda_{k(j)}$ are fixed effects for advisor k. The samples consist of all investor-fund observations over 2000-2020 vintages. Standard errors are double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: PME						
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.079***	-0.061***	-0.007	-0.128***	-0.046*	-0.010
	(0.025)	(0.021)	(0.025)	(0.044)	(0.027)	(0.016)
3m-10m	-0.063***	-0.045***	-0.011	-0.065*	-0.051**	-0.006
	(0.021)	(0.018)	(0.023)	(0.036)	(0.022)	(0.015)
10m-30m	-0.035**	-0.031**	0.008	-0.069**	-0.025	0.007
	(0.016)	(0.014)	(0.018)	(0.028)	(0.017)	(0.012)
30m-100m	-0.026*	-0.023*	0.009	-0.044*	-0.030**	-0.005
	(0.014)	(0.013)	(0.016)	(0.024)	(0.014)	(0.009)
Constant	1.120***	1.115***	1.170***	1.104***	1.045***	1.094***
	(0.022)	(0.017)	(0.016)	(0.036)	(0.025)	(0.012)
Category × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	45,484	45,484	16,324	18,137	11,023	45,484
R^2	0.003	0.156	0.111	0.151	0.168	0.212

B.4.2 Median Wealth Investors

Table B17. Excess Performance of Individual Investors: Median Wealth Group

This table presents the excess performance of individual investors, only for investors in the wealth group with AUM between $10 and $30 million. For each performance metric, we report the equal-weighted average and value weighted average based on committed capital. Excess performance of each fund is calculated by deducting the average performance in the Preqin/MSCI database for funds of the same vintage and category (buyout/venture capital/funds of funds). We use the Russell 3000 as the benchmark index in PME calculations to align our benchmark with the one used in the data provided by MSCI. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: TVPI

	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
TVPI	1.94	1.81	1.81	1.66	2.14	2.09	1.72	1.71
Excess $TVPI_{Preqin}$	0.09***	0.13***	-0.07***	-0.08***	0.28***	0.52***	-0.11***	0.02
Excess $TVPI_{MSCI\text{-}Burgiss}$	0.04	0.08***	0.02	-0.09***	0.02	0.27***	0.12***	0.13***
Observations	2,546		942		1,162		442	

Panel B: IRR

	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
IRR	14.0	14.4	16.4	14.7	12.5	14.7	12.9	13.6
Excess IRR_{Preqin}	-3.3***	-2.2**	-2.5***	-2.0***	-3.8***	-0.4	-3.7***	-4.7**
Excess $IRR_{MSCI\text{-}Burgiss}$	-1.3***	-0.3	0.1	-1.4***	-2.9***	1.5	0.2	-0.5
Observations	2,539		940		1,158		441	

Panel C: PME

	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
PME	1.22	1.18	1.22	1.13	1.27	1.34	1.09	1.09
Excess PME_{Preqin}	-0.04**	-0.05***	-0.13***	-0.16***	0.07**	0.23***	-0.16***	-0.18***
Excess $PME_{MSCI\text{-}Burgiss}$	0.13***	0.13***	0.11***	0.04***	0.14***	0.30***	0.10***	0.08***
Observations	2,404		893		1,109		402	

B.4.3 Early Vintages

Table B18. Excess Performance of Individual Investors: 2000-2015 Vintages

This table presents the excess performance of individual investors, for vintages from 2000 to 2015. For each performance metric, we report the equal-weighted average and value weighted average based on committed capital. Excess performance of each fund is calculated by deducting the average performance in the Preqin/MSCI database for funds of the same vintage and category (buyout/venture capital/funds of funds). We use the Russell 3000 as the benchmark index in PME calculations to align our benchmark with the one used in the data provided by MSCI. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: TVPI								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
TVPI	2.12	2.15	1.93	1.81	2.42	3.07	1.88	1.85
Excess $TVPI_{Preqin}$	0.11***	0.23***	-0.09***	-0.09***	0.39***	1.04***	-0.07*	0.01
Excess $TVPI_{MSCI\text{-}Burgiss}$	-0.01	0.12***	0.05	-0.04*	-0.17**	0.40***	0.22***	0.19***
Observations	2,178		843		907		428	
Panel B: IRR								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
IRR	12.4	13.9	15.0	13.4	10.4	16.7	11.6	11.6
Excess IRR_{Preqin}	-0.5	0.1	-0.9*	-1.4**	0.4	4.6***	-1.4***	-1.8***
Excess $IRR_{MSCI\text{-}Burgiss}$	-2.1***	-0.5	-0.3	-1.2	-5.1***	0.1	0.7	0.6
Observations	2,161		840		896		425	
Panel C: PME								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
PME	1.26	1.29	1.28	1.17	1.29	1.66	1.13	1.09
Excess PME_{Preqin}	-0.01	0.02	-0.09***	-0.17***	0.11**	0.47***	-0.09***	-0.08***
Excess $PME_{MSCI\text{-}Burgiss}$	0.11***	0.16***	0.14***	0.06***	0.06	0.41***	0.16***	0.12***
Observations	1,888		745		801		342	

B.5 Additional Results

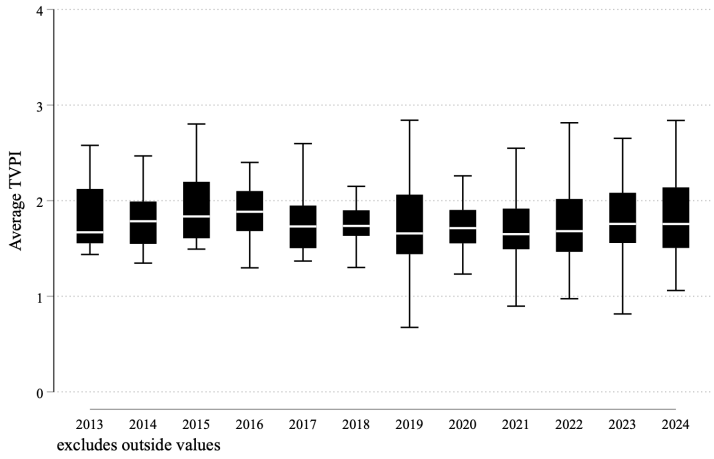
B.5.1 Advisor Performance by Year of Joining the Platform

To assess possible concerns about the selection of investors on the platform, we analyze whether performance varies by the year of the advisor joining the platform.

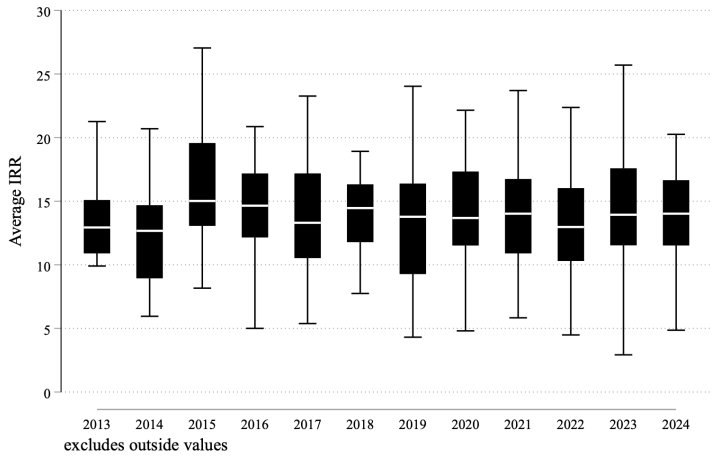
Figure B8. Performance by Year of Joining the Platform

These figures display box plots of the average advisor performance by year of joining the platform. Only advisors with at least five investments and years with at least five advisors are included.

(a) TVPI



(b) IRR



B.5.2 Performance: Strategies

Table B19. PME of Individual Investors by Strategy

This table presents summary statistics of PME for funds closed between 2000 and 2020, by strategy. PME is the Kaplan and Schoar (2005) public market equivalent, calculated using the Russell 3000 as the benchmark index.

Panel A: Buyout								
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N
Buyout	1.30	0.61	0.42	0.96	1.19	1.46	3.98	1,034
Growth	1.16	0.73	0.04	0.85	1.05	1.33	3.25	462
Balanced	1.20	0.39	0.35	0.99	1.14	1.37	2.19	38
Panel B: Venture Capital								
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N
Venture (General)	1.21	0.99	0.10	0.73	0.98	1.37	5.13	767
Early Stage	1.24	1.25	0.15	0.73	0.96	1.36	7.21	750
Early Stage: Seed	1.27	1.20	0.13	0.74	0.99	1.43	4.87	262
Early Stage: Startup	1.30	1.02	0.18	0.75	1.04	1.44	6.39	136
Expansion / Late	1.15	1.06	0.06	0.68	0.92	1.28	3.84	155
Venture Debt	0.92	.	0.92	0.92	0.92	0.92	0.92	1
Panel C: Fund of Funds								
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N
Fund of Funds	1.14	0.35	0.39	0.93	1.09	1.29	2.26	446
Secondaries	1.15	0.33	0.71	0.99	1.10	1.23	2.43	142
Direct Secondaries	0.92	0.39	0.15	0.68	0.85	1.20	1.64	25

Table B20. Investor Wealth and Fund Performance: Robustness within Strategies

The table reports results from OLS regressions of fund performance on advisor characteristics. All columns report versions of the following regression:

$$PME_{i(j)} = \beta_0 + \sum_m \beta_{1m} InvestorWealth_{m(j)} + \lambda_{stk} + \epsilon_{i(j)}.$$

$PME_{i(j)}$ is the medium beta PME of fund i held by investor j, which is based on category–specific betas estimated from Dimson regressions and benchmarked to the CRSP value-weighted market index. The independent variables are the investor wealth groups. The omitted category is investors with >100m of AUM. λ_{stk} are fixed effects for strategy s, vintage t, and advisor k. The samples consist of all investor-fund observations over 2000-2020 vintages. Standard errors are double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: PME						
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.075***	-0.053***	-0.003	-0.110***	-0.053***	-0.017
	(0.022)	(0.016)	(0.019)	(0.034)	(0.020)	(0.011)
3m-10m	-0.045***	-0.035***	0.011	-0.069**	-0.053***	-0.013
	(0.017)	(0.013)	(0.019)	(0.028)	(0.016)	(0.010)
10m-30m	-0.025**	-0.027**	0.005	-0.053**	-0.037***	-0.004
	(0.013)	(0.011)	(0.014)	(0.023)	(0.013)	(0.009)
30m-100m	-0.016	-0.019**	0.011	-0.040**	-0.034***	-0.010
	(0.011)	(0.009)	(0.012)	(0.018)	(0.010)	(0.006)
Constant	1.104***	1.102***	1.160***	1.070***	1.056***	1.091***
	(0.016)	(0.012)	(0.012)	(0.025)	(0.015)	(0.010)
Strategy × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	65,449	65,445	25,383	26,111	13,951	65,389
R^2	0.002	0.201	0.149	0.196	0.259	0.262

B.5.3 Variation Associated with LP Tiers

Table B21. Performance Variation Associated with LP Tiers

The table reports results from the regression of the deviation from baseline performance measured from median-investor cash flows $f_{ij}^{Tier} = r_{ij} - r_i$ on investor wealth groups. Columns (1) and (2) include the sample of investors for whom we do not observe any access fee charge. Columns (3) and (4) include the sample of investors with access fee charges. We use the constant plus the coefficient on wealth group j from Column (1) as our estimate of performance drag associated with LP Tiers, $\hat{f}_{m(j)}^{Tier}$, in Section 4.

	Dep. Var.: Excess PME			
	No Access Fee		Has Access Fee	
	(1)	(2)	(3)	(4)
3m-10m	0.026	0.024	0.015	0.008
	(0.018)	(0.022)	(0.010)	(0.009)
10m-30m	0.017	0.019	0.024**	0.018*
	(0.014)	(0.018)	(0.011)	(0.010)
30m-100m	0.024*	0.026	0.007	0.002
	(0.014)	(0.017)	(0.007)	(0.007)
>100m	0.032**	0.039*	0.005	-0.003
	(0.016)	(0.020)	(0.008)	(0.009)
Constant	-0.008	-0.009	-0.012*	-0.006
	(0.014)	(0.017)	(0.006)	(0.005)
Fund FE	Yes	No	Yes	No
Fund × Advisor FE	No	Yes	No	Yes
Observations	20,906	17,296	5,861	5,205
R^2	0.23	0.35	0.89	0.91