

Democratizing Private Markets: Private Equity Performance of Individual Investors

Cynthia Balloch Federico Mainardi Sangmin S. Oh Petra Vokata*

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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. We identify two innovations that democratize access to private equity: funds with low minimum commitments and pooling capital via advisors. On average, individual investments in private equity perform similarly to institutions and outperform public markets. The most affluent investors outperform the least affluent by 6 to 10 percentage points in public market equivalent. Advisor skill is more likely to explain the performance gap than preferential access. Intermediary fees impose a sizable drag on performance, especially for less affluent investors.

JEL Classification: G11, G24, D14

Keywords: Private equity, individual investors, democratization of private equity, household finance, financial advisors

*Balloch is with London School of Economics, Mainardi is with Columbia Business School, Oh is with Columbia Business School, and Vokata is with Fisher College of Business, Ohio State University and CEPR. Email addresses: c.m.balloch@lse.ac.uk, fm2913@columbia.edu, oh@gsb.columbia.edu, vokata.1@osu.edu. We thank Ron Akke, Ulf Axelson, Aras Canipek (discussant), Rowena Carreon, Joan Farre-Mensa (discussant), Dan Golosovker, Robert Harris, Vlad Ivanov (discussant), Dirk Jenter, Steve Kaplan, Tong Liu (discussant), Amar Patel, René Stulz, Selale Tuzel (discussant), Mike Weisbach, Katie Zhou and conference participants at the Western Finance Association, RCFS Winter Conference, Columbia PE Conference, IPC Alternative Investments Conference & Spring Research Symposium 2025, 12th Annual Conference on Financial Market Regulation (SEC), Private Capital Symposium (LBS), European Summer Symposium in Financial Markets (Gerzensee) and Aalto Institutional Investor Conference for helpful comments and discussions, and PERC and MSCI-Burgiss for providing data on aggregate private equity performance. Kris Shen provided helpful research assistance.

In 2024, individual investors held approximately \$1 to 2 trillion of the \$13 trillion in assets managed by private equity (PE) funds.¹ Industry analyses forecast that individual PE investments will grow 50% faster than institutional investments, sustaining double-digit growth rates and capturing 30-50% of market share in the near future.² While extensive research has examined PE performance among institutional investors (e.g., [Kaplan and Schoar, 2005](#); [Harris et al., 2014](#); [Brown et al., 2025](#)), the performance of individual investors remains largely unexplored. This represents an important knowledge gap amidst the ongoing democratization of private equity—“the effort of substantially lowering investment minimums to target non-institutional investors” ([Ivashina and Mylavarapu, 2024](#)).

In this paper, we provide the first systematic study of individual investors’ private equity performance using data from Addepar, a technology and data platform for wealth and asset management. Our anonymized dataset covers 65,000 investments made by 17,900 high-net-worth investors across more than 4,500 funds closed between 2000 and 2020, representing \$700 billion in PE assets by 2024. The median investor in our data has assets under management (AUM) of \$16 million, an order of magnitude smaller than institutional investors. Our data covers investors working with a range of wealth managers—including registered investment advisers (RIAs), brokers, family offices, and private banks—and thus captures the dominant channels through which individual investors access private equity. Crucially, the data include detailed cash flows for more than 1,000 funds that are missing from standard commercial databases. These data allow us to compute standard PE performance metrics and address selection concerns that can bias studies relying solely on disclosed fund performance.

How individual investors perform in PE is an open empirical question. On one hand, it is well understood that access to private equity is far from perfect ([Lerner et al., 2007](#); [Sensoy et al., 2014](#); [Lerner et al., 2022](#)), and individual investors may be disadvantaged given their smaller size. Moreover, they may pay higher fees or make investment mistakes that lead to poor performance. On the other hand, financial innovation could reduce frictions and increase access to investment opportunities for smaller investors. Furthermore, access to funds, fees, and sophistication may vary with investor wealth. Understanding the role of these factors in shaping individual investor outcomes is not only important in its own right, but also relevant to the ongoing debate on the democratization of private equity.

¹The estimate of the total size of private markets is from [McKinsey & Company \(2024\)](#). The individual investor share is based on the Global Private Equity Report by [Bain & Company \(2023\)](#). See also estimates of individual assets in private equity by [Boston Consulting Group \(2023\)](#).

²See [Bain & Company \(2023\)](#) and [S&P Global Market Intelligence \(2021\)](#).

We provide three main findings regarding the private equity performance of individual investors. First, individual investors perform similarly to institutions and outperform public markets. This finding holds true across standard metrics used in the literature—including Total Value to Paid-In (TVPI), Internal Rate of Return (IRR), and Public Market Equivalent (PME)—as well as variants that adjust for category-specific systematic risk exposures. Second, in the cross-section, the most affluent ($> \$100$ million in financial wealth) outperform the least affluent ($< \$3$ million in financial wealth), with the gap most pronounced in venture capital and in settings with greater information frictions. We find that advisor quality primarily drives this performance heterogeneity. Third, fees amplify this wealth gradient and, for the least affluent, largely eliminate their outperformance relative to public markets. In particular, fees paid to financial advisors represent a more substantial drag on performance than fees for platform access or differential terms with fund managers.

We start by documenting two innovations that democratized access to private equity. First, using novel data on minimum commitments, we show that since the 2010s, general partners (GPs) began offering funds with significantly lower commitment thresholds. Second, advisors further reduced effective minimums by pooling client investments, which we identify through excess bunching of pooled investments at minimum thresholds. These two innovations have brought minimum commitments down from the typical \$5 million for institutional investors (Korteweg et al., 2022) to as low as \$10,000 for individuals.

The most significant difference between funds invested by individuals versus institutions is the level of minimum commitment. A natural question is whether funds with lower minimum commitments are of lower quality. We find lower-quality GPs are more likely to offer low-commitment funds: GPs with below median past five-year performance are 7 percentage points more likely to offer funds with minimum commitments below \$1 million. However, the higher propensity to offer low-commitment funds by underperforming GPs is statistically significant only for funds of funds, and not for buyout or venture capital funds. Moreover, by the 2020s, 70 to 90% of GPs, including the most established ones, have been offering funds with low minimums. Taken together, this indicates that the narrative that mainly low-quality firms offer funds to individual investors is misleading.

Perhaps most surprisingly, individual investments in private markets perform similarly to those of institutions and outperform public markets. We compare TVPI, IRR and the Kaplan and Schoar (2005) PME to institutional benchmarks, including Preqin and MSCI Private Capital Universe data (MSCI-Burgiss). For both the full sample and the median wealth group of investors (\$10–30 million in AUM), the equal- and value-weighted averages are comparable to institutional averages controlling for vintage and fund category. Moreover,

the PME's adjusted for category-specific beta average 1.26 for buyout, 1.04 for venture capital, and 1.07 for funds of funds. These results imply that on average, the funds that individual investors selected in our data outperform public markets, even after adjusting for risk.

This average performance, however, masks substantial heterogeneity across individual investors. Our data cover a wide range of investor wealth: 3,500 investors have financial wealth below \$3 million, while 2,700 have financial assets exceeding \$100 million, including 230 billionaires. The most affluent investors substantially outperform the least affluent by more than 10 percentage points in PME: 1.16 versus 1.05. This performance gap is not due to differences in fund category composition or vintage timing: category choice explains only one percentage point of the gap, and vintage timing explains only two percentage points.

This performance gap could instead reflect either preferential access by affluent investors to top GPs or their superior ability to select high-quality funds (Cavagnaro et al., 2019). Our results suggest that skill, rather than differential access, drives the performance gap. First, the gap is most pronounced precisely where access constraints are minimal: among first-time funds, where GPs compete for capital and are less likely to restrict access, the PME performance gap widens to 16 percentage points. We observe similar patterns among funds with low minimums (<\$1 million) and among investments where individual investors committed less than \$100,000.

Second, the gap is most pronounced where information frictions are likely most important: it is fully driven by funds that do not have performance reported in Preqin. Fund selection is likely more difficult and the role of skill more important in contexts with limited performance information. These information frictions may be particularly important for individual investors in PE: 45% of funds held by individuals are not covered in Preqin performance data. Crucially, we find no performance gap among funds with performance in Preqin. This result underscores the critical importance of comprehensive data, as standard databases may paint an incomplete picture of individual investor performance.

Perhaps most importantly, we find that financial advisors appear to be the primary driver of performance differences across individual investors. Individual investors work with various types of wealth managers, including registered independent advisors, brokers, family offices, and private banks, which we collectively refer to as advisors. We find no performance gap across wealth levels when comparing investors using the same advisor. These patterns suggest that advisor quality, rather than investor wealth per se, drives the performance heterogeneity we observe.

Across advisors, we find that more experience is significantly associated with better

performance. Advisors who invested in at least five funds over the past three vintages outperform others by 13 percentage points of PME. This effect could reflect either advisor-investor matching, as experienced advisors might attract more sophisticated clients, or true advisor value-added. To isolate the role of advisors, we look within the sample of investors making their first PE investment. Since these investors have no prior experience in PE, their ability to select superior funds is likely less developed. Even within this subsample, we find similarly higher performance among experienced advisors, consistent with advisor expertise contributing to investment outcomes.

Up to this point, all our analyses use performance data net of typical GP fees, but abstract from the impact of GP fee rebates or additional intermediary fees. In the last section, we estimate performance net of three additional sources of fee variation. First, about 20% of investors in the data pay access fees (such as platform or feeder fund fees) to access specific funds. Second, for about half of the sample, we observe variation in performance across investors in the same fund that may arise from variation in GP terms (LP tiers), such as fee rebates offered to specific investors. We complement these observed fees with simulated advisory fees based on typical AUM-based charges. Our net-of-fee analysis indicates that while access fees and LP tier differences are generally modest, estimated advisory fees impose a substantial drag of approximately 7 percentage points of PME. The combined fee drag nearly doubles the performance gap across wealth and, for the least affluent investors, offsets much of the baseline outperformance relative to public markets.

Our findings relate to the current policy debate about expanding retail access to private equity. This debate is particularly relevant given the broader transformation of capital markets, including the well-documented decline in public listings ([Doidge et al., 2013, 2017](#); [Ewens and Farre-Mensa, 2020](#)). 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 ([Morningstar, 2025](#)). Our results speak to both the promise and the pitfalls of such reforms. On the positive side, we find no evidence that funds available to individuals underperform on average, suggesting that blanket restrictions are hard to justify and that greater private equity exposure could improve outcomes for some investors. On the other hand, our evidence highlights frictions that erode net returns for less affluent households: heavier reliance on less experienced advisors and materially higher fee layers appear to offset underlying fund outperformance. 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 paper connects to three strands of the literature. First, we contribute new evidence to the literature on PE performance (Kaplan and Schoar, 2005; Phalippou and Gottschalg, 2009; Harris et al., 2014; Korteweg and Nagel, 2016; Gupta and Van Nieuwerburgh, 2021) by focusing on a previously unexplored class of individual investors. We introduce a new dataset of PE funds with superior coverage, especially among low-commitment funds offered to individuals. The broadening access to PE we document provides novel evidence of industry maturation (Sensoy et al., 2014) and challenges the view that PE outperformance is limited to sophisticated institutional investors.

Second, our results complement a large literature on the performance of household portfolios (see Gomes et al., 2021, for a review). To the best of our knowledge, ours is the first systematic study of household performance in private equity funds and the first attempt to analyze sources of performance heterogeneity among accredited individual investors.³ Our results on the performance gap across wealth complement earlier work that identifies risk (Bach et al., 2020) and entrepreneurial skill (Fagereng et al., 2020) as the main drivers of inequality in returns to wealth.

Third, we contribute to the literature on financial advisors. Existing work has primarily focused on the conflicts of interest (Foerster et al., 2017; Egan, 2019) and mistakes (Linnainmaa et al., 2021) of retail financial advisors. In contrast to this earlier work, our work focuses on advisors to the wealthy. Our results suggest some advisors add value by enabling access to private equity funds and by improving fund selection. Our paper thus adds nuance to the prevailing negative perception of financial advisors.

Other studies of individual investor private equity investments are also now emerging. Miller et al. (2024) conduct a survey experiment of professional and individual investors and identify the weak response of individual investors to past performance as a potential contributor to lower individual returns. Gocmen et al. (2025) use data from Pitchbook and the Qualified Small Business Stock (QSBS) tax exclusion as a natural experiment to study the role of early-stage investments for wealth inequality. Relative to these studies using surveys, limited investor-level data, and fund performance from commercial databases, we provide the first large-scale, cash flow-based evidence on realized private equity performance

³Two recent papers precede our work in utilizing the Addepar dataset to study U.S. household investments. Balloch and Richers (2023) first introduce these data, documenting portfolio allocations and returns across the wealth distribution and showing how wealthy households achieve higher risk-adjusted returns. Gabaix et al. (2024) leverage the dataset’s granularity to analyze household portfolio rebalancing behavior and asset demand across multiple asset classes. We extend these works by being the first to utilize Addepar’s detailed cash flow data, enabling us to measure and benchmark the performance of private equity funds in wealthy households’ portfolios.

for individual investors across a broad spectrum of PE strategies.

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 documents the mechanisms individual investors use to access private equity funds. The fund-level performance of investments made by individuals is described in Section 3. Section 4 analyzes the drivers of performance heterogeneity. Section 5 assesses the impact of fees, and the final section concludes.

1 Data and Institutional Background

In this section, we present institutional background on individual investors in the private equity market, describe our data sources, and report summary statistics.

Our focus is the market for private equity funds categorized as buyout, venture capital, and funds of funds, and with a regional focus on North America. Our categorization follows Harris et al. (2014). Within buyout, we include balanced, buyout, and growth strategies. Venture capital includes seed, early-stage startup, expansion/late stage, general venture, and venture debt strategies. Funds of funds include traditional fund of funds, secondaries, and direct secondaries.⁴

To maintain comparability with the existing literature on PE performance and ensure our analysis focuses on the most prevalent forms of individual investments in private markets, we employ several data screens. Our sample excludes direct stakes in private companies, crowdfunding investments, and other alternative investments in private markets such as co-investments (Lerner et al., 2022). Moreover, we exclude from our sample a small number of evergreen funds and semi-liquid interval funds.

1.1 Institutional Background

We first provide institutional background on how individual investors access private equity markets and the mechanics of private equity investing, focusing on aspects most relevant to individual investors.

⁴A description of the fund strategies within each fund category is provided in Table A1.

1.1.1 Access to Private Equity for Individuals

In the U.S., direct investments in private equity are limited to accredited investors, whose definition has changed over time. Prior to 2020, an individual accredited investor needed to have either an annual income of at least \$200,000 (or \$300,000 combined with their spouse), for each of the last two years, or net worth of at least one million, excluding the value of the individual's primary residence. In 2020, the SEC amended the definition of accredited investors to include investment professionals holding a Series 7, 65, or 82 license (for general securities, investment adviser, or private securities offerings, respectively), for investments in specific private funds any general partners or knowledgeable employees of that fund, and family clients of family offices that qualify.⁵

Individual investors typically access private equity through financial intermediaries including RIAs, family offices, broker-dealers, and private banks. These advisors play an important role in sourcing investment opportunities, conducting due diligence, and providing ongoing monitoring of portfolio investments.

1.1.2 Private Equity Fund Structure, Lifecycle, and Cash Flows

Private equity funds are typically structured as limited partnerships where the GP manages the fund and limited partners (LPs) provide capital. GPs typically contribute 1–3% of fund capital and receive management fees plus carried interest. LPs commit a specified amount of capital that is called over time as investment opportunities arise. The typical fund lifecycle spans roughly ten years and consists of three main phases: fundraising (6–18 months), an investment period (3–5 years) during which the GP makes new investments, and a harvesting period (5–10 years) focused on growing and exiting the portfolio of investments.

Private equity investing involves irregular cash flows that differ markedly from traditional securities. LPs receive capital calls when the GP identifies investment opportunities, with called capital used for new investments, follow-on funding, fees, and expenses. Distributions occur when portfolio companies are sold or go public, with proceeds flowing back to LPs according to the partnership agreement. These cash flows, combined with periodic net asset

⁵Entities can also be qualified as accredited investors, including entities owning investments in excess of \$5 million, corporations, partnerships, LLCs, trusts, 501(c)(3) organizations, employee benefit plans, family offices, SEC or state-registered investment advisors, SEC-registered broker-dealers, and various financial entities. This exception is permitted under Rule 506(b) of Regulation D. While the accredited investor requirement generally applies, companies can sell to up to 35 non-accredited investors if they avoid general solicitation or advertising.

value updates, enable calculation of standard performance metrics including TVPI, IRR, and PME.

Private equity fees traditionally follow a 2-and-20 structure, with annual management fees of approximately 2% of committed or invested capital and carried interest of around 20% of profits above a hurdle rate, typically 8%. However, these baseline terms can vary significantly across investors within the same fund. GPs frequently establish tiered fee schedules or negotiate individualized side letters that modify standard terms for management fees, carried interest rates, or expense allocations (Begenau and Siriwardane, 2024). Larger institutional investors with substantial commitments often secure preferential terms—such as reduced management fees or lower carry rates—while smaller investors typically accept standard or higher fee tiers. In addition, individual investors may face intermediary fees charged by platforms, feeder funds, or advisors that facilitate fund entry.

1.2 Data

We next describe the individual investor data used in our analysis, discuss data coverage and selection concerns, and the institutional data sources we use for reference and comparison.

1.2.1 Individual Investor Data

Our data on individual investors’ private equity investments come from Addepar. Addepar is a technology and data platform that specializes in data analytics and reporting for investment managers and financial advisors, whose clients typically hold complex investment portfolios that span both public and private assets. The services that advisors provide using the Addepar platform include keeping track of the securities held, monitoring portfolio performance, and reporting investor activities, including for tax purposes. As a result, the underlying data on individual asset holdings and returns are highly scrutinized and therefore reliable. Addepar data has been previously used in academic research by Balloch and Richers (2023), Gabaix et al. (2024), Gabaix et al. (2025), and Mainardi (2025).⁶ We primarily use a novel version of the data specially designed to study private equity investments.

Investor Holdings. For each investor, we observe comprehensive holdings managed by

⁶In related work, Balloch and Peng (2025) use surveys to explore advisors’ subjective beliefs and their effects on portfolio allocations.

the advisor on the platform across both liquid and illiquid asset classes.⁷ We use these data to identify individual investors’ PE holdings and to calculate investors’ total assets under management (AUM). We use the total AUM to categorize investors into five wealth groups: <\$3 million, \$3–10 million, \$10–30 million, \$30–100 million, and >\$100 million.⁸ Throughout our analyses, we restrict our sample to 17,886 investors who made at least one PE investment between 2000–2020. Our final sample covers 64,736 investments in PE funds.

Fund Cash Flows. For each investor’s investment in a fund, the data provides detailed quarterly information on position-level valuations and cash flows. Specifically, we observe the beginning-of-quarter valuation, end-of-quarter valuation, and any cash flows that occur within the quarter. The data also include each investor’s commitments and the quarters when commitments are made. Cash flows and valuations in our data are reported net of management fees and carried interest charges, allowing us to analyze the actual returns earned by investors. The cash flow data spans the period from 2000 Q1 to 2024 Q3. We exclude funds raised after 2020, as more recent funds are less likely to have realized returns.

To accurately measure fund performance, we implement careful cleaning steps to ensure that our analysis accurately represents the performance of underlying private equity funds. First, we focus on positions where we observe consistent valuation reporting and complete cash flow histories from fund inception. Second, we remove funds with potential data quality issues and investments with characteristics that could distort performance calculations such as extreme outlier returns or incomplete reporting. These steps ensure our performance metrics accurately capture fund-level returns while maintaining comparability with established benchmarks in the private equity literature. The final cash flow data covers 84% of fund observations and about half of fund-investor observations in our sample.

In most of our analyses, we use performance metrics measured on the fund level as the median value across investors with complete cash flow data in the same fund: $r_i = \text{median}(r_{ij})$ for fund i held by investor j , computed for each performance metric (e.g. TVPI, IRR, PME). This approach allows us to measure performance even for investor-fund observations in the holdings data where complete cash flows are unobserved. For a small number of funds where Addepar cash flow data does not cover the complete period since inception, we supplement

⁷Holdings are observed at the account level and cannot be linked to named individuals or specific advisory firms. Addepar applies strict confidentiality filters and additional data screens to ensure that all identifying information is removed prior to researcher access.

⁸A natural concern is that the assets managed on the platform may not represent investors’ full portfolios. For instance, some investors may work with an advisor specifically to access private equity while holding the remainder of their wealth in non-advised accounts. We investigate evidence of such incomplete portfolios and for the small subset of investors with an abnormally high PE share, we impute their total wealth following the procedure described in Appendix A.

our calculated metrics with performance metrics reported in Preqin, using the latest reported values as of 2024 Q3.

Access Fees. In addition to the baseline cash flow dataset that records performance net of management fees and carried interest, we also observe intermediary fees that investors pay to access specific funds. These access fees cover a wide range of access mechanisms, including feeder funds, platforms, investment consultants or other specialized advisors.

Advisors. We observe unique identifiers linking each investor to their advisory firm. While investor and advisor identities are anonymized, the data include broad categories of advisory firms, such as independent RIAs, broker-dealers, and family offices. For simplicity, we refer to all these entities as “advisors,” though they encompass diverse roles ranging from family office chief investment officers to individual brokers. Using these advisor-investor links, we construct advisor-level characteristics including total assets under management and the number of private equity funds in which each advisor has invested.

The resulting dataset provides a unique window into a segment of the private equity market that has been largely absent from prior research. Existing studies of private equity performance (e.g., [Harris et al. 2014](#); [Kaplan and Sensoy 2015](#)) rely on institutional data sources that tend to oversample large LPs and exclude most individual investors. In contrast, our data include detailed cash flows for over 2,000 funds absent in Preqin and at least 1,000 funds absent in MSCI-Burgiss, many of which cater to smaller investors. This expanded coverage and the granularity of our data also allow us to evaluate how performance varies across the wealth distribution and to assess mechanisms that enable individual investors to participate in private equity.

1.2.2 Data Coverage

Our analysis relies on data from individual investors whose professional advisors use the Addepar platform. This raises questions about both the breadth of coverage within this population and whether systematic selection effects could bias our performance findings. We take two approaches to assess these concerns: (1) examining the breadth of coverage by comparing our data to estimates of the overall wealth distribution and portfolio characteristics, and (2) testing for platform-specific selection bias based on when advisors joined the platform.

First, we assess the breadth of coverage by comparing our investors to estimates of the overall U.S. wealth distribution. Portfolios in our data offer broad—and, at the very top

of the distribution, markedly deep—coverage of wealthy U.S. households. As described in [Balloch and Richers \(2023\)](#), more than 4,000 investors on the Addepar platform meet the [Smith et al. \(2023\)](#) threshold for the top 0.01 percent of U.S. households. This implies that roughly one-fifth of the wealthiest U.S. individuals are captured in the data.

We also examine whether investors in our sample exhibit unusual portfolio characteristics that might affect performance outcomes. For less wealthy investors (defined as those with less than \$3 million in direct equity positions), [Gabaix et al. \(2024\)](#) show that positions in cash, equities, and fixed income in Addepar align well with the SCF. For wealthier investors, the Addepar data reveal systematically higher amounts invested in liquid assets than those captured in the SCF.⁹ One additional difference is that Addepar portfolios have lower shares of wealth invested in equities than SCF respondents, consistent with private equity allocations increasing with wealth and low rates of SCF survey completion among the wealthy ([Kennickell, 2017](#)).

For the very top of the wealth distribution, [Smith et al. \(2023\)](#) estimate portfolio shares by capitalizing investment income reported in tax filings. Relative to these imputed shares, the portfolio shares of Addepar investors appear to accurately represent individuals in the top percentiles of the wealth distribution. In particular, the allocations of these individuals to pass-through businesses—the typical structure of private equity and venture capital funds—appear similar in the Addepar data and the capitalization method ([Balloch and Richers, 2023](#)). Taken together, these comparisons support the notion that the Addepar data are overall representative and potentially more accurate for the wealthiest households in the U.S. than other sources, since they are based on portfolio data and not subject to imputation, recall, or other biases.

Second, we evaluate potential platform-specific selection bias by examining performance variation by the year advisors joined the platform. In our data, advisors joined the Addepar platform between 2013 and 2024. It is plausible that those joining later in the period are more marginal, so a downward gradient in performance by joining year would suggest potential selection bias. We find no trends in average advisor performance by year of entry.¹⁰ Taken together, the evidence thus does not raise significant concerns about selection bias.

⁹As shown by [Gabaix et al. \(2024\)](#), households with more than \$10 million in direct equity investments have a median net worth in the Addepar data roughly double that estimated in the SCF, reflecting the SCF’s inability to accurately capture wealth at the extreme right tail of the distribution. Limitations of the SCF in capturing extreme wealth are also discussed extensively elsewhere (e.g. [Bricker et al., 2019, 2020](#)).

¹⁰This analysis is shown in Figure C10.

1.2.3 Institutional Investor Data

We use two main sources for institutional private equity performance: Preqin and MSCI-Burgiss, both of which have been extensively used in the academic literature. Preqin primarily sources its data from Freedom of Information Act (FOIA) requests and voluntary disclosures by fund managers, while MSCI-Burgiss relies on confidential, verified cash flow data reported by institutional investors.

From Preqin, we obtain fund characteristics including vintage and fund category, which we use to categorize investments into categories commonly analyzed in the literature. We classify a fund as oversubscribed if its size recorded in Preqin exceeds its reported target size. To use Preqin data as a proxy for institutional performance in private equity, we obtain the latest IRR or TVPI reported on or before the end of our sample period (2024 Q3). Because the [Kaplan and Schoar \(2005\)](#) PME is not available via WRDS, we estimate it directly using Preqin cash flow data.

Separately, we also collect data on fund minimum commitments from Preqin. These data are not available for all funds, as private equity funds are not required to publicly disclose minimums. We observe minimum commitments for approximately two-thirds of the funds held by individual investors in our sample.

From MSCI-Burgiss, we obtain aggregate performance statistics by fund vintage and category, covering the same cash flow period up to 2024 Q3. For funds of funds, MSCI-Burgiss reports performance separately for buyout and venture capital; we take the average of both categories as our institutional benchmark.

1.3 Summary Statistics

Table 1 shows summary statistics for the 4,523 funds invested by 17,886 individual investors via 744 advisors. We describe the fund universe, individual investors, and advisors, in turn.

1.3.1 Fund Universe

Panel A in Table 1 presents descriptive statistics at the fund level. The first salient fact that emerges from our analyses is the large number of funds invested by individual investors: our sample covers 1,663 buyout funds, 2,163 venture capital funds, and 697 funds of funds. On average, the funds in our data are held by 17, 13, and 23 individual investors for buyout,

venture capital, and funds of funds, respectively (medians: 8, 6, and 8). Between 20 and 30 percent of these funds are oversubscribed. On average, individual investors hold the third or fourth fund in a series, and between the fifth and the fourteenth fund overall raised by a GP.

Figure 1 compares the number of funds held by individual investors to the number of funds covered by Preqin performance data. While for most of the vintages in the 2000s individuals in our data held fewer funds than the number of funds in Preqin, the number of Addepar funds exceeds that of Preqin funds starting from 2011. Preqin sources its performance data from FOIA requests and therefore its coverage broadly represents the universe of funds invested by public pension funds or public university endowments. By the end of our sample, the number of buyout and venture capital funds held by individuals is more than double the number of funds in Preqin, and also larger than MSCI-Burgiss.¹¹ Moreover, there is only partial overlap between funds with performance data in Preqin and those held by individual investors: a significant share of the funds we study are not covered in the existing academic literature.

Importantly, the new funds in our dataset are not simply “twin” vehicles issued in parallel with institutional offerings by the same GPs. Rather, 84% of the funds represent the sole fund issued by the GP within a given vintage-fund category and the vast majority of these funds (92%) are managed by GPs who seldom report performance data to Preqin. This limited transparency may reflect a deliberate choice to avoid public disclosure, including a preference for raising capital from investors who are not subject to FOIA requirements. Table A3 shows that GPs with low reporting rates in Preqin span several categories: (i) prominent venture capital firms known to avoid public performance disclosure; (ii) GPs affiliated with family offices and wealth managers; and (iii) GPs targeting high-net-worth investors directly.

Table 2 compares the characteristics of funds that are newly covered in the Addepar data, relative to the set of funds that are covered in both datasets and those that have performance covered in Preqin but not in Addepar. These new funds are held by a similar number of individual investors, on average, as funds with performance reported in Preqin. The funds that are covered in both datasets tend to be larger funds, with a mean size of \$1.1 billion, while the funds covered in only one of the two datasets are considerably smaller: \$215 million in Addepar, and \$332 million in Preqin. There are similar percentages of oversubscribed funds for funds whose performance is exclusively in the Addepar data (30%),

¹¹Table A2 shows the number of funds for each vintage and category separately for our data, Preqin, and MSCI-Burgiss.

funds with performance reported in both datasets (24%), and funds in the Preqin data only (42%).

Consistent with standard databases’ oversampling of funds held by large institutional investors, the biggest difference between the funds covered in Addepar and those in Preqin is the level of minimum commitment. On average, the minimum commitment is \$1.4 million among newly covered funds, \$4.2 million among funds in both datasets, and \$8.6 million among funds exclusively in Preqin.¹² Going back to Table 1, we observe a large dispersion in the minimum commitments required by GPs and systematic variation across fund categories. For example, the average minimum is \$5.2 million for buyout funds with a standard deviation of \$8.9 million. Minimum commitments are dramatically lower for venture capital funds (\$1 million) and funds of funds (\$2.5 million). The distribution of minimums is positively skewed, with the median values well below the averages. For example, the median venture capital fund in our data has a minimum commitment of \$100,000.¹³

In addition, the new funds in Addepar are more skewed towards venture capital funds, more recent vintages, and earlier-sequence funds, relative to the universe of funds covered in Preqin. The new funds in Addepar include a significant percentage of funds that are both in the top (24%) and bottom quartile (35%), based on TVPI and Burgiss-MSCI vintage by fund category cutoffs.

1.3.2 Individual Investors

Panel B in Table 1 provides the descriptive statistics for the individual investors in our data categorized by wealth. Our data includes 3,541 investors with less than \$3 million in average AUM and 2,720 investors with more than \$100 million. For the investors in our sample, private equity accounts for a significant fraction of portfolios. The average PE share is 13%, and average private equity assets are \$0.2 (\$107.8) million for the lowest (highest) wealth group.

Several statistics increase with wealth: the share allocated to buyout and venture capital, the number of funds, and the median commitment. In contrast, the portfolio share allocated to funds of funds decreases with wealth. These patterns are consistent with less affluent

¹²Figure A1 shows that fund size is comparable across the whole distribution for funds only in Addepar and Preqin. In contrast, Figure A2 shows differences in the distribution of minimum commitments between the datasets. The median performance of funds in either one or both datasets is shown by category and vintage in Figure A3.

¹³These patterns are not unique to our sample of funds: Table B4 presents descriptive statistics for all Preqin funds with available minimum commitments.

investors facing diversification frictions, having a lower amount of capital to invest and, as a result, being able to invest in only a few funds. Consequently, less affluent investors may opt for funds of funds to gain diversification benefits.

The commitments we observe are an order of magnitude lower than the minimum commitments usually discussed in the academic literature. For example, [Korteweg et al. \(2022\)](#) mention a typical minimum commitment of \$5 million for institutional investors. In contrast, the median commitment values range from \$0.1–\$1.5 million from the lowest to the highest wealth group. This large difference suggests individual investors use distinct mechanisms to access private equity funds.

1.3.3 Advisors

Finally, Panel C in Table 1 presents descriptive statistics for advisors. Most investors in our data (more than 12,000) are advised by RIAs, followed by more than 3,000 investors organized under family offices, and 2,000 using broker dealers. Family offices tend to be smaller, both in terms of the number of investors as well as the number of private equity funds. The median number of investors by advisor type are 15, 21, and 3 for advisors, broker dealers, and family offices, respectively. The median advisor manages a relatively small private equity portfolio, with a median number of funds over the whole sample period of 11, 27, and 9 for advisors, broker dealers, and family offices, respectively.

There is substantial dispersion in the AUM of all advisor types. While the average private equity AUM is largest for advisors and broker dealers, the median private equity AUM is highest for broker dealers, and private equity AUM is the largest share of total AUM for family offices.

2 How Do Individual Investors Access PE?

We begin by providing new stylized facts about individual investors’ access to private equity funds. Specifically, we examine how the proliferation of low minimum commitment funds has allowed individual investors to access private equity and explore the role of lower minimum commitments and financial advisors in shaping individual investments.

2.1 Minimum Commitments

The most significant historical barrier to household access to private equity has been the high minimum commitment requirement. Traditionally, private equity funds have required commitments of around \$5 million, effectively restricting participation to institutions and ultra-high-net-worth individuals. However, the summary statistics in Table 1 reveal that the median commitment in our dataset is dramatically lower, at less than \$0.5 million for most wealth categories. This raises the question of how households with such significantly lower commitments have been able to gain access to private markets.

We find that one key driver of individual investors’ access is the proliferation of funds with low minimum commitments. Figure 2, Panel A shows the evolution of minimum commitments over time, by fund category. While buyout and funds of funds minimums averaged around \$5 million in the early 2000s—consistent with prior literature (Korteweg et al., 2022)—they declined substantially after 2010, falling below \$2.5 million by 2023. Venture capital minimums, consistently lower than buyout, also dropped from \$2 million to \$0.5 million over the same period. These trends reflect the proliferation of funds tailored to smaller investors and expanded private market access over the last two decades.

The decline in minimum commitments could potentially be driven by lower-quality GPs who struggle to raise capital from institutional investors and thus turn to smaller investors as an alternative source of funding. This would suggest that individual investors are primarily accessing inferior funds that institutions avoid. We explore this possibility by regressing an indicator for low-commitment funds, defined as funds with a minimum commitment of less than \$1 million, on various fund characteristics such as past performance, and indicators for new firms, firm size quartiles, and firms with oversubscribed funds in the past.

Table 3 presents the results. Column (1) indicates that funds raised by firms whose average PME exceeded the median over the past five vintages are roughly 7 percentage points less likely to issue a new fund with low minimum, controlling for category by vintage fixed effects. We also find that low-commitment funds are strongly associated with private equity firm size, as shown in column (2): the firms in the top size quartile are 40 percentage points less likely to issue a low-commitment fund compared to the bottom size quartile. New firms are also more likely to issue low-commitment funds, consistent with facing more difficult fundraising.

In columns (3)–(5), we analyze the relationship between the offering of low-commitment funds and firm characteristics in each category separately. For all categories, larger firms

are less likely to issue low minimum commitment funds, and new firms are more likely to issue them. However, the association between past performance and the offering of low-commitment funds is significant only for funds of funds. Here, the bottom half of firms by performance is eight percentage points more likely to offer low-commitment funds.

Figure 2, Panel B, provides a second piece of evidence that low-commitment funds are not universally restricted to low-quality GPs. The figure plots the proportion of firms offering at least one fund with the minimum commitment below \$1 million in each vintage year. The figure makes clear that this low-commitment market segment is far from limited to a small number of firms. Instead, the majority of firms offer at least one such fund in each vintage year. For venture capital funds, which have the lowest commitment requirements, the fraction exceeds 90% by the early 2020s. For buyout funds, the proportion is lower but still reaches approximately 75% by the early 2020s. For example, even large firms such as Apollo, Blackstone, and BlackRock offer funds with low minimum commitments in our sample.

Overall, the patterns suggest the emergence of a new market segment in private equity. Both large firms and smaller firms are offering low-commitment products, consistent with efforts to either compete for capital or diversify their capital sources. For the more than 6,000 funds with minimum commitments below \$1 million, the total capital raised according to Preqin exceeded \$900 billion. This suggests that the economic significance of this market segment is comparable to, or even greater than, other new segments of the private equity market, such as co-investments or alternative vehicles (Fang et al., 2015; Braun et al., 2020; Lerner et al., 2022).

2.2 Commitment Pooling via Advisors

Approximately half of the committed capital in our data is invested in funds with minimum requirements above \$1 million, suggesting that there are other economically significant channels that enhance access to private markets. One such channel is financial advisors. In the context of institutional limited partners (LPs), prior work highlights the role of investment consultants in shaping asset allocations and facilitating access to private equity (Andonov et al. 2023; Andonov 2024). Similarly, financial advisors help individual investors navigate mutual funds and other financial products, often serving as certifiers or access-enablers.¹⁴ Industry reports emphasize that these advisors play a comparable role in private markets,

¹⁴See Egan et al. (2024) for a review.

coordinating and pooling client capital to meet fund minimums and leveraging relationship networks to access sought-after opportunities.

To analyze the role of advisors in pooling investments, we examine the distribution of total commitments per advisor around the minimum commitment of each fund. In Figure 3, we plot histograms of committed capital values around the minimum requirement. The values shown are the differences between individual commitments and the minimum requirement. For expositional purposes, we restrict the range to $\pm \$10$ million. The unit of observation is the investor-fund commitment and the sample covers only funds with minimum commitments above \$1 million, which are the funds where pooling is likely to be more important.

We test for evidence of pooling by examining whether commitments bunch exactly at fund minimums. If minimum commitments constrain a significant fraction of investors, we would expect to observe excess mass of commitments at exactly the minimum level. Our empirical approach does not require assuming that minimums are universally binding, but rather tests whether they create observable discontinuities in the commitment distribution that would be consistent with pooling behavior.

In Panel A, we limit the sample to observations where there is only one investor per advisor in a fund. That is, we restrict the sample to investors who do not benefit from pooling as they are the sole investor with that advisor in a fund. The histogram shows pronounced bunching exactly at the minimum commitment, consistent with the requirement being binding for many investors.

The picture looks very different in Panel B, where we plot investor-fund observations for cases where there are at least two investors sharing the same advisor and investing in the same fund—that is, the sample of investors who can pool together with other investors sharing the same advisor. Instead of bunching at the minimum requirement, the values now cluster around $-\$1$ million, $-\$5$ million, and $-\$10$ million, implying that most investors in this sample commit substantially lower amounts than the minimum.

Finally, in Panel C, we focus on the same sample as in Panel B but aggregate commitments up to the advisor-fund level. Here, bunching at the minimum requirement reappears. This pattern is exactly what we would expect if investors were pooling commitments through an advisor to collectively meet investment minimums.

In addition to providing evidence of pooling access, the histograms also reveal a significant number of observations below the minimum commitment even after aggregating at the advisor level. There are at least three possible explanations for these observations. First,

we observe commitments for roughly 80% of the investments in our data, which means that aggregated advisor commitments may be understated. Second, some investors may pool their commitments through other investment consultants in addition to (or instead of) the advisors captured in our data. Finally, some funds may allow access below the minimum requirement threshold for limited partners who have special relationships with the fund or offer unique strategic value.

Having established evidence for pooling, we now examine the prevalence of this access mechanism across our sample. Table B6 presents summary statistics on pooled versus direct access, classifying investments as direct if the individual commitment exceeds the minimum, pooled if advisor-aggregated commitments surpass the requirement, and undefined otherwise. Panel A shows that pooling is economically significant, with more than 30% of investments pooled on an equal-weighted basis. Panel B reveals meaningful variation across categories: pooling is most important for buyout funds (38% of investments), likely due to their higher minimum requirements, compared to venture capital (20%) and funds of funds (29%). Panel C confirms the economic intuition that pooling becomes more valuable as minimums rise—for funds requiring \$1-5 million commitments, almost half of investments are pooled, while even for the highest-minimum funds (above \$5 million), 46% rely on pooling. These results demonstrate that the pooling mechanism enables access across categories of private equity offerings.

3 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 whether individual investors’ performance persists after adjusting for systematic risk exposure, and how performance varies across the wealth distribution.

3.1 Performance of Individual Investors

To evaluate PE performance, we primarily focus on three standard metrics that account for different aspects of investment returns: (i) TVPI, (ii) IRR, and (iii) PME. In our main analyses, we follow a large literature on PE performance by measuring the performance net of management fees and carried interest. We defer the analyses of the impact of additional

intermediary fees to Section 5.

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 return rate, taking into account the timing of cash flows. Finally, the [Kaplan and Schoar \(2005\)](#) PME compares private investment performance to public market indices. We use the CRSP value-weighted market index as a benchmark in our baseline PME computation. 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.

To further refine the risk adjustment, we also calculate risk-adjusted PMEs following [Brown et al. \(2025\)](#). Standard PME metrics implicitly assume a market beta of one, which accurately adjusts for risk only if private equity investments exhibit risk levels identical to public benchmarks. To improve on this, we account for the fact that specific fund categories may have betas different from one. We estimate category-specific betas using [Dimson \(1979\)](#) regressions, which account for potential biases arising from smoothed reported valuations common in private equity returns.¹⁵ We then use the beta estimates to generate a “medium beta” PME using the point estimate, and a “high beta” PME using the point estimate plus two standard errors. These two levels span a plausible range of systematic risk exposure, reflecting both central estimates and a conservative upper bound.¹⁶

Table 4 reports summary statistics for each of the performance metrics across the three categories. For buyout funds, we find strong overall performance with a mean TVPI of 1.83 and a mean IRR of 16.8%. The mean PME of 1.18 indicates outperformance relative to public markets, although the 25th percentile PME falls below one (0.89), suggesting that underperformance is common in the left tail.¹⁷ Adjusting for risk using category-specific betas modestly raises the mean PME to 1.26 (medium beta) and leaves it largely unchanged at 1.17 under the high beta scenario, reflecting the fact that buyout funds exhibit market exposure close to one.

Venture capital investments show higher average returns and greater dispersion across all metrics. The mean TVPI is 2.07 and the mean IRR is 12.0%, with wide variation. The

¹⁵We estimate betas that 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. Further details are provided in Appendix C.

¹⁶We adopt the terminology of “medium beta” and “high beta” from [Brown et al. \(2025\)](#).

¹⁷The breakdown of PME by substrategy is shown in Table C10.

mean PME is also 1.18, but the standard deviation is substantially higher than in buyouts, at 1.10. Once we account for higher systematic risk, the mean beta-adjusted PME declines to 1.04 (medium beta) and 0.91 (high beta). These adjustments suggest that risk accounts for a meaningful share of the apparent outperformance in raw PME metrics.

Funds of funds in our sample deliver the lowest performance across all three categories. The mean TVPI is 1.78 and the mean IRR is 13.2%. The mean PME is 1.06, with relatively low dispersion (standard deviation of 0.29). Risk adjustment has little effect at the medium beta level, where the PME remains 1.06, but lowers the mean to 0.97 under the high beta assumption. This pattern suggests performance close to public benchmarks once modest risk is taken into account. Overall, these results indicate that, on average, the funds held by individual investors in our sample have delivered positive absolute and relative performance in all three categories.

The last two columns of Table 4 provide statistics on the coverage of our performance metrics. The column “% calculated” shows the proportion of funds for which we calculate performance metrics from the Addepar cash flow data, rather than relying on TVPI and IRR reported in Preqin. The coverage exceeds 75% for all three categories, implying that the bulk of our performance metrics are directly derived from individual investor cash flows, rather than from Preqin data sourced from institutional investors. The column “% 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, indicating excellent coverage.¹⁸

3.2 Comparison with Institutional Investors

We next compare the performance of individual investors’ funds with institutional benchmarks from Preqin and MSCI-Burgiss. For this comparison, 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-Burgiss.¹⁹

We begin by plotting patterns by vintage in Figure 4. The figure displays the median fund PME for each vintage year and category, separately for individual investors, Preqin,

¹⁸For funds with TVPI available in both Addepar and Preqin, Figure C5 shows a scatterplot of performance measures. The correlation of our calculated TVPI and reported TVPI in Preqin is 91%.

¹⁹Our preferred benchmark, the CRSP value-weighted index, is not available from MSCI-Burgiss. For analyses that do not compare to institutional benchmarks, we use the “medium beta” PME based on the CRSP value-weighted benchmark.

and MSCI-Burgiss. The results show that the performance of funds held by individual investors largely tracks the median performance in Preqin and MSCI-Burgiss across all three categories. We observe somewhat greater discrepancy between Preqin and MSCI-Burgiss 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 deviations in the performance of individual investors' funds.²⁰

So far, the results in Table 4 and Figure 4 provide evidence on the performance of funds held by individual investors, with each fund assigned equal weight. This evidence may be misleading if, for example, individual investors allocate a larger share of their portfolios to underperforming funds. In Table 5, we therefore examine the commitment-weighted performance of individual investors and benchmark it to institutional performance.

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 significantly 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 very similar. These patterns hint at superior performance of more affluent investors in venture capital, a point to which we return in Section 4.1.

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-Burgiss for the same vintage and category. We find limited evidence of systematic 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-Burgiss. At the same time, the value-weighted excess TVPI is 0.14 compared to Preqin and 0.06 relative to MSCI-Burgiss, both statistically significant. For PME, individual investors' value-weighted performance is 0.04 lower than Preqin, and

²⁰Figures C6 and C7 plot the corresponding patterns for TVPI and IRR metrics and reinforce this conclusion. Figures C8 and C9 show the interquartile ranges and 5th and 95th percentiles of PME, respectively, and show that the distributions look similar as well.

0.13 higher than MSCI-Burgiss.

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%, whereas our largest excess performance measures are mostly under 3 percentage points.

Across categories, venture capital is the only category that 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-Burgiss; excess performance metrics are mostly negative when compared to Preqin, but turn positive when compared to MSCI-Burgiss.²¹

3.3 Performance Across Wealth Distribution

Up until now, we have focused on the average performance across all individual investors. A natural question is how performance varies with wealth. Several factors suggest that less affluent investors may achieve inferior private equity 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 diversification requires substantial capital ([Brown et al., 2024](#)), less wealthy investors may 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 6, which presents the medium beta PME on an equal-weighted (by investor-fund) and value-weighted (by commitment) average basis, by wealth group. Panel A reveals a clear performance gradient across the wealth distribution. The least affluent investors earn an average value-weighted PME of 1.08, while the most affluent achieve 1.14—a difference of 6 percentage points that is both statistically and economically significant. This wealth-performance gradient is most pronounced in venture capital, where the most affluent investors outperform the least affluent

²¹These results are robust to comparing only the group of investors with AUM between \$10 and \$30 million to the institutional benchmarks, as shown in Table C8, as well as to excluding the most recent five vintages of data, as shown in Table C9.

by 13 percentage points (1.15 vs. 1.02). The gradient is more modest in buyout funds and in funds of funds.

Panel B of Table 6 reports the number of funds invested in by any investor within a given wealth group. We find that the least affluent investors, as a group, 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 3,336 out of the total 4,523 funds.

These wealth-based performance differences raise several important questions about their underlying drivers. First, do these gaps reflect differential access to high-quality funds, or do they stem from superior fund selection abilities among more affluent investors? Second, what role do financial advisors play in mediating these performance differences, and can advisor quality explain the observed wealth gradient? Third, how do various fee structures—including GP fees, access fees, and advisory fees—exacerbate this wealth performance gap? We address these questions in the following two sections by examining the mechanisms behind performance heterogeneity and quantifying the impact of fees on net investor returns.

4 Drivers of Performance Heterogeneity

While the average performance of individual investors in private equity is comparable to that of institutions, we still observe meaningful dispersion across investors. In this section, we explore the underlying drivers of this performance heterogeneity.

4.1 Explaining the Wealth-Performance Gradient

We first explore the drivers of performance heterogeneity across the investor wealth distribution. As discussed earlier, the evidence in Table 6 shows that the most affluent investors achieve on average 0.11 higher PME compared to the least affluent group. A natural question to ask is whether these patterns are robust to controlling for the vintage during which the investments were made, as different wealth groups may have entered private equity at different times or market conditions. We explore this question in Table 7.

Specifically, we estimate investment performance regressions of fund median beta PME on investor and fund characteristics. The unit of observation is investor by fund. In doing so, we follow the empirical design of [Lerner et al. \(2007\)](#) and [Sensoy et al. \(2014\)](#), which

assigns fund-level performance to all LPs in that fund and compares outcomes across investor types. As we assign a single performance metric to each fund, our focus is on cross-sectional variation across funds—examining whether different types of investors systematically invest in funds with different performance—rather than within-fund variation, which we analyze later in Section 5. We control for the fact that we have multiple observations per fund and 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 Panel A, we regress fund PME on dummies for investor wealth categories: <\$3 million, \$3-10 million, \$10-30 million, \$30-100 million, and >\$100 million. The omitted category is >\$100 million. We first explore the average return across wealth groups with category fixed effects in column (1) and category-vintage fixed effects in column (2). The coefficient on the lowest wealth category implies that these investors earn 0.09 lower PME compared to the wealthiest group on average. Around one third of this difference is due to fund category selection and investment timing, as the coefficient in column (2) falls to 0.06, but remains statistically significant.²²

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 0.12 in PME. The pattern is somewhat weaker for funds of funds with a 0.05 difference and is not statistically significant in buyouts. These findings confirm the earlier results that the differences in performance are driven by venture capital and funds of funds, even after controlling for the timing of the investment.

In column (6), we explore whether advisor sorting—the tendency for wealthier investors to work with higher-quality advisors—accounts for these wealth-performance patterns by adding advisor fixed effects. Once we condition on the advisor, the coefficient on the lowest wealth group falls to -0.013 and becomes statistically insignificant. This result suggests that most of the observed wealth gradient in performance is attributable to differences in advisor characteristics.

The wealth performance gap could reflect either preferential access by affluent investors to top GPs or the superior ability of investors or their advisors to select high-quality funds (Cavagnaro et al., 2019). We next follow standard approaches in the literature (Lerner et al., 2007; Sensoy et al., 2014) to distinguish between these two explanations. Specifically, Panel B investigates whether the wealth-performance gradient persists in subsamples where

²²These results are robust to including substrategy-by-vintage fixed effects, as shown in Table C11.

access frictions are likely to be minimal. Column (1) focuses on first-time funds, which are generally more open to new capital as GPs build their LP base. Figure 5 shows in panel (a) that about 15–19% of the investments are in first-round funds, with a slightly higher frequency for the least wealthy group. In this sample, the performance gap between the least and most affluent investors widens to -0.158 . Columns (2) and (3) restrict to funds with minimum commitments below \$1 million and commitments below \$100,000, respectively—samples where financial constraints are likely less important. The gaps remain large, at -0.099 and -0.180 , indicating that financial accessibility alone does not eliminate return disparities. Column (4) shows that even among under-subscribed funds, where any investor capital is presumably welcome, the gap persists at -0.053 . Together, these results suggest that differences in investment outcomes are not primarily driven by access.

Columns (5) and (6) compare outcomes for funds depending on whether their performance metrics are reported in Preqin. While not a direct measure of information frictions, this distinction captures differences in fund visibility and track record availability. Figure 5, panel (b), shows that within each wealth group, investments are divided roughly evenly between funds with and without Preqin reporting. In funds for which Preqin does not have performance metrics in column (5), the performance gap between the least wealthy and wealthiest investor group is -0.121 and statistically significant. In contrast, among funds with Preqin coverage in column (6), we observe no significant differences across wealth groups. These results are suggestive of affluent investors being better able to navigate less standardized or less well-known opportunities.

Overall, three findings emerge from this analysis. First, there is a clear gradient in performance across the wealth distribution, on the order of 5 to 10 percentage points in PME. Second, the gradient largely disappears once we control for advisor fixed effects, suggesting that differences in advisor quality or investor-advisor sorting are a primary driver. Third, the persistence of performance differences in subsamples with low access frictions—such as first-time funds, low-minimum funds, and under-subscribed funds—implies that limited access is unlikely to be the main explanation. Instead, the results point to other mechanisms such as differential screening ability or informational advantages that correlate with investor wealth.

These findings are also pertinent to the broader discussion of scale advantages in private equity investing. Prior work has documented that larger institutional investors achieve superior returns through preferential access to top funds (Dyck and Pomorski 2016), more favorable fee arrangements (Begenau et al. 2024), and a wider scope of due diligence and investment activities (Da Rin and Phalippou 2017). Our results suggest that scale effects

may not extend linearly across all investor types. The comparable performance of individual investors relative to institutions indicates that alternative mechanisms such as advisor relationships and pooled investments can effectively substitute for direct scale advantages. Within the individual investor population, the wealth gradient appears driven primarily by advisors rather than investor size per se, pointing to intermediation frictions as an important determinant of private equity performance alongside traditional scale effects.

4.2 Advisors and Performance Heterogeneity

Advisors are a key driver of the performance gradient across wealth groups. To better understand the mechanism behind this relationship, we examine whether advisor characteristics explain performance heterogeneity. To the extent that access to the best-performing funds may be driven by existing relationships with GPs ([Lerner et al., 2007](#)), advisors with limited experience and a small network of GP relationships may be associated with weaker performance. Limited experience may also lead to weaker fund selection skills.

Table 8 explores how advisor characteristics relate to fund performance with a particular focus on proxies for advisor quality. In column (1), we find no systematic performance differences across advisor types: broker-dealers and family offices perform similarly to independent advisors. Column (2) and column (3) then shift focus to advisor experience. Using the number of funds an advisor invested in over the prior three vintages as a proxy for advisor experience, we find that each additional fund is associated with a 0.003 increase in PME, in column (2). When we instead use an indicator for the most experienced advisors—those managing more than five funds, approximately the top quartile—this group delivers 13.6 percentage points higher PME, in column (3).

The performance, experience, and relationships of advisors and investors are likely to be jointly determined. One possibility is that observed differences in advisor performance reflect the characteristics of the investors they serve. For example, ultra-high-net-worth individuals may systematically select into higher-quality advisors or gain access to better funds through their own networks. To isolate the role of the advisor, we restrict 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. Columns (4) and (5) show that even within this sample, advisors with greater prior activity are associated with better performance. While this does not fully disentangle investor–advisor complementarities, the results are consistent with advisor quality playing an independent role.

In column (6), we further explore the role of investor experience, measured using the number of funds invested in by the investor over the last three vintages. This variable is positively and significantly associated with performance, suggesting that investor experience also contributes to return differences. However, the advisor experience measure remains highly significant and stable in magnitude, reinforcing the interpretation that advisor quality is an independent and important driver of performance outcomes.

These advisor quality differences manifest clearly in the composition of advisory relationships across wealth groups. Figure 5 shows the distribution of investments across our five wealth categories by advisor characteristics. Panel (c) shows that roughly 40% of investments made by the wealthiest group are advised by family offices, compared to only around 20% for the bottom three wealth groups. Panel (d) shows that wealthier investors are also more likely to work with advisors with greater experience investing in PE—those who have invested in more than five funds in the past three vintages within the same category. However, consistent with the relatively low median number of funds per advisor in our data, the majority of investments across all wealth groups are supervised by advisors outside this experienced category, suggesting that advisor experience, while important, is not uniformly distributed even among the wealthiest clients.

4.3 Performance Heterogeneity by Minimum Commitments

We conclude our analysis by examining whether fund minimum commitments help explain performance heterogeneity across investors. If funds with different minimum commitment thresholds systematically vary in quality, this could help explain the performance heterogeneity we observe across individual investors. Table 9 reports regressions of fund PME on indicators for three tiers of minimum commitments: less than \$1 million (omitted), \$1–5 million, and greater than \$5 million. The sample covers all funds with available minimum commitment data and PME calculated from either Addepar or Preqin cash flows. All regressions include category-by-vintage fixed effects to absorb common return variation across time and fund categories.

Column (1) presents results pooling across all fund categories. We find no evidence of underperformance for funds with low minimum commitments. In fact, funds requiring \$1–5 million in capital underperform those requiring less than \$1 million by 5 percentage points in PME (significant at the 10% level), while funds requiring more than \$5 million deliver similar returns. These findings reject the idea that low-minimum funds are negatively selected or offer worse performance in aggregate.

Columns (2) through (4) disaggregate the results by fund category. In buyout, we find small differences in performance across commitment tiers, none of which are statistically significant. In contrast, we observe more pronounced patterns in venture capital. Here, funds with minimums between \$1 and \$5 million underperform the low-minimum category by 8.6 percentage points, and those with minimums above \$5 million underperform by 5.1 percentage points. These estimates suggest that VC funds with higher barriers to individual investor entry deliver lower returns. While we cannot directly observe whether this reflects fund size effects or other factors associated with higher minimum commitments, the pattern suggests that accessibility constraints in venture capital may not necessarily correlate with superior performance.

For funds of funds, we find a different pattern. Funds with higher minimum commitments outperform low-minimum peers by approximately 6-7 percentage points, with the latter group earning a baseline PME of just 1.07. These results suggest that in this segment, higher barriers to entry may be associated with improved fund selection or better access to underlying managers. These patterns mirror the results in Table 3, where we find an association between past performance and the offering of low-commitment funds only within the funds of funds segment. Taken together, minimum commitment levels do not systematically explain performance differences across investors’ fund choices, except in the funds of funds segment, where higher barriers to entry appear to signal better fund quality.

5 Fees

Up until now, our analyses abstracted from the potential variation in fees across investors in the same fund. In the last section of the paper, we assess the impact of fees on performance across the wealth distribution.

5.1 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 tier adjustment”. 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 specialized advisors 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 typically decreasing in wealth. We refer to this fee as “advisor fee.”

While these fees can have a material impact on the net-of-fee performance of investors, data on private equity fees are scarce in most datasets. 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 about half of 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.²³

5.2 Estimated Net-of-Fees Performance

For fund i , investor j in wealth group m , and advisor k , we model net of fee performance, r_{ijk}^N , as:

$$r_{ijk}^N = r_i - \hat{f}_{m(j)}^{Tier} - \hat{f}_{ik}^{Access} - \tilde{f}_{i,m(j)}^{Advisor}, \quad (1)$$

where r_i is the baseline performance metric measured from the median-investor cash flows in fund i as described in Section 3, $\hat{f}_{m(j)}^{Tier}$ is the performance drag or lift associated with differential terms imposed by GPs, \hat{f}_{ik}^{Access} are intermediary fees paid to access fund i by advisor k , $\tilde{f}_{i,m(j)}^{Advisor}$ are fees charged by the advisor as a percentage of investor’s AUM. We can only partially observe terms $\hat{f}_{m(j)}^{Tier}$ and \hat{f}_{ik}^{Access} from the investor cash flow data, whereas the advisor fees, $\tilde{f}_{i,m(j)}^{Advisor}$, 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 $\hat{f}_{m(j)}^{Tier}$. For investor-fund observations, we can calculate this term exactly using the following identity:

$$\hat{f}_{ij}^{Tier} = r_{ij} - r_i, \quad (2)$$

where r_{ij} is the performance of investor j in fund i . Table C12 presents results from the regressions of \hat{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 \hat{f}_{ij}^{Tier} is positive and statistically significant for the wealthiest investor group. For individuals for whom we do

²³Fee structures are disclosed in reports made by investment professionals called Form ADVs.

not observe full cash flow data, we set $\hat{f}_{m(j)}^{Tier}$ equal to the average values implied from Table C12, thereby assuming that tier drags or lifts are constant across investor 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

$$f_{ij}^{Access} = r_{ij} - r_{ij}^{Access}, \quad (3)$$

where r_{ij}^{Access} is performance calculated net of access fees. We find that 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 cleanly observe fees charged by advisors in our dataset. This fee is assumed to begin at 1.75%, and declines for wealthier investors.²⁴ 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 recompute all our baseline measures of performance and estimate the drag from advisory fees as

$$f_{ij}^{Advisor} = r_{ij}^{Access} - r_{ij}^{Advisor}, \quad (4)$$

where $r_{ij}^{Advisor}$ is the performance 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 $\hat{f}_{im}^{Advisor} = \bar{f}_{i,j(m)}^{Advisor}$, where the latter denotes the average advisory fee drag across investors by fund and wealth group.

Figure 6 illustrates how different types of fees impact the baseline performance advantage of wealthier investors. Specifically, the figure decomposes the impact of fees on PME performance 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

²⁴Specifically, 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 of a large advisor that manages private equity investments in Form ADV.

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 roughly double the performance gap between the least and most wealthy investors (in light blue). For the least affluent investors, the combined fee burden absorbs most of their outperformance relative to public markets, reducing their net-of-fees PME equal to one, on average. Overall, our results suggest that while individual investors can successfully access high-quality private equity funds, the fee structure creates a meaningful barrier to realizing these returns, particularly for less affluent investors.

6 Conclusion

This paper provides the first systematic analysis of private equity performance among individual investors using comprehensive cash flow data. We document that individual investors achieve performance comparable to institutional benchmarks and outperform public markets on aggregate. However, this overall success masks important heterogeneity, with a significant wealth gradient where the most affluent investors substantially outperform the least affluent. We identify two key innovations that have democratized access—the proliferation of low minimum commitment funds and capital pooling through advisors—but show that fees, particularly advisor fees, appear to create substantial performance drags that disproportionately affect less wealthy investors.

Our findings challenge the prevailing narrative that private equity access should remain restricted due to concerns about performance. Individual investors access a largely distinct universe of funds from those studied in prior institutional research, providing us with a unique opportunity to expand our understanding of private equity performance beyond traditional institutional channels. This expanded dataset demonstrates that the private equity market has matured without sacrificing performance quality. Rather than fund selection or access constraints, our analysis points to fee structures and advisor quality as the primary determinants of investor outcomes, suggesting that the democratization of private equity hinges on addressing intermediation costs rather than restricting access.

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Table 1. Descriptive Statistics

This table presents descriptive statistics for the sample of 4,523 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	1,663	2014	5	2000	2015	2020	2,163	2015	5	2000	2017	2020	697	2012	6	2000	2013	2020
Size (m)	1,573	1,443	2,737	3	475	24,714	1,880	221	360	0	100	3,750	641	633	1,331	1	269	14,000
N. of individual investors	1,663	17	28	1	8	583	2,163	13	25	1	6	360	697	23	56	1	8	768
Oversubscribed	1,302	0.2	0.4	0.0	0.0	1.0	1,450	0.3	0.5	0.0	0.0	1.0	413	0.3	0.5	0.0	0.0	1.0
Fund number overall	1,663	5.2	6.6	1.0	3.0	59.0	2,159	4.7	6.7	1.0	3.0	102.0	694	13.5	16.1	1.0	8.0	98.0
Fund number series	1,647	3.3	2.4	1.0	3.0	14.0	2,123	2.9	2.7	1.0	2.0	27.0	681	4.3	3.0	1.0	4.0	15.0
Min commitment (m)	1,269	5.2	8.9	0.0	3.0	100.0	1,231	1.0	5.2	0.0	0.1	100.0	399	2.5	8.6	0.0	0.5	100.0

Panel B: Descriptive Statistics—Investors									
Wealth group	Number of investors	Total AUM (m)	Private Equity AUM (m)	PE portfolio share			Number of funds	Median commitment	
				Buyout	Venture Capital	Fund of Funds			
<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															
	Advisors					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	6,497	14,176	1	2,273	90,456	1,722	3,878	1	693	52,170
Private Equity AUM	710	4,087	0	36	48,032	549	960	0	208	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	74	1	21	351	8	28	1	3	520
Number of Funds	43	101	1	11	985	57	74	1	27	345	17	25	1	9	276
Number of Advisory Firms	241					47					456				

Table 2. 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 Burgiss-MSCI vintage by category cutoffs. The samples cover North American funds closed between 2000 and 2020.

	Only Addepar ($N = 2,027$)		Both Datasets ($N = 2,496$)		Only Preqin ($N = 2,202$)	
	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	0.29	0.20	0.40	0.36	0.48
Vintage	2016.08	4.13	2012.46	5.96	2009.79	6.18
Size (m)	215.10	503.22	1128.17	2335.26	331.76	578.25
N. of individual investors	15.47	29.85	16.36	34.72	—	—
Oversubscribed	0.30	0.46	0.24	0.43	0.42	0.49
Fund number overall	4.57	7.13	7.57	10.61	8.33	14.60
Fund number series	2.46	2.26	3.87	2.80	3.26	2.75
Minimum commitment	1.44	6.33	4.23	8.44	8.63	20.56
Performance quartile						
Top	0.24	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

Table 3. Minimum Commitments and Firm Characteristics

The table reports the results of regressions of an indicator for funds with a minimum commitment below \$1 million on firm characteristics. The sample consists of 7,201 North American funds closed between 2000 and 2020 with available minimum commitment data. All columns report results of versions of the regression:

$$\begin{aligned} DummyLowCommitment_{i(nt)} = & TopGP_{nt} + NewFirm_{nt} + \sum_k \beta_k DummyFirmSize_{kt} \\ & + Oversubscribed_{nt} + \lambda_{ct} + \epsilon_{i(nt)}. \end{aligned}$$

$DummyLowCommitment_{i(nt)}$ is an indicator for minimum commitment below \$1 million for fund i offered by firm n in vintage t . $TopGP_{nt}$ is an indicator for firms with above median performance over the past five vintages based on average PME, $NewFirm_{nt}$ is an indicator for firms offering their first fund, $DummyFirmSize_{kt}$ are four dummy variables for firm size quartiles based on total fund size over the past five vintages. The base category are firms with no size, either new firms or firms that do not report size to Preqin. $Oversubscribed_{nt}$ is an indicator for firms with an oversubscribed fund in the past five vintages. λ_{ct} are category by vintage fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: Minimum Commitment <\$1m					
Fund category	All Funds	All Funds	Buyout	VC	Fund of Funds
	(1)	(2)	(3)	(4)	(5)
Top GP	-0.0715*** (0.0184)	-0.0259 (0.0181)	-0.0543 (0.0353)	0.0441 (0.0274)	-0.0806** (0.0366)
New firm		0.0687*** (0.0157)	0.0886*** (0.0263)	0.0416** (0.0202)	0.104* (0.0568)
Dummy for firm size quartile					
1		-0.245*** (0.0273)	-0.209*** (0.0480)	-0.328*** (0.0410)	-0.120* (0.0646)
2		-0.128*** (0.0250)	-0.0565 (0.0449)	-0.234*** (0.0354)	-0.0532 (0.0608)
3		0.0525** (0.0231)	0.114*** (0.0429)	-0.0477 (0.0313)	0.128** (0.0590)
4		0.173*** (0.0215)	0.338*** (0.0435)	0.0501* (0.0272)	0.283*** (0.0632)
Oversubscribed		-0.0000546 (0.000174)	0.000132 (0.000341)	-0.000638*** (0.000234)	0.000770* (0.000399)
Constant	0.507*** (0.0130)	0.602*** (0.0264)	0.412*** (0.0531)	0.826*** (0.0348)	0.445*** (0.0657)
Category \times Vintage FE	Yes	Yes	Yes	Yes	Yes
Observations	7201	7201	2544	3445	1212
R^2	0.184	0.226	0.144	0.110	0.166

Table 4. Performance of Individual Investors

This table presents summary statistics of performance metrics for 4,523 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 CRSP value-weighted index as the benchmark index. Medium and high β are estimated for each fund category using Dimson regressions reported in [Table C7](#). *% calculated* is the fraction of funds with performance metrics calculated from investor-level cash flow data. *% 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	% calculated	% of investments
TVPI	1.83	0.89	0.51	1.31	1.65	2.15	4.74	1,664	0.82	0.96
IRR	16.82	19.71	-21.84	8.46	15.00	22.54	72.32	1,663	0.82	0.96
PME ($\beta = 1$)	1.18	0.56	0.33	0.89	1.11	1.35	2.92	1,357	1.00	0.92
PME (Medium β)	1.26	0.60	0.36	0.95	1.17	1.44	3.07	1,357	1.00	0.92
PME (High β)	1.17	0.56	0.32	0.89	1.10	1.34	2.92	1,357	1.00	0.92
Panel B: Venture Capital										
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N	% calculated	% of investments
TVPI	2.07	2.10	0.26	1.05	1.50	2.29	10.94	2,176	0.88	0.93
IRR	12.00	17.59	-23.51	1.47	10.13	19.41	71.15	2,163	0.89	0.93
PME ($\beta = 1$)	1.18	1.10	0.13	0.70	0.94	1.29	5.04	1,920	1.00	0.90
PME (Medium β)	1.04	0.96	0.11	0.62	0.84	1.14	4.45	1,920	1.00	0.90
PME (High β)	0.91	0.85	0.08	0.54	0.74	1.01	3.94	1,920	1.00	0.90
Panel C: Fund of Funds										
	Mean	Std.Dev.	p1	p25	p50	p75	p99	N	% calculated	% of investments
TVPI	1.78	0.75	0.71	1.36	1.63	2.00	4.50	703	0.74	0.80
IRR	13.24	8.92	-9.49	8.05	13.21	17.80	37.77	697	0.75	0.80
PME ($\beta = 1$)	1.06	0.29	0.36	0.90	1.04	1.20	1.84	523	1.00	0.76
PME (Medium β)	1.07	0.29	0.36	0.90	1.04	1.20	1.85	523	1.00	0.76
PME (High β)	0.97	0.27	0.32	0.82	0.95	1.10	1.70	523	1.00	0.76

Table 5. 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-Burgiss 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-Burgiss. *, **, *** 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	2.07	2.10	1.78	1.72
Excess TVPI _{Preqin}	0.08***	0.14***	-0.05**	-0.06***	0.22***	0.48***	-0.06**	0.03
Excess TVPI _{MSCI-Burgiss}	0.02	0.06***	0.03	-0.07***	-0.05	0.20***	0.17***	0.13***
Observations	4,543		1,664		2,176		703	
Panel B: IRR								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
IRR	14.0	14.5	16.8	15.1	12.0	14.3	13.2	13.6
Excess IRR _{Preqin}	-2.8***	-1.8**	-1.7***	-1.5***	-3.7***	-0.5	-2.8***	-4.4**
Excess IRR _{MSCI-Burgiss}	-1.2**	-0.3	0.6	-1.0**	-3.3***	0.6	0.7	-0.3
Observations	4,523		1,663		2,163		697	
Panel C: PME								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
PME	1.22	1.19	1.26	1.16	1.23	1.31	1.13	1.09
Excess PME _{Preqin}	-0.04***	-0.04***	-0.10***	-0.14***	0.03	0.19***	-0.12***	-0.18***
Excess PME _{MSCI-Burgiss}	0.12***	0.13***	0.14***	0.06***	0.10***	0.26***	0.14***	0.09***
Observations	4,147		1,521		2,030		596	

Table 6. 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 medium beta 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	1.05	1.08	1.24	1.20	0.99	1.02	1.03	1.02
3-10 m	1.09	1.05	1.24	1.11	1.00	1.07	1.06	1.00
10-30 m	1.13	1.11	1.24	1.19	1.07	1.12	1.04	1.02
30-100 m	1.14	1.10	1.27	1.20	1.07	1.06	1.04	1.01
>100 m	1.16	1.14	1.26	1.18	1.06	1.15	1.07	1.06
Panel B: Number of Funds								
	All Funds		Buyout		Venture Capital		Fund of Funds	
<3 m	1,031		416		436		179	
3-10 m	1,490		543		661		286	
10-30 m	2,254		834		1,053		367	
30-100 m	2,755		986		1,364		405	
> 100 m	3,336		1,219		1,665		452	

Table 7. Investor Wealth and Fund Performance

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

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

$PME_{i(j)}$ 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 . In Panel A, the samples consist of all investor-fund observations over 2000-2020 vintages. In Panel B, the samples consist of first funds of a firm (column 1), funds with minimum commitment below \$1 million (column 2), investments with less than \$0.1 million in committed capital (column 3), funds that are not oversubscribed (column 4), and funds with (column 6) and without (column 5) performance data in Prequin. Standard errors double clustered at the fund and investor level are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Full Sample						
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	-0.0873*** (0.0236)	-0.0594*** (0.0179)	-0.00880 (0.0218)	-0.122*** (0.0382)	-0.0519** (0.0232)	-0.0131 (0.0138)
3–10m	-0.0509*** (0.0181)	-0.0321** (0.0153)	0.0175 (0.0219)	-0.0681** (0.0326)	-0.0528*** (0.0185)	-0.00540 (0.0133)
10–30m	-0.0305** (0.0135)	-0.0217* (0.0123)	0.00981 (0.0160)	-0.0444* (0.0248)	-0.0365*** (0.0138)	0.00596 (0.0110)
30–100m	-0.0169 (0.0115)	-0.0142 (0.0108)	0.0205 (0.0132)	-0.0369* (0.0212)	-0.0361*** (0.0104)	-0.00520 (0.00770)
Constant	1.139*** (0.0170)	1.133*** (0.0135)	1.207*** (0.0136)	1.100*** (0.0287)	1.059*** (0.0206)	1.120*** (0.0108)
Category × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	64736	64736	25247	25779	13710	64678
R^2	0.003	0.140	0.099	0.124	0.141	0.205

Table 7. Investor Wealth and Fund Performance (continued)

Panel B: Subsamples by ease of access and information asymmetry						
Dep.Var.: PME						
Sample	First Fund	Minimum < 1m	Commitment <0.1m	Under- subscribed	In Preqin	
					No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.158*** (0.0502)	-0.0985*** (0.0298)	-0.180*** (0.0386)	-0.0531*** (0.0187)	-0.121*** (0.0282)	0.0106 (0.0195)
3–10m	-0.0976*** (0.0365)	-0.0639** (0.0268)	-0.118*** (0.0406)	-0.0262 (0.0159)	-0.0880*** (0.0249)	0.0285* (0.0165)
10–30m	-0.0540* (0.0278)	-0.0264 (0.0225)	-0.119*** (0.0371)	-0.0199 (0.0129)	-0.0536*** (0.0199)	0.0125 (0.0124)
30–100m	-0.0377* (0.0221)	-0.0124 (0.0213)	-0.0901** (0.0360)	-0.0158 (0.0107)	-0.0426** (0.0182)	0.0184* (0.0104)
Constant	1.146*** (0.0291)	1.145*** (0.0268)	1.253*** (0.0349)	1.139*** (0.0137)	1.136*** (0.0235)	1.124*** (0.0117)
Category × vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9093	21296	9204	57314	29985	34749
R^2	0.140	0.232	0.164	0.166	0.172	0.222

Table 8. 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:

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

$PME_{i(j)}$ 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 advisor categories, the number of funds the advisor invested in over the previous three vintages, the number of funds invested by the investor in the previous three vintages, or a dummy variable equal to one if the advisor invested in more than five funds in the previous three vintages within the same fund category. The omitted advisor category is Advisors. 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 columns 4 and 5, the sample consists only of the investments in the first vintage an investor makes a PE investment. 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						
Investors:	All	All	All	New	New	All
	(1)	(2)	(3)	(4)	(5)	(6)
Advisor category						
Broker Dealer	-0.0477 (0.0317)	-0.0255 (0.0259)	-0.0225 (0.0213)	-0.00343 (0.0292)	-0.00688 (0.0290)	-0.0256 (0.0261)
Family Office	-0.0166 (0.0279)	0.0157 (0.0219)	0.0401** (0.0173)	0.0114 (0.0257)	0.0123 (0.0231)	0.0145 (0.0219)
Advisor number of funds		0.00315*** (0.000391)		0.00352*** (0.000275)		0.00308*** (0.000362)
> 5 funds			0.136*** (0.0452)		0.125** (0.0615)	
Investor number of funds						0.00649** (0.00323)
Constant	1.143*** (0.0273)	1.098*** (0.0185)	1.066*** (0.0161)	1.074*** (0.0234)	1.065*** (0.0198)	1.089*** (0.0186)
Category \times vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor Wealth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64733	64733	64733	14853	14853	64733
R^2	0.141	0.149	0.152	0.241	0.242	0.149

Table 9. Minimum Commitments and Fund Performance

The table reports results from OLS regressions of fund performance on fund characteristics. The samples consist of funds with available minimum commitment data and PME calculated from either Addepar or Preqin cash flows closed over 2000–2020. All columns report versions of the following regression:

$$PME_i = \beta_0 + \sum_k \beta_{1k} FundCharacteristics_{k(i)} + \lambda_{ct} + \epsilon_i.$$

PME_i is the medium beta PME of fund i , which is based on Dimson betas and benchmarked to the CRSP value-weighted market index. The independent variables are the three categories for fund minimum commitments. The omitted category is <\$1 million. λ_{ct} are fixed effects for fund category and vintage. Standard errors are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dep.Var.: PME				
Fund category	All Funds	Buyout	Venture Capital	Fund of Funds
	(1)	(2)	(3)	(4)
Minimum Commitment				
1-5m	-0.0505* (0.0274)	-0.0540 (0.0449)	-0.0863* (0.0462)	0.0552 (0.0412)
>5m	0.0188 (0.0245)	0.0366 (0.0344)	-0.0512 (0.0533)	0.0749** (0.0366)
Constant	1.118*** (0.0146)	1.275*** (0.0275)	0.967*** (0.0196)	1.066*** (0.0249)
Category \times vintage FE	Yes	Yes	Yes	Yes
Observations	3203	1349	1331	523
R^2	0.122	0.065	0.041	0.087

Figure 1. Fund Universe Overlap Between Individual and Institutional Investors

The 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.

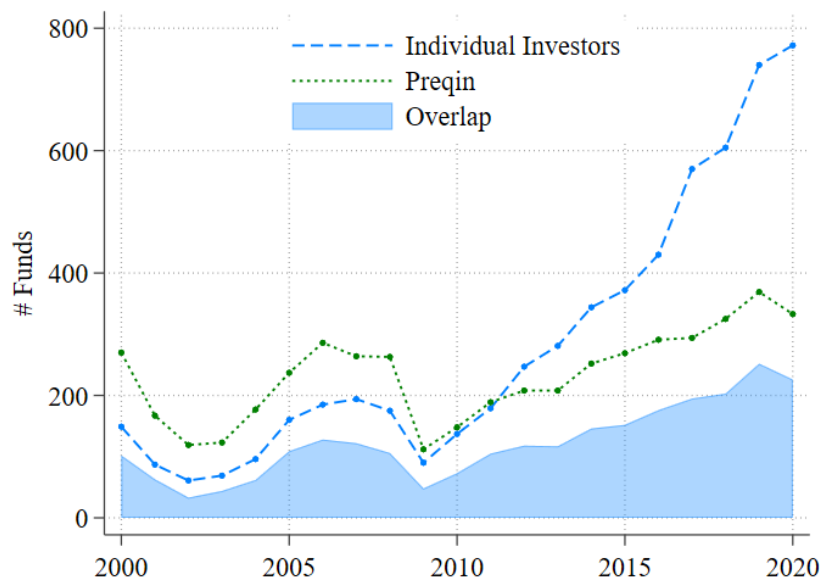


Figure 2. Evolution of Minimum Commitments

Panel A plots the average minimum commitment level by fund category and vintage. The horizontal dashed line denotes the \$5 million minimum commitment requirement considered in prior literature (Korteweg et al., 2022). Panel B plots the fraction of firms that issued a fund with a low minimum commitment limit below \$1 million in a given vintage and fund category. The sample consists of 12,751 North American funds with available information on minimum commitment.

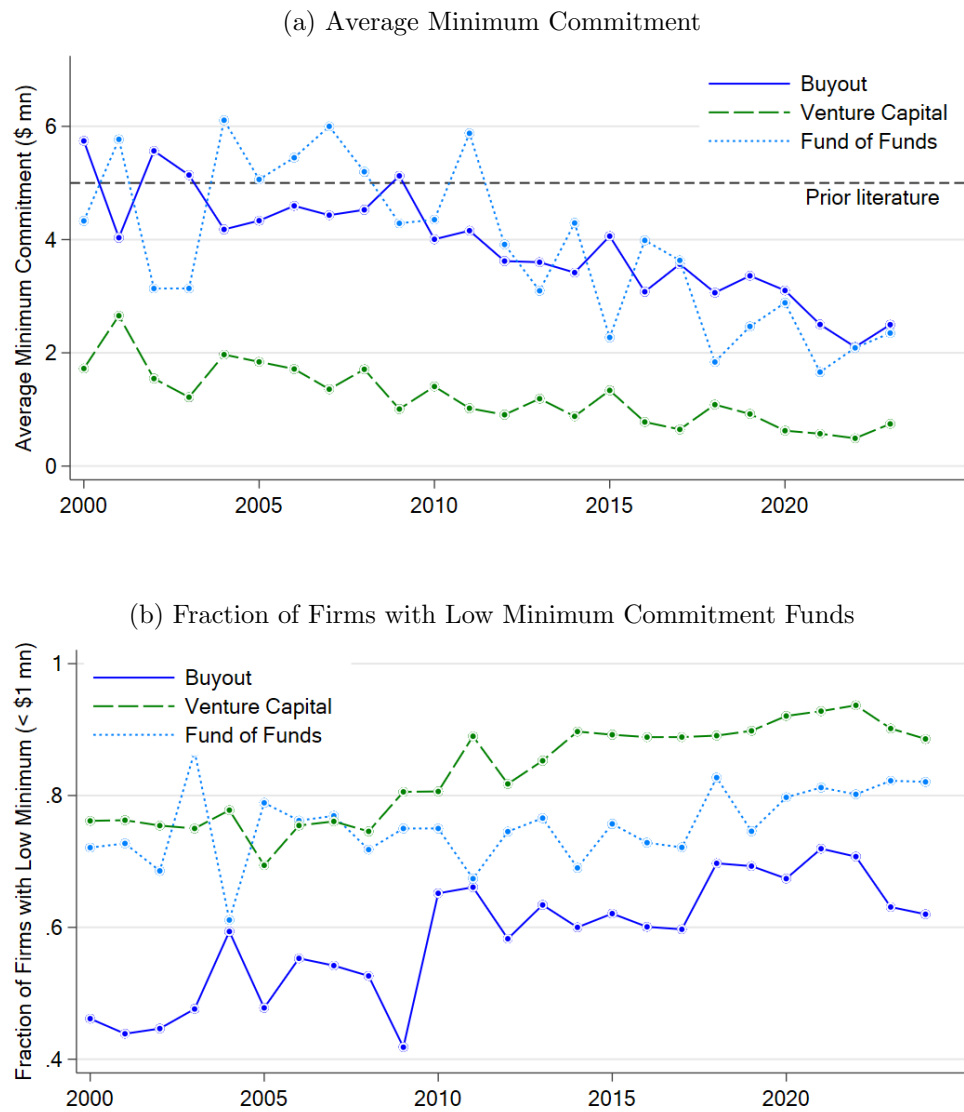


Figure 3. Pooling Test: Distribution of Committed Capital Around Minimum Requirements

The figures plot histograms of the distance between committed capital and the fund minimum commitment. Panel A plots the histogram for investor-funds observations with only one investor in a given fund per advisor. Panel B plots the histogram for observations with at least two investors in a given fund per advisor. Panel C plots the histogram for aggregated commitments on advisor-fund level. The samples cover funds with minimum commitments of \$1 million or higher and commitments that are within \$10 million distance to the fund minimum.

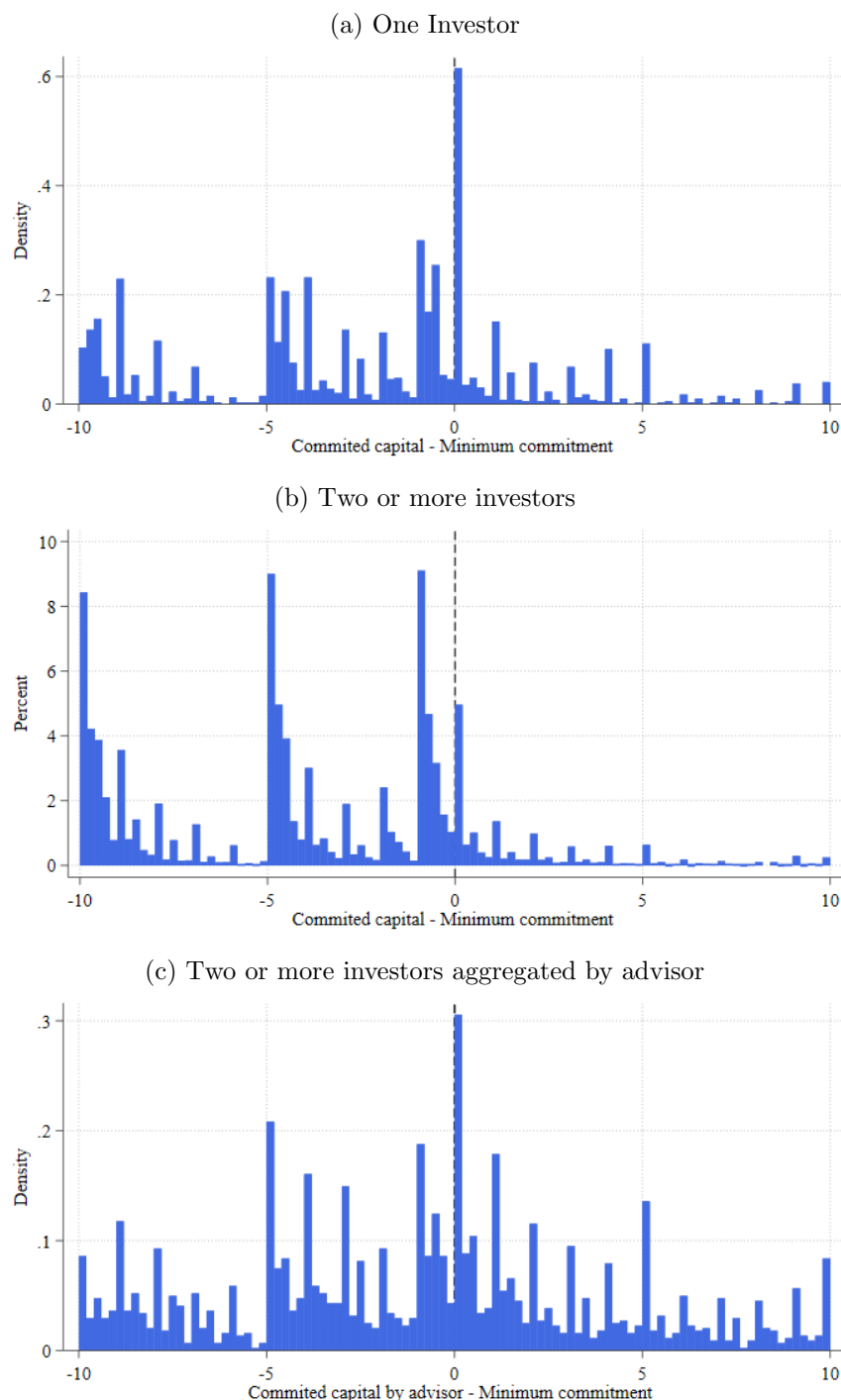


Figure 4. Comparison of Performance Metrics to Institutional Investors

This figure compares the performance of private equity investments across the Addepar, MSCI-Burgiss, 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 vintage year and fund category.

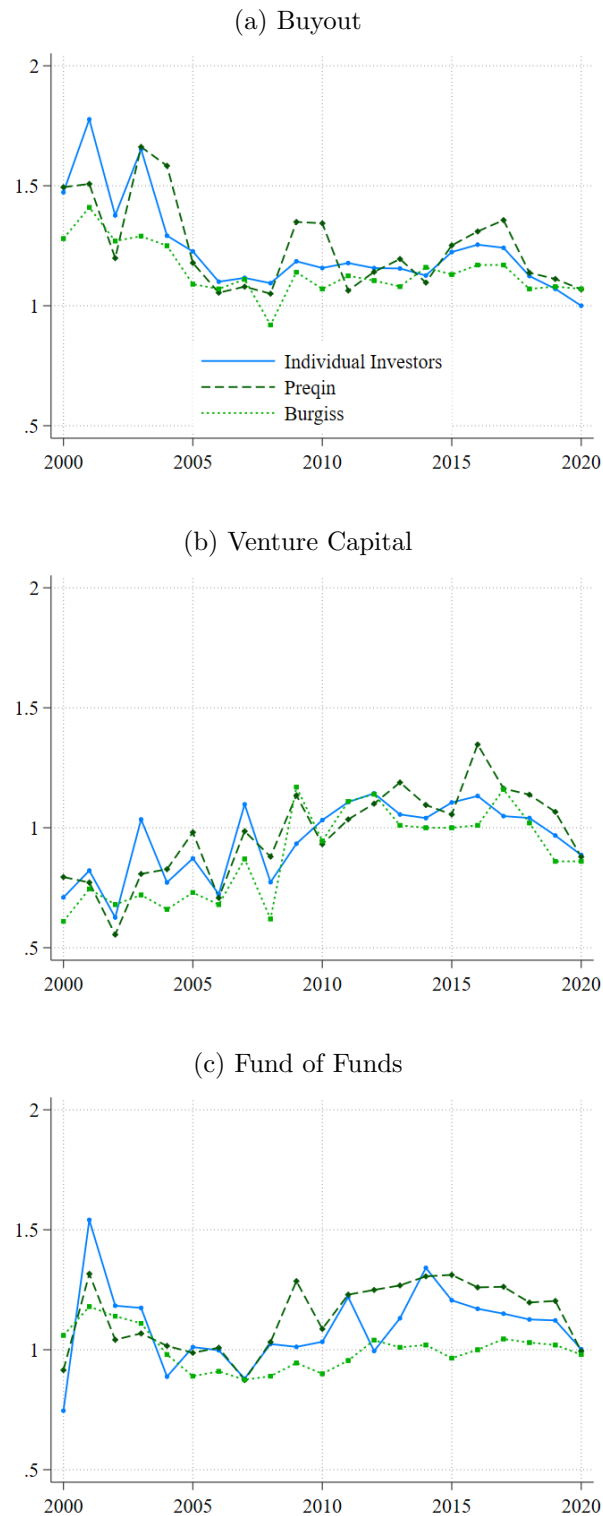


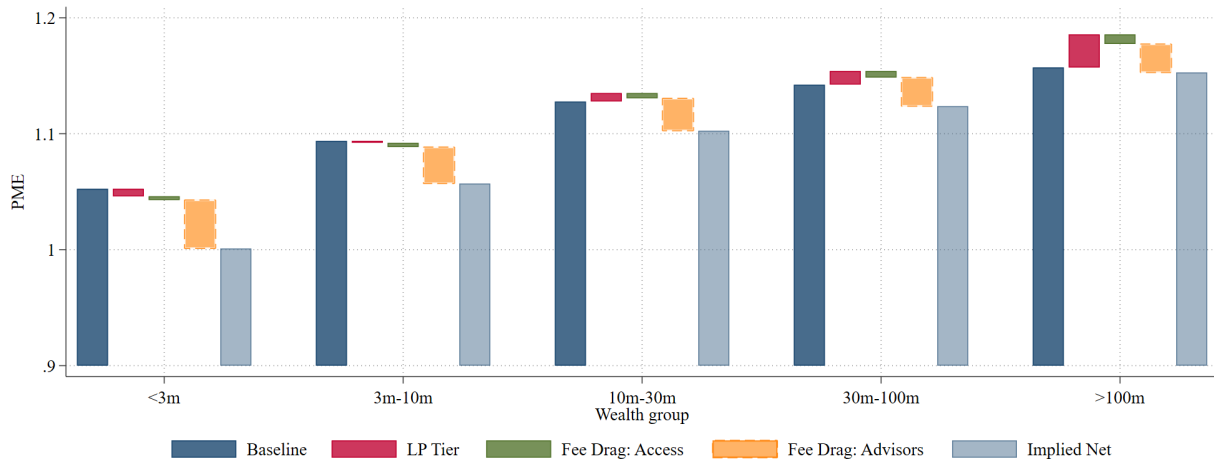
Figure 5. Access, Information, and Advisor Characteristics Across Wealth

The figures plot portfolio shares weighted by the number of investments across investor wealth categories. The categorization is based on the average value of financial assets over our sample period. In Panel (a), we show portfolio shares invested in first round versus later round funds. In Panel (b), we show portfolio shares invested in funds according to whether or not their performance data is available in Preqin. Panel (c) shows the proportion of investors whose advisor is an RIA, broker-dealer, or family office. In Panel (d), advisor number of funds refers to the number of funds within a given category that the advisor invested in over the past three vintages.



Figure 6. 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 3. 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. Access Fee Drag measures the decline in net performance associated with paying intermediary fees for accessing specific funds. Advisors Fee Drag simulates the impact of typical fees charged by advisors. Net Implied 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

August 2025

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A Data Appendix

i. 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 Seed	Stage:	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 Start-up	Stage:	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)	(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.

ii. Summary Statistics

This appendix describes how the investor-level private equity data from Addepar for Private Equity Buyout, Venture Capital, and Private Equity 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-Burgiss. For all datasets we report the number of funds with available IRR metric.

Vintage	Buyout			Venture Capital			Fund of Funds		
	Addepar	Preqin	MSCI-Burgiss	Addepar	Preqin	MSCI-Burgiss	Addepar	Preqin	MSCI-Burgiss
2000	16	86	53	43	123	133	9	37	41
2001	6	48	31	19	69	68	7	35	27
2002	6	35	21	6	48	23	4	27	35
2003	9	34	26	11	45	27	8	37	40
2004	14	55	48	17	61	47	6	45	58
2005	37	89	57	22	61	66	18	74	59
2006	43	100	75	25	84	89	20	86	85
2007	42	99	70	31	77	81	18	75	76
2008	34	87	70	42	65	63	22	95	75
2009	16	37	22	17	30	28	6	35	38
2010	32	51	30	29	38	36	16	47	36
2011	43	67	50	39	50	49	22	65	46
2012	61	85	54	70	50	61	28	61	42
2013	71	76	48	84	57	59	38	60	59
2014	90	89	79	106	75	97	29	68	55
2015	87	101	58	135	79	113	30	67	56
2016	114	111	84	140	74	88	45	87	65
2017	136	100	65	224	90	114	49	73	62
2018	136	128	89	228	94	132	42	70	65
2019	188	167	112	318	99	140	52	68	58
2020	177	151	87	316	90	177	55	65	66

iii. New Fund Universe

Figure A1. Fund Size Distribution Across Data Sources

This figure shows histograms of the fund size distribution for the funds where performance is calculated only in Addepar data, funds in both datasets, and funds where performance is available in Preqin but not Addepar. Funds covered in both datasets tend to be larger, while funds that are in Addepar data only include more smaller funds. However, the distribution of funds with performance data only available in Preqin is similar to that of the only Addepar group, highlighting that the sizes of funds newly covered in our data does represent a market segment that is completely different from institutional funds.

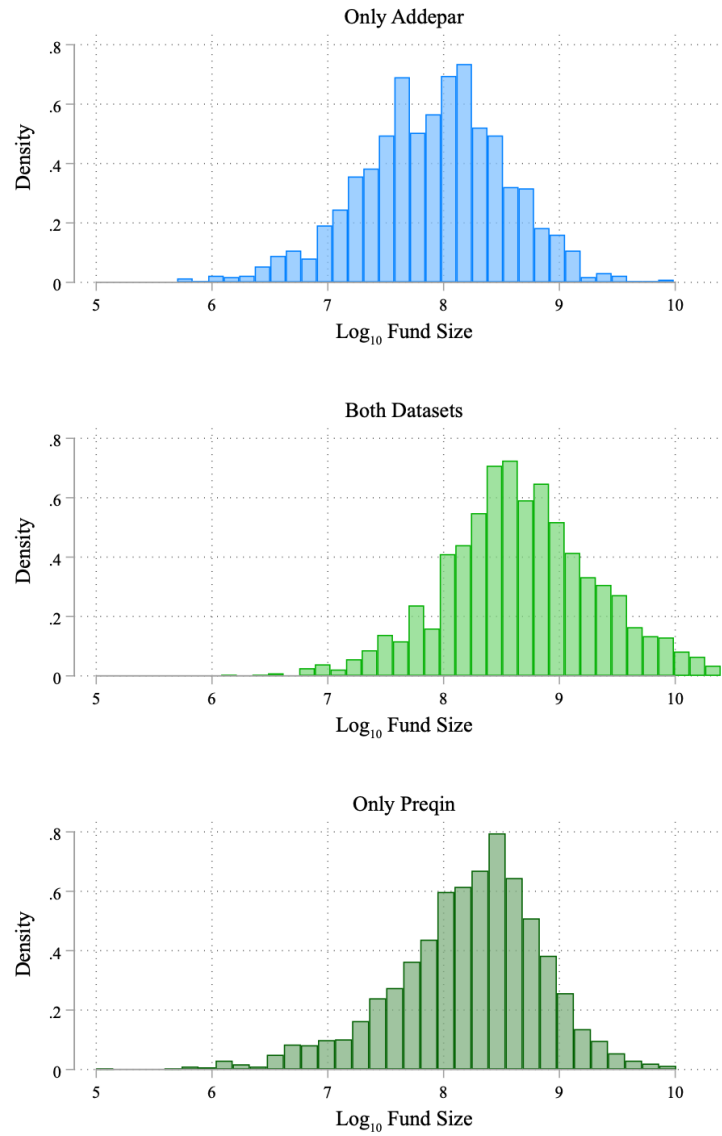


Figure A2. Fund Size and Minimum Commitment Across Data Sources

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 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 include some smaller funds.

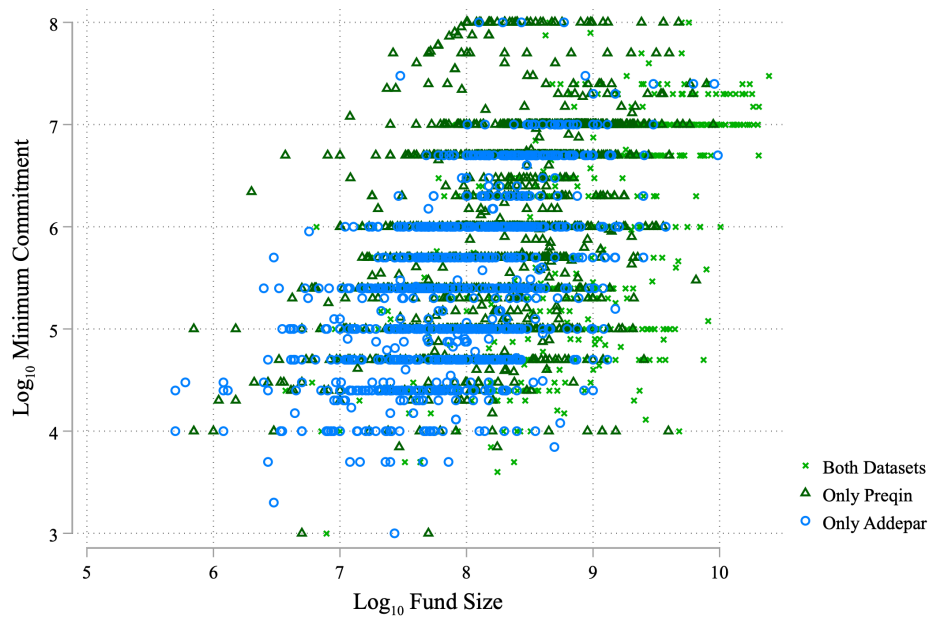


Figure A3. Comparison of Performance Across Data Sources

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.

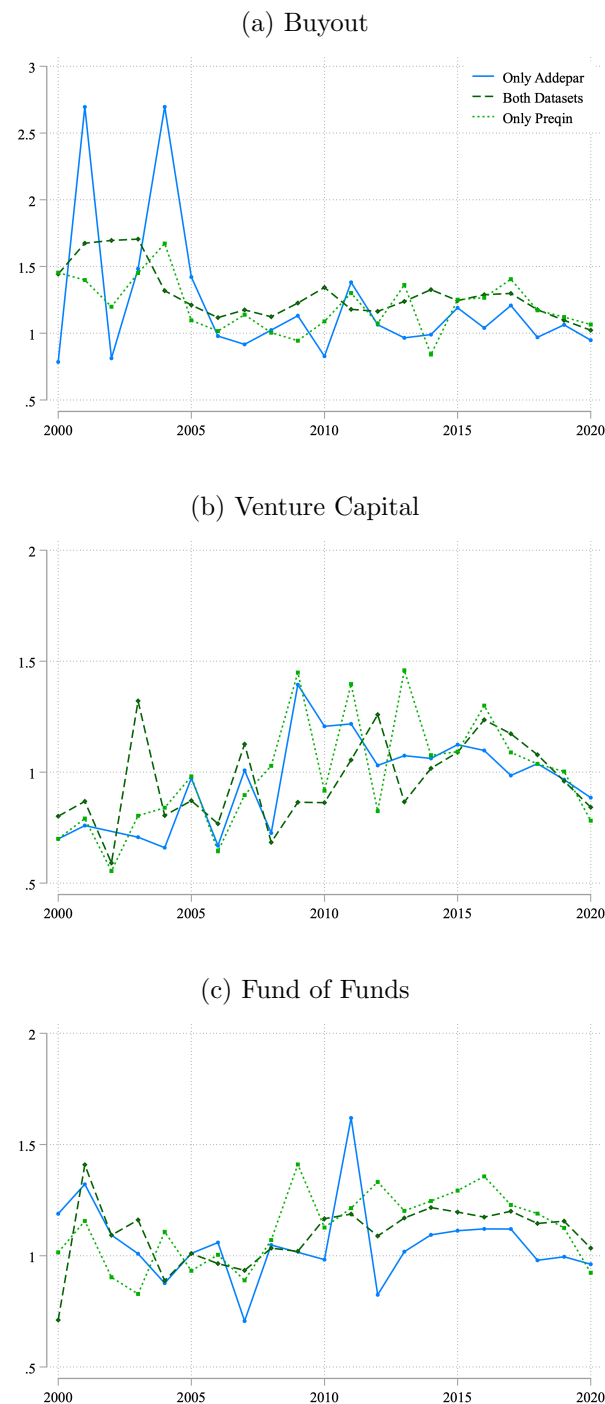


Table A3. Firms by Performance Reporting Rate in Preqin

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		

iv. Wealth Imputation

To classify investors into wealth categories, we use the average total assets managed on the platform. This approach may lead to a measurement error if an investor decides to invest only a fraction of their wealth with an advisor. To assess whether we observe incomplete portfolios for investors with lower wealth, we plot the share in private equity against investor wealth in Figure A4. While the PE share is constant, slightly above 10% for investors with AUM above \$7 million, we observe an increasing average share in PE as wealth declines below \$7 million.

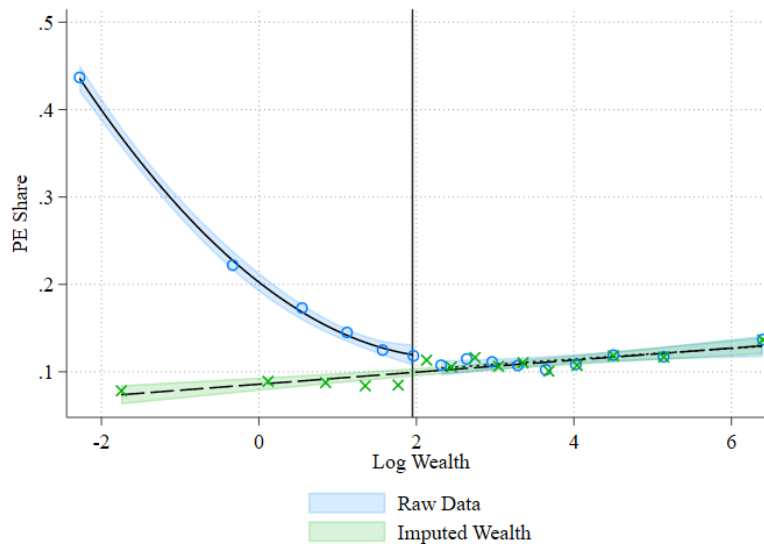
To correct for the possible miscategorization of investors with lower wealth, we impute wealth for investors with wealth below \$7 million and with PE share above 35%, which represents the 75th percentile for investors with observed wealth above \$7 million. We calculate imputed wealth as

$$\text{Imputed Wealth} = \frac{\text{Observed PE Holdings}}{0.1035}, \quad (\text{A1})$$

where 0.1035 is the average PE share observed for investors with wealth above \$7 mn.

Figure A4. PE Share Across the Wealth Distribution

This figure plots a binned scatterplot of the PE share in investor portfolio against logged investor wealth. Blue circles represent the raw data. Green crosses represent the data after wealth imputation described in Section iv..



B Access

i. Minimum Commitments For All Preqin Funds

Table B4. Minimum Commitments For All Preqin Funds

Summary statistics of fund minimum commitment in \$ mn, for all funds in Preqin.

	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

ii. Individual Portfolio Shares Compared to Institutional Shares

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, 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). These shares are reported in Table B5. 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 B5. Individual Portfolio Shares Compared to Institutional Shares

The table reports portfolio shares in percents 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 asset-class 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

iii. Summary Statistics on Pooled Access

Table B6. Summary Statistics on Pooled Access

The table reports the fraction of investments by access channel. We classify observations where an investor's commitment exceeds the fund minimum commitment as Direct. Those observations where the sum of commitments for all investors sharing the same advisor exceeds the minimum requirement are classified as Pooled. The remaining observations are classified as Undefined. We report both shares based on equally weighted investor-fund observations (EW) and shares based on commitment-weighted observations. The sample covers 41,988 observations with available data both on fund minimum commitment level and investor commitment.

Panel A: Full Sample						
	EW	VW				
Direct	51.93	79.49				
Pooled	30.23	13.35				
Undefined	17.84	7.16				
Observations	41,988	41,988				
Panel B: By Fund Category						
	Buyout		Venture Capital		Fund of funds	
	EW	VW	EW	VW	EW	VW
Direct	32.62	68.62	71.29	91.94	62.55	90.67
Pooled	38.18	20.30	20.24	5.07	29.18	6.59
Undefined	29.20	11.08	8.47	2.99	8.27	2.74
Observations	19,053	19,053	14,244	14,244	8,691	8,691
Panel C: By Minimum Capital Requirement						
	< 1m		1-5m		> 5m	
	EW	VW	EW	VW	EW	VW
Direct	81.35	98.97	37.17	89.02	8.27	56.03
Pooled	16.70	0.90	46.34	8.71	45.62	27.87
Undefined	1.95	0.13	16.50	2.27	46.10	16.11
Observations	22,510	22,510	6,511	6,511	12,967	12,967

C Performance

i. 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. The Dimson regression estimates are shown in [Table C7](#).

Table C7. 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.

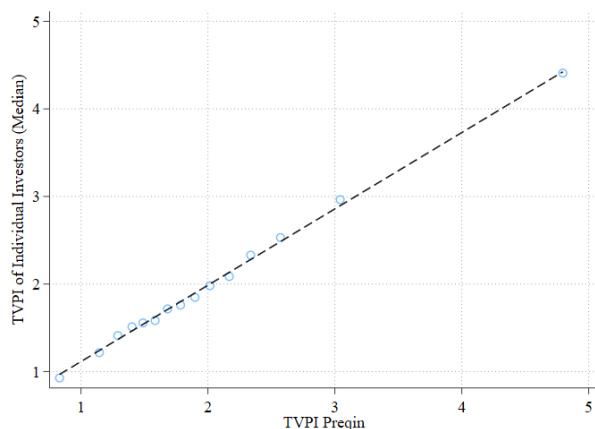
	Buyout	Venture Capital	Funds of Funds
Beta	0.82	1.30	0.99
SE	0.10	0.19	0.13
R^2	0.66	0.48	0.62
Quarters	97	98	98
High Beta	1.02	1.68	1.25

ii. Validation of Performance Measures

We validate our computed performance metrics in Section 3 by cross-referencing them with reported metrics to Preqin. Preqin receives most of their performance metrics from FOIA requests and complements missing metrics with their own estimates based on cash flow data using the same approach as we do. We observe both the Preqin TVPI and our computed TVPI for 1,042 funds that satisfy the following criteria. The lifespan of the fund is at least 4 years, the start of the cash flow data in Addepar is within one year of the vintage year, the end of the cash flow data in Addepar is within one year of the closest reported date of TVPI in Preqin. We condition on an approximately same time of computing both TVPIs to increase the comparability of both variables. Figure C5 displays the binned scatter plot of both measures. We find that both measures are highly correlated: The Pearson correlation coefficient between the two measures is 91%.

Figure C5. Computed TVPI versus reported TVPI

This figure plots a scatter plot of the TVPIs computed from individual investors' cash flow data versus TVPIs reported to Preqin. The blue line depicts a 45-degree line. The Pearson correlation coefficient between our measure (Individual Investors) and the TVPI reported to Preqin is 91%. The sample covers 1,043 funds for which we observe both the Individual Investors' and Preqin TVPIs.



iii. Comparison to Institutional Investors: TVPI, IRR, Distributions

Figure C6. Comparison of Performance Metrics to Institutional Investors: TVPI

This figure compares the performance of private equity investments across individual investors, MSCI-Burgiss, 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.

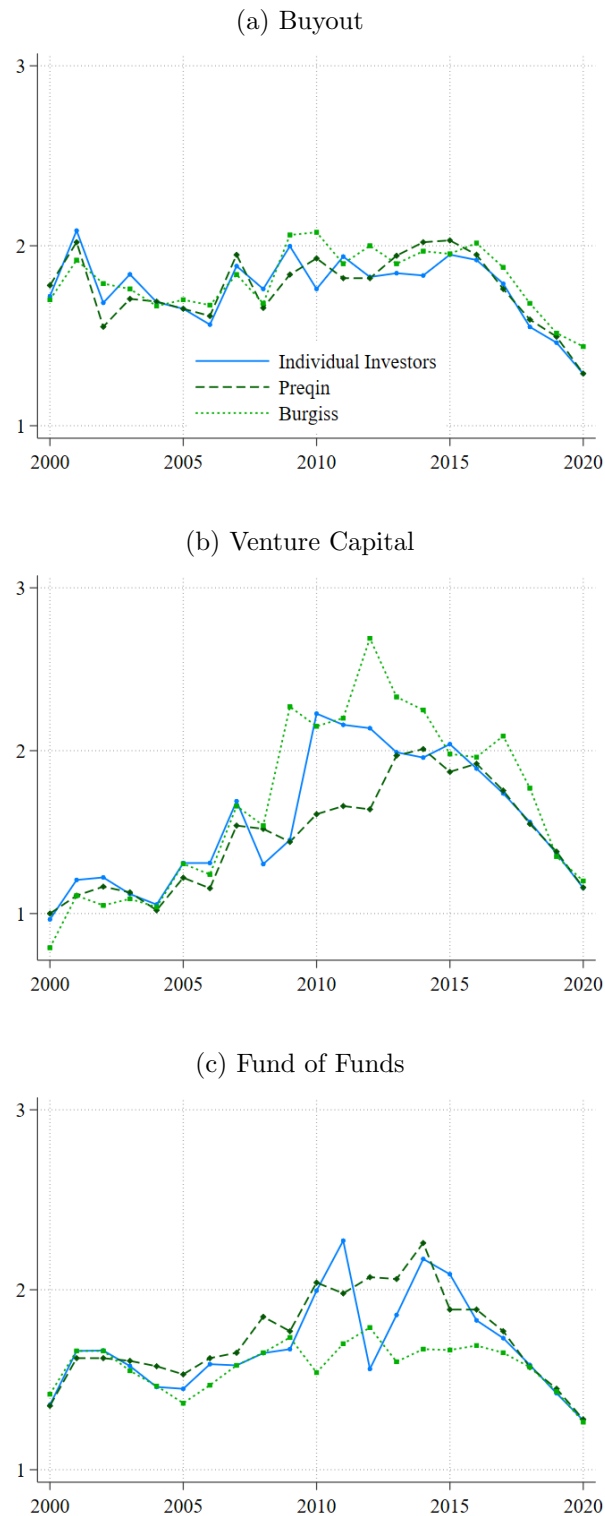


Figure C7. Comparison of Performance Metrics to Institutional Investors: IRR

This figure compares the performance of private equity investments across individual investors, MSCI-Burgiss, 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.

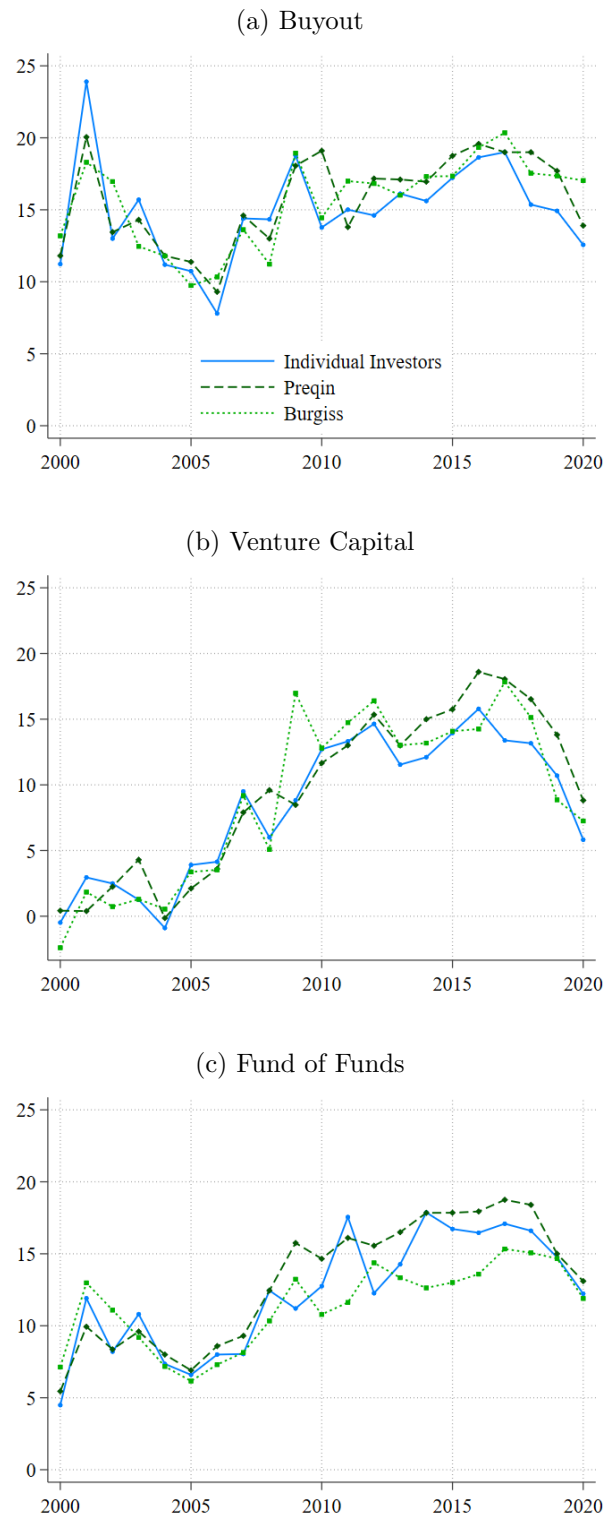


Figure C8. Comparison of Performance Metrics to Institutional Investors: PME IQR

This figure compares the performance of private equity investments across individual investors, MSCI-Burgiss, 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.

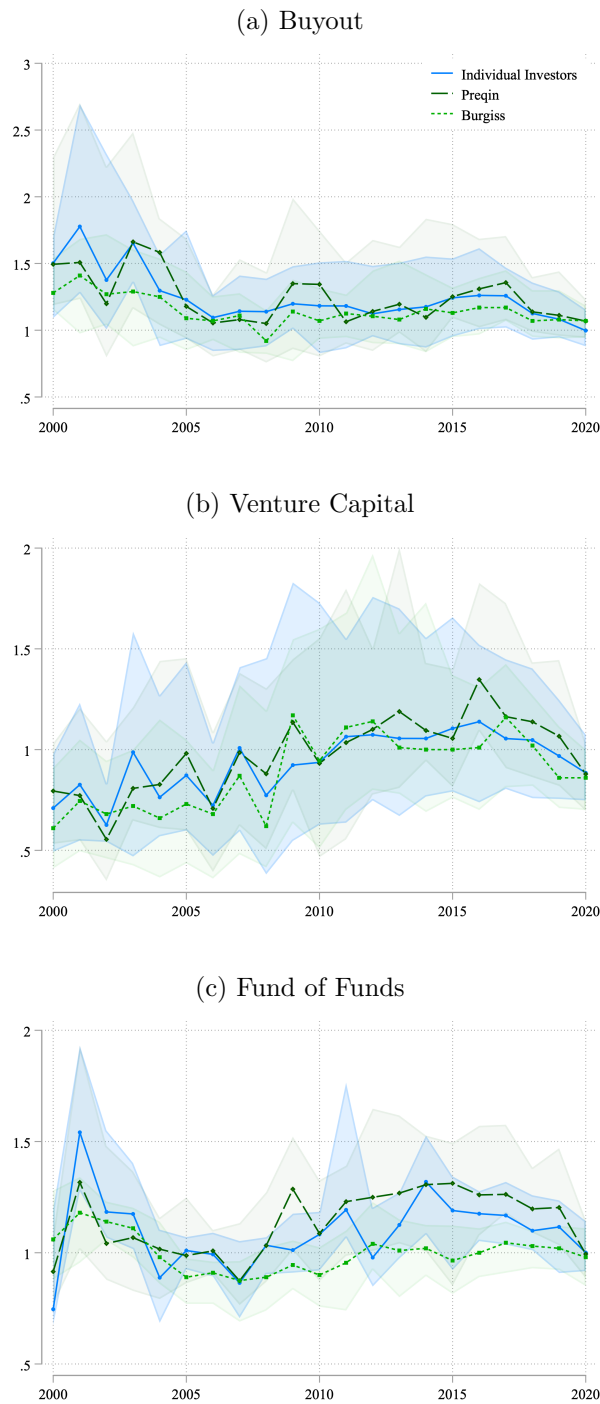
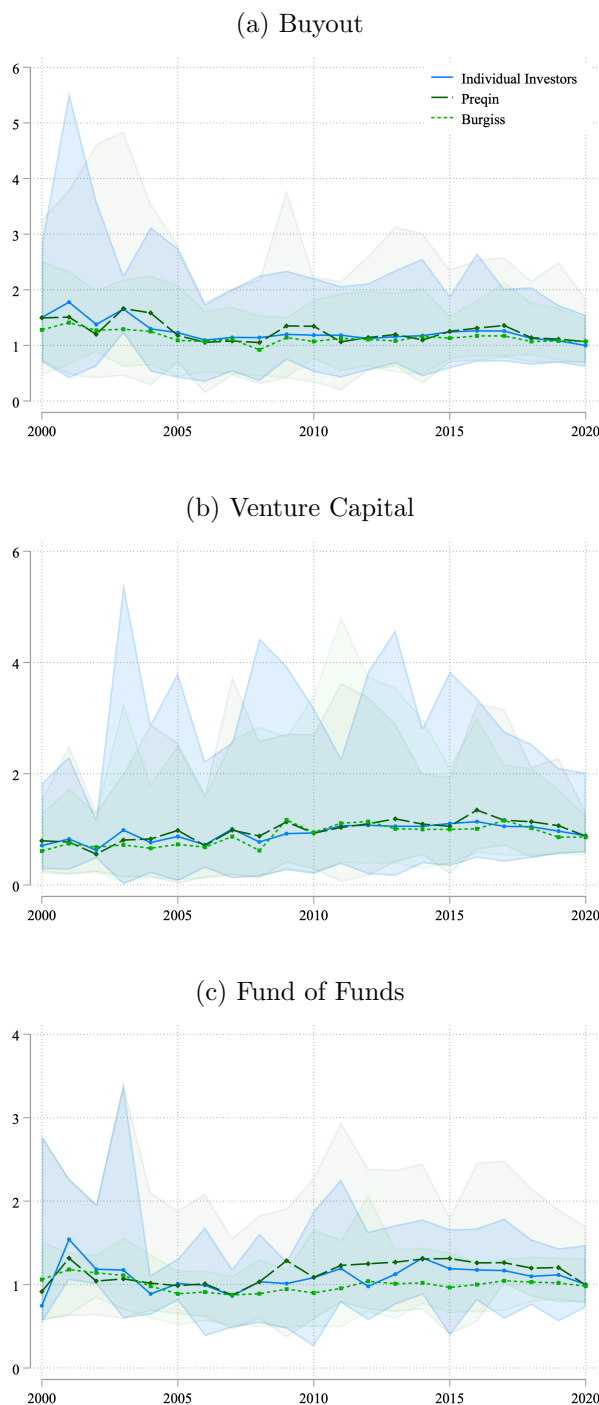


Figure C9. Comparison of Performance Metrics to Institutional Investors: PME 5th and 95th percentiles

This figure compares the performance of private equity investments across individual investors, MSCI-Burgiss, 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.

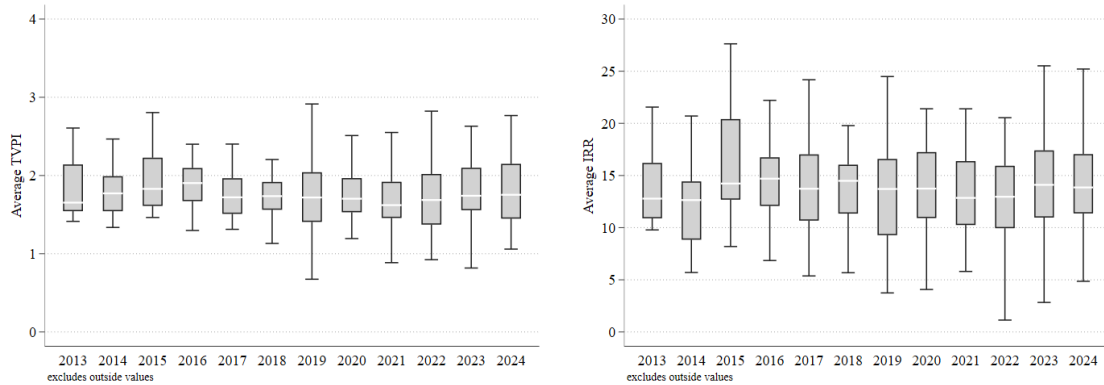


iv. Performance by Year of Joining

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 C10. 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.



v. Robustness: Median Wealth Investors

Table C8. Excess Performance of Median Wealth Individual Investors

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-Burgiss 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-Burgiss. *, **, *** 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	1.75	1.81	1.66	2.13	2.00	1.71	1.64
Excess TVPI _{Preqin}	0.08***	0.08***	-0.07***	-0.05***	0.28***	0.42***	-0.12***	-0.05**
Excess TVPI _{MSCI-Burgiss}	0.03	0.04*	0.02	-0.08***	0.01	0.16***	0.11***	0.06**
Observations	2,518		939		1,144		435	
Panel B: IRR								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
IRR	14.0	14.8	16.4	15.9	12.5	14.4	12.9	13.8
Excess IRR _{Preqin}	-3.3***	-2.0*	-2.5***	-0.9	-3.7***	-0.5	-3.7***	-4.3***
Excess IRR _{MSCI-Burgiss}	-1.2**	0.1	0.1	-0.3	-2.8***	1.0	0.2	-0.1
Observations	2,513		938		1,141		434	
Panel C: PME								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
PME	1.22	1.16	1.23	1.17	1.27	1.30	1.09	1.06
Excess PME _{Preqin}	-0.04**	-0.06***	-0.12***	-0.12***	0.07*	0.18***	-0.16***	-0.19***
Excess PME _{MSCI-Burgiss}	0.13***	0.12***	0.12***	0.07***	0.14***	0.25***	0.10***	0.06***
Observations	2,366		888		1,087		391	

vi. Robustness: Early Vintages

Table C9. Excess Performance of Individual Investors, 2000-2015

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-Burgiss 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-Burgiss. *, **, *** 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	1.94	1.82	2.39	3.05	1.89	1.85
Excess TVPI _{Preqin}	0.11***	0.23***	-0.09***	-0.09***	0.37***	1.03***	-0.06	0.01
Excess TVPI _{MSCI-Burgiss}	-0.01	0.12***	0.05*	-0.04*	-0.19**	0.39***	0.23***	0.19***
Observations	2,161		839		896		426	
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	10.2	16.6	11.5	11.6
Excess IRR _{Preqin}	-0.5	0.1	-0.9	-1.3**	0.3	4.5***	-1.4***	-1.8***
Excess IRR _{MSCI-Burgiss}	-2.1***	-0.5	-0.3	-1.2	-5.2***	0.0	0.7	0.6
Observations	2,144		836		885		423	
Panel C: PME								
	All funds		Buyout		Venture Capital		Fund of Funds	
	EW	VW	EW	VW	EW	VW	EW	VW
PME	1.26	1.29	1.29	1.18	1.28	1.65	1.13	1.09
Excess PME _{Preqin}	-0.01	0.02	-0.09***	-0.17***	0.10**	0.46***	-0.10***	-0.08***
Excess PME _{MSCI-Burgiss}	0.11***	0.17***	0.15***	0.06***	0.05	0.40***	0.16***	0.12***
Observations	1,864		739		790		335	

vii. Robustness: Sub-strategies

Table C10. PME of Individual Investors by Sub-strategy

This table presents summary statistics of PME for funds closed between 2000 and 2020, by substrategy. PME is the [Kaplan and Schoar \(2005\)](#) public market equivalent, calculated using the CRSP value-weighted index as the benchmark index.

Panel A: Buyout								
	Mean	Std.Dev.	p1	p25	p50	p75	p99	<i>N</i>
Buyout	1.21	0.48	0.41	0.93	1.14	1.37	2.92	891
Growth	1.12	0.71	0.11	0.81	1.02	1.27	3.22	434
Balanced	1.13	0.35	0.33	0.99	1.13	1.30	2.04	32
Panel B: Venture Capital								
	Mean	Std.Dev.	p1	p25	p50	p75	p99	<i>N</i>
Venture (General)	1.17	0.96	0.12	0.70	0.95	1.31	4.82	700
Early Stage	1.18	1.21	0.13	0.69	0.93	1.28	6.76	697
Early Stage: Seed	1.23	1.20	0.10	0.72	0.95	1.39	4.51	256
Early Stage: Startup	1.21	0.97	0.18	0.73	0.98	1.36	6.01	126
Expansion / Late Stage	1.09	1.07	0.17	0.64	0.88	1.20	3.85	141
Panel C: Fund of Funds								
	Mean	Std.Dev.	p1	p25	p50	p75	p99	<i>N</i>
Funds of Funds	1.06	0.31	0.36	0.89	1.03	1.21	1.91	380
Secondaries	1.09	0.21	0.70	0.97	1.06	1.18	1.76	120
Direct Secondaries	0.91	0.38	0.15	0.73	0.89	1.27	1.54	23

Table C11. Investor Wealth and Fund Performance: Robustness within Substrategies

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

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

$PME_{i(j)}$ is the medium beta PME of fund i held by investor j , which is based on asset-class-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 sub-strategy s , vintage t , and advisor k . In Panel A, the samples consist of all investor-fund observations over 2000-2020 vintages. In Panel B, the samples consist of first funds of a firm (column 1), funds with minimum commitment below \$1 m (column 2), investments with less than \$0.1 million in committed capital (column 3), funds that are not oversubscribed (column 4), and funds with (column 6) and without (column 5) performance data in Preqin. 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.: PME					
Fund category	All Funds	All Funds	Buyout	VC	Funds of Funds	All Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Group						
<3m	-0.0873*** (0.0236)	-0.0612*** (0.0163)	-0.0138 (0.0197)	-0.117*** (0.0354)	-0.0579*** (0.0191)	-0.0192* (0.0116)
3–10m	-0.0509*** (0.0181)	-0.0354*** (0.0137)	0.0116 (0.0201)	-0.0698** (0.0293)	-0.0535*** (0.0158)	-0.0122 (0.0105)
10–30m	-0.0305** (0.0135)	-0.0286** (0.0116)	0.00368 (0.0147)	-0.0545** (0.0238)	-0.0390*** (0.0129)	-0.00210 (0.00886)
30–100m	-0.0169 (0.0115)	-0.0183* (0.00970)	0.0137 (0.0124)	-0.0415** (0.0186)	-0.0331*** (0.0102)	-0.00885 (0.00642)
Constant	1.139*** (0.0170)	1.136*** (0.0122)	1.210*** (0.0131)	1.103*** (0.0259)	1.059*** (0.0156)	1.123*** (0.0102)
Sub-strategy × vintage FE	No	Yes	Yes	Yes	Yes	Yes
Advisor FE	No	No	No	No	No	Yes
Observations	64736	64732	25244	25779	13709	64674
R^2	0.003	0.213	0.157	0.201	0.277	0.274

viii. Variation Associated with LP Tiers

Table C12. 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 2 and 3 include the sample of investors for whom we do not observe any access fee charge. Columns 4 and 5 include the sample of investors with access fee charges. We use the constant plus the coefficient on wealth group j from Column 2 as our estimate of performance drag associated with LP Tiers, $\hat{f}_{m(j)}^{Tier}$, in Section 5.

	Dep. Var.: Excess PME			
	(1)	(2)	(3)	(4)
	No Access Fee		Has Access Fee	
3–10m	0.03 (0.02)	0.03 (0.03)	0.04* (0.02)	0.03 (0.02)
10–30m	0.02 (0.02)	0.03 (0.02)	0.01 (0.01)	0.01 (0.01)
30–100m	0.03* (0.02)	0.03 (0.02)	0.00 (0.01)	-0.01 (0.01)
>100m	0.04** (0.02)	0.05** (0.03)	0.00 (0.01)	-0.01 (0.01)
Constant	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.01)	-0.00 (0.01)
Fund FE	Yes	No	Yes	No
Fund \times Advisor FE	No	Yes	No	Yes
Observations	19,826	16,494	5,710	5,090
R^2	0.25	0.38	0.89	0.91