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

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Abstract – 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 that 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

To the extent that financial markets are integrated, value-relevant information embedded in the price of a particular claim on firm cash-flows should be fully reflected in the prices of related claims with little or no delay. In this paper, we document a surprising failure of market integration involving two important U.S. markets for related claims. Using the secondary market for syndicated loans as a laboratory to understand how information is transmitted across markets when some participants receive privileged disclosures, we demonstrate that the publicly observable prices of private debt reveal non-public information that predicts stock returns. The implied trading strategy earns risk-adjusted returns on par with the returns to insider trading. We proceed by examining the potential frictions preventing more efficient information transmission.

Our examination of the secondary loan market is motivated by its potential as a conduit for private information concerning firm value. Because bank and non-bank lenders are exempt from fair disclosure rules, loan market participants enjoy a significant flow of material non-public information from borrowers.[1] Investors receive frequent disclosures detailing borrowers' monthly financials, projections, covenant compliance certificates, amendment requests, acquisition and divestiture plans, and collateral account valuations (Gustafson, Ivanov, and Meisenzahl, 2016). Given the non-public nature of this information, private investors are restricted from sharing information directly or trading in the stocks of the same underlying firm, although recent work suggests that institutional participants in loans may improperly trade in public markets nonetheless (examples discussed below include Ivashina and Sun (2011), Massoud, Nandy, Saunders, and Song (2011), and Bushman, Smith, and Wittenberg-Moerman (2010)).

However, because loan syndications and participations are not considered securities, nothing prevents lenders from trading loans while in possession of private information. Indeed, Drucker and Puri (2009) and Irani and Meisenzahl (forthcoming) show that re-

[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.

lationship banks actively use the secondary loan market to manage liquidity. Meanwhile, over the normal course of business, debt and equity values co-move strongly in the same direction (Kwan, 1996); we confirm the same across loan and equity markets, consistent with both loading predominantly on news about the value of the firm. As a result, a liquid secondary market where insiders can transact and/or publicly post privately informed bid-offer quotes on loans may provide an efficient mechanism for revealing lenders' private information.

Given this logic, 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 one-month lag in the response of equity prices to the news embedded in loan prices. A zero-cost portfolio that buys the equities of recent winners in the loan market and sells recent losers earns monthly abnormal returns of up to 2.2%. Although the strategy is stronger among smaller firms, it is robust to focusing on firms above median NYSE size breakpoints. Further, the profits appear inconsistent with risk-based explanations and the strategy does not appear to be limited to stocks with characteristics traditionally associated with 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 that 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 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 earns 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, equity market participants fail to incorporate that information in a timely fashion.

Our second hypothesis, and the one for which we find more support, is that specialized equity investors are unable 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. To the extent that debt and equity desks trade side by side and equity traders enjoy some level of loan market expertise, the markets should move together closely.

We explore this idea by examining the effect of hybrid 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 that own both equities and loans. We conjecture that such funds 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 held by so-called integrated funds (those that 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 that 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 are those of Gande, Altman, and Saunders (2006, 2010), 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 that 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 and earn excess returns as a result. Bushman, Smith, and Wittenberg-Moerman (2010) suggest that, as a result, 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. 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, which collect and aggregate dealer quotes for widely traded syndicated loans. Their data are produced and distributed daily and are used widely as a source of mark-to-market pricing for loan market investors, both banks and non-bank institutions.

Note that 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 that 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 that 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 are not likely to shed light on that 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. Based on its relative liquidity and presumed efficiency, we choose the equity market as a natural benchmark. 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 U.S. dollar currency loans, including term loans, both so-called A and B tranches (or TLA and TLB), respectively designed to be held by banks and non-banks, 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 an average bid of 95.9 and an average ask price of 97. The loans have a median maturity of six years, although the average loan appears in the mark-to-market database for only 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 five (7.25) distinct loans traded.

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. In the common 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 common shares, those with share codes of 10 or 11. 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 $1 at portfolio formation.

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.[2]

We end up with 18,335 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 are −0.079% and 2.477%, respectively. For the same firms, stock return in the next month has 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

[2]The match between traded loans and Dealscan is provided by Thompson Reuters, which owns both databases. With few exceptions, traded loans covered by the LSTA data are a subset of loans covered by Dealscan.

billion.

Meanwhile, it is important to note that contemporaneous loan returns and stock returns are strongly positively correlated. In pooled regressions, stock returns load on loan returns with a beta of 1.9, a t-statistic of 39, and an R^2 of 4.26%. In Fama-Macbeth regressions, the cross-sectional beta is 1.3 (with a t-statistic of 6.7) and an average R^2 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 good news for equities and vice-versa. In other words, while we cannot 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 and would work against our finding a result.

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 six-month lag 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. Stocks held by U.S. mutual funds are identified by *permno*. To identify syndicated loan 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. Because of 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. Formal cross-sectional tests in the next section are motivated by Figure 1, which plots pooled variation in loan returns against equity returns for the same set of borrowers over the subsequent month. The x-axis sorts borrowers into 25 quantiles based on mean monthly loan return, ranging from -9.33% to 8.06% in the extremes. For the same set of borrowers, the y-axis shows the average equity returns in the subsequent month for each bucket of firms and finds a spread of almost 10% among the most extreme loan market winners and losers. As we demonstrate in the following sections, similar variation can be captured using dollar-neutral portfolios constructed in real time using cross-sectional sorts of equities based on publicly available loan performance information.

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.[3] We then form six portfolios and track the performance of each over month $t + 1$.

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 the Long−Short portfolio, a dollar-neutral portfolio that 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.

[3] 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.

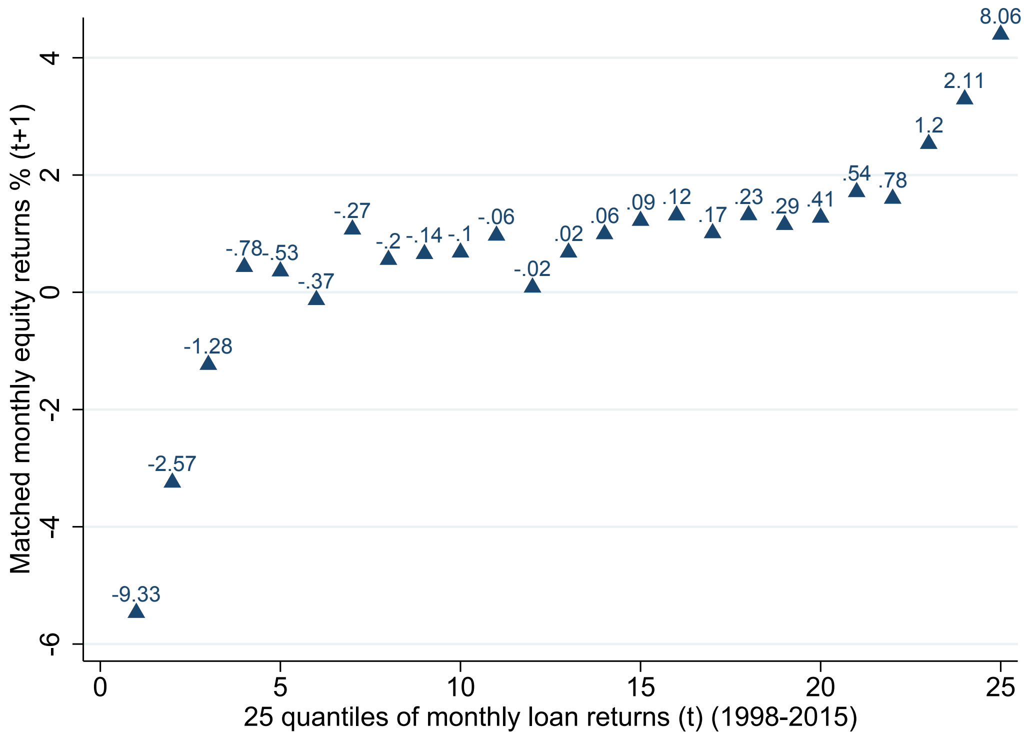

Figure 1

Equity Returns vs. Lagged Loan Returns. The plot above combines both time-series and cross-sectional relationships between loan returns and linked equity returns in the next month. Loan returns are sorted into 25 quantiles over the entire sample period and plotted against the next-month equity returns for the same borrowers. Average loan returns for each quantile are reported next to the triangles.

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 portfolio. 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.[4] The t-statistics reported in parentheses below the coefficient estimates are calculated using Newey and West (1987) adjusted standard errors using a six-month lag.

[4]For brevity, we report only factor model alphas in Tables 2 and 3. We present the full set of corresponding factor loadings for the Long, Short, and Long−Short portfolios in Tables A1 and A2 of the appendix.

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. Figure 2 plots the cumulative abnormal returns from column 2 of Table 2. Although the profitability of the strategy appears to flatten in the latter half of the sample, splitting the sample confirms that even in the second half of the sample, the strategy generates an economically and statistically important 8-factor monthly alpha in excess of 1%.

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 stronger among smaller stocks. To ensure that our main predictability results are not isolated to the smallest stocks, we rerun our analysis focusing only on the subset of stocks with market capitalization above the median NYSE size breakpoints. In results reported in Table A3 of the appendix, we continue to find economically and statistically significant Long−Short portfolio returns among the largest stocks.

It is also important to highlight the economic significance of our evidence of pre-

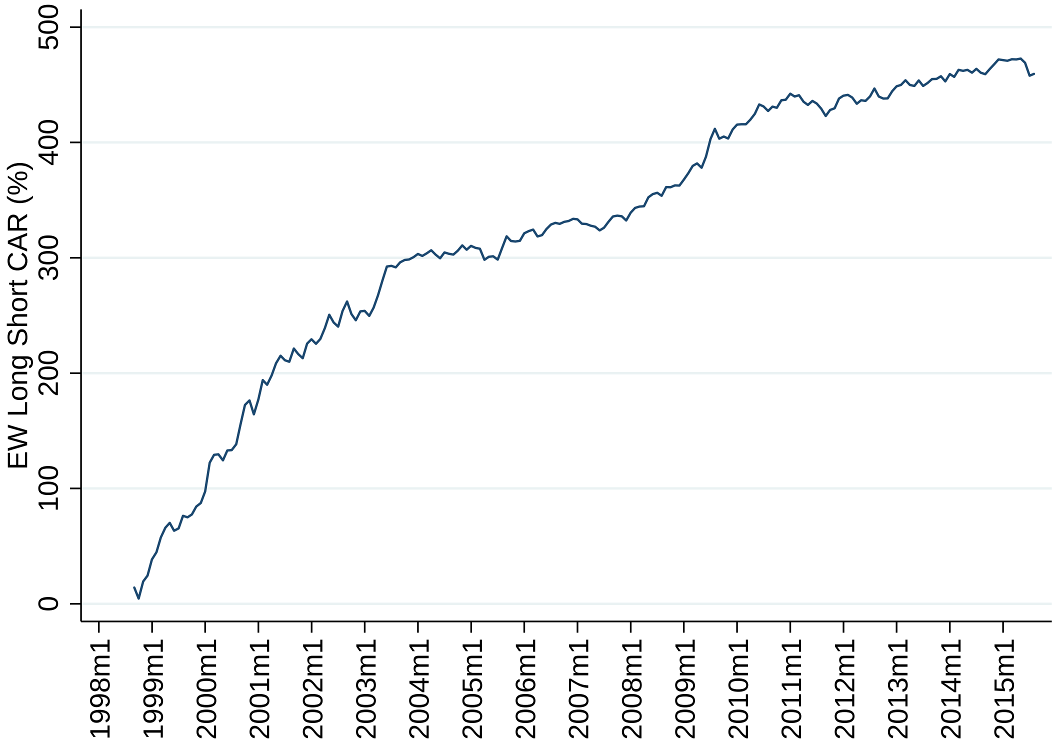

Figure 2
Cumulative Equal Weighted Portfolio Returns. We plot the monthly cumulative abnormal returns from the equal weighted Long−Short strategy, calculated as alpha plus the cumulative residuals from a CAPM regression over the sample period.

dictability in stock returns. In particular, the profitability of our trading strategy is comparable to the findings in 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.

While at 2.2% monthly alpha, our equal-weighted portfolio earns significantly more than the strategies mentioned above on a nominal basis, by construction, it is an implicitly levered portfolio. This is due to the fact that all portfolio stocks have a significant volume of traded debt and that portfolio alphas and betas both scale with firm leverage. As a useful exercise to put our returns in perspective, we can de-lever the Long−Short strategy so that the average market beta of each side (currently 1.65 on the short side and 1.35 on the long side of the equal-weighted book) is equal to one. When we do that, the equal-weighted alphas are more consistent with prior results from the return predictability literature at 1.5% per month. A similar exercise for the value-weighted strategy generates monthly alphas of 1.12% per month.[5] Alternatively, it is perhaps easiest to interpret the strategies in terms of Sharpe ratios, which are on par with momentum at 0.6 for the value-weighted strategy and 1.2 for the equal-weighted strategy.

3.3. Interpreting the information in loan prices

It is difficult to pin down the specific types of information that drive the predictability, but we explore some possibilities here and in appendix Table A3. Revolving credit facilities, for example, might convey a natural advantage to loan participants, given that lenders might learn about draw-downs in advance. Revolvers secured with floating liens on collateral accounts (e.g., receivables) will provide lenders with a constant stream of information on the value of those accounts, information not available to equity markets (see Gustafson, Ivanov, and Meisenzahl (2016)). In Table A3 (row b), we find that trading on only the prices of revolving loan facilities generates slightly higher returns than

[5]We de-lever the long and short portfolio using the same factor in order to ensure that t-statistics on the alpha are unaffected. De-levering each side separately generates economically similar effects.

the unconditional strategy. However, trading on the prices of term loans held by non-bank institutions that do not participate in revolvers still yields monthly alphas of 1.26 to 1.46% (row c).

The availability of monthly financial statements is another obvious source of material private information for lenders. Figure 3 presents evidence that suggests earnings information may be a large component of the trading strategy. The figure plots average returns to the equal weighted Long−Short strategy for each calendar month of the year based on the equity holding period. Dashed vertical lines highlight common annual and quarterly earnings announcement dates. Interestingly, February returns are negative in only one month during the sample period, consistent with early information on year-end earnings provided to lenders in January as a source of informational advantage. Further, we find that strategy returns exhibit a marked downtick in the month after earnings announcements. We interpret this as earnings announcements serving to reduce the level of information asymmetry between the loan in equity markets. As a result, the value of loan market information is dampened in earnings announcement months.

At the same time, in row d of Table A3, we restrict the trading strategy to equities that do not have earnings announcements in the holding period month. Importantly, we find that the strategy still earns substantial excess profits outside of firms' earnings announcement windows. Together, these results suggest that while earnings news is an important component of the information in loan prices, it is not the entire story.

Loan prices might also provide early warnings about immediate distress. In some of the early important work using the secondary loan data, Gande, Altman, and Saunders (2006) show that, in the months leading up to firm defaults and bankruptcies, loan prices provide more timely indicators of the severity of distress. In row e of Table A3, we condition on borrowers outside of distress by dropping loans with prices below 90 (the threshold below which the Loan Syndications and Trading Association differentiates par from distressed loans) and again find a healthy result. This suggests that loan prices contain non-public information that is value-relevant even well outside of distress for levered firms but not yet captured by equity prices.

Finally, to assess our trading strategy's potential for implementation over the sample period, we consider an alternative weighting scheme in forming the quintile portfolios. Specifically, in row f of Table A3, we calculate and report the average raw and risk-adjusted returns to the turnover-weighted Long−Short portfolio, where turnover is calculated over the month prior to portfolio formation. Since algorithmic traders may focus on stocks with high turnover to minimize the trading costs and price impact of their orders, we may find that the strategy returns are dampened when using this alternative weighting scheme. Instead, the estimates in row f of Table A3 indicate that the turnover-weighted trading strategy delivers statistically significant average alphas of over 2% per month.

As an alternative method of understanding the potential role of transaction costs on the trading strategy's profitability, we adopt the approach of Grundy and Martin (2001). That is, we calculate the round-trip trading costs needed to render the strategy returns statistically insignificant at the 5 and 10% levels. This helps clarify the extent to which high average returns to the strategy may be offset by the need for frequent rebalancing implied by the monthly average portfolio turnover of 81%. We find that for the equal-, value-, and turnover-weighted strategies, the respective round-trip trading costs of 1.46, 0.44, and 1.08% (1.63, 0.61, and 1.32%) eliminate the statistical significance of the raw strategy returns at the 5% (10%) level. For comparison, these round-trip trading costs are comparable to the thresholds documented by Grundy and Martin (2001) for the momentum strategy, which has been widely implemented. Further, the average returns to the respective strategies remain economically large under these circumstances,[6] suggesting that the syndicated loan market represents a source of trading signals that were implementable over the sample period.

[6] Average monthly Long−Short returns at the 5% thresholds for the equal-, value-, and turnover-weighted strategies are 0.91, 0.95, and 1.33%, respectively.

Figure 3
Calendar Month Returns. The plot shows the average returns to the equal weighted Long−Short strategy grouped by calendar month, based on the equity holding period. Dashed vertical lines highlight common annual and quarterly earnings announcements months.

3.4. Fama-MacBeth regression estimates

In the next set of baseline tests, we estimate Fama and MacBeth (1973) predictive regressions, allowing us to control for other characteristics known to generate excess returns that might plausibly be correlated with loan returns. 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.

Of the firm characteristics known to predict excess stock returns, we begin by 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 six months, with a one-month lag, to capture momentum effects (Jegadeesh and Titman, 1993). Further, we control for the contemporaneous stock return in month t to account for short-term reversals (Jegadeesh, 1990), the ratio of debt to equity to account for the market leverage effect of Bhandari (1988), and standardized unexpected earnings (SUE) announced in months $t-2$ through t (Livnat and Mendenhall, 2006). Leverage controls are natural given the sample, and SUE is inspired by the suggestion in Figure 3 that loans may contain earnings information.

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 six-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 and 2 of Table 4 are highly statistically significant, with t-statistics ranging from 2.46 to 2.84. 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 0.468 (t-statistic = 2.84). 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 0.444 (t-statistic = 2.46). In economic terms, this estimate indicates that a one standard deviation change in syndicated loan return translates to a $0.444 \times 2.477 = 1.099\%$ increase in next-month excess stock return after accounting for firm characteristics.

We find similar results when controlling for known predictors of excess stock returns in columns 3 through 5 of Table 4. Specifically, we find that the syndicated loan return remains a strong predictor of excess stock returns when individually adding controls for contemporaneous stock returns, market leverage, and SUE announced in the previous quarter. Across these specifications, the syndicated loan return loads with a coefficient ranging from 0.407 to 0.494 and t-statistics between 2.14 and 2.61.

Finally, we find a similar result in column 6, where we control for all characteristics simultaneously. We also incrementally interact the syndicated loan return with the size characteristic in this specification.[7] 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 = 0.667; t-statistic = 3.14) signals the existence of a significant predictive relation between syndicated loan market returns and subsequent stock returns, consistent with our main conjecture.

4. Return Predictability Mechanism

To better understand the perhaps surprising fact that the syndicated loan market significantly leads the equity market, we examine a handful of explanations, ranging from traditional risk-based interpretations to those grounded in limits to arbitrage. Finally, our last tables explore investor inattention and the new idea that equity markets lack cross-market expertise required to interpret the information contained in loan prices.

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. However, it is also not difficult to construct scenarios under which changes in loan value are associated with changing firm characteristics that amplify or attenuate equities' exposure to priced risk factors.[8]

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

[7] We demean size in each cross-section before computing the interaction so that the syndicated loan return coefficient measures the predictive effect for a firm of average size.

[8] Imagine, for example, that a borrower agrees to increase the spread on its loan to procure a covenant waiver or amendment. The higher spread translates 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.

portfolio return should exhibit a large degree of persistence if loan market returns signal changes in equityholders' exposure to systematic risks.

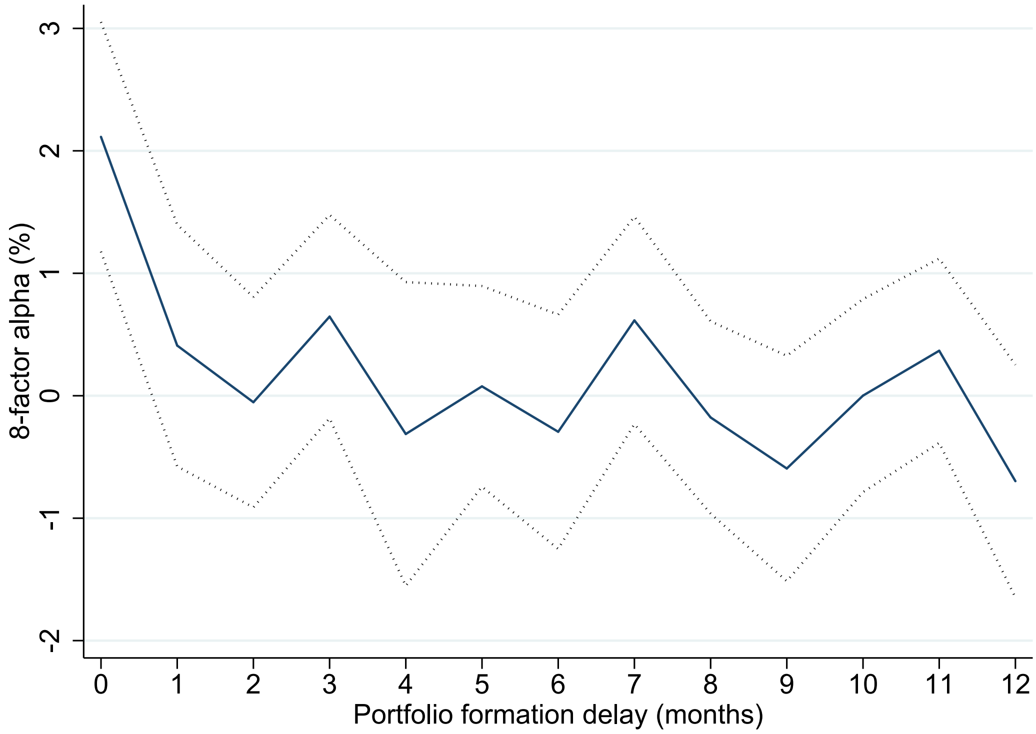

Figure 4
Delayed Portfolio Formation. The figure plots the 8-factor alpha from equal-weighted Long−Short portfolios formed based on the past month's loan returns (i.e., as in Table 2), alongside the returns from the same portfolio formed with a one to 12-month delay. Dashed lines surrounding the alpha estimates (solid line) represent the two standard error bands.

Figure 4 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 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 one-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 4 support our conjecture that the predictive power of loan returns reflects 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

Another potential explanation for the short-term predictability apparent in Figure 4 is that the mispricing is afforded by limits to arbitrage. While the predictability results – in particular portfolios weighted based on turnover in Table A3 – tell us that equity market participants are trading in volume at prices that do not reflect the information available from debt markets, they do not rule out the existence of sophisticated participants who recognize the mispricing, but cannot profitably correct it because of implementation costs or risks associated with the implied trading strategy. Predictability may be concentrated among stocks that arbitrageurs have difficulty buying and selling in large quantities, or arbitrageurs may perceive the eventual payoffs of taking positions in mispriced stocks as excessively risky. Further, they may find it difficult to take short positions, either due to a simple lack of inventory or high borrowing costs (De Long, Shleifer, Summers, and Waldmann, 1990; Shleifer and Vishny, 1997; Engelberg, Reed, and Ringgenberg, forthcoming).

To test whether arbitrage constraints can help explain the relationship between loan returns and subsequent stock returns, we consider several standard proxies for characteristics associated with limits to arbitrage. The proxies are idiosyncratic volatility, institutional ownership, the bid-ask spread, and illiquidity. 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. The bid-ask spread is calculated as the difference between the Ask and Bid prices reported by CRSP as a percentage of the share price at the end of month t. Finally, following Amihud (2002), illiquidity is calculated as the average ratio of daily absolute return to dollar trading volume in the prior year. To reduce the distributional skewness of the institutional ownership measure, we take its natural log.[9]

We include the interactions between each of the arbitrage constraint measures and the loan return predictor in columns 1 through 4 of 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, bid-ask spread, and illiquidity. Across the four specifications, 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, suggesting the predictive relation between the syndicated loan and stock markets is significant for firms with average arbitrage constraints.

In column 5, we simultaneously control for idiosyncratic volatility, institutional ownership, bid-ask spread, illiquidity, and size. Again, the estimates in column 5 indicate that simultaneously controlling for all the arbitrage constraint measures does not help explain the level effect associated with syndicated loan returns. For a hypothetical firm with average size and arbitrage constraints, the syndicated loan predictor remains an economically and statistically significant predictor of next-month excess stock returns (coefficient = 0.635; t-statistic = 2.42).

As an additional test of the effect of limits to arbitrage, we consider to what extent the cost of shorting shares of recent losers in the loan market serves as a barrier to implementation of the strategy. While the equal-weighted portfolio earns 0.81% to 1.58% on the long side, we find that the value-weighted strategy earns much of its returns from the short leg of the portfolio. The cost and availability of shares for shorting is therefore relevant to strategy profits. The dynamics of short interest in our portfolio, however, seem to suggest that the shares we might like to short in the portfolio are indeed generally

[9]Our results are qualitatively unchanged whether or not we take this log transformation.

available, and eventually do attract substantial interest from short-sellers. However, we find that interest comes with a lag, consistent with informational frictions facilitating the disconnect across markets.

To show this, Table 6 maintains the sample of loan-equity pairs from earlier tables, but replaces the dependent variable in Fama-Macbeth regressions with the change in the equity short ratio over the month, and projects this on contemporaneous loan returns as well as lagged loan returns (column 1), alongside controls for size, value, momentum (column 2), and contemporaneous equity returns (column 3). The short ratio is calculated as the number of shares held short divided by total shares outstanding.[10]

In each column of Table 6, we see that short interest rises with poor loan returns, but not just in the current period. Holding current loan returns fixed, negative loan returns in the previous month are significantly associated with increases in short interest today with a magnitude nearly double that of the contemporaneous relationship. The fact that short interest responds to loan market information with a lag does not rule out the possibility that short selling costs reduce the profitability of the strategy, but it does suggest that, even facing those costs, short sellers find it profitable to respond to the news on these stocks eventually. Unless shorting costs happen to systematically decrease in the month following poor loan returns, the evidence would suggest that there is capacity to short poor performers in the loan market, but that short sellers react to the information content of syndicated loan returns with a lag.

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 that they are aware, believe that little can be learned from paying attention to loan

[10]Changes in the short interest ratio are taken either at month end or (in the earlier part of the sample) between the 15th day of the month and the 15th day of the prior month. When changes in the short interest ratio are measured as of mid-month, loan returns (and lagged loan returns) are also measured as of mid-month.

markets. Indeed, it is 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, particularly price movements, is made salient, we would expect predictability to dissipate. To test this, we focus on weekly loan price 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 7 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.[11] If we believe that appearing in the WSJ

[11] The second row and fourth row of Table 7 confirm this by examining the returns to the 1 and 5 portfolios in Tables 2 and 3, excluding names reported in the WSJ. Of course, the WSJ list also represents the most extreme loan returns; the Long−Short returns partially reflect that.

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 226 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.)
Alpha Natural Resources	B1/BB-	L+275	May 31, '20	88.95	**-0.36**
Arch Coal Inc	B1/B+	L+500	May 17, '18	89.63	**-1.04**
Burger King Corp	(P)B1/B+	L+350	Sept. 15, '21	99.53	**0.32**
Caesars Entertainment Inc	B2/B+	L+525	April 2, '21	94.00	**-0.60**
Caesars Entertainment Inc	B2/CCC+	L+600	Sept. 24, '20	95.00	**-0.60**
Cequel Communications Holdings	Ba2/BB	L+275	Feb. 15, '19	98.60	**0.41**
CityCenter	B2/BB-	L+325	Oct. 16, '20	99.23	**0.50**
Dell Computer Corp	Ba2/BB+	L+350	March 25, '20	99.75	**0.40**
Delta Airlines	Ba1/BBB-	L+275	April 15, '17	98.92	**0.31**
Getty Images Inc	B2/B	L+350	Oct. 14, '19	93.46	**1.38**
Go Daddy Group	Ba3/B	L+375	April 30, '21	99.08	**0.67**
International Lease Finance Corp	N.R./N.R.	L+275	Feb. 18, '21	99.38	**0.66**
J. Crew.	B1/B	L+300	Feb. 27, '21	96.00	**0.92**
Kronos Worldwide	B1/B+	L+375	Feb. 17, '20	99.98	**0.31**
Regal Cinemas	Ba1/BB	L+250	Aug. 23, '17	98.93	**0.73**
Reynolds Group	B1/B+	L+300	Dec. 15, '18	99.25	**0.55**
Sears Holdings Corp	B1/B	L+450	June 30, '18	96.50	**-0.50**
Seaworld Parks and Entertainment Inc	Ba3/BB	L+225	May 10, '20	94.96	**0.86**
Southwire Co	Ba3/BB+	L+250	Dec. 20, '20	97.40	**-1.21**
SunGard Availability	Ba3/BB-	L+500	March 27, '19	91.70	**-0.38**
SuperValu	B1/B+	L+350	March 21, '19	97.60	**-0.44**
Univar NV	B3/B+	L+350	June 30, '17	99.23	**0.33**
Virgin Media Investment Hldgs(NTL)	Ba3/BB-	L+275	Feb. 6, '20	97.79	**0.54**
Walter Energy Inc	B3/B-	L+575	March 14, '18	88.96	**0.68**
Zebra Technologies	Ba2/BB+	L+375	Oct. 2, '21	100.48	**0.56**

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 5
Wall Street Journal Biggest Movers. Between August 2000 and August 2015, the Wall Street Journal printed a weekly table of the 25 "Biggest Movers" in the syndicated loan market. This figure provides an example from October 2014.

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. However, if equity traders believe that understanding loan prices requires additional background, they may choose to ignore the information available. Note that 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 CRSP 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 that are generally active, that describe themselves as balanced or hybrid funds, and that 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 75% 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 owned by integrated funds in the month prior to changes in loan prices for the corresponding firms. Table 8 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 5. 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, 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 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, in column 3, because we might think that stocks owned by integrated funds are likely to be different along several dimensions, we add interactions for the characteristics associated with arbitrage constraints presented in Table 5. While we cannot rule out that the dummy for integrated funds captures some other important characteristic of the stocks that also happens to predict the degree of market integration, it is encouraging to note that the economic and statistical magnitude of the interaction is largely unaffected by the inclusion of other plausibly important characteristics like size, liquidity, and institutional ownership as interactions. Thus, even the most conservative interpretation of the result would suggest that knowledge of who owns equities is a useful predictor of market integration across firms' capital structure.[12] Meanwhile, in each case, the level effect on loan returns is positive, significant, and larger than the Fama-Macbeth coefficients reported in Tables 4 and 5. This suggests that the strategy to trading on loan market integration survives even late in the sample, but only for equities that 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. A solution that precludes shutting down liquidity in the secondary market or limiting bankers' access to non-public information, both of which

[12]Future work may be able to further explore the mechanism by which integrated funds integrate markets by documenting their trading patterns around loan returns. However, given that funds in our sample predominantly report quarterly holdings data, our ability to separate trading around monthly loan returns from trading around the lagged equity returns is limited to a handful of funds.

would have significant consequences for credit markets, is difficult to imagine. In the meantime, our findings that stocks held by institutions with fluency in both markets are better integrated suggest 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 using a six-month lag.

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 using a six-month lag.

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, lagged stock return over the previous six months, stock return in month t, the ratio of short- and long-term debt to market capitalization, and standardized unexpected earnings (SUE) announced in months $t-2$ through 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 using a six-month lag.

Excess Stock Return (t+1)	(1)	(2)	(3)	(4)	(5)	(6)
Synd Loan Return (t)	0.468	0.444	0.407	0.494	0.414	0.667
	(2.84)	(2.46)	(2.14)	(2.61)	(2.27)	(3.14)
Size		-0.245	-0.265	-0.225	-0.245	-0.203
		(-1.75)	(-1.80)	(-1.73)	(-1.72)	(-1.25)
Book-to-market		-0.505	-0.481	-0.437	-0.543	-0.452
		(-1.46)	(-1.38)	(-1.31)	(-1.59)	(-1.17)
Lagged 6mRet		0.281	0.183	0.164	0.311	0.128
		(0.32)	(0.19)	(0.19)	(0.38)	(0.14)
Stock Return (t)			-0.007			-0.013
			(-0.54)			(-1.06)
Market Leverage				-0.201		-0.218
				(-1.46)		(-1.61)
SUE					0.058	0.040
					(2.46)	(1.65)
Synd Loan Return × Size						-0.254
						(-1.86)
Constant	0.879	4.097	4.326	3.984	4.136	3.740
	(1.72)	(1.98)	(1.99)	(2.14)	(1.99)	(1.53)
Avg R-squared	0.028	0.108	0.133	0.141	0.130	0.200
N obs	18,335	18,335	18,335	17,883	18,335	17,883
N months	204	204	204	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, illiquidity, 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. Illiquidity is calculated as the average ratio of daily absolute return to dollar trading volume in the prior year (Amihud, 2002). 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 using a six-month lag.

Excess Stock Return (t+1)	(1)	(2)	(3)	(4)	(5)
Synd Loan Return (t)	0.377	0.630	0.465	0.783	0.635
	(2.03)	(2.78)	(2.09)	(3.03)	(2.42)
Size	-0.286	-0.256	-0.281	-0.342	-0.261
	(-1.90)	(-1.83)	(-2.14)	(-2.43)	(-1.64)
Book-to-market	-0.440	-0.500	-0.819	-0.633	-0.824
	(-1.25)	(-1.41)	(-2.09)	(-1.72)	(-2.00)
Lagged 6mRet	0.537	0.248	0.125	0.246	0.357
	(0.62)	(0.30)	(0.16)	(0.28)	(0.47)
IVOL	-0.271				-0.209
	(-2.22)				(-1.42)
Log(IO)		-1.210			-0.945
		(-1.04)			(-0.71)
Bid-Ask Spread			-0.306		-0.308
			(-0.34)		(-0.28)
Illiquidity				-0.146	-0.315
				(-0.86)	(-1.76)
Synd Loan Return × IVOL	-0.047				-0.197
	(-0.29)				(-0.95)
Synd Loan Return × Log(IO)		-0.733			-4.063
		(-0.73)			(-1.52)
Synd Loan Return × Bid-Ask Spread			0.333		2.271
			(0.32)		(1.28)
Synd Loan Return × Illiquidity				0.152	-0.244
				(0.57)	(-0.59)
Synd Loan Return × Size					-0.096
					(-0.49)
Constant	5.206	5.090	4.859	5.576	5.675
	(2.36)	(2.37)	(2.67)	(2.80)	(2.24)
Avg R-squared	0.151	0.142	0.153	0.138	0.268
N obs	18,329	18,335	17,986	18,335	17,980
N months	204	204	204	204	204

Table 6

Short Interest. This table reports estimates from Fama and MacBeth (1973) regressions of changes in equity short-interest, scaled by shares outstanding on loan returns in the same period, loan returns from the prior period, and controls for size, value, momentum, and contemporaneous equity returns. Changes in the short interest ratio are taken either at month end or (in the earlier part of the sample) between the 15th day of the month and the 15th day of the prior month. When changes in the short interest ratio are measured as of mid-month, loan returns (and lagged loan returns) are also measured as of mid-month. 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 using a six-month lag.

Δ Short Interest Ratio (t)	(1)	(2)	(3)
Synd Loan Return (t)	-0.036	-0.033	-0.042
	(-1.72)	(-1.44)	(-1.63)
Synd Loan Return (t-1)	-0.061	-0.086	-0.074
	(-2.17)	(-2.74)	(-2.32)
Size		-0.023	-0.020
		(-1.60)	(-1.32)
Book-to-market		0.071	0.065
		(2.01)	(1.74)
Lagged 6mRet		-0.272	-0.261
		(-3.44)	(-3.45)
Stock Return (t)			0.000
			(0.12)
Avg R-squared	0.057	0.133	0.161
N obs	11,991	11,991	11,991
N months	203	203	203

Table 7

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 using a six-month lag.

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 8

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, an integrated mutual fund indicator, log market capitalization at the end of the previous month, book-to-market ratio, lagged stock return over the previous six months, idiosyncratic volatility, institutional ownership, bid-ask spread, and illiquidity. The integrated mutual 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 using a six-month lag.

Excess Stock Return (t+1)	(1)	(2)	(3)
Synd Loan Return (t)	1.738	1.417	2.235
	(3.11)	(2.64)	(2.66)
Synd Loan Return × Integrated Fund	-1.840	-1.436	-2.461
	(-3.11)	(-2.40)	(-2.58)
Integrated Fund	0.193	0.158	0.690
	(0.40)	(0.29)	(1.26)
Size		0.055	0.081
		(0.29)	(0.33)
Book-to-market		-0.857	-0.598
		(-2.32)	(-1.86)
Lagged 6mRet		0.368	0.336
		(0.37)	(0.41)
IVOL			-0.250
			(-1.17)
Log(IO)			-0.145
			(-0.20)
Bid-Ask Spread			1.027
			(0.39)
Illiquidity			-0.161
			(-0.43)
Synd Loan Return × Size			0.784
			(2.74)
Synd Loan Return × IVOL			-0.087
			(-0.23)
Synd Loan Return × Log(IO)			-0.950
			(-0.68)
Synd Loan Return × Bid-Ask Spread			3.832
			(0.68)
Synd Loan Return × Illiquidity			0.109
			(0.12)
Constant	1.182	0.730	0.067
	(1.69)	(0.24)	(0.02)
Avg R-squared	0.061	0.132	0.267
N obs	5,633	5,633	5,631
N months	60	60	60

Table A1

Equal Weighted Portfolio Factor Model Estimates. This table reports factor model estimates of a trading strategy that sorts stocks on matched non-zero loan returns into quintiles. We report the performance of three 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, and (iii) the "Long−Short" portfolio, which captures the difference in returns of the Long and Short portfolios. We report estimates for the CAPM as well as 3, 6, and 8-factor models 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 using a six-month lag.

Factor	Long (1)	Short (2)	Long-Short (3)	Long (4)	Short (5)	Long-Short (6)	Long (7)	Short (8)	Long-Short (9)	Long (10)	Short (11)	Long-Short (12)
Constant	0.964	-1.289	2.253	0.628	-1.527	2.155	0.889	-1.259	2.148	0.812	-1.289	2.101
	(2.12)	(-3.26)	(4.83)	(1.70)	(-3.59)	(4.77)	(3.09)	(-3.71)	(4.89)	(2.86)	(-3.54)	(4.52)
RMRF	1.349	1.652	-0.302	1.304	1.552	-0.248	1.103	1.294	-0.192	1.129	1.254	-0.126
	(10.40)	(13.43)	(-2.23)	(14.60)	(14.40)	(-2.20)	(12.58)	(12.51)	(-1.80)	(13.06)	(13.14)	(-1.11)
SMB				0.679	0.663	0.015	0.800	0.916	-0.117	0.805	0.918	-0.113
				(4.56)	(4.42)	(0.11)	(7.71)	(8.12)	(-0.75)	(7.49)	(7.83)	(-0.67)
HML				0.702	0.283	0.419	0.565	0.225	0.340	0.440	0.165	0.275
				(4.04)	(1.34)	(2.10)	(3.58)	(1.32)	(1.70)	(2.53)	(1.02)	(1.33)
UMD							-0.441	-0.478	0.037	-0.487	-0.493	0.006
							(-5.56)	(-6.89)	(0.40)	(-5.99)	(-6.23)	(0.07)
ST REV							-0.047	0.108	-0.155	-0.046	0.113	-0.159
							(-0.60)	(0.76)	(-1.19)	(-0.58)	(0.78)	(-1.17)
LT REV							-0.019	-0.309	0.290	0.042	-0.262	0.303
							(-0.11)	(-1.83)	(1.71)	(0.25)	(-1.70)	(1.69)
LIQ										-0.005	0.101	-0.106
										(-0.09)	(1.55)	(-1.49)
BAB										0.173	0.064	0.109
										(2.08)	(0.40)	(0.78)
Adj R-squared	0.581	0.608	0.048	0.697	0.656	0.093	0.777	0.738	0.105	0.779	0.741	0.110
N obs	204	204	204	204	204	204	204	204	204	204	204	204

Table A2

Value Weighted Portfolio Factor Model Estimates. This table reports factor model estimates of a trading strategy that sorts stocks on matched non-zero loan returns into quintiles. We report the performance of three 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, and (iii) the "Long−Short" portfolio, which captures the difference in returns of the Long and Short portfolios. We report estimates for the CAPM as well as 3, 6, and 8-factor models 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 using a six-month lag.

Factor	Long (1)	Short (2)	Long-Short (3)	Long (4)	Short (5)	Long-Short (6)	Long (7)	Short (8)	Long-Short (9)	Long (10)	Short (11)	Long-Short (12)
Constant	0.341	-1.224	1.565	0.212	-1.253	1.465	0.338	-1.061	1.400	0.289	-1.079	1.369
	(1.01)	(-3.07)	(3.31)	(0.62)	(-3.25)	(3.23)	(1.05)	(-2.92)	(3.26)	(0.84)	(-3.09)	(3.09)
RMRF	1.167	1.626	-0.459	1.205	1.646	-0.441	1.091	1.426	-0.335	1.179	1.384	-0.205
	(9.16)	(12.78)	(-2.99)	(13.24)	(13.55)	(-3.54)	(10.45)	(12.20)	(-2.86)	(13.94)	(12.26)	(-1.81)
SMB				0.112	-0.007	0.119	0.156	0.282	-0.126	0.160	0.284	-0.124
				(0.80)	(-0.03)	(0.57)	(0.93)	(1.74)	(-0.59)	(0.97)	(1.65)	(-0.56)
HML				0.447	0.136	0.311	0.360	0.168	0.191	0.297	0.128	0.169
				(2.99)	(0.62)	(1.20)	(2.49)	(0.91)	(0.71)	(1.63)	(0.66)	(0.62)
UMD							-0.218	-0.360	0.142	-0.251	-0.368	0.117
							(-2.54)	(-4.72)	(1.54)	(-3.05)	(-3.45)	(0.99)
ST REV							0.022	0.190	-0.168	0.016	0.194	-0.178
							(0.28)	(1.28)	(-1.06)	(0.21)	(1.26)	(-1.05)
LT REV							0.029	-0.466	0.495	0.034	-0.429	0.464
							(0.16)	(-2.57)	(2.47)	(0.20)	(-2.57)	(2.48)
LIQ										-0.150	0.098	-0.248
										(-2.29)	(1.01)	(-2.07)
BAB										0.115	0.037	0.078
										(0.74)	(0.20)	(0.36)
Adj R-squared	0.514	0.580	0.069	0.547	0.578	0.077	0.565	0.641	0.108	0.579	0.642	0.142
N obs	204	204	204	204	204	204	204	204	204	204	204	204

Table A3

Trading Strategy Sample Robustness. This table reports performance estimates, as described in Table 2, of various modifications of the equal weighted trading strategy. These include focusing on firms above the median NYSE size cutoff, limiting the loan signal to revolvers only, limiting the loan signal to institutional tranches of term loans only, trading only in equities without earnings announcements during the holding period, dropping distressed borrowers based on loan prices less than 90, and weighting portfolio constituents by equity turnover.

	EW Long-Short Portfolio Returns	Raw Return	CAPM Alpha	3-factor Alpha	6-factor Alpha	8-factor Alpha
(a)	Above median size cutoff	0.872	0.894	0.832	0.851	0.840
		(2.01)	(1.99)	(1.96)	(2.00)	(1.92)
(b)	Revolvers	2.559	2.527	2.297	2.308	2.347
		(2.93)	(2.79)	(2.89)	(2.88)	(2.93)
(c)	Institutional Term Loan Bs	1.382	1.460	1.257	1.313	1.267
		(3.52)	(3.76)	(2.59)	(3.00)	(2.67)
(d)	Non-earning announcement months	1.962	2.147	1.933	1.985	2.028
		(3.65)	(4.17)	(3.75)	(3.85)	(3.73)
(e)	Non-Distressed Loans	1.783	1.861	1.765	1.806	1.740
		(4.28)	(4.38)	(3.49)	(3.78)	(3.41)
(f)	Turnover Weighted	2.273	2.520	2.092	2.177	2.030
		(3.35)	(3.55)	(3.09)	(3.19)	(2.79)