Credit Market Equivalents and the Valuation of Private Firms

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Abstract

We propose to value leveraged buyout investments by credit market equivalents (CME). Our method relies on the observation that portfolio companies held by private equity funds have loans traded in secondary markets. Motivated by Merton's insight that debt and equity are claims on the same asset, we back out equity valuations from debt prices by constructing a stochastic discount factor that prices secondary market loan returns of private equity portfolios from deal-level data. We identify a credit factor model to price buyout cash flows to derive their CME valuation. We find no evidence for buyout outperformance after controlling for credit market factors. In contrast, funds raised during favorable credit conditions underperform. Our method works whenever credit and private equity markets are sufficiently integrated, for which we provide evidence.

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1 Introduction

In a leveraged buyout (LBO), a company is taken private with substantial amounts of borrowed funds, most notably from the leveraged loan market[1], with the objective of a later sale after restructuring. LBOs have been an increasingly popular investment opportunity for long-term investors such as endowments and pension funds. Since the financial crisis, for example, the number of deals that private equity (PE) funds executed grew almost fourfold. Plausibly, this growth has been fueled by attractive credit conditions in a low interest rate environment. Indeed, we show that indicators of credit conditions in the leveraged loan market are tightly linked to LBO activity (see Figure 1). Notably, we find that prominent investors in buyouts are also important direct investors in risky credit instruments, such as leveraged loans (directly or indirectly through CLO investments), private debt funds, as well as high-yield bonds, and have significant exposure to credit conditions to begin with. According to recent data from the IMF, pension funds, for example, hold around 25 percent of all of these assets, making them the largest investors in leveraged loans. Indeed, U.S. pension fund investment in private loans reached an eight-year high in 2022, even as banks pulled back on lending and default rates started rising [2] At the same time, in the wake of rising rates, retirement funds are reducing allocations to alternative investments such as private equity[3]. This calls for further investigation of the risk-reward tradeoffs of buyouts in the context of changing credit conditions.

In view of the popularity of LBOs among investors, evaluating the performance of these investments is an important question in asset management. It remains challenging, however, as their valuations are known only at investment and exit times, and are

[1] See, for example, Ivashina and Kovner (2011), Axelson et al. (2013), or Haddad, Loualiche, and Plosser (2017).

[2] See https://www.wsj.com/articles/pension-investments-in-private-credit-hit-eight-year-high-116749586 mod=article_inline.

[3] See https://www.wsj.com/articles/rising-rates-take-some-shine-off-private-markets-e1e0f4b3? mod=markets_lead_pos3.

traded infrequently, so that return data for these assets are necessarily sporadic. The majority of the buyout literature relies on heuristic performance metrics along the lines of the Public Market Equivalent (PME) measure of Kaplan and Schoar (2005) or the generalized PME (GPME) by Korteweg and Nagel (2016). These performance metrics ask how much investing in LBOs would improve the risk-return profile of an investor who is invested in the public stock market, and (in GPME) in a risk-free asset, and thus effectively provide a benchmark for PE valuation by discounting their cash flows with a CAPM-type stochastic discount factor (SDF). The broad consensus that emerges from these metrics is that buyout investments typically outperform, or in other words have positive alpha, both before and after fees.

In the light of the observation that prominent buyout investors have significant credit exposure, we propose a credit market equivalent (CME) valuation of such highly levered LBO deals. Effectively, we ask how much investing in LBOs improves the risk-return profile of an investor who is invested in the public stock market and a risk-free asset, *and a set of credit-linked instruments*. We view this as the realistic benchmark for an investment manager at a pension fund or an endowment. Our CME valuation is based on two tenets. First, we account for the observation that LBO activity is sensitive to credit conditions. Second, we infer equity valuations from real-time market signals about the debt side of the same private companies. This allows to control for the effect of private equity firms' ownership on the exposure to common risk factors.[4]

Our starting point is the simple observation that for many portfolio companies held by private equity funds we observe transaction data on bonds and loans and dealer quotes of loans in the secondary market. In the spirit of Merton's (1974) seminal insight that equity and debt can be viewed as options written on the same underlying asset, loan prices provide real-time market signals about private equity valuations as credit

[4]It has been widely stated in the literature that the objective of private equity buyout ownership is to improve operating performance (see, e.g., Kaplan (1989), Kaplan and Strömberg (2009), Davis et al. (2014), Bloom, Sadun, and van Reenen (2015); Bernstein and Sheen (2016)).

risk makes them sensitive to the same future asset values. Indeed, to motivate our analysis, we exploit a version of the Leland (1994) dynamic capital structure model with defaultable debt to illustrate how asset values can be recovered from observed debt prices, and subsequently used to impute equity prices[5]. In such a setting, debt prices are especially informative about equity valuations when credit risk looms large, which is relevant and plausible in the context of LBOs. We empirically implement this simple insight by applying modern asset pricing tools to extract information about the valuation of private equity from loan prices. Specifically, we estimate a stochastic discount factor that prices portfolios of loans issued by portfolio companies of private equity funds and traded on the secondary market. We use this stochastic discount factor to value private equity cash flows and thereby derive their CME valuations. Our approach thus provides a novel benchmark for buyout performance evaluation.

In our empirical implementation, we critically rely on two datasets, namely i) data on equity cash flows and company characteristics on the deal level from US buyout funds, and ii) data on prices of loans traded in the secondary loan market from the mark-to-market pricing database of Refinitiv LPC (Loan Pricing Corporation)/LSTA (Loan Syndications and Trading Association). After carefully merging, we obtain a rich dataset linking real-time loan market valuations to equity cash flows and characteristics of companies held by US buyout funds. About 80 percent of our sample private equity funds hold leveraged investments with loans that are traded until exit of the equity or last observed equity valuation in the secondary market.

With our dataset at hand, using standard cross-sectional asset pricing methodologies, we build portfolios of loan returns sorted on portfolio company characteristics and ask what factors, $f_{i,t}$,[6] help best explain the cross-section of loan returns on PE portfolio companies in our sample. Once we obtain exposures ("βs") in time-series regressions of

[5]Philippon (2009) uses a similar idea to recover Tobin's Q from corporate bond spreads and link it to corporate investment.

[6]i indices factors and t quarters.

quintile portfolio returns from a broad set of candidate factors, we use LASSO variable selection techniques to identify the factors relevant for pricing.

We identify five common risk factors that line up with average loan portfolio returns in a cross-sectional regression. The credit market (c) factors ($f^c_{i,t}$) that price the cross section of loan returns reasonably well are all "internal" to the loan market, i.e., high-minus-low quintile portfolio (Q5-Q1) loan returns sorted on five loan characteristics. Intriguingly, we basically find a credit market equivalent of some of the characteristics that have been shown to predict returns in public stock markets. These characteristics/factors—all from loan markets—are momentum, volatility, price, that is, the current price relative to par value, market capitalization, and the bid-ask spread. In contrast, we find that factors extracted directly from public stock market data, such as stock market excess returns, or the Fama-French factors, have only limited predictive power for our loan returns.

In a second step, we express the five factor asset pricing model through its equivalent stochastic discount factor (SDF) representation. In other words, we construct an SDF M_t^{CME} of the form

$$\mathcal{M}_t^{CME} = exp\left(a + b^T f_t^c\right), \tag{1}$$

where f_t^c is a $[F\ X\ 1]$ vector of the previously described factors and a and b are parameters, chosen to match the factors and the risk-free asset returns. In practice, this procedure amounts to replacing the returns on the stock market portfolio $f^m_{i,t}$ that are at the core of PME or GPME valuation with returns on a number of credit market instruments, $f^c_{i,t}$. The exponential affine SDF is well suited for multi-period payoffs measured over varying time horizons.

In the third and last step, we can use $\mathcal{M}_t^{CME}$ to discount private equity cash flows from our sample and thereby derive valuations, which we label the *Credit Market Equivalent* (CME) valuations of PE companies' cash flows and compare them to PME and GPME valuations. To rule out concerns that our results are driven by large fees that might be systematic in nature we test our results based on 'our' as well as on Preqin US buyout fund data. For 'our' sample we observe deal-level cash flows and aggregate those on the portfolio level so that cash flows are gross-of-fees. Cash flows in Preqin are net-of-fees. Results are qualitatively similar without evidence that fees impact our findings.

In contrast to previous findings in the literature, in our baseline results we find no evidence of overperformance of buyout funds using CME valuations. In fact, we find alphas for buyout funds neither economically nor statistically different from zero. If anything, the point estimate under the CME valuation points to slight underperformance of buyout funds after accounting for exposure to credit market factors. In other words, we find that the performance of buyout funds is entirely spanned by credit factors, and can be replicated by the investors' existing investments in public equity, and credit-linked assets. Moreover, we find that funds that raise significant leverage when credit conditions are favorable, or when credit is 'cheap', tend to underperform. These findings leave a rather bleak outlook for the future performance of buyout funds in the wake of currently rising interest rates, especially with their substantial floating rate exposure through leveraged loans in their debt structure.

We confirm that accounting for credit market exposure is important for buyouts in a subsample analysis. We split our sample into subsamples based on boom and bust cycles by vintage year, and leverage, among others. We find that funds that were raised during recessions have slightly positive alphas, while funds raised in boom periods experience negative abnormal performance based on the CME. Intriguingly, our evidence shows that this underperformance is particularly stark for funds raised during the LBO boom years between 2004 and 2007 (see e.g. Shivdasani and Wang (2011)). Rather than arbitraging debt markets against equity markets when debt is 'cheap', our results suggest that increasing leverage in better credit conditions has a negative impact on performance, plausibly because of rising coupon payments on leveraged loans that predominantly come with floating rates (see e.g. Beyhaghi and Ehsani (2017)). Indeed, we find that the negative effect of leverage is driven by funds with deal leverage above the sample median, while funds with below median leverage show marginal CME outperformance. These findings leave a rather bleak outlook for the future performance of buyout funds in the wake of currently rising interest rates given the floating rate exposure in their debt structure. In contrast, since the GPME and PME do not reflect credit conditions, we observe similarly high alphas under these valuations for funds below and above median leverage under these valuations. However, while our novel credit-sensitive performance benchmarks appear natural for highly levered deals such as buyouts, they may be less critical for alternative PE investments, such as venture capital (VC).[7]

To account for the fact that prominent buyout investors have significant credit as well as public equity exposure, we augment our stochastic discount factor with additional factors, including the public market factor, and a small-value portfolio, in light of the recent findings that buyout funds target small companies with distinct value characteristics (see Stafford, 2022). This extension also addresses concerns of weak factors, as loan returns may not display cross-sectional variation in risk exposures to public market factors (see Giglio, Xiu, and Zhang, 2021). That said, rather surprisingly, the public market factor is *not* priced in the cross-section of buyouts after adding loan factors to the SDF. This can be explained by the importance of credit markets for LBOs as well as private equity ownership which is accounted for in credit factors that are directly linked to companies with private equity ownership. In addition, investments in private and public equity differ in illiquidity, diversification of portfolios, clientele, and sophistication of investors. These differences suggest that private equity and loan investors could have more in common than private equity and public equity investors. While we report all our results based on an SDF that also considers the public market factor we exclude it in our baseline SDF since the price for the risk of the public market is insignificantly

[7]Ljungqvist and Richardson (2003), e.g., show PME results with the Nasdaq as the discount rate for distributions, which could be a natural choice for VC.

different from zero when loan factors are added to the SDF.

Our approach is natural when secondary loan and private equity markets are reasonably well integrated, so that the debt and equity claims on portfolio companies' assets are valued by a similar set of investors. To address some concerns that these markets may be rather segmented, we verify that there is a direct connection between loan valuation and equity performance. Indeed, when sorting the average quarterly exit valuation multiple by average quarterly loan returns we find that higher average loan returns command higher exit valuation multiples as well. We also find strong evidence that exit performance of private equity investments is positively correlated with performance of loans traded by the same company. The exit PE deal valuation multiple increases by about four percent with a one percent increase in the associated average loan bid price. This indicates that loan and equity markets are not entirely segmented.

Similarly, we verify that, for the case of public equity markets, information from loan markets is informative about the pricing of stocks. Indeed, first, we find a strong correlation between firms' loan returns and their stock returns, and second, that risk factors constructed from credit market information improve the pricing of the cross-section of stock returns beyond the benchmark five-factor models commonly used in empirical work. The first finding also helps us addressing the concern that in the case of risky firms, debt has limited sensitivity to the upside of the equity investment. Moreover, when sorting average quarterly factor returns of our loan pricing model into quintiles by average quarterly equity returns of the same publicly traded company we observe a significant increase in loan factor returns in the top quintile relative to the median factor return.

Overall, we propose a new performance benchmark for buyout investments that we view as a relevant one in practice for prominent LBO investors such as pension funds and endowments given their significant existing exposure to credit-linked assets. Our analysis suggests buyout returns are spanned by credit factors and therefore LBO investments do not provide return enhancements for such investors.

1.1 Contribution to the Literature

We make two main contributions to the literature. First, we contribute to the literature that have proposed SDFs to evaluate private equity performance (see Koretweg 2022 for a thorough review). Kaplan and Schoar (2005) propose in their groundbreaking work to value PE investments through

$$\mathcal{M}_t = \exp(-f_{m,t}). \tag{2}$$

In fact, Sorensen and Jagannathan (2015) and Korteweg and Nagel (2016) point out that the public market equivalent (PME) is an application of a stochastic discount factor (SDF) valuation in the special case of log-utility (a = 0 and b = 1), which is equivalent to the SDF of an investor who is fully invested in the public stock market. The PME approach has been widely used in papers that analyze private equity fund and deal performance (Kaplan and Schoar 2005, Higson and Stucke 2012, Axelson et al. 2013, Robinson and Sensoy 2013, Harris, Jenkinson, and Kaplan 2014, and Robinson and Sensoy 2016, Braun, Jenkinson, and Stoff 2017). A few papers (e.g., Ljungqvist and Richardson, 2003, Phalippou and Gottschalg, 2009, Harris, Jenkinson, and Kaplan, 2014, and Phalippou, 2014) recognize that the market return may not accurately reflect the riskiness of PE and that the beta should not be one. The average leverage ratio of companies in the S&P500 is about 0.3, while portfolio companies in private equity funds often have leverage ratios of about 0.7-0.8. In that regard, Harris, Jenkinson, Kaplan (2014), Phalippou (2014), and Robinson and Sensoy (2016) use a levered market return to compute PMEs. Instead of assuming a leverage number, Driessen, Lin, and Phalippou et al. (2012) estimate the loading on the market return. Their work is also related to Ewens, Jones, and Rhodes-Kropf (2013), who estimate the risk and return of private equity funds from the time series of returns constructed from NAVs. In contrast to their linearized version of the SDF, Korteweg and Nagel (2016) generalize the PME by using an exponential-affine SDF and relax the assumption that a = 0 and b = 1. They propose to value PE investments through

$$\mathcal{M}_t = \exp(a - bf_{m,t}). \tag{3}$$

This generalized public market equivalent (GPME) valuation is based on the SDF of an investor who is invested in the public stock market and a risk free asset. This approach is in line with work by Gupta and Van Nieuwerburgh (2019) who estimate an SDF from various listed equity and fixed income instruments. That being said, debt claims written on the same assets are lacking in the PME, the GPME, and Gupta and Van Nieuwerburgh's (2019) SDF approach. Thus, the question remains whether the valuation would improve if we replace returns on the stock market portfolio which are in the SDF of previous studies with returns on a number of credit market instruments that are directly related to portfolio companies. In a similar spirit, Haddad, Loualiche, and Plosser (2017), provide an asset pricing perspective on LBO performance, and show that movements in aggregate risk premia are important drivers of buyout activity. Giommetti and Jørgensen (2021) point out that leverage can affect GPMEs.

Stafford (2022) shows that a portfolio of publicly traded small firms with low EBITDA multiples can produce returns that are consistent with prefee PE index returns. Koijen, Lustig, and Van Nieuwerburgh (2017) show that the returns of small cap value stocks depend on credit markets. We combine these two findings and identify a credit factor model to price buyout cash flows to derive their credit market equivalent valuation.

Second, we contribute to the literature on the loan sale market. Güner (2006), Drucker and Puri (2009), Berndt and Gupta (2009), and Gande and Saunders (2012) study the consequences of lenders' activities in the secondary market on borrowers' short-term and long term performance and also on borrowers' debt liquidity and cost of borrowing. Pennacchi (1988), Wittenberg-Moerman (2008), Parlour and Plantin (2008), and Parlour and Winton (2013) considered the benefits of the secondary loan market for lenders in terms of efficient risk sharing and balance-sheet management. Altman, Gande, and Saunders (2010) examined whether banks have an informational advantage relative to public bondholders prior to a loan default. Billet et al. (2015) examine secondary loan market prices' response to corporate events, while Schwert (2020) examines the relative pricing of loans and bonds of the same firms. Despite the tremendous growth in the secondary market trading, this market is largely unexplored in the context of empirical asset pricing literature. To the best of our knowledge, Beyhaghi and Ehsani (2017) are the first who examine the pricing of characteristics and betas in the cross-section of expected loan returns in the secondary market. They find that momentum is significantly related to future loan returns which is in line with our findings. However, their analysis is based on the entire DealScan sample of loans issued by private and public firms that can be matched with LPC/LSTA data, instead of focusing on private equity backed companies that notably differ in leverage ratios and allow to control for changed in systematic risk due to PE ownership as mentioned earlier. Notably, we provide first evidence that the cross-section of loan returns on private equity backed companies is well described by a five-factor model for debt returns which are based on characteristics of portfolios that are relatively similar to what we see in stock markets. Our work is also related to Addoum and Murfin (2020), who highlight the importance of loan market information for stock returns.

The rest of the paper proceeds as follows. Section 2 discusses the sample and provides suggestive evidence that private equity and debt markets are not entirely segmented. Section 3 provides a comprehensive empirical analysis of the cross-section of loan returns on PE portfolio companies in our sample. Section 4 presents our valuation results of private equity portfolios. Section 5 shows evidence on pricing of stock returns using information from loan markets. Section 6 concludes.

2 Credit and Private Equity Markets

Before we apply the CME method to data on private equity investments, we start by laying out some theoretical background as a motivation, and then provide a description of the data that we use in our empirical implementation, as well as some evidence on which investors invest in LBO loans.

2.1 Motivation

The starting point of our analysis is the simple observation that for many portfolio companies held by private equity funds we observe transaction data on bonds and loans and dealer quotes of loans in the secondary market. In the spirit of Merton's (1974) seminal insight that equity and debt can be viewed as options written on the same underlying asset, loan prices provide real-time market signals about private equity valuations as credit risk makes them sensitive to the same future asset values. Indeed, to motivate our analysis, we now exploit a version of the Leland (1994) dynamic capital structure model with defaultable debt to illustrate how asset values can be recovered from observed debt prices, and subsequently used to impute equity valuations.

In Leland (1994), firms' asset values are assumed to follow a diffusion process with constant volatility under the risk neutral measure, of the form

$$dV/V = \mu dt + \sigma dW, \tag{4}$$

where W is a standard Brownian motion. Exploiting tax benefits of debt in the spirit of a trade-off theory of capital structure, firms can issue a consol bond that pays a non-negative coupon C, per instant of time as long as the firm is solvent. The firm declares bankruptcy at a possibly endogenous level of the asset value, denoted V_B. If bankruptcy occurs, a fraction $0 \leq \alpha \leq 1$ of value are lost to bankruptcy costs , so that debtholders are left with a value $(1-\alpha)V_B$ and stockholders are left with nothing. Leland shows that the debt value, $D(V)$ can be computed as the solution of an ordinary differential equation and is available in closed form, namely as

$$D(V) = C/r + [(1-\alpha)V_B - C/r]\,(V/V_B)^{-X}\,, \tag{5}$$

where $X = 2r/\sigma^2$, and r denotes the risk-free rate. Our strategy is to invert that expression, to obtain asset values from observed debt prices. To get intuition, it is useful to rewrite it as

$$D(V) = (1-p_B)\,(C/r) + p_B\,((1-\alpha)V_B)\,,$$

where $p_B = (V/V_B)^{-X}$ can be interpreted as the price of an Arrow-Debreu security that pays one dollar contingent on future bankruptcy. This expression makes it clear that debt values depend on asset values directly only through their dependence on asset values in default, so that only credit risk makes debt values sensitive to future asset values. In other words, absent credit risk, it is not feasible to recover asset values from debt prices. In a simple Merton setting, this is because risk-free bonds pay off a face value F independent of the asset value with certainty. With credit risk, however, debt prices reflect fractions of asset values recovered in default. In context of LBOs the high leverage ratios in deals make the dependence on credit risk relevant and plausible.

With that in mind, we can easily recover the asset value V from debt prices by inverting the function $D(V)$ obtaining

$$V = \left(\frac{D - C/r}{(1-\alpha)V_B - C/r}\right)^{-1/X} V_B, \tag{6}$$

thereby defining a function $V(D)$. With that expression for the asset value V given observations of debt prices D at hand, we can substitute the asset value in the pricing function for equity, to obtain

$$E(D) = V(D) - (1-\tau)C/r + ((1-\tau)C/r - V_B)\,(V(D)/V_B)^{-X}, \tag{7}$$

where τ denotes the corporate tax rate. This expression suggests that when credit risk is sufficiently important, observed debt prices can be informative about equity values. This insight based on the seminal work of Merton and Leland motivates us to devise a strategy to implement links between debt and equity prices in an empirically relevant way in the context of LBOs where credit risk looms large. Two potential caveats are in order, in that i) the exact relationship between debt and equity valuations in Leland's model depends on a host of structural assumptions that are unlikely to hold up exactly in empirical settings, and ii) that Leland's model applies in the context of a risk-neutral measure. To make what we refer to as Leland's insight operational empirically beyond the structural assumptions of the model in a risk-sensitive world, in much of what follows, we use the data we describe below to construct a stochastic discount factor pricing debt instruments and link equity cash flows to debt valuations.

2.2 Data

We use five main data sources in our analysis. The first is provided by one of the largest international LPs in the world on an anonymous and confidential basis (henceforth to be called "our sample"). Our sample includes deal-level information, from which we observe individual portfolio companies. The identity of portfolio companies allows us to trace the prices of their loans and bonds traded on the secondary market from other data sources, as we describe below. Although the data provider is a large, global investor who invests in various private equity asset classes, we restrict our analysis to U.S. buyout funds as they have sufficient debt claims traded in secondary markets. The dataset comprises 2,451 fund-investment pairs of 121 funds raised between 1996 and 2010. The fund-investment pairs cover 2,100 unique portfolio companies. We only use the loan data of a company as long as it is part of the buyout fund's portfolio and the loan is traded until exit of the equity or last observed equity valuation in the secondary market. For example, if a company is in the portfolio of a buyout fund from 2005 to 2009, we require the company to have traded loans in 2009, but do not use its loan data after 2009. About 40% of the funds' exited investments are realized below cost and 17% are completely written off.[8]

The second data source is the mark-to-market pricing database of Refinitiv LPC/LSTA (Loan Syndications and Trading Association), which tracks loans sold in the secondary market and reports daily quotes from dealers and traders. The LPC/LSTA dataset reports borrower names, average bid and ask quotes, number of quotes, type of facility and a loan identification number. The latter can be used to merge secondary market quotes to the third data source, i.e., the widely used Refinitiv DealScan dataset. The Dealscan dataset has been extensively described in the literature[9] and includes information about the loan at origination. We use such information to compute individual quarterly loan returns as in Beyhaghi and Ehsani (2017).[10] That means, in quarter t the return on each loan consists of price, principal repayment, and interest returns:

$$r_t = \frac{Par_t(P_t - P_{t-1}) + (Par_t - Par_{t-1})(1 - P_{t-1}) + (AI_t - AI_{t-1}) + C_t}{Par_{t-1}P_{t-1} + AI_{t-1}}, \qquad (8)$$

where Par_t is the par value (remaining balance) of the loan, adjusted for any principal payments. The average market bid and ask quotes are defined by P_t (market price). A market price of one means that the loan is trading at par. The principal repayment (if any) in quarter t is assumed to be made at par and described by $(Par_t - Par_{t-1})$. The principal repayment return (second term of equation 8) enters the equation because the

[8]This is consistent with Lopez-de-Silanes et al. (2015) who report 15% of complete write-offs in their sample.

[9]See, for example, Carey and Hrycray (1999), Chava and Roberts (2008), and Ivashina (2009).

[10]The quarterly returns for individual loans are also in line with the procedure described in S&P/LSTA U.S. Leveraged Loan 100 Index Methodology.

date and amount of each payment are agreed on at origination, although the loan may not be priced at par on the repayment dates. The interest, AI_t, is the accrued interest as of quarter t. Accrued interest is reduced to zero after each coupon payment. The coupon payment (if any) is defined by C_t and paid on quarterly anniversaries of the loan's origination date.

To calculate individual loan returns for our sample we need to match our sample portfolio companies to the LPC/LSTA dataset. Since we do not have an identifier we manually match borrower names on name, headquarter and location. After merging, we find that about 80% (97) of funds in our sample have traded loans in the secondary loan market. We retain 623 fund-investment pairs, of which 52% are fully realized and which correspond to 490 unique sample portfolio companies and 1,655 loans. For investments that are not yet fully realized by the end of the sample period, performance metrics are calculated using self-reported NAV at the end of the sample period as a proxy for a final cash flow.

We consider a fourth data source, the Trade Reporting and Compliance Engine (TRACE) database, to obtain corporate bond transactions data for private-equity-backed private firms in our sample. Out of the 16,064 TRACE transactions that can be merged to the LPC/LSTA database, only 157 bonds were issued at or before exit of the equity or last observed equity valuation. Merging TRACE data to our sample of borrowers with available loan transactions results in only 53 matched fund-investment pairs, which correspond to 49 unique sample portfolio companies. This represents only one percent of the total number of bonds in TRACE whose borrower could be successfully matched to the LPC/LSTA database. This fact is in line with the evidence in Axelson et al. (2013), who find that the bank loan market provide the majority of debt to fund leverage buyouts (LBOs). Given the modest increase in observations, we focus on traded loans in the remainder of our analysis. Table 1 summarizes the results of our merging procedure.

Finally, we apply our valuation approach to a large sample of US buyout funds raised between between 1980-2017, obtained from the Preqin dataset, which reports data at the fund level. Preqin data contains capital calls by the fund from LPs, which are cash flows into the private equity partnership, cash distributions from the fund to LPs, and quarterly NAVs. For comparison to prior literature, we follow Kaplan and Schoar (2005) and Korteweg and Nagel (2016) and restrict the sample to U.S. funds with committed capital of at least $5 million in 1990 dollars. We also drop funds raised after 2013, as very few of their investments will have been realized by the end of the sample period and hence their performance is likely to be misleading. As in our deal-level data, for funds that are not yet liquidated by the end of the sample period, performance metrics are calculated using self-reported NAV at the end of the sample period as a proxy for a final cash flow. Our sample of Preqin data covers 31,553 cash-flows of 1,219 funds raised by 460 GPs.

In addition to these five data sources, we use various databases to retrieve candidate factors for our loan pricing exercise, as outlined in Section 3.1. These data sources include French Data Library (for equity factors), Ibbotson Associates, CRSP and Moody's (for bond factors), Stambaugh's data library (for Pástor and Stambaugh (2003) liquidity factor), Tyler Muir's data (for Adrian, Etula, Muir (2014) leverage factor), Asaf Manela's data (for He, Kelly, Manela (2017) intermediary capital risk factor), ORBIS (size factor, i.e., shareholder funds (shfd)).

Finally, we use S&P's Capital IQ data to display LBO activity in Figure 1 and Figure 2. Specifically, we use valuation and leverage multiples (transaction value / EBITDA and total debt / EBITDA), as well as the numbers and volume aggregated per quarter of all U.S. LBOs with a value larger than $1 million. Table 2 provides the definitions of the main variables.

2.3 Sample Representativeness and Summary Statistics

Table 3 compares our merged deal-level sample with LPC/LSTA data (as described in Section 2.2), our Preqin sample and another benchmark study, Braun et al. (2017), who also uses deal-level information.[11]

Panel A of Table 3 shows that our sample covers fewer funds than Preqin and Braun et al. (2017). However, our data has more detailed information on the portfolio company level. Having deal-level information is generally a big advantage, as normally GPs transmit only quarterly net-of-fees fund-level performance (see, e.g., Metrick and Yasuda 2010, Robinson and Sensoy 2013).

Splitting the number of deals by investment year shows that our sample size increases over time. Braun et al. (2017) have slightly older investments which were predominately made in the early 2000s. In addition, their sample is more tilted towards European deals, whereas by far the majority of our sample deals are located in the U.S. The distribution across industries differs as well with more consumer discretionary oriented companies and less deals in consumer staples as compared to Braun et al. (2017). The median equity investment is also slightly higher in our sample which could be due to observing more and larger deals after 2005.

Descriptive statistics of the funds and their GPs are reported in Panel B of Table 3. The average (median) vintage year in our sample is 2004 (2005), which is comparable to Preqin. However, we find that our sample consists of statistically and economically larger funds that are raised by more established GPs than the average and median counterparts from Preqin. This is partly attributable to the fact that the large size of the Investor in question precluded them from investing in small funds. This indicates that our deal-level sample GPs appear experienced as active investors which is an important feature

[11] While we consider Preqin funds with vintage years until 2013 for our valuation (see Section 4) we only include funds with vintage years until 2010 in Table 3—last vintage year for our PE sample—for comparison purposes.

in the distinction of private equity to public equity markets where passive investors are prevalent.

Table 4 presents traded loans' characteristics. Loans in the overall LPC/LSTA database are traded at just at a slighlty higher bid-ask spread and are a bit larger in size as compared to loans matched with our PE sample (Panel A versus Panel B, Table 4). The bid–ask spread is estimated based on bid and ask price quotes aggregated across dealers and measured as the average annual bid–ask spread of the traded facility. Bid and ask prices are quoted as a percent of par. The time to maturity is similar in the LPC/LSTA and the matched LPC/LSTA-PE data sample.

2.4 Who Invests in LBO loans?

To learn about the valuation of private equity from debt markets, the two need not to be entirely segmented. We now provide evidence that equity investors also makes investments in credit and vice versa. Since our data provider is an institutional investor who operates a fund-of-funds we can observe their investments beyond buyout funds. Within the same vintage year sample period, 1996-2010, they invested in 264 funds in total. Figure 3 shows their fund investments by type (based on numbers (Panel A), and asset under management (Panel B)). In reference to section 2, Panel A shows that 45% of their portfolio consists of buyout funds. They invested an additional 35% in venture capital funds, 18% in private debt funds and 2% in infrastructure funds. With regard to assets under management, the numbers are tilted more towards buyout and private debt, which is attributable to the smaller size of venture capital funds (42% buyout, 30% private debt and 26% venture capital, 2% infrastructure).

Since we also test our valuation approach on a buyout fund sample from Preqin, we want to test whether LPs that invest in Preqin buyout funds also invest in leveraged loans. Thus, we merge our Preqin funds with funds in PitchBook which provides information on the overall portfolio allocation of the invested LPs and the type of LPs. Figure 4 plots the average percentage of investment type by size of investments of LPs invested in our Preqin buyout sample (Panel A), and the percent of investor type (Panel B). Apart from public equities, fixed income, private equity and other alternative assets, investors in Preqin buyout funds are also invested in leveraged loans, on average by 11%. Perhaps not surprisingly, the largest group of investors are public pension funds, corporate pension funds, and endowments (see Panel B of Figure 4).

Besides using our data and Preqin matched with PitchBook, we also test the validity of our benchmarking approach based on external references. According to the IMF's Global Financial Stability Report all major private equity players are directly and indirectly (through CLOs and private debt funds) invested in leverage loans.[12] As of 2020, followed by banks pensions, insurers, and mutual funds hold the largest direct exposure in LBO loans. Regarding indirect exposure in LBO loans through private debt funds, pension funds represent the largerst investors with roughly 30%, followed by endowments with 22%, fund-of-funds 11%, private wealth managers 16% and insurers 9%. In addition, according to information from the Federal Reserve CLOs hold about one-quarter of leveraged loans after origination (i.e., LBO loans traded in the secondary market).[13] Banks ($280 bn), insurers ($130 bn), asset managers ($115 bn) and pensions ($75 bn) are reported the lagest investors in CLOs as of 2020. All these investors are invested in private equity as well which shows that markets are integrated and no Chinese walls exist between the two portfolios. As a consequence, benchmarking against credit factors makes sense since the underlying portfolios are achievable by a PE investor.

In addition, we test if there are observable links between debt and private equity performance. Table 5 reports the average exit valuation multiple per quarter sorted by average quarterly loan returns of our PE sample (constructed as described in Section 2.2).

[12]See IMF's Global Financial Stability Report April 2020 Chapter 2: Risky Credit Markets: Interconnecting the Dots.

[13]See FEDS Notes 2019: The U.S. Syndicated Term Loan Market: Who holds what and when?.

Deal exit multiples are defined as (cumulative deal cash outflows to date)/cumulative investments into the deal to date. Only deals that are fully realized in a quarter are considered. Since exit multiples are no longer observable after deal exit in quarter t all portfolios are rebalanced quarterly. A clear positive link between loan and exit valuation multiples emerges in that portfolios that exhibit higher average loan returns tend to command higher valuation multiples as well. This pattern obtains qualitatively both in the case of equal and value weighting.

In the internet appendix, we also document that exit performance of private equity investments is positively correlated with performance of loans traded by the same company. As mentioned in the introduction, Table A1, column 2, shows that the exit PE deal valuation multiple increases by about four percent with a one percent increase in the associated average loan bid price ($1.01^{3.824} - 1 = 0.039$). [14] In all, these results suggests that risks that are priced in credit markets are informative about private equity performance as well.

3 Pricing Loan Returns with Credit Factors

In order to evaluate private equity performance from debt market characteristics, we first need to understand which of those determine loan returns. As an initial step, we sort loans to PE firms into quintile portfolios according to loan characteristics and compute portfolio excess returns. We then follow the standard two-stage regression approach common in cross-sectional asset pricing.

First, return spreads associated with the loan characteristics are regressed on candidate portfolio factor returns in form of quarter-time regressions. These include "external" as well as "internal" candidate factor returns, such as high-low quintile portfolio

[14] Results hold when we include all our sample deals and use measures of last observed sample equity performance as the dependent variable, instead of conditioning on realized deals and exit returns (see Table A2 to **??**).

(Q5-Q1) returns sorted on characteristics. Second, once we get exposures ('βs') we check whether average portfolio returns line up with exposures in a cross-sectional regression to get risk prices ('λs'). We use LASSO variable selection techniques to select the relevant factors.

3.1 Portfolio Sorts

At the end of July of each year from 2001 to 2017, loans are sorted into five portfolios based on one of eight characteristics that we observe. The first two characteristics, spread-to-maturity (STM) and price, pertain to loan risk characteristics. As Beyhaghi and Ehsani (2017), to calculate STM, we solve for STM in

$$Price = \sum_{t=1}^{T} \frac{Principal_t + Spread_t}{(1 + STM)^t}, \tag{9}$$

where $Spread_t$ refers to the fixed coupon payment above base rate in quarter t—typically LIBOR—since these loans are floating rate instruments.[15] $Principal_t$ refers to principal repayments in quarter t. The STM in this equation can be interpreted as a measure of credit spread. That means, the return on the loan if the benchmark rate is equal to zero over the loan's lifetime. The price is the average of bid and ask market quotes, expressed as a percentage of the par value of the loan. Intuitively, this is akin to a market-to-book valuation ratio. In addition, we compute loan spreads for loans sorted on momentum which is the loan's cumulative return over the past three months. Market capitalization, which is the product of the outstanding balance and market price, plus accrued interest, is another characteristic on which we sort. Volatility is a standard risk measure that we use in the equity market as well. It is calculated as the annualized standard deviation of residuals in a regression with daily excess loan returns as the dependent variable, and the market, term, and default factors as the independent variables. We also look at

[15] See, for example, Carey and Nini (2007).

a number of liquidity related variables. The first measure is the bid-ask spread and is computed as the ratio of the difference between bid and ask quotes to their average. Our second measure of liquidity is the number of bid and ask dealer quotes. Complementing our dataset with data from ORBIS we also consider return spreads based on size. Since market capitalisation does not exist for private companies we use shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (Banz (1981), Fama and French (1992)).

Once we sort loans into quintile portfolios based on these characteristics, we compute equal- and value-weighted quarterly returns for each portfolio keeping the same weights over the next four quarters, thus rebalancing annually. We report the time-series average returns with the corresponding Newey and West (1987) adjusted t-statistics. For each variable, we also compute the average value of other characteristics to investigate the univariate relationships between possible pricing characteristics. Table 6 reports the results.

Overall, across Panel A to Panel H, we find quarterly return spreads in the order of magnitude of around 1 to 3 percent associated with these characteristics. These spreads are thus not only statistically, but also economically significant. The first (fourth) row displays equally (value) weighted quarterly return spreads. The remaining rows report average characteristics (i.e., not loan returns) other than the one on which has been sorted on in each panel.

3.2 Second Stage Regression Results

As standard in the cross-sectional asset pricing literature, we attempt to rationalize the observed spreads through exposure to risk factors. We initially adopt a broad perspective in a data rich environment and consider a wide of range of risk factors that have been proposed in the literature across asset classes. Some of these candidate factors are what we refer to as “internal”, in that they are constructed from loan market data, while others are “external”, in that they are factors that exhibit predictive power for alternative asset classes. Specifically, the candidate factors that we consider in the first-stage time-series regressions include the returns of the loan market index, size (SMB), value (HML), profitability (RMW) and investment (CMA) factors (from Fama and French, 2015), two bond factors (TERM and DEFAULT), the Pástor and Stambaugh (2003) liquidity factor, the Adrian, Etula, Muir (2014) leverage factor, and the He, Kelly, Manela (2017) intermediary capital risk factor. The TERM factor is defined as the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one month treasury bill rate measured at the end of the previous month (from CRSP). The DEFAULT factor is constructed as the difference between the return on a portfolio of AA and a portfolio of BBB bonds - as is standard in the literature. Besides these external factors, we include internal factors in our time-series regression which are high-minus-low quintile portfolio (Q5-Q1) returns sorted on the characteristics described in Section 3.1.

In the time-series regressions, the slopes and R^2 values are direct evidence on whether different risk factors candidates capture common variation in excess loan returns. More precisely, once we obtain exposures ("βs") in time-series regressions of quintile portfolio returns on our candidate factors, we use LASSO variable selection techniques to identify the relevant factors by narrowing down the set of candidate factors. We identify five common risk factors that line up with average loan portfolio returns in a cross-sectional regression. Table 7 displays risk prices ("λs") of this cross-sectional regression of value-weighted average quarterly excess returns on the estimated "βs" from the time-series regressions. Standard errors are corrected with Shanken (1992) EIV correction.

The selected factors that price the cross section of loan returns well are all internal factors, which means these are all high-low quintile portfolio (Q5-Q1) loan returns sorted on five characteristics. These factors are momentum, volatility, price, that is, the current price relative to par value, market capitalization, and the bid-ask spread. As expected, momentum and volatility have a significant positive risk price. The pricing of the loan momentum factor is in line with Beyhaghi and Ehsani (2017). The bid-ask spread factor, which is related to illiquidity, is positively priced as well. The price factor is essentially the market-to-book portfolio, which requires a negative price of risk. This is in line with economic intuition since you would expect a positive risk price for book-to-market. The results of the second pass regression suggest a five factor model for debt returns which is based on characteristics of portfolios that are relatively similar to what has been shown in stock markets. In addition, we find that average returns of the quintile portfolios that we build line up with predicted returns, as depicted in Figure 5.

In an ideal scenario, the points in Figure 5 would lined up on a 45-degree line. This is relatively close to our empirical findings. In addition, we can see that the cross-sectional alpha is small. Overall, it appears that the five factor model prices our quintile portfolios well.

4 Valuation of Private Equity Portfolios

We now construct a stochastic discount factor to value highly levered buyout investments based on our loan portfolio pricing results. We label the valuation associated with that stochastic discount factor the *credit market equivalent* (CME) valuation. To account for the fact that prominent buyout investors have significant credit as well as public equity exposure we also present valuation results based on a stochastic discount factor augmented with a public equity market factor, that we refer to as *credit equity market equivalent* (CEME) valuation. This also addresses concerns regarding the omission of weak factors, as loan returns may not display cross-sectional variation in risk exposures to public market factors (see Giglio, Xiu, and Zhang, 2021). Since we show in section 4.3 that the public market factor is *not* priced in the cross-section of buyouts after adding loan factors to the SDF we exclude it in our baseline CME valuation.

4.1 Credit Market Equivalent Pricing

Our objective is to evaluate private equity portfolios from debt prices, or, in other words, to derive their credit market equivalent valuations, on the basis of the five factors selected by LASSO in Table 7.

To do so, we construct an exponentially-affine SDF from the beta-pricing relationship from our second stage regression in the previous section. The one-period SDF takes the following form:

$$M_{t+1}^{CME} = e^{a+b^T f_{t+1}}, \tag{10}$$

where a is a scalar, and b and f_{t+1} are five-dimensional column vectors of factor loadings and factor realizations (Q5mQ1mom, Q5mQ1vola, Q5mQ1price, Q5mQ1MV, Q5mQ1BA), respectively. We recover the values from b through a log-linear approximation of (10) around the SDF mean, that is

$$M_{t+1}^{CME} \simeq E[M_{t+1}^{CME}]\left(1 + \log M_{t+1}^{CME} - \log(E[M_{t+1}^{CME}])\right). \tag{11}$$

Internet appendix B shows that

$$b^T = -(1+r_F)\frac{1}{\alpha} \cdot \lambda^T \cdot E[f_{t+1}\ f_{t+1}^T]^{-1}, \tag{12}$$

where r_F is the average risk-free rate in our sample and $\alpha = 1 + r_F + \alpha_0$, where α_0 is the estimated intercept in Table 7.[16]

To pin down the value for a we follow Korteweg and Nagel (2016) and match each sample fund $i = 1, ..., N$ with cash-flows realized at $j = 1, ..., J$ to an artificial fund

[16] The term $1 + r_F$ is present in α as as the left-hand side variable in Table 7 is an excess return.

that invest in T-bills.[17] The risk-free rate is therefore weighted according to the funds' typical pattern of capital accumulation and payout. As a first step, we normalize each fund's cash flows by fund size so that estimation gives each fund equal weight and the normalized cash flows, $CF_{i,t+h(j)}$, can be interpreted as resulting from an investment with a total commitment of \$1. If fund i makes a payout at $t+h(j)$, then we assume that the artificial funds also make a payout equal to the sum of two components. The first component is equal to the return accumulated since the last cash flow date, $t+h(j-1)$. The second component pays out a fraction π_j of the capital that was in the artificial fund after the last cash flow at $t+h(j-1)$ occurred. The payout ratio is determined by

$$\pi_j = min\left(\frac{h(j)-p}{40-p}, 1\right), \tag{13}$$

where p is the time (measured relative to fund inception) of the most recent payout prior to time $t+h(j)$. If there was no prior payout yet, then $p=0$. Time periods are measured in quarters. This assumption sets the fund's lifetime to roughly 10 years.

With the artificial T-bill fund cash flow streams $CF_{ib,t+h(j)}$ set up, we define

$$u_i(a) = \sum_{j=1}^{J} M_{t+h(j)}^{CME}(a) CF_{ib,t+h(j)}, \tag{14}$$

and estimate a by GMM, i.e.,

$$\widehat{a} = \arg\min_a \left(\frac{1}{N}\sum_i u_i(a)\right)' W \left(\frac{1}{N}\sum_i u_i(a)\right), \tag{15}$$

where N is the number if funds and the weighting matrix W is the identity matrix. As this GMM is exactly identified, a is estimated to price the artificial T-bill funds with zero pricing errors.

[17]We refer the reader to Korteweg and Nagel (2016) for a detailed description of the estimation procedure.

As a final step, with the time series of the SDF at hand, we evaluate private equity portfolios by discounting their cash flows as

$$CME_i = \sum_{j=1}^{J} M^{CME}_{t+h(j)} CF_{i,t+h(j)}. \tag{16}$$

.

4.2 Credit Equity Market Equivalent Pricing

In the previous sections we described that the CME valuation consists of identifying risk factors from loans, estimating risk prices from loans, and that the SDF derived from these risk prices is applied to price private equity funds. This makes sense since the credit conditions have a strong effect on prices paid in buyouts (see Section 2.4, and Axelson et al. (2013)). Despite that evidence prominent buyout investors have significant credit as well as public equity exposure. In addition, there might be a lingering concern of weak factors since LASSO variable selection techniques did not identify public market factors as relevant for loan pricing. A factor is weak with respect to a set of testing assets when the assets do not display cross-sectional variation in risk exposures to that factor (see Giglio, Xiu, and Zhang 2021). The concern is: if public market factors are relevant for private equity pricing they will not be priced within loan returns based on our LASSO selection because loan assets don't span equity factor loadings (βs) enough.

To mitigate concerns about the typical PE investor and the weak factors problem, we use the LASSO analysis only to determine what factors are useful in pricing loans, add the risk-free and public market factor and estimate those two extra loadings.[18] Our SDF derived from risk prices in credit markets now also contains risk factors that price public equities. We label valuation based on this SDF the Credit Equity Market Equivalent (CEME).

[18] Estimating all seven parameters would not be feasible due to numerical convergence issues.

Formally, we follow Korteweg and Nagel (2016) as in Section 4.1 and we add an artificial fund matched to each PE fund, that is invested in the CRSP value-weighted index and in T-bills. We first define the one-period-ahead SDF for the CEME as:

$$M_{t+1}^{CEME} = e^{a+b_M R_{t+1}^m + b^T f_{t+1}}, \tag{17}$$

where R_{t+1}^m is the the one-period-ahead return of the CRSP value-weighted index. We define

$$u_i(a, b_M) = \sum_{j=1}^{J} M_{t+h(j)}^{CEME}(a, b_M) CF_{ib,t+h(j)}, \tag{18}$$

and estimate a and b_M by GMM as follows:

$$(\widehat{a, b_M}) = \arg\min_{a,b_M} \left(\frac{1}{N} \sum_i u_i(a, b_M) \right)' W \left(\frac{1}{N} \sum_i u_i(a, b_M) \right). \tag{19}$$

The CEME valuation metric can finally be computed as:

$$CEME_i = \sum_{j=1}^{J} M_{t+h(j)}^{CEME} CF_{i,t+h(j)}. \tag{20}$$

.

4.3 Baseline Valuation Results

As a starting point for our valuations, Figure 6 plots the time series for the realized SDFs estimated in our sample for the Generalized Public Market Equivalent (GPME, dotted line), the Public Market Equivalent (PME, dashed line), for the Credit Market Equivalent (CME, solid line), and for the Credit Equity Market Equivalent (CEME, dashed-dotted line). The PME and GPME SDFs are estimated as is Korteweg and Nagel (2016). We note large differences in the time series of SDFs based on the GPME, PME, and CME. The SDFs based on the CME and CEME are highly correlated. This questions whether public equity factors are priced in the cross-section of buyout funds after adding loan factors to the SDF. The GPME reflects the most volatile SDF. While a larger variance of an SDF is useful according to the equity premium puzzle of Mehra and Prescott (1985), a more volatile SDF implies lower power to detect abnormal performance which is crucial in pricing private equity. The SDF of the CME increases between 2004 and 2008 when prices for LBOs are low, and once LBO activity picks up again towards the end of 2009, and is notably less volatile than the SDF under the GPME.

Table 8 displays the valuation of the 1,219 Preqin funds and our 97 fund portfolios, for which we observe traded loans that are traded until exit of the equity or last observed equity valuation in the secondary market. These funds are priced by discounting cash flows with the SDF of the CME, GPME, PME, and CEME approaches, respectively. The cash flow data run through the end of 2017 with the last vintage year of 2013, so we have at least four years of cash flow data for all funds in our samples.[19] The PME measure is expressed as a difference between inflows and outflows rather than as a traditional ratio, in which $a = 0$ and $b = 1$ (see also Korteweg and Nagel 2016). That means a PME of zero in our setting corresponds to a traditional PME of one.

To rule out concerns that our results are driven by large fees that might be systematic in nature we use two data sets. While cash flows in Preqin are net-of-fees cash flows in our portfolio data are observed on the deal-level and are aggregated on the fund level gross-of-fees. Indeed,Table 8 shows that valuations in the Preqin sample tend to be lower than in our sample, consistent with the idea that the former are net-of-fees.

Column (1) in panel A of Table 8 shows valuations based on the CME, GPME, and PME for the 1,219 buyout funds in Preqin, and column (2) displays results for the 97 fund

[19]Robinson and Sensoy (2016) find that none of their performance assessments are sensitive to the inclusion of non-liquidated funds. We exclude these recent vintage years to be assured that there is a high correlation between liquidated and non-liquidated performance while preserving large enough sample sizes for our estimations.

portfolios from the institutional investor. Since the cash flow series include the initial investment, equation (16) implies, under the null hypothesis, that $E[CME_i] = 0$, that is, that the NPV is zero. Test statistics and standard errors are computed as in Korteweg and Nagel (2016). Table 8 shows that the GPME and PME estimates across US buyout funds in Preqin and in our sample are economically large and positive. The PME is also statistically significantly different from zero in our data, as indicated by the $p-$value of $t-$tests, while the overperformance is notably larger with GPME. The reason why the GPME is not statistically different from zero is that the GPME requires estimation of the SDF parameters, whereas PME assumes they are fixed and given. Relaxing the PME restrictions raises the standard error of estimated GPME. This means that, from a GPME and PME perspective these valuations come with overperformance in Preqin and in our sample. This finding lines up with evidence by Korteweg and Nagel (2018), who document overperformance for US buyout funds by reporting a GPME 0.207 and a PME of 0.148, significantly different from zero only for the PME. It is also in line with the results by Giommetti and Jørgensen (2021) who find that buyout funds provide investors with 28 (20) cents of abnormal profits per dollar of committed capital based on the GPME by Korteweg and Nagel (2016) (and the PME by Kaplan and Schoar 2005).

Intriguingly, the CME approach provides a different perspective on the pricing of private equity by showing marginally negative prices in the Preqin sample and an alpha close to zero for US buyout funds in our sample. The CME is far from being statistically different from zero across both samples. That means, through the lens of the CME we find a more accurate valuation estimate that is not economically and statistically significantly different from the fair price (i.e., alphas close to zero). Overperformance may therefore reflect credit market exposure, that both the GPME and PME approaches are abstracting from.

Based on the discussion in Section 4.2 we also control for weak factors and test whether the CME SDF should also contain risk factors that price public equities. Thus, Panel B of Table 8reports valuation results by adding the public market, which is in the SDF of the GPME by Korteweg and Nagel (2016), and estimate the extra loading. Maybe not surprisingly, we find overperformance which is still lower than under the GPME. Rather surprisingly, the public equity market factor is *not* priced in the cross-section of buyouts after adding loan factors to the SDF. While, perhaps counterintuitively, the estimated loading on the market is positive for both the Preqin sample, it is statistically insignificantly different from zero (see last row Panel B of Table 8). This finding is in line with the high correlation between the CME and CEME SDFs as shown in Figure 6. Economically, this can be explained by the importance of credit markets for LBOs as well as private equity ownership which is accounted for in credit factors that are directly linked to companies with private equity ownership. In addition, investments in private and public equity differ in illiquidity, diversification of portfolios, clientele, and sophistication of investors. These differences seem to suggest that private equity and loan investors have more in common than private equity and public equity investors. Overall, accounting for only credit market exposure helps understanding private equity valuations in Preqin and in our sample.

In panel C, we also account for potential exposure to a small-value portfolio, as advocated by Stafford (2022). In a provocative paper, Stafford (2022) argued that direct investments in private equity funds are largely replicable by levered investments in publicly traded small firms with distinct value characteristics. We recover positive, albeit somewhat modest, point estimates, indicating moderate overperformance in this case. Some of the overperformance with respect to alternative benchmarks may thus indeed reflect exposure to a small-value factor, especially in our sample. The loadings with on the small-value portfolio are negative, as expected, and statistically significant. We note, however, that the small-value portfolio has a correlation with the market portfolio of about 0.75 in our data.

In panels D and E, finally, we check to what extent our 5-factor credit pricing model could be subsumed by a simple one-factor credit index model. For our purposes, it is most natural to use a S&P/LSTA U.S. Leveraged Loan 100 Index. Panel D reports the results from discounting cash flows with that loan index only, that is by using a one-factor credit pricing model, while panel E adds the public equity market to the pricing model. The results are similar throughout these specifications. In sharp contrast to our benchmark CME valuations based on a 5-factor credit pricing model, the valuations are economically large and positive, in similar orders of magnitude as the valuations implied by the GPME. At the same time, the loadings on the loan index are plausibly negative, as expected, while statistically insignificant. Why are the valuation results with a loan index so starkly different from our benchmark CME valuations? The intuition is simple. While the CME valuations are based on a factor model that is designed to price loan portfolios well, the loan index is not. Indeed, the loan index does not price our loan portfolios well, and therefore does not properly take into the overall credit market risk exposure of the buyout deals, leading to large α. In turn, our credit factor model does.

4.4 Valuation Results for Subsamples

To illustrate the sources of the differences between the GPME/PME and CME we split the sample into subsamples based on boom and bust cycles by vintage year (Table 9, Panel A), leverage (Table 9, Panel B), and fund size (Table 9, Panel C). As shown in Panel A, funds that were raised during economic recessions have a slightly positive alpha while funds raised in boom periods before the financial crisis (2004-2007) experience negative abnormal performance based on the CME.[20]. Alphas are marginally negative, close to zero, for funds with vintage years in boom periods after the financial crisis and last observed cash flow in 2017. A simple rationale here is that funds increase leverage when credit conditions are good, but start struggling when interest rates rise in

[20]Economic recession in the US are defined according to https://www.nber.org/cycles.html.

market downturns since leveraged loans are typically floating rate instruments, paying a fixed coupon above LIBOR (see, e.g., Beyhaghi and Ehsani 2017) so that coupon payments increase for funds raised in boom times. Companies in these funds also may lack resources to pay increasing coupons on existing debt in market downturns. Thus, rather than arbitraging debt markets against equity markets when debt is "cheap", we find that increasing leverage in better credit conditions has a negative impact on performance. This underperformance is particularly stark for funds raised in the LBO boom years from 2004 to 2007 (see e.g. Shivdasani and Wang (2011)).

The GPME and PME valuation also drops in the LBO boom years. Based on the theoretical model by Axelson, Strömberg, and Weissbach (2009) returns to investments made in boom times are expected to be lower on average than returns to investments made during poor times. We confirm this result empirically in Table 10. The estimations are the same as in Table A1 in the internet appendix where we show that exit performance of private equity investments is positively correlated with performance of loans traded by the same company. In Table 10 we drop the investment years fixed effects and include a dummy equalling one for investments made between the 2004-2007 LBO boom years. Exit performance of private equity investments is negatively correlated with LBO boom years when controlling for loan performance.[21] That said, the valuation based on the GPME and PME drops to a lesser extent than on the CME in LBO boom years (Table 9, Panel A). This implies that funds do not simply apply a lower threshold in selecting investments, which tend to underperform during times of easy credit, but also face unexpectedly high cost of debt funding in future years, which is captured by the CME.

Panel B of Table 9 shows that the negative effect of leverage is driven by funds with deal leverage above the sample median, while funds with below median leverage show marginal CME outperformance. This suggests that low leverage levels do not

[21]Results hold when we consider the last observed sample equity performance (Table A3)—which includes the NAV—instead of the realized performance as in Table 10.

hurt performance, but high leverage levels do. This result is in line with the literature arguing that high leverage negatively impacts performance, and vice versa (see Axelson, Jenkinson, Strömberg, and Weisbach 2013, Kaplan and Strömberg 2009, and Harris, Jenkinson, and Kaplan, 2014). These findings leave a rather dim outlook for the future performance of buyout funds in the wake of currently rising interest rates. Since the GPME and PME do not reflect credit conditions we observe similarly high alphas under these valuations for funds below and above median leverage.

Next, we consider how valuations vary with fund size (see Table 9, Panel C). We find that the fund size/performance relationship depend on sampling considerations. With regard to sampling, Robinson and Sensoy (2016) state that data from Preqin which tend to focus on large funds raised in hot markets (as shown in Table 3) do rather poorly in the wake of these boom periods. We confirm this finding with the CME. In addition, we find outperformance for funds above median size from the institutional investor. This can be explained with the fact that our sample contains large funds with mean vintage year during the economic recession following the dot-com boom (see Table 3). Alphas are similarly large and positive under GPME and PME valuations for different fund sizes. Valuations based on the CEME remain in magnitude between the GPME and CME for all sample splits.

Overall, the results in Table 9 illustrate the benefits of our proposed CME evaluation approach. The reflection of credit market characteristics in the CME squares with findings in the private equity literature. Our novel credit-sensitive performance benchmarks indicate that the GPME/PME overstates PE fund performance over time and across fund characteristics by neglecting to control for credit market conditions. On the other hand, controlling for credit market exposure is likely less critical for alternative PE investments, such as VC investments.

5 Credit and Public Equity Markets

The idea underlying our approach is that we can use observable debt market valuations to infer benchmarks for unobservable private equity valuations. Clearly, the basic tenet that information from the debt side of a company's balance sheet should be useful to value equities applies to public companies as well. Indeed, as a validation for our approach, we now provide evidence that debt returns match up well with stock returns for the sample of public firms for which we have sufficient data on debt prices.

In constructing our sample, we require that public companies have loans traded in secondary markets. Internet appendix Table A5 gives a quick account of the matching outcomes and shows that for our sample (1998-2017) just about ten percent of firms in the Compustat/CRSP universe have loans traded in the secondary market. Table A6 presents summary statistics of our matched sample of public firms and provides some sense of the type of public companies whose loans are traded in the secondary market. A few observations are in order. As Internet appendix Table A6 shows, our matched firms tend to be larger than the average Compustat firm, they tend to grow more slowly and exhibit lower growth prospects as most public firms, and have significantly more leverage and less cash. Casually, it appears natural to associate the average firm in our sample with a firm that may approach distress in the future. Accordingly, we can assess the validity of our credit-factor approach on a very particular sample, for whose constituent firms leverage plays a special role.

Table 11 documents first linkages between loan returns and stock returns of the firms in our sample. Along the lines of Table 5 it reports the average quarterly stock returns sorted by average quarterly loan returns, both for case of equal and value weighting. A clear positive link between loan and stock return emerges in that firms that exhibit higher average loan returns tend to command higher stock returns as well. This pattern obtains qualitatively both in the case of equal and value weighting, but is statistically stronger and significant in the latter case. These results suggests that risks that are priced in credit markets are informative about stock market performance as well. Table A7 in the Internet appendix provides further evidence along these lines by extending the analysis to loan-characteristic sorted portfolios.

One concern is that in the case of risky firms, debt has limited sensitivity to the upside of the equity investment. If you think of equity as a call option on the value of the firm written by the debt-holders, the two might not have have similar returns. In that regard, instead of sorting stock returns by average quarterly loan returns, as in Table 11, Table 12 reports the average quarterly factor returns of our loan pricing model (Table 7) sorted into quintiles by average quarterly equity returns of the same publicy traded company. As Table 12 shows there is comovements between returns in these two markets. Importantly, we observe an increase in loan factor return for the fourth equity quintile relative to the median factor return up to 1000 percent, which even doubles in quintile 5. Overall, these results indicate that debt payoffs are not constant in solvency.

We next apply our factor pricing approach to the public companies in our sample. As a first test, we proceed just as in the case of private companies, and evaluate what risk factors are effective in pricing *loan* returns across portfolios sorted on a variety of characteristics. As in the case of private companies, we use LASSO variable selection techniques to identify the factors relevant for pricing. We view the results reported in Table 13 as comforting, as LASSO identifies a very similar factor model for loan pricing in the cross-section of public and private loan returns. Indeed, for public companies it identifies a four-factor model that differs from the five-factor model for private companies only because the price factor, that is, the current price relative to par value, becomes insignificant in the public sample. Overall, however, our approach is similarly effective in pricing loan returns for public companies as it is for private companies.

Critically, with this background, we now establish linkages between factor pricing of loan and stock returns for public companies. Clearly, when it comes to public equity, standard risk factors captured in state-of-the-art five factor models contribute significantly to the pricing of the cross-section of stock returns. We start by verifying this by forming decile portfolios in our sample based on stock characteristics such as Size, B/M, OP, and Inv, and evaluate how a state-of-the-art five factor model along the lines of the models of Fama and French (2015), and Hou, Xue, and Zhang (2015) perform in pricing these portfolios. Not surprisingly, as reported in Table 14 the standard Fama-French 3-factors augmented with a profitability and an investment factor give a good account of the cross-section of these stock returns, indicated by a cross-sectional R^2 of about 0.6.

Most importantly, giving credence to our approach, Table 15 shows that including credit factors into the analysis significantly improves the power of factor models for our sample. Indeed, once we include the five debt factors as identified in pricing of the cross-section of loan returns (Table 7) now in the pricing of the cross-section of stock returns raises the cross-sectional R^2 from 0.6 to more than 0.7. Figure 7 provides a graphical representation. We acknowledge that these results may be particular to our sample of matched firms, but given their high leverage, these firms share many characteristics with the sample of private firms that is the focus of our attention, as Table A6 documented. Overall, this suggests that including information from credit markets into factor-pricing models for stocks is a fruitful direction to explore, and provides us with some external validation for our approach to value private companies.

6 Conclusion

We propose an SDF approach to the valuation of private equity payoffs based on credit market instruments. Our approach shares the advantages of the PME and GPME methods in that it is well suited for irregularly spaced, and endogenously timed payoffs. Our method relies on the observation that many portfolio companies held by private equity funds have loans traded in secondary markets and is particularly well suited for the valuation of highly levered buyout investments. Our method deviates from the PME and GPME in that we exploit the market valuations embedded in these prices by constructing a stochastic discount factor that prices loan returns of private equity portfolios. In this sense, by applying our stochastic discount factor to value private equity investments, we compute their credit market equivalent valuations (CME) and we refer to our method as the CME approach. Our approach is natural in view of Merton's classic insight that loans are claims written on the same assets as equity shares, and credit risk makes them sensitive to future asset values.

We find no evidence of overperformance of buyout funds using CME valuation. This is in sharp contrast to valuations based on the GPME and PME approaches that are abstracting from exposure to credit conditions when evaluating these highly levered deals. In fact, we find alphas for buyout funds neither economically nor statistically different from zero. Moreover, in sample splits, we find that funds that raise significant leverage when credit conditions are favorable, or when credit is 'cheap', tend to underperform. These findings leave a rather bleak outlook for the future performance of buyout funds in the wake of currently rising interest rates, especially with their substantial floating rate exposure through leveraged loans in their debt structure.

In this paper, we apply our CME methodology to provide novel benchmarks for the valuation of buyout investments. Our approach is likely also useful to evaluate the performance of alternative credit-linked investments such as CLOs (see, e.g., Cordell, Roberts, and Schwert (2022)) or the rapidly evolving market for direct lending and private debt (see, e.g., Davydiuk, Marchuk, and Rosen (2022), or Chernenko, Erel, and Prilmeier (2022)). We leave this for future research.

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Figures and Tables

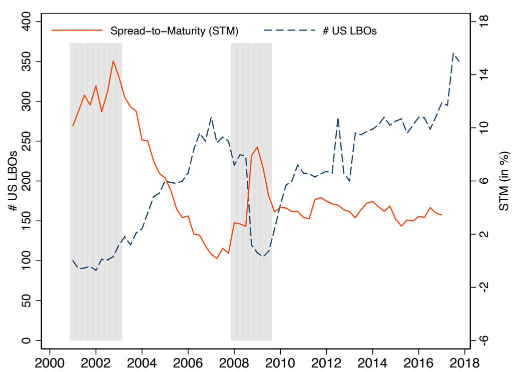
Figure 1: Spreads-to-Maturity and the LBO Market

This figure plots the average spread-to-maturity (STM) for loans in the secondary market from our sample of 490 unique sample portfolio companies versus: numbers of US LBOs per quarter (Panel A), the volume of US LBOs per quarter in billion USD (Panel B), quarterly leverage levels of US LBOs—defined as total debt / EBITDA (Panel C), quarterly prices for US LBOs to EBITDA—that means, the ratio is defined as transaction value / EBITDA (Panel D). Our sample is constructed as described in Section 2. We measure LBO activity from S&P's Capital IQ data. To calculate STM, we solve for STM in

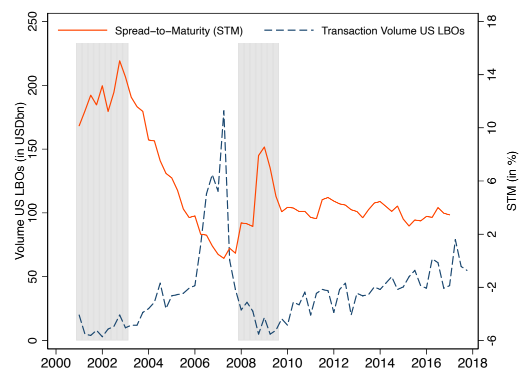
$$Price = \sum_{t=1}^{T} \frac{Principal_t + Spread_t}{(1+STM)^t},$$

where $Spread_t$ refers to the fixed coupon payment above base rate in quarter t—typically LIBOR—since these loans are floating rate instruments. $Principal_t$ refers to principal repayments in quarter t. Grey shaded areas represent years for economic recession in the US according to https://www.nber.org/cycles.html.

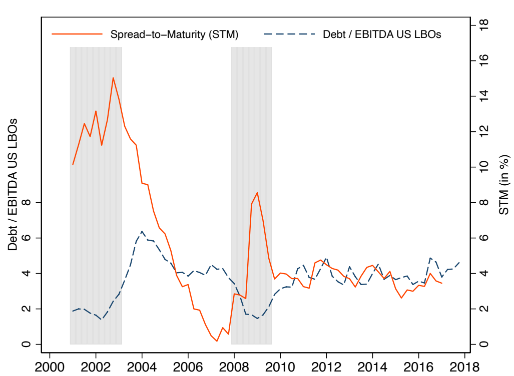
(a) STMs and Number of LBOs



(b) STMs and Volume of LBOs



(c) STMs and Leverage of LBOs



(d) STMs and Valuations of LBOs

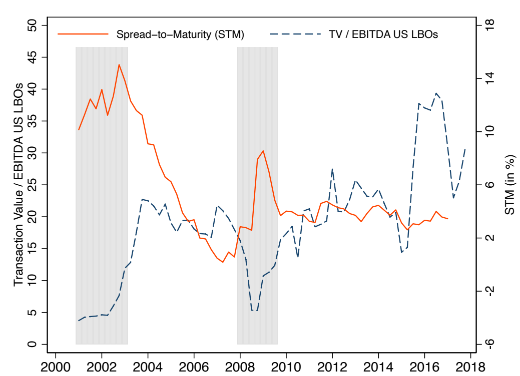
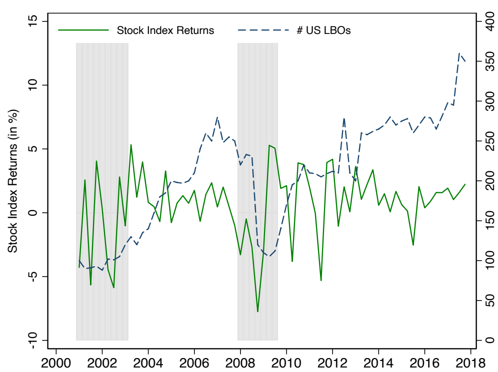


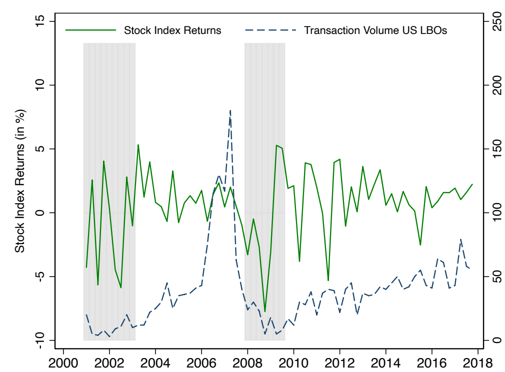
Figure 2: Stock Returns and LBO Market

This figure plots the average U.S. stock market returns (CRSP universe) versus numbers of US LBOs per quarter (Panel A), the volume of US LBOs per quarter in billion USD (Panel B), quarterly leverage levels of US LBOs—defined as total debt / EBITDA (Panel C), quarterly prices for US LBOs to EBITDA—that means, the ratio is defined as transaction value / EBITDA (Panel D). We measure LBO activity from S&P's Capital IQ data. Grey shaded areas represent years for economic recession in the US according to https://www.nber.org/cycles.html.

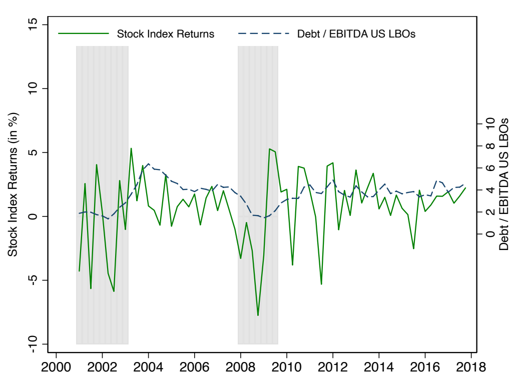
(a) Stock Returns and Number of LBOs



(b) Stock Returns and Volume of LBOs



(c) Stock Returns and Leverage of LBOs



(d) Stock Returns and Valuations of LBOs

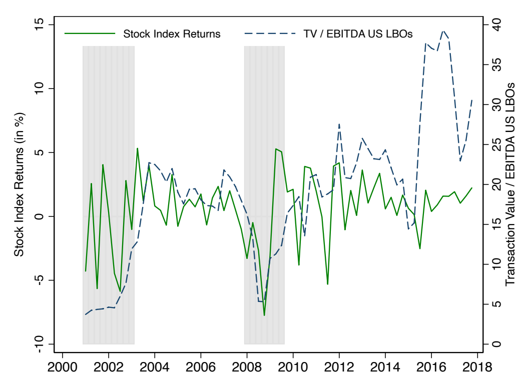
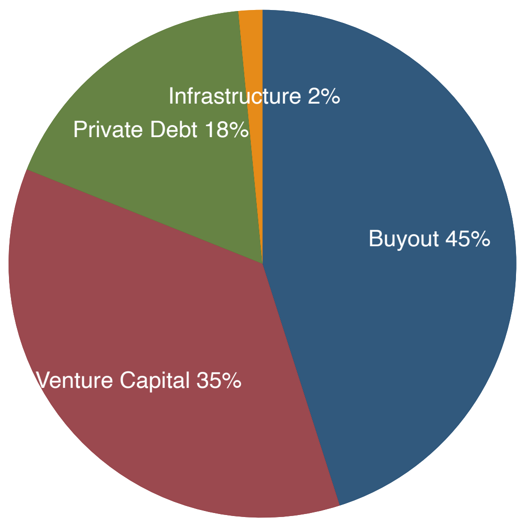


Figure 3: Our Investor by Fund Type

This figure plots the percent of investment type by number of investments (Panel A), and size of investments (Panel B) of our data provider who is an institutional investor that operates a fund-of-funds.

(a) Investment Type by # of Investments



(b) Investment Type by Size of Investments

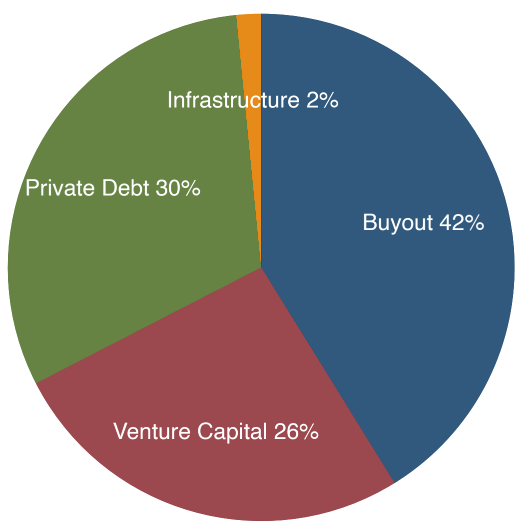
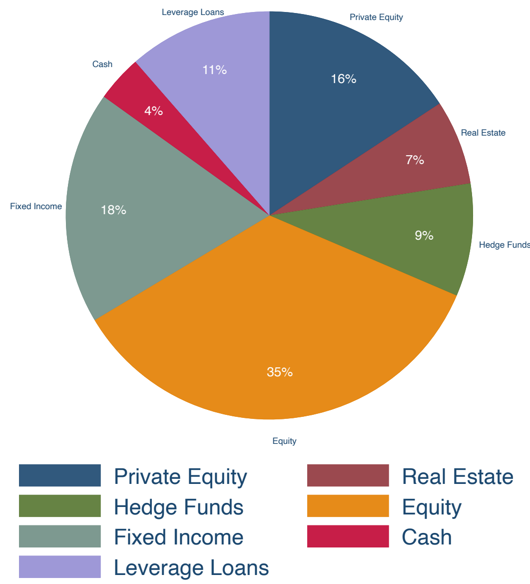


Figure 4: Preqin Sample Average Asset Allocation and Investor Type

This figure plots the average percent of investment type by size of investments of LPs invested in our Preqin buyout fund sample (Panel A), and the percent of investor type invested in our Preqin buyout fund sample (Panel B).

(a) Investment Type



(b) Investor Type

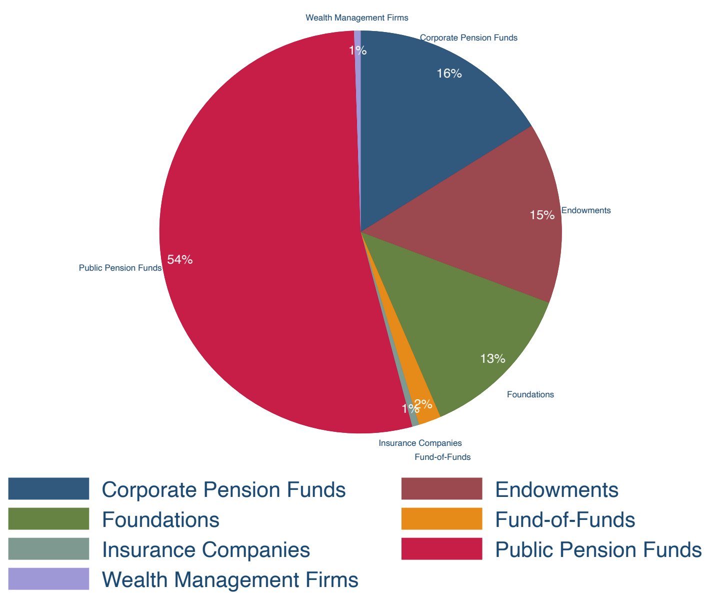


Figure 5: Predicted Loan Returns versus Observed Loan Returns

In this figure, we plot the predicted loan returns from risk prices ('λs') of our five identified factors (all high-low quintile portfolio (Q5-Q1) loan returns) from the second pass cross-sectional regression in relation to value-weighted average cross-sectional loan returns. Loan returns stem from quintile portfolios sorts based on eight loan characteristics we observe: spread-to-maturity (STM), price, momentum, market capitalization, volatility, bid-ask spread, number of bid and ask dealer quotes, and size. Size is the natural logarithm of shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (in millions of dollars) (Banz (1981), Fama and French (1992)).

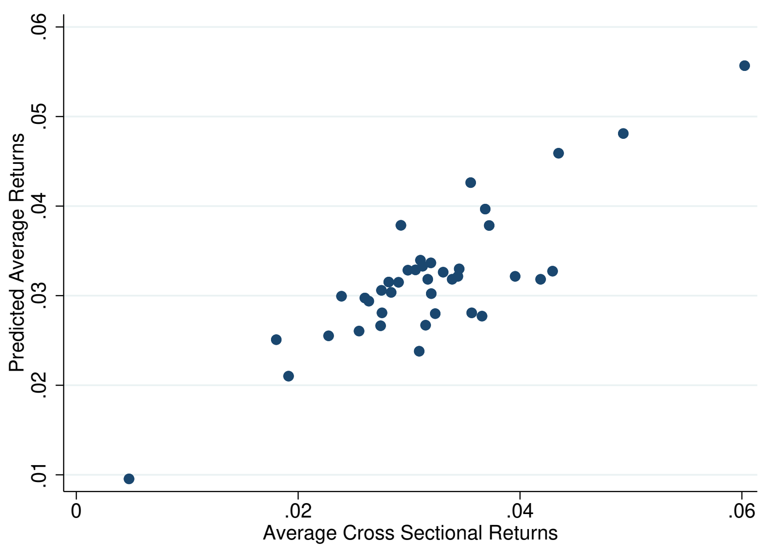


Figure 6: Time Series of Realized SDFs

This figure depicts the time series for the realized stochastic discount factors (SDFs) estimated in our sample for the Generalized Public Market Equivalent (GPME, dotted line), the Public Market Equivalent (PME, dashed line), for the Credit Market Equivalent (CME, solid line), and for the Credit Equity Market Equivalent (CEME, dashed-dotted line). The four SDFs are estimated as described in Section 4.

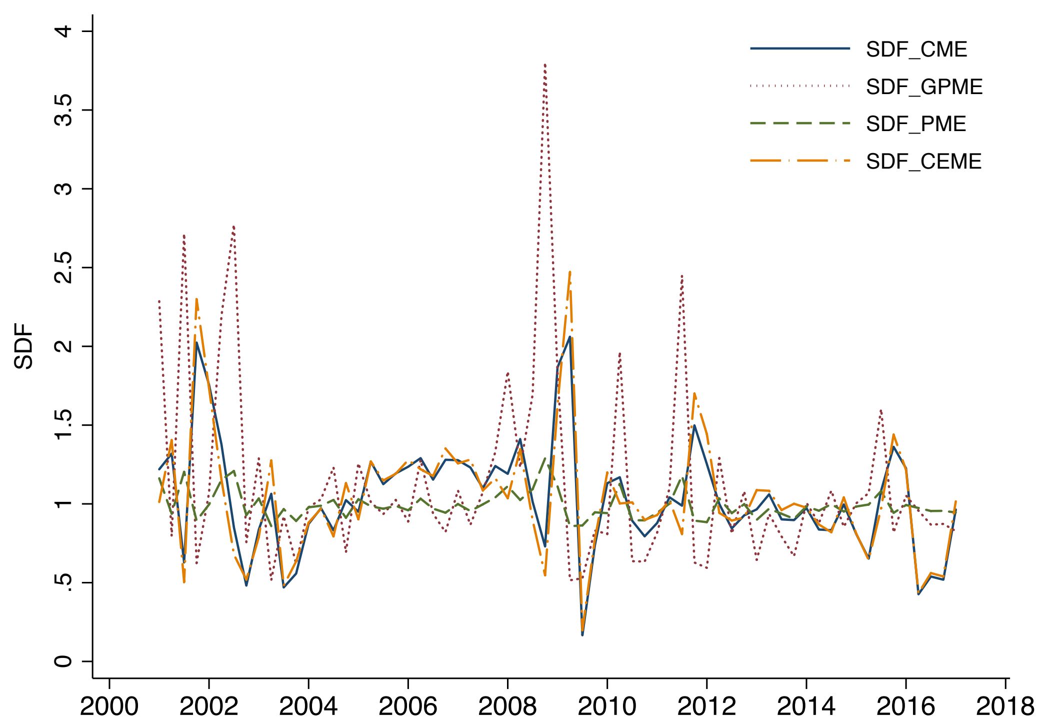


Figure 7: Predicted Equity Returns versus Observed Equity Returns (Public Companies)

In this figure, we plot the predicted equity returns from risk prices ('λs') of ten factors (Fama-French five factors + our five identified internal loan factors based on LASSO) from the second pass cross-sectional regression in relation to value-weighted average cross-sectional equity returns. Equity returns stem from decile portfolios sorts based on Size, B/M, OP, and Inv. As shown in this figure, average returns of the decile equity portfolios that we build line up well with predicted equity returns.

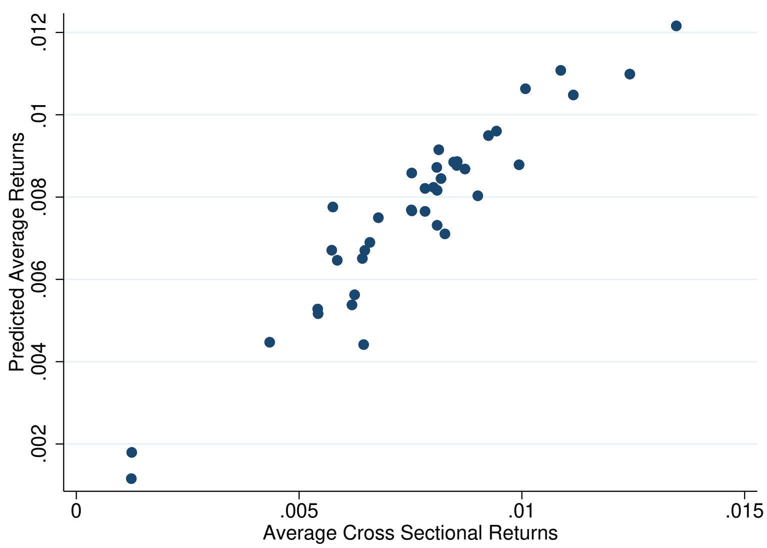


Table 1: Sample

This table displays all loans with bid and ask prices from market makers for secondary market syndicated loans based on LPC/LSTA data (Panel A) and OTC trades in corporate bonds covered by TRACE for observations with a traded loan (Panel B) between 1998 and 2017.

Panel A: LPC loan data			
	# of facilities	# of borrowers	# fund-borrower pairs
Total trading observations	31,314	7,551	
Trading obs. with available identifier—Facility-ID and/or LIN	22,032	6,610	
Obs. successfully matched with DealScan	31,068	7,373	
Obs. successfully matched with DealScan and with available identifier	21,934	6,519	
Obs. successfully matched with PE data and with available identifier	5,600	719	912
Obs. successfully matched with PE data, with available identifier and loan traded at least at exit of equity or last observed equity valuation	1,655	490	623

Panel B: TRACE bond data			
	# of facilities	# of borrowers	# fund-borrower pairs
Total trading observations matched with LPC	16,064	2,556	
Obs. successfully matched with LPC and DealScan	5,805	793	
Obs. successfully matched with LPC and PE data	648	103	125
Obs. successfully matched with LPC and PE data and bond traded at least at exit of equity or last observed equity valuation	157	49	53

Table 2: Variable Description

This table provides definitions of the main variables used throughout the text.

Variable	Description
Distress loan	Distress loan is a dummy variable that takes the value of one for a loan traded at a bid price below 90% of the par value at the time of PE exit (according to the conventions of the secondary loan market, see also Wittenberg-Moerman 2008).
Log average bid price	Log(average bid price of traded loans) measured at the time of PE exit.
Holding loan return (in %) (holding time as equity)	Return is measured as the average return (relative percentage change) of traded loans of the same deal as equity investment from the equity investment quarter to exit quarter.
Loan maturity	Average Loan maturity by deal and quarter (in years).
# of quotes	Average # of quotes by deal and quarter.
Fund size (m)	Total committed capital of the fund in million.
Taken private	Dummy variable the takes the value of one if the company was taken private in that quarter, and zero otherwise.
Leverage	Leverage is the debt-to-assets ratio defined as book value of debt divided by book value of total assets in the quarter of going private, measured quarterly.
Growth	Growth is the growth rate of sales in the quarter of going private over the previous quarter.
Stock return	Stock return is measured as the return (relative quarterly percentage change) of traded stocks from PE investment in the quarter of going private.

(continued)

Variable	Description
STM	Spread-to-maturity (STM). To calculate STM, we solve for STM in $$Price = \sum_{t=1}^{T} \frac{Principal_t + Spread_t}{(1+STM)^t},$$ where $Spread_t$ refers to the fixed coupon payment above base rate in quarter t—typically LIBOR—since these loans are floating rate instruments. $Principal_t$ refers to principal repayments in quarter t. The STM in this equation can be interpreted as the return on the loan if the benchmark rate is equal to zero over the loan's lifetime.
Momentum	Momentum is the loan's cumulative return over the past three quarters.
MV	MV is the market value of the loan, the product of the outstanding balance and market price, plus the accrued interest.
Volatility	Volatility is the annualized standard deviation of residuals in a regression with daily excess loan returns as the dependent variable, and the market, term, and default characteristics as the independent variables over the time period t-2 to t.
BA-Spread	BA-Spread is computed as the difference between average bid and ask quotes by quarter.
Size	Since market cap does not exist for private companies we use shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (Banz (1981), Fama and French (1992)), measured quarterly.

Table 3: Sample Representativeness and Summary Statistics

This table shows sample representativeness by comparing our PE sample (constructed as described in Section 2) to Braun et al. (2017) and Preqin as of 12/31/2013, with vintage years between 1996 and 2010 (Panel A). Panel B presents the p-values of t-tests and Wilcoxon rank-sum tests (in brackets). "Yrs. before next fund raised" describes the timing of subsequent buyout funds. "Size of GP" expresses the size of the GPs in questions (across it's previous funds of the last then years) as a fraction of the total capital it raised relative to the total amount raised by all GPs (i.e., investors' commitments) over the ten years preceding each fund; "Age of GP" shows the age of the GP, i.e., the time of the closing of the first partnership that the GP raised to the closing of this fund; "# of past funds" gives the number of past funds of the GP.

Panel A: Sample representativeness			
	Our Sample	Preqin	Braun et al.:
Fund Data:			
# of funds	97 (out of total 121 ≡ 80% with traded loans)	890	1,021
# of corresponding GPs	56	460	269
Portfolio Company Data:		N/A	
# of unique companies	490		N/A
# of fund-portfolio-comp pairs	623		12,541
— Fully realized	324		7,568
— Not fully realized	299		4,973
Inv. times			
— 1996-1999	54		2,410
— 2000-2004	137		2,267
— 2005-2013	432		793
Region			
— Asia/Pacific	5		193
— Europe	131		3,718
— North America	478		3,121
— Other	9		536
Industry			
— Industrials	137		1,885
— Consumer Staples	13		1,191
— Consumer Discretionary	208		1,038
— Technology	70		945
— Other	195		2,509
Equity investment			N/A
— # of deals with size > 300m	146		
— # of deals with 50m < size ≤ 300m	303		
— # of deals with 10m < size ≤ 50m	104		
— # of deals with size < 10m	70		
— Median Deal Size	35m		16m

(continued)

Table 3: Sample Representativeness and Summary Statistics—*Continued*

Panel B: Summary statistics

	Our Sample	Preqin	P-values Testing for Diff. between Our Sample & Preqin
Vintage year	2003	2005	0.001
	(2005)	(2007)	(0.000)
Fund size (in m.)	3,993	1,413	0.000
	(2,300)	(648)	(0.000)
Yrs. before next fund raised	3.3	3.5	0.38
	(3.0)	(3.3)	0.622
Size of GP (% of industy $)	0.059	0.028	0.004
	(0.041)	(0.001)	(0.000)
Age of GP (years)	15	10	0.000
	(13)	(6)	(0.000)
# of past funds	6	2	0.000
	(3)	(1)	(0.000)

Table 4: Summary Statistics on Loans

This table displays characteristics of traded loans based on LPC/LSTA data (Panel A) and characteristics of traded loans of our PE sample (constructed as described in Section 2) (Panel B).

	Mean	Median	N	SD	p25	p75
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: LPC/LSTA						
BA-Spread (basis points)	151	100	48,140	273	50	172
Loan maturity (years)	5	5	48,305	2.740	3	7
Loan size ($ millions)	450	175	46,619	1,177	69	427
Panel B: Our Sample						
BA-Spread (basis points)	136	100	7,991	155	54	165
Loan maturity (years)	5	5	10,809	2	4	7
Loan size ($ millions)	363	150	10,853	758	55	368

Table 5: Exit Multiples of Private Equity Portfolios Sorted on Loan Returns

This table reports average exit multiples per quarter sorted by average quarterly loan returns of our PE sample (constructed as described in Section 2). Deal exit multiples are defined as (cumulative deal cash outflows to date)/cumulative investments into the deal to date. Only deals that are fully realized in a quarter are considered. In each quarter t, we sort deal exit multiples into quintile portfolios based on associated loan returns. The table reports the average exit multiple of each portfolio in quarter t, as well as the loan return that quarter. AREW and ARVW are the average realized multiples on equal-weighted and value-weighted portfolios. Loan return is the average quarter loan return. Returns and exit multiples are winsorized at the 1st and 99th percentile to deal with outliers. The sample period covers 1998 to 2017. Newey and West (1987) adjusted t-statistics with 4 lags are reported.

	Low	2	3	4	High
AREW	1.909	2.036	2.170	2.201	2.210
t-stats	5.105	13.314	12.007	19.144	7.772
p-value	0.000	0.000	0.000	0.000	0.000
ARVW	1.673	1.746	1.835	1.952	2.034
t-stats	6.255	14.148	9.580	8.756	8.139
p-value	0.000	0.000	0.000	0.000	0.000
Loan Return	0.019	0.023	0.029	0.040	0.066

Table 6: Returns and Characteristics of Loan Portfolios Sorted on Characteristics

This table reports average quarterly loan returns and characteristics sorted by characteristics from loans of our PE sample (constructed as described in Section 2). At the end of July, we sort loans into quintile portfolios based on one characteristic and rebalance them annually. The table reports the average characteristics of each portfolio at the end of quarter t, as well as the returns that quarter. AREW and ARVW are the average returns (in percentage) on equal-weighted and value-weighted portfolios. STM is the loan's spread-to-maturity, the initial loan spread over the base rate, adjusted for loan price and repayments, over the life of the loan. Price is the average of the bid and ask quotes as a percentage of the loan's remaining balance (par value). Momentum is the loan's cumulative return from the beginning of quarter t - 3 to the end of quarter t. MV is the market capitalization of the loan, the product of the outstanding balance and market price, plus accrued interest. Volatility is the annualized standard deviation of the residuals of a regression with daily loan excess returns as the dependent, and (excess) returns on market, term spread, and default spread factors as the independent variables over the time period t -2 to t. Number of quotes is the number of bid and ask dealer quotes. B-A is the bid-ask spread, the average of the bid and ask quotes. Size is the natural logarithm of shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (in millions of dollars) (Banz (1981), Fama and French (1992)). The sample period covers June 1998 to February 2017. Newey and West (1987) adjusted t-statistics with 4 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Panel A: STM							**Panel B: Momentum**						
AREW	4.10	2.06	3.69	3.79	3.58	-0.40	AREW	0.63	2.53	3.13	3.45	6.18	4.67
t-stats	3.62	1.56	4.55	6.53	4.01	-1.77	t-stats	0.29	3.99	5.57	4.35	5.68	6.38
p-value	0.00	0.12	0.00	0.00	0.00	0.08	p-value	0.78	0.00	0.00	0.00	0.00	0.00
ARVW	3.29	2.88	3.36	3.54	3.45	0.19	ARVW	2.05	2.93	2.96	3.45	4.80	2.84
t-stats	4.34	4.69	5.17	5.80	5.86	0.91	t-stats	1.82	4.69	5.66	5.35	6.15	8.23
p-value	0.00	0.00	0.00	0.00	0.00	0.36	p-value	0.07	0.00	0.00	0.00	0.00	0.00
STM	-0.17	0.05	0.22	0.36	0.74	.	STM	0.23	0.21	0.24	0.28	0.22	.
Momentum	0.16	0.10	0.12	0.13	0.11	.	Momentum	0.02	0.07	0.09	0.12	0.29	.
Price	92.63	94.87	94.08	91.73	88.28	.	Price	84.49	93.86	95.56	95.19	91.58	.
MV	415.84	439.90	497.18	543.41	428.23	.	MV	406.06	621.58	465.81	409.69	368.93	.
Volatility	0.01	0.00	0.00	0.00	0.00	.	Volatility	0.02	0.00	0.00	0.00	0.01	.
Quotes	2.93	3.02	3.11	3.17	3.26	.	Quotes	3.20	3.59	3.41	2.97	2.88	.
BA-Spread	1.65	1.62	1.39	1.18	1.35	.	BA-Spread	1.93	1.32	1.15	1.28	1.52	.
Size	-30.21	423.78	512.76	222.51	559.87	.	Size	155.42	488.54	498.87	243.10	236.40	.
Panel C: Price							**Panel D: MV**						
AREW	3.24	3.07	2.97	2.98	3.39	0.13	AREW	3.87	3.59	3.35	2.90	2.70	-0.95
t-stats	1.15	2.85	5.37	7.05	9.68	0.14	t-stats	1.69	3.91	4.76	4.47	5.31	-1.28
p-value	0.25	0.01	0.00	0.00	0.00	0.89	p-value	0.10	0.00	0.00	0.00	0.00	0.20
ARVW	4.38	3.26	2.81	2.91	3.37	-1.01	ARVW	4.88	3.97	3.68	3.24	3.04	-1.84
t-stats	3.00	3.02	5.58	7.08	14.53	-1.72	t-stats	4.23	4.46	5.33	5.45	5.57	-5.71
p-value	0.00	0.00	0.00	0.00	0.00	0.09	p-value	0.00	0.00	0.00	0.00	0.00	0.00
STM	0.30	0.29	0.19	0.21	0.15	.	STM	0.20	0.20	0.26	0.27	0.22	.
Momentum	0.19	0.10	0.10	0.10	0.11	.	Momentum	0.22	0.12	0.11	0.10	0.09	.
Price	75.53	92.27	96.52	97.61	99.10	.	Price	84.15	92.66	93.86	94.68	95.27	.
MV	372.10	531.26	466.66	473.14	390.29	.	MV	117.17	174.55	254.60	445.81	1221.66	.
Volatility	0.03	0.00	0.00	0.00	0.00	.	Volatility	0.03	0.00	0.00	0.00	0.00	.
Quotes	2.83	3.21	3.18	3.18	3.65	.	Quotes	1.87	2.12	2.96	3.93	5.29	.
BA-Spread	2.61	1.59	1.13	0.96	0.86	.	BA-Spread	2.07	1.56	1.39	1.24	0.97	.
Size	-321.40	104.38	564.64	523.18	674.57	.	Size	46.15	289.73	303.52	167.21	633.26	.

(continued)

Table 6: Returns and characteristics of loan portfolios sorted on characteristics—*Continued*

	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Panel E: Volatility							**Panel F: Quotes**						
AREW	2.43	2.78	2.76	3.53	5.08	2.19	AREW	3.71	3.04	3.33	3.83	2.90	-0.69
t-stats	6.73	5.77	3.57	2.93	2.37	3.07	t-stats	4.23	1.71	3.93	4.75	4.61	-3.52
p-value	0.00	0.00	0.00	0.00	0.02	0.00	p-value	0.00	0.09	0.00	0.00	0.00	0.00
ARVW	2.57	2.74	3.19	3.80	4.30	1.75	ARVW	3.54	3.96	2.90	3.28	2.90	-0.70
t-stats	6.82	5.72	5.12	4.05	3.48	4.03	t-stats	5.75	5.10	4.19	4.86	4.93	-4.61
p-value	0.00	0.00	0.00	0.00	0.00	0.00	p-value	0.00	0.00	0.00	0.00	0.00	0.00
STM	0.23	0.21	0.28	0.21	0.24	.	STM	0.16	0.23	0.24	0.28	0.32	.
Momentum	0.08	0.10	0.10	0.13	0.23	.	Momentum	0.15	0.13	0.13	0.13	0.09	.
Price	96.84	96.62	94.41	91.17	80.35	.	Price	92.35	89.31	92.82	92.71	94.56	.
MV	473.50	543.19	450.54	418.96	321.10	.	MV	234.62	361.72	374.29	584.92	908.04	.
Volatility	0.00	0.00	0.00	0.00	0.03	.	Volatility	0.00	0.02	0.00	0.00	0.00	.
Quotes	3.16	3.91	3.44	3.00	2.61	.	Quotes	1.47	2.33	2.95	4.05	6.79	.
BA-Spread	1.09	1.09	1.30	1.63	2.18	.	BA-Spread	1.66	1.61	1.32	1.23	1.05	.
Size	459.92	444.11	272.53	121.02	187.12	.	Size	194.19	452.48	347.73	430.41	388.74	.
Panel G: BA-spread							**Panel H: Size**						
AREW	2.89	3.29	1.96	3.24	4.50	1.36	AREW	3.29	3.26	3.20	4.43	4.32	0.84
t-stats	8.32	6.91	1.45	2.78	2.63	2.40	t-stats	3.75	3.35	3.43	5.18	3.89	3.26
p-value	0.00	0.00	0.15	0.01	0.01	0.02	p-value	0.00	0.00	0.00	0.00	0.00	0.00
ARVW	3.13	3.21	3.21	3.24	4.72	1.70	ARVW	3.64	3.39	3.39	3.44	3.28	-0.38
t-stats	9.43	5.84	4.43	3.57	3.67	3.49	t-stats	4.95	5.57	5.04	6.05	7.02	-2.64
p-value	0.00	0.00	0.00	0.00	0.00	0.00	p-value	0.00	0.00	0.00	0.00	0.00	0.01
STM	0.28	0.25	0.24	0.15	0.21	.	STM	0.19	0.28	0.23	0.23	0.26	.
Momentum	0.09	0.10	0.10	0.14	0.17	.	Momentum	0.11	0.11	0.11	0.16	0.17	.
Price	98.23	97.41	95.35	91.78	77.60	.	Price	91.55	92.87	92.12	91.88	91.23	.
MV	655.73	579.16	445.58	350.32	230.43	.	MV	588.42	334.05	410.77	356.78	583.19	.
Volatility	0.00	0.00	0.03	0.00	0.01	.	Volatility	0.00	0.00	0.00	0.00	0.00	.
Quotes	3.60	3.64	3.33	2.95	2.60	.	Quotes	3.50	2.71	3.17	2.85	3.02	.
BA-Spread	0.69	0.86	1.15	1.65	2.85	.	BA-Spread	1.35	1.58	1.44	1.43	1.48	.
Size	624.60	457.44	153.91	279.19	74.79	.	Size	-926.11	206.57	206.70	547.94	1895.51	.

Table 7: Cross-Sectional Regression of Excess Returns on First-Step Factor Exposures

This table reports risk prices ('λs') of a cross-sectional regression of value-weighted average quarterly excess loan returns of private companies on the 'βs' from time-series regressions of quintile portfolio returns on a set of candidate factors. We use LASSO variable selection techniques to identify the factors relevant for pricing. Loans are sorted into quintile portfolios based on 8 loan characteristics (i.e., 40 test portfolios): spread-to-maturity (STM), price, momentum, market capitalization, volatility, bid-ask spread, number of bid and ask dealer quotes, and size. Size is the natural logarithm of shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (in millions of dollars) (Banz (1981), Fama and French (1992)). Candidate factors that we consider in the first-pass time-series regressions include the returns of the loan market index, SMB, HML, profitability and investment factors (from Fama and French 2015) – RMW and CMA – two bond factors (TRM and DEF), the Pástor and Stambaugh (2003) liquidity factor, the TERM factor, the Adrian, Etula, Muir (2014) leverage factor, and the He, Kelly, Manela (2017) intermediary capital risk factor. Besides these external factors, we include internal factors in our time-series regression which are high-low quintile portfolio (Q5-Q1) returns sorted on eight loan characteristics: spread-to-maturity (STM), price, momentum (mom), market capitalization (MV), volatility, bid-ask spread (BA), number of dealer quotes, and size. Three asterisks represent two-tailed significance at the 1% level.

	(1) rmrf β / SE
Q5mQ1_mom	0.018***
	(0.004)
Q5mQ1_vola	0.017***
	(0.004)
Q5mQ1_price	-0.014***
	(0.003)
Q5mQ1_MV	-0.014***
	(0.003)
Q5mQ1_BA	0.014***
	(0.003)
Observations	40
Adj. R^2	0.596

Table 8: Valuation: Fund Portfolios

This table reports valuation results of 1,219 US buyout funds from Preqin, and 97 US buyout funds from a large institutional investor with vintages before 2014 as described in Section 4.3. The cash flow data run through the end of 2017, so we have at least four years of cash fow data for all funds in our samples. In Panel A, we discount cash flows with the SDF of the Credit Market Equivalent (CME), Generalized Public Market Equivalent (GPME), and Public Market Equivalent (PME) approaches, respectively. In Panel B, we discount cash flows with the SDF of the Credit Equity Market Equivalent (CEME), which includes the public stock market. In Panel C, we discount cash flows with the SDF of the CEME and small value (SV). In Panel D, we discount cash flows with the SDF of the S&P/LSTA U.S. Leveraged Loan 100 index. In Panel E, we discount cash flows with the SDF of the S&P/LSTA U.S. Leveraged Loan 100 index and the CRSP value-weighted index. Fund cash flows are normalized by the present value of cash injections by the fund. Standard errors of the valuations are in parentheses. P-values for testing the null of zero net present value for the four approaches are reported in brackets.

		Preqin	Our Sample
Panel A: Baseline. $M_{t+1}^{CME} = e^{a+b_{Credit}^T f_{t+1}^{Credit}}$			
CME		-0.075	0.007
		(0.221)	(0.238)
	$H_0 : CME = 0$	[0.732]	[0.976]
GPME		0.224	0.584
		(0.318)	(0.398)
	$H_0 : GPME = 0$	[0.481]	[0.142]
PME		0.093	0.252
		(0.035)	(0.081)
	$H_0 : PME = 0$	[0.007]	[0.002]
Panel B: CME + public stock market (CEME). $M_{t+1}^{CEME} = e^{a+b_m r_{t+1}^m + b_{Credit}^T f_{t+1}^{Credit}}$			
CEME		0.108	0.140
		(0.253)	(0.179)
	$H_0 : CEME = 0$	[0.667]	[0.432]
SDF parameter estimates for risk-free rate and public stock market			
	a	0.256	0.244
		(0.046)	(0.034)
	b_m	1.211	1.318
		(1.241)	(0.789)

(continued)

Table 8: Valuation: Fund Portfolios—*Continued*

	Preqin	Our Sample
Panel C: CEME + Small Value (SV). $M_{t+1}^{CEME+SV} = e^{a+b_m r_{t+1}^m + b_{SV} r_{t+1}^{SV} + b_{Credit}^T f_{t+1}^{Credit}}$		
CEME + SV	0.124	0.166
	(0.348)	(0.478)
$H_0 : CEME + SV = 0$	[0.721]	[0.889]
SDF parameter estimates for risk-free rate, public stock market and SV		
a	0.257	0.303
	(0.037)	(0.046)
b_m	4.068	2.906
	(2.205)	(1.864)
b_{SV}	-3.164	-2.870
	(1.267)	(1.321)
Panel D: Loan index (l). $M_{t+1}^{l} = e^{a+b_l r_{t+1}^l}$		
Loan index (l)	0.398	0.488
	(0.241)	(0.301)
$H_0 : l = 0$	[0.102]	[0.108]
SDF parameter estimates for risk-free rate and loan index		
a	0.058	0.046
	(0.016)	(0.016)
b_l	-4.933	-4.238
	(3.003)	(3.103)
Panel E: Loan index + public stock market (lm). $M_{t+1}^{lm} = e^{a+b_l r_{t+1}^l + b_m r_{t+1}^m}$		
loan index + public stock market (lm)	0.220	0.342
	(0.163)	(0.210)
$H_0 : lm = 0$	[0.176]	[0.106]
SDF parameter estimates for risk-free rate, loan index and public stock market		
a	0.063	0.049
	(0.030)	(0.035)
b_l	-2.220	-1.857
	(1.687)	(2.212)
b_m	-2.200	-1.949
	(0.668)	(0.676)

Table 9: Valuation: Fund Portfolios for Subsamples

The table reports valuation for subsamples of 1,219 US buyout funds from Preqin, and 97 US buyout funds from a large institutional investor with vintages before 2014. The cash flow data run through the end of 2017, so we have at least four years of cash fow data for all funds in our samples. We discount cash flows with the SDF of the Credit Market Equivalent (CME), the Credit Equity Market Equivalent (CEME), CEME + the public stock market, Generalized Public Market Equivalent (GPME), and Public Market Equivalent (PME) approaches, respectively. Panel A shows valuation estimates for funds that were raised in bust periods (2001-2003, 2008, and 2009), and funds raised in boom periods, separated between pre-financial crisis (2004-2007) and post -financial crisis (2011-2013). Economic recession in the US are defined according to https://www.nber.org/cycles.html. Panel B displays results for sample spits above and below the median leverage in our sample funds, where we observe deal level leverage levels, and Panel C shows valuation results of sample splits by fund size. Fund cash flows are normalized by the present value of cash injections by the fund. Standard errors of the valuations are in parentheses. P-values for testing the null of zero NPV for the three approaches are reported in brackets.

Panel A: Valuation by Vintage Years

		Bust:		**Boom:**			
		2001-2003, 2008, 2009		Pre-Financial Crisis 2004-2007		Post-Financial Crisis 2010-2013	
		Preqin	Our Sample	Preqin	Our Sample	Preqin	Our Sample
CME		0.023	0.075	-0.423	-0.194	-0.040	-0.046
		(0.194)	(0.054)	(0.216)	(0.370)	(0.239)	(0.278)
	$H_0 : CME = 0$	[0.904]	[0.168]	[0.050]	[0.554]	[0.811]	[0.857]
CEME		0.139	0.409	0.191	-0.146	-0.040	-0.083
		(0.153)	(0.103)	(0.213)	(0.000)	(0.241)	(0.648)
	$H_0 : CEME = 0$	[0.360]	[0.000]	[0.368]	[0.000]	[0.813]	[0.899]
CEME + SV		0.071	0.265	0.012	-0.157	0.040	0.046
		(1.594)	(0.178)	(0.120)	(1.422)	(0.000)	(0.000)
	$H_0 : CEME + SV = 0$	[0.964]	[0.137]	[0.920]	[0.912]	[0.997]	[0.996]
GPME		0.404	0.801	0.018	-0.046	0.117	0.171
		(0.362)	(0.306)	(0.465)	(0.319)	(0.943)	(0.827)
	$H_0 : GPME = 0$	[0.263]	[0.009]	[0.992]	[0.885]	[0.906]	[0.824]
PME		0.209	0.538	0.089	0.058	0.040	0.038
		(0.091)	(0.109)	(0.122)	(0.007)	(0.104)	(0.160)
	$H_0 : PME = 0$	[0.021]	[0.000]	[0.461]	[0.000]	[0.697]	[0.813]

(continued)

Table 9: Valuation: Fund Portfolios for Subsamples—*Continued*

Panel B: Valuation by Leverage

		Funds Below Median Leverage	Funds Above Median Leverage
CME		0.039	-0.073
		(0.045)	(0.076)
	$H_0 : CME = 0$	[0.379]	[0.351]
CEME		0.123	0.111
		(0.045)	(0.032)
	$H_0 : CEME = 0$	[0.007]	[0.000]
CEME + SV		0.098	0.079
		(0.132)	(0.064)
	$H_0 : CEME + SV = 0$	[0.455]	[0.221]
GPME		0.571	0.350
		(0.617)	(0.228)
	$H_0 : GPME = 0$	[0.364]	[0.124]
PME		0.371	0.353
		(0.216)	(0.087)
	$H_0 : PME = 0$	[0.086]	[0.000]

Table 9: Valuation: Fund Portfolios for Subsamples—*Continued*

Panel C: Valuation by Fund Size

		Funds Below Median Size		Funds Above Median Size	
		Preqin	Our Sample	Preqin	Our Sample
CME		-0.049 (0.186)	0.061 (0.206)	-0.112 (0.276)	0.018 (0.323)
	$H_0 : CME = 0$	[0.792]	[0.767]	[0.685]	[0.954]
CEME		0.211 (0.206)	0.224 (0.157)	-0.013 (0.317)	0.230 (0.208)
	$H_0 : CEME = 0$	[0.306]	[0.154]	[0.966]	[0.271]
CEME + SV		0.248 (0.267)	-0.032 (0.446)	-0.034 (0.632)	0.064 (0.345)
	$H_0 : CEME + SV = 0$	[0.353]	[0.941]	[0.956]	[0.851]
GPME		0.192 (0.245)	0.359 (0.291)	0.281 (0.432)	0.769 (0.534)
	$H_0 : GPME = 0$	[0.433]	[0.217]	[0.515]	[0.149]
PME		0.130 (0.039)	0.240 (0.084)	0.053 (0.042)	0.162 (0.118)
	$H_0 : PME = 0$	[0.001]	[0.005]	[0.212]	[0.170]

Table 10: Realized Equity and Traded Loan Performance

This table presents regressions of exit equity performance of private equity investments on several variables. The unit of observation is the PE fund - target pair. The dependent variable in columns (1)-(4)-(7), "Exit uc", is a dummy variable equal to one if the deal equity was liquidated below cost. The dependent variable in columns (2)-(5)-(8) is the log of equity valuation multiple (VM) at exit ("log(VM)"). The dependent variable in column (3)-(6)-(9) is the equity holding return as ("Holding R_E')'. We consider following independent variables. "Distress loan" is a dummy variable that takes the value of one for a loan traded at a bid price below 90% of the par value at the time of PE exit (according to the conventions of the secondary loan market, see also Wittenberg-Moerman, 2008). "Log Average bid price" of traded loans measured at the time of PE exit. "Return of loan" is measured as the average return (relative percentage change) of traded loans of the same deal as equity investment from the equity investment quarter to exit quarter. "LBO boom years" is a dummy variable that takes the value of one for an investment made between 2004 to 2007 (in line with the definition by Shivdasani and Wang (2011)). Regression estimates are based on models of investment calendar year, and industry fixed effects (FE). Standard errors are in parentheses, clustered at the private equity firm level. The results are based on our PE sample (constructed as described in Section 2). One/ two/ three asterisks represent two-tailed significance at a 10%/ 5%/1% level, respectively.

	All PE deals			PE deals privately held at exit			PE deals privately held entire time		
	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distress loan	0.464***			0.510***			0.534***		
	(0.110)			(0.099)			(0.113)		
Log average bid price		3.850***			3.641***			3.329***	
		(0.664)			(0.676)			(0.856)	
Holding loan return (in %)			0.692			1.274**			0.676
(holding time as equity)			(0.571)			(0.554)			(0.541)
Loan maturity (yrs)	-0.008	-0.132*	3.386	-0.012	-0.155	5.186	-0.002	-0.238*	-3.883
	(0.012)	(0.078)	(6.368)	(0.014)	(0.101)	(7.618)	(0.015)	(0.136)	(9.592)
# of quotes	-0.022	0.227***	8.075	-0.028	0.168**	11.896	-0.054***	0.345***	17.827
	(0.020)	(0.070)	(14.572)	(0.019)	(0.078)	(15.428)	(0.019)	(0.124)	(20.696)
Fund size (m)	-0.000	-0.000	-0.000	0.000	0.000	0.002	-0.000	-0.000	0.001
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.003)
LBO boom years	-0.218*	-0.029**	-6.029*	-0.284***	-0.829***	-1.123***	-0.087	-0.730	-1.071**
	(0.121)	(0.014)	(3.461)	(0.101)	(0.299)	(0.399)	(0.241)	(1.468)	(0.469)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	299	299	82	222	222	62	202	202	56
Adj. R^2	0.230	0.220	0.083	0.271	0.245	0.083	0.271	0.213	−0.020

Table 11: Public Equity Returns for Portfolios Sorted on Loan Returns

This table reports the average quarterly expected stock returns sorted by average quarterly loan returns. At the end of July of every year from 1998 to 2017, we sort equity returns into quintile portfolios based on associated loan returns. The table reports the average equity return of each portfolio at the end of quarter t (in percent), as well as the loan return that quarter (in percent). All portfolios are rebalanced annually. AREW and ARVW are the average expected equity returns on equal-weighted and value-weighted portfolios. Loan Return is the average quarter loan return. Returns are winsorized at the 1st and 99th percentile to deal with outliers. Newey and West (1987) adjusted t-statistics with 4 lags are reported in parentheses.

	Low	2	3	4	High
AREW	0.858	1.768	2.057	2.634	3.571
t-stats	0.451	1.199	1.660	1.526	1.97
p-value	0.654	0.234	0.101	0.131	0.052
ARVW	3.383	3.423	3.520	5.203	5.463
t-stats	2.129	3.162	3.288	3.254	3.642
p-value	0.037	0.002	0.001	0.001	0.001
Loan Return	1.144	1.942	2.438	3.170	4.689

Table 12: Factor Returns of Portfolios Sorted on Equity Returns

This table reports the average quarterly factor returns of our loan pricing model Table 7 sorted into quintiles by average quarterly equity returns of the same publicy traded company. That means, we only consider publicly traded companies that have loans traded in the secondary market. We display the average factor return of value-weighted portfolios (FactorR) at the end of quarter t (in percentage and percentage difference relative to the median). Returns are winsorized at the 1st and 99th percentile to deal with outliers. The sample period covers January 2001 to Februrary 2017. Newey and West (1987) adjusted t-statistics with 2 lags are reported in parantheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4	5
Panel A: Momentum factor returns of portfolios sorted on equity returns					
FactorR (percent)	1.855	2.404	2.428	2.887	3.981
FactorR (percentage diff. rel. to the median)	-17.485	6.944	8.013	28.449	77.085
t-stats	3.774	4.964	5.158	3.227	3.561
p-value	0.002	0.000	0.000	0.007	0.003
Panel B: Volatility factor returns of portfolios sorted on equity returns					
FactorR (percent)	-1.666	0.390	2.885	1.771	4.250
FactorR (percentage diff. rel. to the median)	-232.990	-68.883	130.372	41.424	239.352
t-stats	-1.111	0.444	2.675	1.749	2.405
p-value	0.287	0.664	0.019	0.104	0.033
Panel C: Price factor returns of portfolios sorted on equity returns					
FactorR (percent)	-5.188	-1.891	-0.241	0.393	4.144
FactorR (percentage diff. rel. to the median)	-1457.968	-594.894	-162.993	2.905	984.677
t-stats	-2.663	-1.428	-0.326	0.525	2.447
p-value	0.021	0.177	0.750	0.608	0.029
Panel D: MV factor returns of portfolios sorted on equity returns					
FactorR (percent)	-0.801	-1.024	-0.430	-0.103	0.382
FactorR (percentage diff. rel. to the median)	-605.153	-745.618	-371.393	-165.092	141.135
t-stats	-1.835	-1.551	-0.747	-0.203	0.902
p-value	0.089	0.145	0.468	0.843	0.385
Panel E: BA-spread factor returns of portfolios sorted on equity returns					
FactorR (percent)	-2.807	0.513	1.300	2.241	3.385
FactorR (percentage diff. rel. to the median)	-396.208	223.553	719.604	1313.136	2034.268
t-stats	-2.266	0.563	1.566	1.745	3.623
p-value	0.041	0.583	0.141	0.104	0.003

Table 13: Cross-Sectional Regression of Excess Returns on First-Step Factor Exposures: Loans of Public Companies

This table reports risk prices ('λs') of a cross-sectional regression of value weighted average quarterly excess loan returns of companies with publicly traded equity on the 'βs' from time-series regressions of quintile portfolio returns on a set of candidate factors. We use LASSO variable selection techniques to identify the factors relevant for pricing. Loans are univariately sorted into 12 portfolios based on 4 equity characteristics: Size, B/M, OP, and Inv, and 8 loan characteristics: spread-to-maturity (STM), price, momentum, market capitalization, volatility, bid-ask spread, number of dealer quotes, and size. Size is the natural logarithm of shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (in millions of dollars) (Banz (1981), Fama and French (1992)). Candidate factors that we consider in the first-pass time-series regressions include the returns of the loan market index, SMB, HML, profitability and investment factors (from Fama and French 2015) -RMW and CMA, two bond factors (TRM and DEF), the Pástor and Stambaugh (2003) liquidity factor, the TERM factor, the default factor, the Adrian, Etula, Muir (2014) leverage factor, and the He, Kelly, Manela (2017) intermediary capital risk factor. Besides these external factors, we include internal factors in our time-series regression which are high-low quintile portfolio (Q5-Q1) returns sorted on eight loan characteristics: spread-to-maturity (STM), price, momentum (mom), market capitalization (MV), volatility (vola), bid-ask spread (BA), number of dealer quotes, and size. Three asterisks represent two-tailed significance at the 1% level.

	β / SE
Q5mQ1_mom	0.020***
	(0.003)
Q5mQ1_vola	0.009***
	(0.003)
Q5mQ1_MV	-0.005***
	(0.002)
Q5mQ1_BA	0.005***
	(0.002)
Observations	60
Adj. R^2	0.411

Table 14: Cross-Sectional Regression of Excess Returns on First-Step Factor Exposures: Equity of Public Companies with Traded Loans

This table reports risk prices ('λs') of a cross-sectional regression of value weighted average quarterly excess equity returns of companies with traded loans on 'βs' from time-series regressions of quintile portfolio returns on loanmmrf, mmrf, smb, hml, rmw, cma, tradedliq, def, trm, lev, inter, Q5mQ1_mom, Q5mQ1_vola, Q5mQ1_STM, Q5mQ1_price, Q5mQ1_MV, Q5mQ1_quotes, Q5mQ1_BA, Q5mQ1_size (related to Table 7). Equity claims are univariately sorted into five decile portfolios based on Size, B/M, OP, and Inv. Only the five Fama French factors are selected for the cross-sectional regression. Two/ three asterisks represent two-tailed significance at the 5%, and 1% level, respectively.

	β / SE
mmrf	-0.001
	(0.001)
smb	0.002***
	(0.000)
hml	0.003**
	(0.001)
rmw	0.002**
	(0.001)
cma	0.003**
	(0.001)
Observations	40
Adj. R^2	0.621

Table 15: Cross-Sectional Regression of Excess Returns on First-Step Factor Exposures: Equity and Credit Market Factors

This table reports risk prices ('λs') of a cross-sectional regression of value weighted average quarterly excess equity returns of companies with traded loans on the 'βs' from time-series regressions of quintile portfolio returns on a set of candidate factors. We add the five factors of our loan pricing model Table 7 to the five Fama French factors as shown in Table 14 in our cross-sectional regression. Equity claims are univariately sorted into five decile portfolios based on Size, B/M, OP, and Inv. To be in line with Table 7, we consider the same factor returns in the first-pass time-series regressions. These include the returns of the loan market index, SMB, HML, profitability and investment factors (from Fama and French 2015) -RMW and CMA, two bond factors (TRM and DEF), the Pástor and Stambaugh (2003) liquidity factor, the TERM factor, the default factor, the Adrian, Etula, Muir (2014) leverage factor, and the He, Kelly, Manela (2017) intermediary capital risk factor. Besides these external factors, we include internal factors in our time-series regression which are high-low quintile portfolio (Q5-Q1) returns sorted on eight loan characteristics: spread-to-maturity (STM), price, momentum, market capitalization, volatility, bid-ask spread, number of dealer quotes, and size. Size is the natural logarithm of shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (in millions of dollars) (Banz (1981), Fama and French (1992)). Two/ three asterisks represent two-tailed significance at the 5%, and 1% level, respectively.

	β / SE
mmrf	-0.001
	(0.001)
smb	0.002***
	(0.000)
hml	0.004***
	(0.001)
rmw	0.003***
	(0.001)
cma	0.003***
	(0.001)
Q5mQ1_mom	0.003
	(0.004)
Q5mQ1_vola	0.009**
	(0.005)
Q5mQ1_price	-0.013**
	(0.005)
Q5mQ1_MV	-0.003
	(0.002)
Q5mQ1_BA	0.005
	(0.006)
Observations	40
Adj. R^2	0.712

Internet Appendix A: Supplementary Tables

Table A1: Realized Equity and Traded Loan Performance

This table presents regressions of exit equity performance of private equity investments on several variables. The unit of observation is the PE fund - target pair. The dependent variable in columns (1)-(4)-(7), "Exit uc", is a dummy variable equal to one if the deal equity was liquidated below cost. The dependent variable in columns (2)-(5)-(8) is the log of equity valuation multiple (VM) at exit ("log(VM)"). The dependent variable in column (3)-(6)-(9) is the equity holding return as ("Holding R_E')'. We consider following independent variables. "Distress loan" is a dummy variable that takes the value of one for a loan traded at a bid price below 90% of the par value at the time of PE exit (according to the conventions of the secondary loan market, see also Wittenberg-Moerman, 2008). "Log Average bid price" of traded loans measured at the time of PE exit. "Return of loan" is measured as the average return (relative percentage change) of traded loans of the same deal as equity investment from the equity investment quarter to exit quarter. Regression estimates are based on models of investment calendar year, and industry fixed effects (FE). Standard errors are in parentheses, clustered at the private equity firm level. The results are based on our PE sample (constructed as described in Section 2). One/ two/ three asterisks represent two-tailed significance at a 10%/ 5%/1% level, respectively.

	All PE deals			PE deals privately held at exit			PE deals privately held entire time		
	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distress loan	0.514***			0.532***			0.585***		
	(0.078)			(0.080)			(0.090)		
Log average bid price		3.824***			3.392***			3.244***	
		(0.614)			(0.671)			(0.818)	
Holding loan return (in %)			1.182*			1.521*			1.187*
(holding time as equity)			(0.632)			(0.798)			(0.626)
Loan maturity (yrs)	-0.004	-0.155*	11.019*	-0.008	-0.191	12.751	0.001	-0.279*	5.083
	(0.013)	(0.077)	(5.431)	(0.015)	(0.115)	(8.398)	(0.017)	(0.144)	(8.163)
# of quotes	-0.021	0.262***	11.656	-0.031	0.201**	8.677	-0.054**	0.385**	16.239
	(0.020)	(0.090)	(15.875)	(0.021)	(0.086)	(19.246)	(0.020)	(0.144)	(23.382)
Fund size (m)	0.000	-0.000	0.003	0.000	-0.000	0.005	0.000	-0.000	0.004
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.003)
Equity investment year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	299	299	82	222	222	62	202	202	56
Adj. R^2	0.272	0.231	0.213	0.320	0.291	0.302	0.306	0.208	0.056

Table A2: Equity and Traded Loan Performance - Last Observed Equity Performance

This table is a replica, in which the dependent variable refer to the last observed sample equity performance, of Table A1.

	All PE deals			PE deals privately held at exit			PE deals privately held entire time		
	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distress loan	0.361***			0.360***			0.390***		
	(0.064)			(0.060)			(0.066)		
Log average bid price		3.017***			2.656***			2.451***	
		(0.614)			(0.608)			(0.686)	
Holding loan return (in %)			0.027**			0.021***			0.880*
(holding time as equity)			(0.011)			(0.005)			(0.446)
Loan maturity (yrs)	0.006	-0.071	2.217	0.013	-0.094	2.108	0.014	-0.113	-1.147
	(0.010)	(0.049)	(3.800)	(0.011)	(0.060)	(4.024)	(0.014)	(0.083)	(3.575)
# of quotes	-0.016**	0.043	4.426	-0.015*	0.018	0.175	-0.024	0.157**	8.603
	(0.007)	(0.035)	(7.923)	(0.008)	(0.031)	(8.102)	(0.015)	(0.062)	(8.425)
Fund size (m)	-0.000	0.000	-0.001	-0.000	0.000	-0.002	-0.000**	0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Equity investment year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	623	623	202	493	493	168	434	434	145
Adj. R^2	0.172	0.207	0.226	0.192	0.269	0.221	0.208	0.201	0.223

Table A3: Equity and Traded Loan Performance - Last Observed Equity Performance

This table is a replica, in which the dependent variable refer to the last observed sample equity performance, of Table A1.

	All PE deals			PE deals privately held at exit			PE deals privately held entire time		
	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E	Exit uc	log(VM)	Holding R_E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distress loan	0.351***			0.356***			0.378***		
	(0.077)			(0.073)			(0.076)		
Log average bid price		3.094***			2.902***			2.586***	
		(0.626)			(0.620)			(0.708)	
	(0.663)								
Holding loan return (in %)			-0.028**			-0.015***			0.636
(holding time as equity)			(0.014)			(0.004)			(0.406)
Loan maturity (yrs)	0.011	-0.071	-0.265	0.017	-0.083	-0.726	0.019	-0.106	-4.657
	(0.009)	(0.046)	(3.822)	(0.011)	(0.052)	(3.277)	(0.011)	(0.072)	(3.550)
# of quotes	-0.020***	0.052*	6.368	-0.021**	0.036	7.663	-0.033**	0.152***	10.946
	(0.007)	(0.027)	(7.556)	(0.008)	(0.029)	(7.540)	(0.013)	(0.056)	(9.876)
Fund size (m)	-0.000	0.000	-0.002	-0.000	0.000	-0.002	-0.000***	0.000*	-0.000
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)
LBO boom years	-0.128*	-0.204**	-33.489	-0.138*	-0.026	-37.647	-0.157*	-0.269	-6.1278**
	(0.071)	(0.103)	(24.776)	(0.081)	(0.149)	(25.107)	(0.092)	(0.359)	(2.7594)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	623	623	202	498	498	168	440	440	145
Adj. R^2	0.142	0.193	0.094	0.153	0.209	0.038	0.191	0.187	0.052

Table A4: Fund Investment Exit Times with Unobserved Heterogeneity

This table presents hazard ratios associated with the GP's decision to sell/hold portfolio investments unregarding outcome and at loss/gain. We estimate frailty models to account for unobserved heterogeneity. We assume that the underlying distribution for the frailty (unobserved heterogeneity) is gamma distributed. From an analytical point of view the gamma distribution is convenient, because it is easy to derive the closed form expressions of survival, density and the hazard function, which is why this distribution is used in most applications (see e.g. Hougaard 2000). The data are well fit by a Weibull model, which we use for the distribution of survival time. Hazard ratios are reported which can easily be converted into coefficients. The failure event is the exit so that each portfolio company is at risk during the holding period. If the fund exits the investment in several stages, we use the last transaction date. Investments that are not exited by the end of our sample period are treated as right-censored with corrected estimators. "Distress loan" is a dummy variable that takes the value of one if a loan is traded at a bid price below 90% of the par value in the quarter $t-1$ (according to the conventions of the secondary loan market, see also Wittenberg-Moerman 2008). "Log average bid price" of traded loans are measured in the quarter $t-1$. "Stock return" are measured as the return (relative quarterly percentage change) of traded stocks from PE investment in the quarter $t-1$. "Fundraising dummy" equals one for the quarter a fund advertises a new fund, i.e., sends out due diligence materials (fundraising quarter). Standard errors are in parentheses, clustered at the private equity firm level. One/ two/ three asterisks represent two-tailed significance at a 10%/ 5%/1% level, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	time-varying?			with distressed loan	w/o distressed loan	w/o distressed loan	w/o distressed loan	w/o distressed loan
Distress loan	yes	1.335*						
		(0.229)						
Loan maturity (yrs) (t-1)	yes	0.451***	0.451***	0.556***	0.435***	0.703***	0.436***	0.704***
		(0.044)	(0.043)	(0.106)	(0.048)	(0.080)	(0.049)	(0.081)
# of quotes (t-1)	yes	0.922**	0.923**	0.936	0.917**	0.925	0.919*	0.926
		(0.036)	(0.037)	(0.081)	(0.040)	(0.062)	(0.041)	(0.062)
Log average bid price (t-1)	yes		0.987***	0.980***	0.989	1.027	0.988	1.025
			(0.003)	(0.005)	(0.024)	(0.032)	(0.024)	(0.032)
Stock return (t-1)	yes					0.677		0.685
						(0.332)		(0.342)
Fundraising dummy	yes						0.005	0.000
							(0.060)	(0.000)
Log avg bid price (t-1) X fundr.	yes						1.060**	1.328*
							(0.040)	(0.154)
Number of fund-deal-quarters		5,856	5,856	1,753	4,103	743	4,103	743

Table A5: LPC/LSTA Loan Data Matched with Compustat and CRSP

This table displays all loans with bid and ask prices from market makers for secondary market syndicated loans based on LPC/LSTA data and those that could successfully be matched to firms in the Compustat/CRSP universe between 1998-2017.

	# of facilities	# of borrowers
Total trading observations in LPC	31,314	7,551
Trading obs. with available identifer—Facility-ID and/or LIN	22,032	6,610
Obs. where loan (\w ID) traded while price quote for stock is in Compustat OR CRSP	6,912	2,091
Obs. where loan (\w ID) traded while EPS are in Compustat and price quote for stock is in Compustat OR CRSP	6,832	2,063

Table A6: Summary Statistics for Public Companies with Traded Loans

This table presents characteristics of companies with publicly traded equity and loans (in LPC) (6,556 gvkey-year pairs) and the Compustat universe between 1998 and 2017 (62,121 gvkey-year pairs). We keep only observations for which no characteristics are missing in a year. The first four columns report the # of our sample gvkey-year pairs, mean, median, and standard deviation of the characteristics for our sample companies. Columns 5 through 7 report average differences between our sample companies and companies within the overall Compustat dataset, p-values of t-tests and Wilcoxon rank-sum tests. The last five columns report the proportion of our firms that fall into each of the quintile groups formed by the Compustat 'universe'. All variables are retrieved from the years during which the publicly traded company had loans traded as well. MV is the market value of equity in millions of dollars; Q is defined as (market value of equity plus book value of debt) divided by book value of total assets; $GROWTH$ is the growth rate of sales over the previous year; ROA is return on assets, calculated as operating income before depreciation divided by lagged book value of total assets. CF is cash flow, defined as (net income plus depreciation and amortization) divided by lagged book value of total assets; LEV is the debt-to-assets ratio defined as book value of debt divided by book value of total assets; $CASH$ is defined as (cash plus cash equivalents) divided by book value of total assets; $DIVYIELD$ is dividend yield calculated as (common dividend plus preferred dividend) divided by (market value of equity plus book value of preferred stock), where book value of preferred stock is defined as the first non-missing value of its redemption value, or its liquidating value, or its carrying value; $PAYOUT$ is the payout ratio, defined as the total dividend payments divided by net income before extraordinary items; RAD is R&D scaled by lagged book value of total assets (set to zero if XRD is missing - see Leary/Roberts (2010)); HHI is the Herfindahl-Hirschman index of sales in different industry segments defined from Compustat at the four-digit SIC level; $ANRET$ is the buy-and-hold return during the year in which a loan was traded; $LIQAM$ is the -1 times (the natural logarithm of one plus the target's Amihud (2002) illiquidity ratio, defined as the daily price response associated with one dollar of trading volume, averaged over trading days in the year in which a loan was traded; $ANALYST$ is the number of analysts covering the company from I/B/E/S.

	Our Sample				Difference with Compustat 'Universe'			Compustat 'Universe' Quintiles				
	N	Mean	Median	SD	Diff. mean	p-Value ttest	Wilcoxon	% in Q1	% in Q2	% in Q3	% in Q4	% in Q5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MV	6,556	7828.492	1955.237	13987.744	3805.889	0.000	0.000	0.028	0.108	0.220	0.297	0.347
Q	6,556	1.547	1.363	0.767	-0.310	0.000	0.011	0.155	0.212	0.277	0.244	0.113
$GROWTH$	6,556	0.182	0.057	0.895	-0.037	0.038	0.000	0.156	0.283	0.208	0.180	0.174
ROA	6,556	0.132	0.123	0.195	0.044	0.000	0.000	0.070	0.206	0.301	0.258	0.165
CF	6,556	0.072	0.072	0.224	0.033	0.000	0.413	0.133	0.230	0.286	0.212	0.139
LEV	6,556	0.677	0.687	0.175	0.152	0.000	0.000	0.033	0.097	0.210	0.300	0.360
$CASH$	6,556	0.083	0.052	0.097	-0.076	0.000	0.000	0.229	0.269	0.271	0.176	0.056
$DIVYIELD$	6,556	0.017	0.002	0.03	0.001	0.000	0.000	0.468	0.000	0.106	0.211	0.215
$PAYOUT$	6,556	0.231	0	0.72	0.013	0.106	0.029	0.618	0.000	0.000	0.175	0.207
RAD	6,556	0.014	0	0.038	-0.027	0.000	0.000	0.616	0.000	0.000	0.292	0.092
HHI	6,556	0.23	0.174	0.195	0.019	0.000	0.000	0.160	0.204	0.194	0.209	0.233
$ANRET$	6,556	0.146	0.09	0.545	0.010	0.191	0.000	0.163	0.191	0.215	0.226	0.205
$LIQAM$	6,556	-0.053	-0.002	0.284	0.279	0.000	0.000	0.040	0.100	0.209	0.282	0.370
$ANALYST$	6,556	10.499	9	7.706	3.433	0.000	0.000	0.065	0.133	0.227	0.265	0.310

Table A7: Returns and Characteristics of Loan Portfolios Sorted on Characteristics: Public Companies

This table reports the average quarterly expected returns and characteristics sorted by loan characteristics of companies with publicly traded equity. At the end of July, we sort loans into quintile portfolios based on one characteristic. The table reports the average characteristics of each portfolio at the end of quarter t, as well as the returns that quarter. All portfolios are rebalanced annually. AREW and ARVW are the average expected returns (in percentage) on equal-weighted and value-weighted portfolios. STM is the loan's spread-to-maturity, the initial loan spread over the base rate, adjusted for loan price and repayments, over the life of the loan. Price is the average of the bid and ask quotes as a percentage of the loan's remaining balance (par value). Momentum is the loan's cumulative return from the beginning of quarter t - 3 to the end of quarter t. MV is the market capitalization of the loan, the product of the outstanding balance and market price, plus accrued interest. Volatility is the annualized standard deviation of the residuals of a regression with daily loan excess returns as the dependent, and (excess) returns on market, term spread, and default spread factors as the independent variables over the time period t -2 to t. Number of quotes is the number of bid and ask dealer quotes. B-A is the bid-ask spread, the average of the bid and ask quotes. Size is the natural logarithm of shareholder funds (shfd) which is sort of the net worth, meaning what shareholders get at liquidation (in millions of dollars) (Banz (1981), Fama and French (1992)). The sample period covers June 1998 to February 2017. Newey and West (1987) adjusted t-statistics with 4 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Panel A: STM							**Panel B: Momentum**						
AREW	1.80	2.57	2.13	2.90	-1.97	-3.71	AREW	-3.87	2.18	2.61	2.76	3.07	6.87
t-stats	7.19	7.26	3.86	6.68	-0.72	-3.16	t-stats	-1.41	6.37	7.95	8.18	4.07	6.40
p-value	0.00	0.00	0.00	0.00	0.47	0.00	p-value	0.16	0.00	0.00	0.00	0.00	0.00
ARVW	1.64	2.36	2.69	2.99	3.49	1.85	ARVW	1.33	2.15	2.66	2.80	3.86	2.53
t-stats	7.47	7.66	7.05	6.00	5.42	8.70	t-stats	3.08	7.28	7.25	7.74	7.57	18.53
p-value	0.00	0.00	0.00	0.00	0.00	0.00	p-value	0.00	0.00	0.00	0.00	0.00	0.00
STM	0.10	0.14	0.16	0.19	0.31	.	STM	0.19	0.16	0.16	0.18	0.20	.
Momentum	0.06	0.08	0.08	0.09	0.10	.	Momentum	0.00	0.06	0.08	0.09	0.18	.
Price	98.52	97.78	97.27	95.85	88.75	.	Price	87.85	97.54	97.63	97.72	94.95	.
MV	694.22	567.23	485.03	479.74	383.47	.	MV	571.41	475.23	568.96	495.18	445.93	.
Volatility	0.00	0.01	0.02	0.01	0.03	.	Volatility	0.03	0.00	0.01	0.01	0.03	.
Quotes	3.28	3.63	3.37	3.05	2.43	.	Quotes	2.91	3.29	3.23	3.07	2.98	.
BA-Spread	0.85	0.90	0.95	1.13	1.63	.	BA-Spread	1.62	0.96	0.95	0.96	1.14	.
Size	1926.38	597.29	578.10	613.35	1452.31	.	Size	1139.07	973.29	787.78	539.50	1900.35	.
Panel C: Price							**Panel D: MV**						
AREW	-3.19	2.34	2.28	2.44	3.14	6.24	AREW	-3.25	2.73	2.39	2.46	2.31	5.49
t-stats	-0.99	5.96	7.65	9.80	13.06	4.46	t-stats	-0.99	7.15	5.92	6.04	6.11	3.79
p-value	0.32	0.00	0.00	0.00	0.00	0.00	p-value	0.33	0.00	0.00	0.00	0.00	0.00
ARVW	3.28	2.41	2.10	2.20	3.03	-0.25	ARVW	2.83	3.02	2.65	2.59	2.42	-0.41
t-stats	3.94	5.68	7.77	8.69	13.27	-0.78	t-stats	5.43	7.62	6.50	6.65	6.13	-2.52
p-value	0.00	0.00	0.00	0.00	0.00	0.43	p-value	0.00	0.00	0.00	0.00	0.00	0.01
STM	0.25	0.18	0.16	0.15	0.16	.	STM	0.23	0.19	0.17	0.16	0.15	.
Momentum	0.09	0.08	0.07	0.08	0.10	.	Momentum	0.11	0.08	0.08	0.08	0.07	.
Price	82.58	96.78	98.20	99.08	100.04	.	Price	90.56	95.89	95.87	96.71	97.11	.
MV	560.38	534.49	539.97	484.36	429.65	.	MV	138.92	213.24	311.63	501.14	1377.65	.
Volatility	0.05	0.01	0.01	0.01	0.01	.	Volatility	0.05	0.01	0.01	0.01	0.01	.
Quotes	3.32	2.92	2.88	3.04	3.30	.	Quotes	1.88	2.20	2.62	3.41	5.42	.
BA-Spread	1.98	1.12	0.89	0.80	0.76	.	BA-Spread	1.58	1.17	1.07	0.97	0.81	.
Size	-219.30	504.38	1432.74	893.73	2564.00	.	Size	253.56	570.58	2478.42	813.18	1457.91	.

Table A7: Continued

	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Panel E: Volatility							**Panel F: Quotes**						
AREW	1.88	2.33	2.74	1.97	-8.12	-9.87	AREW	0.81	1.96	0.29	2.22	2.44	1.63
t-stats	9.44	8.63	7.48	2.44	-1.15	-3.16	t-stats	0.73	2.69	0.21	4.90	6.21	3.56
p-value	0.00	0.00	0.00	0.02	0.25	0.00	p-value	0.47	0.01	0.83	0.00	0.00	0.00
ARVW	1.69	2.26	2.67	3.34	3.07	1.38	ARVW	2.43	3.00	2.42	2.57	2.63	0.22
t-stats	7.48	7.85	6.78	5.53	4.62	5.92	t-stats	7.67	9.89	6.09	5.47	6.39	2.51
p-value	0.00	0.00	0.00	0.00	0.00	0.00	p-value	0.00	0.00	0.00	0.00	0.00	0.01
STM	0.15	0.16	0.17	0.20	0.21	.	STM	0.19	0.18	0.17	0.17	0.16	.
Momentum	0.06	0.07	0.09	0.10	0.12	.	Momentum	0.09	0.11	0.07	0.08	0.08	.
Price	98.02	98.30	97.58	93.36	86.72	.	Price	95.03	95.95	94.63	94.98	96.00	.
MV	580.87	500.52	535.18	511.23	416.30	.	MV	304.07	441.98	483.36	548.10	1060.29	.
Volatility	0.00	0.00	0.00	0.01	0.10	.	Volatility	0.02	0.03	0.01	0.01	0.01	.
Quotes	2.98	3.17	3.27	3.27	2.78	.	Quotes	1.39	2.27	2.88	4.02	6.93	.
BA-Spread	0.93	0.92	0.95	1.25	1.63	.	BA-Spread	1.29	1.04	1.16	1.04	0.84	.
Size	1382.13	825.28	532.07	201.29	2783.35	.	Size	2060.51	1306.38	1067.87	414.52	611.26	.
Panel G: BA-spread							**Panel H: Size**						
AREW	2.64	2.53	1.87	1.62	-2.13	-4.71	AREW	0.65	2.66	1.39	2.49	0.96	0.30
t-stats	8.39	10.10	3.05	2.34	-0.88	-4.54	t-stats	0.36	4.18	1.79	7.72	0.96	0.61
p-value	0.00	0.00	0.00	0.02	0.38	0.00	p-value	0.72	0.00	0.08	0.00	0.34	0.54
ARVW	2.42	2.45	2.60	2.73	3.03	0.61	ARVW	3.14	2.72	2.70	2.47	2.46	-0.71
t-stats	8.41	8.78	5.85	5.36	3.94	2.42	t-stats	5.89	6.24	6.48	7.76	7.21	-5.38
p-value	0.00	0.00	0.00	0.00	0.00	0.02	p-value	0.00	0.00	0.00	0.00	0.00	0.00
STM	0.16	0.15	0.17	0.18	0.24	.	STM	0.18	0.17	0.17	0.16	0.19	.
Momentum	0.09	0.08	0.08	0.09	0.08	.	Momentum	0.10	0.11	0.08	0.08	0.08	.
Price	98.76	98.70	97.63	96.30	84.47	.	Price	93.35	95.78	95.91	97.86	95.64	.
MV	729.44	657.19	498.13	406.82	295.31	.	MV	594.95	491.80	454.09	562.62	566.20	.
Volatility	0.01	0.01	0.01	0.01	0.05	.	Volatility	0.03	0.02	0.02	0.01	0.01	.
Quotes	3.64	3.49	3.15	2.82	2.50	.	Quotes	3.22	3.08	3.06	3.21	3.36	.
BA-Spread	0.62	0.72	0.87	1.14	2.25	.	BA-Spread	1.19	1.10	1.08	0.91	1.11	.
Size	1450.58	781.98	750.83	377.30	2106.01	.	Size	986.59	412.08	441.74	886.34	2657.99	.

Internet Appendix B: SDF and Expected Return-Beta Pricing

In this section, we derive the SDF loadings b from the expected return - beta representation from the second-stage regression of Table 7. For readability, we omit time subscripts and we denote the CME SDF as M.

A first-order expansion of the SDF around its unconditional mean yields

$$M \simeq E[M]\left(1 + \log M - \log(E[M])\right).$$

Imposing the restriction that $E[M] = \frac{1}{1+r_F}$, we obtain:

$$M = a_L + b_L^T \cdot f,$$

where

$$\begin{aligned} a_L &= \frac{1 + a + \log\left(1 + r_F\right)}{1 + r_F} \\ b_L^T &= \frac{b^T}{1 + r_F}. \end{aligned}$$

Consider now the no-arbitrage condition $E[MR^T] = 1$ for a gross return on an asset R (R is a $[T\ X\ 1]$ vector). Then:

$$\begin{aligned} E[R] &= \frac{1}{E[M]} - \frac{Cov(M,R)}{E[M]} \\ &\simeq \frac{1}{a_L + b_L^T \cdot E[f]} - \frac{1}{a_L + b_L^T \cdot E[f]} Cov(b_L^T f, R) \\ &= \frac{1}{a_L + b_L^T \cdot E[f]} - \frac{1}{a_L + b_L^T \cdot E[f]} b_L^T [E[fR] - E[f]E[R]] \\ &= \frac{1}{a_L + b_L^T \cdot E[f]} - \frac{1}{a_L + b_L^T \cdot E[f]} b_L^T E[f\ f^T] \cdot \beta + \frac{1}{a_L + b_L^T \cdot E[f]} b_L^T E[f] E[R], \end{aligned}$$

where $\beta \equiv E[f\ f^T]^{-1}E[fR]$.

Thus

$$E[R] = \left(1 - \frac{1}{a_L + b_L^T \cdot E[f]} b_L^T E[f]\right)^{-1} \frac{1}{a_L + b_L^T \cdot E[f]} + \lambda^T \beta.$$

where

$$\lambda^T = -\left(1 - \frac{1}{a_L + b_L^T \cdot E[f]} b_L^T E[f]\right)^{-1} \frac{b_L^T E[f\ f^T]}{a_L + b_L^T \cdot E[f]}.$$

Defining

$$\alpha = \left(1 - \frac{1}{a_L + b_L^T \cdot E[f]} b_L^T E[f]\right)^{-1} \frac{1}{a_L + b_L^T \cdot E[f]}$$

one obtains $E[R] = \alpha + \beta^T \lambda$.

Using the definition of α and λ we recover factor loadings as

$$b_L^T = -\frac{1}{\alpha} \cdot \lambda^T \cdot E[f\ f^T]^{-1},$$

from which we obtain $b = b_L(1 + r_F)$. Notice that, as the regressions of Table 7 involve net excess returns, $\alpha = \alpha_0 + 1 + r_F$, where α_0 is the estimated intercept using net excess returns.