Bank Loan Undrawn Spreads and the Predictability of Stock Returns *

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Abstract

We document a novel empirical finding that the private information contained in bank loans' undrawn spreads can predict firms' future stock returns across a range of time horizons. This effect is separate from previously documented asset pricing puzzles related to idiosyncratic volatility, analyst forecast dispersion, and credit risk. Further investigations show that our private information measure could predict firms' future cash flow uncertainty and cash flow level, which may potentially explain the negative relation between this measure and future stock returns. Notably, a long-short strategy based on this finding can generate a significant alpha of around 7% per year.

JEL Classifications: G12, G20.

Keywords: Return Predictability, Asset Pricing, Bank Loan, Private Information, Operating Performance Predictability

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1. Introduction

It is widely believed that banks have an important advantage in resolving information asymmetries due to their ability to access private information and incorporate that information in loan contracting (Scholes et al., 1976; Campbel and Kracaw, 1980; Fama, 1985; Armstrong et al., 2010). For example, Carrizosa and Ryan (2017) identify loan covenants as a tool for banks to acquire private information since some covenants require borrowing firms to periodically disclose non-public accounting information to lenders. They also show that these private-information-related covenants increase the timeliness and frequency of loan amendments, indicating banks actively make use of the privileged information obtained from the disclosure. While a number of studies have examined market response to banks' loan decisions (James, 1987; Lummer and McConnell, 1989; Billett et al., 1995; Gande and Saunders, 2012), the question of whether banks' loan-related decisions have predictive power for future stock returns of borrowing firms has been underexplored. Since banks possess private information about the future prospects of borrowers, their lending decisions might have asset pricing implications. This paper aims to examine whether the information contained in bank loan spreads is useful to predict firms' stock returns.

In this paper, we focus on lines of credit, or revolving credit facilities, which are one of the most common types of corporate loan contracts. Roberts and Sufi (2009) and Sufi (2009) report that more than 80% of U.S. firms have a line of credit and that credit lines consist of a non-trivial portion of book assets.[1] Credit lines are utilized even among all-equity firms and the access to public debt does not cease the usage of revolving credit facilities (Sufi, 2009). The credit line is priced through both an ''All-in-Undrawn spread'' and an ''All-in-Drawn spread''. The All-in-Undrawn (AIU) spread is the annual cost charged by the bank on the portion of a loan that is not drawn down, while the All-in-Drawn spread is the annual cost

[1] According to Sufi (2009), in his sample between 1996 and 2003, the average of this proportion is 16%.

the borrower pays for the portion of a loan that has been drawn down.[2]

Berg et al. (2016) suggest that credit lines contain option-like features. By offering lines of credit, the bank is essentially writing an option to the firm in that the firm can draw down the credit whenever necessary. In this context, the price of the option is the AIU spread, and the underlying asset is the firm's creditworthiness. As discussed below, the option feature of credit lines provides clear asset pricing implications for the private information incorporated in its AIU spread. Hence, we concentrate on the All-in-Undrawn spread of credit lines.

What would a high AIU spread imply? Relatedly, what does the private information in the AIU spread really capture? We propose two hypotheses. The first is that a higher AIU spread implies that the firm is assessed *ex ante* by the bank to have higher subsequent cash flow volatility (i.e., higher cash flow uncertainty). Consistent with the standard option pricing theory (Black and Scholes, 1973), Berg et al. (2016) find that AIU spread increases with the realized volatility of borrower's equity returns and the volatility of borrower's profitability. This indicates that the volatility of borrower's cash flow is an important determinant for AIU spread and leads us to expect that the spreads would contain information on borrowers' future cash flow volatility. Moreover, prior studies show empirically (Huang, 2009) and theoretically (Bhamra and Shim, 2017) that higher cash flow volatility is associated with lower stock returns. Therefore, we conjecture that the private information contained in the AIU spread would have predictive power for future stock returns. We denote this hypothesis as the *uncertainty risk hypothesis*.

Our second hypothesis is that the AIU spread is higher for firms that are assessed *ex ante* by the bank to entail higher distress risk. Due to the drawn down option feature, credit lines can be viewed as a protection to the firm against distress risk. Specifically, the firm has the

[2] As indicated in Bord and Santos (2014), although Dealscan uses the terminology "All-in-Undrawn spread", when referring to the cost firms pay on undrawn commitments, it is a fee containing both the commitment fee, which is charged on unused loan commitments, and the annual fee, which is charged on the entire committed amount regardless of usage. It should be noted that credit lines contain either commitment fees or facility fees but not both. Thus, "All-in-Undrawn spread" is not a spread *per se* since the fees are not markups over measures of interest rates such as LIBOR. Incidentally, the Dealscan "All-in-Drawn spread" is indeed a spread standardized to be measured over LIBOR in the Dealscan database.

right to call on the credit line if it is in distress and needs additional funding, although the firm would not necessarily need to do so if it is not distressed. Hence, the option embedded in credit lines is more valuable for firms with worse operating performance. Consistent with this argument, Berg et al. (2016) show that a borrower is more likely to draw down a credit line if it experiences larger deterioration in profitability after the loan initiation. It is reasonable for us to conjecture that the information contained in the loan spread may capture borrower's future cash flow level. More specifically, we suspect that, firms that banks assess to entail a high level of *ex ante* distress risk, as reflected in the AIU spread, would have a lower *ex post* level of cash flow. Evidence from existing studies suggests a negative link between distress risk and subsequent equity returns.[3] Therefore, we postulate that private information contained in the AIU spread would predict subsequent equity returns. We denote this hypothesis as the *distress risk hypothesis*.[4]

To test these hypotheses, we rely on the data from the Thomson Reuters Dealscan database. The sample consists of 23705 credit line contracts from January 1994 to December 2016. Since loan spreads have been shown to be affected by various publicly-known factors (Strahan, 1999; Graham et al., 2008; Ross, 2010), it is not proper to use AIU spread itself as a proxy for banks' assessment based on their private information. To extract banks' private information, we adopt a similar methodology as in Agarwal and Hauswald (2010) and run a regression of AIU spread on a set of publicly-known determinants of loan spreads, yielding a residual which we denote as All-in-Undrawn-Residual (AIUR).[5]

We begin our empirical analysis by investigating the univariate relation between firm's AIUR and its future stock returns. In the baseline case, we form portfolios based on firms'

[3] Campbell et al. (2008) find that stocks of distressed firms have much higher market beta yet offer returns that are very low, too low to be reconciled within a rational framework. Also see among others, Chava and Purnanandam (2011), Djankov et al. (2007), Dichev (1998), Gao et al. (2017), Griffin and Lemmon (2002), and Hackbarth et al. (2015).

[4] We would like to emphasize that these two hypotheses are not mutually-exclusive.

[5] In order to construct a clean measure of the bank's private information, Agarwal and Hauswald (2010) orthogonalize *Proprietary Score* with two publicly available indicators of borrowers' credit quality, *Experian's Commercial Intelliscore (XCI)* and the owner's personal *National Risk Model score*, and use the residual from the regression to proxy for banks' subjective credit assessment.

AIUR in the past 9 months, where the AIUR is computed from 5-year rolling-window regressions. We find that high AIUR firms earn lower returns than low AIUR firms over 3- to 15-month horizons. And the economic significance is large: a long-short strategy can generate an alpha of 7% per annum, which is comparable to the momentum strategy. The results are robust to alternative ways to calculate abnormal returns, various portfolio formation periods, and different methods to construct the residual. We then run multivariate regressions. The results from Fama-Macbeth regressions and panel regressions indicate that AIUR can indeed predict the cross-section of firm stock returns over a range of horizons. Moreover, this effect cannot be absorbed by existing well-known determinants of expected returns.

If, as we argue, AIUR represents banks' private information, we expect that the predictive power of AIUR on future stock returns would depend on firms' information environment. With analyst coverage, analyst forecast error, and institutional ownership as proxies for information asymmetry, we find that our results are stronger for firms suffering from worse information environment. In particular, double-sorting tests show that the outperformance of low AIUR firms is mainly concentrated among firms with low analyst coverage, high analyst forecast error, and low institutional ownership. The evidence that AIUR is more informative for stock returns of firms with greater information asymmetry supports the private-information argument.

To better understand the negative AIUR-return relation documented above, we proceed by exploring what banks' private information in loan spreads really captures. First, we document that firms with higher AIUR have higher *ex post* cash flow volatility. To this end, we construct two measures of cash flow volatility. One is the standard deviation of quarterly operating cash flow over the next two years, and the other is the dispersion of the analysts' one-year-ahead forecast of future firm cash flow, specifically, cash per share, times the shares outstanding and scaled by the book value of total assets, with the analysts' opinion evaluated at two years in the future. We include the second measure since it is a forward-looking assessment of firm cash flow uncertainty that is not yet realized.[6] The results based on both measures confirm the conjecture that AIUR captures banks' private information on borrower's future cash flow volatility in the sense that higher AIUR implies firms are *ex ante* assessed by banks to have higher cash flow volatility. Second, we show that firms with higher AIUR have poorer subsequent operating performance which is measured by industry-adjusted firm cash flow and industry-adjusted return on assets (ROA). These findings are consistent with the hypothesis that AIUR contains information on borrower's cash flow level in the sense that higher AIUR indicates higher *ex ante* distress risk assessed by the bank.[7]

This paper makes contributions in several aspects. First, it adds to the literature on the informational advantage of banks. A large body of research has documented that banks could gain access to private information about their borrowers during initial loan negotiations as well as over the process of maintaining the loan contracts.[8] In this paper, we further confirm the existence of banks' information advantages by showing that the information contained in loan spreads is useful in predicting firms' future performance. This evidence complements the study by Demiroglu and James (2010) who find that the choice of loan covenant thresholds conveys information about the bank's expectations on the riskiness and future prospects of a borrower, including investment, leverage and performance.

More importantly, to the best of our knowledge, this paper is the first one to document the predictability of stock returns based on the information contained in the bank loan undrawn

[6] One can draw an analogy of these two measures with two similar volatility measures of stocks, namely: the historical volatility and option implied volatility of stocks. The former is a backward-looking measure, calculated *ex post*, based on actually realized historical data; the later is a forward-looking measure based on market participants's expectation of future return variation, and these two measures do not necessarily coincide with each other (Bollerslev et al., 2009).

[7] Unfortunately, Dealscan does not contain data on whether the credit line is actually drawn or not. Presumably, actual utilization of credit lines happens more frequently in firms encountering cash flow (liquidity) problems. Chodorow-Reich and Falato (2017) have used the Shared National Credit (SNC) Program data set which does contain information on the draw down of the unused portion of the credit line. However, the SNC data set can only be accessed by Federal Reserve employees upon internal approval.

[8] See, among others, Best and Zhang (1993), Gande and Saunders (2012), James (1987), Lummer and McConnell (1989), Parlour and Plantin (2008), and Plumlee et al. (2015).

spreads. Despite the wide-spread consensus that banks possess private information, the evidence on whether the information in loan market can be used to predict equity returns of borrowing firms is limited. The recent research by Addoum and Murfin (2018) documents that the value-relevant non-public information reflected in publicly posted loan prices significantly predicts borrowers' stock returns in the subsequent month. Our paper differs from their work because we focus on the private information contained in the undrawn spreads of credit lines at initiation rather than loan pricing information in the secondary market. Addoum and Murfin (2018) suggest that loan market and equity market in the United States are not integrated as well as what has been believed to be. In this regard, the findings in our study echo their conclusion.

Last but not least, our paper contributes to the literature on empirical asset pricing. First, our paper provides a new piece of empirical evidence that is tangentially related to the literature of "low beta anomaly".[9] Indeed, we find that high AIUR firms earn low *ex-post* equity returns, despite the fact that they have higher market betas. Here, we wish to emphasize our finding is not just a rediscovery of the "low beta anomaly" as we specifically use information contained in bank loans without resorting to any beta calculation in relation to the equity market. Second, our findings are related to but distinctively different from the "distress risk puzzle". The notable differences are as follows. For one thing, we do not utilize any Merton-type distress risk or bankruptcy risk model in our baseline analysis but instead base our analysis on bank loans' AIU spreads. For another, and more importantly, AIUR is not simply a measure of distress risk due to the option like feature of the credit line, as previously discussed in the context of the *uncertainty risk hypothesis*.[10] Finally, we

[9] Both Baker et al. (2011) and Frazzini and Pedersen (2014) find that high beta assets deliver lower expected returns than low beta assets. This is contrary to the positive risk and return trade-off paradigm (Sharpe, 1964). There is a large literature on the beta anomaly. See among others, Baker and Wurgler (2015) Hong and Sraer (2016), and Bali et al. (2017).

[10] As an extension, to disentangle our findings from the "distress risk anomaly" literature and to focus on the uncertainty risk channel alone, in Section 3.5 we also find that our results remain robust after explicitly controlling for proxies for distress, namely expected default probabilities, although doing so would result in a sizeable reduction in sample size.

document a trading strategy that works in the 3- to 15-month horizon with a sizable alpha. Often, trading strategies generate abnormal returns (alphas) from short-selling overpriced stocks (Avramov et al., 2009; Stambaugh et al., 2012). This is not the case in our results. The profits in our strategy come from the long leg of the long-short portfolio.

The rest of the paper proceeds as follows. Section 2 describes data and the construction of the AIUR measure. Section 3 presents our empirical results. Specifically, we document the relation between AIUR and future stock returns using univariate sorts as well as regression analysis, investigate the role of information environment, provide evidence on the predictive power of AIUR on firms' operating performance, and demonstrate the robustness of our results. We conclude this study with Section 4.

2. Data and Measures

2.1. Data

We obtain loan data from Dealscan, a database provided by Loan Pricing Corporation. The database contains comprehensive information on loan pricing and contract details for commercial loans made to companies in the U.S. as well as in other countries. In Dealscan, loans are recorded as facilities that could be packaged into deals. Each deal, consisting of one facility or multiple facilities initiated at the same time, has a single borrower and may have one or more lenders due to loan syndication.

Our sample period spans from January 1994 and ends in December 2016. We focus on the revolving loans (revolving credit lines) of U.S. corporations. With the initial sample from Dealscan, we first merge it with the Compustat database for borrowers' accounting information.[11] And firms are then matched to the Center for Research in Security Prices (CRSP) database for stock data with the linking file from CRSP/Compustat Merged (CCM) database. Figure 1 depicts the number and dollar amount (in billions) of new revolving credit facilities issued in each month. These facilities are issued by 3,566 unique firms over our sample period for which we are able to calculate valid AIUR measures following the procedure to be described in Section 2.2. As expected, there are more facilities in the month that is a end-of-quarter month, i.e., there are more facilities in the month of March, June, September and December relative to the adjacent month and once every three-month there is a notable increase in the number as well as in the dollar amount of facilities, as shown in Figure 1. We further collect information about analyst coverage and analyst earnings forecast from Institutional Brokers Estimate System (I/B/E/S) database. Additionally, our data on institutional holdings come from the Thomson Reuters institutional holding database (form 13F).

[Insert Figure 1 Here]

2.2. The AIUR Measure

As noted earlier, the AIU spread is related to bank's private information but is also mechanically related to a number of determinants such as maturity and size of the loan. To measure banks' private information, we use the residual of the regression of AIU spread on a series of loan spread determinants. Specifically, we run the following regression:

$$Log(AIU) = \alpha + \beta Loan\_Charac + \gamma Firm\_Charac + \delta Macroeconomic + \epsilon, \tag{1}$$

where AIU is the All-in-Undrawn spread which equals to the fees (commitment fee and annual fee) that the borrower must pay its bank for funds committed under the credit line

[11] We utilize the linktable constructed by Michael Roberts between Dealscan and the merged CRSP-Compustat files on the official WRDS website (Chava and Roberts, 2008), that, in its newest release covers observations from August, 1987 to August, 2012. The link between Dealscan and Compustat is extended to December, 2016.

but not drawn down. The regressors in this regression are a set of well-known determinants of loan spread, including loan characteristics, firm characteristics, and variables related to macroeconomic conditions. The detailed definitions of these variables are presented in Table 1.

[Insert Table 1 Here]

Following Strahan (1999), we include several well-known loan characteristics in the equation. MATURITY is the natural logarithm of loan maturity, measured in months. AMOUNT is the natural logarithm of the facility amount. SECURED and SECUREDMIS are two indicator variables for the loan secured status. SECURED takes the value of one if the loan is secured by collateral, while SECUREDMIS is equal to one if the information about the loan secured status is missing. We also introduce COVENANTS, the total number of financial covenants in the loan contract, since covenant structure is tightly associated with debt yield (Bradley and Roberts, 2015).

We also incorporate a few firm-level variables that may influence loan pricing. First, larger firms tend to have a lower cost of borrowing, presumably due to easier access to various sources of funding, less information asymmetry and smaller monitoring costs (Graham et al., 2008; Ross, 2010). We use ASSETS, which is the natural logarithm of total assets (Compustat item AT), to represent the borrower's firm size. Second, Ross (2010) suggests that Tobin's q of the borrower is positively associated with loan spread since it could be a proxy for risk-shifting opportunities. Therefore, we include Tobin's q in Equation (1). It is calculated as the market value of equity (Compustat item CSHO times Compustat item PRCC_F) plus the difference between total assets and the sum of book value of common shareholder equity (Compustat item CEQ) and deferred taxes (Compustat item TXDB), divided by lagged total assets. In addition, loan spread is expected to be negatively related to the level of assets tangibility because higher tangibility indicates lower firm opaqueness (Strahan, 1999) and a higher recovery rate in the case of default (Graham et al., 2008).

Thus, we include TANGIBILITY in our analysis. This variable is the ratio of tangible assets to total assets, where tangible assets are calculated as net property, plant and equipment (Compustat item PPENT) plus total inventories (Compustat item INVT). In addition, as in (Strahan, 1999), we include two indicator variables related to a firm's credit rating status: SPECULATIVE and UNRATED. The former is equal to one if the borrowing firm is rated as speculative grade (S&P rating of BB+ or worse) and zero otherwise, while the latter takes the value of one if the credit ratings of the borrowing firm are unavailable.

Several additional variables are related to the risk level of the firm. Prior studies (Strahan, 1999; Graham et al., 2008) suggest that firms with a higher leverage ratio tend to face higher borrowing costs since the default risk of these firms is usually considered to be higher. In our regression, LEVERAGE is used to control for this aspect. It is calculated as the sum of total long-term debt (Compustat item DLTT) and debt in current liabilities (Compustat item DLC) divided by total stockholders' equity (Compustat item SEQ). CFVOL is the cash flow volatility which represents the earnings risk of a firm. Following Graham et al. (2008), we define it as the standard deviation of change in the quarterly net cash flow from operating activities (Compustat item OANCFY) over sixteen fiscal quarters prior to the loan initiation, scaled by the sum of total long-term debt (Compustat item DLTT) and debt in current liabilities (Compustat item DLC). Moreover, IDVOL, which is the idiosyncratic volatility as constructed by Ang et al. (2006), is used to capture the idiosyncratic risk of the firm. It is computed as the standard deviation of the residuals from the Carhart (1997) four-factor model with daily stock returns in the past three months. In the calculation, we require at least 20 daily returns of a firm's stock are available over the three-month period.

As in Graham et al. (2008), we also consider the effects of macroeconomic conditions. Specifically, we include TERMSPR and CREDSPR, which represent term spread and credit spread, respectively. Term spread is the difference between the 10-year Treasury yield and the 2-year Treasury yield. And credit spread is the difference between AAA corporate bond yield and BAA corporate bond yield. Finally, we use dummy variables to control for the effect of loan purpose, year-fixed effects and industry effects.

In the main analysis reported in this paper, we estimate Equation (1) with 5-year backward rolling-window regressions using facility-level observations.[12] The rationale for the rolling-window procedure is to accommodate the notion that the information contained in loans initiated in the far past may not be relevant now. In addition, if we estimate the model with all facility observations over the entire sample period, it would create forward-looking bias as it would involve data points in the future. Nevertheless, as robustness checks, we still try the specification in which we estimate the model only once but with all facility-level observations over the entire sample period, as well as running 10-year rolling-window regressions. We find that our main findings remain robust under these alternative specifications. These results on robustness tests are presented in the appendices.

After obtaining the residuals from Equation (1), we aggregate them into firm-month level if multiple facilities are initiated simultaneously. In other words, if one firm initiates multiple facilities within a month, we calculate the weighted average of residuals associated with these facilities where the facility amount is used as the weight. Then, for each borrowing firm in every month, we calculate the moving average of the aggregated residuals of the firm over the past J months. This average residual is labeled as "AIUR". We consider various choices of J in our subsequent analysis, from 3 to 12 months. We choose to use J larger than 1 for two reasons. First, we believe, as is the case for firm fundamentals such as book-to-market ratio and other accounting measures, of which the values at the end of the 'previous' fiscal year are often used (Fama and French, 1992), banks' opinions on firms' future prospects are stable over time, which can justify a choice of J as large as 12. Second, the average number of firms initiating a facility per month is small, thus a choice of J larger than 1 can substantially increase the sample size and allow us to conduct exercises such as portfolio

[12] Starting from the first month in our sample, we estimate one regression in each month and obtain the parameter estimates for Equation (1), and calculate the regression residuals based on these parameter estimates. For the initial five years, we add observations month by month. Except for these years, we run the regression with observations in the previous 60 months.

sorts and double-sorts more soundly. Panel A and Panel C in Table 2 present the summary statistics of variables included in AIUR calculation and the AIUR measure, respectively. In addition, Panel D of the same table indicates that high AIUR firms have significantly higher market beta than low AIUR firms.

[Insert Table 2 Here]

3. Empirical Results

3.1. Portfolio Sorts

To document the relation between AIUR and future stock returns, we first examine the returns of portfolios sorted on this measure. Every month, firms that had ever borrowed a loan within the past J months are ranked into quintile groups based on their AIUR, and one portfolio is formed for each quintile that equally weights the stocks contained in the group. This strategy treats all firms within the quintile group equally. However, it is reasonable to argue that firms that borrowed loans with larger amounts relative to their firm size deserve higher weights since the information contained in the loan spread is likely to be more informative for stock returns of these firms. Therefore, as an alternative strategy, we consider quintile portfolios that weight stocks with the facility amount borrowed by a firm scaled by its book value of total assets. All these portfolios are held for K months. The profitability of portfolios is evaluated with returns in excess of the risk-free rate which is the one-month Treasury bill rate.[13] We also investigate the portfolio performance by calculating abnormal returns (alpha) from the Fama and French (2015) five-factor model and the Hou et al. (2015) four-factor model using the equally-weighted portfolio returns.[14]

[13] The monthly risk-free rate is obtained from Kenneth R. French's online data library http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[14] The data on Fama and French (2015) factors are downloaded from Kenneth R. French's online data library. The data on Hou et al. (2015) factors are obtained from Lu Zhang. We thank the authors for sharing the data.

Table 3 presents the portfolio returns where AIUR is constructed as a 9-month moving average of residuals. We investigate the performance of portfolios held for 3, 6, 9, 12, and 15 months, and the results are reported in Panels A through E respectively[15]. Consistent with our conjecture, we find that returns decrease across the AIUR portfolios. Take the portfolio with 6-month holding period as an example. Moving from the lowest AIUR quintile to the highest AIUR quintile, the average monthly equally weighted excess return (EW) decreases monotonically from 1.17% to 0.75%. And the difference of 0.43% is significant at the 1% level ($t = 3.09$). The facility amount weighted portfolio returns (VW) exhibit a similar pattern, with the return spread between the lowest and highest AIUR quintile portfolios equal to 0.57% per month. Moreover, the decreasing pattern holds for abnormal returns (alpha) from the Fama and French (2015) five-factor model and the Hou et al. (2015) four-factor model, and the alpha spreads are also significant at the 1% level. In the case of K equal to 6, the differences in alphas between the lowest AIUR portfolio and the highest AIUR portfolio are 0.51% ($t = 3.86$) and 0.57% ($t = 4.24$) respectively when measured against these two asset pricing models. In the case of J=9 and K=3, the Hou et al. (2015) four-factor model alpha is equal to 0.59% per month ($t = 4.11$), or 7.08% per year.

[Insert Table 3 Here]

The results in Table 3 suggest that there exists a strong negative relationship between a firm's AIUR and its future stock returns. A zero-investment strategy that longs the lowest AIUR quintile portfolio and shorts the highest AIUR quintile portfolio could generate substantial excess returns. These returns are significant both statistically and economically, robust to different portfolio holding periods, and cannot be explained by risk factors established in recent asset pricing models. Prior literature (Stambaugh et al., 2012; Avramov et al., 2013) documents that many anomaly-based trading strategies such as those related to idiosyncratic volatility, analyst dispersion, and credit risk derive their profitability from short selling

[15] We begin with 3-month holding period rather than a shorter horizon to alleviate the concern that the loan details may become available to the market months after the deal was made.

overpriced stocks. However, as shown in Table 3, the abnormal return (alpha) in our trading strategy originates from the long leg of the long-short portfolio, indicating that our results are sperate from those previously documented asset pricing anomalies.

As robustness tests, we experiment with alternative formation periods: J=3, 6, and 12. These results are reported in Table 4. We find that the return spreads between the lowest and highest AIUR quintile portfolios are statistically significant for most J and K combinations. In addition, in general, the economic magnitude of these returns is also comparable to that in Table 3. These results indicate that the predictive power of AIUR for stock returns is robust to various portfolio formation periods.

[Insert Table 4 Here]

In the untabulated results, we calculate the cumulative equally-weighted excess returns of the lowest and highest AIUR quintile portfolios, where the excess return is computed as the raw stock return minus one-month Treasury bill rate. We find that there is a substantial performance difference between these two portfolios. For example, when J equals 9 and K equals 3, the cumulative excess return of the lowest AIUR portfolio over the 1994 to 2016 period is 1660.43%, while the cumulative excess return of the highest AIUR portfolio is only 279.55%. The other J-K combinations yield quantitatively similar results.

3.2. Regression Analysis

The results documented in the previous subsection represent the univariate relation between AIUR and stock returns. To control for other determinants of expected returns, we now implement the regression analysis. Specifically, we run Fama-MacBeth and panel regressions. As in the portfolio sorting analysis, the values for K considered here are 3, 6, 9, 12, and 15. The regression specification is as follows:

$$R_{i,t+1\to t+K} = \alpha + \beta AIUR_{i,t} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t+1\to t+K}, \tag{2}$$

where $R_{i,t+1 \to t+K}$ is the arithmetic average of a firm's monthly excess returns over the K months; $AIUR_{i,t}$ is the AIUR of firm i in month t; and $\mathbf{X}_{i,t}$ represents control variables. The coefficient β in Equation (2) is our focus.

The first set of controls are the standard control variables, including reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and size (SZ). R01 is the stock return over the previous month; R12 is the stock return over the 11 months preceding the previous month; BM is the natural logarithm of the ratio of book value of equity to market value of equity; ML is the natural logarithm of the market leverage ratio defined as book value of long-term debt divided by the sum of market value of equity and book value of long-term debt; SZ is the log of the market value of equity.

In the extended model, we include additional well-known factors in the asset pricing literature, namely, illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), and credit risk proxies (UNRATED and SPECULATIVE). ILLIQ is the monthly illiquidity measure based on Amihud (2002), defined as the monthly average of the ratio of absolute daily stock return to daily dollar volume (in millions). We calculate this measure for stocks with valid trading data for at least 10 days in the month. To account for the effect of idiosyncratic volatility documented in Ang et al. (2006), we include IDVOL which is defined as in Section 2.2. Given that stocks with higher analyst dispersion earn lower future returns (Diether et al., 2002), we control the analyst forecast dispersion (DISP). It is the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts scaled by the absolute value of the mean forecast. In addition, we introduce the growth rate of total assets in the previous fiscal year (AG) since Cooper et al. (2008) document a strong negative relationship between a firm's asset growth and subsequent abnormal returns. Finally, Avramov et al. (2009) show that high credit risk firms earn lower future returns than low credit risk firms. Thus, we include UNRATED and SPECULATIVE as control variables in the return regressions, and they are defined as in Section 2.2.

3.2.1. Fama-MacBeth Regressions

Table 5 reports the results of Fama-MacBeth regressions where AIUR is calculated with J equal to 9. The coefficients are the time-series average of estimated coefficients from monthly cross-sectional regressions and the t-statistic is computed based on Newey-West adjusted standard errors. In the first column of each panel, AIUR alone is included as the regressor. We find that the coefficients on AIUR are all negative, with the magnitude varying from -0.14% to -0.45%, and they are statistically significant. This finding confirms our results in Section 3.1. According to the second of each panel, after including the standard control variables, the coefficients on AIUR remain significantly negative, with statistical significance varying from 1% level to 5% level. For example, when K equals to 6 (Column (5)), the coefficient on AIUR is -0.23% with a t-statistic of 2.87. Furthermore, we find that although adding illiquidity, idiosyncratic volatility, analyst dispersion, asset growth, and credit rating dummies slightly reduces the magnitude of the coefficient on AIUR (shown in the third column of each panel), the negative relation between AIUR and stock returns remains significant at least at the 5% level. The results from these multivariate regressions suggest that firms with high AIUR will under-perform firms with low AIUR in the future, and this effect cannot be absorbed by a set of existing determinants of stock returns.

[Insert Table 5 Here]

As in Section 3.1, we also examine the specifications with J equal to 3, 6, and 12. The coefficients on AIUR are presented in Table 6. We find that these results are quantitatively and qualitatively similar to those in Table 5. For example, consider the case of K equal to 6, the coefficients on AIUR in the full model (Column (6)) are -0.28%, -0.25%, and -0.19%, respectively, when J equals to 3, 6, and 12. And all these three coefficients are statistically significant at the 1% level ($t = 2.36, 2.97$, and 2.81, respectively). In other words, the negative relation between AIUR and stock returns documented above does not rely on the choice of the value for J.

[Insert Table 6 Here]

3.2.2. Panel Regressions

To check whether our results are robust to alternative regression frameworks, we rerun the analysis with panel regressions, in which standard errors are clustered by firm and month. Table 7, where AIUR is computed with J equal to 9, shows that the coefficients on AIUR remain negative and are statistically significant in most cases. For example, when K equals to 6, the coefficient on AIUR is -0.39% ($t = 3.46$) after controlling other determinants of expected stock return (Column (6)). As shown in Table 8, the negative relation between AIUR and stock return is still significant when J varies from 3 to 12. The results in this subsection provides additional supporting evidence for our hypothesis that higher AIUR predicts lower future stock returns of borrowing firms.

[Insert Table 7, and 8 Here]

3.3. Information Environment

Dealscan obtains its information from a variety of sources including "SEC filings, press releases, bank submissions". When a firm enters into a credit facility (loan) agreement, if it constitutes a material definitive agreement (which it is generally deemed to be), then the firm is mandated to disclose the details of such agreements to the SEC and the public through 8-K filings and/or news releases. If the key provisions of facility agreements including loan spreads are available to the public, why do we find predictability at all? We argue that not all information that is used by banks to make decisions in their roles as financial intermediaries, and as lenders in particular, is released to the public and banks have substantial private information on their clients. Furthermore, the public fail to timely incorporate the terse information that is revealed through the terms of the facility agreements, although on the surface they reflect the underlying private information that banks use to determine the terms of the loans, including undrawn spreads.

The fact that information relevant to future firm cash flow and equity prices that are seemingly available to the public yet are ‘‘hidden under plain sight’’ to the equity market participants, and such information are only incorporated with delay has been documented by Addoum and Murfin (2018). Using the secondary market for syndicated loans, they find that equity markets fail to account for value relevant non-public information enjoyed by syndicated loan participants and reflected in publicly posted loan prices, even when loan prices are featured prominently in a publication with wide circulation. We wish to emphasize that in our paper, we do not use secondary market syndicated loan pricing information but instead use information contained in the undrawn spread of revolving credits.

If, as we argue, AIUR represents banks' private information about borrowing firms, we may expect that AIUR is more informative for firms with worse information environment. To test this conjecture, we explore the variation in returns across AIUR portfolios conditional on proxies of information asymmetry.

As important information intermediaries, financial analysts are closely related to the information environment of firms. The prior research suggests that several characteristics of analyst forecasts could serve as indicators for information asymmetry (Lang and Lundholm, 1996; Lang et al., 2003). We follow these studies and construct two measures: analyst coverage and analyst forecast error. Specifically, analyst coverage refers to the total number of financial analysts following the firm during the fiscal year, and analyst forecast error is defined as the absolute difference between the actual annual earnings per share and the mean of analysts' estimates, scaled by the absolute value of actual earnings. A higher value of analyst coverage indicates lower information asymmetry and better information environment, while a larger forecast error represents worse information environment.

Our double-sort analysis is conducted as follows. Each month, we first split firms that borrowed loans over the past J months into two groups by the median of analyst coverage, and firms in each group are then sorted into quintile portfolios based on AIUR. These portfolios are held for K months. The first two columns in Table 9 report the return spreads between the highest and lowest AIUR quintile portfolios in the low and high analyst coverage group respectively, with J equal to 9.[16] The results show that AIUR significantly predicts returns only among firms with low analyst coverage. For example, when the portfolios are held for 6 months, the spread in equally weighted excess returns (EW) in the low analyst coverage group is -0.60%, which is statistically significant at the 1% level (t = 2.78). In contrast, the return difference in the high analyst coverage is only -0.05% and it is statistically insignificant (t = 0.26). Similarly, when the portfolio performance is measured using facility amount weighted returns (VW), abnormal returns (alpha) from the Fama and French (2015) five-factor model and the Hou et al. (2015) four-factor model, the return spread in the low analyst coverage group is -0.70%, -0.78%, and -0.91%, respectively; and all are significant at the 1% level. However, the corresponding return spreads in the high analyst coverage group are not significantly different from zero.

[Insert Table 9 Here]

Next, we split the sample based on the median analyst forecast error. As shown in Table 9 (the middle two columns), the return spreads among firms with high forecast error are significantly negative. For example, when the holding period is 3 months, the return differences between the highest and lowest AIUR quintile portfolios in the high forecast error group could vary from -0.44% to -0.74%, depending on performance measures, and they are significant at least at 5% level. Conversely, in the low forecast error group, return spreads have smaller magnitude and they are not statistically significant.

[16] For the analysis in this section and the subsequent sections, we focus on the case where J is equal to 9. We repeat all the analysis for J equal to 3, 6, and 12, and obtain similar results. These results are not tabulated for brevity.

Finally, we focus on the effects of AIUR conditional on institutional ownership. Previous studies suggest institutional investors could enhance firms' information environment by influencing their disclosure policy (Ajinkya et al., 2005; Boone and White, 2015).[17]. Thus, we expect the effect of AIUR to be stronger for firms with lower institutional ownership. The last two columns in Table 9 present the results when the sample is partitioned by the median value of institutional ownership. The institutional ownership is defined as the percentage of shares outstanding owned by institutions measured at the end of the previous quarter. Consistent with our conjecture, we find that the outperformance of low AIUR firms relative to high AIUR firms is concentrated among firms with low institutional ownership. Consider the case where K is equal to 12 as an example. Although the return spreads in the high institutional ownership group are negative, they are statistically insignificant. However, in the low institutional ownership group, the return differences between the highest and lowest AIUR quintile portfolios are significantly negative, regardless of which performance measure is used.

Overall, the results in this section imply that AIUR has higher predictive power for future stock returns when the firm suffers from greater information asymmetry. And this conditional effect of AIUR is robust to alternative portfolio formation periods and holding periods.

3.4. AIUR and Operating Performance

We have so far shown that the AIUR measure has strong predictive power for future stock returns presumably because banks possess private information about the future prospects of borrowing firms. One particular type of private information banks could possibly have is the information related to firms' subsequent operating activities. In this subsection, we provide evidence on this view by investigating the relationship between AIUR and borrowers' future

[17] Earlier papers show that institutional investors are likely to be attracted by firms with more voluntary disclosures (Healy et al., 1999; Bushee and Noe, 2000). These findings also indicate institutional ownership is positively associated with firms' information environment.

cash flow uncertainty and future cash flow level.

3.4.1. Volatility of Cash Flow

As discussed in Berg et al. (2016), a credit line can be viewed as an option where the writer (i.e., the bank) grants the purchaser (i.e., the firm) the right to borrow money from the writer when the buyer decides to do so. From this perspective, the AIU spread is the price of the option which depends on, among others, the volatility of the underlying asset. And the option pricing theory suggests that, *ceteris paribus*, the option price should increase with the volatility of the underlying asset. Therefore, with everything else being equal, banks would charge a higher spread if they anticipate that the firm's performance will be more volatile. In other words, AIUR may contain banks' private information about firms' future cash flow volatility: higher AIUR predicts higher cash flow volatility. To examine whether this conjecture is true, we estimate the following regression:

$$Cash\ Flow\ Volatility_{i,t+1} = \alpha + \beta AIUR_{i,t} + \gamma \mathbf{X}_{i,t} + Year\text{-}month + Industry + \epsilon_{i,t+1}, \quad (3)$$

where the dependent variable is future cash flow volatility; $AIUR_{i,t}$ is the monthly AIUR in year t and is the variable of interest; $\mathbf{X}_{i,t}$ represents a vector of control variables. In addition, we include year-month and industry fixed effects.

Following prior studies (e.g., Gao et al., 2013), we first measure cash flow volatility with the standard deviation of quarterly operating cash flow that is realized over the next two years, where the operating cash flow is computed as earnings before interest, taxes, depreciation and amortization (Compustat item OIBDPQ) scaled by total assets (Compustat item ATQ) and is adjusted by subtracting the industry median in a given Fama and French 48 industry and quarter. The results are reported in the first three columns of Table 10. In Column (1), we regress the cash flow volatility on AIUR and include the time and industry fixed effects. Consistent with our expectation, the coefficient on AIUR is positive (0.08), with a t-statistic of 5.36. To account for the effect of historical volatility, we introduce the lagged dependent variable which is the standard deviation of quarterly operating cash flow over the past two years. As shown in Column (2), the coefficient on AIUR remains positive (0.06) and significant at 1% level ($t = 5.48$).

[Insert Table 10 Here]

In Column (3), we consider additional controls that may influence the volatility of firm performance. We include the control variables contained in the return regressions. Additionally, based on the existing literature (e.g., Larcker et al., 2013; Francis et al., 2016), we add the following: the ratio of R&D expenses to sales (R&D); the natural logarithm of firm age (AGE), where a firm's age refers to the number of years since its first appearance in Compustat; the natural logarithm of total assets (ASSETS); and the natural logarithm of total sales (SALES). After introducing these variables, we find that the positive relation between AIUR and cash flow volatility remains significant ($t = 6.00$). These results support our conjecture that a higher AIUR predicts higher subsequent cash flow volatility.

As an alternative measure of cash flow volatility, we consider the dispersion of analysts' forecasts on the firm's future cash flow. Specifically, we calculate the standard deviation of analysts' one-year-ahead forecast (I/B/E/S item FY1) of cash per share times the shares outstanding and scaled by the book value of total assets, where the analysts' opinion is evaluated at two years in the future. The regression results (reported in the last three columns of Table 10) show that the analyst dispersion on future cash flow is higher for firms with higher AIUR.[18] After including the lagged dependent variable (i.e., the dispersion of analysts' one-year-ahead forecasts evaluated in the current year) and other control variables, the coefficient on AIUR is 1.31, with a t-statistic of 3.38. To conclude, the results in this subsection show that high AIUR is associated with high subsequent cash flow volatility, and this is consistent with our *uncertainty risk hypothesis*.

[18] The number of observations decreases because the analysts' forecasts on cash flow per share for certain firms in our loan sample are not available in I/B/E/S.

3.4.2. Level of Cash Flow

After documenting the relation between AIUR and the volatility of subsequent cash flow, we now turn to the level of future cash flow. If, based on their assessment, banks perceive a firm would become less profitable or would have decreased cash flow and thus entail higher distress risk, they would charge a higher AIU spread since the credit line, as an insurance against liquidity crisis and financial distress, is now more valuable for such a firm. Therefore, one may expect that higher AIUR indicates poorer future operating performance. To explore whether this is the case, we run a regression that is similar to Equation (3):

$$Performance_{i,t+1} = \alpha + \beta AIUR_{i,t} + \gamma \mathbf{X}_{i,t} + Year\text{-}month + Industry + \epsilon_{i,t+1}, \qquad (4)$$

where $Performance_{i,t+1}$ is the operating performance in fiscal year $t+1$; $AIUR_{i,t}$ is the monthly AIUR in year t and is the variable of interest; $\mathbf{X}_{i,t}$ represents a vector of control variables, including the lagged dependent variable, reversal, momentum, book-to-market ratio, market leverage, firm size, illiquidity, idiosyncratic volatility, asset growth, credit risk, R&D expenses, firm age, total assets, and total sales; $Year\text{-}month$ and $Industry$ are the year-month and industry fixed effects.

We consider two proxies of operating performance: operating cash flow (CF) and return on assets (ROA). CF is the earnings before interest, taxes, depreciation and amortization (Compustat item OIBDP) scaled by the book value of total assets (Compustat item AT), and ROA is the net income (Compustat item NI) divided by total assets. To account for the difference in the nature of operation in different industries, we adjust these measures by subtracting their industry median based on Fama and French's (1997) 48-industry classification.

The regression results are presented in Table 11. The dependent variable in the first three columns is industry-median-adjusted operating cash flow. Column (1) includes only the AIUR and time and industry fixed effects. We find that AIUR is significantly and negatively associated with future cash flow. To account for the impact of past performance, we introduce the lagged operating performance in Column (2). The magnitude of the coefficient on AIUR decreases; however, it remains highly significant. In Column (3), we further include additional control variables as in Table 10. We find that the coefficient on AIUR remains negative (-0.61) and significant at the 1% level (t = 7.94). The finding that high AIUR predicts low operating cash flow is consistent with the hypothesis that AIUR reflects banks' private information about borrowers' subsequent operating performance.

[Insert Table 11 Here]

Columns (4) through (6) of Table 11 present the results from the regressions of industry-median-adjusted ROA. The results are similar to the cash flow results. Essentially, the coefficients on AIUR are negative and significant. For instance, in the full model shown in Column (6), the coefficient on AIUR is -0.75 (t = 7.66). In summary, the evidence in this subsection suggests that firms with high *ex ante* AIUR would have poor subsequent operating performance. In other words, these results support our *distress risk hypothesis*.

3.5. Further Discussions

We have proposed two hypotheses regarding under what circumstances a firm would be charged a high AIU spread—the *uncertainty risk hypothesis* and the *distress risk hypothesis*. The empirical results in the previous subsection, namely the predictability of cash flow uncertainty as well as the predictability of firm's operating performance, lend support to both hypotheses. In this subsection, we attempt to minimize the effects from distress risk by introducing two additional controls related to distress risk into the construction of AIUR.

The first control variable we add is the KMV-Merton expected default probability (EDF) (Merton, 1974). Even though many of the control variables included in our baseline analysis such as TANGIBILITY, CFVOL, LEVERAGE, ASSET, SPECULATIVE already capture the lender's concern with default to a certain degree, none of them is as explicit a measure of default probability as the KMV-Merton EDF, which is one of the most commonly used distress risk measures in the literature (Vassalou and Xing, 2004; Garlappi and Yan, 2011).

The second control variable we introduce is the sales growth over the prior two years. This variable has been used by Bolton et al. (2014) as a measure for investment opportunity, which they label as μ. As in our baseline analysis, many studies have used *average* Tobin's q to control for the investment opportunities of a firm, although theoretically one should have utilized the hard-to-observe *marginal* Tobin's q (Gala, 2015). However, in the model developed by Bolton et al. (2011), even marginal q does not measure the firm's investment opportunities. Bolton et al. (2014) provide the insight that firm behavior changes according to different levels of investment opportunity and idiosyncratic volatility. Since we have already controlled for Tobin's q and idiosyncratic volatility, among other things, in our baseline analysis, we now include μ as well to control for investment opportunity.

We denote the residual obtained from this extended version of Equation (1) as AIUR2. And we redo our baseline analysis with this alternative measure. As shown in Table 12 and Table 13, the results we obtained using AIUR2 are generally robust and similar to those when AIUR is employed. The test results in this subsection suggest that the *uncertainty risk hypothesis* contributes significantly to our main findings on the relation between AIUR and stock returns and thus this relation is principally distinct from the existing distress risk anomaly literature.

[Insert Table 12 and 13 Here]

4. Conclusion

Existing studies suggest that banks possess private information about borrowing firms. Using a large sample of credit lines, we construct a measure, AIUR, which is defined as the residual from the regression of the AIU spread on a set of publicly available determinants of loan spreads, to capture bank's private information.

We document a novel empirical finding that banks' private information contained in the AIU spread can robustly predict subsequent stock returns and future firm performance. Specifically, we find that firms with higher *ex ante* AIUR would subsequently have lower stock returns, lower ROA, lower cash flows, and higher cash flow volatility. Notably, a long-short strategy based on our AIUR measure can generate a sizable alpha (around 7% per year) over a range of holding periods. These results remain robust after controlling for idiosyncratic volatility, analyst forecast dispersion, and distress risk, suggesting that our findings are distinct from the asset pricing puzzles related to these variables. Moreover, we show that the negative relationship between AIUR and future stock returns is more pronounced among firms with lower analyst coverage, higher analyst forecast error, or lower institutional ownership, confirming that banks do possess private information.

We provide two potential explanations for the negative AIUR-return relationship. First, a higher AIU spread may indicate that the bank *ex ante* assesses the firm to have higher cash flow uncertainty. Our findings that firms with higher AIUR would have higher future cash flow volatility confirm this *uncertainty risk hypothesis*. Second, firms with higher AIU spread might be those which are perceived *ex ante* by the bank to entail higher distress risk. Consistent with this *distress risk hypothesis*, we find that a higher AIUR predicts lower future cash flow.

Overall, our paper confirms bank's information advantage and suggests that banks' private information contained in the undrawn spreads of credit lines can predict borrowing firms' future stock returns. Given the magnitude and robustness of our results, it would be interesting for researchers to continue exploring the asset pricing implications of bank's private information contained in other dimensions of bank loans.

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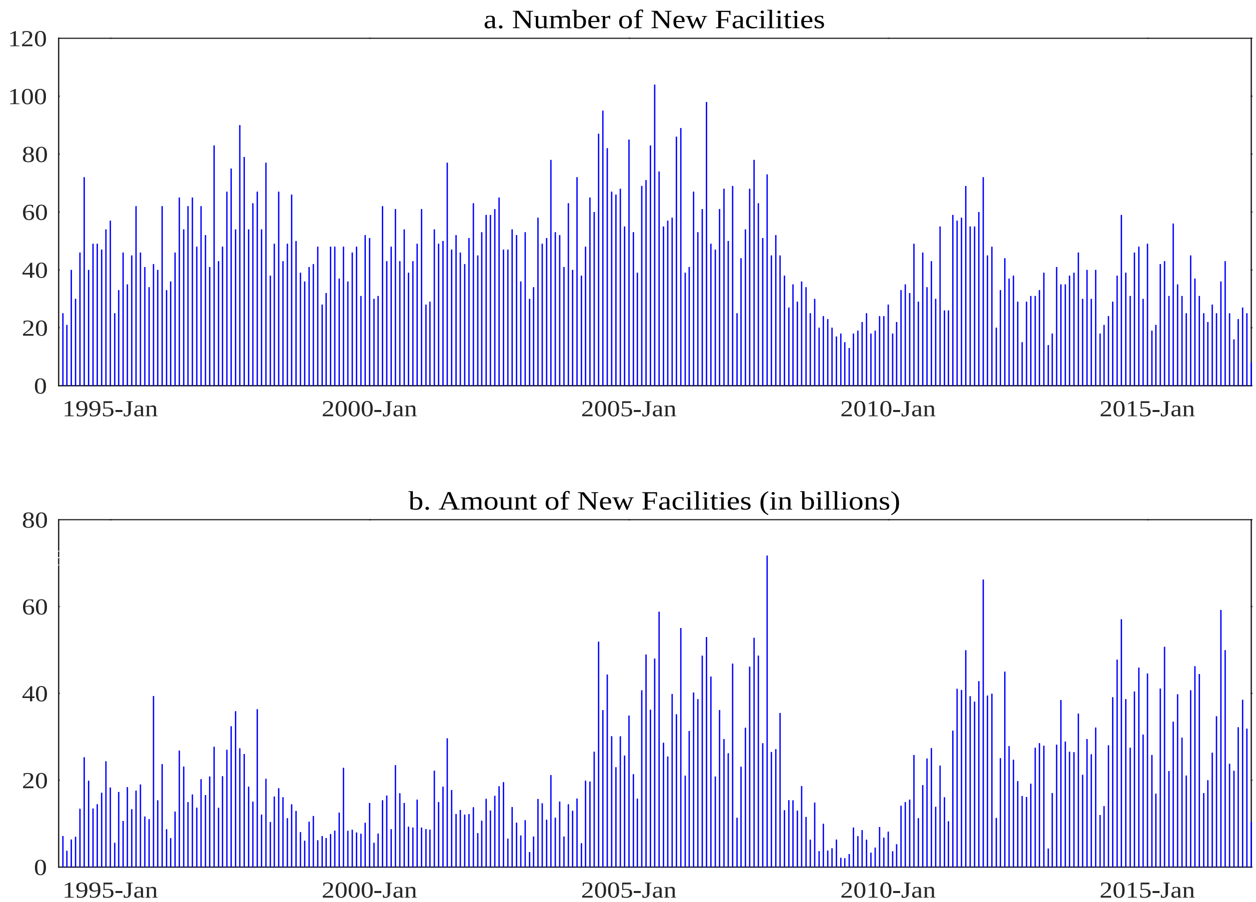

Figure 1

Monthly Credit Line Issuance

This figure demonstrates the time-series variation in credit line issuance. The top plot (subfigure a) illustrates the number of new facilities issued in each month. The bottom plot (subfigure b) shows the dollar amount of new revolving credit facilities issued in each month. The sample period is from January 1994 to December 2016. These plots only include observations with valid AIUR.

Table 1
Variable Definitions

Variable	Definition
AG	the growth rate of total assets in the previous fiscal year
AGE	the number of years since a firm's first appearance in Compustat
AIUR	the J-month moving average of residuals from regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants
AMOUNT	the natural logarithm of facility amount (unit: log of dollars)
Analyst Coverage	the total number of analysts following the firm in the fiscal year
Analyst Dispersion on Cash Flow	the standard deviation of the analysts' one-year-ahead forecast (I/B/E/S item FY1) of future firm cash flow, specifically, cash per share (or CPS), times the shares outstanding and scaled by the book value of total assets, with the analysts' opinion evaluated at two years in the future
Analyst Forecast Error	the absolute difference between the actual earnings and the mean forecast by all analysts, scaled by the absolute value of actual earnings
ASSETS	the natural logarithm of total assets (Compustat item AT) (unit: log of million dollars)
BM	the natural logarithm of the ratio of book value of equity to market value of equity, where book value of equity is the sum of book value of common shareholder equity (Compustat item CEQ) and deferred taxes (Compustat item TXDB), and market value of equity is monthly closing price times number of shares outstanding
CFVOL	the standard deviation of change in quarterly net cash flow from operating activities (Compustat item OANCFY) over sixteen fiscal quarters prior to the loan initiation, scaled by the sum of total long-term debt (Compustat item DLTT) and debt in current liabilities (Compustat item DLC)
Cash Flow Volatility	the standard deviation of industry-median-adjusted quarterly operating cash flow that is realized over the next two years, where quarterly operating cash flow is the earnings before interest, taxes, depreciation and amortization (Compustat item OIBDPQ) scaled by total assets (Compustat item ATQ)
COVENANTS	the total number of financial covenants in the loan contract
CREDSPR	the difference between AAA and BAA corporate bond yield (unit: %)
DISP	the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts scaled by the absolute value of the mean forecast
IDVOL	the standard deviation of the residuals from the Carhart (1997) four-factor model with daily stock returns in the past three months
ILLIQ	the monthly average of the ratio of absolute daily stock return to daily dollar volume (in millions)
Industry-adjusted CF	industry-median-adjusted annual operating cash flow, where operating cash flow is the earnings before interest, taxes, depreciation and amortization (Compustat item OIBDP) scaled by total assets (Compustat item AT)
Industry-adjusted ROA	industry-median-adjusted annual return on assets, where return on assets is net income (Compustat item NI) divided by total assets (Compustat item AT)
Institutional Ownership	the percentage of shares owned by institutions
LEVERAGE	the sum of total long-term debt (Compustat item DLTT) and debt in current liabilities (Compustat item DLC) divided by total stockholders' equity (Compustat item SEQ)
MATURITY	the natural logarithm of loan maturity (unit: log of months)
ML	the natural logarithm of the market leverage ratio, defined as book value of long-term debt (Compustat item DLTT) divided by the sum of market value of equity and book value of long-term debt
Q	i.e., Tobin's q, the market value of equity (Compustat item CSHO times Compustat item PRCC_F) plus the difference between total assets (Compustat item AT) and the sum of book value of common shareholder equity (Compustat item CEQ) and deferred taxes (Compustat item TXDB), divided by lagged total assets
R01	the stock return over the previous month
R12	the stock return over the 11 months preceding the previous month
R&D	the ratio of research and development expenses (Compustat item XRD) to sales (Compustat item SALE)
SALES	the natural logarithm of sales (Compustat item SALE) (unit: log of million dollars)
SECURED	dummy variable which equals to one if the loan is secured by collateral and zero otherwise
SECUREDMIS	dummy variable which equals to one if the information about the loan secured status is missing and zero otherwise
SPECULATIVE	dummy variable which equals to one if the borrowing firm is rated as speculative grade (S&P rating of BB+ or worse) and zero otherwise
SZ	the log of the market value of equity (unit: log of thousand dollars)
TANGIBILITY	the sum of net property, plant and equipment (Compustat item PPENT) and total inventories (Compustat item INVT), scaled by total assets (Compustat item AT)
TERMSPR	the difference between the 10-year and the 2-year Treasury yield (unit: %)
UNRATED	dummy variable which equals to one if credit rating of the borrowing firm is not available and zero otherwise

Table 2
Summary Statistics
This table reports the descriptive statistics. Panel A summarizes variables included in Equation (1) to calculate AIUR, and Panel B presents the summary statistics of variables used in the return and operating performance analysis. The detailed definitions of these variables are provided in Table 1. Panel C reports the summary statistics of AIUR, where J-month AIUR is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. Panel D reports the average beta of stocks in each AIUR-sorted quintile portfolio. The betas are calculated from monthly returns based on the market model. The estimation window is 36 months and we require at least 12 monthly returns to calculate beta.

Panel A: Variables in AIUR Calculation

	Mean	Standard Deviation	Minimum	Median	Maximum
Raw Loan Spread					
AIU	31.454	20.655	1.000	25.000	375.000
Loan Characteristics					
AMOUNT	18.786	1.625	10.131	18.891	23.901
COVENANTS	1.299	1.327	0.000	1.000	7.000
MATURITY	3.754	0.573	0.000	4.078	5.642
SECURED	0.475	0.499	0.000	0.000	1.000
SECUREDMIS	0.297	0.457	0.000	0.000	1.000
Firm Characteristics					
ASSETS	7.100	1.908	2.917	7.006	12.007
CFVOL	0.815	3.373	0.016	0.165	28.523
IDVOL	0.025	0.019	0.001	0.020	0.419
LEVERAGE	1.163	2.870	-9.963	0.700	17.975
Q	2.215	1.987	0.493	1.605	13.767
SPECULATIVE	0.270	0.444	0.000	0.000	1.000
TANGIBILITY	0.454	0.248	0.007	0.453	0.920
UNRATED	0.454	0.498	0.000	0.000	1.000
Macroeconomic Variables					
CREDSPR	0.910	0.312	0.550	0.860	3.380
TERMSPR	1.147	0.910	-0.410	1.170	2.830

Panel B: Variables in Performance Analysis

	Mean	Standard Deviation	Minimum	Median	Maximum
AG	0.189	0.747	-0.844	0.072	102.790
Analyst Coverage	12.281	9.188	1.000	10.000	57.000
Analyst Dispersion on Cash Flow	3.845	32.455	0.010	1.334	1548.711
Analyst Forecast Error	0.505	2.920	0.000	0.080	133.297
BM	0.652	1.081	-33.184	0.499	65.657
Cash Flow Volatility	1.309	1.512	0.000	0.870	26.698
DISP	0.565	6.620	0.000	0.090	667.430
ILLIQ	0.233	4.321	0.000	0.002	921.667
Industry-adjusted CF	4.814	12.611	-117.582	2.924	163.759
Industry-adjusted ROA	2.031	12.831	-202.136	1.619	212.807
Institutional Ownership	0.608	0.246	0.000	0.662	0.966
ML	0.260	0.211	0.000	0.211	0.990
SZ	13.996	1.834	6.440	13.949	19.803

(Continued)

Table 2 ---*Continued*

Panel C: AIUR

	Mean	Standard Deviation	Minimum	Median	Maximum
J=3	-0.004	0.410	-3.331	0.002	2.251
J=6	-0.004	0.408	-3.375	0.003	2.271
J=9	-0.005	0.406	-3.393	0.002	2.294
J=12	-0.007	0.403	-3.397	0.002	2.294

Panel D: Average Market Beta

AIUR	L	2	3	4	H	H-L	*t*-stat
J=3	1.067	1.119	1.174	1.183	1.215	0.148***	(7.10)
J=6	1.067	1.115	1.181	1.178	1.224	0.158***	(8.36)
J=9	1.060	1.114	1.183	1.179	1.226	0.166***	(9.07)
J=12	1.057	1.113	1.186	1.176	1.228	0.171***	(9.57)

Table 3

Returns of AIUR Portfolios: J=9

This table reports the monthly excess returns or abnormal returns (in percentage) of quintile portfolios sorted on AIUR, which is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR measure and held for K months. The average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), abnormal returns (alpha) from Fama and French (2015) five-factor model and Hou et al. (2015) four-factor model are presented in each panel for different values of K. The sample period is from January 1994 to December 2016. *t*-statistics for the return spread between the highest and lowest AIUR quintile portfolios are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	AIUR						
	L	2	3	4	H	H-L	*t*-stat
Panel A: J=9, K=3							
EW	1.21	0.99	1.01	0.90	0.69	-0.52***	(3.41)
VW	1.27	0.98	1.02	0.76	0.63	-0.64***	(3.01)
FF 5-factor alpha	0.33	0.03	-0.00	-0.03	-0.18	-0.51***	(3.65)
HXZ 4-factor alpha	0.56	0.23	0.12	0.12	-0.03	-0.59***	(4.11)
Panel B: J=9, K=6							
EW	1.17	1.00	0.97	0.94	0.75	-0.43***	(3.09)
VW	1.25	1.06	0.93	0.87	0.68	-0.57***	(3.02)
FF 5-factor alpha	0.36	0.05	-0.01	-0.03	-0.14	-0.51***	(3.86)
HXZ 4-factor alpha	0.58	0.24	0.14	0.12	0.02	-0.57***	(4.24)
Panel C: J=9, K=9							
EW	1.16	1.02	0.96	0.96	0.79	-0.37***	(2.97)
VW	1.26	1.10	0.91	0.92	0.72	-0.53***	(3.02)
FF 5-factor alpha	0.35	0.09	-0.02	-0.02	-0.13	-0.48***	(4.01)
HXZ 4-factor alpha	0.55	0.26	0.15	0.15	0.04	-0.51***	(4.17)
Panel D: J=9, K=12							
EW	1.10	1.05	0.95	0.95	0.80	-0.29**	(2.38)
VW	1.17	1.13	0.90	0.93	0.75	-0.41**	(2.44)
FF 5-factor alpha	0.28	0.13	-0.03	-0.04	-0.12	-0.40***	(3.42)
HXZ 4-factor alpha	0.46	0.30	0.14	0.15	0.06	-0.40***	(3.38)
Panel E: J=9, K=15							
EW	1.05	1.05	0.94	0.92	0.78	-0.28**	(2.27)
VW	1.10	1.10	0.89	0.91	0.77	-0.33**	(1.99)
FF 5-factor alpha	0.24	0.13	-0.05	-0.06	-0.14	-0.38***	(3.33)
HXZ 4-factor alpha	0.41	0.30	0.13	0.14	0.04	-0.37***	(3.21)

Table 4
Returns of AIUR Portfolios: J=3, 6 and 12

This table reports the monthly return spreads (in percentage) between the highest and lowest quintile portfolios sorted on AIUR, which is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR measure and held for K months. The return spreads for the average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), abnormal returns (alpha) from Fama and French (2015) five-factor model and Hou et al. (2015) four-factor model are presented in each panel for different values of K. The sample period is from January 1994 to December 2016. *t*-statistics for the return spread are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	J=3		J=6		J=12	
	H-L	*t*-stat	H-L	*t*-stat	H-L	*t*-stat
Panel A: K=3						
EW	-0.44**	(2.09)	-0.30*	(1.74)	-0.40***	(3.01)
VW	-0.46	(1.51)	-0.48*	(1.93)	-0.58***	(3.05)
FF 5-factor alpha	-0.41**	(2.05)	-0.27	(1.61)	-0.49***	(3.96)
HXZ 4-factor alpha	-0.40**	(2.00)	-0.31*	(1.83)	-0.53***	(4.19)
Panel B: K=6						
EW	-0.26	(1.49)	-0.41**	(2.51)	-0.33***	(2.60)
VW	-0.28	(1.16)	-0.51**	(2.33)	-0.50***	(2.87)
FF 5-factor alpha	-0.24	(1.43)	-0.38**	(2.39)	-0.43***	(3.64)
HXZ 4-factor alpha	-0.29*	(1.76)	-0.45***	(2.87)	-0.45***	(3.75)
Panel C: K=9						
EW	-0.49***	(3.25)	-0.42***	(3.02)	-0.30**	(2.41)
VW	-0.50**	(2.51)	-0.55***	(2.87)	-0.45***	(2.63)
FF 5-factor alpha	-0.43***	(2.99)	-0.48***	(3.50)	-0.39***	(3.35)
HXZ 4-factor alpha	-0.51***	(3.48)	-0.53***	(3.84)	-0.39***	(3.30)
Panel D: K=12						
EW	-0.38***	(2.92)	-0.31**	(2.47)	-0.27**	(2.16)
VW	-0.45**	(2.50)	-0.43**	(2.50)	-0.37**	(2.14)
FF 5-factor alpha	-0.44***	(3.51)	-0.41***	(3.39)	-0.37***	(3.22)
HXZ 4-factor alpha	-0.47***	(3.67)	-0.42***	(3.47)	-0.36***	(3.04)
Panel E: K=15						
EW	-0.28**	(2.31)	-0.25**	(2.06)	-0.25**	(2.02)
VW	-0.33**	(2.01)	-0.32*	(1.96)	-0.28*	(1.66)
FF 5-factor alpha	-0.34***	(3.00)	-0.33***	(2.85)	-0.36***	(3.21)
HXZ 4-factor alpha	-0.36***	(3.09)	-0.33***	(2.83)	-0.34***	(2.93)

Table 5

Fama-MacBeth Regressions: J=9

This table shows results from Fama-MacBeth regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The control variables include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. The sample period is from January 1994 to December 2016. t-statistics (based on Newey-West standard errors) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
AIUR	-0.45***	-0.37***	-0.33***	-0.29***	-0.23***	-0.21***	-0.20***	-0.15**	-0.14**	-0.14*	-0.14**	-0.14**	-0.14**	-0.16***	-0.17***
	(3.91)	(3.99)	(3.87)	(3.13)	(2.87)	(2.89)	(2.60)	(2.34)	(2.30)	(1.96)	(2.47)	(2.58)	(1.97)	(3.06)	(3.32)
R01		-0.01	-0.00		-0.00	-0.00		0.00	0.00		0.00*	0.00*		0.00	0.00
		(0.98)	(0.86)		(0.28)	(0.13)		(0.86)	(0.93)		(1.75)	(1.79)		(1.25)	(1.34)
R12		0.00	0.00		-0.00	0.00		-0.00	0.00		-0.00	-0.00		-0.00	-0.00
		(0.35)	(0.91)		(0.04)	(0.37)		(0.43)	(0.03)		(0.90)	(0.47)		(1.23)	(0.81)
BM		0.16*	0.16*		0.06	0.03		0.03	-0.01		0.02	-0.02		0.07	0.03
		(1.72)	(1.70)		(0.79)	(0.44)		(0.40)	(0.20)		(0.39)	(0.28)		(1.18)	(0.49)
ML		-0.08	0.12		0.03	0.08		0.15	0.15		0.21	0.20		0.23	0.23
		(0.22)	(0.35)		(0.08)	(0.28)		(0.54)	(0.60)		(0.91)	(0.91)		(1.15)	(1.24)
SZ		-0.04	-0.06		-0.06	-0.08*		-0.08**	-0.09***		-0.09***	-0.10***		-0.09***	-0.10***
		(0.78)	(1.15)		(1.53)	(1.87)		(2.24)	(2.80)		(2.83)	(3.42)		(3.20)	(3.64)
ILLIQ			-3.75			0.80			0.58			0.09			-0.42
			(1.12)			(0.86)			(0.69)			(0.17)			(0.78)
IDVOL			-0.08			-0.04			0.01			0.03			0.05
			(0.94)			(0.57)			(0.23)			(0.67)			(1.09)
DISP			-0.07			-0.03			0.00			0.02			0.02
			(1.64)			(1.13)			(0.03)			(0.81)			(1.07)
AG			-0.54***			-0.65***			-0.69***			-0.66***			-0.61***
			(3.46)			(5.78)			(7.21)			(8.15)			(8.20)
UNRATED			-0.04			-0.16*			-0.25***			-0.29***			-0.26***
			(0.34)			(1.74)			(3.09)			(3.93)			(4.47)
SPECULATIVE			-0.17			-0.18*			-0.24***			-0.25***			-0.29***
			(1.27)			(1.86)			(3.01)			(3.88)			(4.98)
Intercept	0.93***	0.98	1.55*	0.94***	1.35*	1.85***	0.95***	1.65***	2.06***	0.95***	1.85***	2.20***	0.93***	1.88***	2.18***
	(2.72)	(1.07)	(1.76)	(3.39)	(1.94)	(2.59)	(4.22)	(2.82)	(3.57)	(4.91)	(3.54)	(4.30)	(5.48)	(3.95)	(4.52)
Adj. R^2	0.23%	6.86%	10.06%	0.22%	6.52%	10.02%	0.20%	7.03%	10.57%	0.31%	7.25%	10.69%	0.43%	7.13%	10.55%
Obs	85,222	85,222	85,222	83,696	83,696	83,696	81,965	81,965	81,965	80,145	80,145	80,145	78,239	78,239	78,239

Table 6

Fama-MacBeth Regressions: J=3, 6, and 12

This table shows results from Fama-MacBeth regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The standard controls include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and firm size (SZ); the extended controls include Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. Coefficients on control variables and intercept are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on Newey-West standard errors) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: J=3															
AIUR	-0.59***	-0.63***	-0.58***	-0.37***	-0.33***	-0.28**	-0.39***	-0.35***	-0.31***	-0.22***	-0.21***	-0.18**	-0.19**	-0.24***	-0.23***
	(3.89)	(4.38)	(3.90)	(3.49)	(3.08)	(2.36)	(3.96)	(3.52)	(3.10)	(2.60)	(2.70)	(2.18)	(2.46)	(3.91)	(3.57)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.23%	8.93%	13.89%	0.14%	7.69%	13.87%	0.22%	8.20%	14.39%	0.15%	8.53%	14.86%	0.09%	8.79%	14.73%
Obs	29,683	29,683	29,683	29,267	29,267	29,267	28,703	28,703	28,703	28,113	28,113	28,113	27,483	27,483	27,483
Panel B: J=6															
AIUR	-0.37***	-0.33***	-0.28**	-0.32***	-0.29***	-0.25***	-0.22**	-0.19**	-0.17**	-0.14*	-0.14**	-0.14**	-0.13	-0.17***	-0.17***
	(2.79)	(2.93)	(2.52)	(3.23)	(3.24)	(2.97)	(2.54)	(2.33)	(2.20)	(1.90)	(2.30)	(2.24)	(1.63)	(2.92)	(2.98)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.28%	7.23%	10.94%	0.18%	6.87%	11.20%	0.21%	7.37%	11.65%	0.22%	7.64%	11.78%	0.36%	7.70%	11.80%
Obs	58,290	58,290	58,290	57,322	57,322	57,322	56,183	56,183	56,183	54,974	54,974	54,974	53,707	53,707	53,707
Panel C: J=12															
AIUR	-0.34***	-0.28***	-0.26***	-0.22***	-0.19***	-0.19***	-0.16**	-0.14**	-0.14**	-0.14*	-0.14***	-0.15***	-0.12*	-0.15***	-0.16***
	(3.14)	(3.26)	(3.26)	(2.61)	(2.73)	(2.81)	(2.12)	(2.45)	(2.53)	(1.91)	(2.81)	(3.13)	(1.71)	(3.09)	(3.47)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.19%	6.43%	9.15%	0.18%	6.59%	9.68%	0.23%	7.06%	10.08%	0.34%	7.10%	10.30%	0.40%	6.89%	10.20%
Obs	110,032	110,032	110,032	107,960	107,960	107,960	105,641	105,641	105,641	103,211	103,211	103,211	100,767	100,767	100,767

Table 7

Panel Regressions: J=9

This table shows results from panel regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The control variables include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. The sample period is from January 1994 to December 2016. t-statistics (based on standard errors clustered by firm and month) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
AIUR	-0.36***	-0.53***	-0.52***	-0.22**	-0.40***	-0.39***	-0.17*	-0.36***	-0.35***	-0.12	-0.32***	-0.31***	-0.09	-0.31***	-0.29***
	(3.07)	(4.21)	(4.19)	(2.11)	(3.56)	(3.46)	(1.71)	(3.51)	(3.40)	(1.27)	(3.37)	(3.26)	(1.07)	(3.36)	(3.27)
R01		0.00	-0.00		-0.00	-0.00		0.00	-0.00		0.00	0.00		0.00	0.00
		(0.00)	(0.07)		(0.41)	(0.57)		(0.22)	(0.01)		(0.68)	(0.40)		(0.43)	(0.05)
R12		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00		-0.00	-0.00
		(1.12)	(1.38)		(1.26)	(1.60)		(0.78)	(1.17)		(0.03)	(0.46)		(0.73)	(0.23)
BM		0.41***	0.38***		0.40***	0.35***		0.42***	0.36***		0.38***	0.32***		0.35***	0.29***
		(3.37)	(3.21)		(3.39)	(3.14)		(3.58)	(3.26)		(3.50)	(3.12)		(3.70)	(3.27)
ML		0.73*	0.72*		0.75**	0.60*		0.75**	0.59*		0.79***	0.69**		0.83***	0.78***
		(1.83)	(1.74)		(2.22)	(1.68)		(2.41)	(1.84)		(2.80)	(2.35)		(3.25)	(2.90)
SZ		-0.05	-0.05		-0.06	-0.05		-0.09***	-0.09*		-0.12***	-0.10**		-0.12***	-0.09**
		(0.84)	(0.64)		(1.52)	(0.91)		(2.66)	(1.67)		(3.53)	(2.16)		(4.17)	(2.19)
ILLIQ			-0.00			0.01*			0.01			0.01			0.01
			(0.05)			(1.67)			(1.18)			(0.92)			(0.99)
IDVOL			0.13			0.18*			0.19**			0.21***			0.24***
			(0.99)			(1.70)			(2.19)			(2.85)			(3.65)
DISP			0.00			-0.00			-0.00			-0.00			-0.00
			(1.45)			(0.34)			(1.56)			(1.63)			(1.46)
AG			-0.29*			-0.30*			-0.33*			-0.31*			-0.28*
			(1.77)			(1.73)			(1.93)			(1.93)			(1.91)
UNRATED			-0.32*			-0.41***			-0.44***			-0.42***			-0.38***
			(1.84)			(2.62)			(3.26)			(3.42)			(3.37)
SPECULATIVE			-0.40**			-0.36**			-0.40***			-0.43***			-0.45***
			(2.15)			(2.34)			(3.07)			(3.39)			(3.69)
Intercept	0.81***	0.99	0.97	0.80***	1.18*	1.04	0.79***	1.61***	1.52*	0.79***	1.97***	1.68**	0.80***	2.11***	1.47**
	(4.04)	(1.07)	(0.78)	(5.60)	(1.83)	(1.03)	(6.69)	(2.93)	(1.68)	(7.35)	(3.85)	(2.12)	(8.16)	(4.64)	(2.12)
Adj. R^2	0.03%	0.43%	0.57%	0.03%	0.72%	1.11%	0.02%	1.15%	1.82%	0.01%	1.52%	2.40%	0.01%	1.93%	3.10%
Obs	85,222	85,222	85,222	83,696	83,696	83,696	81,965	81,965	81,965	80,145	80,145	80,145	78,239	78,239	78,239

Table 8

Panel Regressions: J=3, 6, and 12

This table shows results from panel regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The standard controls include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and firm size (SZ); the extended controls include Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. Coefficients on control variables and intercept are omitted for brevity. The sample period is from January 1994 to December 2016. *t*-statistics (based on standard errors clustered by firm and month) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: J=3															
AIUR	-0.54***	-0.70***	-0.70***	-0.33**	-0.47***	-0.46***	-0.28**	-0.44***	-0.43***	-0.14	-0.33***	-0.31***	-0.13	-0.34***	-0.33***
	(3.33)	(4.06)	(4.06)	(2.55)	(3.49)	(3.38)	(2.51)	(3.72)	(3.59)	(1.40)	(3.13)	(2.99)	(1.39)	(3.57)	(3.43)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.08%	0.60%	0.68%	0.06%	0.55%	0.70%	0.06%	0.98%	1.41%	0.02%	1.20%	1.83%	0.02%	1.84%	2.92%
Obs	29,683	29,683	29,683	29,267	29,267	29,267	28,703	28,703	28,703	28,113	28,113	28,113	27,483	27,483	27,483
Panel B: J=6															
AIUR	-0.31**	-0.46***	-0.46***	-0.24**	-0.41***	-0.39***	-0.16	-0.34***	-0.32***	-0.11	-0.31***	-0.30***	-0.08	-0.30***	-0.29***
	(2.29)	(3.24)	(3.27)	(2.02)	(3.20)	(3.12)	(1.49)	(3.02)	(2.88)	(1.10)	(3.08)	(2.95)	(0.94)	(3.21)	(3.10)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.02%	0.33%	0.43%	0.03%	0.63%	0.91%	0.02%	0.97%	1.53%	0.01%	1.36%	2.15%	0.01%	1.89%	2.98%
Obs	58,290	58,290	58,290	57,322	57,322	57,322	56,183	56,183	56,183	54,974	54,974	54,974	53,707	53,707	53,707
Panel C: J=12															
AIUR	-0.28***	-0.47***	-0.46***	-0.20**	-0.41***	-0.39***	-0.15*	-0.36***	-0.35***	-0.11	-0.32***	-0.31***	-0.07	-0.28***	-0.27***
	(2.64)	(4.18)	(4.12)	(2.11)	(3.95)	(3.84)	(1.66)	(3.71)	(3.59)	(1.22)	(3.44)	(3.33)	(0.82)	(3.24)	(3.14)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.02%	0.43%	0.57%	0.02%	0.82%	1.25%	0.02%	1.24%	1.94%	0.01%	1.57%	2.50%	0.00%	2.02%	3.24%
Obs	110,032	110,032	110,032	107,960	107,960	107,960	105,641	105,641	105,641	103,211	103,211	103,211	100,767	100,767	100,767

Table 9

Returns of Double-Sort Portfolios

This table reports the performance of portfolios sorted on proxies of information asymmetry and AIUR. Each month, we split firms that borrowed loans over the past 9 months by the median of analyst coverage (total number of analysts following the firm in the fiscal year), analyst forecast error (the absolute difference between the actual earnings and the mean forecast by all analysts, scaled by the absolute value of actual earnings), or institutional ownership (percentage of shares owned by institutions). And then firms in each group are sorted into quintile portfolios based on AIUR and held for K months. The panels present the average monthly return spread (in percentage) between the highest and lowest AIUR quintile portfolios for different values of K, using the equally weighted excess returns (EW), the weighted excess returns with the facility amount scaled by total assets as the weight (VW), alphas from Fama and French (2015) five-factor model and Hou et al. (2015) four-factor model. t-statistics are reported in parentheses. The sample period spans from 1994 to 2016. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Analyst Coverage		Analyst Forecast Error		Institutional Ownership	
	Low	High	Low	High	Low	High
Panel A: J=9, K=3						
EW	-0.79***	-0.02	-0.16	-0.44**	-0.89***	0.12
	(3.51)	(0.12)	(1.00)	(1.99)	(4.17)	(0.70)
VW	-0.87***	0.14	-0.16	-0.74**	-0.97***	0.08
	(2.97)	(0.66)	(0.72)	(2.30)	(3.24)	(0.34)
FF 5-factor alpha	-0.81***	0.01	0.06	-0.60***	-0.90***	0.20
	(3.86)	(0.04)	(0.35)	(2.65)	(4.53)	(1.14)
HXZ 4-factor alpha	-0.98***	0.00	-0.03	-0.69***	-1.01***	0.07
	(4.62)	(0.02)	(0.17)	(3.01)	(5.01)	(0.39)
Panel B: J=9, K=6						
EW	-0.60***	-0.05	-0.08	-0.36*	-0.64***	0.10
	(2.78)	(0.26)	(0.52)	(1.81)	(3.20)	(0.59)
VW	-0.70***	0.01	-0.07	-0.65**	-0.70***	0.02
	(2.60)	(0.07)	(0.38)	(2.33)	(2.60)	(0.10)
FF 5-factor alpha	-0.78***	-0.05	0.08	-0.65***	-0.79***	0.12
	(4.12)	(0.28)	(0.54)	(3.18)	(4.24)	(0.72)
HXZ 4-factor alpha	-0.91***	-0.05	0.05	-0.73***	-0.89***	0.06
	(4.73)	(0.30)	(0.30)	(3.53)	(4.70)	(0.33)
Panel C: J=9, K=9						
EW	-0.48**	-0.08	-0.00	-0.42**	-0.49***	0.02
	(2.49)	(0.43)	(0.01)	(2.36)	(2.77)	(0.10)
VW	-0.60**	-0.06	-0.00	-0.71***	-0.59**	-0.07
	(2.42)	(0.30)	(0.03)	(2.92)	(2.44)	(0.37)
FF 5-factor alpha	-0.68***	-0.09	0.13	-0.72***	-0.67***	0.02
	(4.18)	(0.55)	(0.92)	(3.99)	(4.08)	(0.12)
HXZ 4-factor alpha	-0.77***	-0.08	0.12	-0.78***	-0.75***	0.00
	(4.53)	(0.46)	(0.91)	(4.20)	(4.43)	(0.02)
Panel D: J=9, K=12						
EW	-0.37**	-0.06	0.04	-0.36**	-0.37**	-0.01
	(2.14)	(0.34)	(0.33)	(2.14)	(2.24)	(0.04)
VW	-0.51**	-0.00	0.08	-0.66***	-0.43*	-0.06
	(2.28)	(0.00)	(0.45)	(2.91)	(1.91)	(0.32)
FF 5-factor alpha	-0.52***	-0.09	0.16	-0.63***	-0.52***	-0.00
	(3.36)	(0.58)	(1.22)	(3.72)	(3.47)	(0.02)
HXZ 4-factor alpha	-0.58***	-0.05	0.19	-0.69***	-0.56***	-0.01
	(3.68)	(0.31)	(1.47)	(3.91)	(3.66)	(0.06)
Panel E: J=9, K=15						
EW	-0.35**	-0.10	0.03	-0.36**	-0.34**	-0.02
	(2.17)	(0.63)	(0.23)	(2.18)	(2.19)	(0.13)
VW	-0.48**	0.02	0.11	-0.60***	-0.34	-0.04
	(2.35)	(0.13)	(0.67)	(2.77)	(1.58)	(0.23)
FF 5-factor alpha	-0.43***	-0.13	0.14	-0.58***	-0.47***	-0.03
	(2.93)	(0.87)	(1.12)	(3.63)	(3.28)	(0.20)
HXZ 4-factor alpha	-0.49***	-0.07	0.18	-0.63***	-0.48***	-0.03
	(3.23)	(0.47)	(1.48)	(3.79)	(3.33)	(0.19)

Table 10

AIUR and Cash Flow Volatility

This table presents the relation between AIUR and future cash flow volatility. AIUR is constructed as the 9-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The control variables include the lagged dependent variable (Lagged Y), reversal (R01),momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), speculative-grade indicator (SPECULATIVE), ratio of R&D expenses to sales (R&D), firm age (AGE), log of total assets (ASSETS), and log of sales (SALES). The detailed definitions are provided in Table 1. In columns (1), (2), and (3), the dependent variable is cash flow volatility, defined as the standard deviation of quarterly operating cash flow over the next two years. The operating cash flow is computed as earnings before interest, taxes, depreciation and amortization (Compustat item OIBDPQ) scaled by total assets (Compustat item ATQ) and it is adjusted by subtracting the industry median in a given Fama and French 48 industry and quarter. In columns (4), (5), and (6), the dependent variable is analyst dispersion on cash flow, defined as the standard deviation of analysts' forecasts on cash flow per share times the shares outstanding, scaled by the book value of total assets. The dispersion is calculated based on the one-year-ahead forecast (I/B/E/S item FY1) for the value at the end of year $t+2$, where year t denotes the year when AIUR is calculated. The dependent variables are measured in percentage. Year-month fixed effect and industry fixed effect are included but the coefficients on these dummies are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on standard errors clustered by year-month) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Y	Cash Flow Volatility			Analyst Dispersion on Cash Flow		
	(1)	(2)	(3)	(4)	(5)	(6)
AIUR	0.08***	0.06***	0.08***	1.29**	1.26**	1.31***
	(5.36)	(5.48)	(6.00)	(2.49)	(2.50)	(3.38)
Lagged Y		0.42***	0.38***		0.54***	0.53***
		(30.99)	(28.09)		(10.94)	(10.91)
R01			-0.12*			-2.71
			(1.72)			(1.60)
R12			0.02**			-1.55***
			(2.07)			(4.25)
BM			0.04***			0.29
			(5.23)			(1.32)
ML			-0.27***			-2.74**
			(4.73)			(2.53)
SZ			0.10***			0.17
			(7.20)			(0.52)
ILLIQ			-0.00			-0.32***
			(0.26)			(3.52)
IDVOL			0.09***			0.15
			(15.63)			(0.76)
AG			-0.09***			-0.28*
			(7.67)			(1.91)
UNRATED			0.05**			-0.47
			(2.44)			(0.54)
SPECULATIVE			0.07***			-0.01
			(3.27)			(0.01)
R&D			0.44***			1.03***
			(4.23)			(2.73)
AGE			-0.06***			-1.29*
			(6.53)			(1.83)
ASSETS			-0.19***			-0.34
			(8.54)			(1.20)
SALES			0.01			-0.42*
			(0.62)			(1.72)
Intercept	1.46***	0.73***	0.72***	0.95***	1.08***	8.35
	(19.17)	(7.99)	(4.40)	(3.71)	(4.11)	(1.53)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	12.86%	30.18%	32.64%	1.19%	15.19%	16.23%
Obs	66,453	66,453	66,453	20,103	20,103	20,103

Table 11

AIUR and Operating Performance

This table reports the coefficients from regressions where measures of operating performance are regressed on the AIUR measure and control variables. AIUR is constructed as the 9-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The control variables include the lagged dependent variable (Lagged Y), reversal (R01),momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), speculative-grade indicator (SPECULATIVE), ratio of R&D expenses to sales (R&D), firm age (AGE), log of total assets (ASSETS), and log of sales (SALES). The detailed definitions are provided in Table 1. In columns (1), (2), and (3), the dependent variable is cash flow (CF), defined as earnings before interest, taxes, depreciation and amortization (Compustat item OIBDP) scaled by total assets (Compustat item AT). In columns (4), (5), and (6), the dependent variable is return on assets (ROA), defined as net income (Compustat item NI) divided by total assets. The dependent variables are calculated in year $t+1$, where year t denotes the year when AIUR is calculated. The dependent variables are measured in percentage and adjusted by subtracting the industry median in a given Fama and French 48 industry and year. Year-month fixed effect and industry fixed effect are included but the coefficients on these dummies are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on standard errors clustered by year-month) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Y	Industry-adjusted CF			Industry-adjusted ROA		
	(1)	(2)	(3)	(4)	(5)	(6)
AIUR	-3.06***	-0.98***	-0.61***	-3.06***	-1.47***	-0.75***
	(26.06)	(11.14)	(7.94)	(24.01)	(12.89)	(7.66)
Lagged Y		0.63***	0.56***		0.45***	0.36***
		(61.82)	(49.21)		(28.32)	(23.53)
R01			1.69***			2.29***
			(4.70)			(4.12)
R12			0.02			0.70***
			(0.20)			(3.64)
BM			0.15***			0.04
			(2.95)			(0.57)
ML			8.75***			3.50***
			(31.42)			(9.07)
SZ			3.70***			2.92***
			(25.75)			(18.28)
ILLIQ			0.01***			-0.00
			(3.18)			(0.29)
IDVOL			-0.20***			-0.61***
			(5.22)			(9.72)
AG			-0.30***			-0.27***
			(2.78)			(2.86)
UNRATED			-0.56***			-0.40***
			(5.43)			(3.37)
SPECULATIVE			-1.01***			-0.75***
			(9.31)			(7.07)
R&D			-0.02***			-0.05***
			(3.37)			(6.39)
AGE			0.04			0.34***
			(0.84)			(5.02)
ASSETS			-5.20***			-3.81***
			(30.46)			(21.72)
SALES			1.50***			1.30***
			(22.04)			(17.78)
Intercept	3.17***	0.29	-25.03***	-4.50***	-4.88***	-26.85***
	(4.32)	(0.62)	(22.44)	(4.51)	(5.87)	(17.75)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	34.83%	63.86%	66.64%	28.12%	42.15%	45.69%
Obs	72,617	72,617	72,617	72,936	72,936	72,936

Table 12
Returns of AIUR2 Portfolios: J=9

This table reports the monthly excess returns or abnormal returns (in percentage) of quintile portfolios sorted on AIUR2, which is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on the same set of loan spread determinants as AIUR, plus two additional controls: 1) the KMV-Merton expected default probability per Merton (1974) and 2) sales growth over the prior two years, i.e., the μ variable as defined in Bolton et al. (2014). Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR2 measure and held for K months. The average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), abnormal returns (alpha) from Fama and French (2015) five-factor model and Hou et al. (2015) four-factor model are presented in each panel for different values of K. The sample period is from January 1994 to December 2016. t-statistics for the return spread between the highest and lowest AIUR2 quintile portfolios are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	AIUR2						
	L	2	3	4	H	H-L	t-stat
Panel A: J=9, K=3							
EW	1.23	1.12	1.03	0.78	0.81	-0.42***	(2.73)
VW	1.11	0.73	1.10	0.96	0.51	-0.61	(1.42)
FF 5-factor alpha	0.07	-0.05	-0.18	-0.42	-0.41	-0.47***	(2.90)
HXZ 4-factor alpha	0.34	0.12	-0.05	-0.28	-0.25	-0.59***	(3.63)
Panel B: J=9, K=6							
EW	1.20	1.09	1.06	0.81	0.80	-0.39***	(2.78)
VW	1.14	0.77	1.09	0.95	0.39	-0.75**	(1.98)
FF 5-factor alpha	0.07	-0.08	-0.13	-0.39	-0.40	-0.47***	(3.20)
HXZ 4-factor alpha	0.32	0.10	0.00	-0.23	-0.23	-0.56***	(3.79)
Panel C: J=9, K=9							
EW	1.18	1.12	1.06	0.87	0.78	-0.39***	(2.97)
VW	1.28	0.85	1.07	0.85	0.42	-0.86**	(2.50)
FF 5-factor alpha	0.06	-0.05	-0.12	-0.35	-0.41	-0.47***	(3.49)
HXZ 4-factor alpha	0.30	0.13	0.03	-0.18	-0.24	-0.54***	(3.87)
Panel D: J=9, K=12							
EW	1.12	1.12	1.05	0.87	0.79	-0.33***	(2.60)
VW	1.32	0.92	1.06	0.79	0.50	-0.82***	(2.65)
FF 5-factor alpha	0.01	-0.04	-0.12	-0.37	-0.40	-0.42***	(3.28)
HXZ 4-factor alpha	0.23	0.14	0.03	-0.19	-0.23	-0.46***	(3.45)
Panel E: J=9, K=15							
EW	1.06	1.12	1.04	0.85	0.76	-0.30**	(2.44)
VW	1.25	1.00	1.03	0.71	0.56	-0.69**	(2.46)
FF 5-factor alpha	-0.03	-0.03	-0.13	-0.39	-0.43	-0.39***	(3.17)
HXZ 4-factor alpha	0.17	0.15	0.03	-0.20	-0.25	-0.43***	(3.30)

Table 13

Fama-MacBeth Regressions: J=9

This table shows results from Fama-MacBeth regressions of firm's K-month average excess returns (in percentage) on the measure AIUR2 as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR2 is constructed as the J-month moving average of residuals from 5-year rolling-window regressions of the logarithm of all-in-undrawn spread on the same set of loan spread determinants as AIUR, plus two additional controls: 1) the KMV-Merton expected default probability per Merton (1974) and 2) sales growth over the prior two years, i.e., the μ variable as defined in Bolton et al. (2014). The control variables include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. The sample period is from January 1994 to December 2016. t-statistics (based on Newey-West standard errors) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
AIUR2	-0.43***	-0.32***	-0.29***	-0.33***	-0.23***	-0.22***	-0.28***	-0.19***	-0.19***	-0.25***	-0.21***	-0.21***	-0.25***	-0.24***	-0.25***
	(3.58)	(3.55)	(3.36)	(3.24)	(2.84)	(3.00)	(3.40)	(2.83)	(2.89)	(3.40)	(3.66)	(3.75)	(3.36)	(4.51)	(4.68)
R01		-0.01	-0.00		-0.00	-0.00		0.00	0.00		0.00	0.00		0.00	0.00
		(0.98)	(0.69)		(0.45)	(0.12)		(0.69)	(0.93)		(1.53)	(1.58)		(1.01)	(1.00)
R12		0.00	0.00		-0.00	0.00		-0.00	-0.00		-0.00	-0.00		-0.00	-0.00
		(0.12)	(0.76)		(0.25)	(0.14)		(0.74)	(0.31)		(1.34)	(1.00)		(1.63)	(1.26)
BM		0.21**	0.21**		0.10	0.06		0.09	0.03		0.11*	0.05		0.16**	0.11*
		(2.14)	(2.15)		(1.23)	(0.79)		(1.25)	(0.46)		(1.73)	(0.84)		(2.55)	(1.88)
ML		-0.46	-0.22		-0.31	-0.21		-0.19	-0.12		-0.12	-0.06		-0.12	-0.06
		(1.22)	(0.56)		(1.00)	(0.71)		(0.69)	(0.46)		(0.48)	(0.27)		(0.56)	(0.29)
SZ		-0.04	-0.06		-0.07	-0.08*		-0.08**	-0.09***		-0.09***	-0.10***		-0.09***	-0.10***
		(0.86)	(1.24)		(1.61)	(1.87)		(2.17)	(2.66)		(2.65)	(3.23)		(3.05)	(3.47)
ILLIQ			-2.55			1.75			0.55			-0.51			-1.12
			(0.78)			(1.34)			(0.63)			(0.70)			(1.22)
IDVOL			-0.10			-0.05			0.00			0.03			0.04
			(1.21)			(0.71)			(0.03)			(0.48)			(0.82)
DISP			-0.12**			-0.03			-0.00			0.02			0.03
			(1.98)			(0.87)			(0.08)			(0.80)			(1.39)
AG			-0.58***			-0.65***			-0.65***			-0.63***			-0.57***
			(3.69)			(5.63)			(6.69)			(7.42)			(7.43)
UNRATED			-0.00			-0.13			-0.22**			-0.27***			-0.23***
			(0.03)			(1.29)			(2.32)			(2.98)			(3.15)
SPECULATIVE			-0.10			-0.15			-0.21**			-0.23***			-0.27***
			(0.70)			(1.37)			(2.49)			(3.41)			(4.77)
Intercept	0.97***	1.14	1.69*	0.97***	1.50**	1.96***	0.98***	1.71***	2.14***	0.97***	1.85***	2.28***	0.96***	1.91***	2.26***
	(2.84)	(1.28)	(1.92)	(3.54)	(2.15)	(2.62)	(4.38)	(2.90)	(3.52)	(5.08)	(3.51)	(4.15)	(5.71)	(3.98)	(4.43)
Adj. R^2	0.19%	7.03%	10.45%	0.24%	6.62%	10.33%	0.26%	7.15%	10.77%	0.33%	7.33%	10.79%	0.50%	7.41%	10.95%
Obs	75,966	75,966	75,966	74,572	74,572	74,572	73,058	73,058	73,058	71,491	71,491	71,491	69,853	69,853	69,853

Supplementary Material—Appendix A

The results reported in this appendix are obtained when Equation (1) is estimated in one regression with the full sample. As described in the main paper, after estimating Equation (1), we aggregate the residuals into firm-month level. And AIUR of a firm in a certain month is constructed as the moving average of its residuals over the past J months.

Table A1 shows the return spreads for the highest and lowest quintile portfolios sorted on AIUR, with J equal to 3, 6, 9, and 12. Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR measure and held for K months. The values of K are 3, 6, 9, 12, and 15. For each K, we report the monthly return spreads (in percentage) between the highest and lowest quintile portfolios sorted on AIUR. The return spreads are computed from the average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), alphas from Fama and French (2015) five-factor model and alphas from Hou et al. (2015) four-factor model.

Table A2 presents results from Fama-MacBeth regressions of future stock returns on AIUR as well as controls for expected returns, with J equal to 3, 6, 9, and 12. The dependent variable is firm's K-month average excess returns where K takes the value of 3, 6, 9, 12, and 15. The control variables include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1 of the paper. In addition to Fama-MacBeth regressions, we also estimate these models with panel regressions, and the corresponding results are reported in Table A3.

Table A1

Returns of AIUR Portfolios: AIUR from Full-sample Regression

This table reports the monthly return spreads (in percentage) between the highest and lowest quintile portfolios sorted on AIUR, which is constructed as the J-month moving average of residuals from regression of the logarithm of all-in-undrawn spread on a set of loan spread determinants where the regression is run with the full sample. Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR measure and held for K months. The return spreads for the average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), abnormal returns (alpha) from Fama and French (2015) five-factor model and Hou et al. (2015) four-factor model are presented in each panel for different values of K. The sample period is from January 1994 to December 2016. t-statistics for the return spread are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	J=3		J=6		J=9		J=12	
	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat
Panel A: K=3								
EW	-0.56***	(2.80)	-0.39**	(2.14)	-0.54***	(3.43)	-0.42***	(2.92)
VW	-0.56*	(1.87)	-0.52**	(2.01)	-0.75***	(3.47)	-0.66***	(3.33)
FF 5-factor alpha	-0.44**	(2.30)	-0.34*	(1.91)	-0.50***	(3.28)	-0.48***	(3.54)
HXZ 4-factor alpha	-0.45**	(2.34)	-0.33*	(1.89)	-0.56***	(3.54)	-0.50***	(3.64)
Panel B: K=6								
EW	-0.39**	(2.28)	-0.42**	(2.58)	-0.42***	(2.87)	-0.31**	(2.28)
VW	-0.34	(1.45)	-0.52**	(2.34)	-0.62***	(3.12)	-0.57***	(3.06)
FF 5-factor alpha	-0.34**	(1.99)	-0.41**	(2.53)	-0.48***	(3.43)	-0.40***	(3.17)
HXZ 4-factor alpha	-0.37**	(2.15)	-0.46***	(2.79)	-0.52***	(3.63)	-0.41***	(3.20)
Panel C: K=9								
EW	-0.50***	(3.38)	-0.39***	(2.82)	-0.34**	(2.57)	-0.25*	(1.85)
VW	-0.52***	(2.61)	-0.57***	(2.89)	-0.59***	(3.18)	-0.48***	(2.62)
FF 5-factor alpha	-0.47***	(3.16)	-0.45***	(3.29)	-0.42***	(3.32)	-0.34***	(2.73)
HXZ 4-factor alpha	-0.54***	(3.60)	-0.48***	(3.46)	-0.43***	(3.37)	-0.33***	(2.63)
Panel D: K=12								
EW	-0.36***	(2.79)	-0.27**	(2.12)	-0.25*	(1.86)	-0.19	(1.43)
VW	-0.48***	(2.63)	-0.47**	(2.59)	-0.43**	(2.42)	-0.36*	(1.96)
FF 5-factor alpha	-0.44***	(3.45)	-0.37***	(3.00)	-0.33***	(2.73)	-0.30**	(2.42)
HXZ 4-factor alpha	-0.47***	(3.61)	-0.37***	(2.96)	-0.32***	(2.61)	-0.26**	(2.14)
Panel E: K=15								
EW	-0.27**	(2.31)	-0.21*	(1.67)	-0.21	(1.60)	-0.17	(1.25)
VW	-0.39**	(2.37)	-0.35**	(2.08)	-0.33*	(1.88)	-0.27	(1.49)
FF 5-factor alpha	-0.31***	(2.70)	-0.28**	(2.38)	-0.29**	(2.45)	-0.27**	(2.24)
HXZ 4-factor alpha	-0.33***	(2.79)	-0.27**	(2.28)	-0.26**	(2.22)	-0.22*	(1.83)

Table A2

Fama-MacBeth Regressions: AIUR from Full-sample Regression

This table shows results from Fama-MacBeth regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from regression of the logarithm of all-in-undrawn spread on a set of loan spread determinants where the regression is run with the full sample. The standard controls include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and firm size (SZ); the extended controls include Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. Coefficients on control variables and intercept are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on Newey-West standard errors) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: J=3															
AIUR	-0.53***	-0.57***	-0.59***	-0.35***	-0.32***	-0.31***	-0.35***	-0.32***	-0.33***	-0.18**	-0.17**	-0.19**	-0.15**	-0.21***	-0.25***
	(3.71)	(4.05)	(4.13)	(3.27)	(2.98)	(2.67)	(3.73)	(3.20)	(3.35)	(2.23)	(2.19)	(2.29)	(2.17)	(3.54)	(3.84)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.17%	8.91%	13.83%	0.15%	7.68%	13.82%	0.21%	8.20%	14.33%	0.11%	8.53%	14.83%	0.02%	8.75%	14.70%
Obs	29,683	29,683	29,683	29,267	29,267	29,267	28,703	28,703	28,703	28,113	28,113	28,113	27,483	27,483	27,483
Panel B: J=6															
AIUR	-0.35***	-0.31***	-0.30***	-0.31***	-0.27***	-0.27***	-0.20**	-0.16*	-0.17**	-0.11	-0.12*	-0.14**	-0.10	-0.15***	-0.18***
	(2.75)	(2.76)	(2.72)	(3.14)	(2.87)	(3.09)	(2.32)	(1.89)	(2.30)	(1.60)	(1.80)	(2.29)	(1.42)	(2.65)	(3.25)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.24%	7.22%	10.94%	0.17%	6.89%	11.21%	0.18%	7.41%	11.65%	0.14%	7.67%	11.78%	0.21%	7.70%	11.79%
Obs	58,290	58,290	58,290	57,322	57,322	57,322	56,183	56,183	56,183	54,974	54,974	54,974	53,707	53,707	53,707
Panel C: J=9															
AIUR	-0.42***	-0.33***	-0.33***	-0.26***	-0.20**	-0.22***	-0.16**	-0.12*	-0.15**	-0.11	-0.11*	-0.14***	-0.11*	-0.14***	-0.18***
	(3.65)	(3.35)	(3.67)	(2.84)	(2.30)	(2.82)	(2.19)	(1.75)	(2.27)	(1.62)	(1.92)	(2.61)	(1.66)	(2.64)	(3.47)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.23%	6.87%	10.08%	0.21%	6.56%	10.05%	0.19%	7.08%	10.60%	0.22%	7.28%	10.70%	0.31%	7.14%	10.56%
Obs	85,222	85,222	85,222	83,696	83,696	83,696	81,965	81,965	81,965	80,145	80,145	80,145	78,239	78,239	78,239
Panel D: J=12															
AIUR	-0.30***	-0.24***	-0.26***	-0.19**	-0.16**	-0.19***	-0.12	-0.12*	-0.14**	-0.10	-0.11**	-0.15***	-0.08	-0.12**	-0.16***
	(2.77)	(2.72)	(3.21)	(2.18)	(2.14)	(2.72)	(1.64)	(1.80)	(2.44)	(1.44)	(2.08)	(3.03)	(1.24)	(2.44)	(3.38)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.20%	6.44%	9.16%	0.19%	6.63%	9.70%	0.21%	7.12%	10.11%	0.28%	7.14%	10.32%	0.32%	6.92%	10.22%
Obs	110,032	110,032	110,032	107,960	107,960	107,960	105,641	105,641	105,641	103,211	103,211	103,211	100,767	100,767	100,767

Table A3

Panel Regressions: AIUR from Full-sample Regression

This table shows results from panel regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from regression of the logarithm of all-in-undrawn spread on a set of loan spread determinants where the regression is run with the full sample. The standard controls include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and firm size (SZ); the extended controls include Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. Coefficients on control variables and intercept are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on standard errors clustered by firm and month) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: J=3															
AIUR	-0.40**	-0.55***	-0.57***	-0.26*	-0.40***	-0.40***	-0.25**	-0.41***	-0.41***	-0.12	-0.31***	-0.31***	-0.11	-0.32***	-0.32***
	(2.38)	(3.18)	(3.24)	(1.93)	(2.92)	(2.87)	(2.20)	(3.47)	(3.44)	(1.18)	(2.94)	(2.90)	(1.18)	(3.34)	(3.31)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.04%	0.55%	0.63%	0.03%	0.52%	0.67%	0.05%	0.96%	1.41%	0.01%	1.19%	1.83%	0.01%	1.82%	2.92%
Obs	29,683	29,683	29,683	29,267	29,267	29,267	28,703	28,703	28,703	28,113	28,113	28,113	27,483	27,483	27,483
Panel B: J=6															
AIUR	-0.22	-0.37***	-0.39***	-0.20*	-0.37***	-0.37***	-0.14	-0.33***	-0.32***	-0.09	-0.29***	-0.29***	-0.07	-0.29***	-0.29***
	(1.64)	(2.63)	(2.74)	(1.70)	(2.93)	(2.93)	(1.37)	(2.92)	(2.90)	(0.96)	(2.96)	(2.94)	(0.78)	(3.06)	(3.07)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.01%	0.32%	0.41%	0.02%	0.62%	0.90%	0.02%	0.97%	1.53%	0.01%	1.36%	2.15%	0.00%	1.88%	2.98%
Obs	58,290	58,290	58,290	57,322	57,322	57,322	56,183	56,183	56,183	54,974	54,974	54,974	53,707	53,707	53,707
Panel C: J=9															
AIUR	-0.30***	-0.47***	-0.48***	-0.20*	-0.38***	-0.38***	-0.15	-0.35***	-0.35***	-0.10	-0.31***	-0.31***	-0.07	-0.28***	-0.29***
	(2.59)	(3.78)	(3.85)	(1.89)	(3.37)	(3.37)	(1.58)	(3.39)	(3.41)	(1.13)	(3.24)	(3.27)	(0.87)	(3.17)	(3.20)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.02%	0.42%	0.56%	0.02%	0.71%	1.10%	0.02%	1.14%	1.82%	0.01%	1.51%	2.40%	0.01%	1.92%	3.09%
Obs	85,222	85,222	85,222	83,696	83,696	83,696	81,965	81,965	81,965	80,145	80,145	80,145	78,239	78,239	78,239
Panel D: J=12															
AIUR	-0.24**	-0.43***	-0.43***	-0.18*	-0.38***	-0.38***	-0.13	-0.34***	-0.34***	-0.08	-0.29***	-0.29***	-0.04	-0.25***	-0.25***
	(2.26)	(3.87)	(3.90)	(1.85)	(3.74)	(3.73)	(1.49)	(3.56)	(3.58)	(0.99)	(3.24)	(3.28)	(0.51)	(2.97)	(2.98)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.01%	0.42%	0.57%	0.02%	0.81%	1.24%	0.01%	1.24%	1.94%	0.01%	1.56%	2.50%	0.00%	2.01%	3.23%
Obs	110,032	110,032	110,032	107,960	107,960	107,960	105,641	105,641	105,641	103,211	103,211	103,211	100,767	100,767	100,767

Supplementary Material—Appendix B

The results reported in this appendix are obtained when Equation (1) is estimated with 10-year rolling-window regressions. As described in the main paper, after estimating Equation (1), we aggregate the residuals into firm-month level. And AIUR of a firm in a certain month is constructed as the moving average of its residuals over the past J months.

Table B1 shows the return spreads for the highest and lowest quintile portfolios sorted on AIUR, with J equal to 3, 6, 9, and 12. Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR measure and held for K months. The values of K are 3, 6, 9, 12, and 15. the monthly return spreads (in percentage) between the highest and lowest quintile portfolios sorted on AIUR. The return spreads are computed from the average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), alphas from Fama and French (2015) five-factor model and alphas from Hou et al. (2015) four-factor model.

Table B2 present results from Fama-MacBeth regressions of future stock returns on AIUR as well as controls for expected returns, with J equal to 3, 6, 9, and 12. The dependent variable is firm's K-month average excess returns where K takes the value of 3, 6, 9, 12, and 15. The control variables include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), firm size (SZ), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1 of the paper. In addition to Fama-MacBeth regressions, we also estimate these models with panel regressions, and the corresponding results are reported in Table B3.

Table B1

Returns of AIUR Portfolios: 10-year Rolling-window Regression

This table reports the monthly return spreads (in percentage) between the highest and lowest quintile portfolios sorted on AIUR, which is constructed as the J-month moving average of residuals from 10-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. Every month, firms which borrowed loans over the past J months are sorted into quintile portfolios based on the AIUR measure and held for K months. The return spreads for the average monthly equally weighted excess returns (EW), the average monthly weighted excess returns with the facility amount scaled by total assets as the weight (VW), abnormal returns (alpha) from Fama and French (2015) five-factor model and Hou et al. (2015) four-factor model are presented in each panel for different values of K. The sample period is from January 1994 to December 2016. *t*-statistics for the return spread are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	J=3		J=6		J=9		J=12	
	H-L	*t*-stat	H-L	*t*-stat	H-L	*t*-stat	H-L	*t*-stat
Panel A: K=3								
EW	-0.50**	(2.42)	-0.34*	(1.80)	-0.51***	(3.11)	-0.35**	(2.38)
VW	-0.54*	(1.72)	-0.40	(1.44)	-0.58***	(2.60)	-0.49**	(2.44)
FF 5-factor alpha	-0.42**	(2.18)	-0.31*	(1.76)	-0.47***	(2.96)	-0.46***	(3.30)
HXZ 4-factor alpha	-0.41**	(2.12)	-0.33*	(1.85)	-0.51***	(3.20)	-0.46***	(3.32)
Panel B: K=6								
EW	-0.31*	(1.79)	-0.39**	(2.34)	-0.39***	(2.60)	-0.29**	(2.10)
VW	-0.30	(1.25)	-0.42*	(1.85)	-0.49**	(2.45)	-0.45**	(2.42)
FF 5-factor alpha	-0.25	(1.48)	-0.37**	(2.28)	-0.45***	(3.12)	-0.39***	(3.03)
HXZ 4-factor alpha	-0.29*	(1.73)	-0.43**	(2.58)	-0.49***	(3.31)	-0.39***	(3.02)
Panel C: K=9								
EW	-0.49***	(3.23)	-0.38***	(2.61)	-0.33**	(2.47)	-0.25*	(1.91)
VW	-0.48**	(2.41)	-0.46**	(2.37)	-0.47**	(2.52)	-0.41**	(2.27)
FF 5-factor alpha	-0.43***	(2.91)	-0.44***	(3.13)	-0.41***	(3.17)	-0.34***	(2.75)
HXZ 4-factor alpha	-0.50***	(3.32)	-0.48***	(3.32)	-0.43***	(3.23)	-0.33***	(2.62)
Panel D: K=12								
EW	-0.34***	(2.61)	-0.27**	(2.03)	-0.25*	(1.90)	-0.22*	(1.69)
VW	-0.41**	(2.27)	-0.37**	(2.05)	-0.36**	(2.04)	-0.34*	(1.87)
FF 5-factor alpha	-0.42***	(3.22)	-0.36***	(2.84)	-0.33***	(2.66)	-0.32***	(2.60)
HXZ 4-factor alpha	-0.43***	(3.32)	-0.36***	(2.84)	-0.32**	(2.58)	-0.29**	(2.33)
Panel E: K=15								
EW	-0.26**	(2.16)	-0.21	(1.64)	-0.23*	(1.80)	-0.21	(1.59)
VW	-0.32*	(1.96)	-0.27	(1.59)	-0.29*	(1.66)	-0.26	(1.46)
FF 5-factor alpha	-0.31***	(2.67)	-0.27**	(2.23)	-0.30**	(2.55)	-0.30**	(2.53)
HXZ 4-factor alpha	-0.32***	(2.71)	-0.26**	(2.17)	-0.29**	(2.39)	-0.26**	(2.17)

Table B2

Fama-MacBeth Regressions: 10-year Rolling-window Regression

This table shows results from Fama-MacBeth regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from 10-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The standard controls include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and firm size (SZ); the extended controls include Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. Coefficients on control variables and intercept are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on Newey-West standard errors) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: J=3															
AIUR	-0.59***	-0.63***	-0.60***	-0.38***	-0.34***	-0.30**	-0.37***	-0.33***	-0.31***	-0.19**	-0.18**	-0.18**	-0.16**	-0.22***	-0.23***
	(4.09)	(4.36)	(4.05)	(3.54)	(3.05)	(2.52)	(3.94)	(3.27)	(3.11)	(2.40)	(2.32)	(2.14)	(2.28)	(3.57)	(3.60)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.19%	8.93%	13.88%	0.10%	7.69%	13.87%	0.14%	8.17%	14.37%	0.06%	8.52%	14.86%	0.06%	8.76%	14.73%
Obs	29,683	29,683	29,683	29,267	29,267	29,267	28,703	28,703	28,703	28,113	28,113	28,113	27,483	27,483	27,483
Panel B: J=6															
AIUR	-0.36***	-0.34***	-0.30***	-0.31***	-0.28***	-0.25***	-0.19**	-0.16**	-0.16**	-0.11	-0.12*	-0.13**	-0.10	-0.15***	-0.17***
	(2.89)	(2.99)	(2.66)	(3.15)	(2.99)	(2.90)	(2.31)	(1.98)	(2.03)	(1.56)	(1.87)	(2.09)	(1.37)	(2.65)	(3.00)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.24%	7.22%	10.93%	0.15%	6.87%	11.20%	0.15%	7.37%	11.65%	0.11%	7.64%	11.77%	0.20%	7.68%	11.78%
Obs	58,290	58,290	58,290	57,322	57,322	57,322	56,183	56,183	56,183	54,974	54,974	54,974	53,707	53,707	53,707
Panel C: J=9															
AIUR	-0.43***	-0.36***	-0.33***	-0.26***	-0.21**	-0.21***	-0.16**	-0.13*	-0.13**	-0.11	-0.12**	-0.13**	-0.11*	-0.15***	-0.17***
	(3.75)	(3.68)	(3.69)	(2.87)	(2.50)	(2.72)	(2.20)	(1.91)	(2.13)	(1.60)	(2.07)	(2.53)	(1.65)	(2.77)	(3.37)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.22%	6.87%	10.06%	0.20%	6.52%	10.03%	0.15%	7.03%	10.57%	0.21%	7.24%	10.68%	0.31%	7.11%	10.54%
Obs	85,222	85,222	85,222	83,696	83,696	83,696	81,965	81,965	81,965	80,145	80,145	80,145	78,239	78,239	78,239
Panel D: J=12															
AIUR	-0.31***	-0.27***	-0.26***	-0.19**	-0.17**	-0.18***	-0.12*	-0.12**	-0.14**	-0.11	-0.13**	-0.15***	-0.09	-0.14***	-0.16***
	(2.86)	(3.03)	(3.19)	(2.17)	(2.36)	(2.67)	(1.67)	(2.05)	(2.40)	(1.51)	(2.42)	(3.11)	(1.32)	(2.80)	(3.52)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.19%	6.43%	9.16%	0.17%	6.59%	9.69%	0.18%	7.07%	10.08%	0.27%	7.10%	10.30%	0.31%	6.88%	10.20%
Obs	110,032	110,032	110,032	107,960	107,960	107,960	105,641	105,641	105,641	103,211	103,211	103,211	100,767	100,767	100,767

Table B3

Panel Regressions: 10-year Rolling-window Regression

This table shows results from panel regressions of firm's K-month average excess returns (in percentage) on the measure AIUR as well as controls for expected returns. The values of K are 3, 6, 9, 12, and 15. AIUR is constructed as the J-month moving average of residuals from 10-year rolling-window regressions of the logarithm of all-in-undrawn spread on a set of loan spread determinants. The standard controls include reversal (R01), momentum (R12), book-to-market ratio (BM), market leverage (ML), and firm size (SZ); the extended controls include Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IDVOL), analyst forecast dispersion (DISP), asset growth (AG), unrated indicator (UNRATED), and speculative-grade indicator (SPECULATIVE). The detailed definitions are provided in Table 1. Coefficients on control variables and intercept are omitted for brevity. The sample period is from January 1994 to December 2016. t-statistics (based on standard errors clustered by firm and month) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	3-month			6-month			9-month			12-month			15-month		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: J=3															
AIUR	-0.51***	-0.68***	-0.68***	-0.31**	-0.45***	-0.45***	-0.26**	-0.42***	-0.42***	-0.11	-0.30***	-0.30***	-0.08	-0.29***	-0.30***
	(3.08)	(3.95)	(3.96)	(2.32)	(3.34)	(3.26)	(2.25)	(3.57)	(3.51)	(1.05)	(2.86)	(2.82)	(0.89)	(3.16)	(3.15)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.07%	0.59%	0.67%	0.05%	0.54%	0.70%	0.05%	0.97%	1.41%	0.01%	1.18%	1.82%	0.01%	1.80%	2.90%
Obs	29,683	29,683	29,683	29,267	29,267	29,267	28,703	28,703	28,703	28,113	28,113	28,113	27,483	27,483	27,483
Panel B: J=6															
AIUR	-0.29**	-0.44***	-0.46***	-0.23*	-0.39***	-0.39***	-0.13	-0.31***	-0.31***	-0.07	-0.27***	-0.27***	-0.04	-0.26***	-0.26***
	(2.15)	(3.24)	(3.27)	(1.88)	(3.16)	(3.11)	(1.25)	(2.85)	(2.79)	(0.70)	(2.76)	(2.72)	(0.48)	(2.83)	(2.84)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.02%	0.33%	0.42%	0.03%	0.62%	0.90%	0.01%	0.96%	1.52%	0.00%	1.34%	2.13%	0.00%	1.86%	2.96%
Obs	58,290	58,290	58,290	57,322	57,322	57,322	56,183	56,183	56,183	54,974	54,974	54,974	53,707	53,707	53,707
Panel C: J=9															
AIUR	-0.34***	-0.52***	-0.52***	-0.21*	-0.39***	-0.38***	-0.13	-0.33***	-0.32***	-0.08	-0.28***	-0.28***	-0.05	-0.26***	-0.26***
	(2.91)	(4.21)	(4.21)	(1.93)	(3.47)	(3.43)	(1.35)	(3.23)	(3.21)	(0.84)	(3.00)	(3.01)	(0.57)	(2.92)	(2.95)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.03%	0.43%	0.57%	0.02%	0.72%	1.10%	0.01%	1.13%	1.81%	0.00%	1.49%	2.39%	0.00%	1.90%	3.07%
Obs	85,222	85,222	85,222	83,696	83,696	83,696	81,965	81,965	81,965	80,145	80,145	80,145	78,239	78,239	78,239
Panel D: J=12															
AIUR	-0.26**	-0.45***	-0.46***	-0.17*	-0.38***	-0.38***	-0.11	-0.32***	-0.32***	-0.06	-0.27***	-0.27***	-0.02	-0.23***	-0.24***
	(2.43)	(4.16)	(4.13)	(1.77)	(3.72)	(3.68)	(1.21)	(3.34)	(3.33)	(0.72)	(2.99)	(3.01)	(0.26)	(2.73)	(2.76)
Standard Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Extended Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Adj. R^2	0.02%	0.43%	0.57%	0.01%	0.81%	1.24%	0.01%	1.22%	1.93%	0.00%	1.55%	2.48%	0.00%	1.99%	3.22%
Obs	110,032	110,032	110,032	107,960	107,960	107,960	105,641	105,641	105,641	103,211	103,211	103,211	100,767	100,767	100,767

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