Private Credit at Scale: Evidence from US Regulatory Data*

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Abstract

Using confidential regulatory data, we assemble a comprehensive view of the U.S. corporate private credit fund market. We document five novel facts about the industry: (i) it is larger than commonly reported estimates; (ii) dry powder has remained over 60% in the past decade; (iii) fund-level leverage is minimal; (iv) concentration is lower than in the banking sector; and (v) larger advisers are less specialized in private credit and deploy significantly less capital. Our central finding is that private credit fund performance declines with adviser size. We link this relationship to rapid capital inflows and scope diseconomies introducing deployment frictions at large advisers.
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1 Introduction

The private credit market has experienced remarkable growth over the past decade, becoming an increasingly important source of debt financing for private middle market firms. Growth has occurred not only through the expansion of pure-play private credit firms, but also through the entry by large, multi-product asset managers historically associated with private equity and other alternative asset classes. Prior research shows that private credit relies heavily on information-intensive lending technologies (Jang, Kim and Sufi, 2025). Consequently, it is an open empirical question whether, and how, such technologies can scale as private credit providers grow in size and organizational complexity, without compromising value creation.

Answering these questions has been difficult because the private credit market remains highly opaque. According to commercial data sources, it reached nearly $1.7 trillion in North America as of 2024. Yet the actual size of the market and other key aspects of the market, such as dry powder, leverage, concentration, and performance, are still poorly understood. Much of the available information is inferred from indirect or imprecise sources, and adviser-level metrics are particularly difficult to observe, as existing data sources rely on reporting by limited partners who may not invest in all funds managed by a given adviser.

This paper leverages a confidential dataset that provides the most comprehensive view on the U.S. private credit fund market. Specifically, the SEC Form PF requires standardized, fund-level disclosures from all U.S. investment advisers with at least $150 million in private fund assets. We assemble the universe of Form PF filings from 2013 through 2025 and build a harmonized panel of private credit funds that includes balance sheet detail, financing, and performance. The data provide a near-census of private credit funds rather than the opt-in coverage of commercial products. This allows for internally consistent aggregation, which is essential to quantify their macro-financial footprint and enable proper estimates of the market structure of the U.S. corporate private credit industry. It also allows us to directly evaluate performance for the broader universe of private credit funds, complementing survey evidence (Block, Jang, Kaplan and Schulze, 2024) and existing studies focusing on subsets of private credit funds (Erel, Flanagan and Weisbach, 2024) or business development companies (BDCs) (Suhonen, 2024).

From this data, we begin by documenting five novel facts about the U.S. private credit fund industry. First, we estimate the total size of U.S. corporate private credit funds to be larger than previously thought. Based on our regulatory data, the total gross assets under management (AUM)

for corporate private credit funds are estimated at approximately $1.38 trillion as of 2024. This exceeds Preqin's estimate of $1.24 trillion for North American private credit funds, which also include non-corporate private credit funds; therefore, the true difference is likely even greater. When combined with business development companies (BDCs), we estimate that the total size of the U.S. corporate private credit industry is at least $1.95 trillion as of the first half of 2025.

Second, the amount of unutilized capital commitments, or dry powder, is even more grossly underestimated by commercial sources, and importantly, has remained over 60% of total raised capital in the past decade. Estimates based upon the regulatory data indicate that the total amount of dry powder as of 2024 is $0.86 trillion.[1] Third, fund-level leverage is minimal. 73% of funds use no leverage, and the equal-weighted average leverage is 9.4% of total gross assets, corresponding to 13.4% of deployed capital. These levels are lower than the survey estimates in Block et al. (2024) – mean (median) leverage of 40% (25%) – and well below the 50-60% leverage typical of BDCs.

Fourth, the private credit industry lacks the same degree of concentration as the banking industry. Despite rapid aggregate growth, it is not dominated by a handful of large advisers. In 2024, the top five advisers account for only 23% based on aggregate private credit AUM. In contrast, a comparable calculation for the banking industry is 37% based on aggregate bank commercial and industrial loans. Fifth, and lastly, advisers exhibit significant heterogeneity in fundraising, deployment, specialization, and returns across the size distribution. Despite the modest concentration, larger adviser fundraising have outpaced small advisers on a per-adviser basis. However, they are less specialized in private credit, deploy a significantly smaller share of committed capital, and ultimately earn lower returns. Funds at the very largest advisers earn 9.7% IRR on a gross basis, compared with 14.2% at smaller advisers, and the gap persists on a net basis.

Altogether, these facts provide an important snapshot of the private credit industry and point to adviser scale as a first-order consideration for understanding heterogeneity in capital deployment and performance. Despite substantial growth, the private credit industry remains far from fully intermediating the capital it has raised, and scale does not appear to confer a competitive advantage in this business. While large advisers can raise substantial capital, they appear to face meaningful frictions in converting that scale into profitable investment opportunities.

[1]The difference between regulatory and commercial estimates is economically large, on the order of $510 billion. For context, this figure is comparable to the entire authorized capacity of the Main Street Lending Program and roughly one-fifth of commercial and industrial loans on bank balance sheets. This re-sizing alters the denominator for policy, changing how we benchmark the sector against other credit markets and how we assess its potential to propagate or absorb macro shocks.

To examine this more definitively, we turn to regression analyses and establish a robust, negative relationship between adviser size and future fund returns. This relationship holds after controlling for fund size, leverage, and deployment rate, as well as fund life-cycle dynamics and risk heterogeneity across strategies using fund vintage-by-year and fund strategy-by-year fixed effects. While we refrain from interpreting the results as causal, this pattern fits the equilibrium intuition of decreasing returns in active management at the industry level (Pástor et al., 2015) and mirrors organizational diseconomies in private markets and hedge funds (Teo, 2012; Lopez-de Silanes et al., 2015; Yin, 2016; Bhardwaj et al., 2025)).

Next, we formally test two mechanisms behind adviser-level diseconomies of scale. First, rapid capital inflows may outpace deployment capacity. That is, large advisers may be able to attract capital from investors faster than they can identify appropriate investment opportunities. The general opaqueness of the private fund markets may allow advisers to better "lock-in" investors despite relatively weaker performance. Consistently, we find that league-table ranks based on past private credit fundraising are strongly predictive of subsequent fundraising, and large prior-year fundraising is associated with lower subsequent fund returns.

Second, smaller, more specialized advisers may operate with higher deployment capacity. Larger advisers often manage multiple strategies, such as private equity and hedge funds, alongside private credit. While broader product offerings may facilitate cross-selling and reduce fundraising frictions, lack of specialization may weaken sourcing networks and repeat-borrower relationships central to the information-intensive lending technologies in private credit (Jang et al., 2025).

Supporting this hypothesis, we find that non-private credit AUM exhibits a negative relationship with future private credit fund performance of similar magnitude to that of private credit AUM. This pattern implies that private credit specialists experience less underperformance than diversified advisers with comparable private credit AUM. Furthermore, the aforementioned negative relationship between prior-year fundraising and subsequent fund returns is concentrated when private-credit fundraising coincides with fundraising in other strategies, suggesting that cross-selling ultimately depresses returns. We also find a negative relationship between prior-year fundraising and subsequent fund deployment rates, driven entirely by fundraising in non-private-credit asset classes, indicating that the resulting lack of specialization could hinder advisers' ability to build and sustain deal sourcing networks. Hence, when advisers stretch to deploy capital, marginal deals would be of lower quality, helping to explain why smaller, focused advisers earn higher returns.

Related Literature. Our findings relate directly to and extend the recent literature studying private credit fund performance. Previous studies have shown that private credit funds and BDCs have outperformed leveraged loans and high-yield bond markets (Munday, Hu, True and Zhang, 2018; Boni and Manigart, 2023; Suhonen, 2024). Erel, Flanagan and Weisbach (2024) highlight the importance of appropriate factor benchmarks and discounting conventions, and find that private credit funds generate positive gross-of-fee alphas but not net-of-fee alphas once equity risk factors are accounted for. This literature is primarily concerned with asset allocation by investors (i.e. limited partners) between public and private markets and therefore focuses on net returns and risk adjustments across asset classes. In contrast, we study within-class, cross-sectional heterogeneity in gross returns across investment advisers (i.e. general partner firms) and document diseconomies of scale and scope in private credit.[2] Our adviser level tests are feasible only with comprehensive regulatory data, whereas traditional datasets rely on limited partner reporting that may not capture the full set of funds at the adviser level.

Our results contrast with those observed in other types of investment funds, notably open-ended mutual funds. Several institutional differences are particularly relevant for interpreting these facts. In open-ended mutual funds, daily liquidity and public security holdings allow capital to flow toward managers with higher expected ability, until decreasing returns eliminate abnormal performance (Berk and Green, 2004). In contrast, private credit vehicles are typically closed-ended, with capital drawn at the adviser's discretion over multi-year periods. This structure reflects the negotiated and illiquid nature of private credit positions, and the reliance on appraisal-based valuations (Jang and Kim, 2025). Consequently, flow-based dilution of alpha is slower and is mediated by fundraising cycles and investment periods rather than daily flows. For this reason, the private equity literature provides a closer analogue: performance dispersion is wide, adviser level performance exhibits persistence, flows respond concavely to past success, and organizational scale can undermine execution quality (Kaplan and Schoar, 2005; Robinson and Sensoy, 2016; Lopez-de Silanes, Phalippou and Gottschalg, 2015; Braun, Dorau, Jenkinson and Urban, 2025; Bhardwaj, Gupta, Howell and Zimmerschied, 2025).

Within the broader financial intermediation landscape, our measurement and structural evidence reinforce the view that private credit has grown to become a significant pillar of the financial system.

[2]Higher returns among smaller advisers may reflect compensation for greater risk. While deal-level data would allow for more precise adjustments, we attempt to mitigate risk differences using strategy-time fixed effects, the most granular information available at the fund level.

One strand of research emphasizes the role of bank regulation as a driver of private credit growth (Chernenko, Erel and Prilmeier, 2022; Davydiuk et al., 2024a; Block, Jang, Kaplan and Schulze, 2024), and the resulting interplay between banks and private credit (Haque, Mayer and Stefanescu, 2025a; Chernenko, Ialenti and Scharfstein, 2025; Haque, Jang and Wang, 2025b). A second strand focuses on features of private credit as potential levers for value creation. Jang (2025) highlights covenant-based monitoring, while Jang, Kim and Sufi (2025) emphasize industry specialization and blanket liens as key dimensions of the direct lending strategy within private credit. Rintamäki and Steffen (2025) and Ivashina (2025) document private credit's flexibility in providing payment deferrals, and Erel, Flanagan and Weisbach (2024); Davydiuk, Erel, Jiang and Marchuk (2024b); Robinson and Wallskog (2025) underscore the blending of equity-like features into contract design. Our study relates to the latter studies by focusing on the role of organizational scope at the adviser level and highlighting performance tradeoffs associated with the one-stop-shop nature of large, diversified advisers.

Finally, our findings on private credit fund leverage contribute to the ongoing debate on the financial stability implications of private credit (Federal Reserve Board, 2023; International Monetary Fund, 2024; Chernenko et al., 2025; Jang and Rosen, 2025; Ivashina, 2025; Berrospide et al., 2025; Levin and Malfroy-Camine, 2025). While using different approaches, these studies broadly agree that any financial fragility associated with private credit is unlikely to arise through the leverage-driven contagion of failures historically observed in banking. Existing evidence relies on publicly available estimates of BDC leverage, typically 50-60% of total capital, and survey-based estimates of private credit fund leverage of 20-40% (Block et al., 2024). In contrast, we find that 73% of funds employ no leverage, and only 3.9% use leverage exceeding 50% of gross assets. Given that survey respondents tend to be larger direct lenders and that BDCs account for at most 30% of the industry, our results suggest that the broader private credit industry is even less levered than previously believed.

The remainder of the paper is organized as follows. Section 2 provides an overview of the regulatory data. Section 3 establishes and discusses five novel facts about the private credit fund industry. Section 4 presents the main findings on private credit fund performance and the underlying mechanisms. Section 5 concludes.

2 Data

2.1 Sample Construction

For our analysis, we draw on confidential regulatory filings from SEC Form PF, established under the Dodd-Frank Act and jointly adopted by the SEC and CFTC in 2011. Form PF must be filed by SEC-registered advisers that manage one or more private funds and have at least $150 million in private-fund regulatory AUM. The form covers a broad universe of private funds and reports detailed information on assets and leverage, portfolio and financing exposures, liquidity, investor and counterparty concentrations, and rates of return, with more granular and more frequent reporting for large advisers. The procedures from Kim and Sorensen (2025) are used to clean the data. Recent academic studies that use Form PF have focused primarily on hedge funds and market-wide risk monitoring, not on private credit.

A key limitation of the data is taxonomic: the regulatory fund-type field within the form is limited and does not include a "private credit" category. Instead, funds are labeled under pre-specified, broader rubrics (i.e., hedge funds, private equity funds, real estate funds, venture capital funds, asset securitization funds, liquidity funds). Commonly employed approaches to surmount this issue includes matching with commercial data sources where private credit funds self-report their identities. Other approaches use keywords in fund names or descriptions. However, this approach can generate false positives, especially when names or marketing language are ambiguous about underlying strategy.

This paper adopts a conservative strategy aimed at estimating a greatest lower bound for identifying private-credit funds within the regulatory data. The strategy involves two approaches. First, we use self-reported fund information from Preqin and PitchBook. Because our focus is corporate private credit, we exclude funds that primarily target infrastructure or real estate. For these funds, we hand-match identities to reduce classification error. Manual matching is essential as the regulatory data oftentimes lists different sleeves of the same fund separately, so that automated matching is not possible. Another important note is that not all funds identified in commercial data sources can be matched to the regulatory data. Form PF is required only of SEC-registered advisers with a U.S. filing obligation, so vehicles without such an obligation will not appear in the regulatory sample.

Second, we collect web "snippets" associated with each fund name in the regulatory data. Given

confidentiality issues, we rely on fund identities from Form ADV for this exercise, as the data is publicly accessible via the SEC's IAPD and, in practice, provides a broader set of seed identifiers than Form PF. These snippets reflect information from the adviser website or other sources that may include details related to the fund's investment strategy. Once collected, we analyze the web snippets and infer the fund type. Importantly, we only use information in the snippet content alone and not infer from the fund or adviser name alone. When coded, we return no classification if there is insufficient information. In this way, the procedure is conservative by design. We assess accuracy by randomly sampling 100 funds and manually verifying match quality. We are able to confirm that all funds flagged as private credit are correctly classified.

We take a similar approach in identifying each private credit fund's strategy type. We begin by using the self-reported fund strategy types from commercial data sources, where available. For the remaining funds, we utilize only the information in the web snippets to sort funds into the following fund strategies: asset-backed lending, co-investment, direct lending, distressed debt, fund of funds, hybrid, mezzanine debt, secondaries, special situations, specialty finance, and venture debt. Again, we take a conservative approach and categorize the fund strategy only if there is sufficient information is available in the web snippets. Those with insufficient information are classified as having "other" fund strategy. The percentage of funds that are classified with the "other" strategy following both of these approaches is approximately 3.1 percent.

Another limitation of the regulatory data concerns adviser identification. The data is structured where the adviser information is restricted to the CRD/SEC file number. The limitation is that larger advisers often use multiple CRD numbers. One potential approach is to use the related person information. However, this approach is regarded to be inappropriate given that related persons listed in the form in many cases involve individuals or entities that are unrelated to the adviser. In order to properly group common CRD numbers, we use an approach developed in Kim and Sorensen (2025). Specifically, we use the domain of the email addresses for the individual filer. In manual checks, we find that this approach is quite effective in identifying the adviser and minimizes false positive matches.

Table 1 displays summary statistics along with variable descriptions of the variables used in the analysis.

2.2 Comparison with Existing Studies

Before proceeding with our analyses, we compare the distribution of private credit strategies and fund returns with those reported in existing studies that rely on the MSCI-Burgiss database, which is widely regarded as the state-of-the-art source for studying private capital fund returns (Erel et al., 2024; Brown et al., 2025).

As shown in Table 1, the fractions of our sample that can be classified under direct lending, distressed debt, mezzanine debt, and special situations are 35.2%, 16.0%, 15.2%, and 20.7%, respectively. In comparison, the U.S. private credit fund sample in Brown et al. (2025) reports 22.1% of funds as "Generalist," 14.4% as "Senior," 27.9% as "'Mezzanine," and 25.4% as "Distressed." Their data do not separately report direct lending or special situations. If we broadly classify "Generalist" and "Senior" funds as direct lending and treat special situations as part of the distressed category, the comparison is as follows: direct lending 35.2% versus 36.5%, distressed/special situations 36.7% versus 25.4%, and mezzanine 15.2% versus 27.9%. While Brown et al. (2025) include 18% non-US funds and cover 2002–2019 (versus our 2013–2025 sample), these results suggest that the samples are broadly comparable.

Next, we turn to fund annual returns. Table 2 summarizes the distribution of internal rates of return (IRR) on a gross basis (Panel A) and a net basis (Panel B). To mitigate the influence of extreme values-some of which likely reflect data-entry or reporting anomalies, we winsorize all IRRs at the 1st and 99th percentiles.

The sample mean is broadly comparable to estimates based on the MSCI–Burgiss cash-flow series for an earlier period in Erel et al. (2024), which analyzes private credit performance from 1992 to 2015. As shown in Table 1, our mean gross IRR is 11.9% and mean net IRR is 8.9%, compared to 8.6% net IRR reported in Erel et al. (2024).

More striking than the level, however, is the heterogeneity across funds. On a gross basis, 11.7% of funds report a loss year, while 10.4% do so on a net basis. At the other extreme, 16.8% of funds post gross IRRs above 20% and 26.0% post net IRRs above 20%, highlighting a fat-tailed and highly dispersed return distribution.

Table 4 reports returns by years-since-inception. Consistent with a seasoning dynamic, performance rises in the first several years after inception, when deployment and fee ramps are most pronounced, and then declines as portfolios season, loans amortize or refinance, and capital is returned to limited partners. This pattern mirrors institutional narratives about early-life leverage

and origination intensity followed by gradual de-risking (Jang, 2025) and accords with theories of cash-flow-based lending in which information production and monitoring front-load value creation (Hartman-Glaser et al., 2025).

3 Novel Facts

In this section, we establish five novel facts about US corporate private credit funds.

Fact 1: Industry is larger than implied by commercial sources.

We start by aggregating the data to properly size the U.S. corporate private credit fund industry. Figure 1 displays gross AUM constructed from the filings, showing that the private credit fund sector has grown substantially since 2013. The total gross assets under management reach approximately $1.38 trillion as of 2024, up from $0.36 trillion in 2013, an increase of 347.5%. While the 2025 filing cycle is still incomplete as of the time of writing, the partial data imply gross AUM of $1.52 trillion for 2025. For comparison, Preqin reports total gross AUM of $1.24 trillion for North American funds in 2024. This figure includes non-corporate private credit funds, so that the figures are not necessarily directly comparable. Additionally, because commercial providers extrapolate from proprietary samples and may include vehicles not marketed to U.S. investors, whereas the regulatory filings cover U.S.-registered advisers at the fund level, such differences in levels are expected.

To bound the investable private credit universe, we append the officially reported assets of U.S. business development companies (BDCs) to our regulatory-based fund total. As of year-end 2024, public and non-traded BDC assets were on the order of $430-$440 billion (e.g., $418.5 billion in total fair value across public and private BDC portfolios in 4Q24; industry tallies citing roughly $434 billion are consistent with this range). Together with our estimates, the total size of the US corporate private credit industry tallies at $1.95 trillion. At this scale, private credit stands shoulder-to-shoulder with other large corporate credit markets: the broadly syndicated loan market carried roughly $1.4 trillion in par outstanding at end-2024 (with estimates clustering around $1.40 - $1.42 trillion), and the U.S. high-yield bond market's free-float market value was about $1.34 trillion on December 31, 2024.

Fact 2: Dry powder level has remained over 60% in the past decade.

The gross AUM series decomposes into deployed and undeployed capital. We compute undeployed capital ("dry powder") directly from the filings as the difference between gross regulatory AUM and the aggregation of funds' reported asset values (including Level-1/2/3 marks and cost-basis valuations). This measure is suggestive about the forward supply of credit from private credit funds. In particular, the larger the overhang, the more immediate capacity funds have to originate and hold new loans.

As shown in Figure 1, the fraction of dry powder relative to total committed capital has exceeded 60% since 2016, reached nearly 70% by 2021, and has declined slightly to 61% as of 2025. Such high levels of dry powder imply that, despite an estimated near $2 trillion in AUM, the actual capital deployed to investments amounts to only $0.9 trillion (roughly $500 billion by private credit funds in the regulatory data and $400 billion by BDCs[3]). This suggests that, despite substantial growth, the private credit industry has been far from fully intermediating the capital it has raised.

Benchmarking again our dry-powder series against commonly cited commercial estimates, we find an even larger discrepancy of about $510 billion: Preqin places US dry powder at approximately $0.35 trillion as of 2024, whereas the regulatory filings imply a figure closer to $0.86 trillion. The gap is economically large. A mismeasurement of this magnitude would alter assessments of how much nonbank balance-sheet capacity is available to middle-market borrowers and, by extension, how sensitive aggregate credit supply is to shocks. To fix ideas, $510 billion is on the order of the headline authorization sizes for major crisis-era credit facilities and thus plausibly large enough to shift conclusions about whether nonbank lenders amplify or dampen credit cycles (Elliott et al., 2024). Understating the sector by this amount risks biasing macro-finance narratives about the sources of corporate credit and the channels through which monetary policy and financial conditions transmit to the real economy (Chernenko et al., 2022; Avalos et al., 2025).

While some discrepancy is unsurprising given that commercial providers infer totals from non-public samples, the magnitude is. If dry powder is materially larger than widely believed, then private credit funds have more slack capacity to extend loans than practitioners and policymakers may have assumed. That, in turn, may affect deal pricing, borrower access, and the macro transmission of credit. Specifically, a larger overhang can smooth lending during periods of bank retrenchment but can also spur more aggressive terms and thinner spreads when competition for

[3]BDCs hold minimal cash for tax treatment purposes. For more information about BDCs, see Davydiuk et al. (2024a).

deals is acute (Aldasoro et al., 2024; Chernenko et al., 2022; Avalos et al., 2025). Put differently, accurate measurement of undeployed capital is not just an accounting refinement; it is important for evaluating private credit's role in bridging funding gaps, substituting for bank credit, and shaping risk in the broader corporate credit universe (Davydiuk et al., 2024a; Boyarchenko and Elias, 2024; Darmouni and Papoutsi, 2024).

Fact 3: Use of leverage is minimal.

We now turn to fund use of leverage. Shown in Table 3, 73% of the funds employing zero leverage and only 3.9% of the funds use more than 50% of leverage over total gross assets. Shown in Table 1 Panel B, the equal-weighted average fund-level leverage is 9.4% of total gross assets. Given an equal-weighted average utilization rate of 61%, this corresponds to a leverage ratio of 13.35% (= 0.094 / (0.61 + 0.094)) relative to total deployed capital.

These estimates are substantially lower than survey results reported in Block et al. (2024), where U.S. private credit funds report mean (median) leverage of 40% (25%) of deployed capital, and they stand in sharp contrast to the 50-60% leverage typically observed among BDCs. Because survey respondents tend to be larger direct lenders and BDCs account for at most 30% of the industry, our results suggest that the overall private credit industry is even less levered than previously believed.

Fact 4: Industry is less concentrated than the banking industry.

We next characterize the market structure and concentration of private credit funds. Estimates of industry market structure based upon commercial datasets are likely to be measured with error. Private credit funds differentially select into these data sources for a variety of reasons, and can result in both overweighting of smaller and larger advisers, making the net effect unclear. The regulatory data mitigate these selection issues and allows us to directly evaluate concentration at the adviser-level.

Table 5 reports concentration statistics as of end-2024, grouping advisers by aggregate private-credit AUM into large (Top 5), medium (Next 20), and small (Rest). Sorting by total private-fund AUM yields qualitatively similar patterns. Despite the rapid expansion of the sector, growth is not dominated by a handful of incumbents: the Top 5 advisers account for only 22.9% of AUM, while the long tail of smaller advisers accounts for 44.5%. In contrast, top 5 banks represent 37% of the market based on aggregate bank commercial and industrial loans.

Figure 2 tracks concentration over the full sample. Concentration declines over the past decade, reflecting broadened entry into direct lending by new advisers and the diffusion of private credit beyond early incumbents. Taken together with Table 2, the time-series and cross-section evidence point to an industry whose aggregate growth has been relatively unconcentrated, with persistent capacity additions outside the top tier of advisers.

Fact 5: Larger advisers raise faster, deploy less, specialize less, and earn less.

Lastly, we examine heterogeneity in fundraising, deployment, specialization, and returns across the adviser size distribution.

Fundraising. Figure 3 plots new fund issuance along with a breakdown by adviser-size group over time. Figure 4 displays the average adviser-level fundraising by adviser size cohorts. Despite the relatively lower overall share of aggregate AUM, the largest advisers have outpaced the other adviser size groupings in fundraising. Regardless, the figures indicate that the aggregate trends are not an artifact of a single vintage or a transient wave of "mega-funds," but reflects a sustained pattern in which entry and fundraising scale across the distribution.

Deployment. The picture reverses when we turn to deployment. Shown in Table 5, utilization rates – i.e. deployed assets relative to gross committed capital – are substantially lower for large advisers than for smaller ones. The top 25 advisers, by total AUM, deploy an average of around 24% of their raised capital, whereas the remaining advisers deploy an average of 53%. Figure 5 Panel A plots a binscatter of utilization rates against adviser size quintiles, illustrating the same negative, monotonic relationship.

Specialization. Figure 5 Panel B plots a binscatter of adviser-level specialization in private credit (measured by AUM allocation) against adviser size quintiles and reveals a negative association. Although this relationship is not strictly monotonic, advisers in the largest size quintile allocate 37.7% of assets to private credit, compared with 44.8% for advisers in the smallest size quintile.

Performance. Lastly, we examine how performance varies with adviser scale. We find a systematic size gradient: funds affiliated with larger advisers underperform those affiliated with smaller advisers. Figure 5 Panels C and D report results for the full sample using the same size groupings

based upon quintile rankings. The average fund IRR for largest advisers equals 9.7% gross and 7.7% net, whereas the average for small advisers equals 14.2% gross and 10.3% net.

Table 6 conditions on years-since-inception and re-estimates performance by adviser size. The small-minus-large performance differences remain economically and statistically meaningful on both a gross and net basis, indicating that the size gradient is not merely an artifact of age composition. These results show that adviser size has explanatory power within comparable points in the fund life cycle.

Taking Stock

The facts presented in this section provide an important snapshot of the private credit industry and point to adviser scale as a key dimension explaining heterogeneity in fund deployment patterns and returns. Despite substantial growth, the private credit industry has been far from fully intermediating the capital it has raised. Importantly, scale does not appear to confer a competitive advantage in this business. Although large advisers are able to raise substantial capital, they appear to face meaningful frictions in deploying it into profitable investments.

One potential driver is that rapid fundraising inflows at the largest complexes temporarily outpace deal flow. The combination of faster fundraising and lower utilization observed among these large advisers is consistent with intensified competition for scarce opportunities that constrains scalable deployment. This could arise due to a higher option value of waiting for larger funds or intensifying competition for scarce opportunities that make it difficult to scale investments. These dynamics may also relate to "money-chasing-deals" effects and recent evidence on private credit performance over fundraising cycles (Gompers and Lerner, 2000).

Another possibility is that smaller, more specialized advisers achieve higher deployment efficiency. Specialization may lead to deeper sourcing pipelines and fewer internal capital-allocation frictions, thereby shortening screening horizons and accelerating origination. This pattern is consistent with classic diseconomies of scale in active investing (Berk and Green, 2004; Pástor et al., 2015) and with evidence that smaller private-market vehicles can deploy capital more nimbly (Kaplan and Schoar, 2005; Lopez-de Silanes et al., 2015; Bhardwaj et al., 2025).

We investigate these questions more systematically using regression analyses in the next section.

4 Regression Analysis

In this section, we use regression analyses to characterize the relationship between adviser size and private credit fund performance. We then explore two potential mechanisms underlying this relationship: rapid capital inflows and scope-related diseconomies that introduce deployment frictions at large advisers.

4.1 Diseconomies of Scale

We employ the following regression specification to examine the relationship between subsequent fund performance and adviser size for fund i, adviser j, and sample year t:

$$\text{IRR}_{i,j,t+1} = \beta_0 + \beta_1 \ln\big(1 + \text{Adviser AUM}_{j,t}\big) + \beta_2 \Gamma_{i,j,t} + \phi_{i,s\times t} + \phi_{i,v\times t} + \varepsilon_{i,j,t+1}\,. \quad (1)$$

The dependent variable is the next-year gross IRR for fund i. The key regressor measures adviser size, defined as the total AUM aggregated across all funds managed by the adviser as of year t. Control variables include net fund AUM, which captures ex-ante demand and pipeline strength; leverage, which proxies for risk-taking, timing, and access to credit facilities (Boyarchenko and Elias, 2024); and utilization, a measure of deployment intensity that may compress spreads when high (Erel et al., 2024). Fund strategy type × year fixed effects absorb time-varying strategy conditions; vintage year × year fixed effects flexibly capture life-cycle dynamics in closed-end funds (Robinson and Sensoy, 2016). We report fund-clustered robust standard errors to address serial correlation and smoothed valuations typical in illiquid vehicles (Getmansky et al., 2004).

Table 7 reports the estimates. Column (1) uses total adviser AUM (excluding fund i); Columns (2) uses private-credit adviser AUM (excluding fund i); Columns (3) uses non-private-credit adviser AUM; Columns (4) includes both private-credit and non-private-credit AUM simultaneously.

Across all specifications, adviser-size measures are negative and statistically significant, consistent with adviser-level diseconomies of scale. We find similar results when replacing the dependent variable with net IRR, shown in Table A1 in the Appendix. Notably, the coefficients on private-credit and non-private-credit AUM are similar in magnitude and remain significant when included jointly. These findings suggest that scope, as much as size, drives the underperformance. We examine the role of scope in greater detail in Section 4.3.

4.2 Inflow-related Deployment Frictions

In Section 3, we documented that the largest advisers have outpaced smaller advisers in fundraising but struggled to deploy capital at the same pace. This raises a natural question: to what extent does the negative relationship between adviser scale and subsequent fund returns reflect capital inflows at large complexes that exceed origination capacity?

We first examine the extent to which larger advisers attract disproportionate flows. In opaque private markets, LPs face high evaluation costs: returns are appraisal-based, positions are illiquid, and disclosures are limited. In this environment, "league table" signals—recent fundraising volume, adviser scale, and headline deal activity—serve as sufficient statistics for GP quality in the absence of fully comparable performance records. This channel is consistent with equilibrium flow dynamics in active management and with private-markets evidence that past success and brand visibility draw follow-on capital even when true skill is hard to disentangle from scale and market cycles. Unlike public-market funds, however, there is no single, universally accepted league table in private credit; LPs often construct their own rankings from a mix of external sources and private information obtained in due diligence. Accordingly, we build a transparent, reproducible ranking from the regulatory data and use it to study the flow–rank relation.

Methodologically, we estimate annual fundraising by adviser from the regulatory filings, aggregating new private-credit vehicles and commitments raised in year t. We then form an adviser-level rank in year t based on fundraising over $t-1$ to t (our "league table"). Our primary explanatory variable is the share of new funds launched by an adviser in year t+1 relative to its existing fund count (or, in alternative specifications, new capital raised relative to lagged committed capital). By focusing on changes scaled by the adviser's own base, we capture intensive-margin expansion rather than mechanical effects of sheer size. Throughout, we allow for adviser characteristics and control for vintage composition, and we report robustness to alternative ranking windows and definitions (e.g., top-k cutoffs based on capital versus fund counts).

Table 8 presents the results. Column (1) shows that being in the Top 20 of the fundraising league table in year t is positively associated with higher fundraising in $t+1$: ranked advisers raise a larger percentage of new funds relative to their existing base. Because some calendar years are "hot" fundraising years—with broad shifts in risk appetite, bank retrenchment, or macro regimes that lift all boats (Gompers and Lerner, 2000; Robinson and Sensoy, 2016)—we include year fixed effects to absorb common shocks; the rank–flow gradient remains stable, indicating that our results

are not driven by a few exuberant vintages. Finally, as a placebo test, we estimate the relationship between the private credit league table rankings and other, non-private credit fundraising. We show that the model estimates are statistically insignificant at the 10% level in these specifications.

Taken together, these findings show that league-table prominence predicts incremental fundraising even after normalizing by adviser size and controlling for time effects. Conceptually, the evidence adds three margins to the literature. First, Berk and Green (2004) intuition—capital chases perceived ability and pushes returns toward decreasing-returns equilibria—into a closed-end, appraisal-based setting where flows are gated by fundraising cycles rather than daily subscriptions. Second, it complements private-equity results on persistence and concave flow responses (Kaplan and Schoar, 2005; Lopez-de Silanes et al., 2015) by demonstrating a systematic rank-to-flows channel in private credit constructed from comprehensive regulatory microdata rather than proprietary cash-flow databases. Third, by pairing these flow responses with our earlier evidence on utilization and subsequent performance, we document a feedback loop—ranked advisers raise more, deploy more slowly, and earn lower subsequent IRRs—that links branding and visibility to decreasing returns at scale (Pástor et al., 2015; Erel et al., 2024). This combination of facts suggest that league-table prominence is informative about fundraising dynamics but not necessarily about future alpha. Additionally, to our knowledge, these results provide the first market-wide, regulatorily grounded rank–flow estimates for direct lending.

We next examine how past fundraising affects subsequent fund performance. We measure fundraising at the adviser level by aggregating the total AUM of new funds issued by the same adviser over the prior year.

Table 9 reports the main estimates. Columns (1) uses all new funds, Columns (2) restricts to newly launched private-credit funds, and Columns (3) restricts to new non-private-credit funds. Across specifications, new fundraising is negatively associated with subsequent performance, even after controlling for adviser size, and the magnitudes are similar whether we scale by gross or net AUM. Notably, the coefficients are also significant when the flow measure is based solely on non-private-credit fundraising. A natural interpretation is that adviser-level fundraising surges correlate with binding organizational constraints that depress returns for the adviser's private-credit vehicles regardless of whether the immediate inflow is earmarked to private credit.[4]

[4]Interestingly, when the dependent variable is replaced with net IRR, as shown in Table A2 in the Appendix, the relationships are no longer statistically significant.

4.3 Scope-related Deployment Frictions

The results presented earlier in Section 4.1 that large advisers that specialize in private credit do not display the same underperformance as large, diversified advisers with comparable private credit AUM. We further examine the extent to which adviser-level diseconomies of scale reflect diseconomies of scope.

First, we probe whether contemporaneous cross-selling or bundling drives these patterns. In practice, large diversified advisers, such as BlackRock, Apollo, or KKR, can attract LP flows via bundled relationships and distribution, but the pace of scalable, high-quality cash-flow-based lending may lag those inflows, producing lower subsequent IRRs at the adviser level. If cross-selling pushes the adviser to launch (or upsize) private-credit vehicles despite a thin pipeline, then the effective dilution of investable opportunities is even stronger.

We decompose fundraising episodes into (i) years with new private-credit fundraising unaccompanied by other fund types and (ii) years with fundraising only in non-private-credit strategies. Table 10 shows that the negative association in Table 9 is concentrated when private-credit fundraising coincides with fundraising in other strategies, consistent with the idea that, while cross-selling may facilitate larger fundraising volumes, it does not necessarily translate into higher returns. We find similar results replacing the dependent variable with net IRRs, as shown in Table A3 in the Appendix.

Next, we examine how specialization in private credit is related to deployment capacity. To do so, we revisit the regressions from Table 9 that relate returns to past fundraising, replacing the dependent variable with the fund level utilization rate. Table 11 reports the estimation results.

Column (1), which uses all new funds as the regressor illustrates that the estimated relationship with deployment is negative and statistically significant. Column (2) restricts the sample to newly launched private-credit funds, and Column (3) to new non-private-credit funds. The estimated coefficients for both measures are negative, but only the coefficient on new non–private-credit funds is statistically significant at the 1% level. Column (4) includes both new private-credit and non–private-credit funds simultaneously and again finds significance only for new non–private-credit funds. Column (5) replaces the dependent variable with changes in the utilization rate while maintaining the same regressors as in Column (4), yielding similar results.

These findings suggest that smaller, more specialized advisers operate with greater deployment capacity. While broader product offerings may facilitate cross-selling and reduce fundraising fric-

tions, the resulting lack of specialization could hinder advisers' ability to build and sustain deal sourcing networks. As a result, when advisers stretch to deploy capital, marginal deals tend to be of lower quality, which may explain why smaller, focused advisers earn higher returns.

5 Conclusion

This paper brings new measurement and structure to the study of private credit. Using confidential regulatory microdata, we re-establish the aggregate footprint of the sector and document novel facts about dry powder, leverage, concentration, and performance. The industry is larger than previously estimated, with total corporate private credit assets nearly $2 trillion as of early 2025. Despite this growth, much of the capital remains undeployed, with dry powder consistently exceeding 60% over the past decade. Leverage among private credit funds is minimal, and the industry is far less concentrated than banking. These facts indicate that private credit remains a significant, yet underutilized, source of corporate financing.

Cross-sectionally, larger advisers raise capital faster but deploy it more slowly, specialize less in private credit, and underperform smaller advisers. These patterns reflect both inflow-related frictions, where rapid fundraising outpaces origination capacity, and scope-related diseconomies, where diversification into other strategies reduces specialization and constrains deal sourcing. Collectively, these findings highlight persistent diseconomies of scale in private credit, with a long tail of smaller advisers intermediating more and generating higher returns.

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Figure 1: Aggregate Statistics on US Corporate Private Credit

The figure displays the aggregate gross AUM, dry powder, and capital utilization rates. This figure splits the sample by year. Sources: SEC Form PF, Authors' Analysis.

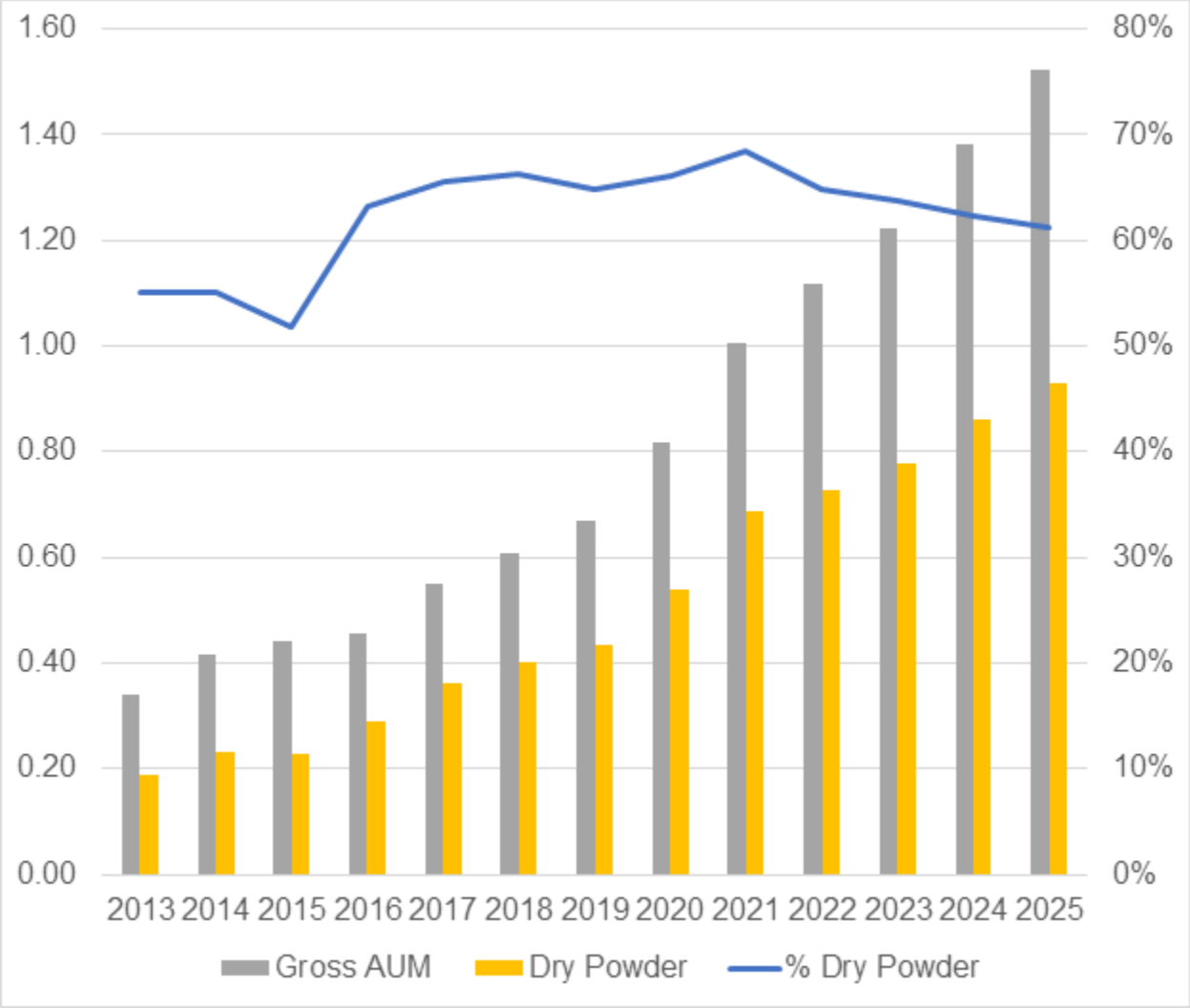


Figure 2: Industry Concentration

The figure displays the top 5 concentration ratios based upon gross AUM and dry powder. This figure splits the sample by year. Sources: SEC Form PF, Authors' Analysis.

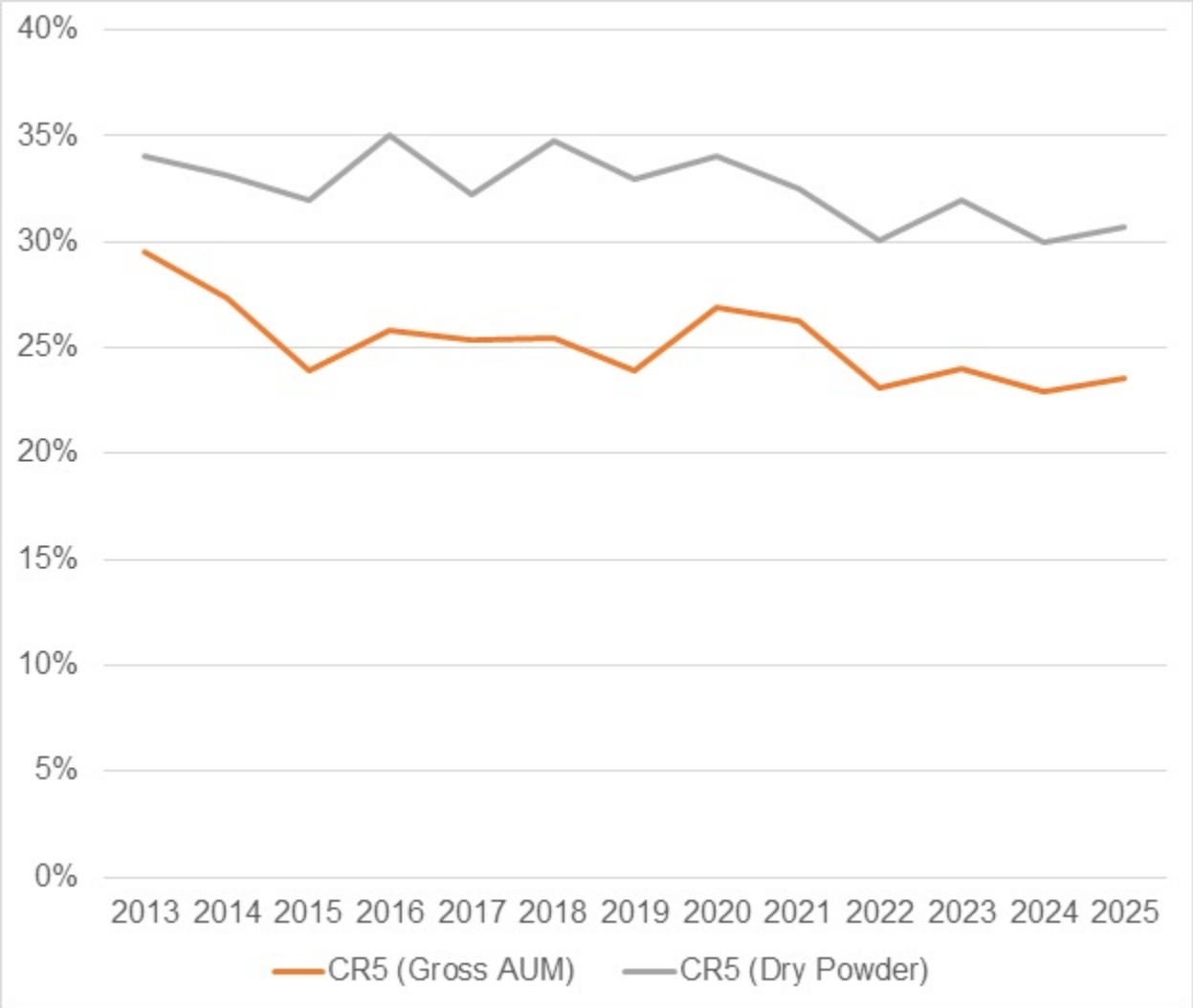


Figure 3: New Private Credit Funds

The figure displays the gross AUM and fund counts based upon all new private credit funds. This figure splits the sample by year. Sources: SEC Form PF, Authors' Analysis.

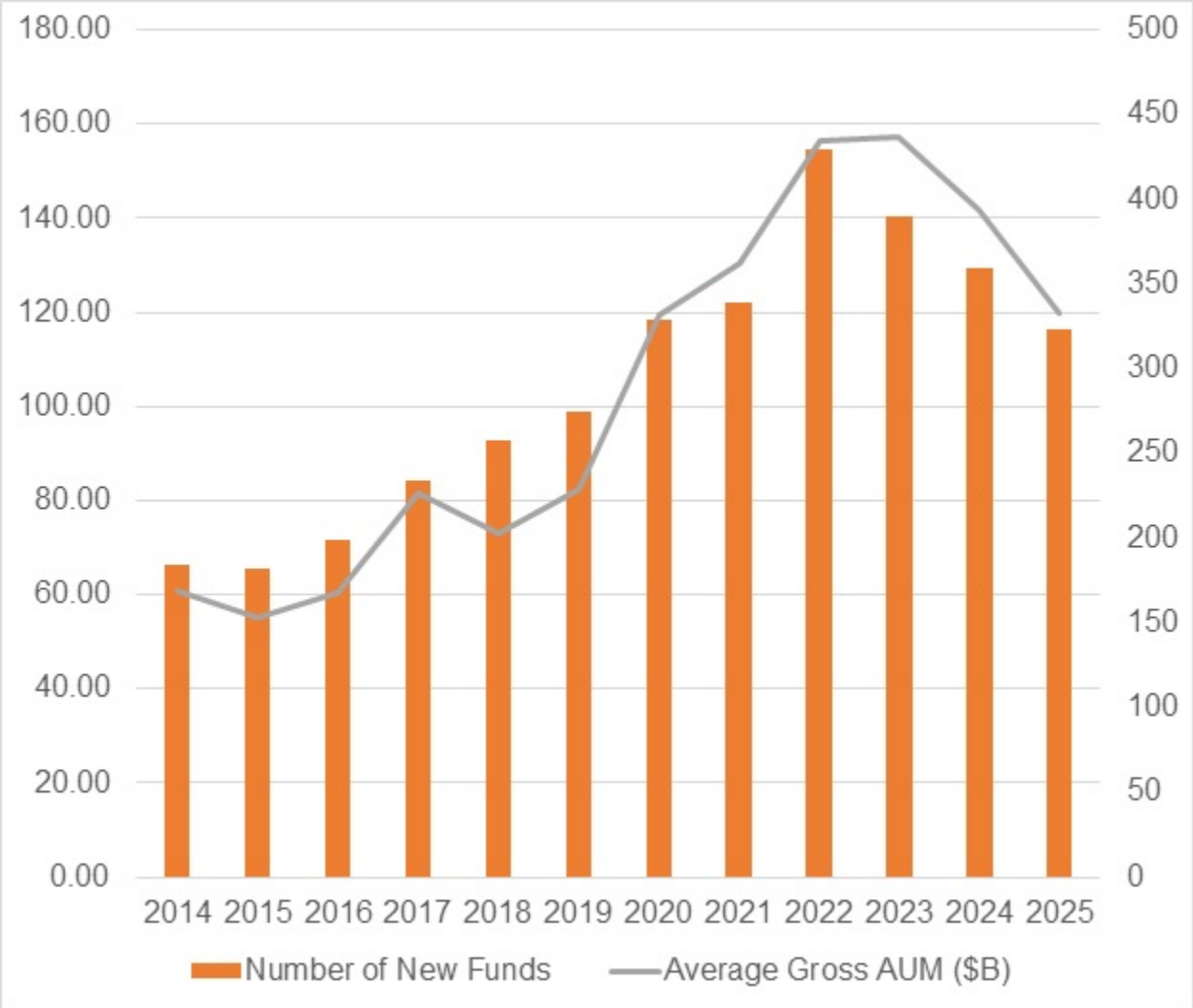


Figure 4: Average Fundraising by Adviser Size

The figure displays the gross AUM based upon all new private credit funds. This figure splits the sample by year and adviser size grouping cohort. The adviser size cohorts are top 5 (rank 1 – 5), next 20 (rank 6-25) and rest (rank ¿ 25), where the adviser size rankings are reestimated each year. Sources: SEC Form PF, Authors' Analysis.

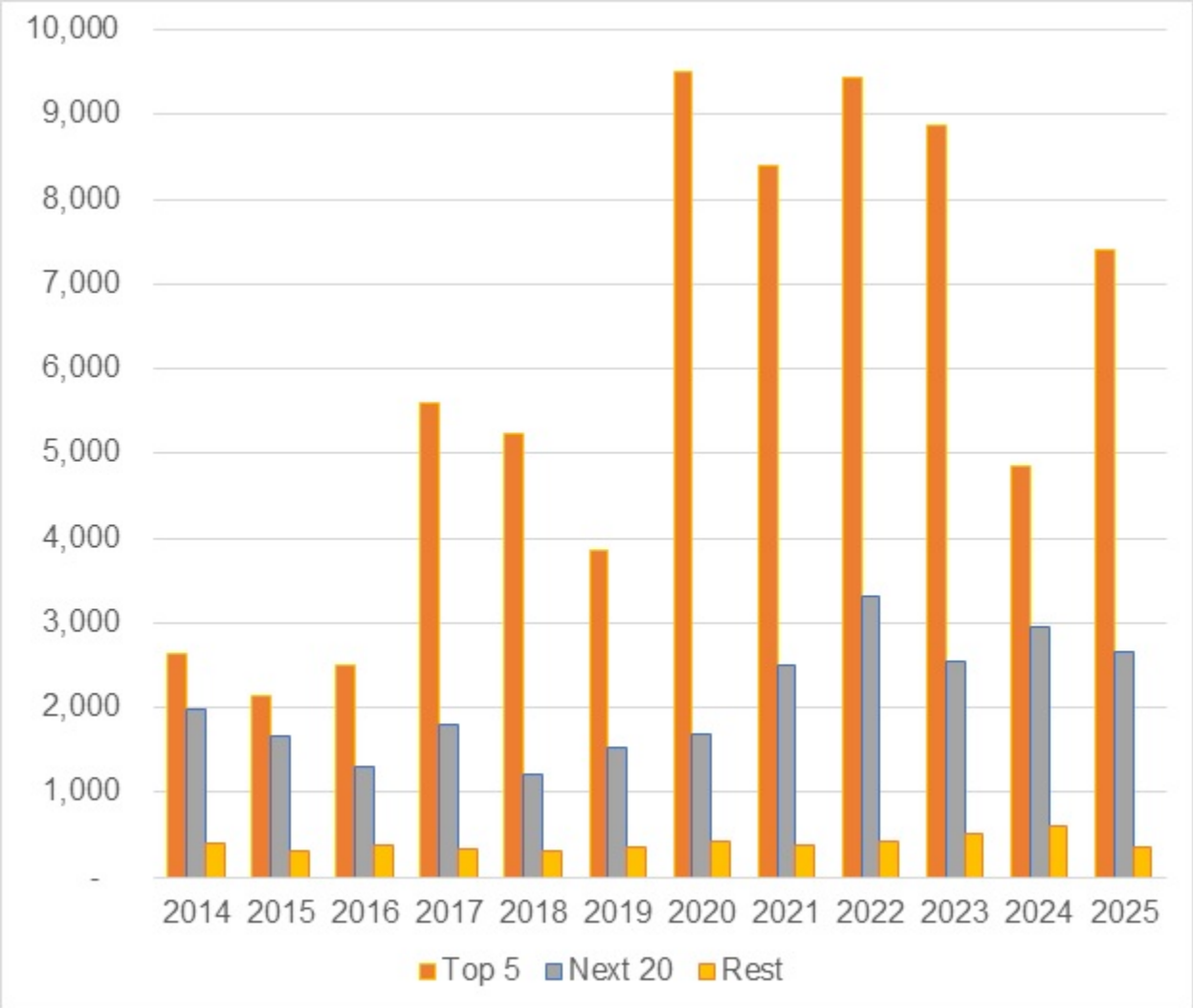
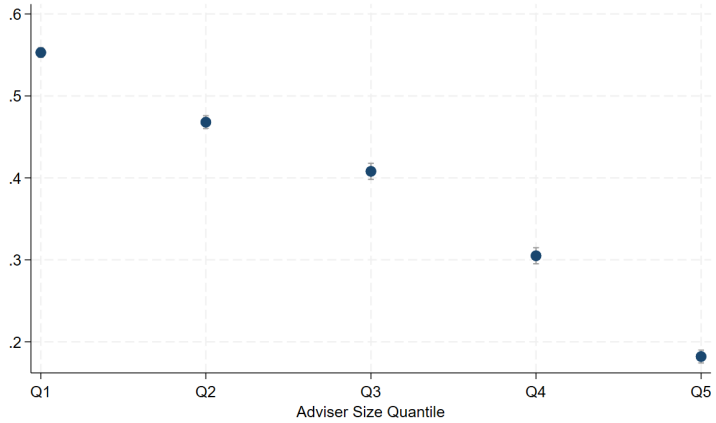
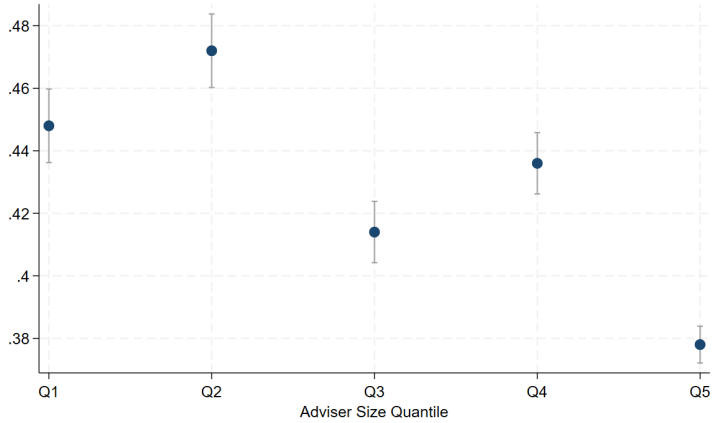


Figure 5: Fund Characteristics by Adviser AUM

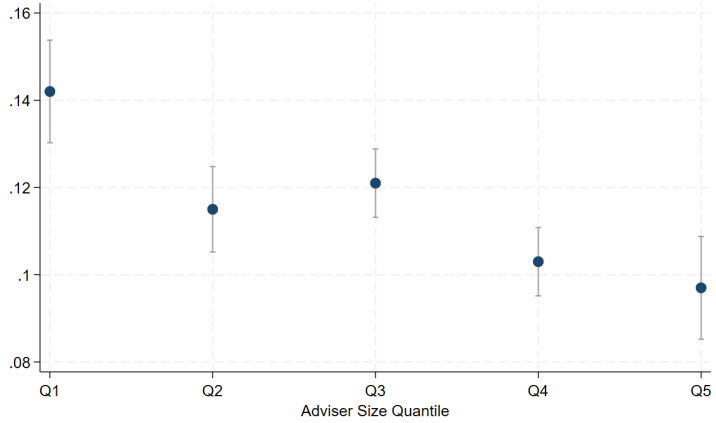
The figure displays bin-scatters of various fund characteristics by adviser AUM quintiles. The dependent variables in Panels A, B, C, and D are the utilization rate, share of private credit AUM, gross IRR, and net IRR, respectively. The explanatory variables are identical across the specifications and correspond with dummy variables related to each adviser size ranking quintile. The adviser size ranking is based upon the adviser size in the prior year. Robust standard errors clustered on the fund-level. Sources: SEC Form PF, Authors' Analysis.



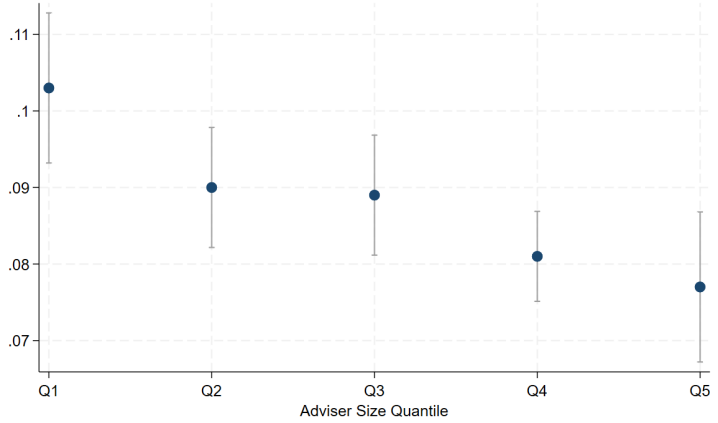
(a) Panel A: Utilization rate



(b) Panel B: PC AUM Share



(c) Panel C: Gross IRR



(d) Panel D: Net IRR

Table 1: Variable Descriptions and Summary Statistics

Table 1 displays variable descriptions (Panel A) and summary statistics (Panel B). The summary statistics include the observation count, mean, standard deviation, 25th percentile band, 50th percentile band, and 75th percentile band. This table splits the sample by the overall sample as well as the 25th percentile band sample, the 50th percentile band sample and the 75th percentile band sample based upon each variable. The 25th percentile band sample is based upon the sample within the 20th and 30th percentile for each variable. The 50th percentile band sample is based upon the sample within the 45th and 55th percentile for each variable. The 75th percentile band sample is based upon the sample within the 70th and 80th percentile for each variable. The 25th, 50th, and 75th percentile band estimate is calculated as the midpoint of the band range.Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

Panel A: Variable Descriptions

Variable	**Description**	**Sources**
Fund NAV	Fund net asset value.	Form PF
Fund Leverage	Fund borrowings scaled by fund gross asset value.	Form PF
%Utilization	Fund asset valuation scaled by fund gross asset value. Asset valuation is the sum of the Levels 1/2/3 assets as well as the cost-basis valuation.	Form PF
IRR (Gross)	Fund gross internal rate of return.	Form PF
IRR (Net)	Fund net internal rate of return.	Form PF
Total Adviser AUM	Adviser total AUM across all managed funds.	Form ADV, Form PF
PC Adviser AUM	Adviser total AUM across all private credit funds.	Form ADV, Form PF
Non-PC Adviser AUM	Adviser total AUM across all non-private credit funds.	Form ADV, Form PF
Total New Fund AUM	Adviser total AUM across all new managed funds.	Form ADV, Form PF
PC New Fund AUM	Adviser total AUM across all new private credit funds.	Form ADV, Form PF
Non-PC New Fund AUM	Adviser total AUM across all new non-private credit funds.	Form ADV, Form PF

Continued on next page

Table 1: Panel A (continued)

Variable	**Description**	**Sources**
PC Specialization	Adviser total AUM across all private credit funds scaled by adviser total AUM across all managed funds.	Form ADV, Form PF
Strategy – Direct Lender	Dummy associated with private credit funds that specialize in direct lending.	Form ADV, Web Searches
Strategy – Distressed Debt	Dummy associated with private credit funds that specialize in distressed debt.	Form ADV, Web Searches
Strategy – Mezzanine Debt	Dummy associated with private credit funds that specialize in mezzanine debt.	Form ADV, Web Searches
Strategy – Special Situations	Dummy associated with private credit funds that specialize in special situations.	Form ADV, Web Searches

Panel B: Summary Statistics						
Variable	**N**	**Mean**	**SD**	**25th Percentile Band**	**50th Percentile Band**	**75th Percentile Band**
Fund NAV	10,181	411.255	805.632	46.712	152.598	440.462
Fund Leverage	10,181	0.094	1.301	0.000	0.000	0.014
%Utilization	10,181	0.610	0.421	0.126	0.803	1.000
IRR (Gross)	10,181	0.119	0.160	0.047	0.111	0.169
IRR (Net)	10,149	0.089	0.140	0.037	0.086	0.132
Total Adviser AUM	10,181	33,976.935	51,900.169	2,011.861	11,830.799	46,714.275
PC Adviser AUM	10,181	7,695.403	11,439.959	574.868	2,813.362	10,223.061
Non-PC Adviser AUM	10,181	26,129.845	44,520.692	488.706	7,974.727	31,089.597
Total New Fund AUM	10,181	4,877.444	10,737.069	128.693	1,143.190	4,818.407
PC New Fund AUM	10,181	1,102.852	2,893.635	0.000	191.565	1,038.087
Non-PC New Fund AUM	8,737	4,398.435	9,760.423	76.077	943.124	4,703.269
PC Specialization	10,181	0.424	0.352	0.108	0.331	0.765
Strategy – Direct Lender	10,181	0.352	0.478	0.000	0.000	1.000
Strategy – Distressed Debt	10,181	0.160	0.367	0.000	0.000	0.000
Strategy – Mezzanine Debt	10,181	0.152	0.359	0.000	0.000	0.000
Strategy – Special Situations	10,181	0.207	0.405	0.000	0.000	1.000

Table 2: Private Credit Fund Performance Distribution

The table displays the histogram for fund gross and net IRRs over the full sample period. This table splits the sample for the samples for which gross IRRs and net IRRs are available, separately, by various IRR ranges. Sources: SEC Form PF, Authors' Analysis.

Year	$(-\infty, -20\%]$	$(-20\%, 0\%)$	$[0\%, 0\%]$	$(0\%, 5\%]$	$(5\%, 10\%]$	$(10\%, 15\%]$	$(15\%, 20\%]$	$(20\%, +\infty)$
Gross IRR	2.2%	8.2%	5.6%	9.0%	16.4%	20.6%	12.0%	26.0%
Net IRR	2.4%	9.3%	6.3%	10.1%	18.5%	23.1%	13.6%	16.8%

Table 3: Private Credit Fund Leverage Distribution
The table displays the proportion of observations associated with each leverage bucket. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
0%	**(0,5%]**	**(5,10%]**	**(10,20%]**	**(20,30%]**	**(30,40%]**	**(40,50%]**	**(50,100%)**
0.730	0.070	0.034	0.050	0.031	0.023	0.022	0.039

Table 4: Fund Performance Life Cycle Statistics

The table displays the average fund gross and net IRRs over the full sample period. This table splits the sample for the samples for which gross IRRs and net IRRs are available, separately, by fund age. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

Fund Age	**Gross IRR**	**Net IRR**
1	10.91%	6.70%
2	13.80%	10.59%
3	14.09%	11.18%
4	13.31%	10.53%
5	11.21%	9.20%
6	11.49%	9.26%
7	10.27%	8.06%
8	9.01%	7.31%
9	10.24%	8.33%
10	7.13%	5.51%

Table 5: Statistics by Adviser Size Groupings

The table displays aggregated statistics of private credit as of 2024. This table splits the sample by adviser size grouping cohort. The adviser size cohorts are top 5 (rank 1-5), next 20 (rank 6-25) and rest (rank $>$ 25), where the adviser size rankings are estimated for 2024. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

Adviser Size Grouping	Gross AUM	Deployed Capital	Dry Powder	Utilization (%)
Top 5	324.3	78.1	246.1	24.1%
Next 20	440.9	104.1	336.8	23.6%
Rest	592.0	313.6	278.4	53.0%

Table 6: Fund Performance Life Cycle Statistics by Adviser Size Groupings
The table displays the average fund gross and net IRRs over the full sample period. This table splits the sample for the samples for which gross IRRs and net IRRs are available, separately, by fund age and adviser size cohort. The adviser size cohorts are constructed using rankings based upon the adviser size in the prior year. The subsamples for the adviser size cohort is for quintile one, quintiles two – four, and quintile five. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

Panel A: Quintile 5 (Largest)		
Fund Age	**Gross IRR**	**Net IRR**
1	8.15%	7.16%
2	13.07%	11.61%
3	11.10%	8.54%
4	10.73%	7.49%
5	9.31%	6.35%
6	9.49%	7.65%
7	9.49%	6.90%
8	8.27%	6.15%
9	3.38%	2.93%
10	6.93%	6.15%

Panel B: Quintile 2 through 4		
Fund Age	**Gross IRR**	**Net IRR**
1	10.93%	6.73%
2	13.66%	10.90%
3	13.70%	10.70%
4	12.26%	9.75%
5	10.47%	8.38%
6	10.32%	8.23%
7	9.34%	7.05%
8	8.41%	6.76%
9	10.41%	8.76%
10	8.78%	6.60%

Panel C: Quintile 1 (Smallest)		
Fund Age	**Gross IRR**	**Net IRR**
1	13.68%	8.90%
2	16.02%	10.70%
3	16.28%	12.62%
4	14.95%	10.88%
5	13.52%	10.89%
6	13.14%	10.27%
7	12.60%	10.63%
8	12.60%	9.07%
9	11.90%	8.37%
10	10.96%	7.86%

Table 7: Adviser AUM and Gross IRRs

The table displays regression results on fund gross IRRs over the full sample period. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable:		$\mathrm{IRR}_{i,t+1}^{\mathrm{Gross}}$		
Total Adviser $\mathrm{NAV}_{i,t}$	-0.006^{***}			
	(0.001)			
PC Adviser $\mathrm{NAV}_{i,t}$		-0.003^{***}		-0.002^{***}
		(0.001)		(0.001)
Non-PC Adviser $\mathrm{NAV}_{i,t}$			-0.002^{***}	-0.002^{***}
			(0.000)	(0.000)
Control Variables	YES	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES	YES
N	10,181	10,181	10,181	10,181
Adjusted R^2	7.75%	7.15%	7.38%	7.79%

Table 8: League Table Tests

The table displays regression results on new private credit fundraising over the full sample period. Top 20 Ranking is a dummy associated with whether the adviser ranked within the top 20 in terms of PC fundraising in the prior year. Control variables include the lagged dependent variable and the cubic polynomial transformation of total adviser size. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable:		$\text{NewFund}^{\text{PC}}_{j,t+1}$			$\text{NewFund}^{\text{All}}_{j,t+1}$	$\text{NewFund}^{\text{Non-PC}}_{j,t+1}$
Top 20 Ranking$_{j,t}$	6.903***	5.689***	5.875***	2.450***	-0.911	-0.995
	(1.072)	(1.071)	(1.092)	(0.847)	(0.647)	(0.609)
Lagged Dependent Variable	NO	YES	YES	YES	YES	YES
Adviser Size Controls	NO	NO	YES	YES	YES	YES
Year FEs	NO	YES	YES	YES	YES	YES
N	2,506	2,506	2,506	2,506	2,506	2,506
Adjusted R^2	3.55%	4.08%	11.71%	20.55%	30.75%	38.26%

Table 9: Past Fundraising

The table displays regression results on fund gross IRRs over the full sample period. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**
Dependent Variable:		$\text{IRR}_{i,t+1}^{\text{Gross}}$	
New Fund AUM — $\text{Total}_{i,t}$	-0.004		
	(0.003)		
New Fund AUM — $\text{PC}_{i,t}$		-0.007^{***}	
		(0.002)	
New Fund AUM — $\text{Non-PC}_{i,t}$			-0.006^{**}
			(0.003)
Baseline Control Variables	YES	YES	YES
Adviser Size Control Variables	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES
N	10,181	10,181	10,181
Adjusted R^2	7.77%	7.89%	7.82%

Table 10: Fundraising Decomposition

The table displays regression results on fund gross IRRs over the full sample period. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable:		$\text{IRR}_{i,t+1}^{\text{Gross}}$		
New Fund PC AUM — Only $\text{PC}_{i,t}$	0.001*		0.000	0.000
	(0.000)		(0.000)	(0.000)
New Fund PC AUM — Both PC & Non-$\text{PC}_{i,t}$		-0.001^{***}	-0.001^{***}	-0.001^{***}
		(0.000)	(0.000)	(0.000)
New Fund Non-PC $\text{AUM}_{i,t}$				0.000
				(0.000)
Baseline Control Variables	YES	YES	YES	YES
Adviser Size Control Variables	YES	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES	YES
N	10,181	10,181	10,181	10,181
Adjusted R^2	7.79%	8.00%	7.99%	7.98%

Table 11: Utilization Rates

The table displays regression results on utilization rates over the full sample period. $\%Util$ is transformed using a inverse hyperbolic sine function. $\Delta Util$ is the one-year change in the utilization rate. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable:	$\%\text{Util}_{i,t+1}$	$\%\text{Util}_{i,t+1}$	$\%\text{Util}_{i,t+1}$	$\%\text{Util}_{i,t+1}$	$\Delta\text{Util}_{i,t+1}$
New Fund AUM — Total$_{i,t}$	-0.070^{**}				
	(0.034)				
New Fund AUM — PC$_{i,t}$		-0.019		-0.009	-0.017
		(0.025)		(0.025)	(0.028)
New Fund AUM — Non-PC$_{i,t}$			-0.078^{***}	-0.077^{***}	-0.089^{***}
			(0.027)	(0.027)	(0.031)
Adviser Size Controls	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES	YES	YES
N	10,181	10,181	10,181	10,181	10,181
Adjusted R^2	69.74%	69.73%	69.76%	69.75%	16.69%

Appendix

Table A1: Adviser AUM and Net IRRs

The table displays regression results on fund net IRRs over the full sample period. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable:		$\text{IRR}_{i,t+1}^{\text{Net}}$		
Total Adviser $\text{AUM}_{i,t}$	-0.003^{***}			
	(0.001)			
PC Adviser $\text{AUM}_{i,t}$		-0.002^{***}		-0.002^{***}
		(0.000)		(0.000)
Non-PC Adviser $\text{AUM}_{i,t}$			-0.001^{***}	-0.001^{***}
			(0.000)	(0.000)
Control Variables	YES	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES	YES
N	10,149	10,149	10,149	10,149
Adjusted R^2	6.75%	6.60%	6.52%	6.78%

Table A2: Past Fundraising

The table displays regression results on fund net IRRs over the full sample period. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**
Dependent Variable:		$\text{IRR}^{\text{Net}}_{i,t+1}$	
New Fund AUM — Total$_{i,t}$	-0.001		
	(0.003)		
New Fund AUM — PC$_{i,t}$		-0.003	
		(0.002)	
New Fund AUM — Non-PC$_{i,t}$			-0.002
			(0.002)
Baseline Control Variables	YES	YES	YES
Adviser Size Control Variables	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES
N	10,149	10,149	10,149
Adjusted R^2	6.74%	6.76%	6.75%

Table A3: Fundraising Decomposition

The table displays regression results on fund net IRRs over the full sample period. See Table 1 for variable descriptions. Control variables from Table 7 are included where indicated. Fixed effects specifications are indicated in the bottom of the table. Robust standard errors clustered on the fund-level are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively. Sources: SEC Form PF, SEC Form ADV, Authors' Analysis.

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable:		$\text{IRR}^{\text{Net}}_{i,t+1}$		
New Fund PC AUM — Only $\text{PC}_{i,t}$	0.002		0.000	0.000
	(0.003)		(0.003)	(0.003)
New Fund PC AUM — Both PC & Non-$\text{PC}_{i,t}$		-0.004^{*}	-0.004^{*}	-0.004^{*}
		(0.002)	(0.002)	(0.002)
New Fund Non-PC $\text{AUM}_{i,t}$				0.000
				(0.003)
Baseline Control Variables	YES	YES	YES	YES
Adviser Size Control Variables	YES	YES	YES	YES
Fund Vintage $\times$ Year FEs	YES	YES	YES	YES
Fund Strategy $\times$ Year FEs	YES	YES	YES	YES
N	10,149	10,149	10,149	10,149
Adjusted R^2	6.75%	6.79%	6.78%	6.77%