The Cross-Section of Expected Returns in the Secondary Corporate Loan Market

Internet Appendix

1 Bivariate portfolio sorts

We examine whether the spread in average returns between momentum portfolios can be explained by other loan characteristics. We perform dependent and independent bivariate portfolio sorts on momentum while controlling for each of the aforementioned characteristics separately. For dependent sorts, we first sort loans into five portfolios based on a characteristic. Then, within each quintile portfolio, five additional portfolios are formed based on momentum, resulting in 5×5 portfolios. The returns of each momentum quintile are averaged across the five "characteristic" quintiles to produce portfolios that are similar in terms of one characteristic but different in terms of momentum. We then form a zero-cost portfolio that buys loans in the top momentum quintiles and shorts loans in the bottom momentum quintiles. For independent sorts, we create quintile portfolios by a characteristic and momentum separately, and then create 25 portfolios at the intersection of characteristic and momentum quintile portfolios. The rest of the procedure is the same as in dependent sorts. Table 1 reports average returns and alphas with their corresponding t-statistics that are Newey and West (1987) adjusted. For all cases, we test the null that alphas of five $5-1$ portfolios are jointly equal to zero by utilizing GRS F-test. Alpha is the intercept of a 2-factor model with term and default factors.

Table 1 demonstrates that STM and price do not fully explain the momentum effect. After controlling for STM and price, the monthly premia of the strategy range from 51 to 69 basis points with t-stats between 3.29 and 3.90. The third control variable is rating. We report individual portfolio returns within three rating groups. The momentum effect is concentrated in the worstrated loans. The effect is positive but weaker among better-rated loans. These results are consistent with findings of Avramov et al. (2007), who show that equity momentum is generated by high credit risk firms, and Jostova et al. (2013), who document the absence of momentum strategies in investment grade bonds. The row labeled "Controlling for rating" confirms that momentum cannot be explained by rating. Like corporate bonds and unlike equities, loan momentum is primarily driven by winners. Consider the two-way sort on rating. For all rating terciles, momentum winners contribute to more than twothirds of the momentum profits compared to loser loans with similar rating.

Ang et al. (2006) and Ang et al. (2009) show that idiosyncratic volatility is negatively related to stock in the United States and 23 developed countries, suggesting a broad return-generating factor. The momentum effect may be explained by a possible volatility-expected return relationship documented in other asset classes. The row labeled "Controlling for volatility" reports the results when we repeat the double-sort exercise to control for volatility. The premia and the corresponding t-stats remain large and statistically significant.

Many asset pricing anomalies exist in small and illiquid securities that face high constraints and transaction costs. If the momentum effect only exists in small loans, then the strategy might be impracticable. To investigate a possible size explanation, we report the results for all 15 individual size/momentum portfolios as well as the results regarding the average of the five momentum portfolios across size terciles. Within all size terciles, the top momentum portfolio has a dramatically higher return than the other quintiles. Hence, size is not driving the momentum effect.

Between 25 and 30% of observations have only one average dealer quote. That is, one bid and one ask is posted for the trading date. If the momentum effect is limited to loans with few quotes, we may be picking a systematic measurement error instead of a pricing characteristic. We perform the bivariate sort procedure by repeating the double-way sort to control for the effect of the number of quotes. Results in Table 1 show that the effect is largest among loans with many quotes. In fact, excluding loans with fewer quotes further increases the size and the statistical significance of the effect. Since investing in more liquid assets is more convenient for investors, we next examine whether transaction costs, measured by the bid-ask spread, can explain the momentum effect. In order for the bid-ask spread to be a possible explanation, high momentum loans must have high bid-ask spreads to carry a liquidity premium. Controlling for the bid-ask spread does little to explain the momentum effect, and the premia and alphas remain large and statistically significant at the 1% level. Hence, transaction costs do not explain the momentum effect either. Controlling for characteristics does not improve the performance of the factor model as the GRS F-stat rejects the null at better than 1% level in all cases. The results with value-weighted portfolios are similar to those reported here but are ommited to save space.

Table 1: Excess returns of portfolios sorted on loan characteristic and momentum.
This table reports the average monthly excess returns of quintile portfolios and a zero-cost portfolio on loan characteristics and momentum. Momentum is the loan cumulative return over the last three months. The table reports the return on each momentum portfolio after controlling for one characteristic in dependent and independent bivariate settings. At the end of each month, we sort loans into quintile portfolios based on a characteristic. For dependent sorts, within each quintile, we further sort loans into five additional portfolios based on momentum. We track the next month return of each of the 25 individual portfolios. We then average the returns of each momentum quintile over each of the five characteristic quintiles. The column "$5-1$" refers to the average of the difference in excess returns between the 5 high and the 5 low momentum portfolios. For independent sorts, we independetly sort loans into momentum and characteristic quintiles. Twenty-five portfolios are created at the intersection of the two sorting criteria. The rest of the procedure is the same as dependent bivariate sorts. F_{GRS} reports F-values for a test of the null that the alphas of five $5-1$ momentum portfolios with respect to the two factor model with term and default risks are jointly equal to zero. For rating, size, and quotes, we report the returns of an additional 15 individual portfolios sorted on characteristic (terciles) and momentum (quintiles). Robust Newey and West (1987) t-statistics with 12 lags are reported in parantheses.

	Ranking on momentum													
	Dependent sorts							Independent sorts						
	1	2	3	4	5	$5-1$	F_{GRS}	1	2	3	4	5	$5-1$	F_{GRS}
Cont. for STM	-0.16	0.11	0.15	0.27	0.38	0.54	6.17	-0.26	0.09	0.15	0.15	0.40	0.69	10.36
	(-0.65)	(0.59)	(0.71)	(1.40)	(1.74)	(3.43)		(-0.88)	(0.48)	(0.82)	(0.79)	(1.72)	(3.29)	
Cont. for price	-0.14	0.09	0.18	0.25	0.37	0.51	8.90	-0.30	0.08	0.15	0.18	0.39	0.69	9.82
	(-0.58)	(0.49)	(0.92)	(1.15)	(1.80)	(3.90)		(-1.03)	(0.47)	(0.78)	(0.88)	(1.76)	(3.49)	
Rating terciles														
Low	-0.15	-0.03	0.21	0.34	0.79	0.94		-0.08	0.09	0.20	0.34	0.60	0.68	
	(-0.37)	(-0.14)	(0.73)	(1.22)	(2.02)	(3.59)		(-0.20)	(0.38)	(0.90)	(1.35)	(1.75)	(3.04)	
2	0.09	0.21	0.16	0.24	0.29	0.20		0.06	0.25	0.23	0.28	0.39	0.34	
	(0.42)	(1.55)	(1.65)	(1.52)	(1.42)	(1.51)		(0.25)	(1.50)	(2.01)	(1.67)	(1.46)	(1.85)	
High	-0.03	0.13	0.18	0.18	0.24	0.26		-0.04	0.06	0.15	0.27	0.36	0.41	
	(-0.15)	(1.73)	(3.06)	(2.44)	(1.98)	(1.75)		(0.22)	(0.39)	(1.78)	(1.97)	(2.20)	(1.46)	
Cont. for rating	-0.02	0.05	0.17	0.27	0.41	0.44	7.56	-0.04	0.11	0.17	0.27	0.43	0.47	5.84
	(-0.08)	(0.27)	(1.24)	(1.57)	(1.96)	(3.01)		(-0.14)	(0.64)	(1.19)	(1.56)	(1.89)	(2.89)	
Cont. for volatility	-0.14	0.01	0.17	0.28	0.41	0.55	7.29	-0.21	0.01	0.20	0.21	0.40	0.61	11.35
	(-0.52)	(0.04)	(1.02)	(1.53)	(1.67)	(3.67)		(-0.65)	(0.05)	(1.42)	(1.13)	(1.42)	(2.76)	
Size terciles														
Small	-0.38	0.02	0.19	0.26	0.64	1.02		-0.46	-0.05	0.13	0.31	0.65	1.11	
	(-1.12)	(0.12)	(1.36)	(1.54)	(1.98)	(4.16)		(-1.34)	(-0.23)	(0.80)	(1.45)	(2.13)	(4.29)	
2	-0.27	0.14	0.11	0.28	0.60	0.87		-0.29	0.09	0.14	0.27	0.62	0.91	
	(-0.98)	(0.88)	(0.69)	(1.40)	(2.16)	(4.14)		(-1.03)	(0.52)	(0.97)	(1.54)	(2.15)	(4.16)	
Large	-0.33	-0.01	0.19	0.30	0.50	0.83		-0.30	0.07	0.22	0.28	0.55	0.84	
	(-1.01)	(-0.04)	(1.34)	(1.55)	(1.60)	(2.98)		(-0.87)	(0.45)	(1.47)	(1.56)	(1.74)	(2.97)	
Cont. for size	-0.31	0.04	0.16	0.30	0.58	0.90	8.08	-0.36	0.04	0.17	0.28	0.60	0.96	8.31
	(-1.04)	(0.23)	(1.07)	(1.59)	(1.97)	(3.97)		(-1.15)	(0.23)	(1.20)	(1.54)	(2.01)	(3.82)	
Quote terciles														
Quotes=1	-0.24	0.04	0.15	0.26	0.54	0.78		-0.40	-0.01	0.16	0.23	0.61	1.01	
	(-0.99)	(0.31)	(1.18)	(2.08)	(1.94)	(4.28)		(-1.37)	(-0.07)	(1.22)	(1.38)	(2.00)	(3.95)	
Quotes=2,3	-0.22	0.05	0.12	0.31	0.55	0.77		-0.21	0.03	0.12	0.30	0.51	0.72	
	(-0.70)	(0.25)	(0.67)	(1.39)	(1.88)	(3.74)		(-0.69)	(0.16)	(0.78)	(1.49)	(1.70)	(3.75)	
Quotes>=4	-0.46	0.04	0.16	0.33	0.63	1.09		-0.37	0.11	0.24	0.36	0.76	1.00	
	(-1.23)	(0.19)	(0.90)	(1.22)	(2.03)	(3.25)		(-0.90)	(0.70)	(1.38)	(1.75)	(2.38)	(3.57)	
Cont. for quotes	-0.24	0.01	0.16	0.28	0.59	0.84	9.25	-0.28	0.05	0.18	0.25	0.61	0.89	10.58
	(-0.83)	(0.06)	(1.04)	(1.40)	(1.98)	(4.00)		(-0.89)	(0.28)	(1.25)	(1.31)	(1.97)	(4.08)	
Cont. for BA	-0.14	0.02	0.13	0.29	0.46	0.60	7.84	-0.16	0.04	0.19	0.23	0.44	0.60	8.12
	(-0.57)	(0.10)	(0.75)	(1.44)	(1.86)	(3.85)		(-0.61)	(0.21)	(1.19)	(1.17)	(1.88)	(3.39)	

2 An analysis of loan momentum

In this section, we search for alternative explanations and examine the consistency of the momentum effect by performing a battery of robustness tests.[1]

2.1 Momentum in out-of-sample loans

To evaluate the robustness of the momentum effect in loans and address data-snooping concerns, we test the strategy in another subsample of the LSTA database. This subsample consists of term loans that were initially omitted due to missing data on the payment schedule. Neglecting payments biases average returns negatively because loans usually trade below par and pre-payments mostly generate positive returns. The absence of principal payments may positively bias the momentum premium if loans in the low momentum decile trade at a higher discount relative to those in the high momentum decile. This is indeed the case. Loser loans are usually cheaper than winners. We attempt to address this problem by setting rules for frequency, date, and repayment amount to create an artificial time-series of outstanding balance and payments. We assume all loans pre-pay the principal in equal amounts (0.25% of the remaining balance) on quarterly anniversaries of the facility's beginning date, with the remaining balance paid on expiration. Obviously, the "quarterly schedule" assumption does not hold for all firms, but it is a reasonable assumption given that the majority of issues in this market make quarterly payments. Returns of loans in some months will now include noise, which may be diversified in portfolios, or even if not, it is highly unlikely for this random noise to systematically bias the premium of the strategy. The noise regarding the "principal payment date" assumption can be removed by extending the return estimation window to three months. Most loans make one payment every quarter, hence, in addition to monthly returns, we compute three-month rolling returns. This procedure obviates the need for the exact payment date but introduces moving average effects due to the overlapping information in the series. To control for these effects, we adjust standard errors using twelve Newey-West lags.

There are 59,368 monthly observations in this sample, of which 77.80% belong to private issuers and the remaining to public issuers. The average monthly return of all loans in this sample

[1]Additional robustness tests not reported in this section include a one-month implemenation lag, and different formation and holding periods ranging from one to twelve months.

is 30 bps, lower than the 39 bps for the original sample. We perform tests on this sample and two subsamples distinguished by the listing status of the issuers. Table 2 reports expected one- and three-month excess returns for equal-weighted decile portfolios.[2] Both one- and three-month premia of the momentum strategy are very close across private and public firms and the effect is highly significant in all subsamples. The positive and significant premia in this table provide confidence that our results hold out-of-sample.

2.2 Momentum returns in recessions and during equity crashes

In Panel (a) of Table 3, we test the robustness of the momentum effect in different subperiods. One subsample consists of months classified as "Recession", as determined by NBER (28 months), and the remaining are classified as "Expansion". For all subperiods, regardless of the macroeconomy condition, the high portfolio outperforms the low portfolio significantly. Consistent with our previous finding in time-series tests, the momentum premium in bad times is much higher than in good times. Not only do winner loans outperform losers in economy expansions, the relative performace hedge investors against economy downturns.

Loan momentum returns are subject to momentum crashes. For example, the loan market return is -29.32% during 2008, and the return on the momentum strategy is 36.59%. Market then rebounds in the following six months with a total return of 34.06%, while momentum profits are -10.99%. During "worst equity momentum crashes" as defined by Daniel and Moskowitz (2013), loan momentum profits are between 0.57% and 0.90% lower compared to other times. This pattern in loan momentum returns is similar to what Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2013) document for equity momentum.

[2] Computing market values using the aritificial remaining balance of loans will add extra noise to estimations. In unreported results, we find that results are qualitatively similar if returns are weighted using artifical capitalizations.

Table 2: Out-of-sample momentum tests.
This table reports average one- and three-month expected excess returns of decile and a zero-cost portfolio sorted on momentum in a sample of loans with missing payment schedules that was ommited from previous tests. We split this sample according to the loan issuer's listing status. We repeat the sorting exercise for loans issued by private and public companies separately and report the average one- and three-month expected excess returns with Newey and West (1987) adjusted t-statistics.

Alternative sample										
Monthly return										
1	2	3	4	5	6	7	8	9	10	10 − 1
-0.31	-0.06	-0.03	0.11	0.16	0.17	0.26	0.40	0.54*	1.10***	1.41***
(-0.89)	(-0.27)	(-0.14)	(0.55)	(0.69)	(0.83)	(1.13)	(1.61)	(1.74)	(3.06)	(6.40)
Three-month return										
1	2	3	4	5	6	7	8	9	10	10 − 1
1.08	0.32	0.42	0.60	0.76	0.78	0.88	0.96	1.18	3.13***	2.04***
(1.19)	(0.50)	(0.77)	(1.06)	(1.26)	(1.33)	(1.35)	(1.34)	(1.35)	(3.09)	(3.10)
Private firms										
Monthly return										
1	2	3	4	5	6	7	8	9	10	10 − 1
-0.26	-0.02	-0.02	0.07	0.21	0.19	0.30	0.40*	0.50	1.16***	1.42***
(-0.78)	(-0.08)	(-0.12)	(0.37)	(1.44)	(1.02)	(1.31)	(1.71)	(1.56)	(2.98)	(5.13)
Three-month return										
1	2	3	4	5	6	7	8	9	10	10 − 1
1.10	0.33	0.57	0.62	0.76	0.77	0.93	1.04	1.27	3.18***	2.08**
(1.05)	(0.51)	(1.00)	(1.08)	(1.25)	(1.31)	(1.47)	(1.46)	(1.53)	(3.18)	(2.36)
Public firms										
Monthly return										
1	2	3	4	5	6	7	8	9	10	10 − 1
-0.40	-0.08	0.00	0.13	0.18	0.17	0.23	0.52**	0.59**	1.02***	1.42***
(-0.97)	(-0.34)	(-0.02)	(0.63)	(0.78)	(0.84)	(1.02)	(2.00)	(2.08)	(2.88)	(5.09)
Three-month return										
1	2	3	4	5	6	7	8	9	10	10 − 1
1.02	0.29	0.57	0.66	0.74	0.79	0.92	0.98	1.31	3.13***	2.12**
(0.98)	(0.43)	(1.00)	(1.18)	(1.19)	(1.36)	(1.43)	(1.37)	(1.59)	(3.16)	(2.47)

Table 3: An analysis of momentum.
Panel (a) reports the average monthly returns in two subperiods for portfolios sorted on momentum. Expansions and recessions correspond to economic cycles as determined by the National Bureau of Economic Research (NBER). In panel (b), every month, we sort loans into decile portfolios and then compute interest and price return over the subsequent month separately. We report the average expected interest and price returns for each decile portfolio. The first row of panel (c) reports the ratio of non-stale quotes to total observations for each momentum decile. A non-stale monthly quote is one that both bid and ask quotes change at least once over that month. We divide the sample into two subsamples based on the loan-month stale status. We repeat the sorting exercise for each sample, and report average returns of portfolios sorted on momentum. α is the intercept of the regression with returns of the zero-cost portfolio as the dependent and the term and default factors as independent variables. *, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

(a) Momentum returns in subperiods

	Equal weighted							Value weighted						
	1	2	3	4	5	$5-1$	α	1	2	3	4	5	$5-1$	α
Expansion	-0.13	0.18***	0.22***	0.30***	0.57***	0.70***	0.67***	-0.06	0.16***	0.19***	0.26***	0.52***	0.58***	0.56***
($n=96$)	(-1.02)	(4.38)	(6.58)	(6.29)	(5.64)	(6.03)	(5.65)	(-0.48)	(3.65)	(4.89)	(5.19)	(4.25)	(5.01)	(4.73)
Recession	-1.08	-0.42	-0.03	0.18	0.66	1.74**	1.73***	-1.11	-0.24	0.23	0.32	0.75	1.86**	1.79***
($n=28$)	(-1.06)	(-0.62)	(-0.06)	(0.33)	(1.15)	(2.72)	(4.50)	(-1.03)	(-0.35)	(0.38)	(0.64)	(1.38)	(2.38)	(3.34)

(b) Decomposing the momentum effect

	1	2	3	4	5	6	7	8	9	10	$10-1$
$E[R_I]$	0.63***	0.52***	0.51***	0.51***	0.51***	0.52***	0.54***	0.55***	0.56***	0.63***	-0.01
	(10.47)	(11.06)	(12.21)	(12.46)	(12.71)	(12.88)	(13.15)	(12.84)	(12.36)	(11.64)	(-0.20)
$E[R_P]$	-0.83*	-0.54*	-0.25	-0.21	-0.12	-0.11	-0.07	-0.00	0.17	0.30	1.13***
	(-1.96)	(-1.79)	(-1.44)	(-1.07)	(-0.83)	(-0.73)	(-0.42)	(-0.01)	(0.63)	(0.88)	(3.85)

(c) Effect of stale quotes

1	2	3	4	5	6	7	8	9	10	10−1	α
Percentage of non-state quotes											
78.41	69.70	63.68	60.28	58.65	58.71	60.26	61.90	66.76	74.38		
Non-stale quotes, $n=38,258$											
-0.47	-0.34	-0.08	0.04	0.10	0.15	0.26	0.37	0.44	0.83**	1.30***	1.21***
(-1.03)	(-1.16)	(-0.40)	(0.23)	(0.57)	(0.87)	(1.47)	(1.45)	(1.47)	(2.25)	(3.76)	(3.58)
Stale quotes, $n=20,350$											
-0.17	0.02	0.04	0.10	0.08	0.01	0.05	0.29***	0.31**	0.29	0.46**	0.42**
(-0.87)	(0.16)	(0.30)	(1.08)	(0.69)	(0.04)	(0.28)	(3.91)	(2.08)	(1.35)	(2.61)	(2.22)

2.3 Decomposing returns

The returns on loans consist of both price and interest returns. We examine the contribution of each part to the momentum premium separately. Panel (b) shows that the momentum effect is only caused by the price return, as the difference between the interest return of the down and up portfolios is negligible. This finding is consistent with our initial results, where momentum was mostly orthogonal to STM and loan price, because if momentum is associated with interest return, then facilities with a high momentum should have higher STMs.

The facilities in portfolios 1 and 10 have the highest interest returns. Obviously, these loans have higher STM, as STM and interest earning are highly correlated. If so, then why do some of the high-STM loans produce the highest expected returns, while others produce the lowest? Apparently, agents invest in some high-STM loans hoping to earn higher interest returns but tend to overpay for their positions. As a result, although these loans do earn higher interest in the future, their market price underperformance more than offsets their marginal interest advantage. Hence, the strategy of investing in high yield facilities can be substantially improved if combined with the momentum effect.

The average price return over our sample period is negative due to the two financial downturns of the 2000s. This phenomenon, combined with the momentum effect being only through the price channel, raises an important question regarding the robustness of the momentum effect in all states of the economy. Highlighting our results in panel (a), we confirm that this is indeed the case. The momentum effect persists in different economic conditions.

2.4 Is momentum driven by stale prices?

The aggregate loan index exhibits positive autocorrelation up to the third lag. In addition, the momentum effect mostly stems from the one- to three-month ranking period. An important question to be answered is whether the momentum effect is driven by stale prices. To test this possibility, we consider a monthly quote non-stale if both bid and ask quotes change more than once over that month. With this definition, 65% of monthly returns fall into the non-stale category. The first row of panel (c) shows that 78.41% of loans in the first momentum decile are non-stale, higher than all other deciles. Also, 74.38% of loans in the winner portfolio are among the non-stale quote, therefore the tenth decile ranks second. That the majority of loans in extreme portfolios are non-stale suggests that loans in extreme portfolios, which drive the momentum effect, are probably priced more accurately. In fact, this can be related to the bivariate sort results of Table 1 where the momentum effect was strongest among loans with the most dealer quotes, because when several dealers post quotes on a loan, there is a higher chance that the price adjusts more frequently to news.

To formally test the impact of stale prices on momentum premium, we divide the sample into two based on loan's stale/non-stale status and repeat the sorting exercise. The momentum effect primarily stems from non-stale quotes with a monthly spread of 130 basis points.

[Table 3 here]

2.5 Stock momentum and loan expected returns

Is loan momentum related to equity momentum or other firm-specific characteristics? To test cross-market spillovers from equities to loans, we merge the sample of loans issued by public firms with Center for Research in Securities Prices (CRSP) database and obtain stock prices, shares outstanding, volume, and returns. For cross-sectional tests, firms must also have data on other variables such as book-value of equity for the fiscal year ending at the prior year. The intersection of CRSP and COMPUSTAT tilts this sample towards bigger companies. The most inclusive sample in this section is the intersect of companies with available observations on stock momentum, loan momentum, and loan expected returns. This sample has 28,266 loan-month observations. The average market capitalization of the firms in this sample ($2.48 bil) is close to that of the CRSP universe ($2.26 bil) over the same period.

We assign loans to decile portfolios in ascending order based on their prior returns at the end of every month. For each month and each portfolio, we also compute the average equity returns of the issuing firm at portfolio formation. We do not double count the stock-specific characteristic for a company that has more than one loan in a portfolio, but if loans of one firm are assigned to different portfolios, the characteristic of that company is represented more than once. We then compute the average time-series for loan and stock momentums over the sample period to evaluate how stock momentum characteristics vary across loan momentum deciles. Two measures of equity past returns (momentum) are considered. The first measure is consistent with the loan momentum formation period, defined by stock cumulative return over the past three month. The second measure is the standard measure of equity momentum computed by the stock cumulative return from month $t-12$ to $t-1$.

Panel (a) of Table 4 reports the results. The first row shows that ranking on loan momentum produces a monotonic pattern in stock momentum. Stocks whose loans underperform are among the losers. In fact, although loan momentum has a spread of 13.17% between extreme deciles, the spread of stock momentum between extreme deciles sorted on loan momentum is even higher at 31.84%. The observed correlation is not surprising because loans and stocks are claims on the same underlying asset. Hence, new information about the value of the underlying assets should affect both loans and stocks in a similar manner, except in the case of firm-specific events associated with agency problems such as a change in leverage, a change in dividend policy, or stock buybacks that potentially may affect the wealth of loanholders and shareholders asymmetrically, causing the correlation between stock and loan momentum to become negative. Loan momentum is also positively related to the standard definition of stock momentum. As in previous results, expected returns increase monotonically with portfolio ranking but the $10-1$ premium of 89 (83) bps is weaker in this subsample.

In panel (b), we assign loans to decile portfolios in ascending order based on their stock momentum. Interestingly, trading loans using stock momentum generates higher profits of 125 basis points per month. The last row of panel (b) shows that the percentage of loans that appear in both stock and loan momentum-sorted portfolios is highest for extreme portfolios but close to 10% of sorting on random variables for other deciles. Although loan and stock momentums are related, the overlap between the composition of portfolios sorted on each variable is not large, suggesting that each variable may contain specific information.

We analyze the loan-stock momentum interaction by repeating the bivariate sort procedure. The $5-1$ premiums of loan momentum strategy is positive across all stock momentum quintiles but only significant in the first quintile (panel c). However, the average of all $5-1$ returns remains significant in most cases. Consistent with the high correlation between loan and stock momentums, controlling for stock momentum substantially reduces the GRS F-value for the null of zero alphas for five $5-1$ portfolios. The F-value was always above 5 in previous tests, yet after controlling for stock momentum, the test does not reject the null of jointly zero alphas in all cases. It is also noteworthy that loan momentum is generally weaker in this sample: the benchmark premium is 72 (60) basis points for equal- (value-) weighted portfolios, compared to 94 (87) basis points for the original sample with loans issued by both public and private firms. Therefore, a part of the weaker loan momentum premium can be attributed to the sample. The last row of panel (c) shows that controlling for equity momentum reduces the $5-1$ premium between 16 and 29 basis points or between 26% and 40% of the loan momentum benchmark premium.

The next panel examines the effect of stock momentum on loan returns after adjusting for loan momentum. Stock momentum predicts loan returns across all loan momentum-sorted quintiles. Loan momentum explains between 18% to 33% of the stock momentum effect. The GRS F-stats of five $5-1$ stock momentum portfolios are substantially larger than those of panel (c). Overall, these findings suggest that in the cross-section of loans with public equity, stock momentum might be a stronger predictor of expected loan returns than loan momentum. However, the loan momentum effect is still economically and (mostly) statistically significant.

We run monthly cross-sectional regressions of loan expected returns on loan momentum, stock momentum, and other stock characteristics to test for the contribution of stock loan momentums to loan expected returns simultaneously (panel e). There is an unavoidable issue of implementing tests on samples with different observations due to data availability for each characteristic and stock. The stock characteristics considered are market beta, size (Banz (1981)), book-to-market (Fama and French (1992); Fama and French (1993)), two measures of momentum (Jegadeesh and Titman (1993)), co-skewness (Harvey and Siddique (2000)), cokurtosis, illiquidity (Amihud (2002)), turnover (Datar et al. (1998)), volatility (Zhang (2006)), skewness, and kurtosis.[3] The results suggests that among all stock specific-characteristics, it is only the three-month formation stock momentum that predicts loan returns. Coefficients of column (4) imply that a one-standard-deviation increase in stock (loan) momentum leads to 34 (39) basis points higher loan returns next month, revealing the economic importance of both variables in predicting future returns. In terms

[3]A brief description of each stock characteristic is provided in the appendix.

of model fit, loan momentum performs better with average adjusted R^2 of 11% compared to 4% for stock momentum.

In panel (f), we test if stock and bond momentum factors of Carhart (1997) and Jostova et al. (2013) can explain the time-series of loan momentum profits. The dependent variables are the excess return on loan portfolios sorted on loan momentum. The coefficient for the equity momentum factor is not statistically significant. The coefficient for the bond momentum factor is always negative and statistically significant. This suggests that all loan momentum portfolios, including winner loans, behave like loser bonds. But loser loans behave more like loser bonds relative to winner loans, resulting the zero-investment portfolio to load positively on the bond momentum factor. Although the spread between portfolios 10 and 1 is smaller compared to previous models, decile portfolio intercepts are all positive, and the GRS F-value is the highest of all time-series tests. Putting the results in Table 4 together, there are significant spillover effects from stock momentum to loan returns in the cross-section, yet a considerable portion of loan momentum profits is loan specific. On the other hand, loan momentum is correlated with bond momentum in time-series but not with stock momentum.

Table 4: Equity momentum, loan momentum, and loan returns.
We examine the effects of loan and stock momentums on expected loan returns in a subsection of loans issued by public firms. A firm is public if it has stock return data in CRSP. L-Mom and S-Mom are loan and stock momentums, respectively. We include two measures of stock momentum. The first measure is consistent with loan momentum formation period, defined by the cumulative stock return over the period $t-2$ to t. The second measure is stock's cumulative return over the period $t-12$ to $t-1$. The analysis is performed at the loan level, hence the stock momentum is identical across loans issued by the same company. Panel (a) reports loan momentum, loan expected returns, and stock momentum charateristics when loans are sorted on loan momentum. Panel (b) reports loan portfolio characteristics and expected excess returns for an investor that uses stock momentum to trade loans. We also report the percentage overlap between the components of portfolios sorted on loan momentum (panel a) and portfolios sorted on stock momentum (panel b). In panel (c), for dependent sorts, we first sort loans based on the issuer's stock momentum into quintiles portfolios. We then sort loans in each quintiles portfolio into five more portfolios based on loan momentum. Within each stock momentum quintile, we report returns and alphas of a zero-cost portfolio that buys loans in the high loan momentum quintile (portfolio 5) and shorts loans in the low momentum quintile (portfolio 1). The final row of panel (c) reports the average return of $5-1$ portfolios as well as the GRS F-stat regarding the joint significance of $5-1$ portfolios. For independent sorts, we create 25 portfolios at the intersection of 5 independently sorted portfolios on loan and stock momentum. The rest of the procedure is the same as in dependent sorts. In panel (d), we repeat the procedure of panel (c) when loans are ranked on stock momentum to examine the effect of stock momentum on loan returns after controlling for loan momentum. Panel (e) runs monthly cross-sectional regressions of loan expected excess returns (in percentage) on loan momentum, stock momentum and other stock characteristics. Panel (f) reports the results for time-series regressions of loan momentum return on stock and bond momentum factors. The sample period is from September-1999 to December-2009. *, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 15: Equity momentum, loan momentum, and loan returns. (continued)

	1	2	3	4	5	6	7	8	9	10	$10-1$	α
(a) Sorting on loan momentum												
L-Mom	-4.75	-0.55	0.33	0.81	1.19	1.55	1.96	2.59	3.76	8.42		
S-Mom$_{(t-2,t)}$	-12.55	-5.02	-0.83	1.24	1.82	3.70	3.97	5.07	8.41	19.29		
S-Mom$_{(t-12,t-1)}$	-19.51	-3.61	5.01	9.81	11.22	14.97	14.85	16.36	19.54	8.89		
$E[R_{EW}]$	-0.24	-0.13	0.03	0.08	0.09	0.21*	0.19	0.30*	0.44*	0.65*	0.89***	0.89***
	(-0.65)	(-0.57)	(0.20)	(0.55)	(0.74)	(1.76)	(1.27)	(1.70)	(1.75)	(1.85)	(3.10)	(3.12)
$E[R_{VW}]$	-0.30	-0.11	0.13	0.07	0.13	0.22*	0.21	0.25*	0.33	0.50	0.80**	0.83**
	(-0.78)	(-0.52)	(1.09)	(0.49)	(1.14)	(1.93)	(1.29)	(1.72)	(1.38)	(1.36)	(2.47)	(2.37)
(b) Sorting on stock momentum												
S-Mom$_{(t-2,t)}$	-39.99	-22.28	-14.02	-7.93	-2.63	2.62	8.10	15.01	26.18	63.11		
L-Mom	-0.59	0.60	1.03	1.24	1.41	1.52	1.56	1.96	2.39	4.05		
S-Mom$_{(t-12,t-1)}$	-17.35	-3.34	1.09	7.04	7.65	9.71	11.82	17.04	17.78	25.59		
$E[R_{EW}]$	-0.53	-0.13	0.02	0.14	0.20	0.19	0.29**	0.41**	0.34**	0.72**	1.25***	1.24***
	(-1.40)	(-0.59)	(0.07)	(0.85)	(1.20)	(1.24)	(2.00)	(2.20)	(2.16)	(2.58)	(3.37)	(3.50)
$E[R_{VW}]$	-0.61	-0.12	-0.07	0.09	0.19	0.19	0.23*	0.38**	0.34*	0.64***	1.25***	1.27***
	(-1.61)	(-0.53)	(-0.24)	(0.61)	(1.30)	(1.31)	(1.76)	(2.01)	(1.70)	(2.72)	(3.26)	(3.38)
Portfolio overlap	28%	14%	11%	12%	11%	11%	11%	11%	13%	25%		

(c) Bivariate sorts: Ranking on loan momentum

	Equal weighted						Value weighted					
	Dependent			Independent			Dependent			Independent		
	$5-1$	α	F_{GRS}	$5-1$	α	F_{GRS}	$5-1$	α	F_{GRS}	$5-1$	α	F_{GRS}
S-Mom quintiles												
Low	0.89**	0.83**		0.98***	1.01**		1.00*	0.95*		0.71**	0.72*	
	(2.33)	(2.23)		(2.70)	(2.37)		(1.93)	(1.89)		(2.00)	(1.79)	
2	0.51**	0.54*		0.49*	0.52		0.47	0.48		0.48	0.50	
	(2.21)	(1.87)		(1.95)	(1.65)		(1.38)	(1.21)		(1.22)	(1.09)	
3	0.18	0.22		0.26	0.33		0.16	0.17		0.23	0.30	
	(1.42)	(1.16)		(1.08)	(1.04)		(0.90)	(0.77)		(0.98)	(1.00)	
4	0.19	0.25		0.10	0.26		0.31	0.31		0.27*	0.26	
	(1.22)	(1.17)		(0.61)	(1.12)		(1.64)	(1.60)		(1.75)	(1.54)	
High	0.40	0.40		0.33	0.30		0.21	0.21		0.03	-0.01	
	(1.61)	(1.45)		(1.10)	(0.99)		(0.77)	(0.69)		(0.13)	(-0.03)	
	Benchmark 5−1 premium = 0.72 (t=3.04)						Benchmark 5−1 premium = 0.60 (t=2.28)					
Cont. for S-Mom	0.43**	0.45*	2.58	0.54**	0.59*	3.63	0.43**	0.42*	2.03	0.44*	0.47	1.78
	(2.57)	(1.94)		(2.10)	(1.97)		(2.16)	(1.73)		(1.70)	(1.61)	

(d) Bivariate sorts: Ranking on stock momentum

	Equal weighted						Value weighted					
	Dependent			Independent			Dependent			Independent		
	$5-1$	α	F_{GRS}	$5-1$	α	F_{GRS}	$5-1$	α	F_{GRS}	$5-1$	α	F_{GRS}
L-Mom quintiles												
Low	1.66***	1.54***		1.24***	1.23***		1.77***	1.64**		1.36***	1.34***	
	(2.91)	(2.78)		(3.14)	(3.10)		(2.79)	(2.54)		(3.09)	(2.97)	
2	0.51**	0.52**		0.67**	0.64**		0.36**	0.36**		0.59**	0.54**	
	(2.34)	(2.27)		(2.32)	(2.27)		(2.20)	(2.16)		(2.27)	(2.19)	
3	0.35**	0.32**		0.46**	0.46**		0.32**	0.31**		0.45**	0.45**	
	(2.11)	(2.29)		(2.19)	(2.18)		(2.27)	(2.22)		(2.33)	(2.29)	
4	0.29**	0.31**		0.37*	0.39*		0.17**	0.17**		0.23**	0.22**	
	(2.58)	(2.41)		(1.77)	(1.77)		(2.40)	(2.24)		(2.56)	(2.31)	
High	0.73***	0.70***		0.50*	0.43*		0.73***	0.71***		0.58*	0.52*	
	(2.78)	(2.75)		(1.81)	(1.66)		(2.81)	(2.89)		(1.79)	(1.77)	
	Benchmark 5−1 premium = 0.86 (t=3.41)						Benchmark 5−1 premium = 0.81 (t=3.30)					
Cont. for L-Mom	0.71***	0.68***	10.31	0.58***	0.56***	12.70	0.67***	0.64***	8.98	0.60***	0.57***	8.77
	(3.28)	(3.40)		(3.13)	(3.54)		(3.25)	(3.30)		(3.15)	(3.38)	

Table 15: Equity momentum, loan momentum, and loan returns. (continued)

(e) Fama and MacBeth regressions of expected loan returns on loan momentum, stock momentum and stock characteristics.

Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L-Mom	7.50***			5.75***	4.48***	4.39***	4.41***	4.33***	4.11***
	(3.92)			(3.10)	(3.20)	(3.08)	(3.25)	(3.15)	(3.04)
S-Mom$_{(t-2,t)}$		1.00***		0.90***	0.67***	0.68***	0.68***	0.64***	0.69***
		(3.44)		(3.28)	(4.08)	(4.05)	(3.97)	(3.82)	(3.81)
S-Mom$_{(t-12,t-1)}$			0.07						
			(0.38)						
Beta					0.05	0.05	0.08	0.04	0.09
					(0.53)	(0.64)	(0.93)	(0.52)	(1.22)
BM					0.01	0.01	0.01	0.01	0.01
					(0.59)	(0.37)	(0.86)	(0.41)	(0.33)
Size					0.02	0.02	0.01	0.02	0.01
					(0.62)	(0.53)	(0.42)	(0.57)	(0.35)
Illiq						-0.02			0.05
						(-0.23)			(0.83)
Turn						-0.16			-0.14
						(-1.23)			(-0.95)
Vol							-0.28		-0.28
							(-1.06)		(-1.10)
Skew							-0.00		-0.00
							(-0.12)		(-0.29)
Kurt							0.00		0.00
							(0.91)		(0.88)
CoSkew								0.00	0.00
								(0.93)	(0.09)
CoKurt								0.00	0.00
								(1.05)	(1.36)
Constant	0.05	0.24*	0.09	0.15	-0.27	-0.20	-0.02	-0.26	0.02
	(0.35)	(1.67)	(0.69)	(1.12)	(-0.50)	(-0.36)	(-0.06)	(-0.44)	(0.04)
n	28,266	28,266	27,204	28,266	22,877	22,877	22,877	20,585	20,585
Ave. adj. R^2	0.11	0.04	0.03	0.13	0.17	0.20	0.20	0.20	0.26

(f) Time-series regression with stock and bond momentum factors: $r_{i,t} - r_{f,t} = \alpha_i + \beta_S(WML_S) + \beta_B(WML_B) + \epsilon_{i,t}$

Equal weighted								Value weighted							
Decile	α	t-stat	β_S	t-stat	β_B	t-stat	R^2	Decile	α	t-stat	β_S	t-stat	β_B	t-stat	R^2
1	0.15	(0.42)	-0.06	(-2.06)	-0.67	(-4.18)	0.29	1	0.32	(0.84)	-0.04	(-1.00)	-0.94	(-4.80)	0.39
2	0.23	(1.59)	0.01	(0.55)	-0.58	(-3.31)	0.32	2	0.30	(2.07)	0.02	(0.85)	-0.58	(-3.19)	0.31
3	0.34	(3.17)	0.00	(0.10)	-0.37	(-2.66)	0.20	3	0.39	(3.65)	-0.01	(-0.82)	-0.39	(-2.89)	0.26
4	0.38	(4.83)	-0.00	(-0.13)	-0.37	(-2.93)	0.28	4	0.40	(4.94)	-0.02	(-0.82)	-0.36	(-2.94)	0.31
5	0.41	(3.84)	-0.01	(-0.77)	-0.31	(-3.19)	0.27	5	0.45	(3.26)	-0.02	(-0.83)	-0.34	(-3.02)	0.27
6	0.44	(3.71)	-0.01	(-0.99)	-0.31	(-3.32)	0.31	6	0.50	(3.45)	-0.02	(-1.02)	-0.30	(-3.33)	0.26
7	0.46	(3.40)	-0.01	(-1.36)	-0.26	(-3.11)	0.26	7	0.46	(3.52)	-0.02	(-1.16)	-0.24	(-3.01)	0.24
8	0.62	(3.21)	-0.03	(-1.39)	-0.35	(-3.96)	0.36	8	0.61	(3.20)	-0.03	(-1.77)	-0.34	(-4.08)	0.40
9	0.81	(2.91)	-0.03	(-0.96)	-0.36	(-4.20)	0.36	9	0.73	(2.63)	-0.04	(-1.41)	-0.30	(-3.99)	0.30
10	1.05	(3.27)	-0.04	(-1.42)	-0.41	(-4.32)	0.32	10	1.05	(3.21)	-0.06	(-1.97)	-0.43	(-4.64)	0.35
			GRS F-test: 15.54								GRS F-test: 8.57				
10 − 1	0.90	(2.84)	0.02	(0.71)	0.26	(1.84)	0.07	10 − 1	0.73	(1.95)	-0.02	(-0.57)	0.50	(2.67)	0.17

3 Definitions for stock control variables

This section explains the equity related control variables.

Beta: For each stock and at the end of each month, we estimate Beta using one year of daily returns: $r_s - r_f = \alpha_s + \beta r_{mktrf} + \epsilon_s$, where r_s is the daily stock return over the last year, r_f is the risk-free rate, and r_{mktrf} is the excess return on the market portfolio. r_f and r_{mktrf} are drawn from Kenneth French website. β is the regression coefficient on r_{mktrf}.

Momentum - Jegadeesh and Titman (1993): The cumulative stock return over the 11-month period from $t-12$ to $t-1$. We skip the previous month to remove the short-term reversal effect of Jegadeesh (1990).

Book-to-market - Fama and French (1992) and Fama and French (1993): We define Book-to-market by the ratio of book-value of equity as of the end of previous fiscal year to market capitalization. Book-value is updated every year at the end of June.

Size - Banz (1981): Market capitalization is the stock price times the number of shares outstanding as of the end of the month. Since capitalization is highly skewed, we use the natural logarithm of market capitalization in regression analyses.

Illiquidity - Amihud (2002): The daily absolute value of stock return divided by total daily dollar volume in millions, averaged over a month. $Illiq = \frac{\sum_{t=1}^{n} \frac{|r_t|}{volume}}{n}$. Prior to 2004, we divide the volume by two for NASDAQ firms to adjust for overstated inter-dealer trading.

Turnover - Datar et al. (1998): Total number of shares traded over a month divided by total shares outstanding.

Volatility - Zhang (2006): Defined by the standard deviation of daily stock returns over the most recent 200 days.

Skewness and Kurtosis: Third and fourth order centralized moments of stock returns, respectively. Both moments are calculated at the end of each month using the most recent 200 days of return data.

Co-Skewness and Co-Kurtosis: Following Harvey and Siddique (2000), co-skewness is the slope coefficient on the squared market return term in a two-factor regression with market and squared excess market returns as the independent variables: $r_s - r_f = \alpha_s + \beta_m r_{mktrf} + \beta_{CS} r^2_{mktrf}$. Co-kurtosis is the slope coefficient on the cubic term in a three-factor regression with market, squared market, and cubic market returns as the independent variables: $r_s - r_f = \alpha_s + \beta_m r_{mktrf} + \beta_{CS} r^2_{mktrf} + \beta_{CK} r^3_{mktrf}$. Coefficients are estimated using three years worth of monthly data.

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