Hidden in Plain Sight: Equity Price Discovery with Informed Private Debt*

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Abstract – This paper examines how private information is (or is not) transmitted via prices across markets for related claims on firm cash flows. We show that equity markets fail to account for value relevant non-public information enjoyed by syndicated loan participants and reflected in publicly posted loan prices. A strategy that buys the equities of firms whose debt has recently appreciated and sells the equities of firms whose loans have recently depreciated earns as much as 1.4 to 2.2% alpha per month. The strategy returns are unaffected when focusing on loan returns that are publicly reported in the Wall Street Journal. However, when we condition on the subsample of equities held by mutual funds which also trade in syndicated loans, returns to the strategy are eliminated.

Keywords: Syndicated loans, private information, stock returns, return predictability, market integration.

JEL Classification: G11, G12, G14, G21, G23.

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1. Introduction

A long standing question in finance concerns how information about firm value embedded in one security is transmitted across markets and asset classes with diverse participants. To the extent that markets are integrated, value-relevant information that affects the price of a particular claim on a firm's assets should also be reflected in the prices of all other claims with little or no delay. The central nature of the question has led to its examination across several strands of the finance literature.

For example, Gagnon and Karolyi (2010) and Lamont and Thaler (2001) examine cross-listed equity. Easley, O'Hara, and Srinivas (1998) demonstrate that signed volume in the option market leads stock prices at five-minute intervals. Kwan (1996), Hotchkiss and Ronen (2002), and Mao (2012) examine lead-lag effects between corporate bonds and equity. Similarly, Longstaff, Mithal, and Neis (2005) and Acharya and Johnson (2007) study the extent to which CDS spreads lead stocks. Overall, the conclusions from these studies suggest that modern markets in the United States are generally well-integrated.

In this paper, we provide a surprising counterexample to market integration involving two important U.S. markets for related claims. Using the secondary market for private syndicated loans as a laboratory to understand how private information is transmitted across markets, we demonstrate that the public prices of private debt reveal non-public information that predicts stock returns. The resulting trading strategy earns risk adjusted returns on par with the returns to insider trading. We proceed by breaking down the result to better understand the frictions preventing more efficient information transmission.

Our choice of the syndicated loan market is motivated by its potential as a conduit for private information concerning firm value. Because loans are not securities and lenders are exempt from fair disclosure rules, loan market participants enjoy significant amounts of material non-public information.[1] Investors receive frequent disclosures detailing borrowers' covenant compliance, amendment requests, financial projections, acquisition and

[1]Loan investors can choose to be on the "public side" of a loan transaction, meaning that they agree not to receive non-public information. In return, they retain the right to trade in related securities. Active monitors of the debt, however, such as banks, are likely to receive private disclosures.

divestiture plans, and monthly financial statements. Given the non-public nature of this information, private investors are banned from sharing information directly and trading in the stocks of the same underlying firm, but are free to buy and sell loans in the secondary markets based on any information provided to them in the course of their monitoring.[2]

Though lenders are bound by confidentiality and prevented from trading in public securities, a liquid secondary market where insiders can transact and/or publicly post quotes should provide an efficient mechanism for revealing private information.[3] Hence, we might expect stock market participants to closely follow the value-relevant news contained in private lenders' publicly posted quotes. Instead, we show that over a 17 year time period from 1998 to 2015, there is a strong 1-2 month lag in the response of equity prices to the news embedded in loan prices. Although the strategy is stronger among smaller firms, it is robust to focusing on firms above median NYSE size breakpoints. Importantly, the profits appear inconsistent with both risk-based explanations and limits to arbitrage.

Given the observed profits to trading on information impounded in debt prices, and a simple explanation for the source and value of that information, what prevents equity market participants from fully integrating prices in the two markets? One obvious explanation for the lag is that investors are simply unaware of the availability of loan prices, or perhaps the information about loan prices is not salient to equity market participants.

We test this attention-based explanation by exploiting the fact that from 2000 to 2015, the Wall Street Journal ("WSJ") reported once a week on the prices of syndicated loans, covering the top 25 biggest movers, along with dealer quotes for those names. We interpret this as a shock to both the availability and salience of loan market information and predict that, if inattention is segmenting markets, then reporting returns for a subset

[2]Bushman, Smith, and Wittenberg-Moerman (2010), Ivashina and Sun (2011), and Massoud, Nandy, Saunders, and Song (2011) all provide evidence of information leakage and at least some insider trading.

[3]This assumes information affecting loan value will have a consistent and predictable impact on equity value. Kwan (1996) shows that, on average, contemporaneous prices of debt and equity co-move strongly in the same direction, ruling out the competing hypothesis that changes in the variance of cash flows predominantly drive an inverse relationship between debt and equity returns. We confirm the same in loan and equity markets, consistent with both loading predominantly on news about the level of firm cash flows. That is, in the normal course of business, good news for lenders is good news for equityholders.

of names should reduce the profitability of our trading strategy. Instead, we find that, over the course of our sample, a long-short portfolio buying WSJ reported winners and selling WSJ reported losers could have earned a monthly alpha of 2 to 2.5%. In other words, even when loan market information is presented prominently in a widely read financial periodical, that information fails to be incorporated in a timely fashion.

Our second hypothesis, and the one for which we find more support, is that specialized equity investors don't know how to interpret information embedded in debt prices, or discount the possibility that debt investors might know something not already impounded in equity prices. This specialization hypothesis would predict that market integration should be, at least partially, a function of portfolio integration, whereby the extent to which debt and equity desks trade side-by-side and equity traders enjoy some level of loan market expertise determines how closely the markets move together.

We explore this idea by examining the effect of balanced funds holding both loans and equities on the profitability of our strategy. Beginning in 2010, mutual fund holdings data began including information on fixed income, and in particular, syndicated loan holdings. After that point in time, we see a steady rise in the number of funds which own both equities and loans. We conjecture that funds which own both equities and loans will better understand the value-relevance of loan prices and be able to take advantage of it by trading in the linked equities. Indeed, re-examining our portfolio strategy in this light, we find that stocks which are held by so-called integrated funds (those which hold both loans and equities) respond more quickly to price changes in the loan market. We argue that this suggests that market integration is in large part driven by portfolio integration.

This paper builds on several earlier papers which convincingly establish that loan market participants, including non-bank investors in secondary loans, have access to and take advantage of material non-public information about firms. Among the earliest papers to document the informational advantage of private debt over equity is that of Gande, Altman, and Saunders (2006), who examine the price anticipation of ex-post default events and find that loan market prices reflect these events well in advance of equity markets. Allen and Gottesman (2006) also examine the lead-lag relationship between loan and equity returns. Using data from 1999 to 2003, they show weekly loan returns Granger cause future equity returns, but find that trading strategies based on loan market returns fail to reject cross market integration. Ivashina and Sun (2011) and Massoud, Nandy, Saunders, and Song (2011) show that institutions appear to engage in insider trading related to the private information generated by lending relationships. Bushman, Smith, and Wittenberg-Moerman (2010) suggest that this generates information spillovers in equity markets. They document that equities benefit from faster price discovery around earnings announcements when firms' lenders receive early information via covenants or other forms of monitoring.

Our findings are consistent with private lenders possessing and perhaps even trading on private information, but suggest that to the extent that information leakage does occur, it is insufficient to integrate markets. We show that the remaining predictability translates into a large and meaningful economic magnitude when presented as the return to a trading strategy. This result is especially surprising in light of the fact that price quotes in the active secondary market for private debt claims are publicly available. Hence, no insider trading or direct disclosure of private information should be required to fully integrate private lender information into other markets. We go on to provide evidence on the frictions that might impede a more complete transmission of information across markets.

2. Data and Methods

2.1. Loan data

Our analysis begins with a matched dataset of loan returns and equity returns. The loan data come from Thompson Reuters and the Loan Syndications and Trading Association, who collect and aggregate dealer quotes for widely traded syndicated loans. Their data is produced and distributed daily and is used widely as a source of mark-to-market pricing for loan market investors, both banks and non-bank institutions.

Note, the dealer quotes are only quotes and do not reflect actual transactions. Moreover, while they are described by the provider as quotes at which the dealers would be willing to buy or sell, there is little guidance as to the size of trade one could actually execute at the reported bid or ask. In short, there are reasons to be concerned that the quotes are both stale and perhaps not reflective of prices one could actually trade on. Hence, while it is tempting to wonder about the extent to which one could trade profitably in the loan market on public information, our data is not likely to shed light on that type of question. Instead, we rely on the loan quotes as a signal on which to trade in other, more liquid markets for which transaction data are available. Because of the risk of latency in loan quotes, we also restrict our equity trading to the monthly frequency based on monthly loan signals. At any higher frequency, we observe very little movement for a typical loan.

The median loan in our merged sample has daily quotes for two dealers (average of 2.75), typically large banks, although depth grows over time within the sample. At a minimum, the lead arranger/administrative agent for the loan at origination will remain a dealer in the secondary market for these loans. We include all US dollar currency loans, including term loans– both so-called A and B tranches (or TLA and TLB) designed to be held by banks and non-banks, respectively– as well as revolvers, typically held only by banks. Roughly a quarter of the loans in the sample are revolvers. 30% are designated TLB and 21% are designated TLA or simply term loans.

These are floating rate loans, with an average spread of 273 bps over LIBOR. They also trade at discounts, with the average bid of 95.9 and an average ask price of 97. The loans have a median maturity of 6 years, although the average loan only appears in the mark-to-market database for 23 months (from first appearance to last). The average borrower will have several loans over the course of the sample, some of which may overlap. The median (mean) borrower has 5 (7.25) distinct loans trade.

Although we have referred above to "loan returns" as a potential trading signal, because spreads on the loans are unaffected by new information received by lenders, we focus our attention instead on the price appreciation or depreciation that occurs for a given loan over a given month to track new information acquired by private lenders. Meanwhile, because of the likelihood of stale pricing discussed above, in many cases we ignore loans for which prices did not move in a given month. Finally, in the not uncommon event that a borrower has multiple loans outstanding in a given month, we focus our attention on the price movement of the cheapest loan – that is, the loan with the highest effective spread (the spread over LIBOR offered in the contract, plus any capital gain or loss a lender holding the loan to maturity would earn assuming repayment). By focusing on the riskiest debt claims, we capture more variation in pricing signals, as well as variation that is more likely to be relevant to equityholders. Finally, we use the midpoint between the average bid and the average ask price as the relevant measure of price and calculate returns as the percentage change in price.

2.2. Matching stock and loan data

We obtain monthly stock returns, stock prices, and shares outstanding from the Center for Research on Security Prices (CRSP). We limit our analysis to only common shares, those with share codes of 10 or 11. Further, we require that shares have closing prices of at least $5 in order to eliminate concerns related to arbitrage costs of low-priced stocks.

Given a monthly loan return for a specific borrower, we match borrowers to their traded stocks using the Dealscan–Compustat links produced by Michael Roberts and Sudheer Chava as of 2012 (Chava and Roberts, 2008), and extended through 2015.[4]

We end up with 18,265 monthly matches of loan returns and linked equity returns covering the period from September 1998 to August 2015. Over the course of this sample, we always have a minimum of 30 matched stocks in a given month. The mean and standard deviation of loan returns in the sample -0.079% and 2.477%, respectively. For the same firms, stock return in the next month had a mean of 0.645% and a standard deviation of 15.644%. The average firm in the sample has a market capitalization of $1.6 billion.

[4]The match between traded loans and Dealscan meanwhile is provided upon request by Thompson Reuters, which owns both databases. In fact, it is important to note that the LSTA mark-to-market database is a subset of loans covered by Dealscan.

Meanwhile, it's important to note that contemporaneous loan returns and stock returns are strongly positively related. In pooled regressions, stock returns load on loan returns with a beta of 1.9, a t-stat of 39 and an R-squared of 4.26%. In Fama-Macbeth regressions, the cross-sectional beta is 1.3 (with a t-stat of 6.7) and an average R-squared of 4.56%. This is consistent with Kwan (1996) who shows a positive relationship between bond and equity returns, and confirms that, on average, good news for loans is consistent with good news for equities and vice-versa. In other words, while we can't rule out that on occasion, risk-shifting may drive the value of claims in opposing directions, this would seem to be the exception and not the rule.

2.3. Other data sources

We also obtain monthly Fama-French factor returns over the same period from Ken French's online data library. Monthly data on the liquidity factor (LIQ) are obtained from Lubos Pastor's website, and monthly betting against beta factor (BAB) returns for U.S. stocks are downloaded from AQR's online data repository.

We use data from Compustat to calculate book-to-market ratios for each public firm in our sample. The book-to-market ratio is defined as year-end book equity plus balance sheet deferred taxes scaled by the year-end market value of equity. This calculation is implemented after imposing the usual 6-month lag in order to ensure the observability of measured values.

Finally, we use data on quarterly mutual fund holdings from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. We focus on funds that hold both stocks and syndicated loans. Stock held by U.S. mutual funds are identified by *permno*. To identify syndicated loans holdings, we implement a partial string matching algorithm that searches for security names that include the strings "synd", "loans", or "lns." We then inspect all matches by hand to verify the accuracy of the algorithm. Due to data limitations, our final sample of mutual fund holdings spans the period from September 2010 to June 2015.

3. Evidence of Predictable Stock Returns

Our analysis is based on the conjecture that publicly observable prices in the syndicated loan market are likely to incorporate private information available to dealers. We then test for the timely integration of any private information reflected in loan prices across markets by asking if monthly syndicated loan returns have any predictive power over next-month stock returns.

3.1. Construction of stock portfolios

In our first test of the predictive power of returns in the syndicated loan market, we perform univariate sorts. Specifically, we sort all stocks with a matched non-zero loan return in month t into quintiles.[5] We then form six portfolios.

The Short portfolio contains the quintile of stocks with the lowest observed loan returns in month t. The Long portfolio contains the quintile of stocks with the highest observed loan returns in month t. We then form a Long−Short portfolio, a dollar-neutral portfolio which captures the difference in returns of the Long and Short portfolios in month $t + 1$. Finally, portfolios 2 through 4 contain the remaining quintiles of stocks sorted on loan returns in month t.

To eliminate concerns related to illiquidity among small stocks, we include only stocks with market capitalization above the 10th percentile of NYSE breakpoints at the time of portfolio formation. Further, we restrict the sample to include only firms with a nominal share price of at least $5 at portfolio formation.

3.2. Sorting results

The portfolio performance estimates are presented in Tables 2 and 3. In Table 2, we report raw equal-weighted returns for each of the portfolios. We also report CAPM alphas, as well as 3, 6, and 8-factor alphas for each of the portfolios. The 3-factor model

[5] As a robustness check, we verify that our results hold when we include zero loan returns in the sorts. We also verify that our results hold when we alternatively sort into terciles and deciles.

includes the excess market return (RMRF), the value factor (HML), and the size factor (SMB). The 6-factor model adds the momentum factor (UMD) as well as the short- and long-term reversal factors (STR and LTR). Finally, the 8-factor model further includes the liquidity (LIQ) and betting against beta (BAB) factors.

Consistent with our hypothesis that the loan market leads equities, the estimates in column 1 of Table 2 indicate that portfolio returns increase monotonically with syndicated loan returns. Specifically, the Short portfolio generates an average monthly return of −0.535%, while stocks in the Long portfolio earn 1.580% on average. The difference between the Long and Short portfolios amounts to an average monthly return of 2.115%. This monthly difference is highly statistically significant, with a t-statistic of 4.63.

The factor model alpha estimates presented in the remaining columns suggest that the economic and statistical significance of the Long−Short portfolio returns cannot be explained by factor exposures. Specifically, the Long−Short alphas range between 2.101 and 2.253% per month, and remain highly statistically significant (t-statistics between 4.52 and 4.89). Further, both the Long and Short portfolios contribute to the profitability of the dollar-neutral strategy.

In Table 3, we present analogous results for value-weighted portfolio returns. Specifically, we find that the average monthly raw Long−Short portfolio return is 1.356% (t-statistic = 2.78). In addition, we find that the Long−Short factor model alphas continue to be highly economically and statistically significant, with alpha estimates ranging between 1.369% and 1.565% per month, and t-statistics ranging from 3.09 to 3.31.

The smaller magnitude of the value-weighted portfolio returns suggests that the predictive relation between loan and equity returns is concentrated among smaller stocks. To ensure that our main predictability results are not concentrated only among small stocks, we rerun our analysis focusing only on the subset of stocks with market capitalization above the median NYSE size breakpoints. In untabulated results, we continue to find economically and statistically significant Long−Short portfolio returns among the subsample of larger stocks. Importantly, this suggests that our evidence of predictability is likely to stem from a lack of integration across markets rather than binding limits to arbitrage.

It is also important to highlight the economic significance of our evidence of predictability in stock returns. In particular, the profitability of our trading strategy is comparable to other recent papers highlighting the effects of investors' failure to recognize value-relevant information. For example, Cohen and Frazzini (2008) find that a self-financing trading strategy taking advantage of news about economically related firms generates monthly alphas of over 1.50%. Li, Richardson, and Tuna (2014) demonstrate that geographic segment data contain foreign macroeconomic information that can be used to forecast firm fundamentals. In turn, they show that such forecasts can be used to form a dollar-neutral trading strategy that generates monthly alphas of 1.40%. Similarly, Addoum, Kumar, and Law (2016) show that the slow diffusion of earnings information that is geographically dispersed within the United States can be used to form a trading strategy that offers monthly alphas of over 1.50%.

Of particular importance are the returns to insider trading documented by Ivashina and Sun (2011). Specifically, they find evidence that institutional investors who are privy to loan amendments that are not yet publicly announced engage in insider trading of the same company's stock. This generates outperformance amounting to annual abnormal returns of approximately 5.4%. The relatively small magnitude of this outperformance suggests that insiders may limit their trades to avoid being caught, and hence do not fully integrate the loan and equity markets.

3.3. Fama-MacBeth regression estimates

In the next set of baseline tests, we estimate Fama and MacBeth (1973) predictive regressions. For each sample month, we regress excess stock returns in month $t + 1$ on a set of return predictors observable at the end of month t. Our main predictor of interest is each firm's syndicated loan return in month t. We also include controls for firm characteristics known to predict excess stock returns, including size and the book-to-market ratio. Size is calculated as the log of market capitalization and book-to-market is computed using information available at least six months prior to the end of month t. We also include the return over the previous 6 months, with a month lag, in order to capture momentum effects.

We report the time series averages of monthly cross-sectional predictive regressions, along with t-statistics based on these coefficients, in Table 4. The t-statistics reported in parentheses below the coefficient estimates are calculated using Newey and West (1987) adjusted standard errors using a three month lag.

Again, the estimates in Table 4 indicate a strong predictive relationship between syndicated loan returns and subsequent excess stock returns. Specifically, we find that syndicated loan returns in columns 1 through 3 of Table 4 are highly statistically significant, with t-statistics ranging from 2.72 to 4.70. In column 1, where we include only the syndicated loan return as a predictor, we find that the loan return has a coefficient estimate of 0.467 (t-statistic = 3.12). In column 2, we find that even after including the size, book-to-market, and lagged six month stock return characteristics, the syndicated loan return coefficient is 0.443 (t-statistic = 2.72). In economic terms, this estimate indicates that a one standard deviation change in syndicated loan return translates to a $0.443 \times 2.477 = 1.097\%$ increase in next-month excess stock return after accounting for firm characteristics.

Finally, we find a similar result in column 3 of Table 4, where we incrementally interact the syndicated loan return with the size and book-to-market characteristics[6]. Echoing the results in Tables 2 and 3, the significant negative coefficient on the size interaction indicates that the predictive power of the syndicated loan return is dampened for larger firms in the sample. However, the economically and statistically significant coefficient on the syndicated loan return predictor (coefficient = 0.770; t-statistic = 4.70) indicates the existence of a significant predictive relation between syndicated loan market returns and subsequent stock returns, consistent with our main conjecture.

[6]We demean the characteristics in each cross-section before computing the interactions so that the syndicated loan return coefficient measures the predictive effect for a firm of average size and book-to-market ratio.

4. Return Predictability Mechanism

So far, our evidence suggests that the syndicated loan market significantly leads the equity market. In this section, we aim to understand the economic interpretation of this result.

4.1. Interpreting Predictability: Risk vs. Mispricing

Our assertion thus far has been that loan returns in month t signal the arrival of value relevant information to private-side investors in the loan market. This information is reflected by changes in dealers' quotes. In turn, these changes predict subsequent stock returns, revealing a surprising lack of integration between the loan and equity markets.

However, our results are also consistent with an alternative risk-based interpretation. Specifically, instead of reflecting private information that is valuable to shareholders, loan returns in month t may reflect shocks to shareholders' exposure to systematic risk. For example, consider the case of a firm that is in danger of a covenant violation. In order to avoid violating the covenant, the firm's managers may request that the private-side investors consider relaxing or removing the covenant. In return for amending the loan agreement, the investors may demand a higher spread. In turn, a higher spread would translate to higher financial leverage and greater exposure to systematic risks on the part of shareholders. Thus, expected and average realized stock returns would be higher going forward.

To test between these two competing interpretations, we examine the persistence of portfolio returns. If the abnormal performance of the Long−Short portfolio reflects mispricing that is eventually corrected, then the abnormal portfolio performance should exhibit a marked time-decay when delaying portfolio formation. In contrast, the Long−Short portfolio return should exhibit a large degree of persistence if loan market returns signal changes in equityholders' exposure to systematic risks.

Figure 1 plots the effect of delaying the use of loan market signals observed in month t. The figure plots 8-factor alphas (solid line) as a function of the delay in portfolio

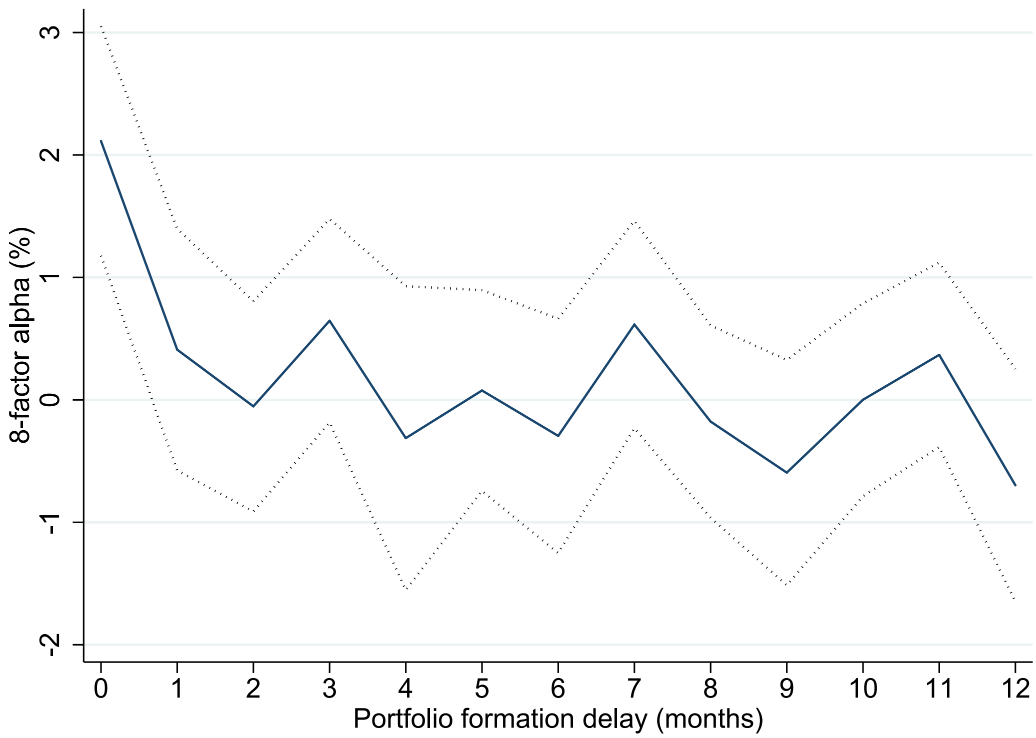

Figure 1
Delayed Portfolio Formation. The figure plots the 8-factor alpha from equal-weighted Long−Short portfolios formed based on the past month's loan returns (i.e., as in Table 2), alongside the returns from the same portfolio formed with a 1 to 12 month delay.

formation (in months). We also show the two standard error bars (dashed lines) surrounding the alpha estimates. Consistent with the mispricing interpretation, we find that the strategy alphas exhibit strong time-decay. Specifically, we find that even a 1-month delay in portfolio formation, i.e., loan market signals in month t are used to form and hold portfolios during month $t+2$ instead of $t+1$, yields a Long−Short alpha that is statistically indistinguishable from zero. Similarly, further delays in portfolio formation yield Long−Short alphas that appear to randomly oscillate around zero.

Overall, the tests summarized in Figure 1 support our conjecture that the predictive power of loan returns reflect the arrival of value relevant information that is incorporated into stock prices with a delay. Further, it appears that either arbitrageurs correct the mispricing, or that private information is made public, on average within about one month.

4.2. Arbitrage Constraints

One potential explanation for the short-term predictability apparent in Figure 1 is that the mispricing is driven by limits to arbitrage. That is, the predictability may be concentrated among stocks that arbitrageurs have difficulty buying and selling in large quantities. For example, arbitrageurs may perceive the eventual payoffs of taking positions in mispriced stocks as excessively risky (De Long, Shleifer, Summers, and Waldmann, 1990). Further, they may find it difficult to take short positions, either due to a simple lack of inventory or high borrowing costs (Shleifer and Vishny, 1997).

To test whether arbitrage constraints can explain the relationship between loan returns and subsequent stock returns, we use several proxies for limits to arbitrage. The proxies are idiosyncratic volatility, institutional ownership, and the bid-ask spread. Following Campbell, Lettau, Malkiel, and Xu (2001), we calculate idiosyncratic volatility by fitting the three-factor Fama and French (1993) model using daily returns for each stock during month t. We calculate institutional ownership as the number of shares held by institutions in the Thomson Reuters 13F Holdings database at the end of the previous quarter divided by the total number of shares outstanding. Finally, the bid-ask spread is calculated as the difference between the Ask and Bid prices reported by CRSP as a percentage of share price at the end of month t.

We include the interactions between the arbitrage constraint measures and the loan return predictor in Table 5. As in Table 4, we demean the arbitrage constraint measures in each cross-section before computing the interactions. The syndicated loan return coefficients then measure the respective predictive effects for a firm with average idiosyncratic volatility, institutional ownership, and bid-ask spread. Across the three specifications in the table, we find that the interactions between the arbitrage constraint proxies and the loan predictor are indistinguishable from zero at standard levels of significance. Further, the effect associated with loan returns continues to be positive and statistically significant in all cases. This suggests that arbitrage constraints cannot explain the predictive relation between the syndicated loan and stock markets for firms with average arbitrage constraints.

To further assess the role of limits to arbitrage in explaining our results, we more closely examine the interaction coefficients in Table 5. In particular, for each measure of arbitrage constraints we analyze whether relaxing the constraint by one cross-sectional standard deviation can offset the level effect for a firm with average arbitrage constraints. We conduct this analysis for both the institutional ownership and bid-ask spread. For these measures, the interaction coefficients are consistent with the predictive effect of syndicated loan returns increasing with arbitrage constraints. In contrast, the positive (insignificant) coefficient on the idiosyncratic volatility interaction in column 1 casts doubt on the role of this measure of limits to arbitrage in explaining our results. In particular, the interaction effect suggests that the predictive relation between syndicated loans and equity is even stronger among firms where arbitrage constraints are more relaxed.

Turning to column 2, we find that over the course of the sample, the average cross-sectional standard deviation of institutional ownership is 0.241. This, together with the level and interaction effects for syndicated loan returns in month t, implies that relaxing this constraint by one cross-sectional standard deviation generates a predictive coefficient of 0.530 ($= 0.631 + 0.241 \times (-0.418)$). This effect is economically large and a Wald test indicates that it is also significantly different from zero at the 5% level (p-value $= 0.048$). Similarly, we examine the bid-ask spread interaction in column 3. The average cross-sectional standard deviation of bid-ask spreads in our sample is 0.744, implying that relaxing this arbitrage constraint by one standard deviation yields a predictive effect of 0.412 ($= 0.555 - 0.744 \times (0.192)$). Though a Wald test fails to reject the null that this effect is equal to zero, the implied coefficient remains economically large.[7] Taken together, the results in Table 5 suggest that limits to arbitrage are unlikely to explain the predictive relation between the syndicated loan and stock markets.

[7]Given the economic significance of this coefficient, the lack of statistical significance is likely driven by the large standard errors on the interaction between syndicated loan returns and the bid-ask spread measure.

4.3. Investor Inattention Channel

Putting risk- and limits-to-arbitrage-based explanations aside, limited attention provides another plausible interpretation of the excess returns to trading on loan market news. Perhaps equity investors are unaware of the secondary market for loans, or to the extent they are aware, believe that little can be learned from paying attention to loan markets. Indeed, it's true that for the modal loan, daily and monthly returns are exactly zero. If tracking prices in this market imposes costs on equity traders, that may go a long way in explaining the delayed response we observe. Equity investors may understand the value of loan prices in theory, but be unaware of the availability of timely public data.

If the frictions preventing full and timely market integration are rooted in inattention, then when syndicated loan market information– in particular prices– is made salient, we would expect predictability to dissipate. To test this, we focus on weekly loan movements reported in the Wall Street Journal. Using the same LSTA/Thompson Reuters loan market data we use in this paper, between August 2000 and August 2015, the Wall Street Journal published a weekly feature reporting the 25 biggest movers in the secondary loan market ("biggest movers" were ranked on absolute value change in the average bid reported by the LSTA). Because the timing used to construct the list is inconsistent (sometimes the ranking is done Monday through Friday, other times Tuesday to Tuesday) and because on occasion, loans that should have been on the list based on the reported methodology are excluded for unexplained reasons, we resort to transcribing the WSJ list by hand.

Table 6 replicates Tables 2 and 3 using only the list of names reported in the biggest movers column for that month and hence focuses the analysis on names for which loan market prices would have been easily observable and more salient to equity market participants. A few modifications to the strategy are necessary. First, we limit ourselves to two portfolios (winners and losers) based on whether or not the loan appreciated during the month. Second, in months for which we have less than three names in either portfolio, we instead invest the portfolio at the risk free rate until the next month.

The returns to the Long–Short portfolio based on this basic strategy are large, earning monthly alphas between 2.088 and 2.564% across value- and equal-weighted portfolios. If anything, we find that returns to the simpler newspaper strategy are larger than the returns to the full portfolio reported in Table 2.[8] If we believe that appearing in the WSJ serves as a meaningful shock to attention, or at least to the cost of paying attention, then the evidence here would seem inconsistent with inattention driving the delayed integration of news across markets.

Syndicated Loans: Past Week's Biggest Movers

Syndicated loans are corporate loans that are bought or traded by a group of banks and/or institutional investors. Investment-grade loans are investment-grade or unrated loans priced at or below the London interbank offered rate (Libor) plus 150 basis points (or 1.5 percentage points). Leveraged loans are speculative-grade or unrated loans priced at or above Libor plus 151 basis points. Below are the biggest gainers and losers among widely-quoted syndicated loans in secondary trading in the week ended Friday among the 182 loans with five or more bids. All loans listed are B-term, or sold to institutional investors.

Name	Loan rating Moody's/S&P	Coupon/interest (Libor + basis pts)	Maturity	Average bid (pct. pts.)	Weekly chg (pct. pts.)
Avis Budget Car Rental LLC	Ba3/B	L+125	April 1, '12	41.45	**1.73**
Charter Communications	B1/D	L+200	March 6, '14	82.13	**3.63**
Cincinnati Bell	Ba2/BB	L+150	Sept. 1, '12	91.80	**1.30**
Coffeyville	B2/BB-	275	Dec. 30, '13	75.50	**1.75**
Dana Corp	B3/B+	L+375	Jan. 31, '15	22.00	**-1.71**
Fairpoint Communications	B1/B	L+275	March 31, '15	44.50	**-1.57**
Georgia Pacific Corp	Ba2/BB+	L+175	Dec. 22, '12	88.47	**1.37**
Graham Packaging	B1/B+	L+200	Sept. 30, '11	85.75	**1.45**
Graphic Packaging International	Ba3/BB-	L+275	May 16, '14	85.86	**1.71**
Hercules Offshore	Ba3/BB	L+175	July 11, '13	68.30	**-1.58**
Hertz	Ba1/BB+	L+150	Dec. 21, '12	76.33	**4.05**
Idearc	Caa3/CCC	L+200	Nov. 17, '14	37.09	**6.23**
Isle of Capri Casinos	B1/B+	L+175	Dec. 19, '13	69.70	**2.13**
Las Vegas Sands	B3/B-	L+175	May 1, '14	53.11	**5.03**
Lear Corp	N.R./N.R.	L+250	March 29, '12	33.97	**1.33**
Manitowoc Co Inc	Ba2/BB+	L+350	April 14, '14	70.92	**-1.98**
Novelis	Ba3/BB	L+225	July 6, '14	62.60	**1.67**
OshKosh Truck	B2/B+	L+175	Nov. 9, '13	74.52	**1.73**
OSI Restaurant Partners, Inc.	B3/B+	L+225	May 9, '14	54.21	**3.21**
Oxbow Carbon & Minerals LLc	B1/BB-	200	May 8, '14	70.04	**1.50**
Service Master	B1/B+	L+300	July 24, '14	67.50	**3.30**
Targa Resources Inc	N.R./N.R.	L+200	Oct. 31, '12	80.45	**6.98**
Toys R Us	B2/BB-	L+425	July 19, '12	62.07	**2.67**
United Air Lines	B3/B+	L+200	Feb. 13, '13	47.22	**-1.84**
Venetian Macau US Finance Co LLC	B3/B-	L+225	May 25, '13	65.05	**1.37**

Note: These are the averages of indicative bid prices provided by bank-loan traders and expressed as a percentage of the par or face value. All ratings are for specific loans and not for the company. These prices do not represent actual trades nor are they offers to trade; rather they are estimated values provided by dealers; N.R. indicates that this issue is not rated

Source: LSTA/Thomson Reuters MTM Pricing

Figure 2
Wall Street Journal Biggest Movers. Between August 2000 and August 2015, the Wall Street Journal printed a weekly table of 25 "Biggest Movers" in the syndicated loan market. This figure provides an example from April 2009.

[8]The second row and fourth row of Table 6 confirm this by examining the returns to the 1 and 5 portfolios in Tables 2 and 3, excluding names reported in the WSJ.

4.4. Cross-Market Information Processing Constraints

If making cross-market information salient and easily accessible falls short of integrating debt and equity markets, what is the relevant friction that sustains the proposed trading strategy? Our second hypothesis is one of specialization, whereby equity and debt investors have unique skill sets, or perhaps believe that their information is more specialized than it really is. Our strategy, of course, is simple and requires no expertise. But if equity traders believe that understanding loan prices requires additional background, they may choose to ignore the information available. Note, this is still a form of inattention. But in contrast with an inattention hypothesis whereby relevant information is easily interpreted, but not salient, our cross market specialization hypothesis suggests that information can be prominently reported on and will still be willfully ignored by participants who believe they lack the expertise to act on it.

To test this, we look to market participants who trade across markets and therefore would have the expertise and wherewithal to take advantage of news embedded in loan prices. Specifically, we focus on hybrid equity funds that actively trade in equities, but also maintain exposure to the syndicated loan market. We identify these funds by looking to WRDS mutual fund holdings data and searching holdings for assets identified as syndicated loans.

Scanning through the Lipper classifications for these funds and reading their prospectuses, we find funds which are generally active, which describe themselves as balanced or hybrid funds, and which have a mandate to invest in loans, bonds, and equities. Hereafter, we refer to these funds as "integrated funds." At any given point in time, roughly 25% of our equity cross section will be owned by at least one integrated fund. Based on the fact that mutual funds holding data tracking syndicated loans begins in 2010, we have a shorter sample, but still enough to tease out some cross-sectional implications.

With integrated funds identified, we then retest our market integration hypothesis for equities which are owned by integrated funds in the month prior to changes in loan prices for the corresponding firms. Table 7 tests for a difference in market integration across equities owned by integrated funds versus the rest of the sample by re-running the Fama-Macbeth regressions from Table 4. Specifically, we interact the loan return predictor with a dummy variable equal to one if an integrated fund owned the corresponding stock in the prior month, and zero otherwise. The implicit hypothesis is that these integrated funds will both understand the relevance of loan prices to equity values and also, because of their existing exposure to a given stock, be predisposed to pay attention and act on that information.

Columns 1 to 3 present a variety of specifications, and in each case, the predictability of loan returns is almost exactly offset by the interaction term on the integrated funds dummy. Column 1 presents the most basic specification, while Column 2 adds controls for size, book-to-market, and lagged six month returns. Finally, because we might worry that stocks owned by integrated funds are likely to be larger (and are thus more likely to be owned by any fund), we add additional interactions for size and book-to-market with loan return. Column 3 suggests that these characteristics are not behind the interaction with integrated funds. Meanwhile, in each case, the level effect on loan returns is positive, significant, and larger than the Fama-Macbeth coefficients reported in Table 4. This suggests the strategy to trading on loan market integration survives even late in the sample, but only for equities which are not owned by hybrid cross market participants.

5. Summary and Conclusion

While it is not surprising that private lenders have access to private information – indeed, credit markets fundamentally depend on lenders constant monitoring of borrower condition – how that information is protected when the secondary market for loans becomes a price discovery market is an open question, and one with policy relevance. In particular, there is an apparent disconnect between SEC mandates for lenders to keep private information private and the failure to prevent the efficient transmission of information through dealer quotes, absent shutting down liquidity in the secondary market or limiting bankers' access to non-public information, both of which would have significant consequences for credit markets. In the meantime, our findings that investment managers who work across markets are able to integrate this information suggests that some firms are able to take advantage of this privileged information.

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Table 1

Summary Statistics. This table reports summary statistics for several key variables in the sample of matched loans and stocks. Syndicated loan return is defined as the percentage change in price for a given loan over a given month. Size is calculated as the log of market capitalization. Book-to-market is calculated as year-end book equity plus balance sheet deferred taxes scaled by the year-end market value of equity, imposing a six-month lag in measured values. The sample period is from September 1998 to August 2015.

Variable	Mean	Median	Std. Dev.	10th pctile	90th pctile
Synd Loan Return (t), %	-0.079	0.026	2.477	-1.198	1.105
Stock Return (t+1), %	0.679	0.556	15.644	-15.179	15.905
Size (market cap, $M)	4,429	1,520	14,650	364	8,410
Book-to-market	0.761	0.502	1.200	0.163	1.418
Lagged 6m Return	0.086	0.048	0.510	-0.360	0.482

Table 2

Equal Weighted Portfolio Returns. This table reports performance estimates of a trading strategy that sorts stocks on matched non-zero loan returns into quintiles. We report the performance of six equal-weighted portfolios: (i) the “Short” portfolio contains the quintile of stocks with the lowest observed loan returns, (ii) the “Long” portfolio contains the quintile of stocks with the highest observed loan returns, (iii) the “Long−Short” portfolio, which captures the difference in returns of the Long and Short portfolios, and (iv)-(vi) portfolios 2-4, which contain the second through fourth quintiles, respectively, of stocks sorted on observed loan returns. We report the raw returns for each of the portfolios. We also report CAPM alphas, as well as 3, 6, and 8-factor alphas for each of the portfolios. The 3-factor model includes the excess market return (RMRF), the value factor (HML), and the size factor (SMB). The 6-factor model adds the momentum factor (UMD) as well as the short- and long-term reversal factors (STR and LTR). Finally, the 8-factor model further includes the liquidity (LIQ) and betting against beta (BAB) factors. The t-statistics reported in parentheses below the coefficient estimates are computed using Newey and West (1987) adjusted standard errors.

Equal-weighted strategy	Raw Return	CAPM Alpha	3-factor Alpha	6-factor Alpha	8-factor Alpha
1 (Short)	-0.535	-1.289	-1.527	-1.259	-1.289
	(-0.75)	(-3.26)	(-3.59)	(-3.71)	(-3.54)
2	0.922	0.352	0.116	0.230	0.185
	(1.77)	(0.91)	(0.39)	(0.78)	(0.58)
3	0.926	0.358	0.188	0.280	0.163
	(1.75)	(1.06)	(0.62)	(0.88)	(0.58)
4	1.052	0.469	0.233	0.308	0.245
	(1.88)	(1.54)	(0.81)	(1.05)	(0.81)
5 (Long)	1.580	0.964	0.628	0.889	0.812
	(2.40)	(2.12)	(1.70)	(3.09)	(2.86)
Long - Short	2.115	2.253	2.155	2.148	2.101
	(4.63)	(4.83)	(4.77)	(4.89)	(4.52)
N months	204	204	204	204	204

Table 3

Value Weighted Portfolio Returns. This table reports performance estimates of a trading strategy that sorts stocks on matched non-zero loan returns into quintiles. We report the performance of six value-weighted portfolios: (i) the "Short" portfolio contains the quintile of stocks with the lowest observed loan returns, (ii) the "Long" portfolio contains the quintile of stocks with the highest observed loan returns, (iii) the "Long−Short" portfolio, which captures the difference in returns of the Long and Short portfolios, and (iv)-(vi) portfolios 2-4, which contain the second through fourth quintiles, respectively, of stocks sorted on observed loan returns. We report the raw returns for each of the portfolios. We also report CAPM alphas, as well as 3, 6, and 8-factor alphas for each of the portfolios. The 3-factor model includes the excess market return (RMRF), the value factor (HML), and the size factor (SMB). The 6-factor model adds the momentum factor (UMD) as well as the short- and long-term reversal factors (STR and LTR). Finally, the 8-factor model further includes the liquidity (LIQ) and betting against beta (BAB) factors. The t-statistics reported in parentheses below the coefficient estimates are computed using Newey and West (1987) adjusted standard errors.

Value-weighted strategy	Raw Return	CAPM Alpha	3-factor Alpha	6-factor Alpha	8-factor Alpha
1 (Short)	-0.482	-1.224	-1.253	-1.061	-1.079
	(-0.60)	(-3.07)	(-3.25)	(-2.92)	(-3.09)
2	0.391	-0.189	-0.309	-0.316	-0.279
	(0.71)	(-0.68)	(-1.09)	(-1.09)	(-0.91)
3	0.772	0.197	0.114	0.187	0.140
	(1.50)	(0.62)	(0.36)	(0.54)	(0.39)
4	0.383	-0.185	-0.284	-0.317	-0.403
	(0.61)	(-0.58)	(-0.87)	(-0.95)	(-1.23)
5 (Long)	0.874	0.341	0.212	0.338	0.289
	(1.50)	(1.01)	(0.62)	(1.05)	(0.84)
Long - Short	1.356	1.565	1.465	1.400	1.369
	(2.78)	(3.31)	(3.23)	(3.26)	(3.09)
N months	204	204	204	204	204

Table 4

Fama Macbeth Predictive Regressions. This table reports estimates from Fama and MacBeth (1973) regressions. We regress excess stock returns in month $t+1$ on the following regressors observable at the end of month t: syndicated loan return, log market capitalization at the end of the previous month, book-to-market ratio, and lagged stock return over the previous six months. We report the time series average of cross-sectional R^2s. The t-statistics reported in parentheses below the coefficient estimates are computed using Newey and West (1987) adjusted standard errors.

Excess Stock Return (t+1)	(1)	(2)	(3)
Synd Loan Return (t)	0.467	0.443	0.770
	(3.12)	(2.72)	(4.70)
Size		-0.251	-0.230
		(-1.92)	(-1.59)
Book-to-market		-0.516	-0.721
		(-1.62)	(-1.97)
Lagged 6mRet		0.284	0.152
		(0.34)	(0.18)
Synd Loan Return X Size			-0.354
			(-2.42)
Synd Loan Return X Book-to-market			-0.579
			(-1.99)
Constant	0.876	4.182	4.027
	(1.67)	(2.11)	(1.83)
Avg R-squared	0.028	0.107	0.139
N obs	18,265	18,265	18,265
N months	204	204	204

Table 5

Arbitrage Constraints. This table reports estimates from Fama and MacBeth (1973) regressions. We regress excess stock returns in month $t+1$ on the following regressors observable at the end of month t: syndicated loan return, idiosyncratic volatility, institutional ownership, bid-ask spread, log market capitalization at the end of the previous month, book-to-market ratio, and lagged stock return over the previous six months. Idiosyncratic volatility (IVOL) is calculated by fitting the three-factor Fama and French (1993) model using daily returns for each stock during month t. Institutional ownership in month t is calculated as the number of shares held by institutions in the Thomson Reuters 13F Holdings database at the end of the previous quarter divided by the total number of shares outstanding. Bid-ask spread is calculated as the difference between the Ask and Bid prices reported by CRSP as a percentage of share price at the end of month t. We report the time series average of cross-sectional R^2s. The t-statistics reported in parentheses below the coefficient estimates are computed using Newey and West (1987) adjusted standard errors.

Excess Stock Return (t+1)	(1)	(2)	(3)
Synd Loan Return	0.366	0.631	0.555
	(2.26)	(3.23)	(2.67)
Synd Loan Return X IVOL	-0.057		
	(-0.29)		
IVOL	-0.255		
	(-1.85)		
Synd Loan Return X IO		-0.418	
		(-0.56)	
IO		-0.822	
		(-1.23)	
Synd Loan Return X Bid-Ask Spread			0.192
			(0.15)
Bid-Ask Spread			-0.236
			(-0.25)
Size	-0.290	-0.259	-0.293
	(-2.12)	(-1.98)	(-2.29)
Book-to-market	-0.458	-0.507	-0.806
	(-1.41)	(-1.56)	(-2.18)
Lagged 6mRet	0.549	0.268	0.092
	(0.66)	(0.34)	(0.12)
Constant	5.261	5.081	5.104
	(2.55)	(2.50)	(2.72)
Avg R-squared	0.151	0.140	0.153
N obs	18,265	18,265	17,916
N months	204	204	204

Table 6

WSJ Sample. This table reports performance estimates of the Long−Short portfolio formed using only names reported in the Wall Street Journal's "Biggest Movers" column. In Panel A, the portfolio returns are value-weighted. In Panel B, the portfolio returns are equal-weighted. We report the raw returns for each of the portfolios. We also report CAPM alphas, as well as 3, 6, and 8-factor alphas for each of the portfolios. The 3-factor model includes the excess market return (RMRF), the value factor (HML), and the size factor (SMB). The 6-factor model adds the momentum factor (UMD) as well as the short- and long-term reversal factors (STR and LTR). Finally, the 8-factor model further includes the liquidity (LIQ) and betting against beta (BAB) factors. The t-statistics reported in parentheses below the coefficient estimates are computed using Newey and West (1987) adjusted standard errors.

VW Long-Short Portfolio Returns	Raw Return	CAPM Alpha	3-factor Alpha	6-factor Alpha	8-factor Alpha
WSJ List	2.334	2.404	2.249	2.384	2.088
	(3.00)	(3.04)	(2.84)	(3.41)	(2.85)
Non-WSJ List	1.315	1.451	1.226	1.222	1.107
	(2.44)	(2.76)	(2.73)	(2.67)	(2.45)

EW Long-Short Portfolio Returns	Raw Return	CAPM Alpha	3-factor Alpha	6-factor Alpha	8-factor Alpha
WSJ List	2.458	2.564	2.349	2.514	2.092
	(3.16)	(3.32)	(3.45)	(4.30)	(3.28)
Non-WSJ List	1.767	1.904	1.643	1.710	1.556
	(3.70)	(4.18)	(4.61)	(4.60)	(4.22)

Table 7

Integrated Funds. This table reports estimates from Fama and MacBeth (1973) regressions. We regress excess stock returns in month $t+1$ on the following regressors observable at the end of month t: syndicated loan return, a syndicated loan fund indicator, log market capitalization at the end of the previous month, book-to-market ratio, and lagged stock return over the previous six months. The syndicated loan fund indicator is equal to one if an integrated fund owned the corresponding stock in the prior month, and zero otherwise. Integrated funds are defined as funds holding both stocks and syndicated funds. We report the time series average of cross-sectional R^2s. The t-statistics reported in parentheses below the coefficient estimates are computed using Newey and West (1987) adjusted standard errors.

Excess Stock Return (t+1)	(1)	(2)	(3)
Synd Loan Return	1.803	1.489	1.922
	(2.73)	(2.40)	(3.00)
Synd Loan Return × Synd Loan Fund	-1.892	-1.505	-1.921
	(-2.87)	(-2.27)	(-2.78)
Synd Loan Fund	0.177	0.163	0.246
	(0.37)	(0.32)	(0.44)
Size		0.050	0.120
		(0.29)	(0.58)
Book-to-market		-0.844	-0.330
		(-2.50)	(-0.92)
Lagged 6mRet		0.400	0.357
		(0.44)	(0.40)
Synd Loan Return × Size			0.563
			(1.77)
Synd Loan Return × Book-to-market			-0.105
			(-0.18)
Constant	1.201	0.794	-0.629
	(1.70)	(0.29)	(-0.20)
Avg R-squared	0.061	0.132	0.159
N obs	5,604	5,604	5,604
N months	60	60	60