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Research

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Private Debt Fund Returns, Persistence, and Market Conditions

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This paper examines net-of-fees private debt fund performance, performance persistence across funds managed by the same general partner and a general partner's ability to time the market. We document that private debt funds outperform bond and equity market benchmarks in the cross-section, with high performance dispersion across strategies and performance quartiles. Lagged performance significantly affects current fund performance. While *ex ante* and *ex post* credit market conditions strongly affect fund performance, general partners can only partially time them.

Keywords: credit market conditions; market timing; performance; performance persistence; private debt; private markets; return; skill

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Introduction

We investigate private debt (PD) fund performance and determinants thereof. PD funds represent an important segment of the private capital industry, which soared on the boom in unlisted assets and tripled their market capitalization since the COVID-19 pandemic induced market sell-off.[1] PD funds emerged as an asset class in the late 1990s and exceeded $1.1 trillion assets under management in 2020 (Preqin Pro 2021). As of today, PD funds' assets under management represent some important 12.3% of the aggregate value of private capital funds. They approximately match the size of real-estate funds ($1.15 trillion) and have outgrown infrastructure ($0.8 trillion) and natural resources ($0.2 trillion) funds (Preqin Pro 2021). This growth has been driven by a surge in the demand for non-bank private debt, as banks retrenched from cash-flow-based lending to the middle market after the Global Financial Crisis due to increased bank regulation and the resulting reduction in risk appetite on the part of the banks (see, for example, Langfield and Pagano 2016; van der Veer and Hoeberichts 2016; Bordo and Duca 2018; Cortés et al. 2020). Also, PD fund growth was spurred by an increase in the supply of capital by yield-seeking institutional investors challenged by a low-yield environment in traditional credit markets.

Despite the growing importance of PD funds, which have reached average fund sizes exceeding $1.3 billion (in 2018 US dollars), our understanding of PD fund returns to limited partners (LPs) is limited

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to date. While there is a large literature on the returns to private equity investing, this study is one of the first to investigate thoroughly the returns to PD fund investing, and especially their outperformance of traded fixed-income benchmarks. Moreover, we analyze whether there is performance persistence over subsequent funds managed by the same general partners (GPs), and whether superior GPs can time credit market conditions.

In a typical private debt transaction, credit funds lend capital to an existing corporation. Each PD fund follows an investment strategy, such as direct lending, distressed debt lending, mezzanine lending, special situations lending and venture debt lending.[2] Comparable to private equity funds,[3] PD funds are organized as partnerships, in which the investor becomes a LP and the asset manager, which also invests in the partnership, is the GP. We investigate closed-end PD funds. Such funds imply that the investor cannot withdraw funds until the fund is liquidated, typically eight to ten years after inception. GPs are tasked with the selection of attractive credit opportunities, the negotiation of lending contracts, their execution, the active monitoring of investments and investee companies, sometimes combined with the execution of advisory roles at the management or board level of the borrower, the renegotiation of lending agreements in case of covenant breaches, the execution of credit workouts and the realization of secondary market transactions. For its services, the GP receives a management fee of 1.5% to 2% and typically also a success fee in the amount of 15% to 20%, the latter paid at the end of the lifetime of a fund and calculated on a return exceeding a preferred return to LPs, which is usually around 6% to 8% per annum.

The LP is a passive investor, does not obtain any decision control over investments and therefore has no influence on the selection and implementation of investments or on the general investment strategy. Both elements, however, are laid out in a detailed limited partnership agreement (LPA) in principle. Given the limited life of a fund, GPs must raise new funds. In general, such new funds are launched when either the existing fund comes to the end of its life or when 75% or more of the committed capital of the current fund has been called from investors. The life of a PD fund hence consists of (i) a fundraising period, in which investors commit capital throughout a series of closings and in which the GP is tasked with deal sourcing, deal evaluation and executing first investments; and (ii) an investment period, in which the GP continues its activity, which lasts two to four years from the final closing in the fundraising period. During the investment period, the GP may recycle its capital, i.e., reinvest the proceeds of early exits. The investment period is followed by (iii) the harvesting period, in which the GP exits investments and distributes all proceeds, net-of-fees, to LPs.

PD funds generate returns from various sources. First, funds earn regular cash coupons paid on the loans. Second, GPs may structure payments in kind (PIK), accruing interest paid out at maturity. Third, they may cash in early repayment penalties (Cumming et al. 2019) and recycle or reinvest capital from early repayments. Fourth, portfolio company's fees may include advisory fees, transaction and deal fees, directors' fees, monitoring fees, capital market fees, organization cost compensations, placement fees and others (CalPERS 2015; ILPA 2016). These are paid to the GP, but typically paid back to the LPs by means of fee-offset provisions, that is, a reduction in management fees, thereby boosting fund performance. Finally, funds may actively exit some of their investments on the secondary markets if valuations are good.

The first aim of this paper is to provide systematic evidence related to the performance a LP may expect from a PD fund. We first focus on the absolute and relative returns to PD funds, using relevant benchmarks. Thereafter, we analyze whether GPs are skilled in managing PD funds in two dimensions: First, we evaluate whether GPs provide performance persistence in subsequent PD funds. Persistence exists if some GPs possess specific skills that allow them consistently to perform better than their peers. Second, we analyze the ability of GPs to time the market, thereby providing more fine-grained insights into the GPs' skillset. Borrowing from Kacperczyk, Nieuwerburgh, and Veldkamp (2014, 1455), we define GP skill as "a general cognitive ability to pick [stocks] or time the market".

We collect data on 448 PD funds with vintage years 1986 to 2018, and calculate PD funds' net-of-fees Internal Rate of Return (IRR) and net multiples. We further calculate the excess return of PD funds compared to public benchmarks, using the public market equivalent (PME) method (Kaplan and Schoar 2005).

We find that the average PD fund renders a 9.19% net-of-fees IRR to LPs. There is a large dispersion between top quartile funds, with an IRR of 23.3%, as compared to the bottom-quartile funds, with an IRR of −3.6%. PD funds achieve a net investment multiple of 1.3 in the cross-section, again with large performance dispersion between top quartile funds (1.76X) and bottom quartile funds (0.98X). PD funds outperform the investment-grade (IG) bond market benchmark with 8%, the high-yield (HY) bond market benchmark with 6% and the S&P500 equity market benchmark with 6%, with relatively equal outperformance across different investment strategies. Against these same benchmarks, top quartile funds reach a market outperformance of 38%, 33%, and 42%, while bottom quartile funds underperform the market by −18%, −19%, and −21%. These results echo Munday et al. (2018), who find an average IRR of 8.1% and a market outperformance of 6.2% to 9.8% in the cross-section.

Multivariate analyses suggest that a GP's prior fund performance is a significant and economically important predictor of its future fund performance: A one standard deviation increase in IRR (net multiple, PME IG, PME HY, PME S&P500) of the previous fund increases the performance of the current fund by 3.42% (0.11X, 5.10%, 4.88%/8.73%). However, our persistence results are largely driven by mature predecessor funds with at least 75% of capital called. Past performance of early-stage funds should thus be considered with more caution when considering an investment in a new PD fund.

Moreover, we find that a higher ex ante level of funding illiquidity, as proxied by the level of the Treasury-EuroDollar rate (TED) spread, significantly and negatively affects the outperformance of a PD fund against the IG and HY benchmark. On the contrary, a higher *ex ante* level of credit risk spreads and equity market volatility are positively related to PD fund multiples and their outperformance against the IG or HY benchmark. These findings are in line with prior research, which shows that *ex ante* credit market conditions affect the performance of debt investments (Cumming and Fleming 2013; Cumming et al. 2019).

We extend our analysis and, to the best of our knowledge, are the first to test whether and how *ex post* credit market conditions affect fund performance. Do GP's have market timing skill and anticipate changes in *ex post* credit market conditions? We find mixed evidence for market timing skills. On the one hand, PD funds that are initiated in periods with *ex post* improvements in funding illiquidity (or a TED spread contraction) perform better. On the other hand, improvements in credit spreads affect fund performance negatively. *Ex post* changing equity market volatility, as proxied by the VIX, does not impact PD fund returns or outperformance. The effect size of changes in *ex ante* funding illiquidity is approximately more than twice as large as that of performance persistence, while the effect of a change in *ex post* funding illiquidity is about as important as past performance. This finding is of particular interest to investors committing capital to PD funds in their fundraising period, which can take two years or more after the inception of the fund. As funds typically have a series of closings, diligent analysis of changes to funding illiquidity and credit spreads during the fundraising and the investment period may importantly improve an LP's investment decision. According to our estimation, performance is highest when credit spreads expand *ex ante* and *ex post*, whilst TED spreads contract, i.e., when funding liquidity improves.

We contribute to the literature in various dimensions. First, we extend the previously sparse empirical evidence that PD funds offer attractive returns (Munday et al. 2018). Second, we are, to the best of our knowledge, the first to investigate performance persistence of PD funds. Third, previous literature remains quiet on the question of market-timing skill. We present a model to analyze skill and find that it significantly affects PD fund performance.

Literature

PD fund performance has not received a lot of attention in the academic literature.[4] Studying loan portfolios of major US life insurance companies, Carey (1998) found that private corporate loans have lower default and higher recovery rates than public bonds. Cumming and Fleming (2013) study the performance of 311 loans used by private firms across 25 countries between 2001 and 2010 and find that performance depends on the portfolio size per manager, highlighting the role of time allocation for due diligence and monitoring. Cumming et al. (2019) study more than 400 loans acquired by PD funds in 13 Asia-Pacific markets between 2001 and 2015. They find that trading private debt delivers higher returns than buying and holding a primary issuance.

In contrast to these studies focusing on gross returns on individual investments, we focus on PD fund net-of-fee investor returns, following Munday et al. (2018). Using the Burgiss database, they analyze net returns to LPs of 476 private credit funds and 155 direct lending funds and find positive IRRs for the top three quartiles across all investment strategies.

Persistence in fund returns is defined as performance persistence across funds of the same GP. In competitive financial markets, GPs shall capture the returns to their skill by either growing fund size or increasing fees, thereby eliminating persistence in net-of-fee performance (Berk and Green 2004). Contrary to the Berk and Green (2004) model, various empirical studies find persistence in PE or VC fund performance (Kaplan and Schoar 2005; Kaplan and Sensoy 2015; Nanda, Samila, and Sorenson 2020; Korteweg and Sorensen 2017). Individual partners employed by the GP also show persistent returns (Ewens and Rhodes-Kropf 2015).

A skill that might explain persistent returns is market timing. Previous literature finds mixed results with respect to the market-timing ability of asset managers. While some studies find evidence for market-timing ability (Ball, Chiu, and Smith 2011; Kim and In 2012; Cao, Simin, and Wang 2013; Chen, Adams, and Taffler 2013; Kacperczyk, Nieuwerburgh, and Veldkamp 2014; Yi et al. 2018; Jenkinson, Morkoetter, and Wetzer 2018), others find mixed or negative evidence (Carhart 1997; Elton, Gruber, and Blake 2012; Ferson and Schadt 1996; Andreu, Matallín-Sáez, and Sarto 2018; Bodson, Cavenaile, and Sougné 2013; Tchamyou and Asongu 2017). More recent studies show that corporates can time the markets when issuing bonds (Frank and Nezafat 2019) or equity (Wadhwa and Syamala 2019). It is thus an empirical question whether GPs of PD funds do possess market-timing skills.

Sample and Data

Sample Description. We use a worldwide PD dataset obtained from Preqin, which contains fund-level data[5] based on the Freedom of Information Act (FOIA), or their equivalent outside the US. Cash-flow data from Preqin are increasingly used in academic research on PE funds and found to be reliable (Ang et al. 2018; Barber and Yasuda 2017; Phalippou 2014; Kaplan and Waldrop 2016).

Our sample consists of 448 PD funds raised between 1996 and 2018; cash-flow data extend to December 2020.[6] The sample size of this study is comparable to early research on the performance of private equity funds. Kaplan and Schoar (2005), for example, draw conclusions on the performance of buyout (VC funds) using a sample of 169 (577) funds. Table 1 provides summary statistics of our sample.

The 448 funds in the sample are managed by 94 GPs. On average, Preqin reports 6.1 PD funds per GP, while the average PD fund in the dataset is the third fund of a GP. Only 22.1% of the PD funds are the first PD fund of a GP. The most prevalent investment strategies are investing in direct lending (24.6%), distressed debt (30.6%) and mezzanine debt (28.6%), followed by special situations (12.7%) and venture debt (3.6%).

The mean size of a PD fund (in 2018 US dollars) is $1.3 billion (median: $831 million). PD funds investing in distressed debt are largest (average: $2.1 billion), while PD funds investing in venture debt are smallest (average: $449 million). Most PD funds (77.9%) are industry-agnostic, although 87.5% of the venture debt funds focus on specific industries. Almost all PD funds are USD-denominated, with 12.3% being EUR-denominated and 1.8% GBP-denominated. Consistent with this observation, 79.0% of the PD funds mainly focus their investments on North America, 17.4% on Europe, 3.1% on APAC and 0.5% on other parts of the world.

16.6% of the PD funds in our sample are fully liquidated, 80.4% are closed, implying that they no longer accept capital from LPs An average PD fund needs 56 days to deploy 10% of its capital, 476 days to deploy 50%, 1,019 days to deploy 90%, and 1,535 days (or slightly more than 4 years) to be fully invested.[7] Mezzanine PD funds are slowest to invest, and direct lending PD funds are fastest.

Panel B in Table 1 indicates the credit market conditions 360 days preceding (*ex ante*) and 720 days following (*ex post*) the first cash contribution from LPs, the latter covering large parts of the investment period of PD funds and allowing us to analyze the credit market conditions and market-timing skills of GPs. Δ is the difference between the condition *ex post* and *ex ante*. The TED spread is the difference between the USD three-month LIBOR and the three-month Treasury bill and is slightly lower on average during the investment period (0.41), as compared to the fundraising period (0.43). Credit spread is the option-adjusted spread (OAS) of the ICE Bank of America US Corporate BB index and the spot Treasury curve. This index tracks the performance of US dollar denominated below IG rated corporate debt securities publicly issued in the US domestic market and includes all securities with a given IG rating BB. The OAS index is constructed using each constituent bond's OAS, weighted by market capitalization. It is again slightly lower during the investment period (3.56) than before (3.59). Data for TED spread and credit spread are from the Federal Reserve Bank of St. Louis. Equity market volatility, measured as the CBOE Volatility S&P 500 Index (VIX), is higher post (18.64) as compared to before inception (18.04).

Table 1. Descriptive Statistics

		All Funds	Direct Lending	Distressed Debt	Mezzanine	Special Situations	Venture Debt
A. Fund characteristics							
General partners (GP)	#	94	36	28	32	13	5
Fund series	#	3.0	2.3	3.6	3.1	2.4	4.1
Funds overall	#	6.1	6.6	8.0	4.1	6.4	4.3
First fund	%	22.1	30.9	18.3	17.2	28.1	12.5
Investment strategy	#	448	110	137	128	57	16
	%	100.0	24.6	30.6	28.6	12.7	3.6
Size (2018 US million dollars)		1,323.3	1,152.4	2,098.7	841.4	1,116.8	449.0
		(831.3)	(727.6)	(1510.5)	(435.1)	(836.2)	(317.9)
Currency (in %)	USD	85.9	76.4	92.7	87.5	80.7	100.0
	EUR	12.3	20.9	5.8	12.5	14.0	0.0
	GBP	1.8	2.7	1.5	0.0	5.3	0.0
Industry-agnostic (in %)		77.9	80.9	83.2	74.2	86.0	12.5
Geographic investment focus in %		100.0	100.0	100.0	100.0	100.0	100.0
US & North America		79.0	67.3	84.7	85.9	66.7	100.0
Europe		17.4	28.2	13.1	12.5	22.8	0.0
APAC		3.1	4.6	2.2	0.0	10.5	0.0
Others		0.5	0.0	0.0	1.6	0.0	0.0
Status (in %)	Liquidated	16.6	4.6	28.5	28.1	8.8	18.3
	Closed	80.4	95.5	71.5	71.9	91.2	81.3
Capital deployment period 10%	Days	56.2	28.7	46.7	92.1	64.0	11.4
Capital deployment period 50%	Days	475.8	338.7	429.4	630.7	523.7	405.4
Capital deployment period 90%	Days	1,018.9	743.1	982.2	1,308.5	1,003.6	967.7
Capital deployment period 100%	Days	1,534.6	1,010.5	1,464.5	2,204.0	1,319.9	1,138.8
B. Credit market conditions							
TED spread$_{ex\ ante}$		0.43	0.34	0.46	0.48	0.38	0.51
TED spread$_{ex\ post}$		0.41	0.33	0.47	0.42	0.39	0.41
ΔTED spread		−0.02	−0.01	0.01	−0.07	0.01	−0.10
credit spread$_{ex\ ante}$		3.59	3.16	3.81	3.81	3.31	4.12
credit spread$_{ex\ post}$		3.56	3.07	3.92	3.58	3.54	3.88
Δ credit spread		−0.03	−0.09	0.11	−0.23	0.23	−0.24
VIX$_{ex\ ante}$		18.04	15.18	19.05	19.75	16.40	21.18
VIX$_{ex\ post}$		18.64	16.66	19.92	19.04	18.15	19.74
ΔVIX		0.60	1.48	0.87	−0.71	1.75	−1.44

Credit spread data are only available as of the end of 1996. *Panel A* of this table reports cross-sectional fund characteristics for 448 private debt funds with vintage years 1996 through 2018. We indicate the number of *general partners (GPs)*. *Fund series* indicates whether a fund is the first, second, third etc. fund of the same GP in a series of funds, *funds overall* is the number of funds of a GP manages. *First fund* indicates whether a PD fund is the first fund launched by a GP in a series of the same investment strategy. *Investment strategies* include *direct lending* (the practice of non-bank lenders extending loans to small- and medium-sized businesses in return for debt securities), *distressed debt* (lending to companies that have filed for bankruptcy or have a significant chance of filing for bankruptcy in the near future), *mezzanine* (investments in debt subordinated to the primary debt issuance and senior to equity positions), *special situations* (including distressed and mezzanine, where loan decision or grade is defined by criteria other than underlying company fundamentals), and *venture debt* (lending to venture capital-backed companies by a specialized financier to fund working capital or expenses). Mean (median) *size* is measured as the US dollar amount that is committed to a fund. Amounts are inflation adjusted by the consumer price index, using 2018 dollars, data are from Federal Reserve Economic Data (FRED). *Currency* indicates the number of funds in the three currencies observed (USD, EUR, and GBP). *Industry-agnostic* is a dummy variable defining whether a fund focuses on specific industries (=0) or follows a diversified, industry-agnostic investment approach (=1). *Geographic investment focus* indicates on which geographic regions private debt funds focus their capital allocation. *Status* defines how many funds have already been liquidated or are still in the investment and harvesting phase, but closed, that is, no longer accepting capital from investors. *Capital deployment period* represents the number of calendar days a fund uses to call 10%, 50%, 90%, and 100% of total contributions from LPs. *Panel B* indicates average financial and credit market conditions, 360 days preceding ($_{ex\ ante}$) and 720 days following ($_{ex\ post}$) the first cash contribution from LPs: *TED spread* is the difference between the USD three-month LIBOR and the three-month Treasury bill. *Credit spread* is the option-adjusted spread (OAS) of the ICE Bank of America US Corporate BB index and the spot Treasury curve. This index tracks the performance of US dollar denominated below investment grade rated corporate debt publicly issued in the US domestic market and includes all securities with a given investment grade rating BB. The OAS index is constructed using each constituent bond's OAS, weighted by market capitalization. Data for TED spread and credit spread are from the Federal Reserve Bank of St. Louis. *VIX* proxies for equity market volatility and is measured using the CBOE Volatility S&P 500 Index (VIX). Private debt fund data are from Preqin, cut-off date December 31, 2020. # indicates the number of observations.

Measuring PD Fund Performance. Following prior research (e.g., Kaplan and Schoar 2005; Korteweg and Nagel 2016; Korteweg and Sorensen 2017) and based upon net-of-fees cash-flow data, we calculate two absolute performance measures widely used by institutional investors, namely, the IRR and net multiples (Gompers, Kaplan, and Mukharlyamov 2016). The latter compares the cash invested by LPs with the cash returned to LPs. Following previous studies (Kaplan and Schoar 2005; Harris, Jenkinson, and Kaplan 2014), we include NAVs of non-liquidated funds as liquidating distributions to LPs.[8]

We calculate IRRs using cash-flow data for N funds. For each fund i ($i = 1, 2, 3\ldots, N$), we observe a series of cash flows between the inception date, denoted $t0i$, and the last available cash flow or NAV of fund i, denoted T_i. Cash flows consist of investments from LPs, called contributions, denoted C, and distributions to LPs, denoted D. The IRR of PD fund i is then calculated using continuous compounding as in Equation (1):

$$\sum_{t=t_{0i}}^{Ti} = \left[\frac{D_{it} - C_{it}}{(1+\mathrm{IRR}_i)^{t-t_{0i}}}\right] = 0 \qquad (1)$$

Using the reported NAV as final distribution is consistent with the PE literature, which suggests that the reported NAV rather understates final performance (Kaplan and Sensoy 2015). A more detailed illustration of how we calculated PD fund IRRs is available in an Online Appendix. Net multiples are provided by Preqin.

We additionally calculate excess return to PD funds compared with public benchmarks using the PME method introduced by Kaplan and Schoar (2005), considered as the state-of-the-art performance measure of fund-level performance both in academia (Kaplan and Sensoy 2015; Lerner, Zhang, and Lerner 2018) and in the asset management industry (L'Her et al. 2016).[9] The PME compares an investment in a fund to an investment in a benchmark index, adjusting the fund return for the market return or the risk of the investments spanned by the benchmark return. More specifically, it is the ratio of the present value of distributions scaled by the present value of contributions (Sorensen and Jagannathan 2015), with the discount rate being the realized market return (R_{ms}) given by the benchmark index. It is calculated as:

$$\mathrm{PME} = \left[\Sigma t \frac{\mathrm{Distributions}_{(t)}}{\prod_{s=to}^{t}(1+R_{ms})}\right] \Big/ \left[\Sigma t \frac{\mathrm{Contributions}_{(t)}}{\prod_{s=to}^{t}(1+R_{ms})}\right] \qquad (2)$$

with distributions equaling cash flows to LPs (including NAVs at the end of the observation period), contributions equaling capital calls or cash flows from LPs to the PD fund, and R_{mt} being the realized market return, as given by the benchmark index from the first cash flows at $s = t_0$ to the time of the distributions or contributions, respectively. The sum runs over the life of the fund from the first cash flows, $s = t_0$, to the time t of the distributions or capital calls, respectively. A more detailed illustration of how we calculated PD fund PMEs is given in an Online Appendix.

A fund with a PME greater than one outperformed the benchmark index over its lifetime. The PME adjusts for risks spanned by the benchmark return, regardless of beta with respect to the benchmark (Sorensen and Jagannathan 2015; Korteweg and Nagel 2016). The choice of the benchmark is critical to measuring performance (Phalippou 2014), but no return index on private debt investments is available (Cumming et al. 2019). Different benchmark indices are therefore used, following the recommendation of Sorensen and Jagannathan (2015). Cumming et al. (2019) use the J.P. Morgan Asia Credit Index (JACI) for their PD study focusing on the Asia-Pacific markets. We use Bloomberg Barclay indices instead, as they are widely used by credit and fixed-income investors. An important advantage of these indices is the availability of historical prices that date back to the early vintage years of the PD fund industry. The Bloomberg Barclays US Corporate Bond Index is a total return index which includes USD-denominated investment-grade, fixed-rate, taxable corporate bonds publicly issued by US and non-US industrial, utility and financial issuers (IG benchmark). It is also available in local currencies, which are used for the PD funds denominated in Euro (EUR) or British Pounds (GBP). The total return Bloomberg Barclays US Corporate High Yield Index includes USD-denominated, high-yield, fixed-rate corporate bonds (HY benchmark). This allows us to tailor PMEs to our specific environment, as in PE analyses (Fang, Ivashina, and Lerner 2015; Robinson and Sensoy 2016). Third, we also use the Standard & Poor's 500 total return index as an equity market benchmark.

Performance of PD Funds

Table 2 presents the cross-sectional performance of the PD funds, overall and per quartile, and over various percentiles. The mean (median) IRR equals

9.19% (8.46%), with a wide variation between the top quartile (mean IRR = 23.3%) and bottom quartile (mean IRR = −3.6%). The 1% worst-performing PD funds have an IRR of −33.90%, while the 1% best-performing PD funds have an IRR of 57.14%. The same picture emerges for net multiple returns (Panel B),[10] with an average of 1.30 (median: 1.24), suggesting that an average PD fund returns 1.30 times the cash invested by the LPs. The 1% worst-performing PD funds return only 57 cents per dollar invested, while the 1% best-performing PD funds return 2.58 dollars per dollar invested. This shows

Table 2. Private Debt Fund Performance (IRR, Multiples, PME)

A. Cross-sectional performance, measured by internal rate of return (IRR), over the sample period 1996–2020

					Percentiles					
IRR	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Internal rate of return (IRR)	448	9.19	8.46	14.81	−33.90	−7.12	5.11	12.28	27.71	57.14
Top quartile	112	23.3	16.6	19.2	12.3	12.9	14.0	25.2	48.1	93.2
Second quartile	112	10.1	10.0	1.0	8.5	8.7	9.1	11.0	11.8	12.2
Third quartile	112	7.0	7.2	1.0	5.1	5.3	6.1	8.0	8.4	8.5
Bottom quartile	112	−3.6	0.9	11.9	−55.7	−28.3	−5.8	3.2	4.4	5.0
High–low (quartiles)		27.0	15.7	18.1	68.0	41.3	19.8	22.0	43.8	88.1

B. Cross-sectional performance, measured by net multiples (multiple)

					Percentiles					
Multiples	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Net multiples (X)	436	1.30	1.24	0.35	0.57	0.85	1.10	1.45	1.93	2.58
Top quartile	106	1.76	1.65	0.35	1.46	1.48	1.54	1.88	2.42	3.12
Second quartile	112	1.33	1.31	0.06	1.24	1.24	1.28	1.38	1.44	1.45
Third quartile	106	1.16	1.16	0.04	1.11	1.11	1.13	1.19	1.23	1.23
Bottom quartile	112	0.98	1.03	0.15	0.50	0.59	0.95	1.08	1.10	1.10
High–low (quartiles)		0.79	0.62	0.31	0.96	0.89	0.59	0.80	1.32	2.02

C. Cross-sectional performance, measured by public market equivalent (PME), using the investment grade benchmark (IG)

					Percentiles					
PME IG	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Public market equivalent (PME) —IG	448	1.08	1.05	0.25	0.51	0.73	0.96	1.15	1.50	2.03
Top quartile	112	1.38	1.30	0.26	1.15	1.16	1.20	1.43	2.00	2.38
Second quartile	112	1.10	1.10	0.03	1.05	1.05	1.07	1.12	1.14	1.15
Third quartile	112	1.01	1.01	0.02	0.96	0.97	0.99	1.03	1.04	1.05
Bottom quartile	112	0.82	0.87	0.14	0.31	0.52	0.79	0.92	0.95	0.96
High–low (quartiles)		0.55	0.43	0.24	0.84	0.63	0.41	0.51	1.05	1.42

D. Cross-sectional performance, measured by public market equivalent (PME), using the high-yield benchmark (HY)

					Percentiles					
PME HY	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Public market equivalent (PME) —HY	448	1.06	1.04	0.24	0.50	0.72	0.95	1.13	1.45	1.90
Top quartile	112	1.33	1.24	0.26	1.13	1.14	1.18	1.39	1.84	2.33
Second quartile	112	1.08	1.08	0.03	1.04	1.05	1.06	1.11	1.12	1.13
Third quartile	112	1.01	1.01	0.03	0.95	0.96	0.99	1.02	1.04	1.04
Bottom quartile	112	0.81	0.85	0.14	0.31	0.50	0.76	0.91	0.95	0.95
High–low (quartiles)		0.52	0.40	0.23	0.82	0.64	0.43	0.48	0.89	1.38

(continued)

Table 2. Private Debt Fund Performance (IRR, Multiples, PME) (continued)

E. Cross-sectional performance, measured by public market equivalent (PME), using the equity market benchmark (S&P500)

					Percentiles					
PME S&P 500	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Public market equivalent (PME) —S&P 500	448	1.06	1.01	0.30	0.51	0.71	0.92	1.14	1.55	2.06
Top quartile	112	1.42	1.34	0.35	1.14	1.15	1.21	1.50	1.95	2.55
Second quartile	112	1.06	1.06	0.04	1.01	1.01	1.03	1.09	1.13	1.14
Third quartile	112	0.96	0.96	0.03	0.92	0.92	0.94	0.98	1.00	1.00
Bottom quartile	112	0.79	0.83	0.13	0.40	0.53	0.74	0.89	0.91	0.91
High–low (quartiles)		0.63	0.51	0.33	0.74	0.62	0.47	0.61	1.04	1.64

This table reports on the performance of private debt funds in the cross-section and by performance quartile. *Panel A* reports on the performance of private debt funds, as measured by their internal rate of return (IRR), showing the mean, median, standard deviation, and performance percentiles, together with quartile performance (top to bottom quartile) and the difference between the best and worst performance (high–low). *Panel B* shows investment multiples. If a fund is not liquidated, the last available net asset value (NAV) is considered to reflect the fair market value and used as a last distribution when calculating the performance results. *Panel C* reports on the public market equivalent (PME), calculated as in Kaplan and Schoar (2005), and using the investment grade (IG) benchmark. The Bloomberg Barclays US Corporate Bond Total Return Index Baa [Ticker: LCB1TRUU] is used to calculate the PME against the IG benchmark. *Panel D* depicts the PME against the high-yield benchmark. The Bloomberg Barclays Corporate High Yield Index [Ticker: LF98TRUU] is used to calculate the PME. *Panel E* shows the PME when using the equity market benchmark, i.e., the Standard & Poor's 500 total return index. Private debt fund data are from Preqin, cut-off date December 31, 2020. Benchmark data are from Bloomberg.

the overall positive, but wide, variation in PD fund returns.

The PME analyses suggest that PD funds generally outperform all benchmark indices. The average (median) PD fund has a PME IG of 1.08 (1.05), a PME HY of 1.06 (1.04), and a PME S&P500 of 1.06 (1.01). The finding that all average PMEs are higher than 1 suggests that PD funds outperformed not only the most conservative IG benchmark by 8% but also the HY and the public equity (S&P500) benchmarks by 6%, respectively. Our PME results echo our earlier findings related to the high performance dispersion between top quartile and bottom quartile funds. Against the IG, HY, and S&P500 benchmarks, the difference between top- and bottom-performing funds is substantial and amounts to 55%, 52%, and 63%, respectively, as proxied by outperformance (PME).

So far, we have not controlled for survivorship bias in sampling. It is conceivable that GPs that provide low-fund performance stop reporting to publicly available databases, leading to sample survivorship bias and creating an upward bias in measured persistence (Kaplan and Schoar 2005). However, Preqin uses the Freedom of Information Act (FOIA) to collect fund-level return data directly from public pension plans. The risk of survivorship bias effects due to a lack of continuation of reporting is hence limited. It might also be the case that low-performing GPs decide to give up their asset management activity in PD entirely. We therefore analyze whether GPs that have only one fund perform worse than those with two or more funds. Of the 448 PD funds, 31 funds have no follow-on funds. The performance of these 31 funds is indeed worse than that of the full sample. The mean IRR, PME IG, PME HY, PME S&P500 and the mean net multiple are 4.82%, 0.96, 0.95, 0.93, and 1.16X, respectively. One-time funds do not provide value to investors, as they do not even render the market-equivalent return. Excluding one-time funds from our sample, the mean IRR, PME IG, PME HY, PME S&P500, and the mean net multiple of our conditioned sample increase to 9.52%, 1.09, 1.07, 1.07, and 1.31X, respectively.

Table 3 presents the returns per investment strategy. The mean IRR is highest for Special Situations (12.6%) and lowest for Venture Debt (8.2%), although the sample size of the latter is very small. The mean for Special Situations is highly skewed due to some very high-performing PD funds.[11] The median IRR is highest for Mezzanine (9.4%) and lowest for direct lending (7.9%). Distressed Debt has the highest performance in terms of net multiples (mean: 1.37; median: 1.30), and Direct Lending the lowest (mean: 1.17; median: 1.14). The PME analyses show that all investment strategies outperform the three

Table 3. Private Debt Fund Performance by Investment Strategy

Performance Measures	All	Direct Lending	Distressed Debt	Mezzanine	Special Situations	Venture Debt
Internal rate of return (IRR)	448	110	137	128	57	16
Mean	9.19	8.78	8.37	9.04	12.62	8.22
Median	8.5	7.9	8.3	9.4	8.0	8.6
SD	14.8	11.0	14.2	14.4	23.1	5.1
Net multiples (X)	436	107	136	125	53	15
Mean	1.30	1.17	1.37	1.34	1.30	1.32
Median	1.24	1.14	1.30	1.29	1.18	1.19
SD	0.35	0.16	0.42	0.33	0.41	0.29
Public market equivalent (PME) - IG	448	110	137	128	57	16
Mean	1.08	1.04	1.08	1.09	1.10	1.09
Median	1.05	1.04	1.04	1.07	1.05	1.08
SD	0.25	0.13	0.29	0.27	0.30	0.18
Public market equivalent (PME) - HY	448	110	137	128	57	16
Mean	1.06	1.05	1.05	1.07	1.10	1.04
Median	1.04	1.05	1.02	1.06	1.03	1.03
SD	0.24	0.12	0.28	0.25	0.29	0.15
Public market equivalent (PME) - S&P 500	448	110	137	128	57	16
Mean	1.06	0.99	1.09	1.07	1.08	1.10
Median	1.01	0.99	0.98	1.04	0.99	1.06
SD	0.30	0.12	0.39	0.28	0.34	0.15

This table reports on the performance of private debt funds in the cross-section and by investment strategy (direct lending, distressed debt, mezzanine, special situations, venture debt), indicating mean, median performance, as well as the standard deviation (SD) of the mean performance. Calculations as described in the previous tables. Private debt fund data are from Preqin, cut-off date December 31, 2020. Benchmark data are from Bloomberg.

benchmarks on average, except direct lending, which outperforms against the IG and HY benchmarks, but slightly underperforms relative to the S&P500 index by 1%. However, the dispersion of the direct lending fund PMEs, as measured by standard deviation, is lowest for all benchmarks, potentially compensating the risk-averse investor for the lower PME against some of the other strategies.

Next, following Cumming and Fleming (2013), we sort PD funds on performance to evaluate differences in characteristics between funds with higher and lower performance. Table 4 compares the characteristics of the PD funds that perform above the 50th and above the 75th percentile of the PME IG (benchmark) to those below.

Panel A of Table 4 shows that the attractive mean fund performance is largely driven by funds with a performance above the 50th or 75th percentile. Performers above the median have an IRR of 16.70% on average, while performers below the median render an asymmetrically lower 1.69%. Likewise, performers above the median render a net multiple of 1.54 to their investors, compared to one of 1.07 for performers below the median. The three mean PME values of above median performers are substantially above 1 (resulting in a lifetime benchmark outperformance of 24%, 21%, and 24%), while they are below 1 for the below median performers (resulting in an underperformance of 8%, 9% and 12%, respectively). Importantly, PMEs remain below 1 for the below 75-percentile performers. This suggests that a large fraction of the PD funds underperforms the market and that the variation in return between the top and bottom performance is wide. This stresses the importance of fund selection.

Panel B of Table 4 shows that funds that outperform the industry have a higher probability of being managed by GPs who have managed high-performing PD funds previously, suggesting persistence of performance in the PD industry. The lagged PME (compared

Table 4. Fund Performance Comparison Tests

A. Performance

Performance Proxy	n	Mean	Median	Above Median	Below Median	Comparison of Means	t-Value	z-Value	Above 75th Percentile	Below 75th Percentile	Comparison of Means	t-Value	z-Value
IRR	448	9.19	8.46	16.70	1.69	15.01**	12.43	18.31	23.33	4.48	18.85**	13.97	15.86
PME IG	448	1.08	1.05	1.24	0.92	0.32**	17.88	18.31	1.38	0.98	0.40**	20.83	15.86
PME HY	448	1.06	1.04	1.21	0.91	0.30**	17.19	18.31	1.33	0.97	0.37**	18.98	15.86
PME S&P500	448	1.06	1.01	1.24	0.88	0.37**	16.43	18.31	1.42	0.94	0.49**	21.07	15.86
Net multiple	436	1.30	1.24	1.54	1.07	0.47**	19.37	18.07	1.76	1.15	0.61**	23.59	15.50

B. Fund characteristics

Variables	n	Mean	Median	PME IG Above Median	PME IG Below Median	Comparison of Means	t-Value	z-Value	PME IG Above 75th Percentile	PME IG Below 75th Percentile	Comparison of Means	t-Value	z-Value
Lagged performance (PME IG)	223	1.12	1.08	1.18	1.07	0.12**	3.38	3.99	1.23	1.09	0.14**	3.27	3.05
Log(size)	442	1337.45	835.08	1186.02	1487.51	−301.49*	−2.08	−1.338	1105.00	1413.53	−308.53	−1.83	−1.26
Industry-agnostic	448	0.78	1.00	0.77	0.79	−0.02	−0.57	−0.569	0.78	0.78	0.00	−0.07	−0.07
US focus	448	0.77	1.00	0.78	0.76	0.02	0.45	0.45	0.75	0.78	−0.03	−0.65	−0.65
Capital deployment period	448	1534.56	1233.00	1665.16	1403.97	261.19**	2.36	2.92	1619.29	1506.32	112.97	0.88	1.51
Funds overall	435	6.15	4.00	5.42	6.88	−1.46**	−1.97	−2.986	4.70	6.64	−1.94**	−2.27	−3.64
Fund series	448	3.03	2.50	2.81	3.26	−0.45*	−2.25	−1.669	2.69	3.14	−0.45*	−1.98	−2.08
First fund	446	0.22	0.00	0.24	0.21	0.03	0.80	0.80	0.25	0.21	0.04	0.85	0.85

C. Debt and equity market conditions for portfolios sorted on PME IG

Variables	n	Mean	Median	PME IG Above Median	PME IG Below Median	Comparison of Means	t-Value	z-Value	PME IG Above 75th Percentile	PME IG Below 75th Percentile	Comparison of Means	t-Value	z-Value
TED spread$_{ex\ ante}$	448	0.43	0.33	0.42	0.43	−0.01**	−0.42	−3.313	0.41	0.43	−0.02*	0.52	2.38
ΔTED spread	448	−0.02	0.00	−0.05	0.01	−0.07*	−2.0933	−0.536	−0.06	−0.01	−0.05	1.34	0.38
Credit spread$_{ex\ ante}$	440	3.59	3.19	3.94	3.24	0.70**	4.99	6.24	4.15	3.41	0.75**	4.54	5.62
Δ credit spread	440	−0.19	0.07	−0.20	0.17	−0.37**	−2.49	−1.85	−0.27	0.06	−0.33	−1.88	−1.81
VIX$_{ex\ ante}$	448	18.04	16.43	19.51	16.57	2.93**	5.15	5.84	20.55	17.20	3.34**	5.08	5.67
ΔVIX	448	0.59	0.82	−0.75	1.94	−2.69**	−4.60	−4.60	−1.16	1.18	−2.34**	−3.43	−3.49

This table presents fund performance comparison tests. We present the mean performance of a portfolio of PD funds with their performance being above and below the 50th (75th) performance percentile in *Panel A*. Fund characteristics of funds performing above and below the 50th (75th) percentile—when using the PME IG as a benchmark—are shown in *Panel B*. Ex ante and ex post debt and equity market conditions for fund portfolios sorted on performance above (below) the 50th (75th) percentile are presented in *Panel C*. Significance at the 5% level is reported using a single asterisk (*), significance at the 1% level is reported using double asterisks (**).

with the IG benchmark) of the previously managed PD funds is 0.12 higher when comparing PD funds that perform above versus below the median. This will be further explored in the next section. Outperforming PD funds are, on average, smaller, use more time to deploy committed capital and are managed by GPs with a lower number of funds.

Panel C of Table 4 focuses on the *ex ante* level of credit market conditions in which over- and underperforming funds are launched. Next, it shows how theses credit market conditions change. The credit market conditions in the first two years of the investment period are compared to those in the fundraising phase. Outperformers are, on average, launched when funding illiquidity (TED spread level) is lower, credit spreads are higher and equity market volatility is higher. The level difference in credit market conditions between better performing and lower performing funds is statistically significant for all three credit market condition proxies. Thus, higher yielding funds are launched at a TED spread level that is one to two basis points lower, a credit spread level which is 70 to 75 basis points higher and a VIX level that is 2.9 to 3.3 points higher.

Interestingly, some *ex post* credit market conditions improve for better performing funds. TED spread (credit spread) contracts more for better performing funds by five to seven basis points (33 to 37 basis points) than those of their lower performing competitors, while VIX decreases by approximately two to three basis points more. We will test the hypothesis that skilled GPs can exploit changes in market conditions in "Market Timing" section.

Performance Persistence in the PD Industry

Using the Kaplan and Schoar (2005) PME, we have shown that PD funds deliver outperformance against a traded market benchmark or risk factor in the cross-section. This is exceptional as market outperformance is rare and departs from the rule in the mutual fund industry.[12] For LPs aiming to invest in PD funds, and given the large dispersion in performance, an important question is: Which funds should be selected? In the private-equity industry, Kaplan and Schoar (2005) were the first to show that returns in private-equity funds are persistent: GPs whose funds outperformed the industry in one fund were likely to outperform the industry in their next two funds (for a comprehensive survey on PE performance and persistence, see Kaplan and Sensoy 2015). Outperformance is driven by the superior ability of top GPs to select investment targets, but also by their ability to create value in their targets through enhancing governance (Jensen 1986), or through providing scarce or specialized resources (Cressy, Munari, and Malipiero 2007; Manigart and Wright 2013a, 2013b). LPs therefore strongly focus on the LPs' past performance when selecting new private-equity funds in which to invest (Vanacker et al. 2020).

We therefore test whether outperformance is also persistent in the PD industry. Do PD GPs have specific skills that allow them consistently to outperform the market?

To address this question, and in line with prior PE studies, we regress current on past performance (Kaplan and Schoar 2005; Korteweg and Sorensen 2017; Robinson and Sensoy 2016). We include the 234 funds in our sample that have an earlier fund[13] managed by the same GP. The dependent variable is the PD fund performance, and the independent variable is the lagged performance, i.e., the performance of the previous fund managed by the same GP.[14] Five OLS models are run for each of the five performance measures introduced earlier. The return-generating process of a GP is modeled as

$$P_i = P_{i,t-1} + \beta_i CMC_t + \beta_i X_{it} + \varepsilon_i, \qquad (3)$$

with P_i being the performance of PD fund i, as proxied by its IRR, net multiple, or Kaplan and Schoar (2005) PME, using different traded benchmarks. $P_{i,\,t-1}$ is the performance of the previous PD fund managed by the same GP, while CMC is the credit market conditions, known *ex ante*, when the first cash contribution is called from LPs at time t. X is a vector of fund-specific control variables, and ε is the error term of fund i. *Ex ante* market conditions are observable to all market participants when deciding to commit to the fund. The *ex ante* period spans 360 days before the inception of a PD fund, the latter defined as the date of the first cash contribution from LPs. The one-year period is chosen because it reflects the typical duration of marketing efforts prior to the first cash contributions from LPs.

Control variables include the log of the size of the PD fund; whether the fund has a focus on a specific industry or is industry-agnostic (dummy variable); whether the fund is focused on the US (dummy variable); and how long (number of days) it takes to invest the fund fully. Additional control variables capture GP experience with managing PD funds: the overall number of PD funds managed by the GP, the fund series and whether the PD fund is the first fund

Table 5. Does Lagged Performance Explain Performance?

Variables	(1) IRR	(2) Net Multiple	(3) PME IG	(4) PME HY	(5) PME S&P500
Performance$_{t-1}$	0.195**	0.328**	0.180**	0.197**	0.290**
	(0.186)	(0.412)	(0.245)	(0.277)	(0.434)
Log(size)	2.175	0.00840	0.00661	0.00247	0.00112
	(0.166)	(0.0269)	(0.0300)	(0.0120)	(0.00447)
Industry-agnostic	_1.886	0.0571	0.0293	0.0345	0.0166
	(_0.0646)	(0.0823)	(0.0599)	(0.0754)	(0.0298)
US_focus	_1.143	0.00302	_0.0337	_0.0383*	_0.0151
	(_0.0372)	(0.00409)	(_0.0654)	(_0.0793)	(_0.0258)
Capital deployment period	_0.00256**	_7.46e_06	_2.76e_05*	_3.25e_05*	_1.57e_05
	(_0.216)	(_0.0262)	(_0.139)	(_0.175)	(_0.0696)
Funds overall	_0.195**	_0.00163	_0.00187	_0.00175	_0.000649
	(_0.148)	(_0.0525)	(_0.0845)	(_0.0843)	(_0.0258)
Fund series	0.0616	0.00496	_0.00527	_0.00348	_0.00505
	(0.0108)	(0.0366)	(_0.0553)	(_0.0390)	(_0.0465)
First fund	0.215	0.0200	_0.0156	_0.0228	_0.0428
	(0.00522)	(0.0198)	(_0.0226)	(_0.0352)	(_0.0545)
TED spread$_{ex\ ante}$	_1.556	0.0982	_0.177**	_0.195**	0.00177
	(_0.0356)	(0.0928)	(_0.242)	(_0.284)	(0.00213)
Credit spread$_{ex\ ante}$	1.363	0.0401*	0.0594**	0.0442**	_0.0209
	(0.156)	(0.187)	(0.407)	(0.323)	(_0.125)
VIX$_{ex\ ante\ /\ orthogonal}$	0.935*	0.0246*	0.0190**	0.0156*	0.0316**
	(0.202)	(0.223)	(0.245)	(0.215)	(0.357)
Constant	_5.164	0.513**	0.755**	0.827**	0.849**
Observations	230	222	231	231	231
R-squared	0.142	0.306	0.216	0.223	0.381
Strategy FE	Y	Y	Y	Y	Y

This table reports the results of cross-sectional regression tests of individual private debt funds using the lagged performance, fund characteristics, and ex ante credit market conditions as independent variables. We regress the performance measures introduced earlier (IRR, net multiple, PME IG, PME HY, PME S&P500) on the lagged performance (t – 1) of a fund in a series, managed by the same GP. In addition, we test fund characteristics and credit market conditions, as defined in Table 1, and control for strategy fixed effects. Standard errors are clustered by general partner (GP). Robust normalized beta coefficients in parentheses are used to indicate the effect size of the used variables. Significance at the 5% level is reported using a single asterisk (*); significance at the 1% level is reported using double asterisks (**).

launched by the GP in a series of the same investment strategy. We further control for *ex ante* credit market conditions, following Kaplan and Strömberg (2009), who consider the relation between the market conditions during a private equity fund's inception period and subsequent fund returns. They showed that economic conditions prevalent in the early life of a private-equity fund, such as the capital flow into private equity relative to the stock markets, may significantly affect its lifetime performance (Kaplan and Strömberg 2009). We include funding liquidity, credit spread and equity market volatility as important credit market conditions. We further include investment-strategy fixed effects, we cluster standard errors by GP, as in Kaplan and Schoar (2005), and we check for multicollinearity using the variance inflation factor (VIF).[15] We verify the correlation between independent variables and use the orthogonal part of VIX[16] in our models to avoid concerns of multicollinearity between equity market volatility (VIX) and credit spread. VIF is smaller than 1.59 for any model, and the average VIF is 1.57.

The results presented in Table 5 show that lagged performance significantly predicts current performance in all specifications at the 1% level. Overall, this suggests that GPs of PD funds have specific skills, allowing them to provide consistent performance over consecutive funds, and that outperformance is not solely due to luck. The effect is economically meaningful: A 5% to 10% increase in lagged outperformance (0.05–0.1), as proxied by the PME HY, increases the outperformance of the follower fund by 0.9% to 2.0% (0.05 or 0.10 X 0.197).

Table 6. Transition Probabilities: Fund Performance

	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
	A. Public market equivalent (PME)			
First quartile (lowest)	40%	26%	18%	13%
Second quartile	25%	30%	21%	21%
Third quartile	10%	29%	35%	27%
Fourth quartile (highest)	24%	15%	26%	38%
	B. Internal rate of return (IRR)			
First quartile (lowest)	39%	30%	19%	12%
Second quartile	25%	30%	22%	23%
Third quartile	11%	27%	33%	29%
Fourth quartile (highest)	25%	14%	27%	35%

We sort all funds for which we have follow-on funds into performance quartiles and calculate the conditional probability that a GP's next fund will either stay in the same performance quartile or move into one of the other three quartiles. The results in Panel A are based on public market equivalent (PME) against the investment grade benchmark, and Panel B is based on the internal rate of return (IRR). For this calculation, we use 258 funds that have at least one follow-on fund in our sample of funds.

The fund-level and GP-level control variables do not significantly predict performance, except for the capital deployment period, which has a negative effect on IRR, PME IG and PME HY. This is consistent with the notion that GPs disposing of a high and qualitatively attractive deal flow at fundraising outperform PD funds that do not dispose of sufficient deal flow, i.e., they are slower to invest.

Ex ante credit market conditions likewise affect performance: a higher TED spread level negatively affects fund performance as proxied by PME IG and PME HY. An increase in the credit spread positively affects outperformance against the IG (HY) benchmark or increases the investment multiple. *Ex ante* equity market volatility, as proxied by VIX, significantly and positively affects all performance proxies.

We further verify whether selection survivorship biases might drive our persistence findings. Selection or survivorship biases would predict that persistence of returns is driven by either the positive or the negative end of the performance distribution. Following Kaplan and Schoar (2005), we sort all 257 funds for which we have follow-on funds into performance quartiles. We then calculate the conditional probability that a GP's next fund will either stay in the same performance quartile or move into one of the other three quartiles. Table 6 shows the results of our analyses, with Panel A based on the PME against the investment-grade benchmark, and Panel B based on IRRs.

If performance were randomly distributed across GPs (null hypothesis), then the conditional probabilities would be equal to 25% in all cells. In both panels, a chi-squared test rejects the equality of all cells at the 1% level. Consistent with the findings of Kaplan and Schoar (2005) for PE funds, we find persistence at both ends of the distribution. We observe that funds in the top quartile have at least a 35% probability of remaining in those quartiles, while funds in the lowest quartile have at least a 39% probability of remaining in the lowest quartile. While we cannot completely rule out selection biases, our additional analyses are in line with the existence of persistence in PD funds, and comparable to the findings of Kaplan and Schoar (2005) for PE funds.

When GPs start the fundraising for a new fund, the predecessor fund is sometimes not very mature, meaning not all of the committed capital has been called or invested. In private equity, this creates a challenge to the investor, as private equity performance depends largely on later stage value development and realization of investments. Value is typically not created in the early years of a private equity fund, resulting in a J-curve pattern with largely negative cash flows in the early investment phase, and positive cash flows later during the harvesting period. Moreover, private equity fund managers have incentives to time investments and cash flows during the investment period.[17] Predecessor fund performance is hence difficult to observe or assess, as early-stage private equity funds did not have sufficient time to provide reliable performance information. Performance persistence information would then have a very limited use for investors.

PD fund performance is created differently than PE fund performance. PD contracts typically deliver cash flows to the PD fund already during the investment period. The main components of a PD fund habitually include fixed-term bullet loans with a balloon payment due at maturity, and regular coupon payments. PD funds therefore already generate performance during the investment period and value is not that much created by later stage developments. Predecessor PD fund performance is therefore not as difficult to observe or evaluate as it is for private equity funds. Nevertheless, it is worth exploring whether persistence is conditional on predecessor PD fund maturity. PD GPs typically start the fund-raising of a new fund when approximately 75% of the aggregate LP commitments are called or invested.[18] To evaluate whether persistence is conditional on predecessor PD fund maturity, we split our sample into three groups based upon the level of capital called of the previous fund: Early-stage funds with less than 75% capital called (85 PD funds), more mature funds with between 75% and 100% capital called (260 PD funds) and very mature funds with above 100% capital called (99 PD funds). Persistence might be significant only when using past performance data of more mature predecessor funds. We therefore rerun the regressions reported in Table 5 for each of the subgroups separately. Results show that previous performance does not significantly predict current performance for the early-stage funds. In contrast, previous performance significantly predicts current performance in the mature funds (for all performance measures) and in the very mature funds (except for the IRR). Persistence is hence largely driven by mature PD funds with a level of capital called equal to or beyond 75%. IRRs in general and past performance of early-stage funds should thus be considered with more caution when considering an investment in a new PD fund.

Market Timing

The previous analyses established that there is persistence in PD fund returns. We have also shown that *ex ante* credit market conditions appear to importantly affect fund performance. Given the importance of *ex ante* credit market conditions, we next address the empirical question whether *ex post* market conditions—and especially the ability of GPs to time the market—affect performance. Persistence has largely been equated to skill (Korteweg and Sorensen (2017), which can be defined as “a general cognitive ability to pick [stocks] or time the market” (Kacperczyk, Nieuwerburgh, and Veldkamp 2014, 1455).

Are GPs skilled to time credit market conditions? Previous research explained PD performance using market factors known *ex ante* as *lagged* variables. Thus, the research focused on information that was publicly available at the inception of a fund (Cumming and Fleming 2013; Cumming et al. 2019). By contrast, we extend their approach with a market signal that was not available at the inception of a fund. In our model, we measure the ability of a GP to process a private market-timing signal, as proxied by *ex post* changes in TED spread, credit spread and equity market volatility (VIX).

Ex post changes to TED spread, credit spread, and equity market volatility are not publicly known *ex ante* and are hence private market-timing signals in the spirit of Ferson and Schadt (1996) and Elton, Gruber, and Blake (2012). GPs should not be given credit for performance in response to publicly available information, but the assessment of market timing must assess the skill of a GP to anticipate and respond to a *private* market-timing signal (Ferson and Schadt 1996; Elton, Gruber, and Blake 2012).

We follow Korteweg and Nagel (2016) and equate the Kaplan and Schoar (2005) PME to the risk-adjusted lifetime excess return, as PME is equivalent to evaluating PE investments under the dynamic version of the CAPM developed by Rubinstein (1976) (Sorensen and Jagannathan 2015).

Prior research established that over 90% of long-term debt contracts are renegotiated prior to maturity (Roberts and Sufi 2009) and that early improvements of credit market conditions especially drive debt contract renegotiation (Roberts and Sufi 2009). For example, a typical bank loan is renegotiated five times, or every nine months (Roberts 2015). *Ex post* changes in credit market conditions may hence lead to contract renegotiations. This may engender PD fund fees and thus affect performance. We therefore estimate timing skill in respect to *ex post* changes in (I) funding liquidity, (II) credit spreads, and (III) equity market volatility, thereby extending our specification (3).

First, funding illiquidity indicates the reluctance of traditional banks to lend to corporates, as they focus on maintaining sufficient funding sources versus regulatory requirements and rating expectations (Brunnermeier and Pedersen 2009). Such a tightening of bank loan supply translates into stronger recourse to alternative financing (Leary 2009; Altavilla, Pariès, and Nicoletti 2019; Dwenger, Fossen, and Simmler 2020). TED spread is used to proxy for funding illiquidity.[19] An increase in the TED spread may reflect liquidity risk in the short term (Brunnermeier 2009) and affect the reluctance of banks to lend to corporates.[20] We expect PD fund performance to be significantly affected by *ex ante* and *ex post* funding illiquidity, as it should have an impact on the initial contract negotiation and its later renegotiation.

Second, credit spreads reflect the compensation for heightened credit or default risk. Credit risk is driven by an asset's growth, volatility, and leverage (Merton 1974) and is widely used to explain bond prices (Bai and Collin-Dufresne 2011; Collin-Dufresne, Goldstein, and Martin 2001; Eom, Helwege, and Huang 2004; Ericsson, Renault, and Calcagno 2006; H. H. Huang, Huang, and Oxman 2015; J.-Z. Huang and Huang 2012) or debt pricing in general (Bai and Wu 2016; Cumming et al. 2019; Elton et al. 2001; Schwarz 2019). Credit risk may be a driver of funding costs in the longer term (Gefang, Koop, and Potter 2011). Tang and Yan (2010) show that credit spreads widen when investors become more risk-averse and therefore expect higher returns, thereby negatively affecting bond prices.

Third, equity market volatility is a factor priced in bond markets (Bao et al. 2015; Campbell and Taksler 2003; Chung, Wang, and Wu 2019; Cremers et al. 2008), as both stocks and bonds are contingent claims for the assets of a company. Aggregate equity volatility risk is priced in the cross-section of expected corporate bond returns (Chung, Wang, and Wu 2019), with times of higher volatility in the financial markets being associated with higher excess returns (Tang and Yan 2010). We hence control for the aggregate level of equity market volatility using the CBOE Volatility S&P 500 Index (VIX).

We calculate changes in credit market conditions (Δ CMC) by subtracting the average of the 360-day *ex ante* values (t-1) from the average of the 720-day *ex post* ($t+1$) values prior to and after the inception of a PD fund, i.e., the first capital contribution of LPs. We use the average *ex ante* level and the average *ex post* level from its first cash contribution (t), as the typical fund allocates and renegotiates a substantial part of its assets during the investment period (see Table 1). The return-generating process of a GP is therefore modeled as

$$P_i = P_{i,t-1} + \beta_i CMC_t + \Upsilon_{it} E(\Delta\ CMC|C_t) + \beta_i X_{it} + \varepsilon_i, \tag{4}$$

with P_i being the performance of PD fund I, as proxied by its IRR, net multiple, and the Kaplan and Schoar (2005) PME, using different traded benchmarks. $P_{i,\ t-1}$ is the performance of the previous PD fund managed by the same GP. CMC_t are the credit market conditions known *ex ante* when the first cash contribution is called from LPs at time t. E is a GP's expectation of *ex post* changes in credit market conditions, when the first cash contribution, C_i, is called from LPs at time t. X is a vector of fund-specific control variables, while ε is the error term of fund i. Thus, Υ_{it} captures market-timing skill, i.e., a GP's forecast with respect to an expected change in credit market conditions. We test the market timing hypothesis by applying our timing model as in Equation (4). Also, we include investment-strategy fixed effects and cluster standard errors by GP, as in Kaplan and Schoar (2005), and we use three benchmarks to calculate PMEs. The VIF is smaller than 2.30 for any model, and the average VIF is 2.28. As before, the correlation between variables in our model is not problematic. Table 7 shows the regression results.

The results in Table 7 suggest that changing credit market conditions significantly affect the market outperformance of PD funds. First, adding changes in market conditions to the regression models significantly enhances the model fit,[21] suggesting that they are important in explaining PD fund performance.

Second, the *ex post* changes in TED spread and in credit spread significantly affect the PD fund performance measures in most models. An increase in *ex post* TED spread, indicating deteriorating funding liquidity after the launch of the PD fund, is negatively associated with the three relative performance measures in models 3 and 4, but not with the absolute performance measures in models 1 and 2. For example, a one standard deviation improvement in *ex post* funding illiquidity (0.334) increases the outperformance against the IG benchmark by 6.5% (β x σ^2 TED $= -0.195$ x -0.334).

Likewise, an *ex post* change in credit spreads significantly affects a fund's absolute performance and its outperformance against the IG benchmark. An *ex post* reduction in credit spread increases both its IRR and net multiple, as well as its outperformance, compared with the IG benchmark. A one standard deviation *ex post* increase in credit spread (0.696) increases PD fund outperformance against the IG benchmark by 4.7% (β x σ^2 credit spread $= 0.068$ x 0.696). Finally, the *ex post* change in equity market volatility affects a fund's net multiple, but none of the other performance measures.

Importantly, lagged performance remains highly significant in all models. A 10% increase in IRR (PME IG)

Table 7. Market Timing Skills

Variables	(1) IRR	(2) Net Multiple	(3) PME IG	(4) PME HY	(5) PME S&P500
Performance$_{t-1}$	0.231**	0.317**	0.205**	0.205**	0.293**
	(0.220)	(0.397)	(0.279)	(0.288)	(0.439)
Log(size)	1.708	−0.00701	−0.00108	−0.000219	0.00202
	(0.130)	(−0.0224)	(−0.00490)	(−0.00106)	(0.00807)
Industry-agnostic	−1.590	0.0574	0.0358	0.0403	0.0148
	(−0.0545)	(0.0827)	(0.0732)	(0.0880)	(0.0266)
US focus	−1.078	−0.0167	−0.0264	−0.0258	−0.0227
	(−0.0350)	(−0.0226)	(−0.0513)	(−0.0534)	(−0.0387)
Capital deployment period	−0.00297**	−4.51e − 05	−3.79e−05*	−3.14e − 05	−2.82e − 05
	(−0.251)	(−0.158)	(−0.191)	(−0.169)	(−0.125)
Funds overall	−0.188**	−0.00159	−0.00168	−0.00164	−0.000467
	(−0.143)	(−0.0511)	(−0.0761)	(−0.0791)	(−0.0186)
Fund series	0.0589	0.00593	−0.00528	−0.00373	−0.00484
	(0.0103)	(0.0438)	(−0.0554)	(−0.0418)	(−0.0447)
First fund	−0.652	−0.0291	−0.0396	−0.0353	−0.0545
	(−0.0158)	(−0.0288)	(−0.0574)	(−0.0545)	(−0.0694)
TED spread$_{ex\ ante}$	−11.04	0.0102	−0.383**	−0.376**	0.0265**
	(−0.253)	(0.00969)	(−0.523)	(−0.548)	(0.300)
Credit spread$_{ex\ ante}$	3.738**	0.108**	0.0915**	0.0520*	−0.0332
	(0.429)	(0.503)	(0.626)	(0.380)	(−0.199)
VIX$_{ex\ ante\ /\ orthogonal}$	0.701	0.0122	0.00873	0.00856	0.116
	(0.151)	(0.111)	(0.112)	(0.118)	(0.139)
Δ TED spread$_{ex\ post}$	−6.288	0.0499	−0.195*	−0.215*	−0.0120
	(−0.166)	(0.0542)	(−0.307)	(−0.361)	(−0.141)
Δ credit spread$_{ex\ post}$	3.478**	0.0794**	0.0687**	0.0415	−0.0171
	(0.407)	(0.385)	(0.481)	(0.310)	(−0.105)
Δ VIX$_{ex\ post\ /\ orthogonal}$	−0.106	−0.0206*	−0.0115	−0.00661	0.101
	(−0.0240)	(−0.193)	(−0.154)	(−0.0948)	(0.139)
Constant	−5.647	0.546**	0.769**	0.868**	0.870**
Observations	230	222	231	231	231
R-squared	0.187	0.394	0.294	0.264	0.394
Strategy FE	Y	Y	Y	Y	Y

This table reports the results of cross-sectional regression tests of individual private debt funds using the lagged performance, fund characteristics and ex ante, *as well as changes in ex post credit market conditions* as independent variables. We regress the performance measures introduced earlier (IRR, net multiple, PME IG, PME HY, and PME S&P500) on the lagged (t − 1) performance of a fund in a series, managed by the same GP. In addition, we test fund characteristics and credit market conditions, as defined in Table 1, and control for strategy fixed effects. Δ TED spread, Δ credit spread, and Δ VIX represent the changes of the average level of these credit market conditions one year prior to the first capital contribution from LPs, and two years thereafter. Standard errors are clustered by general partner (GP). Robust normalized beta coefficients in parentheses are used to indicate the effect size of the used variables. Significance at the 5% level is reported using a single asterisk (*); significance at the 1% level is reported using double asterisks (**).

in a previous fund increases the IRR (PME IG) of the current fund by 2.31% (2.05%).[22] Interestingly, the economic effects of market timing are bigger than those of lagged performance. The impact of other fund, GP and market characteristics are largely in line with earlier findings.

We next reconcile these regression estimation results with the observed *ex ante* and *ex post* credit market conditions in Table 4. As institutional investors typically use the IG benchmark, we base our reconciliation on our public total return IG-index. PD funds above the 50th (75th) performance percentile are launched at TED spreads that are lower by 1 basis point (2 basis points) and experience *ex post* improvements of funding illiquidity that exceed those of lower performing funds by 7 basis points (5 basis points). We find that, all else being equal, the *ex ante* and *ex post* difference in the level and change of TED spread affects a PD fund's market outperformance substantially. The *ex ante* difference in funding illiquidity levels (−1 basis point) explains 0.38% of fund outperformance against the IG benchmark (−1 X −0.383), while the *ex post* difference in the change in funding illiquidity (−7 basis points) explains 1.36% of fund outperformance (−7 X −0.195). In other words, *ex post* changes in the level of funding illiquidity affect performance by a factor approximately three to four times larger. Together, for funds that perform above the 50th percentile, the observed *ex ante and ex post* effects of funding illiquidity explain approximately 1.7% of market outperformance against the IG benchmark. For the best-performing funds (PME IG above the 75th percentile), the combined *ex ante* and *ex post* effect amounts to approximately 1.74% ([−2 basis points X −0.383 = 0.766%] + [−5 basis points X −0.195 = 0.975%]). Market outperformance of the top-performing PD funds is importantly driven by improving TED spreads during the investment phase, suggesting that top GPs can time fundraising by anticipating improved funding illiquidity.

Given the lack of deal level data, we cannot verify why the *ex post* decrease in TED spread is positively related to fund performance. However, it seems plausible to us that an increasing willingness of traditional banks to lend to businesses (as reflected by a decline in the TED spread) encourages loan renegotiation and increases borrowers' demand for improved loan terms (see Roberts 2015; Roberts and Sufi 2009). This may lead to the early termination of debt contracts, yielding extra returns to PD funds in the form of penalty fees or minimum return clauses in PD contracts.[23] Moreover, the fund may recycle this capital, i.e., reallocate the capital a second or third time during the investment period, allowing the fund repeatedly to earn origination fees (instead of only once). This may additionally enhance PD fund performance. Finally, if TED spread contracts and market prices increase, independently of loan renegotiations or early contract termination, a fund may sell debt assets in the secondary market and generate profits. Cumming et al. (2019) show that such a trading orientation, as opposed to a buy-and-hold strategy, may lead to enhanced performance.

The *ex ante* level *and ex post* level changes in credit spread likewise importantly affect market outperformance against the IG benchmark. Funds performing above the 50th (75th) percentile are launched at credit spread levels that are 70 (75) basis points higher (Table 4). Moreover, funds performing above the 50th (75th) percentile experience *ex post* credit spread contractions that are larger by 37 (33) basis points when compared to their lower performing peers. However, this improvement in credit market conditions seems to reduce a fund's outperformance. The observed *ex post* credit spread contractions reduce a fund's outperformance against the IG benchmark by −2.5% (−2.2%) and reduces the IRR by −1.3% (−1.2%). Top-performing GPs hence seem to fundraise when credit spread levels are higher but contract thereafter, the latter reducing their outperformance.

Finally, changes in equity market volatility (ΔVIX) has little impact on performance, except for the net multiple, which is significant at the 5% level.

In our final analysis, we verify whether market timing is also important when we include first-time funds. These were omitted from the previous analyses, as the aim was to understand the combined effects of persistence and market timing. In the new models including all funds, the lagged performance variable is therefore eliminated from our specifications. Controlling for multicollinearity, VIF is s as low as in our previous model. Table 8 shows the results.

Consistent with the previous model, *ex ante* higher levels of TED spread reduce fund performance, while *ex post* increases in TED spread are significantly negatively associated with IG and HY outperformance measures, although the coefficients are somewhat smaller. *Ex ante* higher levels of credit spread positively affect fund performance, as do *ex post* credit spread expansions.

Conclusions and Future Research

We show that including PD funds in an investor's portfolio has the potential to increase returns on average. We find an average PD fund IRR of 9.19%, net-of-fees, returning 1.3X the invested capital to the investor. PD funds outperform the IG benchmark by 8%, and both the HY and the S&P 500 benchmark by 6% in the cross-section. We find large performance dispersion between top-performing and low-performing funds, making fund selection demanding.

How can investors select the best-performing PD funds? We first asked the question whether past performance is a reliable predictor of the next fund managed by the same GP. We find that persistence is present in the PD fund market: the performance realized in a previous fund significantly predicts the performance of its current fund. A 10% increase in lagged IRR (PME IG) increases the IRR (PME IG) of the current fund by 1.95% (1.80%). However, our

Table 8. Market Timing Skill Including First-Time Funds

Variables	(1) IRR	(2) Net multiple	(3) PME IG	(4) PME HY	(5) PME S&P500
TED spread$_{ex\ ante}$	−13.43**	−0.111	−0.400**	−0.353**	0.0326
	(−0.281)	(−0.101)	(−0.509)	(−0.472)	(0.0343)
Credit spread$_{ex\ ante}$	2.569**	0.0926**	0.0719**	0.0299*	−0.0112
	(0.259)	(0.407)	(0.441)	(0.192)	(−0.0565)
VIX$_{ex\ ante\ /\ orthogonal}$	1.047*	0.0170	0.0127	0.0156	0.0427**
	(0.214)	(0.151)	(0.158)	(0.204)	(0.437)
Δ TED spread$_{ex\ post}$	−7.431*	0.0603	−0.188*	−0.195**	0.125
	(−0.168)	(0.0595)	(−0.258)	(−0.282)	(0.142)
Δ Credit spread$_{ex\ post}$	2.172**	0.0518*	0.0448**	0.0172	−0.0170
	(0.227)	(0.236)	(0.285)	(0.115)	(−0.0892)
Δ IX$_{ex\ post}$	0.732	−0.00675	0.000841	0.00523	0.00765
	(0.138)	(−0.0553)	(0.00966)	(0.0631)	(0.0724)
Constant	−0.178	0.857**	0.932**	1.064**	1.003**
Observations	407	396	407	407	407
R-squared	0.073	0.171	0.123	0.095	0.198
Strategy FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

This table reports the results of cross-sectional regression tests of individual private debt funds *not* using the lagged performance variable in order to allow for first-time funds to be included in the sample. We use fund characteristics (not reported for brevity) and ex ante as well as changes in ex post credit market conditions as independent variables. We regress the performance measures introduced earlier (IRR, net multiple, PME IG, PME HY, and PME S&P500) on the lagged (t − 1) performance of a fund in a series, managed by the same GP. In addition, we test fund characteristics and credit market conditions, as defined in Table 1, and control for strategy fixed effects. Δ TED spread, Δ credit spread and Δ VIX represent the changes of the average level of these credit market conditions one year prior to the first capital contribution from LPs, compared to two years thereafter. Standard errors are clustered by general partner (GP). Robust normalized beta coefficients in parentheses are used to indicate the effect size of the used variables. Significance at the 5% level is reported using a single asterisk (*); significance at the 1% level is reported using double asterisks (**).

persistence results are largely driven by mature predecessor funds with at least 75% of capital called. Past performance of early-stage funds should thus be considered with more caution when considering an investment in a new PD fund.

Moreover, we were also able to analyze the impact of *ex ante* credit market conditions on fund performance and whether GPs possess the skill to time credit market conditions *ex post*. On the one hand, our results suggest that PD funds launched in periods of lower TED spreads, indicating a higher willingness of traditional banks to lend to corporates, generate outperformance against the IG benchmark and the HY benchmark, but not against the S&P500 benchmark. The level of credit spread and equity market volatility *ex ante* to fund inception are positively correlated to PD fund performance. On the other hand, our findings suggest that the best-performing GPs indeed anticipate *ex post* TED spread contractions, but not credit spread contractions. More specifically, when TED spreads decrease after fund inception, outperformance against the IG and HY benchmark significantly increases. The *ex post* change in funding illiquidity explains 1.4% of PD fund outperformance, a factor that is approximately three to four times larger than *ex ante* changes in funding illiquidity (0.4%). However, the performance of funds above the 50th percentile is mostly affected by the *ex ante* level (*ex post* change) in credit spread, which affects PD fund performance by 6.4% (−2.5%). GPs seem to demonstrate only partial market timing skills.

As in all empirical analyses, our results are limited to the data at hand. Our analyses are limited to the 1996–2020 period and hence to the prevailing macroeconomic conditions in that period. For example, there were far fewer funds in the PD market at the beginning of the sample period than at the end, implying lower PD market competition. We have not controlled for the potential effect of competition. It is well documented that return persistence in venture capital and private equity has decreased over time (Nanda, Samila, and Sorenson 2020). If the PD market continues to grow, competition for attractive lending transactions will become fiercer in the future. It is therefore an open and interesting research question how competition has affected or will affect PD fund performance and persistence. We leave this as an interesting avenue for further research, when more GPs in the PD industry will have a longer track record.

Following Kaplan and Schoar (2005), we analyze net-of-fees returns to LPs in PD funds. It would be important to analyze gross-of-fees performance and net-of-fees LP returns, more specifically, whether better performing GPs can charge higher fees and thus capture the returns to their skills in the sense of Berk and Green (2004). The persistence of performance for PD funds that we documented suggests that this is not fully happening. Relatedly, Hochberg, Ljungqvist, and Vissing-Jørgensen (2014) showed that the persistence of VC returns can be explained by information advantages of existing LPs, enabling them to hold up the GPs raising a new fund and limiting the GPs' potential to raise fees. However, exploring how fees are related to performance is outside the scope of our analysis.

In this paper, we studied PD performance at the fund level. Mimicking research in PE performance like that of Ewens and Rhodes-Kropf (2015) or Korteweg and Sorensen (2017), for example, future research could study the interesting and important question whether the PD firm or rather specific individuals or groups of individuals in the firm drive performance. Further research might study which human resource capabilities, such as education and experience, allows PD funds to outperform. Also, the question whether PD firm network considerations (Hochberg, Ljungqvist, and Lu 2007), reputation considerations (Hsu 2004) or access to good deal flow quality (Nanda, Samila, and Sorenson 2020) allow PD funds to outperform also promises a fruitful avenue for further research.

Next to performance analysis at the fund level, future research could also explore the drivers of PD investments at the loan level. How do loan characteristics, such as its purpose or loan specific features, or borrower characteristics, such as its financial health, age or private character, impact returns on individual private debt issuances? This would additionally help to understand GPs' specialization or their access to promising deals. Obviously, it would also be of importance to further investigate if and how improvements in credit market conditions drive contract terminations and secondary market transactions and how these affect PD fund performance.

Editor's Note

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Notes

1. See Financial Times (FT), August 17, 2021, on the boom in unlisted assets and the development of the market value of listed US alternative investment companies, which tripled to over $250 billion when taking Apollo, Ares, Blackstone, Carlyle and KKR together.
2. Direct lending is the practice of non-bank lenders extending loans to small and medium-sized businesses in return for debt securities; distressed debt lending includes debt investing to companies that have filed for bankruptcy or have a significant chance of filing for bankruptcy in the near future; mezzanine lending is related to investments in debt subordinated to the primary debt issuance and senior to equity positions; special situations funds include distressed and mezzanine lending, where the loan decision or grade is defined by criteria other than underlying company fundamentals; and venture debt includes lending to venture capital-backed companies by a specialized financier to fund working capital or expenses. We refer to Talmor and Vasvari (2020), who provide a comprehensive overview of the main topics in private capital, including a description of PD funds.
3. Kaplan and Strömberg (2009) provide an overview of the organization of PE funds.
4. See Harris, Jenkinson, and Kaplan (2014) and Kaplan and Sensoy (2015) for comprehensive surveys on private equity performance, and Korteweg (2019) for a review of empirical methods to assess risk and return in private equity.
5. Most cash-flow data are reported on a quarterly basis, although some are on a semi-annual basis.
6. Preqin reported 456 PD funds raised between 1996 and 2018. However, six were dropped, as five of them are fund-of-funds and one is a private equity fund. Our dataset starts in 1996, as the annual number of PD funds raised before 1996 is very low: only 15 PD funds were raised between 1988 (the founding date of the oldest PD fund) and 1996. PD funds incepted after 2018 were discarded, as sufficient time is needed to demonstrate performance. One PD fund, raised between 1996 and 2018, was dropped due to missing cash-flow data and one fund was dropped due to an unreasonably high return (IRR $>$ 200%). This reduced the final sample to 448 PD funds with vintage years 1996 through 2018.

7. We use capital contribution calendar dates to calculate the capital deployment period, and we equate a capital call to capital deployment. GPs decide when capital is called for investment. They typically minimize the period of time during which cash is sitting on the accounts of a fund; this contributes to maximizing return. Our capital deployment period must therefore be considered an approximate rather than an exact capital deployment period.

8. Our sample includes relatively young PD funds with more recent vintage years. By construction, these younger funds have high portions of unrealized remaining values (net asset value or NAV) at the end of the observation period (December 2020). Since 2009, the Financial Accounting Standards Board (FASB) requires funds to value their assets at fair value every quarter, rather than valuing them at cost. Unrealized values should therefore approximate true market values (Harris, Jenkinson, and Kaplan 2014) and are, on average, conservative in private equity funds (Brown, Gredil, and Kaplan 2019; Harris, Jenkinson, and Kaplan 2014; Jenkinson, Sousa, and Stucke 2013; Robinson and Sensoy 2016). We adhere to this view. As in Kaplan and Schoar (2005) and Harris, Jenkinson, and Kaplan (2014), we include NAVs of non-liquidated funds as if they were liquidating distributions to LPs.

9. Although IRRs are frequently used as a performance measure in the private capital fund universe, they may be upward-biased (Phalippou and Gottschalg 2009), as they are very sensitive to the sequencing of cash flows, with very early cash flows potentially leading to an upward bias of IRRs (Phalippou and Gottschalg 2009). Kocis et al. (2009) discuss the difficulties with the interpretation of IRRs.

10. The number of PD funds for which net multiple returns are available is slightly lower than that of the other performance measures, as net multiple returns are directly sourced from Preqin.

11. We omit percentile results here for the sake of brevity; those results are available from the authors upon request.

12. Ferreira et al. (2013), for example, show that mutual funds in 27 countries underperform in the market overall. Earlier studies on the underperformance of fund managers when trying to beat their benchmarks include Carhart (1997) and Fama and French (2010).

13. Note that the earlier fund does not necessarily follow the same investment strategy as the focal fund. Whether a GP has experience with managing a fund with the same investment strategy as the focal fund is captured by a dummy control variable, *First fund*.

14. To remove any concerns about non-liquidated NAVs, we depreciated them by 5% to recalculate all our performance measures. This amount reflects the potential upward bias in the fair market values that Barber and Yasuda (2017) find in the PE industry. Our regression results remain qualitatively and quantitatively similar and are available upon request.

15. The variance inflation factor (VIF) and the reciprocal tolerance level (1/VIF), together with the analysis of bivariate correlations between independent variables, as well as high correlations between the estimated coefficients, are used to detect issues of multicollinearity. No issues of multicollinearity are detected, and the VIF is substantially lower than the critical level of 10 suggested by Maalaoui Chun, Dionne, and Francois (2014).

16. As equity markets become more volatile and credit spreads expand in parallel in less favorable market conditions, VIX and credit spread are by construction strongly correlated. We find a high correlation of 0.89 prior to orthogonalizing. We therefore use the orthogonal part of VIX in our models, i.e., we regress VIX on credit spread and predict the residual of VIX. The latter is used as our new independent variable.

17. See Kocis et al. (2009) for a description of the J-curve effect in PE and the problem of private equity fund choosing size and timing of investments (possibly through the use of credit lines). Phalippou (2009) discusses conflicts of interest between managers of private equity buyout funds and their investors, such as for example the timing of cash flows or early exits generating large early distributions to investors and enhancing IRRs.

18. The average (median) level of capital called by the previous PD fund is 90.7% (95.0%) in our sample.

19. While TED spread has traditionally been interpreted as a proxy for credit risk (Ferson and Harvey 1993), more recent studies have used it as a measure for funding illiquidity in credit market research (Eichengreen et al. 2012; Gorton and Metrick 2012; Frazzini and Pedersen 2014; Boudt, Paulus, and Rosenthal 2017; Bali, Subrahmanyam, and Wen 2021; Cottrell et al. 2021; Duarte and Eisenbach 2021).

20. See Cottrell et al. (2021), who show that a bank's wholesale funding costs are substantially affected by the condition of short-term debt funding markets, in their study proxied by LIBOR- OIS spreads.

21. See also Online Appendix Table 2, which reports on the increments in R^2 when adding ex post credit market conditions to the specifications. The improvement in R^2 is mainly driven by adding the change in TED spread and the change in credit spread, but not the change in equity market volatility. First, adding ex ante credit market conditions to the analysis increases R2 substantially by up to 13.24%; the increment is always statistically significant, as indicated by the respective F values. Second, ex post changes in TED spread and credit spread significantly increase R2, while changes in VIX appear to be of lesser importance with regard to model fit.

22. Kaplan and Schoar (2005) showed that the lagged performance of the second and third previous fund is also positively related to that of the current fund, although

their effect is smaller. We therefore also ran models including the lagged performance of the second previous fund. While the second previous fund's coefficient is positive, it is never significant, potentially due to the small sample size. We did not analyze the effect of the performance of the third previous fund, due to issues of small sample size.

23. The PD industry knows various forms of early termination fees. These include so-called accelerated monitoring fees, break-up fees, the compensation of the GP for minimum investment multiples etc. Such fees are typically paid to the GP, which in turn allows for fund fee-offset provisions (reductions in management fees), thus increasing investor returns.

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