PRIVATE DEBT FUND RETURNS AND GENERAL PARTNER SKILLS

Abstract

This paper examines net of fees private debt fund performance and general partner skills, i.e., performance persistence across funds and a general partner's ability to time the market. We document market outperformance in the cross-section against bond and equity market benchmarks, with high performance dispersion across strategies and performance quartiles. Lagged performance significantly affects current fund performance. Additionally, private debt fund general partners are skilled in timing credit market conditions, as they anticipate beneficial changes in credit market conditions. This skill affects fund performance more than persistence and *ex ante* known credit market conditions.

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

1. Introduction

We investigate private debt (PD) fund performance and general partner (GP) skill. 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 induced market sell-off.[1] They emerged as an asset class in the late 1990s and exceeded $1,1 trillion assets under management in 2020 (Preqin Pro, 2021), with some $150 billion raised annually as from 2017 (Pitchbook, 2021)[2]. As of today, PD funds' assets under management represent some important 12.3% of the aggregate value of private capital funds, approximately match the size of real estate funds ($1.15 trillion) and have outgrown infrastructure ($0.8 trillion) and natural

[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] Fundraising activity dropped to $110 billion in 2020 due to the worldwide Covid pandemic.

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 banks' risk appetite (see, for example, Langfield & Pagano, 2016; van der Veer & Hoeberichts, 2016; Bordo & Duca, 2018; Cortés et al., 2020). Also, PD fund growth was spurred by an increase in the supply of funding to PD funds 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 LPs is limited to date. While there is a large literature on the returns to private equity investing, this study is one of the first to thoroughly investigate the returns to PD fund investing and especially if PD funds outperform 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 are able to time the market and benefit from improving PD investment conditions.

In a typical private debt transaction, a credit fund lends 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.[3] Comparable to private equity funds,[4] PD funds are organized as partnerships, in which the investor becomes a limited partner (LP) and the asset manager, which also invests in the partnership, is the general partner

[3] 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, where 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 (2019), who provide a comprehensive overview of the main topics in private capital, including a description of PD funds.

[4] Kaplan and Strömberg (2009) provide an overview of the organization of PE funds.

(GP). We investigate closed-end PD funds. Such funds imply that the investor can not withdraw funds until the fund is terminated, typically after 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% - 8% per annum, depending on the investment strategy of the fund.

The LP is a passive investor and does not obtain any decision control, 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 consists of a (i) 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 in which the GP executes first investments, an (ii) investment period, in which the GP continues its activity, which lasts two to four years from the final closing in the fundraising period (vintage), this investment period sometimes extended by one or more years. During the investment period, the GP may recycle its capital, i.e., reinvest the proceeds of early exits. The investment period is followed by the (iii) harvesting period, in which the GP exits investments and distributes all proceeds, net of fees, to investors.

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) interest accrued and paid at maturity and third, they may cash in early repayment penalties (Cumming et al., 2019). Finally, funds profit from portfolio company's fees that are paid to the GP but typically paid back to the investor by means of fee offset provisions, that is a reduction in management fees, therefore boosting fund performance. Such additional portfolio company's fees include advisory fees, transaction and deal fees, directors' fees, monitoring fees, capital market fees, organization cost compensations, placement fees and other (CalPERS, 2015; ILPA, 2016). 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 return to PD funds, both in absolute and relative terms using relevant benchmarks. Thereafter, we analyze whether general partners (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 to consistently 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. We lend from Kacperczyk et al. (2014, p. 1455) and define GP skill as "a general cognitive ability to pick [stocks] or time the market".

We collect data on 448 PD funds listed in Preqin providing timed cash flow data, with vintage years 1986 to 2018. This results in diversity in economic cycle, maturity of the PD market, geography (our data cover PD funds worldwide) and investment strategies. We calculate the cross-sectional variation in the net of fees performance of the PD funds based upon timed cash flows to LPs. Next to absolute performance measures - Internal Rate of Return (IRR) and Net Multiples -, we calculate excess return to PD funds compared with public benchmarks using

the public market equivalent (PME) method (Kaplan and Schoar, 2005). We use investment grade, high yield, and equity market benchmarks to calculate PMEs. Bivariate t-tests allow us to compare PD fund characteristics and debt and equity market conditions of high- and low-performing PD funds preceding and following the inception of a fund. We further estimate multivariate regression models to find out whether performance is persistent and whether outperforming GPs can time the markets. In these tests, we control for PD fund characteristics, GP characteristics and credit market conditions at fundraising, using PD fund strategy fixed effects.

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 in our sample reach a net investment multiple of 1.3 in the cross-section, that of top quartile funds (1.76X) being significantly higher than that of bottom quartile funds, which barely return the invested capital to LPs (0.98X). Using the Kaplan and Schoar (2005) PME, we evaluate relative performance against an investment grade (IG) and a high yield (HY) bond market benchmark as well as against an equity market benchmark (S&P 500). We find market outperformance in the cross-section against the IG-, HY- and S&P 500 benchmarks of 8%, 6% and 6% respectively. 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 the research of Munday et al. (2018), who use another database (Burgiss) and a different method to estimate PME. They find an average IRR of 8.1% and a market outperformance of 6.2% to 9.8% in the cross-section. By investment strategy and when considering the IG-benchmark,[5] we find a relatively equal outperformance for distressed debt, mezzanine and

[5] Results are qualitatively similar when using other benchmarks. We highlight outperformance to the IG-benchmark, as this is probably the most relevant benchmark to compare PD returns with.

special situations funds of between 8% and 10%, while direct lending funds outperform the market by 4%. This outperformance remains approximately unchanged when considering the equity market benchmark, against which only direct lending funds slightly underperform by -1%, whilst all other strategies again provide an outperformance between 7% and 10%.

We use OLS regressions including control variables like fund size, industry focus, geographic focus, and capital deployment period. We extend the findings of Munday et al. (2018) by providing fund comparison tests sorted on performance, fund characteristics and credit market conditions, and additionally test the assumption that returns to LPs are persistent over funds managed by the same GP, controlling for *ex ante* credit market conditions and various fund and GP characteristics. We find that persistence is significant across all performance proxies used. Prior fund performance is a significant and economically important predictor of future fund performance: A one standard deviation increase in IRR (PME IG / PME HY / PME S&P500) of the previous fund increases the IRR (PME IG / PME HY) of the recent fund by 2.40% (4.88% / 5.83% / 9.79%). Moreover, we find that funds launched in a NBER recession period, as proxied by a dummy variable, perform better than those launched outside NBER recessions. Likewise, funding illiquidity, as proxied by the level of the Treasury-EuroDollar rate (TED) spread, significantly and negatively affects IRR and outperformance against the IG and 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 & 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, the latter unknown prior to or at fund inception, thus defining a GP's anticipation of changes in *ex post* credit market conditions, or its timing skill. We find that private debt fund GPs are skilled in timing credit market conditions

and these effects are economically significant. For example, PD funds that are initiated in periods with *ex post* improvements in funding illiquidity (or spread contraction), a one standard deviation improvement increases their market outperformance against the IG bond universe by 10.58% (5.70%). *Ex post* changing S&P500 volatility does not consistently impact PD fund returns or outperformance. Importantly, we find that a GPs skill to time credit market conditions affects fund performance more than performance persistence or *ex ante* known credit market conditions. The effect size of changes in *ex post* funding illiquidity is approximately twice as large as that of persistence when using bond market benchmarks.

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 as LPs have their commitments accepted into the partnership, diligent analysis of changes to credit market conditions during the fundraising period may importantly improve an investor's investment decision set.

We contribute to the literature in various dimensions. First, prior literature analyzed the performance of private debt looking at US private bonds (Carey, 1998) or loan instruments (Cumming & Fleming, 2013; Cumming et al., 2019). Only one study has analyzed the net performance of PD funds to LPs (Munday et al., 2018). We are, to the best of our knowledge, the first that investigate persistence of PD funds. Second, previous literature remains quiet on the question of market timing skill of PD fund GPs. We present a model to analyze it and find that it significantly affects PD fund performance. Third, while performance persistence and market timing skill of GPs importantly affect fund performance, GP, or PD fund attributes, such as for example size, geographic focus or industry focus, do not help in explaining fund performance.

The remainder of the paper proceeds as follows. In Section 2, we present a short literature review. In Section 3 we describe the data. Section 4 presents the empirical results in respect to fund performance, followed by Sections 5, in which we explore persistence and market timing skills of GPs. In Section 6, we outline our market timing model and analyze the timing skill of PD fund GPs. Finally, Section 7 concludes.

2. Literature

Other than with PE fund performance and persistence, PD fund performance has not received a lot of attention in the academic literature.[6] Carey (1998) investigated a portfolio of private loans and found that it has lower default and higher recovery rates than a portfolio of public bonds with equivalent risk. His study is based on the data of 13 major life insurance companies in the US, sampling loans from 1986 to 1992. The study of Carey (1998) does, however, not cover a period in which the PD fund industry evolved. Observed PD fund activity starts in 1986 and years with more than 5 PD funds raised per vintage year are only observed from 1996 onwards.

More recent studies include Cumming and Fleming (2013), Cumming et al. (2019) and Munday et al. (2018). Cumming and Fleming (2013) study the performance of 311 individual loans used by private firms across 25 countries over 2001-2010. They find that performance depends on the portfolio size per manager, highlighting the role of time allocation for due diligence and monitoring. Additionally, performance is related to borrower (firm-specific) risk, but market conditions such as TED spreads and country level legal factors such as creditor rights are insignificantly or weakly related to the returns to private debt (Cumming & Fleming, 2013).

[6] See Harris et al. (2014) and Kaplan & Sensoy (2015) for surveys on private equity performance.

Cumming et al. (2019) study more than 400 loans acquired by PD funds through new issuances or secondary market transactions 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. Additionally, they create an index and find that gross private debt investments deliver gross excess returns to public markets over time, these excess returns being affected by volatility, funding liquidity, and the global financial crisis (GFC).

In contrast to these studies focusing on gross returns on individual investments, we focus on net of fee investor returns, following Munday et al. (2018) who use the Burgiss database and analyse net returns to LPs of 476 private credit funds and of 155 direct lending funds. They find positive IRRs for the top three quartiles across all investment strategies and relatively low beta and positive alpha using leveraged loan or high yield indices, indicating diversification benefits. The strong growth of the PD industry creates the necessity to re-examine net performance to LPs and drivers thereof. We further extend Munday et al. (2018) by first investigating a PD fund's persistence in performance, controlling for factors affecting performance or persistence.

Persistence in fund returns is defined as performance persistence across funds of the same delegated asset manager (Berk & Green, 2004). In competitive financial markets, when investor capital flows competitively to GPs, the latter shall capture the returns to their skill by either growing fund size or increasing fees, thereby eliminating persistence in net-of-fee performance (Berk & Green, 2004). In contrast to the theoretical outcome of Berk and Green (2004), various empirical studies find persistence in PE or VC fund performance, albeit declining over time for some PE strategies (Kaplan & Schoar, 2005; Kaplan & Sensoy, 2015; Nanda et al., 2020). Later studies recognize that measuring performance across funds alone is noisy and identifying skilled GPs from past performance is insufficient (Ewens & Rhodes-

Kropf, 2015; Korteweg & Sorensen, 2017). These studies propose performance generating models based on firm fixed effects (Korteweg & Sorensen, 2017) or skill at the level of individual partners employed by the GP (Ewens & Rhodes-Kropf, 2015). However, these studies remain silent on the underlying skill that generates performance, such as for example market timing skill of asset managers or GPs.

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 et al., 2011; Kim and In, 2012; Cao et al., 2013; Chen et al, 2013; 2013; Kacperczyk et al., 2014; Yi et al., 2018; and Jenkinson et al., 2018) others find mixed or negative evidence (Carhart, 1997; Elton et al. , 2012; Ferson & Schadt, 1996; Andreu et al., 2018; Bodson et al., 2013; Tchamyou & Asongu, 2017). More recent studies show that corporates can time the markets when issuing bonds (Frank & Nezafat, 2019) or equity (Wadhwa & Syamala, 2019). It is thus an empirical question whether GPs of PD funds do possess market timing skill.

Jenkinson et al. (2018) analyze this question for PE. They assess the ability of PE funds to create value through market timing over the lifetime of an investment. They find that PE funds sell portfolio companies after a market multiple expansion of 0.5, independent of transaction-specific pricing levels, affecting the overall fund performance by an important 16%, on average. In contrast to Jenkinson et al. (2018), we focus on credit market conditions prevailing at the start of a PD fund.

Our approach lends from Kaplan and Strömberg (2009), who show that economic conditions prevalent in the early life of a private equity fund, such as the capital flow into private markets relative to the stock markets, may significantly affect its lifetime performance. A PD fund's life is typically divided into three periods: First, a fundraising period, in which investors commit capital to the fund, spread over a series of closings, and characterized by first

investments into portfolio companies. This period typically takes two years or more. Second, an investment period, in which the GP is tasked with sourcing, selecting, and further executing evaluated investments. GPs thus deploy committed capital during the fundraising and investment period. The third and final period is a harvesting period in which the GP exits the investments of the fund and distributes the proceeds to LPs. We analyze the change in credit market conditions *ex post*, in the capital deployment period, compared to those *ex ante*, in the fundraising period when LPs decide to commit to the PD fund. *Ex ante* market conditions are hence observable to all market participants when deciding to commit to the fund, but not the *ex post* conditions. The *ex ante* period is defined as 360 days before the inception of a PD fund, defined as the date of the first cash contribution from LPs. The one-year period is chosen as this reflects the typical duration of marketing efforts prior to the first cash contributions from LPs.

The *ex post* period of two years (or 720 days) after inception is chosen for three reasons. First, PD funds are usually allowed to recycle and reinvest capital during the investment period, i.e., they may profit from the early termination of debt contracts, as borrowers have to pay break-up fees and, as the proceeds can be re-invested, multiple transaction fees. Prior research established that over 90% of long-term debt contracts are renegotiated prior to maturity (Roberts & Sufi, 2009) and that especially early improvements of credit market conditions drive debt contract renegotiation (Roberts & Sufi, 2009). For example, a typical bank loan (primarily revolvers and term loans to medium sized companies) is renegotiated five times, or every nine months (Roberts, 2015). When general credit market conditions improve within the investment period, we hence expect more loan renegotiations driven by the demand of corporates to improve loan contract terms, partially leading to early contract terminations. This affects fund performance positively and results in investments yielding a quick return in the

form of penalty fees or minimum return clauses in PD contracts.[7] Moreover, the fund may recycle capital, i.e., reallocate the capital a second or third time during the investment period, allowing the fund to repeatedly earn origination fees (instead of only once).

Second, independent of early contract termination, a fund may sell debt assets in the secondary market with profits compared to their purchase price if market conditions improved. Cumming et al. (2019) show that such a trading orientation, as opposed to a buy and hold strategy, may lead to enhanced performance.

Third, improvements in credit market conditions throughout the *ex post* period may also affect the probability of early contract termination or the conditions to a secondary trade close in time to the investment period (i.e. generate penalty fees, activate minimum return clauses or lead to attractive secondary market transactions).

We use three proxies to gauge for changes in credit market conditions: the change in (I) funding illiquidity, (II) average credit spread levels and (III) equity market volatility. These changes are not visible before fund inception, thus qualifying as private market signals and allowing to assess whether GPs can time the market (Ferson & Schadt; 1996; Elton et al., 2012).

First, funding illiquidity indicates traditional banks' reluctance to lend to corporates. In illiquid markets, banks focus on maintaining sufficient funding sources versus regulatory requirements and rating expectations, reducing the supply of bank loans (Brunnermeier & Pedersen, 2009). Such a tightening of bank loan supply translates into stronger recourse to alternative financing (Leary, 2009; Altavilla et al., 2019; Dwenger et al., 2020). The TED spread is a widely used measure for funding illiquidity in credit market research (Eichengreen et al., 2012; Gorton &

[7] 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), and thus increase investor returns.

Metrick, 2012; Boudt et al., 2017; Cottrell et al., 2021); it is the difference between an interest with credit risk (LIBOR) and one that is generally risk-free (3-month Treasury Bill) and increases in funding illiquidity. While Cumming and Fleming (2013) found no cross-sectional relationship between PD returns to individual investments and funding illiquidity, we expect that returns at the PD fund level are positively related to *ex ante* funding illiquidity, and hence to TED spread levels prior to fund inception. When funding liquidity dries up (the change in TED spread rises), discounts in secondary markets increase and so do returns to secondary market trades (Brunnermeier & Pedersen, 2009). Cumming et al. (2019) find a positive relationship between returns to individual secondary investments in private debt and changes in TED spreads. We expect that *ex post* decreasing TED spreads, or improving credit market conditions, enhance PD fund performance as firms will execute early refinancing and pay early repayment fees, thereby boosting fund performance. Also, PD funds may employ secondary trades to enhance their returns and sell portfolio positions in such credit market conditions (Cumming et al., 2019).

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 & Collin-Dufresne, 2011; Collin-Dufresne, Goldstein, & Martin, 2001; Eom, Helwege, & Huang, 2004; Ericsson, Renault, & Calcagno, 2006; H. H. Huang, Huang, & Oxman, 2015; J.-Z. Huang & Huang, 2012). Other than an increase in the TED spread, which may reflect liquidity risk in the short term (Brunnermeier, 2009) and affect the reluctance of banks to lend to corporates,[8] thereby improving the bargaining power of PD funds during the investment phase, credit risk may be a driver of funding costs in the longer term (Gefang et al., 2011). As credit spread has been widely used in various research settings related

[8] 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.

to debt pricing (Bai & Wu, 2016; Cumming et al., 2019; Elton, Gruber, Agrawal, & Mann, 2001; Schwarz, 2019), we include this factor. 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. In analogy, increasing credit spreads after the inception of a PD fund will lower prices of debt assets in secondary markets, limiting PD funds' opportunities to enhance fund returns by secondary trades. We therefore expect that widening credit spreads will negatively affect PD fund returns. Credit spread is the difference between Moody's Seasoned Baa Corporate Bond Yield relative to the 7-year Treasury constant maturity yield. Data are from St. Louis FED.

Third, equity market volatility is a factor priced in bond markets (Bao et al., 2015; Chung et al., 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 et al., 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 standard deviation of the daily index return of the S&P 500 (Campbell & Taksler, 2003). Cumming et al. (2019) find that increases in equity market volatility are associated with higher returns when investing in primary PD issues. We hence expect that PD funds that are launched in periods of increasing equity market volatility will perform better.

3. Sample and data

3.1. Sample description

We use a worldwide PD data set obtained from Preqin, a commercial data base provider which obtains fund level data[9] gathered from reliable public sources, such as U.S.pension funds, and makes direct requests for submission based on the Freedom Of Information Act (FOIA) or their parallel outside the U.S.A.. Preqin provides fund level as well as GP level information such as size, type, and geography, together with net-of-fees cash flow data to and from LPs. Cash flow data from Preqin are increasingly used in academia and found to be reliable (Ang et al., 2018; Barber & Yasuda, 2017; Phalippou, 2014).[10]

Preqin reports 450 PD funds with cash flow data raised between 1996 and 2018[11]. 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, is dropped due to missing cash flow data and one fund is dropped due to an unreasonably high return (IRR>200%). This reduces the final sample to 448 PD funds with vintage years 1996 through 2018 and cash flows measured through December 2020. 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 the sample.

[9] Most cash flow data are reported on a quarterly basis, although some are on a semi-annual basis.
[10] In a comparison of PE fund returns reported by competing data providers such as Burgiss, Cambridge Associates and Pitchbook, Kaplan and Waldrop (2016) find that returns reported by Preqin are generally comparable, even though slightly lower than those reported by competing data providers. They assume this effect is the result of differing data collection methodologies, with Preqin likely to miss some best performing funds that do not accept LPs who are subject to FOIA. We thus expect the performance data in this paper is reliable and not upward biased.
[11] Preqin reported 456 PD funds raised between 1996 and 2018. However, after careful examination, six were dropped as five of them are fund-of-funds and one is a private equity fund.

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 followed by the PD funds are investing in direct lending, distressed debt, or mezzanine. Direct lending, a strategy followed by 24.6% of the PD funds in the sample, is the practice of non-bank lenders extending loans to small and medium-sized businesses in return for debt securities. Distressed debt (30.6%) represents lending to companies that have filed for bankruptcy or have a significant chance of filing for bankruptcy soon. Mezzanine (28.6%) includes investments in debt subordinated to the primary debt issuance and senior to equity positions. Special situations (12.7%) covers several areas including distressed and mezzanine, where loan decision or grade is defined by criteria other than underlying company fundamentals. Venture debt is the least prevalent strategy (3.6%); it comprised private debt provided to venture capital backed companies to fund working capital or expenses.

The mean size of a PD fund (in 2018 US dollars), measured as the amount committed to the fund, 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.

[Table 1 about here]

16.6% of the PD funds in our sample are fully liquidated, most of which invested in distressed debt or mezzanine. Another 80.4% are closed, implying that they no longer accept capital from LPs, but they are still in the investment and harvesting phase. An average PD fund needs 56 days to deploy 10% of its capital, 476 days to deploy 50%, 1019 days to deploy 90% and 1535 days (or slightly more than 4 years) to be fully invested.[12] Mezzanine PD funds are slowest to invest, and direct lending PD funds are fastest.

Panel B in Table 1 indicates the financial and 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 to analyse 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 3-month LIBOR and the 3-month Treasury bill and is slightly lower on average during the investment period (0.41) as compared to the pre-investment period (0.43). Spread is the average yield spread between Moody's Seasoned Baa Corporate Bond Yield relative to the 7-year Treasury constant maturity yield and is again lower during the investment period (2.62) than before (2.80). Data for the TED spread and credit spread are from the Federal Reserve Bank of St. Louis. Turning to volatility using the S&P500 index, equity market volatility is lower post (63.02) as compared to pre inception (85.93). NBER recession vintages indicate the relative share of all funds that have vintage years equal to a recession year as defined by the National Bureau of Economic Research (NBER). Slightly more than 10% of the PD funds are raised during a recession period.

[12] We are using capital contribution calendar dates to calculate the capital deployment period and equate a capital call to capital deployment. GPs decide when capital is called for investment. They typically minimize the period of time having cash sitting on the accounts of a fund and thereby maximize return. Our capital deployment period must therefore be considered an approximate rather than an exact capital deployment period.

3.2.Measuring PD Fund Performance

As PD funds are unquoted, returns to investors cannot be assessed in traditional ways. We therefore rely upon performance measures used in the private equity fund industry. All measures are calculated based upon the cash flows from and to LPs and net of fees. The 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 - NAV) at the end of the observation period (December 2020). The FASB requires funds to value their assets at fair value every quarter, rather than valuing them at cost, since 2009. Unrealized values should therefore approximate true market values (Harris et al., 2014) and are, on average, conservative in private equity funds (Brown et al., 2017; Harris et al., 2014; Jenkinson et al., 2013; Robinson & Sensoy, 2016). We adhere to this view. As in Kaplan and Schoar (2005) or Harris et al. (2014), we include NAVs of non-liquidated funds as if they were liquidating distributions to LPs.

Based upon the cash flow data and following prior research on the performance of PE funds (e.g. Kaplan & Schoar, 2005; Korteweg & Nagel, 2016; Korteweg & Sorensen, 2017), we calculate two absolute performance measures widely used by institutional investors, namely the IRR and Net Multiples (Gompers et al., 2016). The latter compares the cash invested by LPs with the cash returned to LPs. Following previous studies (Kaplan & Schoar, 2005; Harris et al., 2014), we include NAVs of non-liquidated funds as liquidating distributions to LPs.

We additionally calculate excess return to PD funds compared with public benchmarks using the public market equivalent (PME) method introduced by Kaplan and Schoar (2005) and considered as the state-of-the-art performance measure of fund-level performance both in academia (Kaplan & Sensoy, 2015; Lerner et al., 2018) and in the asset management industry

(L'Her, 2016).[13] 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 & Jagannathan, 2015), with the discount rate being the realized market return (R_{ms}) given by the benchmark index. It is calculated as:

$$PME = \left[\Sigma_{\mathrm{t}} \frac{Distributions_{(\mathrm{t})}}{\prod_{s=to}^{t}(1+R_{\mathrm{ms}})}\right] \Big/ \left[\Sigma_{\mathrm{t}} \frac{Contributions_{(\mathrm{t})}}{\prod_{s=to}^{t}(1+R_{\mathrm{ms}})}\right] \qquad (1),$$

with distributions equalling cash flows to LPs (including NAVs at the end of the observation period), contributions equalling 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 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 & Jagannathan, 2015; Korteweg & 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 used Bloomberg Barclay indices instead, as they are widely used by credit and fixed income investors. An important advantage of these indices is the availability

[13] Althoug IRRs are frequently used as performance measure in the private capital fund universe, they may be upward biased (Phalippou & 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 & Gottschalg, 2009) . Kocis et al. (2009) discuss difficulties with the interpretation of IRRs.

of historical prices that date back to the early vintage years of the PD fund industry. A first index, 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). A second index, the total return Bloomberg Barclays US Corporate High Yield Index, includes USD denominated, high yield, fixed-rate corporate bonds (HY benchmark). This allows to tailor PMEs to our specific environment, as in PE analyses (Fang et al., 2015; Robinson & Sensoy, 2016). Third, we also use the Standard & Poor's 500 total return index as an equity market benchmark.

4. 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 fund has an IRR of -33.90%, while the 1% best performing PD fund has an IRR of 57.14%. The same picture emerges for Net Multiple returns (Panel B), 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 fund returns only 57 cents per dollar invested, while the 1% best performing PD fund returns 2.58 dollars per dollar invested. This shows the overall positive, but wide variation in PD fund returns.

[Table 2 about here]

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 investment grade (IG) benchmark by 8%, but also the high yield (HY) and the public equity (S&P500) benchmarks by 6% respectively. Our PME results echo our earlier finding 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).

[Table 3 about here]

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. Note however that the mean for Special Situations is highly skewed due to some very high performing PD funds.[14] 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 lowest for Direct Lending (mean: 1.17; median: 1.14). The PME analyses show that all investment strategies outperform the three 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.

[14] We omit percentile results here for brevity, those results available from the authors upon request.

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 which perform above the 50th and above the 75th percentile of the PME IG (benchmark) to those below.

[Table 4 about here]

Panel A of **Table 4** shows that the mean performance of the outperformers is significantly ($p<.01$) higher than that of underperformers across all performance measures. Above median performers have an IRR of 16.70% on average, compared to 1.69% for below median performers and a net multiple of 1.54 compared to one of 1.07 for below median performers. 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 underperform the market, stressing the importance of fund selection.

Panel B 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 with the Investment Grade 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 focuses on the credit market conditions in which over- and underperforming funds are launched and shows how theses market conditions change, comparing the average first two years of the investment period to those prevailing in the pre-inception phase. Outperformers are, on average, launched when funding illiquidity (TED spread level) is lower, risk spreads are higher, and equity market volatility is lower. Interestingly, credit market conditions change for the better for performing or high-performing as opposed to non-performing PD-funds (as defined by PME IG below the median). For performing funds, funding illiquidity improves more and credit spreads decrease. Also, performing or high-performing PD funds are also more often launched during NBER recession periods. This suggests that skilled GPs can exploit changes in credit market conditions, i.e., are skilled to time the market, this hypothesis to be tested further in Section 6.

5. Performance Persistence in the PD industry

Using the Kaplan and Schoar (2005) public market equivalent (PME), we have shown that PD funds deliver outperformance against a traded market benchmark or risk factor in the cross-section, which is exceptional when comparing the PD fund to the mutual fund industry, where market outperformance is rare and departs from the rule.[15] For LPs aiming to invest in PD funds, and given the wide disparity in performance, the additional question is which funds to select? In the private equity industry, Kaplan and Schoar (2005) were the first to show that returns in private equity funds are persistent, in that 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 & Sensoy, 2015).

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

Outperformance is driven by top GPs' superior ability to select investment targets, but also by their ability to create value in their targets through enhancing governance (Jensen, 1986), or providing scarce or specialized resources (Cressy et al., 2007; Manigart & Wright, 2013a and 2013b). LPs therefore strongly focus on LPs' past performance when selecting new private equity funds to invest in (Vanacker et al., 2021).

We therefore test whether outperformance is also persistent in the PD industry. Do PD GPs have specific skills which allow them to consistently outperform their peers? As returns in the PD industry depend on the selection, negotiation and monitoring skills of GPs, GPs with superior skills might be able to consistently outperform their peers.

To address this question and in line with prior PE studies, we regress current on past performance (Kaplan & Schoar, 2005; Korteweg & Sorensen, 2017; Robinson & Sensoy, 2016). We include the 234 funds in our sample that have an earlier fund[16] 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[17]. Five OLS models are run, for each of the five performance measures introduced earlier. The return generating process of a GP is modelled as

$$P_i = P_{i,t-1} + \beta_i CMC_t + \beta_i X_{it} + \varepsilon_i, \qquad (2)$$

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

[16] Note that the earlier fund should not have 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, *Firstfund*.

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

PD fund managed by the same GP, CMC is *ex ante* known credit market conditions 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. 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 U.S.A. (dummy variable), and how long it takes to fully invest the fund in number of days. Additional control variables capture GPs' 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 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 & Strömberg; 2009). We include funding liquidity, equity market volatility, and credit spreads as important credit market conditions. We further include investment strategy fixed effects, cluster standard errors by GP as in Kaplan and Schoar (2005) and check for multicollinearity using the variance inflation factor (VIF).[18] VIF is smaller than 3.5 for any variable in our model and the average VIF is 1.81. We also find that correlation between variables[19] in our model is not problematic.

[Table 5 about here]

[18] 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 Chun et al. (2014).

[19] As equity markets get more volatile and funding illiquidity increases in recessionary periods, our dummy variable "recession" is by construction moderately or strongly related to these two credit market conditions variables. The correlation amounts to 0.43 and 0.72 respectively. However, only 7% or 16 funds are launched in NBER recessions in Table 5. Dropping either the recession dummy variable or any of the credit market conditions variables and repeating our estimations does not materially affect our results.

The results presented in **Table 5** show that lagged performance significantly predicts current performance in all specifications. 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 five to ten percent increase in lagged outperformance (.05 – 0.1) as proxied by the PME HY increases the outperformance of the follower fund by 0.9% to 1.8% (0.05 or 0.10 X 0.176).

The fund- and GP-level control variables are not significantly predicting performance, except for the capital deployment period, which has a negative effect on IRR, but not on any of the other performance proxies. This is consistent with the notion that PD funds already having a high qualitative deal flow at fundraising outperform PD funds that do not dispose of sufficient deal flow, i.e., that they are slower to invest.

We find that launching PD funds during NBER recessions increases outperformance by an important 32.3% and 17.3% against the IG or HY benchmark respectively, resulting in an investment multiple that increases by an impressive 0.35 or an IRR expansion by 10.63%. Apparently, NBER recessions affect performance more than persistence. Given that only 10% of all PD funds are launched during NBER recessions, however, this does not explain the attractive cross-sectional PD fund performance.

Other *ex ante* credit market conditions likewise affect performance: worse funding illiquidity (TED spread) preceding the inception of a PD fund negatively affects relative fund performance as proxied by PME IG and PME HY. A 10 basis points increase in TED spread reduces a fund's outperformance against the IG (HY) benchmark by 1.9% (1.8%). When turning to the equity market benchmark or the investment multiple, credit risk spreads significantly affect performance. A 10 basis points increase in the credit spread positively affects outperformance against the S&P500 by 0.8% (0.1 X 0.0759) or increases the investment

multiple, the latter effect however of limited economic importance. Ex ante equity market volatility does not impact PD fund returns.

Overall, echoing earlier research on PE, we find persistence in PD fund returns. Moreover, consistent with Kaplan and Strömberg (2009) for private equity funds, and with Cumming & Fleming (2013) and Cumming et al. (2019) for PD investments, we find that various *ex ante* credit market conditions affect fund performance.

6. Market Timing

While the previous analyses established persistence in PD fund returns while controlling for *ex ante* known credit market conditions, we did not address the question how GPs create persistence? 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 et al., 2014:1455).

In this section we test whether the skill of GPs to time credit market conditions affects PD fund performance. Whereas previous research explained PD performance using *ex ante* known market factors as *lagged* variables and thereby focused on information publicly available at the inception of a fund (Cumming & Fleming, 2013; Cumming et al., 2019), we extend their approach with a market signal not available at the inception of a fund. In our model, we measure the ability of a PD fund GP to process a private market timing signal, as proxied by *ex post* changes in TED spread, credit spread and equity market volatility. At the inception of the fund, the GP can only anticipate changes in these variables. They are, however, not publicly known. *Ex post* changes to TED spread, credit spread, and equity market volatility are therefore private market timing signals in the spirit of Ferson and Schadt (1996) and Elton et al. (2012). We thus

follow the logic that management should not be given credit for performance in response to publicly available information, but that the assessment of market timing must assess the skill of a manager to anticipate and respond to a *private* market timing signal (Ferson & Schadt; 1996; Elton et al., 2012). When a managed portfolio can be replicated using publicly available information, no superior performance can be ascribed to market timing (Ferson & Schadt; 1996; Elton et al., 2012). Ferson and Schadt (1996) were the first to propose a conditional model to evaluate market timing, by capturing the response of an investment manager to available public information plus an additional term capturing the sensitivity of the manager to a private market timing signal.

Ferson and Schadt (1996) use monthly or quarterly market returns to compute betas and assess market timing. As we do not dispose of monthly or quarterly returns in our setting, 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) provide a formal theoretical justification for this assumption and show that the PME is valid regardless of an investment's beta, even if it is time varying.

We 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 (2). We calculate changes in credit market conditions (Δ CMC) by subtracting the average of the 360 days *ex ante* values (t-1) from the average of the 720 days *ex post* (t+1) values prior and posterior to 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 for two years of a fund's lifetime 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 modelled as

$$P_i = P_{i,t-1} + \beta_i CMC_t + \Upsilon_{it} E(\Delta\ CMC|C_t) + \beta_i X_{it} + \varepsilon_i, \quad (3)$$

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, CMC is *ex ante* known credit market conditions when the first cash contribution is called from LPs at time t. E is a GPs 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, ε is the error term of fund i. Thus, Υ_{it} captures market timing skill, i.e., a GP's forecast with respect to expected change in credit market conditions. We test the market timing hypothesis applying our timing model as in equation (3), include investment strategy fixed effects and cluster standard errors by GP as in Kaplan and Schoar (2005), and use three benchmarks to calculate PMEs. The VIF is again used to check for multicollinearity. VIF is smaller than 5.7 for any variable in our model and the average VIF is 2.3. As before, we find that correlation between variables in our model is not problematic. **Table 6** shows the regression results.

[Table 6 about here]

Consistent with our market timing hypothesis, the results in **Table 6** suggest that a GP's skill to time the market significantly affects market outperformance of PD funds. First, adding changes in market conditions to the regression models significantly enhances the model fit,[20] suggesting that they are important in explaining PD fund performance.

Second, the *ex post* changes in TED spread and in credit spread significantly affect PD fund performance measures in most models. In line with our expectations, an increase in *ex post* TED spread, indicating deteriorating market liquidity after the launch of the PD fund, is

[20] See also Appendix Table 1 reporting 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.

negatively associated with the three relative performance measures in models 3 through 5 but not with the absolute performance measures in models 1 and 2. For example, a one standard deviation improvement in *ex post* funding illiquidity (0.33) increases the outperformance against the IG benchmark by 9.05% (β x σ^2 PME IG = 0.271 x 0.334).

Likewise, an *ex post* change in credit spreads significantly affect a fund's absolute performance and its outperformance against the IG and the S&P 500 benchmarks. As expected, 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* reduction in credit spread (0.71) increases PD fund outperformance against the IG benchmark by 4.83% (β x σ^2 PME IG = 0.068 x 0.71). Interestingly, an increase in credit spread affects PD fund outperformance to the S&P500 positively. This appears plausible, as we would expect the equity market benchmark to suffer from unfavorable general market conditions, benefiting the PME calculation systematically.

Finally, the *ex post* change in equity market volatility does not seem to affect a fund's absolute or relative performance

Importantly, lagged performance is now highly significant in all models (including those predicting IRR and PMG IG). A 10% increase in IRR (PME IG) in a previous fund increases the IRR (PME IG) of the current fund with 1.95% (1.57%). Hence, GPs' skills to time the market are complementary to their selection, contracting and monitoring skills. 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. Overall, the results presented in **Table 6** support our market timing hypothesis: GPs with superior skills generate superior returns, which are partly explained by their superior market timing skills.

We next reconcile these regression estimation results with the observed *ex ante* and *ex post* credit market conditions in **Table 4**: 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). As institutional investors typically use the IG benchmark, we base our reconciliation on our public total return IG-index. We find that, all else 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 0.28% of fund outperformance against the IG benchmark (-1 X -0.276), the ex post difference in the change in funding illiquidity (-7 basis points) explains 1.90% of fund outperformance (-7 X -0.271). In other words, ex post changes in the level of funding illiquidity affect performance by a factor approximately seven times larger. Together, for funds that perform above the 50th percentile, the observed *ex ante and ex post* effect of funding illiquidity explain approximately 2.20% 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 1.91% ([-2 basis points X -0.276 = 0.552%] + [-5 basis points X -0.271 = 1.355%]). Overall, the effect of funding illiquidity thus affects market outperformance importantly.

Ex post level changes in credit spread likewise affect market outperformance against the IG benchmark importantly. As we observe (see **Table 4**), funds performing above the 50th (75th) percentile experience ex post credit spread contractions that are larger by 9 basis points (25 basis points) when compared to their lower performing peers. This improvement of credit market conditions seems to affect a fund's outperformance as well: Calculated as above, the observed *ex post* credit spread contractions explain 0.61% (1.72%) of a fund's outperformance against the IG-benchmark.

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 smaller than 4.7 for any variable in our model and the average VIF is 2.1. **Table 7** shows the results.

[Table 7 about here]

Consistent with the previous models (**Table 6**), changes in TED spreads are significantly negatively associated with IG and HY outperformance measures, although the coefficients are somewhat smaller. Changes in credit spread are also negatively associated with both absolute return measures and with the PME IG, but not with the other outperformance measures. Again, coefficients are somewhat smaller. Finally, the change in equity market volatility present a different result, as this is now negatively related with the Net Multiple, but not with the other absolute or relative performance measures. Clearly, the effect of a change in equity market volatility is less consistent across our models.

7. Conclusions

Our empirical findings, based upon a worldwide comprehensive sample of PD funds, show that including PD funds in an investor's portfolio has the potential to increase returns on average. We find an average PD fund net of fees IRR of 9.19%, returning 1.3X the invested capital to the investor. More importantly, PD funds outperform the IG benchmark by 8%, and both the HY and the S&P 500 benchmark by 6% in the cross-section. However, in line with prior private equity fund research, the variation in PD fund returns is large. For example, the top quartile PD

funds reach an IRR of 23.3% and outperform the IG-benchmark by 38%, while the bottom quartile PD funds have a negative IRR of -3.6% and underperform the IG-benchmark by -18%. This large performance dispersion makes fund selection demanding. How can investors select the best performing PD funds when considering their inclusion into a portfolio?

To answer this question, we explore whether performing GPs possess specific skills that allow them to provide persistence in fund performance. If so, past performance can help investors to select funds in an opaque industry. While return persistence is not prevalent in the mutual fund industry, it has been demonstrated in the private equity industry: GPs whose fund outperformed the private equity industry in one fund were likely to outperform the industry in their next two funds (Kaplan and Schoar, 2005). Following the private equity literature, we first asked the question whether past performance is a reliable predictor of the next fund managed by the same GPs. We find that persistence is present in the PD fund market: the performance realized in a previous fund managed by the same GPs 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% (1.57%).

A pertinent question is what drives this persistence. Is it mainly GPs' skills, or entrepreneurs' choice to affiliate with specific investors? For example, Nanda et al. (2020) showed that persistence in venture capital success is mainly driven by initial success improving access to deal flow. Is it this preferential access that raises the quality of subsequent investments by the same GPs, perpetuating performance differences in initial investments, rather than their superior skills? Given the data scarcity in the PD industry, we cannot disentangle GP skills from access to deal flow. However, the dynamics of PD returns are fundamentally different from those in venture capital or private equity, where most of the returns stem from creating value in the underlying portfolio companies and thereby enhancing upside potential. In doing

so, entrepreneurs also benefit from the value created by their GPs and have hence an incentive to seek funding from a high-quality investor (Hsu, 2004). In PD funds, returns are not generated through increasing the value of the portfolio companies, and hence managers have no specific incentives to affiliate with certain investors. Spontaneous access to superior deal flow is therefore not likely to drive persistence in the PD fund industry.

Return persistence in venture capital and private equity decreases over time (Kaplan & Schoar, 2005; Nanda et al., 2020). As the number of GPs managing three or more funds is too small to perform robust statistical analyses, we were not able to replicate this observation in the PD industry. We leave this as an interesting avenue for further research, when more GPs in the PD industry will have a longer track record.

To further understand the nature of GP skills associated with return persistence, we were able to analyze whether GPs possess the skill to time credit market conditions and whether that skill may explain fund performance. Understanding how credit market conditions impact PD fund returns *ex ante* and *ex post* their inception may further help investors in the selection and timing of their PD investments.

Our results suggest that PD funds launched during recession periods as defined by the NBER generate significantly higher IRR and Net Multiples, and outperformance compared with the IG benchmark. PD funds launched in periods of lower TED spreads, indicating high liquidity in the financial markets, generate outperformance against the three benchmarks considered (the IG benchmark, the HY benchmark and the S&P500 benchmark). The credit spread at the time of fund inception does not strongly impact its performance (except for a positive association with the PME S&P500). However, PD funds launched during periods with low volatility in the equity markets provide a higher Net Multiple and a higher PME IG. These market conditions

are visible to GPs and investors at the time of fundraising and investors can adjust their asset allocation strategy to our findings.

We additionally ask whether GPs are skilled in timing credit market conditions and hypothesize such changes may impact fund returns. For example, if credit market conditions improve (TED spreads or credit spreads contract) after fund inception, borrowers might want to renegotiate their contracts or engage in early debt repayments, allowing PD funds to collect early repayment fees and to reinvest the proceeds, thereby generating additional fees and boosting fund returns. Additionally, improving credit market conditions may lead to increasing debt valuations and GPs might sell their debt assets in the secondary markets, likewise boosting fund returns, a tactic that is widely adopted in the PD industry (Cumming et al., 2019). We show that the best performing GPs indeed anticipate changes in credit market conditions and possess valuable market timing skills. More specifically, when TED spreads decrease after fund inception, outperformance against the three benchmarks significantly increases. We reconcile our regression estimates with observed changes to credit market conditions in our sample. The *ex post* change in funding illiquidity explains 1.9% of PD fund outperformance and by a factor that is approximately seven times larger than *ex ante* changes in funding illiquidity. In the same vein, when the credit spreads contract *ex post*, IRR, Net Multiples and the PME IG are positively affected. Using our regression estimates and reconciling them with observed *ex post* changes in credit spread, these explain approximately 1.7% of PD fund outperformance for the best performing funds (PME IG above 75th percentile). These *ex post* changes in credit market conditions are visible to GPs and investors after fund inception and during the fundraising and the initial phase of the investment period. Investors can thus adjust their asset allocation strategy to our findings.

As the PD fund industry has grown exponentially in the last decades, practitioners need to understand the drivers of PD fund performance. This study highlights persistence in PD fund returns, hence supporting the idea that outperforming funds are managed by GPs with valuable skills. One of these skills enhancing PD fund performance is superior credit market timing, both ex ante and ex post the launch of a fund. We find that credit market conditions significantly affect fund performance, especially funding illiquidity and credit spreads.

Further research is needed to disentangle other skills relevant to the performance generating process of GPs managing PD funds.

Declaration of Interest Statement

In accordance with Taylor & Francis policy and our ethical obligation as researchers, we report that one of two researchers acts as consultant to institutional investors interested in PD fund investments. His employer may be affected by the research reported in the enclosed paper. We disclose those interests fully to Taylor & Francis. The views expressed in this paper are those of the authors and not necessarily those of the researcher's employer.

Table 1 Descriptive statistics

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** indicates the number of funds of a GP Preqin is aware of. **First fund** indicates whether a PD fund is the first fund launched by a GP in a series of the same investment strategy. I**nvestment 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** measured as the US dollar amount that is committed to a fund, the amounts 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, does no longer accept 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 3-month LIBOR and the 3-month treasury bill. **Spread** is the average yield spread between Moody's Seasoned Baa Corporate Bond Yield relative to the 7 year Treasury constant maturity yield. Data for TED spread and spread are from the Federal Reserve Bank of St. Louis. **Volatility** is measured using ex ante and ex post S&P500 index values. **NBER recession vintages** indicates the relative share of all funds (by investment strategy) that have vintage years equal to a recession year as defined by the National Bureau of Economic Research (NBER). Private debt fund data are from Preqin, cut-off date December 31, 2020.

Panel A: Fund characteristics							
		All funds	Direct Lending	Distressed Debt	Mezzanine	Special Situations	Venture Debt
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
Panel B: Credit Market Conditions							
TED spread $1y_{ex\ ante}$		0.43	0.34	0.46	0.48	0.38	0.51
TED spread $2y_{ex\ post}$		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 $1y_{ex\ ante}$		2.80	2.11	3.10	3.21	2.41	3.14
credit spread $2y_{ex\ post}$		2.62	2.13	2.77	3.05	2.23	2.96
Δ credit spread		-0.18	0.02	-0.33	-0.17	-0.18	-0.18
volatility S&P500 $1y_{ex\ ante}$		85.93	92.29	81.48	82.90	89.02	93.52
volatility S&P500 $2y_{ex\ post}$		63.02	69.02	66.73	54.52	68.36	38.77
Δvolatility S&P500		-22.91	-23.27	-14.75	-28.38	-20.66	-54.75
NBER recession vintages (%)		10.71	4.55	13.87	13.28	8.77	12.50

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

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 last distribution when calculating the performance results. **Panel C** reports on the public market equivalent (PME), calculated as in Kaplan & 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.

Panel A: Cross-sectional performance, measured by Internal Rate of Return (IRR), over the sample period 1996 - 2020										
IRR					**Percentiles**					
	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
Panel B: Cross-sectional performance, measured by net multiples (Multiple)										
Multiples					**Percentiles**					
	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
Panel C: Cross-sectional performance, measured by public market equivalent (PME), using the investment grade benchmark (IG)										
PME IG					**Percentiles**					
	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
Panel D: Cross-sectional performance, measured by public market equivalent (PME), using the high yield benchmark (HY)										
PME HY					**Percentiles**					
	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
Panel E: Cross-sectional performance, measured by public market equivalent (PME), using the equity market benchmark (S&P500)										
PME S&P 500					**Percentiles**					
	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

Table 3 Private Debt Fund Performance by Investment Strategy

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.

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

Table 4 Fund Comparison Tests

This table presents a comparison of mean performance of the average, the performing and high performing private debt funds (Panel A), ex ante debt and equity market conditions (Panel B) and fund characteristics (Panel C), for portfolios sorted on above the 50th percentile performance and above the 75th percentile performance, the performance criteria being the PME IG. Significance at the 5% level is reported using a single asterisk (*), significance at the 1% level is reported using double asterisks (**).

Panel A: Performance

Performane 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

Panel 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
industryagnostic	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
fundsoverall	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
fundseries	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

Panel 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 $1y_{ex\ ante}$	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 $1y_{ex\ ante}$	448	2.80	2.26	2.81	2.79	**0.02**	-0.19	-0.012	3.03	2.72	**0.32***	2.22	1.85
Δ credit spread	448	-0.17	-0.05	-0.22	-0.13	**-0.09**	1.39	1.54	-0.36	-0.11	**-0.25****	3.38	3.34
volatility S&P500 $1y_{ex\ ante}$	448	85.93	82.78	83.30	88.56	**-5.26****	-1.65	-2.58	83.80	86.64	**-2.84***	-0.77	-1.97
Δvolatility S&P500	448	63.02	59.33	51.67	74.37	**-22.70****	-3.78	-4.09	48.30	67.92	**-19.62****	-2.81	-2.98
recession (1/0)	448	0.11	0.00	0.15	0.06	**0.09****	3.08	3.05	0.18	0.08	**0.10****	2.84	2.82

Table 5 Does lagged performance explain performance?

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 (**).

VARIABLES	(1) IRR	(2) Net Multiple	(3) PME IG	(4) PME HY	(5) PME S&P500
performance$_{t-1}$	**0.170***	**0.293****	**0.144***	**0.176****	**0.223****
	(0.162)	**(0.365)**	**(0.196)**	**(0.245)**	**(0.329)**
log(size)	1.827	-0.00499	-0.00304	-0.000860	-0.000491
	(0.139)	(-0.0158)	(-0.0138)	(-0.00414)	(-0.00193)
Industry agnostic	-2.159	0.0481	0.0186	0.0232	0.00309
	(-0.0746)	(0.0692)	(0.0383)	(0.0508)	(0.00550)
US_focus	-1.075	-0.00936	-0.0246	-0.0231	-0.0421
	(-0.0350)	(-0.0126)	(-0.0477)	(-0.0477)	(-0.0707)
capital deployment period	**-0.00188***	6.21e-06	-7.78e-06	-1.51e-05	-2.05e-05
	(-0.160)	(0.0218)	(-0.0395)	(-0.0816)	(-0.0902)
Funds overall	**-0.202****	-0.00183	-0.00194	-0.00164	-0.000686
	(-0.153)	(-0.0582)	(-0.0874)	(-0.0785)	(-0.0268)
Fund series	0.0295	0.00432	-0.00837	-0.00711	-0.00642
	(0.00522)	(0.0318)	(-0.0881)	(-0.0796)	(-0.0586)
First fund	0.446	0.0247	-0.0156	-0.00694	-0.0403
	(0.0112)	(0.0252)	(-0.0234)	(-0.0110)	(-0.0523)
NBER recession (1/0)	**10.63****	**0.345****	**0.323****	**0.173***	0.0441
	(0.221)	**(0.293)**	**(0.399)**	**(0.227)**	(0.0472)
TED spread 1Y$_{ex\ ante}$	-6.208	0.0224	-0.194*	-0.181*	-0.0410
	(-0.142)	(0.0210)	(-0.264)	(-0.262)	(-0.0485)
credit spread 1Y$_{ex\ ante}$	1.414	**0.0480****	0.00219	-0.00315	**0.0759****
	(0.137)	**(0.194)**	(0.0126)	(-0.0193)	**(0.379)**
volatility S&P500 1Y$_{ex\ ante}$	0.0109	-0.00118	-0.000571	3.73e-05	-0.000574
	(0.0301)	(-0.134)	(-0.0938)	(0.00653)	(-0.0817)
Constant	-2.841	0.773**	1.056**	0.965**	0.760**
Observations	233	225	234	234	234
R-squared	0.133	0.333	0.149	0.156	0.352
Strategy FE	Y	Y	Y	Y	Y

Table 6 Market Timing Skills

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, 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 credit spread, Δ volatility S&P500 and Δ TED spread 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 (**).

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
VARIABLES	**IRR**	**Net Multiple**	**PME IG**	**PME HY**	**PME S&P500**
performance$_{t-1}$	**0.195****	**0.291****	**0.157****	**0.170****	**0.213****
	(0.186)	**(0.363)**	**(0.212)**	**(0.237)**	**(0.315)**
log(size)	1.774	-0.00551	0.000151	0.00263	0.00333
	(0.135)	(-0.0175)	(0.000682)	(0.0127)	(0.0131)
industryagnostic	-1.457	0.0579	0.0380	0.0396	0.00723
	(-0.0503)	(0.0832)	(0.0781)	(0.0865)	(0.0129)
US focus	-0.989	-0.00434	-0.0202	-0.0206	-0.0461
	(-0.0322)	(-0.00583)	(-0.0391)	(-0.0425)	(-0.0774)
capital deployment period	**-0.00151***	-1.37e-06	-5.39e-06	-9.07e-06	-9.40e-06
	(-0.129)	(-0.00480)	(-0.0273)	(-0.0490)	(-0.0413)
fundsoverall	**-0.216****	-0.00196	-0.00215	-0.00187	-0.000691
	(-0.164)	(-0.0623)	(-0.0971)	(-0.0896)	(-0.0270)
fundseries	0.0524	0.00535	-0.00625	-0.00519	-0.00545
	(0.00926)	(0.0394)	(-0.0658)	(-0.0581)	(-0.0498)
firstfund	0.239	0.0224	-0.0165	-0.00774	-0.0386
	(0.00601)	(0.0229)	(-0.0246)	(-0.0123)	(-0.0500)
NBER recession (1/0)	**7.839***	**0.233***	**0.178***	0.0677	0.0699
	(0.163)	**(0.198)**	**(0.220)**	(0.0890)	(0.0749)
TED spread 1Y$_{ex\ ante}$	-8.397	0.0968	**-0.276****	**-0.318****	**-0.254****
	(-0.192)	(0.0908)	**(-0.376)**	**(-0.462)**	**(-0.300)**
credit spread 1Y$_{ex\ ante}$	1.157	0.0227	0.00459	0.0134	**0.124*****
	(0.112)	(0.0917)	(0.0264)	(0.0822)	**(0.617)**
volatility S&P500 1Y$_{ex\ ante}$	-0.0110	**-0.00210****	**-0.00155****	-0.000626	-0.000205
	(-0.0303)	**(-0.237)**	**(-0.255)**	(-0.109)	(-0.0291)
Δ TED spread $_{ex\ post}$	-7.206	-0.0605	**-0.271****	**-0.277****	**-0.190***
	(-0.190)	(-0.0652)	**(-0.425)**	**(-0.464)**	**(-0.259)**
Δ credit spread $_{ex\ post}$	**-2.973***	**-0.0799***	**-0.0681****	-0.0345	**0.0692***
	(-0.168)	**(-0.188)**	**(-0.229)**	(-0.123)	**(0.201)**
Δ volatility S&P500 $_{ex\ post}$	0.0104	-0.000565	-0.000173	7.79e-05	0.000596
	(0.0549)	(-0.123)	(-0.0543)	(0.0260)	(0.162)
Constant	-0.610	0.932**	1.129**	0.995**	0.617**
Observations	233	225	234	234	234
R-squared	0.163	0.356	0.221	0.214	0.388
Strategy FE	Y	Y	Y	Y	Y

Table 7 Market Timing Skill including First Time Funds

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 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, 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 credit spread, Δ volatility S&P500 and Δ TED spread 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 (**).

	(1)	(2)	(3)	(4)	(5)
VARIABLES	IRR	Net Multiple	PME IG	PME HY	PME S&P500
recession (1/0)	0.224	0.212	0.118	0.0123	0.0516
	(0.00462)	(0.190)	(0.146)	(0.0159)	(0.0531)
TED spread 1Yex ante	-10.26*	-0.0339	**-0.296****	**-0.320****	**-0.257****
	(-0.212)	(-0.0303)	**(-0.366)**	**(-0.414)**	**(-0.264)**
credit spread 1Yex ante	1.723	0.0333	0.0108	0.0242	0.137**
	(0.147)	(0.123)	(0.0552)	(0.130)	(0.584)
volatility S&P500 1Yex ante	0.0207	**-0.00237****	**-0.00108***	-0.000305	-0.000363
	(0.0469)	**(-0.232)**	**(-0.147)**	(-0.0434)	(-0.0411)
Δ TED spread ex post	-8.613	-0.0521	**-0.227****	**-0.247****	-0.142
	(-0.192)	(-0.0505)	**(-0.304)**	**(-0.346)**	(-0.158)
Δ credit spread ex post	**-3.008***	**-0.0751***	**-0.0676****	-0.0356	0.0403
	(-0.138)	**(-0.148)**	**(-0.185)**	(-0.102)	(0.0917)
Δ volatility S&P500 ex post	0.00391	**-0.00102****	-0.000468	-0.000192	-0.000181
	(0.0166)	**(-0.188)**	(-0.120)	(-0.0514)	(-0.0385)
Constant	-0.159	1.318**	1.203**	1.124**	0.835**
Observations	415	404	415	415	415
R-squared	0.757	0.205	0.121	0.086	0.235
Strategy FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

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Appendix Table 1: Increments in R2 using Ex Ante and Ex Post Credit Market Condition Variables

This table reports the increments in R2 and their statistical significance (F), as calculated from nested regressions based on seven independent variable blocks. Regression one using lagged performance is nested in regression two, using controls, which is nested in regression three, using ex ante credit market conditions, and so on. We account for seven controls and four ex ante credit market conditions in one block each and focus on each ex post credit market conditions variable separately to show incremental changes in R2. We run nested regressions in this way using the performance measures introduced earlier (IRR, PME IG, PME HY, PME S&P500 and Net Multiple). We do not control for strategy fixed effects. The results show the regressions we ran earlier, now showing the effects of different variable blocks. R2 shows the explanatory power for each block separately, change in R2 shows the increment in R2. F-test-values in column one show whether each increment leads to a significant increment in R2.

IRR	F	Block df	Residual df	Pr > F	R2	**Change in R2**
Lagged performance	3.86	1	231	0.0506	0.0382	
Controls	1	7	224	0.429	0.0606	**0.0223**
Ex ante credit market conditions	6.66	4	220	0	0.0937	**0.0331**
Changes in equity market volatility (S&P500 vola)	1.16	1	219	0.2821	0.1004	**0.0068**
Changes in spread (credit spread)	3.8	1	218	0.0525	0.1142	**0.0138**
Changes in funding illiquidity (TED spread)	2.2	1	217	0.1399	0.1258	**0.0116**
Changes in economic outlook (slope)	2.37	1	216	0.1248	0.1372	**0.0113**
PME IG						
Lagged performance	4.82	1	232	0.0292	0.0567	
Controls	0.83	7	225	0.5645	0.0704	**0.0137**
Ex ante credit market conditions	4.58	4	221	0.0014	0.1339	**0.0636**
Changes in equity market volatility (S&P500 vola)	0.13	1	220	0.7215	0.1344	**0.0004**
Changes in spread (credit spread)	7.66	1	219	0.0061	0.1654	**0.0310**
Changes in funding illiquidity (TED spread)	11.06	1	218	0.001	0.2101	**0.0447**
Changes in economic outlook (slope)	4.02	1	217	0.0462	0.2308	**0.0207**
PME HY						
Lagged performance	6.14	1	232	0.014	0.0801	
Controls	1.23	7	225	0.289	0.1005	**0.0204**
Ex ante credit market conditions	2.43	4	221	0.0485	0.1314	**0.0309**
Changes in equity market volatility (S&P500 vola)	0	1	220	0.9781	0.1314	**0.0000**
Changes in spread (credit spread)	2.48	1	219	0.117	0.1417	**0.0103**
Changes in funding illiquidity (TED spread)	14.23	1	218	0.0002	0.1947	**0.0531**
Changes in economic outlook (slope)	1.47	1	217	0.2268	0.2024	**0.0076**
PME S&P500						
Lagged performance	34.45	1	232	0	0.2202	
Controls	0.49	7	225	0.8415	0.2269	**0.0067**
Ex ante credit market conditions	6.65	4	221	0	0.3375	**0.1106**
Changes in equity market volatility (S&P500 vola)	0.1	1	220	0.7576	0.3378	**0.0003**
Changes in spread (credit spread)	5.81	1	219	0.0168	0.3609	**0.0230**
Changes in funding illiquidity (TED spread)	4.55	1	218	0.034	0.3772	**0.0164**
Changes in economic outlook (slope)	0.35	1	217	0.5566	0.3784	**0.0012**
Net Multiple						
Lagged performance	34.33	1	223	0	0.1791	
Controls	0.95	7	216	0.4687	0.2017	**0.0225**
Ex ante credit market conditions	8.73	4	212	0	0.3291	**0.1274**
Changes in equity market volatility (S&P500 vola)	0.58	1	211	0.4489	0.3306	**0.0015**
Changes in spread (credit spread)	4.88	1	210	0.0283	0.3497	**0.0192**
Changes in funding illiquidity (TED spread)	0.47	1	209	0.4924	0.3513	**0.0015**
Changes in economic outlook (slope)	1.22	1	208	0.2708	0.3558	**0.0045**

Regression one using lagged performance is nested in regression two, using controls, which is nested in regression three, using ex ante credit market conditions, and so on. We account for the seven previously used controls in the controls block and the four ex ante credit market conditions in the respective block and focus on each ex post credit market conditions variable separately. Table 7 shows incremental changes in R^2 and for the performance measures introduced earlier (IRR, PME IG, PME HY, PME S&P500 and Net Multiple). Our results illustrate the importance of considering ex ante *and* ex post credit market conditions when explaining PD fund performance: First, adding ex ante credit market conditions to the analysis increases R^2 substantially by 3.1% to 12.7%, the increment always statistically significant as indicated by the respective F-values. Second, ex post changes in credit spread increase R^2 significantly in all five specifications, the increment amounting to between 1.0% and 3.1%. Third, ex post changes in TED spread significantly increase R^2 in four of five specifications, its incremental increase amounting to between 1.2% and 5.3%.