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This paper extends the analysis of systematic investment approaches to broadly syndicated leveraged loans. We find that exposures linked to (short-term) momentum and valuation styles (and a combination thereof) are well-compensated: monthly rebalanced long-only portfolios of high value and momentum loans generate Sharpe and information ratios well above one and economically and statistically significant alphas. Factor portfolio performance deteriorates but remains significant over longer investment horizons. An important implication of our research is that active credit managers employing loan trading strategies that are momentum- and value-neutral do not make use of a viable source of additional return.

Keywords: factor investing; leveraged loans; momentum; value

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PL Credits: 2.0

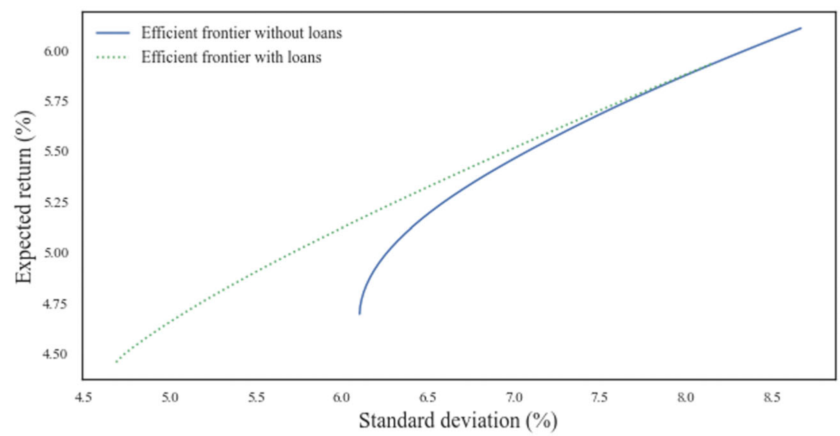
Introduction

This paper is a specific application of style-based investing to a largely unexplored but booming credit asset class with some unique characteristics: loans to non-investment grade issuers, commonly known as leveraged loans. Besides the fact that leveraged loans are interesting in their own right as a relatively new credit asset class, this paper derives its motivation from two additional observations. First, adding leveraged loans to a traditional portfolio likely offers diversification benefits. To illustrate this point, we test whether loan returns contribute to mean-variance efficiency in the classic Markowitz (1952) optimization framework. Figure 1 shows the mean-variance efficient frontiers obtained by including and excluding leveraged loans. Portfolios including loans offer higher expected returns, especially at the lower end of expected risk. That is, adding leveraged loans to a traditional low-risk strategy appears to be particularly beneficial. We notice that by giving loans a 47% share in the minimum variance portfolio (and the remaining weight to sovereign bonds), the annualized (in-sample) volatility of this portfolio drops by 23% (from 6.1 to 4.7%), with only a small cost in terms of expected returns.

Regarding the paper's second motivation, while systematic credit investing with (high yield) bonds has been investigated previously (e.g., by Houweling and van Zundert 2017, and Israel, Palhares, and Richardson 2018), there are several institutional and economic differences between high yield corporate bonds and leveraged loans that warrant a separate loan study. First, because of their first lien, loans are typically ranked senior to bonds in the borrowers' capital structure, which implies higher average recovery rates in case of default. Second, as their principal is partly amortizing, and loan coupons are floating, not fixed, loans have minimal duration risk. Furthermore, while bonds are securities, loans are not. As non-securities, secondary market trading of loans in the U.S. is not directly governed by securities laws or SEC-based regulatory oversight, opening the door for temporary market price inefficiencies which, in turn, may offer attractive opportunities for a well-implemented systematic strategy to exploit.

The views expressed in this article are the authors' and do not necessarily reflect the views of DWS International GmbH ("DWS").

Figure 1. No-Short-Sales Efficient Frontiers Including and Excluding Leveraged Loans



The efficient frontiers are estimated in-sample with 240 months (01/2002–12/2021) of total returns from six asset class indices: MSCI World Net Total Return USD Index (M1WO Index), Dow Jones Equity REIT Total Return Index (REIT Index), LPX50 Listed Private Equity Index TR (LPX50TR Index), Bloomberg Global Aggregate Treasuries Total Return Index Value Unhedged USD (LGTRTRUU Index), Bloomberg Global Aggregate Corporate Total Return Index Value Unhedged USD (LGCPTRUU Index), and the S&P/LSTA LLI100 leveraged loan index. Descriptive statistics on index returns and pairwise correlations are provided in Table IA.1 in the online supplementary materials.

Taking these motivating facts as given, how should then a strategic allocation to leveraged loans be implemented? Passively through a loan index ETF (like, e.g., the Invesco Senior Loan ETF) or within a systematic approach? We offer evidence in favor of the latter possibility. Our purpose is to lay out a framework to understand the risk and return drivers of leveraged loans issued in U.S. dollars and actively traded by mutual funds and CLOs.[1] Their floating rate coupons and the corresponding low duration makes loan prices relatively insensitive to interest rate risk. Instead, loans feature two other major sources of risk. First, as a prototype credit asset class, they contain exposure to the potential inability of the borrowing company to service its principal and interest obligations (credit risk). Second, the limited governance role of securities laws and regulators, their nature as bilateral contracts (non-securities), and the specific microstructure of the secondary market make loans exposed to significant liquidity concerns (liquidity level and risk, see Keßler and Mählmann, 2022).

Because our focus is to understand cross-sectional determinants of the credit risk component of leveraged loan returns, we split off compensation for interest rate risk from loan total returns and refer to the remaining return component as credit excess return. We calculate monthly time series of credit excess returns for each loan from the current level and future changes in secondary market credit spreads. To mitigate cross-sectional differences in loan liquidity as best as possible, we apply a filter to retain only a subset of loans that we deem to be sufficiently liquid. As an additional benefit, this liquidity filter enhances the implementability of our factor approach. Loans passing this filter are typically larger in size, have tighter bid-ask spreads and effective spreads, and are more intensively traded by mutual funds and CLOs, the most active traders in the loan market. Our final dataset includes 16,567 loan-month observations from 1,953 loans over the period from July 2010 to December 2015.

For this sample of leveraged loans, we describe a set of systematic "factors" that can help explain cross-sectional variation in the credit excess returns of these loans. The characteristics that we examine include value and momentum which have been examined extensively in other asset classes (see, e.g., Asness, Moskowitz, and Pedersen 2013). We show that these characteristics (i) both individually, and in combination, are significantly associated with future credit excess returns of leveraged loans, and (ii) translate to an economically significant excess of benchmark and risk-adjusted returns in the context of a systematic long-only portfolio.[2]

To assess whether systematic exposures to value and (one-month) momentum are rewarded in the leveraged loan context, we start by constructing equal weighted long-only tercile portfolios each month from July 2010 to December 2015 (66 months in total). We next investigate the liquidity and return profiles of the extreme (bottom and top tercile) factor portfolios.

With respect to residual liquidity differences that remain between loans that pass our filter, we find that HIGH (top tercile) value or momentum portfolios are on average less expensive to trade than LOW (bottom tercile) value or momentum portfolios. This holds true irrespective of whether we measure transaction costs by quoted bid-ask spreads or by realized (effective) spreads estimated from actual loan trades of CLOs. Hence, for our sample of traded loans, value and momentum rankings produce pronounced liquidity differentials. Since even a strategic passive allocation to the loan market cannot be implemented in a "buy-and-hold" fashion due to (expected or unexpected) loan calls, repayments, or refinancings, their lower trading costs likely benefit net-of-costs outperformance and alphas of HIGH factors *vs.* their own market segment.

With respect to factor returns, if the factors under consideration are priced in the cross-section of corporate loans, then we would expect that more exposure to the given factor results in a higher return. Within this paper, we analyze two-factor portfolio holding periods: 1-month and 12-months. As 1-month holding periods seek to maximize portfolio exposure to each investment theme, the 1-month results establish a necessary condition to demonstrate the potential efficacy of a systematic investment approach in the liquid leveraged loan market. In contrast, the 12-months holding period, implemented using the overlapping portfolio methodology of Jegadeesh and Titman (1993), is more realistic and prevents extreme turnover.

Outperformance (mean active returns) and risk-adjusted returns (Sharpe ratio, CAPM alpha) of factor portfolios over the 1-month horizon are exciting. For example, Sharpe ratios of the HIGH value and momentum portfolios are 1.35 and 1.44, respectively, significantly larger than the Sharpe ratio (1.11) of the market. Sharpe ratios of the LOW portfolios range from 0.54 (value) to 0.57 (momentum), significantly underperforming the market portfolio. Given the low correlation across the value and momentum styles, a bottom-up HIGH (LOW) composite portfolio (COMBI) constructed from a tercile sort of equal-weighted average value and momentum percentile ranks has a Sharpe ratio of 1.47 (0.43).

Because a 1-month investment horizon is unrealistic to implement in the corporate loan market, for our second set of results, we thus analyze long-only portfolios over a 12-months horizon. While we do observe a marked decrease in the risk-adjusted performance across all HIGH portfolios, the VALUE and COMBI styles still deliver mean active returns and alphas that are economically and statistically significant. In contrast to the HIGH portfolios, the LOW factors react far less sensitive to an extension of the holding period. Their Sharpe ratios still fall significantly below the market's Sharpe ratio. In addition, the negative alphas are substantial and statistically highly significant. Interestingly, and contrary to the HIGH portfolios, the LOW factors are more strongly exposed to the market with betas significantly exceeding one. As the average return of the market index is positive, high betas imply that the mean active return is less negative than the CAPM alpha. Finally, because of the modest performance of HIGH MOMENTUM over twelve months, the equal-weighted composite does not beat a strategy that allocates only to the value theme. In sum, the 12-months results suggest that it may be possible to build realistic (implementable) long-only loan portfolios seeking exposure to systematic investment styles.

We perform several additional tests to verify the robustness of our results and to address the remaining implementability concerns. In short, we show that the return forecasting power of loan value and momentum survives in market value-weighted factor portfolios and obtains in loan level Fama and MacBeth (1973) cross-sectional regressions. We further elaborate on trading costs and find that the average realized trading costs of HIGH portfolios are well below estimated alphas. Finally, we address econometric issues with historical volatilities and covariances estimated from returns that are (partly) based on potentially stale price quotes of loan dealers, and we adjust factor performance and test metrics for multiple comparison biases along the lines of Harvey and Liu (2014, 2015).

This paper contributes to several strands of literature. Most importantly, we extend the substantial body of academic research on systematic investing to a unique credit asset class, corporate loans. Compared to the equity asset class, the literature on fixed income factor investing is relatively recent but expanding fast. Value investing for corporate bonds was pioneered by Correia, Richardson, and Tuna (2012), and the seminal paper on the momentum style for investment grade and high-yield bonds is by Jostova et al. (2013). More recent papers on the cross-section of corporate bond returns are Bai, Bali, and Wen (2019), Bali, Subrahmanyam, and Wen (2021), and Chung, Wang, and Wu (2019).

As far as we know, Beyhaghi and Ehsani (2017) is the only paper on systematic credit investing with corporate loans. They find evidence that a simple measure of (three-month) momentum can explain cross-sectional variation in loan returns. We broaden their research in several aspects. First, motivated by previous findings from other asset classes (Asness, Moskowitz, and Pedersen 2013), we extend the set of measures examined to value and a combination of value and momentum. Second, we focus on credit excess (not on excess of cash) returns to remove any term premium. Third, to enhance the practical relevance of our research, we limit the loan universe to actively traded loans (i.e., we remove quoted but non-traded loans) and build turnover-aware portfolios with holding periods longer than one month (i.e., up to one year). At the bottom line, our result that the value and momentum styles also work in the risky corporate loan market represents a nice "out-of-sample" test of the initially equity-focused work on factors and enhances our confidence that factor efficacy is driven by real forces and not the result of data mining.

We also contribute to the emerging literature on the economics and microstructure of private markets. Albuquerque et al. (2017) and Nadauld et al. (2019), for example, study liquidity provision in the secondary market for private equity fund stakes. We confirm and extend several results on the cross-sectional determinants of loan trading costs presented in Keßler and Mählmann (2022). We find that buying value loans is much cheaper than selling them, suggesting that fire sales are one likely source of the value premium, compensating liquidity providers. Furthermore, current price losers are cheap to buy and expensive to sell, consistent with asymmetric information and uncertainty driving up trading costs. Price winners, in contrast, are more expensive to buy than to sell. Unsurprisingly, buying cross-sectional winner loans is more expensive than buying losers, and selling winners are cheaper than selling losers.

Institutional Background

A syndicated loan is a commercial credit structured, arranged, and administered by one or several commercial or investment banks, known as arrangers or agents. This paper looks at the credit risk segment of the syndicated loan market, i.e., loans to highly leveraged borrowers. Leveraged Commentary & Data (LCD), a unit of S&P and one of the major providers of loan industry data, defines leveraged borrowers as issuers whose credit ratings are non-investment grade and who are paying attractive spreads, i.e., premiums above Libor of 200 bp and more (see LCD 2017).

A large fraction of these loans are issued to finance leveraged buyouts, dividend recapitalizations, or other forms of capital restructurings. Leveraged loans are typically packaged into two broad structures: term loan B or institutional facilities and pro rata facilities. The first type comprises first- and second-lien, virtually non-amortizing ("bullet"), fully funded facilities, while the latter includes unfunded revolving credit ("revolvers") and amortizing facilities (term loans A). This paper focuses on U.S. institutional facilities which experienced tremendous growth over the last decade. As estimated by Fitch Ratings, at mid-year 2021, there was $1.5 trillion in U.S. institutional leveraged loans outstanding, almost tripling from slightly more than $0.5 trillion ten years earlier.

The strong primary market presence of institutional investors, such as collateralized loan obligations (CLOs) or loan mutual funds and exchange-traded funds (ETFs) fostered the establishment of a secondary loan market. While outside the radar of regulators and securities laws, the secondary market in the U.S. grew from an annual trading volume of $145 billion in 2003 to $772 billion in 2020 at an annual compound rate of about ten percent. All trading takes place OTC, with most transactions concluded on an intermediated basis, i.e., trades pass through decentralized loan dealer desks located at large investment banks acting as lead arrangers or transfer agents for a given facility. The market generally lacks pre- and post-trade transparency. Hence, any potential trader cannot observe all dealer quotes in a central location or on a computer screen. Instead, the institution must call several dealers for quotes or subscribe to data vendors like Refinitiv LPC or IHS Markit that broadcast near real-time bid and ask quotes aggregated across contributing dealers. As common for OTC markets, quotes are indicative, not firm.

Data and Methodology

Data Sources and Sample Selection.

While an active trader in the secondary loan market likely knows the investable loan set, this type of information is typically not available to an outside econometrician. Outlining an implementable loan investing strategy, thus, requires us to first isolate exactly those loans that are available for trading. The purpose of this section is to describe how we identified what we think represents an investable universe of leveraged loans. We use data from the following four sources: Refinitiv DealScan for primary market (i.e., at issue) loan characteristics, IHS Markit for daily time series of dealer bid and ask quotes, Creditflux CLO-i for information on secondary market loan trades of CLOs, and CRSP (via WRDS) for information about loan holdings of mutual funds. We restrict the sample to the period from July 2010 to December 2015 (66 months) for which we have access to all four databases.

We start our sample selection with the set of IHS Markit loans with at least two consecutive months of daily bid and ask dealer quotes. We hand-match these loans to DealScan to enrich the sample with loan characteristics (e.g., margin, maturity, principal, repayment schedule).[3] Importantly, for the subset of loans that remain after the IHS Markit-DealScan match, we keep only those months during which a loan was traded (bought or sold in the secondary market) by at least one mutual fund and one CLO.[4] As a group, funds and CLOs are the two most important and active loan traders in terms of size and trading frequency (see Irani et al. 2021). This filter is to limit the sample to actively traded loans that can be bought or sold on the market at relatively low costs. We show below (Section "Descriptive statistics" and "Portfolio characteristics") that the filter works as intended. Recall that we implement this filter to approximate the current information set of an active loan trader. That is, the filter does not condition on future liquidity or trading activity, it is based on ex-ante information only. Hence, the filter should not affect the implementability of our trading strategies outlined below.

A considerable number of loans satisfy the filter criteria. In total, we have an unbalanced panel of 16,567 loan $\times$ month observations from 1,953 unique loans issued by 1,161 different borrowers. As depicted in Figure IA.1 in the online supplementary materials, at the start of our sample in 2010, the investable universe contains $<$100 loans and jumps to a size of more than 400 loans since mid-2014. The average of the 66 monthly cross-sections contains 251 loans (median: 192), with a standard deviation of 146. The minimum and maximum cross-sections cover 40 and 529 loans, respectively. The average loan appears for 8.5 months in the sample (median: 6 months), and the minimum and the maximum number of months per loan are 1 and 47, respectively.

Methods and Loan Characteristics.

This section outlines how we calculate (i) secondary market or traded credit spreads, (ii) realized trading costs, and (iii) credit excess returns of leveraged loans. We start with spread-to-maturity (STM) as a measure of secondary market (credit) spreads.

Spread-to-Maturity (STM).

Because loans pay a floating interest rate (fixed margin plus variable base rate) and future coupons are not fixed in advance, a classical yield spread measure for bonds cannot be computed for loans. We follow Beyhaghi and Ehsani (2017), Keßler and Mählmann (2022), and general market practice (see LCD 2017) and calculate credit spreads reflecting any loan price deviations from par value and adjusted for the remaining life of the loan. We set the base rate equal to zero and calculate STMs at the trade level for each of the 133,651 CLO loan trades in our sample. STMs are obtained by solving

$$P = \sum_{i=t}^{T} \frac{Repayment_i}{(1+STM)^i} + \sum_{j=t'}^{T'} \frac{Margin_j}{(1+STM)^j} \qquad (1)$$

for STM. Here, P is the trade price, i is the ratio of remaining days to a principal repayment to 360 and j is the ratio of remaining days to a margin payment to 360. We obtain information on the loan repayment schedule and the fixed initial spread (margin) from DealScan. Because base rates were typically very low ($<$0.5%) over most of our sample period, the precise handling of base rates in the computation of STMs is of second-order importance.

Loan Trading Costs and Liquidity Spreads.

In line with Keßler and Mählmann (2022), we capture loan trading costs in two ways. Our first liquidity measure is the quoted half-spread (QHS, i.e., the difference between the IHS Markit ask and bid quote divided by two), aggregated at a monthly frequency. While loan market investors widely use IHS Markit quotes as a source of mark-to-market pricing, quotes are not without costs. Importantly, in most dealer (OTC) markets, posted quotes are typically indicative, representing just a starting point for bilateral negotiations between dealers and customers and not a binding commitment by a dealer to trade at his posted prices. Therefore, quotes may be stale and infrequently updated to new information.

To circumvent possible shortcomings of indicative quotes in OTC markets, we follow Keßler and Mählmann (2022) and construct a measure of realized trading costs using the trade prices obtained by

CLOs. Among other benefits, this makes it possible to verify whether indicative quoted bid-ask spreads indeed capture cross-sectional variation in transaction costs incurred by investors. As is standard in the market microstructure literature (e.g., Foucault, Pagano, and Roell 2013), we gauge trading costs by the effective half-spread (EHS), defined as the difference between the price at which a customer buy or sell order executes and the average dealer mid quote posted on the day before the trade day. Hence, we benchmark prices against one-day lagged mid quotes (averaged across all dealers active in each loan). This way, we implicitly assume that average mid quotes present an unbiased fundamental value proxy. However, if information dissemination and price formation occur more frequently (i.e., intra-daily), the reported effective spreads are likely systematically inflated. Our results on EHS must therefore be interpreted with this caveat in mind.

Formally, as in Keßler and Mählmann (2022, see their Equation (1) in Section "Methods and loan characteristics"), the EHS of a trade at price P in loan i at time t is defined as:

$$\mathrm{EHS}_{\mathrm{it}} = \mathrm{Q}_{\mathrm{it}}(P_{\mathrm{it}} - \mathrm{M}_{\mathrm{it}-1}), \tag{2}$$

where Q is the trade direction indicator (1 for buyer-initiated and -1 for seller-initiated trades) and M is the pre-trade benchmark price (i.e., the one-day lagged average mid quote). We calculate EHS separately for CLO buys ($Q_{\mathrm{it}} = 1$) and sells ($Q_{\mathrm{it}} = -1$) and aggregate trade level EHS at the loan $\times$ month frequency.[5] A more detailed discussion of different measures of liquidity spreads is provided in Section 2.2 of Foucault, Pagano, and Roell (2013).

Credit Excess Returns. The main purpose of investing in corporate loans is to earn the default premium, which is driven by the current level and future changes in credit spreads (STMs). By using excess returns *vs.* risk-free interest rates, we could focus on the credit risk component. Lok and Richardson (2011) outline an approximate measure of monthly credit returns that separates interest rate risk from credit risk (and from other systematic determinants of loan discount rates). The Lok and Richardson first-order approximation is used by Correia, Richardson, and Tuna (2012) and Frieda and Richardson (2016) in the context of systematic credit investing with bonds and CDS. We slightly modify their approach and calculate credit excess returns (CER) for loan i and month t as follows:

$$\mathrm{CER}_{\mathrm{it}} = \mathrm{STM}_{\mathrm{it}-1}/12 + \log(P_{\mathrm{it}}) - \log(P_{\mathrm{it}-1}), \tag{3}$$

where P denotes the monthly average mid-quote. More background on this formula is presented in Appendix A. The first part reflects the interest return and the second is the price return. Note that Equation (3) is an approximation. It ignores any principal repayment return and assumes that loan prices are not highly sensitive to fluctuations in interest rates, which seems justified by the small duration of floating rate loans.[6] Importantly, the interest return relies on traded prices (via STM), not quotes. Hence, it is less subject to the standard concerns about the reliability and staleness of quotes (see Section "Quote staleness").

Additional Loan Characteristics. In our empirical analysis, we employ a range of loan characteristics to construct measures for the two investment styles and to assess the risk and liquidity profiles of our factor portfolios. The set of (credit) risk characteristics includes spread-to-maturity, return volatility (VOLA), and traded price (PRICE). Asset volatility plays a central role in Merton (1974)-type structural models of default with higher volatility driving up expected default risk ceteris paribus. We proxy for asset volatility by calculating loan mid-quote return volatility. VOLA denotes the absolute difference in the logs of average mid quotes between month t-1 and month t. The last variable in this set, traded price, equals the price (in percent of par) obtained by CLOs in actual (i.e., executed) trades. We calculate the monthly average trade price across all buy and sell trades in a given loan. Price is a continuous signal of distress and loans priced below 80 are typically referred to as discount obligations by practitioners.

Loans that are associated with a larger number of CLO trades are obviously more readily available for trade and generate more trading interest. Hence, an additional measure of liquidity is the monthly number of CLO trades. Finally, SIZE is the market value of the loan, the product of the outstanding balance, and market price (monthly average bid quote), ignoring any accrued income. Trading in larger facilities might be less costly due to more market participants either demanding or supplying liquidity, or less asymmetric information issues.

Descriptive Statistics. Table 1 provides an overview of the sample. As shown in Panel A, the average loan trades at a price of 98.3 close to par, which results in a traded credit spread of 441.7 bp.[7] The monthly mid-quote return volatility amounts to 88.7 bp. The statistics on our liquidity proxies reported

Table 1. Descriptive Statistics

	N	Mean	Median	*SD*	P25	P75
A. Risk						
STM (bp)	16,567	441.68	373.32	815.83	311.93	473.20
VOLA (bp)	16,567	88.69	48.41	172.60	21.12	97.89
PRICE (%)	16,567	98.33	99.75	5.37	98.59	100.25
B. Liquidity						
QHS (bp)	16,567	35.02	19.38	48.57	8.50	40.75
EHS_Buy (bp)	11,309	1.26	5.70	63.66	−14.60	25.00
EHS_Sale (bp)	11,076	19.02	14.69	58.64	−0.00	33.27
No. Trades CLOs	16,567	8.07	5.00	10.40	2.00	10.00
SIZE ($ billion)	16,567	1.25	1.07	0.86	0.66	1.65
C. Credit excess returns						
Loan level (bp)	16,567	14.86	28.50	229.54	−10.11	64.70
Sample index (bp)	66	28.74	31.77	89.58	−1.37	65.09
LLI100 (bp)	66	42.02	42.62	112.57	−14.89	97.17
D. Investment styles						
VAL_R	16,567	54.77	7.81	1248.73	3.84	17.83
$MOM_{t\text{-}1,t}$ (bp)	16,567	6.18	14.40	193.96	−28.72	69.68
$MOM_{t\text{-}2,t\text{-}1}$ (bp)	16,551	7.83	13.34	176.58	−26.36	63.23
$MOM_{t\text{-}4,t\text{-}1}$ (bp)	15,073	21.62	30.63	312.90	−46.62	130.73

The table reports the summary statistics of the individual loan characteristics (risk, liquidity, and returns). The data is at the loan × month level (except for the two indices return time series) and span the period from July 2010 to December 2015, a total of 66 months. STM denotes the secondary market (or traded) credit spread, reflecting any loan price deviations from par value, and adjusted for the remaining life of the loan. VOLA is the absolute difference in log average mid quotes between month *t*-1 and month *t*, and PRICE equals the monthly average price (in percent of par) obtained by CLOs in actual (i.e., executed) buy and sell trades. Across the liquidity proxies, QHS is the quoted half-spread, and effective half-spreads, both for CLO buys ($Q = 1$) and CLO sells ($Q = -1$) are calculated according to Equation (1) in the text. SIZE is the market value of the loan, the product of the outstanding balance, and market price (monthly average bid quote), ignoring any accrued income. Credit excess returns are approximated according to Equation (2) in the text. The sample index is derived from the individual loans in the sample, with monthly rebalancing (i.e., in each month *t*, all accessible loans are bought, and the equal-weighted return of this portfolio is measured over month $t+1$). The S&P/LSTA Leveraged Loan 100 Index (LLI100) is the standard benchmark index for the U.S. market that consists of the 100 most liquid and actively traded loans. VAL_R denotes the ratio of STM and VOLA, and the three momentum measures are based on differences in logs of monthly average mid quotes.

in Panel B are especially interesting. While the average loan is quoted at a bid-ask half-spread of 35.0 bp, realized transaction costs are much lower. Effective round-trip (two-sided) trading costs sum to just (1.3 + 19.0) 20.0 bp for the average CLO. The small costs associated with CLO buys indicate that CLOs frequently act as liquidity providers (not demanders) when they buy on the secondary market. Finally, because of the screening criteria described above that filter out small and illiquid loans, the sample is tilted towards larger loans that are generally more accessible and more easily tracked. The average loan has a market value of $1.25 billion, more than two times the size reported by Beyhaghi and Ehsani (2017) for their sample.

Summary statistics for the loan level excess returns are reported in Panel C of Table 1. The average loan returns 14.9 bp in an average month (median: 28.5 bp). However, the standard deviation is large at 229.5 bp. In addition, the time-series average of the cross-sectional return volatility is 163.9 bp (unreported), suggesting that our sample of investable loans generates enough return variation for a well-implemented systematic approach to exploit.

We construct an investable passive benchmark that includes only loans that are accessible to an investor at a given point in time in the secondary market and that allows for an apples-to-apples comparison with the performance of factor portfolios. Each month, this index invests equally in all loans available for trading in this month. Importantly, the index is rebalanced at the same frequency as the factor portfolio to which it is compared.[8] Return statistics on a monthly rebalanced version of this index are shown in Table 1, Panel C. As a second benchmark, we calculate credit excess returns according to Equation (3) for the LL100 Index that is jointly maintained by S&P and the Loan Syndications and Trading Association (LSTA).[9] Our self-constructed sample index has average monthly credit excess returns of 28.7 bp (median: 31.8 bp) compared to 42.0 bp (median: 42.6 bp) for the S&P/LSTA LL100 Index.[10] The two indices have a time-series correlation of 0.86, indicating that our sample represents the investable segment of the loan market accurately.

Measuring Systematic Investment Styles for Leveraged Loans. For our systematic investment styles, a substantial body of academic research and a long track record of use in portfolios has documented pervasive evidence of robust associations between measures of momentum and value and future excess returns across multiple asset classes. Asness, Moskowitz, and Pedersen (2013) show strong evidence of the combined efficacy of value and momentum across multiple asset classes and time periods. Our aim here is to introduce intuitive measures of these two styles that are deliberately simple to enhance the transparency and replicability of our study. While this approach mitigates any potential data mining concerns, we note that our results on the efficacy of systematic credit investing with loans are likely conservative, leaving room for further improvement with respect to more sophisticated measures and portfolio construction choices.[11]

Cross-sectional momentum is the tendency for an asset's recent relative performance to continue, leading to the outperformance of recent winners relative to recent losers. Recent performance is typically either measured with return data from the asset itself or with returns from other related assets (e.g., using equity momentum to explain bond returns). Due to the specific microstructure of the secondary loan market, loan price quotes are likely to exhibit short-term momentum. Because quotes are provided by decentralized dealers that do not observe their competitors' individual quotes, and the market lacks pre- and post-trade transparency, new information typically takes some time to be fully incorporated into quotes. Hence, price momentum driven by slow information diffusion emerges almost naturally from the market's microstructure (see Jostova et al. 2013, for the argument that slow information diffusion causes momentum in high-yield bond returns).

We measure short-term momentum by the loan's current month mid-quote return $MOM_{t\text{-}1,t}$ (i.e., the difference in log average mid quotes between month t-1 and month t). Mid quotes refer to the sum of bid and ask quotes divided by two. Bid and ask quotes are averaged across all dealers contributing price quotes to IHS Markit for a given loan on a given day.[12] While Beyhaghi and Ehsani (2017) capture cross-sectional momentum by a loan's past three-month excess return over cash, we note that our simpler short-term price return measure has superior performance relative to other choices.

Value can be characterized as mean reversion in valuations. Relatively cheap assets outperform relatively expensive assets in risk-adjusted terms. A cheap loan provides investors excess compensation per unit of expected fundamental credit risk. Hence, to determine whether a loan is cheap or expensive, we need a credible fundamental anchor to compare against the loan's current market credit spreads. Standard structural models of default (e.g., Merton 1974) suggest leverage and asset volatility as the two essential ingredients of a theoretical anchor for credit spreads. We use a reduced-form specification linking trade price-based credit spreads (i.e., spread-to-maturities—STMs) and a proxy for the borrower's asset return volatility. We capture asset volatility by the loan's price (or mid quote) return volatility (i.e., the absolute value of the current month's price return).[13] To construct our value measure (VAL_R), we divide the loan's average traded STM in each month by the corresponding monthly price return volatility (VOLA). Hence, cheap loans offer more compensation (spread) per unit of risk (volatility).

Like previous findings from other asset classes, our loan value and momentum measures are weakly correlated to each other, creating the potential for a combination across them to be diversifying.[14] We construct a bottom-up composite factor (COMBI) from an equal-weighted average of VAL_R and MOM cross-sectional percentile ranks.

Panel D in Table 1 shows descriptive information on our style proxies over the full loan sample. On average, the traded credit spread exceeds the loan's monthly mid-quote return volatility by a factor of 54.8. Our preferred momentum measure is the loan's current mid return (from month t-1 to month t). The table also shows two alternative measures: the cumulative return over the past three months (from t-4 to t-1), leaving out the current month, and the past month return (from t-2 to t-1).

Empirical Results

Factor Portfolios. Our first set of analyses examines the potential efficacy of applying systematic investment styles to leveraged loans through standard tercile portfolios. At the start of each month

Table 2. Loan Characteristics of Factor Portfolios

	VALUE			MOMENTUM			COMBI		
	LOW	HIGH	H-L	LOW	HIGH	H-L	LOW	HIGH	H-L
A. Risk									
STM (bp)	368.17	533.00	164.82**	499.17	464.40	−34.77	383.27	504.03	120.76**
VOLA (bp)	162.32	30.94	−131.38**	114.28	103.46	−10.82	127.63	47.35	−80.28**
PRICE (%)	97.59	97.95	0.36	97.38	97.58	0.20	97.85	98.02	0.17
B. Liquidity									
QHS (bp)	41.79	38.90	−2.88*	44.49	40.59	−3.90	40.10	38.54	−1.56
EHS_Buy (bp)	7.97	−0.72	−8.69**	−10.08	12.89	22.97**	−3.98	1.30	5.29
EHS_Sale (bp)	15.02	18.69	3.67	32.51	5.18	−27.33**	25.90	14.86	−11.03**
No. Trades CLOs	8.27	7.73	−0.54	8.26	7.83	−0.43	7.98	7.55	−0.43
SIZE ($ billion)	1.22	1.26	0.03	1.20	1.23	0.02	1.26	1.25	0.01
C. Investment styles									
VAL_R	2.34	130.39	128.05**	38.94	36.86	−2.08	5.38	126.14	120.76**
$MOM_{t\text{-}1,t}$ (bp)	−8.69	5.01	13.70	−103.98	99.23	203.21**	−84.06	38.16	122.23**
$MOM_{t\text{-}2,t\text{-}1}$ (bp)	0.99	1.06	0.08	−1.49	−2.52	−1.03	2.23	0.04	−2.19
$MOM_{t\text{-}4,t\text{-}1}$ (bp)	−2.42	12.46	14.87	−5.55	8.83	14.38	−0.64	12.65	13.30

The table reports average loan characteristics of value, momentum, and composite factor portfolios. The sample period is from July 2010 to December 2015. Each month, the set of accessible loans is sorted into equal-weighted tercile portfolios according to VAL_R (ratio of STM and VOLA), $MOM_{t\text{-}1,t}$, and a composite (equal-weighted average VAL_R and $MOM_{t\text{-}1,t}$ percentile rank). LOW denotes tercile one and HIGH tercile three. The loan characteristics are described in Table 1. Differences in means tests between LOW and HIGH are based on Newey and West (1987) standard errors. * and ** denote statistical significance at the 5 and 1% levels, respectively.

t, we rank the investable loan universe on our two investment styles, either individually or in aggregate (factor composite). Equal weighted tercile portfolios are rebalanced monthly and do not account for transaction costs.[15] We compute returns for each portfolio over month $t+1$ and report the time-series average returns with the corresponding Newey and West (1987) adjusted t-statistics. The purpose of this analysis is to show the potential for our systematic approach (i.e., whether these characteristics are associated with future credit excess returns). We will address implementability issues in Sections "Portfolio performance: 12-months holding period" and "Robustness".

Portfolio Characteristics. Table 2 summarizes a variety of characteristics for the low and high (tercile one and three) factor portfolios. We are particularly interested in the risk and liquidity profiles of the factors under consideration. The following observations emerge.

First, by construction, the portfolios exhibit the desired exposures to the investment styles. Value loans offer higher spreads per unit of price volatility and momentum loans are recent (short-term) winners. Second, the two investment styles are nearly uncorrelated: value portfolios do not capture a significant momentum spread, and momentum portfolios are almost risk-balanced on average. Third, the current one-month momentum is unrelated to the past one-month or three-month momentum. Hence, somewhat in contrast to other asset classes, momentum in leveraged loans looks more like a short-term phenomenon.

Of particular importance, however, are the liquidity profiles of the portfolios. In terms of quoted half-spreads, HIGH portfolios are on average 3–4 bp less expensive to trade than LOW portfolios. A look at realized transaction costs (effective half-spreads) using the prices obtained by CLOs is insightful too. While buying the high-value portfolio costs on average negligible −0.72 bp, the sale of high-value loans occurs at 18.7 bp below the prevailing mid. Together, the round-trip trading costs of the high-value portfolio amount to 18 bp, and 23 bp for the low-value portfolio. The fact that buying value loans are much cheaper for the average CLO than selling them indicates that some part of the value premium stems from high-quality loans being fire-sold by liquidity demanding investors and bought by liquidity supplying CLOs. Hence, "value" as measured in this paper might partially reflect compensation for liquidity provision.

The realized transaction costs of momentum loans are also revealing. Current price losers can be bought at an average discount to the prevailing mid of 10 bp

Table 3. Performance Statistics of Long-Only Equal-Weighted Factor Portfolios—One-Month Holding Period

		VALUE		MOMENTUM		COMBI	
	Market	LOW	HIGH	LOW	HIGH	LOW	HIGH
A. Return statistics							
Mean (bp)	344.93	183.64	483.39	236.13	468.79	150.45	472.26
Volatility (bp)	310.31	342.93	357.87	410.85	325.78	351.19	321.89
Sharpe ratio	1.11	0.54*	1.35*	0.57	1.44*	0.43*	1.47*
LW p-value	–	0.05	0.02	0.13	0.04	0.04	0.04
B. Outperformance statistics							
Outperformance (bp)	–	−161.29**	138.46**	−108.80	123.86*	−194.48**	127.33**
Tracking error (bp)	–	100.07	100.37	163.00	109.98	121.98	88.64
Information ratio	–	−1.61	1.38	−0.67	1.13	−1.59	1.44
t-Statistic	–	−3.76	3.14	−1.33	2.26	−3.32	3.23
C. CAPM statistics							
Alpha (bp)	–	−181.52**	99.59**	−191.06*	127.90*	−216.26**	128.29**
t-Statistic	–	−3.84	2.61	−2.19	2.52	−3.21	3.20
Beta	–	1.06**	1.11**	1.24**	0.99**	1.06**	1.00**
t-Statistic	–	18.14	28.00	13.15	16.76	15.33	27.05

This table reports the performance statistics of our sample loans (“Market”) and the value, momentum, and composite factors for U.S. leveraged loans. The sample period is from July 2010 to December 2015. All returns are credit excess returns. The return in month $t+1$ is calculated from portfolios constructed in month t. Each month, a HIGH (LOW) factor portfolio takes equal weighted long positions in 33% of the accessible loans: for value, the loans with the highest (lowest) ratio of STM and VOLA; for momentum, the loans with the highest (lowest) current month mid quote return. The composite factor (COMBI) portfolios are constructed from an equal-weighted average of value and momentum percentile ranks. Panel A reports the return statistics, and Panel B, the outperformance statistics. Panel C shows the CAPM alpha and beta from regressions of portfolio returns on market returns (the sample index). Mean, volatility, outperformance, tracking error, and alpha are annualized. Loan credit excess returns are approximated according to Equation (2) in the text. Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the accessible loan market (Panel A; test of Ledoit and Wolf 2008), (2) the outperformance is different from zero (Panel B; t-test), and (3) the alphas are different from zero (Panel C; t-test). The t-tests are calculated with Newey and West (1987) standard errors. * and ** denote statistical significance at the 5 and 1% levels, respectively.

and must be sold at a cost as high as 33 bp. This picture shifts for cross-sectional winner loans: Buying them is about 8 bp more expensive than selling. Not surprisingly, buying winners is 23 bp more expensive than buying losers, and selling winners is 27 bp cheaper than selling losers. The round-trip trading costs sum to 18 bp for the high momentum portfolio and to 22 bp for low momentum loans.

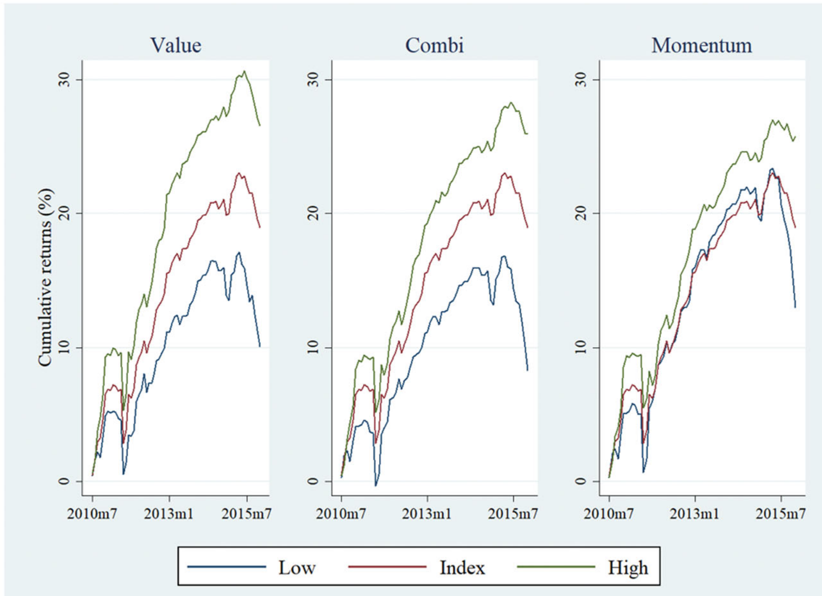
At the bottom line, these findings further highlight the success of our efforts to extract the subset of actively traded, liquid loans from the broader set of all quoted loans. For the universe of loan quotes from IHS Markit, Keßler and Mählmann (2022, Table 1, Panel A) report average bid-ask spreads of well above 200 bp for each year from 2008 to 2016. Even their sample median quoted spreads are typically 100 bp and more.

Portfolio Performance: One-Month Holding Period. In the next two sections, we present our main results—namely, that value and momentum factor portfolios in the liquid segment of the loan market earn alpha beyond the market’s credit risk premium. We also highlight the tension between evaluating factors in an absolute *vs.* relative (to a benchmark) risk context and the importance of the rebalancing frequency (i.e., the investment horizon). In addition, we show the diversification benefits of combining the two factor styles into a composite portfolio, which, compared with single-factor portfolios, substantially reduces tracking error, and improves the information ratio vis-à-vis the loan market.

Table 3 summarizes the performance of hypothetical long-only LOW (tercile one) and HIGH (tercile three) factor portfolios and our customized market benchmark index (“Market”). The index, as well as the portfolios, are rebalanced monthly. Figure 2 reports the cumulative returns for the hypothetical long-only portfolios and the benchmark separately.

Panel A shows that for the period from July 2010 to December 2015, the liquid segment of the leveraged

Figure 2. Cumulative Returns for Factor Portfolios and the Market Index



This figure shows the cumulative performance (credit excess returns) of hypothetical long-only portfolios and a customized market index. Each month, we identify a liquid subset of leveraged loans by limiting the sample to loans traded by both, mutual funds and CLOs, during the month. The sample period is from July 2010 to December 2015. The set of accessible loans is sorted into equal-weighted tercile portfolios each month, according to VAL_R (ratio of STM and VOLA), $MOM_{t-1,t}$, and a composite (equal-weighted average VAL_R and $MOM_{t-1,t}$ percentile rank). LOW denotes tercile one and HIGH tercile three. The index buys all loans and is equal-weighted. All factor portfolios and the index are rebalanced monthly.

loan market generated 3.45% a year in credit excess returns. Importantly, across all investment styles, the LOW portfolios substantially underperform the market while we see significant outperformance for the three HIGH portfolios (Panel B). The annual outperformance is: 1.38% (VALUE), 1.24% (MOMENTUM), and 1.27% (COMBI). These factor premiums are significant: Investors could have raised their average credit excess returns by up to two-fifths when investing in factors compared with passively investing in the accessible loan market.

Risk-adjusted performance metrics are reported in two versions. First, in Panel A of Table 3, we measure returns relative to total volatility using the Sharpe ratio statistic. We employ the studentized time series bootstrap approach of Ledoit and Wolf (2008) to test for significant differences between the Sharpe ratio of the market and that of a factor portfolio. This test is most appropriate in settings with non-normal excess returns and limited time series data.[16] The Sharpe ratios of all HIGH portfolios significantly exceed the market's already high Sharpe ratio of 1.11.[17] In turn, all LOW Sharpe ratios fall substantially below the market. The HIGH COMBI portfolio obtains the highest Sharpe ratio of 1.47.

To cast these Sharpe ratios into a broader context, we provide some benchmarking against widely used asset classes.[18] Since leveraged loan investments are accessible to retail investors through loan mutual funds and ETFs, a comparison of risk-adjusted performance across asset classes is insightful not only for institutional investors. Over the period studied here (07/2010–12/2015), public equities (MSCI World) returned a Sharpe ratio of 0.76, real estate (REIT) of 0.76, listed private equity (LPX50) of 0.65, investment grade bonds of 0.80, and sovereign bonds of 0.23. In addition, Table IA.1 in the online supplementary materials reveals that over the longer period 01/2002–12/2021, corporate bonds possess the highest Sharpe ratio, followed by leveraged loans (i.e., the LLI100 index).

Next, we report annualized CAPM alphas in Panel C. These alphas adjust factor portfolio returns for their systematic exposure (beta) to the investable loan market (the sample index). For the HIGH portfolios, all alphas are positive, large (they range from 1.00 to 1.28% per year), and statistically significant. For LOW portfolios, the alphas are negative, range from −1.82 to −2.16%, and, again, are all highly statistically significant. In economic terms, when compared to the loan market excess return, the magnitude of these factor premiums is substantial. As a robustness check, in Table IA.2 in the online supplementary materials, we report alphas from alternative time series regressions of portfolio credit excess returns on the excess returns of the LLI100, the standard benchmark for active credit managers in the loan market. Results are similar: HIGH alphas range from 0.92 to 1.18% and LOW alphas from −1.70 to −2.07%. However, statistical significance is reduced slightly. Unsurprisingly, our customized index (the accessible loan "Market") has a negligible alpha (−0.018%, not significant) and a highly significant beta (0.69) with respect to the LLI100. We conclude that HIGH (LOW) factor portfolios generate superior (inferior) risk-adjusted returns, measuring risk either as total volatility (Panel A) or as a beta to the loan market (Panel C).

Finally, we view risk in a relative sense and look at the volatility of active returns, i.e., the tracking error. Active returns are defined as portfolio returns minus benchmark returns, using the customized market index as the relevant benchmark. Conceivably, factor portfolios could exhibit a relatively low absolute risk, but simultaneously become quite risky relative to the benchmark. The tracking errors in Panel B range from a maximum of 1.63% p.a. (LOW MOMENTUM) to a minimum of 0.89% p.a. (HIGH COMBI). These numbers are moderately low compared with the market's excess return volatility of 3.10% p.a. As a result, the information ratios of the HIGH portfolios are substantial, with values from 1.13 for MOMENTUM to 1.44 for COMBI. These pronounced information ratios suggest that our HIGH single-factor portfolios and the composite are particularly attractive to credit managers that are benchmarked to the market index.

We end this section with a short discussion of the composite factor (COMBI). In line with the absence of a marked correlation between our two investment style proxies (VAL_R and $MOM_{t\text{-}1,t}$), combining value and momentum factors into a single portfolio using a bottom-up approach generates substantial diversification benefits. Table 3 shows that HIGH COMBI outperforms the two single-factor portfolios. It has the lowest tracking error (0.89%), and the highest alpha (1.28%), Sharpe (1.47), and information ratios (1.44). With the benefit of hindsight, we could easily construct even more favorable composites. However, a composite approach that allocates equally to investment styles is not subject to overfitting the data and cherry-picking the results and represents a robust method for harvesting value and momentum premiums offered in the loan market.[19]

Portfolio Performance: 12-Months Holding Period. While the analysis in Section "Portfolio performance: One-month holding period" supports the case for systematic investing within the liquid corner of the secondary leveraged loan market, it is subject to various criticisms related to implementation. Could exposures to systematic investment styles generate positive excess of benchmark returns when faced with real-world constraints like a turnover-aware 12-months investment horizon? While we put much effort into identifying the actively traded segment of the corporate loan market, loans are bilateral contracts, not securities, that cannot be traded as frictionless and efficient as equities (Keßler and Mählmann, 2022). Hence, a 12-months holding period is a more realistic description of actual credit manager behavior than monthly rebalancing. We now turn to examine the potential for our systematic investment styles to identify attractive loans in the context of a 12-months investment horizon.

Factor portfolios (and the passive, "all market" index) are built each month and held for the subsequent 12 months. To construct a time series of monthly strategy returns, we apply the standard calendar-time method according to Jegadeesh and Titman (1993). That is, the return in month $t+1$ is calculated as the average of the portfolios constructed from month t-11 to t. Note that the market index is held for the same horizon (twelve months) as a factor portfolio to enable a fair comparison between the passive benchmark and active factor. Table 4 reports the results for the 12-months horizon. Several observations are particularly noteworthy.

As factor portfolios with one-month holding periods maximize the style exposure, some form of performance decay is almost inevitable for longer holding periods. In line with this expected lower discriminatory power of factors, across all styles, the performance statistics generally worsen for HIGH portfolios and improve for LOW portfolios. For example, the Sharpe ratio of HIGH VALUE drops from 1.35 to 1.17 (not significantly different anymore from the market Sharpe ratio of 1.06), the information ratio falls from 1.38 to 0.57, and the CAPM alpha from 1.00 to 0.66%. The HIGH MOMENTUM factor experiences even a performance crash when held constant for twelve months: the information ratio falls from 1.13 to 0.18, and the alpha from 1.28 to 0.34%. This suggests that the predictive ability of cross-sectional momentum for credit excess returns in the loan market does not extend to one year.

Table 4. Performance Statistics of Long-Only Equal-Weighted Factor Portfolios—12-Month Holding Period

		VALUE		MOMENTUM		COMBI	
	Market	LOW	HIGH	LOW	HIGH	LOW	HIGH
A. Return statistics							
Mean (bp)	357.56	282.57	430.90	362.35	387.91	308.84	408.88
Volatility (bp)	337.97	450.23	368.78	493.99	374.69	435.86	348.71
Sharpe ratio	1.06	0.63**	1.17	0.73*	1.04	0.71*	1.17
LW *p*-value	–	0.00	0.70	0.05	0.74	0.04	0.58
B. Outperformance statistics							
Outperformance (bp)	–	−74.98	73.35**	4.80	30.36	−48.72	51.33**
Tracking error (bp)	–	166.98	129.55	212.55	168.07	176.97	126.93
Information ratio	–	−0.45	0.57	0.02	0.18	−0.28	0.40
t-Statistic	–	−1.75	3.93	0.11	1.18	−1.65	3.37
C. CAPM statistics							
Alpha (bp)	–	−169.83**	65.53*	−127.65**	33.61	−118.27**	65.00**
t-Statistic	–	−3.01	2.00	−4.82	1.42	−4.58	2.99
Beta	–	1.27**	1.02**	1.37**	0.99**	1.19**	0.96**
t-Statistic	–	10.46	13.49	16.86	10.23	16.72	13.13

This table reports the performance statistics of our sample loans ("Market") and the value, momentum, and composite factors for U.S. leveraged loans. The sample period is from July 2010 to December 2015. Portfolios and the index are built each month and held for the subsequent twelve months. The standard calendar-time method according to Jegadeesh and Titman (1993) is used to calculate a time series of monthly strategy returns. That is, the return in month $t+1$ is calculated as the average of the portfolios (indices) formed from months t-11 to t. The portfolio construction is described in Table 3. Panel A reports the return statistics, and Panel B, the outperformance statistics. Panel C shows the CAPM alpha and beta from regressions of portfolio returns on market returns (the sample index). Mean, volatility, outperformance, tracking error, and alpha are annualized. Loan credit excess returns are approximated according to Equation (2) in the text. Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the accessible loan market (Panel A; test of Ledoit and Wolf 2008), (2) the outperformance is different from zero (Panel B; *t*-test), and (3) the alphas are different from zero (Panel C; *t*-test). The *t*-tests are calculated with Newey and West (1987) standard errors. * and ** denote statistical significance at the 5 and 1% levels, respectively.

Figure IA.3 in the online supplementary materials provides more detail on the holding period dependence of factor alphas. The figure depicts annualized alphas for factors held for K months ($K=1$, 3, 6, 9, 12). The momentum style is particularly attractive for up to three months, while its predictive ability falls sharply after six months. In contrast, the return forecasting power of the factor composite drops more evenly and at a lower rate. The relation between alpha and investment horizon is hump-shaped for value.

While we do observe a marked decrease in the risk-adjusted performance across all HIGH portfolios, the VALUE and COMBI styles still deliver mean active returns and alphas that are economically important (range between 0.51 and 0.73%) and statistically significant (at the 5% level or better). In contrast to the HIGH portfolios, the LOW factors react far less sensitive to an extension of the holding period. For example, the Sharpe ratios of 0.63 (value) and 0.73 (momentum) still fall significantly below the market's Sharpe ratio (1.06). In addition, the negative alphas (−1.70 and −1.28%) are substantial and statistically highly significant. Interestingly, and contrary to the HIGH portfolios, the LOW factors are more strongly exposed to the market with betas significantly exceeding one. As the average return of the market index with a one-year holding period is positive at 3.6% p.a. over the sample period, high betas imply that the mean active return is less negative than the CAPM alpha. Finally, because of the modest performance of HIGH MOMENTUM over twelve months, the equal-weighted composite does not beat a strategy that allocates only to the value theme.

At a minimum, these 12-months results reveal that an active factor strategy that avoids low momentum and value loans and over-weights high-value loans is particularly attractive even over longer holding periods.

Cross-Sectional Regressions. To further explore the statistical robustness and economic significance of our results about the return predictive ability (or pricing) of value and momentum characteristics in the cross-section of investable loans, we estimate Fama and MacBeth (1973) regressions of individual loan returns in this subsection. These tests are helpful to examine the relationship between investment styles and expected credit excess returns while simultaneously controlling for a range of other potentially priced loan characteristics like size or liquidity. Essentially, we run regressions at the loan level of the following form for each month t from July 2010 to December 2015:

$$r^i_{t,t+K} = \alpha_{t+K} + \beta_{t+K} MOM^i_{t-1,t} + \beta_{t+K} VAL\_R^i_t + \sum_{c=1}^{n} \beta^c_{t+K} X^i_{c,t} + \epsilon^i_{t+K}, \quad (4)$$

where $r^i_{t,t+K}$ is the (cumulative) credit excess return from month t to month $t+K$ on loan i. We set $K=1$, 3, 6, 9, and 12. $MOM^i_{t-1,t}$ is the momentum (difference in log average mid quotes between t-1 and t) of loan i in month t, and $VAL\_R^i_t$ denotes loan i's ratio of STM to VOLA, our value measure. $X^i_{c,t}$ is loan i's characteristic c in month t. Since we are primarily interested in whether our investment styles pick up the pricing of loan characteristics like size, liquidity, or popularity, we include as control variables: the log of the loan's current market value (LN_SIZE), the average quoted half-spread (QHS), and the number of (buy and sell) trades of CLOs.

After estimating variants of Equation (4) for each month, we calculate the time-series averages of the slope coefficients. To account for the overlap in cumulative returns for horizons longer than one month, t-statistics are based on Newey and West (1987) standard errors, allowing for serial correlation up to K lags. We report our results in Table 5. Columns labeled (1) show estimates from a benchmark specification that only includes the two investment styles.[20]

For both styles, we find a strong positive predictive relation for future returns which loses statistical significance not until the 1-year horizon. Especially VAL_R turns out to be an economically powerful forecaster of future returns even at longer horizons: a one standard deviation (1-*SD*) higher STM to VOLA ratio raises expected credit excess returns by 0.99 standard deviations over the following month, by 1.27 standard deviations over the following quarter, by 1.56 standard deviations over the next half-year, by 1.64 standard deviations over the next three quarters, and by 1.56 standard deviations over the next year. These are significant numbers since the standard deviation of half-year returns, for example, is 7.04%.[21] This suggests that the performance of the HIGH VALUE (LOW VALUE) portfolio could be substantially improved (worsened) by sorting loans into quintiles or even deciles, rather than terciles. Recall from Table 2 that the HIGH minus LOW spread in average VAL_R is just 128.05, slightly more than 10% of VAL_R's full sample standard deviation (1248.73, see Table 1, Panel D).

The predictive ability of MOM is much weaker in economic terms: the 1-*SD* effect for MOM is 0.12 return standard deviations over the next month, 0.16 standard deviations over the next quarter, 0.13 standard deviations over the next half-year, 0.07 standard deviations over the next three quarters, and 0.04 standard deviations over the next year. The fact that MOM's return forecasting power drops for longer horizons is consistent with our previous findings in Table 4 and Figure IA.3.

The specification in Columns (2) includes the three control variables. No one of the controls shows a statistically significant predictive relation for returns. More importantly, adding the controls further improves, not weakens, the predictive ability of the investment styles, almost all value and momentum coefficients and t-statistics increase between Columns (1) and (2). In sum, the Fama and MacBeth (1973) regressions provide strong evidence for value and momentum being priced characteristics in the cross-section of investable corporate loans.[22]

Robustness

In this section, we provide some additional results and robustness checks. We briefly discuss potential sources of the value premium in Section A of the online supplementary materials.

Adjustment for Multiple Testing.

Performance statistics of strategy backtests reported in academic and practitioner research frequently suffer from the issue of selection bias and data mining. In their search for apparently profitable trading strategies researchers are prone to try different strategy versions until they find one that eventually works and only report those results. In such situations, the use of a t-statistic of, e.g., 2.0 (i.e., testing against a significance level of 5%), which is appropriate in a single test framework, may not be the correct cutoff for statistical significance under a multiple testing approach. Harvey and Liu (2014, 2015) propose several methods by which a strategy Sharpe ratio (and its corresponding t-statistic and p-value) can be adjusted to appropriately reflect multiple testing.

Table 5. Fama and MacBeth (1973) Regressions of Loan Expected Returns on Loan Value, Momentum, and Other Characteristics

	Dependent Variable: Credit Excess Return $r^i_{t,t+K}$									
	$K=1$		$K=3$		$K=6$		$K=9$		$K=12$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
VAL_R	0.181**	0.185**	0.443**	0.474**	0.877**	0.881**	1.175*	1.161*	1.247	1.288
	(2.60)	(2.80)	(2.98)	(3.05)	(2.89)	(3.06)	(2.06)	(2.16)	(1.44)	(1.54)
MOM	0.141**	0.146**	0.354**	0.354**	0.465**	0.468**	0.314	0.354*	0.203	0.258
	(2.87)	(3.02)	(3.68)	(3.90)	(3.06)	(3.43)	(1.73)	(2.18)	(0.66)	(0.94)
LN_SIZE	–	−6.555	–	−15.906	–	−38.953	–	−57.212	–	−55.403
		(−1.90)		(−1.67)		(−1.84)		(−1.47)		(−1.12)
QHS	–	−0.011	–	−0.052	–	−0.192	–	0.218	–	0.493
		(−0.14)		(−0.23)		(−0.53)		(0.54)		(0.82)
No. trades	–	0.128	–	0.077	–	0.007	–	−0.345	–	−1.218
		(0.62)		(0.18)		(0.01)		(−0.34)		(−0.74)
Constant	23.906	116.112*	77.398*	300.454*	158.472*	702.414*	239.538**	1013.260	335.308**	1073.531
	(1.90)	(2.29)	(2.14)	(1.98)	(2.48)	(2.11)	(3.05)	(1.71)	(3.36)	(1.43)
N	16,567		16,226		14,981		13,756		12,462	
Avg. R^2	0.126	0.165	0.097	0.142	0.102	0.151	0.109	0.158	0.119	0.171

Monthly cross-sectional regressions of loan expected credit excess returns (in basis points) on value, momentum, and other loan characteristics are estimated for different return horizons K. $r^i_{t,t+K}$ is the (cumulative) credit excess return from month t to month $t+K$ on loan i. Our value and momentum measures are described in earlier tables. LN_SIZE is the natural logarithm of loan market value (outstanding notional times average bid quote), QHS denotes the monthly average quoted half-spread, and No. Trades sums buy and sell trades of CLOs in a loan month. The table reports the time series average slopes. t-Statistics are based on Newey and West (1987) standard errors, allowing for serial correlation up to K lags. The sample period is from July 2010 to December 2015. * and ** denote statistical significance at the 5 and 1% levels, respectively.

They arrive at a deflated Sharpe ratio that considers the effects of multiple comparisons.

Among the proposed methods, the Bonferroni adjustment is the most conservative one. It basically suggests that the correct *p*-value must be equal to the single-test *p*-value inflated by the number of (independent or dependent) tests performed. In our case, the number of strategy comparisons is rather low. We experimented with different volatility measures to scale STMs (our value proxy), which all gave similar results, and we tried four-momentum proxies (1-, 3-, 6-, and 9-months), and only the short-term (one month) version worked. Hence, any appropriate test number is likely <10. However, we provide robustness by setting the number of trails to 10, 20, and 50, respectively.

Table 6 reports Bonferroni adjusted Sharpe ratios, *t*-statistics, and *p*-values for the high VALUE, MOMENTUM, and COMBI factors, separately for a 1-month and a 12-months holding period. For comparison, Panel A replicates the results from Tables 3 and 4 derived under the standard single test assumption. The unadjusted *t*-statistics are all well above the traditional 2.0 threshold signaling statistical significance.

Panel B considers adjustments for the realistic scenario of ten tests. Not surprisingly, the performance statistics deteriorate across all strategies. In the case with a 12-months holding period, which is of most practical relevance, the Sharpe ratio haircuts amount to 32% (VALUE and COMBI), 39% (Market), and 41% (MOMENTUM), respectively. However, while the adjusted market Sharpe is always insignificant, the strategy Sharpe ratios are either all highly significant (with a 1-month holding period) or only marginally insignificant (*p*-value: 0.06 for VALUE and COMBI) with a 12-months rebalancing frequency. Furthermore, after the Bonferroni adjustment, the VALUE (and COMBI) Sharpe ratio exceeds the one of the market by at least 23%.

For illustration, Panels B and C in Table 6 look at adjustments for 20 and 50 trails, safely more than the number of comparisons we examined. While the market Sharpe is always insignificant, we notice that also with 50 tests, the strategy Sharpe ratios are mostly significant (with 1-month rebalancing) and outperform the market by a factor of two. In sum, the Bonferroni adjustment for multiple testing does not change our general conclusion that the value strategy is profitable, relative to a passive market investment, over longer holding periods as well.

Transaction Costs. Our analysis so far neglects transaction costs. While these costs can indeed be a major trading friction in the secondary loan market, we believe that a net-of-cost analysis only strengthens the case for systematic investing in loans. We highlight several results that support this claim.

First, because of our sample selection strategy that successfully isolates liquid loans, trading costs in our sample are rather low (for a private OTC market). Table 1 reveals a mean QHS of 35 bp (median: 19 bp). Realized round-trip trading costs experienced by the average CLO are even lower at about 20 bp. In addition, viewed relative to the annual mean (178 bp) and standard deviation (794 bp) of loan level credit excess returns, liquidity spreads are moderate.[23]

Second, sufficient liquidity is also available at the factor level. For example, Table 2 reveals that round-trip effective spreads realized by CLOs just average 18 bp for HIGH VALUE and 16 bp for HIGH COMBI. Recall from Table 4 that these two factors generate annual alphas of 66 and 65 bp, respectively, with 12-months rebalancing. Using the average effective spreads, we can ask what is the breakeven turnover that completely eats up those gross alphas? For the HIGH-VALUE factor, we find the breakeven turnover to be (66/18 =) 367%, and (65/16 =) 406% for HIGH COMBI. Note that these numbers exceed the maximum annual turnover of 100% for a 12-months rebalancing strategy by a wide margin.

We further stress that this analysis is rather conservative as it assumes that tracking the market comes at no cost. However, even a passive loan strategy cannot be implemented in a "buy-and-hold" fashion. Regular rebalancing is required to accommodate for contractual repayments or (unexpected) prepayments and refinancings due to loan calls. In addition, the market index invests in the identified subset of tradable loans, and this universe changes dynamically over time. Indeed, we find the average turnover of the index version with 12-months of rebalancing to be rather high at 57%. This turnover comes from loans that have been traded by CLOs and funds in a month *t* but not twelve months later.

As a final remark, Table 2 shows that ranking on investment styles implicitly sorts loans on liquidity: across all styles, HIGH portfolios are on average significantly more liquid (have lower quoted and effective half-spreads) than their LOW peers. This implies that a systematic strategy is more transaction cost efficient than any passive ("buy the market") approach.

Value-Weighted Portfolios. If the value and momentum premia identified above reflect in part

Table 6. Bonferroni Adjustment for Multiple Testing

	Market		VALUE		MOMENTUM		COMBI	
	1M	12M	1M	12M	1M	12M	1M	12M
A. Single test								
Sharpe ratio	1.11	1.06	1.35	1.17	1.44	1.04	1.47	1.17
t-Statistic	2.60	2.49	3.17	2.74	3.38	2.44	3.45	2.74
p-Value	0.01	0.01	0.00	0.01	0.00	0.02	0.00	0.01
B. 10 tests								
Adj. Sharpe ratio	0.72	0.65	0.99	0.80	1.10	0.61	1.10	0.80
Adj. *t*-statistic	1.70	1.51	2.33	1.88	2.58	1.44	2.58	1.88
Adj. *p*-value	0.09	0.13	0.02	0.06	0.01	0.15	0.01	0.06
C. 20 tests								
Adj. Sharpe ratio	0.57	0.48	0.88	0.66	0.99	0.44	0.99	0.66
Adj. *t*-statistic	1.34	1.13	2.05	1.55	2.33	1.04	2.33	1.55
Adj. *p*-value	0.18	0.26	0.04	0.12	0.02	0.30	0.02	0.12
D. 50 tests								
Adj. Sharpe ratio	0.32	0.19	0.70	0.44	0.84	0.14	0.84	0.44
Adj. *t*-statistic	0.76	0.45	1.65	1.04	1.96	0.32	1.96	1.04
Adj. *p*-value	0.45	0.65	0.10	0.30	0.05	0.75	0.05	0.30

This table reports results from adjusting Sharpe ratios and the corresponding *t*-statistics and *p*-values for multiple strategy comparisons. Adjustments are made according to the Bonferroni method outlined in Harvey and Liu (2014, 2015). Panel A shows the unadjusted results under the standard single test assumption. The performance of HIGH factors is examined with one-month (1M) and 12-months (12M) holding periods.

behavioral biases and/or market frictions, we would expect these premia to decrease among larger and highly-priced loans which are less likely exposed to such forces. To investigate this premise, we form market value-weighted (factor and index) portfolios and report their performance in online supplementary material Tables IA.4 and IA.5, structured like Tables 3 and 4.

In line with the idea that larger loans are more efficiently priced (and/or less risky), we found that value-weighted HIGH portfolios generally perform worse across most metrics than their equal-weighted peers. The opposite is true for value-weighted LOW factor portfolios. However, the differences between the two weighting schemes are not dramatic. For the 12-months investment horizon, which is of practical importance, the equal-weighted HIGH COMBI factor in Table 4 generates a Sharpe ratio of 1.17, an information ratio of 0.40, and a statistically significant alpha of 0.65%. The corresponding numbers for the value-weighted factor version in Table IA.5 are: 1.33 (Sharpe), 0.39 (information ratio), and 0.36% (alpha, significant at 1%).

More importantly, all our major findings from the equal-weighted analysis carry over to the value-weighted case: (i) a longer investment horizon impairs the predictive ability of all factor styles, (ii) the forecasting power of the momentum style deteriorates substantially after the first quarter, (iii) the LOW factor portfolios have a large systematic risk exposure (beta) which is reduced by the composite style, and (iv) adjusted for risk, low value and momentum loans significantly underperform the market and high-value loans significantly outperform the market even at a 12-months horizon.

Quote Staleness. As noted previously, the price return component of our credit excess returns is based on mid quotes, not traded prices. To some degree, the momentum effect identified in this paper might in part reflect stale and gradually updated quotes. A frequent econometric concern with respect to quotes is that standard empirical estimates of volatilities and correlations from quote-based returns are artificially low and fall short of comparable estimates from traded returns (see Geltner 1991; Getmansky, Lo, and Makarov 2004). Lower return volatilities and correlations (betas), in turn, might produce upwardly biased Sharpe ratios and CAPM alphas, and ultimately misleading inference. Because our focus is on factor portfolios, not individual loans, this concern is likely less relevant here. In addition, the interest return component in Equation (3) relies on traded prices, not quotes, further attenuating any econometric issues related to quotes. Finally, due to the loan preselection on liquidity, quote staleness should be less pronounced in our sample of actively traded and liquid loans.[24]

Nevertheless, to help mitigate any remaining concerns of potential staleness in quoted returns that may dampen measured correlations or volatilities, in unreported analyses we have repeated our CAPM regressions using two alternative approaches. First, while we still use monthly returns, we add two lags of the index returns on the right-hand side. This approach allows for different exposures of factor returns to contemporaneous and lagged index returns. Second, we use overlapping 3-month factor and index returns and explicitly account for potential serial dependence of regression errors when calculating standard errors. Our basic inferences remain unaffected by these alternative regression specifications.

Conclusion

Secondary markets for credit assets like corporate bonds and loans have evolved substantially over the past 20 years in terms of institutional investor participation, liquidity, trading volume, and transparency. We believe these developments have opened a new opportunity to apply systematic investing techniques to credit investing, allowing for significant diversification benefits within active credit strategies in addition to the potential for substantial performance improvements. In this paper, we take a systematic approach to credit investing with leveraged loans, a booming credit asset class with some unique characteristics.

We find strong evidence that well-known systematic investment styles, such as momentum, value, and a combination thereof are associated with future credit excess returns of leveraged loans. A monthly rebalanced, equal-weighted long-only (top-tercile) portfolio designed to maximize exposure to these systematic styles generates Sharpe ratios of 1.34 (value), 1.44 (momentum), and 1.47 (composite), respectively, significantly larger than the market's Sharpe ratio. In contrast, the corresponding bottom-tercile factor portfolios significantly underperform the market. The predictive ability of the investment styles for future returns weakens but remains significant (i) for market value-weighted factor portfolios, (ii) over longer, turnover-aware holding periods, (iii) in Fama and MacBeth (1973) cross-sectional regressions, and (iv) after considering realistic estimates of trading costs and accounting for possibly inflated performance and test statistics. In sum, the paper's evidence indicates that investors may be able to further enhance performance (relative to a passive allocation to the loan risk premium) by engaging in systematic active management of corporate loans.

Appendix A. Further Background on Credit Excess Returns

Derivation of the Equation to Calculate Credit Excess Returns (Equation 3 in the Text)

Under the assumption that there is no principal repayment between dates t-1 and t, the total return on a loan $R(L)$ with maturity date T at time t can be defined as

$$R(L) \;=\; \frac{V(Y(t),t)+I(t)}{V(Y(t-1),t-1)}-1, \qquad \text{(A1)}$$

where $Y(t)$ denotes the loan's yield at time t, $V(Y(t), t)$ is the value of a loan with yield $Y(t)$ at time t, and $I(t)$ is the interest paid on the loan between t-1 and t. A Taylor series expansion of $V()$ gives:

$$V(Y(t),\ t)=V(Y(t-1),t-1)\left[1+\frac{\partial V}{\partial Y}dY+\frac{\partial V}{\partial t}dt+\ldots\right], \qquad \text{(A2)}$$

where $\partial V/\partial Y = -$Modified Duration and dY is the change in yield for constant time-to-maturity (T-t). The term $\partial V/\partial t$ reflects the "pull-to-par" effect.

Explanation. The first part of the expression in square brackets measures the effect on the loan's present value of a change in the yield for a remaining time-to-maturity T-t. The second part captures the effect on the loan's value when the remaining maturity is reduced by one unit (i.e., the "pull-to-par" effect). Next, we make two additional assumptions: (i) no convexity (i.e., the relation between V and Y is linear), and (ii) the loan is bought in t-1 at par (i.e., $V(Y(t\text{-}1), t\text{-}1) = 1$). Because of assumption (i), all higher-order derivations of V with respect to Y are zero, except for the first one. From the second assumption, it follows that the "pull-to-par" effect is zero (i.e., $\frac{\partial V}{\partial t}=0$). Under these assumptions, Equation (A2) simplifies to:

$$V(Y(t),t)=1+(-\mathit{Modified\ Duration}\cdot dY), \qquad \text{(A3)}$$

Inserting (A3) into (A1) and taking into account that $V(Y(t\text{-}1), t\text{-}1) = 1$, yields:

$$R(L)=1+(-\mathit{Modified\ Duration}\cdot dY)-1+I(t). \qquad \text{(A4)}$$

The credit excess return (CER) equals the loan's total return purged from any term premium (i.e., compensation for risk-free interest rate duration risk). Hence, we must replace the yield Y with the credit spread

(STM), and the yield duration by the spread duration in Equation (A4).

$$CER_t = -Spread\ Duration \cdot \triangle STM_{t-1,t} + \frac{STM_{t-1}}{12}. \quad \text{(A5)}$$

If we assume that loan prices just reflect changes in credit spreads, not changes in risk-free base rates, the first part in Equation (A5) can be replaced by changes in loan prices. This yields the CER equation in the text:

$$CER_t = log(P_t) - log(P_{t-1}) + \frac{STM_{t-1}}{12}. \quad \text{(A6)}$$

Editor's Note

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Notes

1. CLO is the name of an asset-backed security set up to hold and manage pools of leveraged loans (almost exclusively term loans B, C, etc.), and to a lesser extent high-yield bonds. These investments are financed through the issuance of several debt and (one or two) equity tranches that have rights to the collateral and payment stream, in descending order. CLOs are issued by a special purpose vehicle/entity (SPV/SPE).

2. To enable a fair comparison between active factors and passive benchmark, we construct a customized investable market index that only includes loans that are accessible to an investor in the secondary market.

3. Due to the absence of a unique ID number, the loan level match across the four data sources is time-consuming and requires a significant amount of hand-matching. For example, loans are identified in DealScan by a "FacilityID", and by a completely different "lxid" in IHS Markit. A detailed description of how we approached the matching task can be obtained from the authors upon request.

4. Information (e.g., trade date and price) on CLO trades is collected from CLO trustee reports available in CLO-i and the trading behavior of loan participation funds (Lipper style code "LP") is inferred from monthly holding reports (i.e., 13F reports) of funds that file with the SEC. Fund trades are assumed to equal changes in loan par amounts between subsequent holding reports, adjusted for repayments, refinancings, and restructurings. Data source for fund holding reports is CRSP.

5. For the average loan in our sample in an average month with at least one CLO trade, we observe 3.9 CLO buys and 4.2 CLO sells (the median number is two, respectively).

6. Almost all loans in our sample are institutional term loans B that typically repay 1% of par annually over their life and the remaining notional at maturity. Therefore, at a monthly frequency, the principal repayment return should be of second-order importance. Supporting this claim, Beyhaghi and Ehsani (2017) report that the 0.38% average monthly total return for their loan series consists of 0.53% interest return, 0.01% principal repayment return, and -0.16% price return.

7. In sharp contrast to bonds, most loans are callable any time during their life. Because of this callability feature, prices of loans normally do not rise beyond par. Hence, the ability of the borrower of a loan to repay the principal prior to maturity places a cap on the investment's upside potential.

8. For example, with 1-month rebalancing (and equal weights), the month $t+1$ return $r^I_{t,t+1}$ on the index portfolio, formed in month t, is calculated as: $r^I_{t,t+1} = \frac{1}{N_t}\sum_{i=1}^{N_t} r^i_{t,t+1}$, where $r^i_{t,t+1}$ denotes the $t+1$ return of loan i. Note that the monthly set of investable loans, N_t, is dynamic. With a 12-months holding period, the month $t+1$ index return is the simple average of the month $t+1$ returns from the twelve index portfolios formed from month t-11 to t.

9. The S&P/LSTA Leveraged Loan 100 Index (LLI100) is a daily index for the U.S. market that consists of 100 loans (mostly term loans, both amortizing and institutional) and intends to mirror the market weighted performance of the largest institutional leveraged loans to reflect the most-liquid side of the market. The index is published by S&P's Leveraged Commentary & Data (LCD) unit, dates back to 2002, and the pricing source are average bid quotes from the LSTA/LPC mark-to-market service.

10. To calculate credit excess returns for the LLI100, we obtain aggregate (equal weighted) time series of secondary market STMs and average bid quotes of index constituents from LCD. Because these time series exclude the prices and STMs of defaulted loans, our estimated CERs for the LLI100 likely overestimate the actual returns accessible by investors.

11. Besides the fact that value and momentum are probably the two most common styles across asset classes, our choice of these two styles is motivated by two additional considerations: data availability and overfitting. Our data is probably not rich enough to allow for a rigorous assessment of other styles like *betting-against-beta* or *quality*. Recall that we do not have much information on loan issuer characteristics. Second, we wanted to avoid the impression that we cherry-picked the results by fishing for the styles that worked best in-sample.

12. As robustness check, we alternatively calculate price returns from log changes in monthly average bid quotes, or from month-end changes in mid or bid quotes. All results remain similar.

13. In robustness checks, we employ alternative volatility proxies. We estimate historic volatility from the previous 60 days of raw price returns, requiring at least 20 daily returns, and we utilize a market model to calculate idiosyncratic volatility. We use price returns of the LLI100 as the market index. Because the results for the different volatility measures are similar, we stick with the simpler measure (absolute price return) which is also less data demanding.

14. The value and momentum measures VAL_R and $MOM_{t-1,t}$ are weakly negatively correlated ($\rho = -0.0012$, p-value $=$ 0.88) in the full sample.

15. We focus on equal weighted portfolios in the body of the paper. The "Value-Weighted Portfolios" section and online supplementary material Tables IA.4 and IA.5 provide performance statistics for value weighted portfolios, where each loan is weighted by its market value in month t. The market value of a loan is the product of the outstanding balance and market price (monthly average bid quote), ignoring any accrued income. The value weighted portfolio tests are meant to further highlight the economic significance of style investing in loans and to help mitigate concerns that the equal weighted results are entirely driven by the smallest loans in the sample.

16. We thank Michael Wolf for sharing his R code to perform the test. We choose the optimal block size according to Algorithm 3.1 in the Ledoit and Wolf (2008) paper and we set the number of bootstrap resamples to 1000.

17. Their defining and differentiating characteristics (first lien, amortizing notional, floating coupon) likely reduce the volatility of loans compared with corporate bonds with similar maturity and rating. Consistent with such a risk-reducing effect, Beyhaghi and Ehsani (2017) found that returns on loans are less volatile than the returns on speculative grade bonds. This might partly explain our relatively high Sharpe ratios (for comparison, Houweling and van Zundert 2017, report long-only value and momentum factor Sharpe ratios for high yield bonds of below 0.5). Alternatively, quote staleness might artificially depress credit excess return volatilities of loans. We discuss this concern in Section "Quote staleness"

18. The five asset classes are represented by the same total return indexes used in the construction of the efficient frontiers in Figure 1.

19. To illustrate the risk-return tradeoff between the two factor portfolios, Figure IA.2 in the online supplementary materials displays the (in-sample) efficient frontier from a top-down approach that mixes the factor portfolios, and not the loan characteristics that are used to construct the portfolios in the first place. This allows for a better understanding of how factor combinations outperform each factor individually. For example, the maximum Sharpe portfolio has a 97% weight on the momentum style.

20. Note that our dataset is free of survivorship bias: whenever a loan exits the sample (because of calls, repayments, or defaults), the price returns are based on the loan's final quotes. As we require just two consecutive months of daily price quotes for each loan that passes the liquidity filter, the number of observations in Table 5 drops for longer return horizons.

21. The other return standard deviations are: 2.30% (1-month), 4.40% (3-months), 9.38% (9-months), and 10.80% (1-year).

22. Table IA.3 in the online supplementary materials reports results from Fama and MacBeth regressions with only the controls as predictors, leaving out the investment style proxies. Coefficients for LN_SIZE, QHS, and the number of CLO trades are generally insignificant. This strengthens the conclusion that momentum and value do not pick up a predictive ability of these other loan characteristics.

23. As further comparison numbers, Keßler and Mählmann (2022) construct a liquidity index out of a sub-sample of IHS Markit loans assumed to be widely traded (see their Table 1, Panel B). This index depicts lower quoted liquidity (higher spreads) than our trade sample, with mean and median half-spreads of 62 bp and 49 bp, respectively. In addition, S&P's Leveraged Loan Commentary & Data (LCD) unit reports average dealer bid and ask quotes for all 15 constituents in their U.S. "flow-name composite". This composite is a regularly updated sampling of loans widely traded in the U.S. secondary market, per LCD's discussion with dealers and investors in the market. Over the period from May 2002 to July 2020, the 15 most liquid loans possess half-spreads of about 25 bp on average (median: 21 bp), somewhat less than what we found for our sample.

24. Even if loan strategy Sharpe ratios are not comparable to traded return-based Sharpe ratios from other asset classes (e.g., high-yield bonds), any within loan class comparison would only be affected by a systematic association between styles and staleness. To the degree that HIGH portfolios are more liquid, and, hence, their returns are less stale, the staleness argument works against our finding that HIGH portfolios outperform LOW ones.

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