Two Essays on Valuation in Imperfect Capital Markets:

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Two Essays on Valuation in Imperfect Capital Markets

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Information Revelation and Expected Stock Returns *

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Abstract

If information is not perfect, theories prescribe a negative relation between information availability and expected stock returns. Using two readily available variables, price and volume, I construct a new proxy for information and test its relation to returns in the 1964-2007 period on NYSE-listed stocks. I find that information revelation predicts lower future returns, controlling for beta, size, book-to-market ratio, liquidity, and momentum. A long/short trading strategy based on sorts on the information proxy generates alphas of 3% to 4%. These alphas do not have to imply an arbitrage opportunity; they are consistent with time-varying expected returns in a rational model.

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1 Introduction

The notion that stock prices reflect information is an old one. Ever since Hayek (1945) laid forth the idea, it has been tested time and again, in finance as well as in accounting. What has been studied less often however, is the relation between information and expected stock returns. Early asset-pricing models like the CAPM or the APT have assumed a perfect information world, yet, Grossman and Stiglitz (1980) show that equilibrium cannot exist in such a world; if information is costly and there are no rewards for producing it, then no one would rationally choose to do so. In response, models have been extended to incorporate the complexity of the information environment and one prediction they all have in common is that expected returns should be decreasing in the amount of public information. This is the basic hypothesis I empirically test.

Information availability can vary across time or across stocks. In this paper I focus on the time dimension. The relation between information and the cross-section of stock returns is of no less importance but is beyond the scope of this article. Consistent with theory, I find that average returns in the months after information revelation are significantly lower than before. The average difference in returns for a firm one month before an information event and one month after is 0.7%. The difference monotonically decreases as the time window expands, but is still statistically significant up to sixth months. Fixed-effects regressions using all NYSE stocks during the 1964-2007 period further reveal that information revelation in one month can predict stock returns in the next month. This finding is robust to different time periods, changes in systematic risk (beta), size, book-to-market ratio, liquidity, and past returns. Finally, I show that a naive investor could have earned annualized returns around 3-4% on a risk-adjusted basis, by short selling stocks that have recently revealed information and investing the proceeds in others where information is private or has not caught the market attention.

These "abnormal" returns need not be interpreted as arbitrage opportunities. In a rational setting, these findings can represent a risk-return trade-off. Information revelation can reduce uncertainty about the future cash-flows of a firm, hence the discount rate, or it can increase the demand for the stock by attracting uninformed investors who were previously too cautious or negligent about the firm. In either case, investors bid up the price and depress future returns temporarily. Behavioral explanations, such as over/under reaction of investors, are also plausible, however I am not aware of any behavioral model that specifically predicts the pattern I observe in returns.

Because the amount of information (or the asymmetry in the information environment) is unobservable, the first hurdle in any empirical study is constructing a reliable proxy for information. Many have been proposed in the literature, such as the period of listing in Barry and Brown (1984), the PIN measure of Easley, Hvidkjaer, and O'Hara (2002), accruals quality in Francis, LaFond, Olsson, and Schipper (2005), and the number of news articles in the media by Fang and Peress (2007). While each measure has its own merit, one common drawback of all previous measures is that they are only available for short time-series - usually much shorter than what it is commonly used in asset-pricing tests. To overcome this problem, I propose a new information proxy that is based on two most readily available variables: price and volume. Specifically, the proxy is the monthly estimate of the daily correlation between absolute returns and dollar volume. Empirical evidence shows that information revelation elicits a *simultaneous* response in price and volume. Hence, I expect these variables to move together more closely in months when information arrives, than in other months.

The idea to back out the existence of information from price and volume reactions is based on Beaver (1968). He defines information content as *any* change in investors' expectations and motivates the use of price and volume by noting that price change implies a change in the expectations of the market as a whole, and volume implies a change in the expectations of the individual investors. On the day of the earnings announcement he observes abnormal movement in *both* these variables, and thus concludes that information must be revealed. Because magnitude of the price change is closely linked to the stock's total risk, and trading volume is often a proxy for liquidity, I fold these two variables into one, to avoid collinearity with other control variables in the regressions. The correlation between price change and volume turns out to be orthogonal to both systematic and idiosyncratic risk, and liquidity, and at the same time, behaves similarly to price change or volume taken separately around earnings announcements. On top of tractability, this correlation measure has the added benefit of capturing the *importance* of information, since information events are inferred from market reactions (rather than newspaper articles, for example).

More recent evidence on price and volume reactions to earnings announcements and their informativeness can be found in Landsman and Maydew (2002). Earnings announcements though, are not the only type of information events that price and volume react to. Mitchell and Mulherin (1994) find that the number of Dow Jones Newswires announcements are directly related to trading volume and returns. The same phenomena is also observed in the bond market; Balduzzi, Elton, and Green (2001) show that both volatility and trading volume of Treasuries increase around macroeconomic announcements. Tauchen and Pitts (1983) develop a theoretical model to explain the relation between price changes and volume[1]. They derive the covariance between price increments and volume as a function of the variability in the number of news arrivals. According to their model, information arriving all at once, as opposed to smoothly flowing to the market, induces a higher correlation between price and volume. If the model is correct, the months where I observe high correlation should correspond to important and unexpected news events[2].

[1] Price/Volume relations have a long history. See Karpoff (1987) for a review.

[2] However months of low observed correlation are not guaranteed to be low in information. In the Tauchen and Pitts (1983) model, a company that reveals no information and a company that reveals a constant stream of information generates a low price/volume correlation. This potential bias though, would make it more difficult to find statistically significant differences in returns between high and low information months because some of the low information months would be "contaminated" with steady high information.

The results in this paper are consistent with rational asset-pricing theories that relax the assumption of all market participants having perfect and symmetric information. There are various approaches to this problem. Klein and Bawa (1976) and Klein and Bawa (1977) consider portfolio choice with differing amounts of parameter uncertainty. The intuition behind their model is that as the number of observations grows parameters can be estimated more precisely, which reduces risk and the increases the allocation of the risky asset. Building on this idea, Barry and Brown (1985) show that when firms face differential amounts of parameter uncertainty, CAPM betas will be lower than the true betas for low information securities and higher than the true betas for high information securities. In Merton (1987)'s incomplete information model investors agree on parameter values - there is no parameter uncertainty - however not every investor knows about every firm. Thus, firms with more visibility attract more demand from the investor pool and can sustain a lower rate of return in equilibrium. In Easley and O'Hara (2004), every investor knows about every firm, but they do not all share the same information. Uninformed investors know that they are uninformed though, and are aware of their disadvantage in trading with the informed. This raises the risk premium on firms where information is more private. Accounting literature has also offered some new insights in this area. Lambert, Leuz, and Verrecchia (2007) show that the CAPM can be modified to formalize the notion of information risk and forward-looking betas can potentially subsume information risk.

Empirical tests of these models do not always agree. Easley, Hvidkjaer, and O'Hara (2002) report evidence of information risk premium using the "probability of information-based trading" (PIN) measure derived from intraday trading data, but Duarte and Young (2009) argue that PIN is priced because of liquidity, not information. Francis, LaFond, Olsson, and Schipper (2005) and Core, Guay, and Verdi (2007) both use accruals quality as the proxy for information risk, but come to opposite conclusions on whether information risk is priced. Small samples biases may be one reason for these conflicting findings. I contribute to this literature by utilizing a much larger dataset which not only makes the results more generalizable, but also facilitates easier comparisons with classic empirical asset-pricing studies. I believe this is also the first paper to document the *time-series relation* between information availability and stock returns.

Finally, this paper is also related to the strand of literature that studies how media coverage affects asset prices. Chan (2003) and Vega (2006) investigate price movements following news events but their focus is on momentum anomalies, not expected returns. Both Tetlock (2007), and Tetlock (2008) study the content of media articles and find that media pessimism can predict lower stock prices in the future, both in aggregate and in individual stocks. Fang and Peress (2007) test the Merton (1987) model directly by using the number of news articles about a company as a proxy for "investor recognition". They find that in the cross-section, stocks with no media coverage earn higher returns than stocks with high media coverage.

2 Data and Methodology

The two main variables in my study are stock returns and trading volume, at both daily and monthly frequency, which I obtain from CRSP. Balance sheet information required to calculate book-to-market ratios, and earnings announcement dates are from the annual and quarterly files in COMPUSTAT. Merger announcement dates are obtained from SDC. Fama-French factors, the momentum factor, Pastor-Stambaugh liquidity series and Sadka liquidity series are available on WRDS.

My methodology involves two steps: first I construct the information proxy, RHO, by estimating the daily correlation between absolute returns and dollar volume for every stock in every month, second I run a regression of monthly stock returns on these estimates of RHO next to other firm characteristics as controls. To make sure that RHO captures *firm-specific* information, I filter out the market-wide movements in returns and volume and use the residuals for its estimation. Specifically, RHO is defined as:

$$r_{id} = \alpha_i^r + \beta_i^r RM_d + \epsilon_{id}^r \tag{1}$$

$$v_{id} = \alpha_i^v + \beta_i^v VM_d + \epsilon_{id}^v \tag{2}$$

$$\rho_{ABSE,VOLE}^{im} = \frac{Cov^{im}(|\epsilon_{id}^r|, \epsilon_{id}^v)}{\sqrt{var^{im}(\epsilon_{id}^r)}\sqrt{var^{im}(\epsilon_{id}^v)}} \tag{3}$$

where r_{id} is the return of stock i on day d, v_{id} is the dollar volume of stock i on day d, RM_d is the return on the CRSP value-weighted index on day d, VM_d is the mean dollar market volume on day d, and ϵ_{id}^r and ϵ_{id}^v are the residuals from the estimated model. RHO is $\rho_{ABSE,VOLE}^{im}$.

I use the following filters to construct my dataset:

- I drop the first month a stock appears on the CRSP tapes to minimize the effects of IPOs. The reason is that the information environment surrounding IPOs might not be representative of the market's workings in general. I keep the last month's return to avoid survivorship bias. I also adjust delisting returns as in Shumway (1997).

- To improve the accuracy of the estimates, I require at least 125 observations for yearly variables, and 15 for monthly variables.

- I restrict myself to only common stock (CRSP codes 10 and 11) on the NYSE. This is because volume has a different interpretation on NASDAQ and has generally been excluded in previous studies on volume.

- I exclude stocks whose end of month prices were less than \$5 and greater than \$1000.

- To make sure the results are not driven by the outliers, I drop the 1st and the 99th percentiles in my correlation estimates each month.

The resulting dataset has 3342 unique firms over 526 months and there is a total of 578,564 firm-month observations.

3 Results

3.1 RHO around Known Information Events

Because my results on stock returns depend on the validity of RHO as an information proxy, I start by investigating RHO around *known* information events. Undoubtedly, one of the most important information events for investors is the earnings announcement, and there is a large literature on its information content. Merger announcements also make the headlines in media and elicit a strong reaction from the market, which speaks to their information content. In Figure 1 and Table 1, I replicate some of the previous findings in Beaver (1968) and Morse (1981) on earnings announcements (albeit with a much larger dataset), and extend it to merger announcements. The graphs in Panel A and B of Figure 1 display a significant spike in both absolute returns and volume on the day of the earnings announcement and the merger announcement. The information proxy, RHO, also appears to be much higher in the month of the announcement. Table 1 reports the statistics used to generate these graphs. Average RHO in an earnings announcement month is 0.30; compared with the previous month's average of 0.27 and the subsequent month's 0.26, the differences are statistically significant with t-statistics of 45.78 and 54.35, respectively. On merger announcement months, the differences in RHO before and after are even larger in magnitude, and still statistically significant. The before-and-after differences in absolute returns and volume are presented in both Panels as benchmarks. The t-statistics for RHO highly resemble t-statistics for absolute returns and volume.

Figure 1 here

Table 1 here

The differences reported in Table 1 are likely to be conservative. There could be other information events in the months prior or subsequent to the earnings announcement. RHO being a monthly estimate, also attenuates the impact of a single day of information arrival. This downward bias though, would make it *less* likely to find significant results in the return regressions later on.

3.2 RHO and Returns: Event Study Approach

In this section, I frame my tests similar to an event study. This way, the economic significance of RHO is cast in units of return. I define an information event as RHO being above its 90th. percentile value for each individual firm. For comparison, I also include results that use absolute returns or volume as the proxy for information. In Table 2 Panel A, the difference in average returns one month before and after the information event (proxied by RHO) is about 0.7% which is statistically significant with a t-statistic of 11.30. Comparing two months before and two months after reveals a difference of about 0.5%. As we compare periods further out, the differences tend to decrease monotonically, yet still are statistically significant. Because the comparisons are *within* a firm, not *between* firms, it is unlikely that the differences are due to systematic risk.

Table 2 here

In Panels B and C, I run the same tests with absolute returns and volume separately. While these results also come out statistically significant, the signs differ for the two variables. If absolute return is used as a proxy for information, then returns in the months before information arrival seems to be lower than in the months after. If volume is used as a proxy for information, we get the exact opposite result. This indicates that on their own, these variables may be unreliable proxies of information.

Figure 2 here

Figure 2 uses RHO as the proxy for information (as every other test for the rest of the paper), and an information event is again defined as RHO being above its 90th percentile value for a given stock. The x-axis represents event time where zero is the month of the information event, and y-axis represents the cross-sectional averages of stock returns. Our concern is not with the spikes that appear on event months. We are interested in the returns before and after the event. In Panel A, we can visually note the pattern of returns increasing prior to the event month, then sharply dropping off and gradually rising again. This graph is the visual representation of the statistics presented in Table 2 Panel A. Both the statistics and the plot imply an increase in expected returns before information revelation and a decrease right after. A possible explanation of this phenomena is, if investors have a preference for stocks which they have recently been informed about (because they now pose less uncertainty), they will buy them up, increasing prices and depressing returns. Conversely, the stocks that have not revealed information in a long time will need to compensate investors with higher expected returns to induce them into buying them. The pattern is also consistent with the view that stocks in which trading is based more on private information should offer an "information risk" premium. Assuming that the top 10th percentiles of RHO represent some public news events, higher returns before information becomes public could be compensation for the uninformed investors to trade with the informed.

In Panels B, C, and D, I provide more detail on these return differences. In Panel B I drop the months in which earnings announcements were made. If the information in earnings leaked to the market before the announcement, this could be a reason for the rising pattern in returns. I observe the same pattern without the earnings announcements, meaning that the differences are not driven strictly by scheduled new events. In Panel C, a "bad" news event is defined by both a *negative* return and a RHO estimate above its 90th percentile value. Similarly, "good" news is defined by a *positive* return and a RHO falling above its 90th percentile mark. In both cases, the returns are always lower after information arrives, be it good or bad. The differences are still statistically significant, but are not reported here to save space. This result allows me to rule out a few more alternative explanations. If the return pattern based on RHO reflected the post-earnings-announcement-drift, the returns would not be lower after positive news. More generally, lower returns after a month of "good" news, does not support the common behavioral argument that investors are slow to react to news.

3.3 RHO and Returns: Fixed-effects Regression

Having demonstrated the relation between information and returns in event time, I now turn to calender time. The event study methodology of the previous section assumes firm characteristics to be constant over time and no dependence among firms at a point in time. I can now relax these assumptions with a two-way fixed-effects regression. The regression approach also allows me to make full use the variation in RHO, as opposed to limiting myself to extreme values. The model is:

$$r_{it} = \sum_{k=1}^{K} b_k X_{ki,t-1} + \alpha_i + \gamma_t + \epsilon_{it} \tag{4}$$

where r_{it} is the return of stock i in month t, $X_{ki,t-1}$ is characteristic k of stock i in the previous month or year (depending on whether the characteristic is updated on a monthly or yearly basis), b_k is the estimate of the coefficient of characteristic k, α_i is the firm fixed effect and γ_t is the time fixed effect. ϵ_{it} are the residuals. Standard errors are clustered at the firm level.

Because it is unrealistic to assume that the firm effect is "fixed" for a span of forty years, I divide up the dataset into four decades and fit the model separately. The four panels in Table 3 reports the estimates in these time periods. All regressors are lagged so that they are in the investors' information set. The coefficient on RHO therefore represents the effect of information revelation in a given month on *next* month's return. I find that the coefficient is significant in all periods and robust to the inclusion of various controls. In particular, the Amihud (2002) illiquidity measure is derived from the same exact variables as RHO - absolute returns and dollar volume - and therefore one might expect them to be closely related. Yet, its inclusion in the regression seems to have no effect on the coefficient of RHO. In a similar fashion, I find the inclusion of past returns to have no effect on the coefficient of RHO. The same is true when dividend yield and idiosyncratic risk are added to the regression. RHO appears to be orthogonal to all these factors that have been shown to affect stock returns. The negative coefficient indicates that returns following informationally rich months are lower than average. The relationship is strongest in the 1975-1985 period and weakest in the most recent period. These differences among time periods could just be a feature of the data or they could be related to some structural changes in the information environment.

Table 3 here

3.4 Portfolios sorted on RHO

While regressions in the previous section established the statistical significance of RHO, they do not tell us much about the economic significance of this empirical regularity. In this section I use a common portfolio benchmarking approach to illustrate the significance of information in units of return. I first sort stocks on a monthly basis by RHO, the information proxy, and form decile portfolios. Then I regress the time-series returns of these portfolios onto the Fama-French three-factors, the momentum factor, and the liquidity factor. The intercept from this regression, alpha, is the risk-adjusted, "abnormal" return. The regression model is:

$$R_{pm} = \alpha_p + \beta_p^M MKT_m + \beta_p^S SMB_m + \beta_p^H HML_m + \beta_p^U UMD_m + \beta_p^L LIQ^v + \epsilon_{pm} \quad (5)$$

where R_{pm} is the excess return of portfolio p in month m, MKT, SMB, HML are the three factors Fama and French (1996), UMD is the momentum factor, and LIQ^v is the value weighted traded factor of Pastor and Stambaugh (2003). α_p is the abnormal or risk-adjusted return of portfolio p.

The results are presented in Table 4. The last column, 1-10, refers to the long/short portfolio (low RHO stocks minus high RHO stocks). The null hypothesis is that alpha should be zero, because it is zero-net-investment by construction and risk is accounted for by the systematic factors. All the alphas in the equal-weighted portfolios are statistically significant, allowing us to reject the null hypothesis. The equal-weighted portfolios are pure bets on RHO - they do not invest more in larger stocks - and thus the information effect is observed more precisely here than in the value-weighted versions. An equal-weighted portfolio long in low RHO stocks and short in high RHO stocks generates CAPM or Fama-French three-factor alphas around 3%, annualized. Adding momentum and liquidity factors to the mix does not reduce the alphas at all; in fact, alpha increases to about 4% per year.

Table 4 here

The value-weighted portfolios do not exhibit significant alphas. Since value-weighting overweights large stocks, the loss of significance implies that size and information may be related. This also makes economic sense. For large, more visible firms, information may be more public and the premium for "information risk" may be smaller. It could also be that information is more costly to produce for small firms, and therefore the rewards are higher. In Table 5, I do a double-sort; first on size, then on RHO. Rows indicate the size quintiles and columns indicate the RHO quintiles. For brevity, I only report five-factor alphas (results are qualitatively similar with other alphas). With the double-sorted portfolios, we can see that there is indeed a relation between information and size. Both the equal-weighted and the value-weighted spread portfolios in the first two size quintiles, the smallest stocks, have significant alphas. The magnitudes are also larger, close to 7% annualized. The premium for information appears to be strongest among smaller stocks consistent with our expectations.

Table 5 here

3.5 Robustness

3.5.1 Fama-MacBeth Regressions

Most asset-pricing tests utilize the Fama and MacBeth (1973) method due to its intuitive nature and ability to handle time-varying risk characteristics. To make my results more easily comparable with previous studies I also run a Fama-MacBeth regression in this section. With this method I can estimate the model for the full time period, which was not be appropriate with the fixed-effects model. Specifically, the regression I run is:

$$r_{it} = a_t + \sum_{k=1}^{K} b_{kt} X_{ki,t-1} + \epsilon_{it} \tag{6}$$

where r_{it} is the return of stock i in month t, $X_{ki,t-1}$ is characteristic k of stock i in the previous month or year (depending on whether the characteristic is updated on a monthly or yearly basis), b_{kt} is the estimate of the coefficient of characteristic k in month t, and ϵ_{it} are the residuals. This regression is run every month from 1964 to 2007 and the time-average of the coefficients are reported.

Table 6 here

Table 6 presents the coefficient estimates from this regression. In column 1, the coefficient of RHO comes in highly significant with a t-statistic of -5.599. The coefficients of the other variables agree with previous studies (Fama and French (1992)[3]) in that size

[3]The fact that beta is significant in some of the specifications, as opposed to "flat", may come as a surprise. It is likely to be the result of higher variation in the first stage beta estimates. Unlike Fama

is negatively related (t = -6.773), and book-to-market is positively related (t = 3.037) to returns. Next, I add in the constituents of RHO, absolute return and dollar volume, separately to illustrate that it is not the individual movements in these two variables that drive the returns. Furthermore, even when RHO is taken out of the regression, absolute return and volume show no predictive power for returns over the next month.

Columns 5 and 6 add the controls for liquidity. While liquidity variables are significant on their own, they have no effect on RHO. If anything, the significance of RHO slightly increases with their inclusion. Moving onto columns 7 and 8, I find consistent results with the previous studies that have shown past returns to have predictive power for future returns. The coefficient on RHO is even more significant in these specifications. These results imply that the information effect is quite distinct from momentum or liquidity. Controls for dividend yield and idiosyncratic risk seem to have no effect on RHO either, and taking RHO out of the regression leaves other coefficients practically the same. These results suggest that the information effect must be orthogonal to all these other characteristics that have been used previously to characterize the cross-section of returns.

3.5.2 Systematic Liquidity

Even though the both the fixed-effects and the Fama-MacBeth regressions controlled for liquidity, those liquidity variables were designed to relate the *level* of liquidity of a stock to its return. Studies like Chordia, Roll, and Subrahmanyam (2000) show that there is commonality in liquidity and variations in market-wide liquidity may be priced. Following this line of thought, Pastor and Stambaugh (2003) construct a market-wide liquidity measure from firm level daily data, and go on to show that liquidity betas - the sensitivity of a stock's return to aggregate liquidity - are priced. Another similar approach

and French (1992) who use portfolio betas, I estimate beta at the firm level using daily data and update it every month.

is by Sadka (2006). He decomposes aggregate liquidity into two components, temporary fixed and permanent variable, which capture market making costs and informational trading, respectively. In this section, I control for these systematic liquidity factors, or more specifically, the stocks' return sensitivity to market-wide liquidity shocks. In Table 7, I show results similar to the regressions in the previous section using the Fama-MacBeth method, but this time with systematic liquidity betas. BETALIQ is the systematic liquidity measure of Pastor and Stambaugh in Panel A, or Sadka in Panels B and C. RHO keeps its significance in the presence of the liquidity betas and liquidity betas are not significant on their own[4]. The reduction in the significance of RHO in Panels B and C is mostly due to the shorter time period (Sadka liquidity series are only available after 1988). Finally, using the stock's size and book-to-market factor beta, as opposed to using size and book-to-market ratio directly, do not affect the results in any way. In conclusion, RHO does not appear to be related to systematic liquidity.

Table 7 here

4 Conclusion

In this paper I investigate the effects of information revelation on stock returns. Several theoretical models postulate information risk to be priced, or more generally, information revelation to have pricing implications since information reduces uncertainty. I contribute to the empirical literature in this area by developing a new information proxy and demonstrating its relation to expected returns in the over time. I find that returns following high information months tend to be lower, returns following low information months tend to be higher. Moreover, this information effect is not captured by, or itself

[4]The lack of significance of the liquidity betas do not refute the results of these previous studies mentioned. Both Pastor and Stambaugh (2003) and Sadka (2006) have used portfolios to reduce the noise in their estimation and note that at the individual stock level, liquidity betas may not be very useful in explaining the cross-section of returns.

captures, other factors previously shown to be related to returns (e.g., size, book-to-market, beta). Liquidity and momentum also appear to be orthogonal to the information proxy variable.

The results are both statistically and economically significant. A net-zero-investment portfolio constructed to exploit the difference between informationally rich and poor stocks, generates risk-adjusted returns of approximately 3-4%, depending on the factors used to adjust for risk. I find that alphas are even higher among smaller stocks (up to 7% per year), where information production would be more costly. These numbers, in all likelihood, underestimate the true information premium. The portfolios use only stocks from the NYSE, known to have one of the most strict listing requirements in the world, and hence is more likely to be informationally efficient.

These "abnormal" returns are consistent with rational models that predict a negative relation between information and expected returns; they need not imply market inefficiency. As Grossman and Stiglitz (1980) points out, this premium might be necessary to compensate traders for their information production efforts. The same results could also be explained by behavioral arguments. Further research could try to answer the question of whether these abnormal returns are borne out of time-varying expected returns or the over/under reactions of traders.

A Appendix

A.1 Variable definitions

BETA, RMSEDAY: These two variables are controls for systematic and unsystematic risk in the CAPM framework. I estimate the beta of each stock by regressing its daily return on the CRSP value-weighted index on a yearly basis. The regression I run is:

$$r_{idy} = \alpha_{iy} + \beta_{iy} RM_{dy} + \epsilon_{idy} \tag{7}$$

where r_{idy} is the return of stock i on day d in year y, RM_{dy} is the return on the CRSP value-weighted index on day d in year y, and β_{iy} is the estimate of BETA, the systematic risk, for stock i in year y. RMSEDAY is the estimate of the $\sqrt{var(\epsilon_{idy})}$from this regression and is the measure of idiosyncratic risk.

LNSIZE: This is the log of market capitalization of a stock at the end of the year.

LNBTM: This is the log of the book-to-market ratio. Book values are calculated similar to Fama and French (1996): book value is the annual COMPUSTAT item stockholders' equity, plus deferred taxes and investment tax credit, minus the book value of preferred stock. I use redemption, liquidation, or par value (in that order) for the book value of preferred stock. Book values with negative or zero values are omitted and they lagged for six months after the fiscal year end date which is generally considered enough time for financial statements to be released. Book-to-market ratios are then calculated as book value divided by the market value of equity at the end of the year.

ABSRET: This is the absolute value of the monthly market-adjusted return. Market-adjustment entails regressing monthly returns on the market index for the previous 60-month period and using the beta estimates to calculate the residuals each month.

VOLD: "Firm-specific" dollar volume. Dollar volume for each firm is regressed on the mean market dollar volume for the previous 60-month period, and betas from that regression is used to calculate the monthly residuals.

RHO: The correlation between absolute returns and volume. Absolute returns and volume are market-adjusted before their correlation is estimated. The following regressions use a 250 trading day window and are rolled over every month.

$$r_{id} = \alpha_i^r + \beta_i^r RM_d + \epsilon_{id}^r \tag{8}$$

$$v_{id} = \alpha_i^v + \beta_i^v VM_d + \epsilon_{id}^v \tag{9}$$

$$\rho_{im} = \frac{Cov^{im}(|\epsilon_{id}^r|, \epsilon_{id}^v)}{\sqrt{var^{im}(\epsilon_{id}^r)}\sqrt{var^{im}(\epsilon_{id}^v)}} \tag{10}$$

where r_{id} is the return of stock i on day d, v_{id} is the dollar volume of stock i on day d, RM_d is the return on the CRSP value-weighted index on day d, and VM_d is the mean dollar market volume on day d. ϵ_{id}^r and ϵ_{id}^v are the actual residuals from the estimated model. RHO is ρ_{im}, the estimated correlation coefficient between the absolute value of the residual return and the residual dollar volume for stock i in month m

ILLIQ: This is Amihud's liquidity measure. Amihud (2002) shows that stocks that score higher on this measure earn higher returns and interprets this as the illiquidity premium. It is defined as the yearly average ratio of absolute returns to dollar volume. The exact formula is:

$$ILLIQ_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{D_{iy}} \frac{|R_{iyd}|}{VOLD_{iyd}} \tag{11}$$

where R_{iyd} and $VOLD_{iyd}$ are, respectively, the return and dollar volume for stock i on day d in year y. D_{iy} is the number of observation days in month in year y.

TRNOVDY: Daily number of shares traded is divided by the number of shares outstanding, then averaged over a year. This is similar in construction to the turnover measure of Datar, Naik, and Radcliffe (1998) who show that stocks with lower turnover exhibit higher returns.

RLAG13_8, RLAG7_2: Past returns have been shown to affect the cross section of returns by Brennan, Chordia, and Subrahmanyam (1998) and Jegadeesh and Titman (1993). These variables are the geometric averages of the cumulative monthly returns in the last 6 months, and second to last 6 months, respectively. They are lagged for one extra month to avoid problems with bid-ask bounce or thin trading.

DIVYLD: The sum of all periodic dividends (quarterly, annual, etc...) paid in a year divided by the year-end price. Special or extra dividends are excluded. If a stock does not pay dividends it is still kept in the sample with a dividend yield of zero.

BETALIQ, BETAMKT, BETASIZE, BETABTM, RMSEMON: BETALIQ is either the Pastor-Stambaugh liquidity beta as described in Pastor and Stambaugh (2003), or one of the Sadka liquidity betas (Transitory Fixed and Permanent Variable) described in Sadka (2006). The other betas are the factor sensitivities to the Fama and French (1996) factors. They are estimated in one multivariate time-series regression:

$$r_{im} = \beta_i^0 + \beta_i^L L_m + \beta_i^M MKT_m + \beta_i^S SMB_m + \beta_i^H HML_m + \epsilon_{im} \tag{12}$$

where r_{im} is the return of stock i on month m, L_m is the market-wide liquidity measure of Pastor and Stambaugh, or Sadka. β_i^L is the liquidity beta (BETALIQ) of stock i, and MKT, SMB, HML are the Fama-French factors. RMSEMON is the estimate of the $\sqrt{var(\epsilon_{im})}$from this regression and serves as an alternative measure of idiosyncratic risk. In addition to the filters described in the previous section, I require a stock to have at least five years of consecutive return data to estimate its liquidity beta. This 60 month regression is rolled over every month.

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TABLE 1: PRICE CHANGES AND TRADING VOLUME AROUND KNOWN INFORMATION EVENTS

RHO is the monthly estimate of the daily correlation between the absolute returns and dollar trading volume of a stock. ABSRET and VOLD are the residuals calculated from the estimated parameters of a pre-sample 60 month regression of absolute retuns and dollar volume on their market counterparts. The residuals are then divided by their corresponding estimated standard deviations to achieve cross-firm comparability. Tables report the cross-sectional means of these variables calculated in the before and after months of the information event. Month of the event is taken as the base month (t=0), against which mean comparison tests are performed and t-statistics reported. In Panel A the information event is the earnings announcement, in Panel B, the merger announcement for a target.

Panel A: Earnings Announcements

Time to event (months)	RHO_t	Difference (RHO_t-RHO_0)	t-stat	$ABSRET_t$	Difference ($ABSRET_t$-$ABSRET_0$)	t-stat	$VOLD_t$	Difference ($VOLD_t$-$VOLD_0$)	t-stat
-2	0.268	-0.036	45.82	0.768	-0.102	37.41	0.130	-0.115	14.97
-1	0.268	-0.036	45.78	0.785	-0.085	30.80	0.065	-0.180	23.56
0	0.303	0.000	0.00	0.870	0.000	0.00	0.245	0.000	0.00
1	0.261	-0.042	54.35	0.761	-0.110	40.14	0.131	-0.113	14.36
2	0.271	-0.032	41.37	0.794	-0.077	27.36	0.123	-0.122	15.22

Panel B: Merger Announcements

Time to event (months)	RHO_t	Difference (RHO_t-RHO_0)	t-stat	$ABSRET_t$	Difference ($ABSRET_t$-$ABSRET_0$)	t-stat	$VOLD_t$	Difference ($VOLD_t$-$VOLD_0$)	t-stat
-2	0.295	-0.088	19.78	0.821	-0.402	18.16	0.232	-1.934	19.94
-1	0.305	-0.078	17.24	0.901	-0.322	13.88	0.449	-1.717	16.72
0	0.383	0.000	0.00	1.223	0.000	0.00	2.166	0.000	0.00
1	0.268	-0.115	25.47	0.763	-0.460	21.12	0.542	-1.624	16.17
2	0.274	-0.109	23.78	0.793	-0.430	19.50	0.128	-2.038	21.00

TABLE 2: AVERAGE RETURNS OF STOCKS BEFORE AND AFTER INFORMATION REVELATION

A month in which information has been revealed (t=0) is defined as the information proxy variable being above its 90th percentile value for the life of a stock. Returns for that stock in the previous and subsequent six months, along with their respective differences are then averaged cross-sectionally in event time. The t-statistic tests whether the cross-sectional means of these differences are equal to zero. In Panel A the information proxy is RHO, the correlation between (market-adjusted) absolute returns and dollar volume. In Panel B the information proxy is ABSRET, the monthly absolute return, and in Panel C the information proxy is VOLD, the monthly dollar volume.

Panel A: Information Proxy RHO

Time to event (months)	Return (pre-event)	Return (post-event)	Difference	t-stat
1	0.0173	0.0097	0.0072	11.30
2	0.0153	0.0103	0.0047	7.63
3	0.0158	0.0113	0.0044	6.64
4	0.0139	0.0108	0.0020	3.14
5	0.0131	0.0111	0.0016	2.44
6	0.0139	0.0130	0.0017	2.67

Panel B: Information Proxy ABSRET

Time to event (months)	Return (pre-event)	Return (post-event)	Difference	t-stat
1	0.0005	0.0073	-0.0058	-9.15
2	0.0024	0.0079	-0.0054	-8.58
3	0.0041	0.0102	-0.0049	-7.70
4	0.0074	0.0106	-0.0027	-4.24
5	0.0076	0.0111	-0.0042	-6.79
6	0.0093	0.0105	-0.0036	-5.69

Panel C: Information Proxy VOLD

Time to event (months)	Return (pre-event)	Return (post-event)	Difference	t-stat
1	0.0245	-0.0088	0.0227	25.37
2	0.0205	-0.0070	0.0236	29.90
3	0.0199	-0.0050	0.0220	27.22
4	0.0168	-0.0018	0.0191	24.96
5	0.0190	-0.0018	0.0185	24.51
6	0.0171	-0.0002	0.0172	21.62

TABLE 3: FIXED-EFFECTS REGRESSIONS OF STOCK RETURNS ON RHO AND OTHER STOCK CHARACTERISTICS

In addition to the variables reported in this table all regressions include month dummies. Standard errors are clustered at the firm level. BETA is CAPM's measure of systematic risk, estimated at a yearly frequency using daily returns. LNSIZE is the log of market value of equity on the last day of the year prior to the year returns are measured. LNBTM is the log of book-to-market ratio, calculated as the ratio of the book value of equity to the market value of equity on the last day of the year prior to the year returns are measured. RHO is the proxy for information revelation and is defined as the monthly estimate of the daily correlation between (market-adjusted) absolute returns and dollar volume. ABSRET is the firm-specific monthly absolute return and similarly, VOLD is the firm-specific monthly dollar volume. ILLIQ is Amihud's liquidity measure, which is defined as the yearly average ratio of daily absolute returns to dollar volume. TRNOVDY is the yearly average of daily turnover. RLAG7-2 and RLAG13-8 are geometric averages of lagged returns in the previous 6 months and the 6 months before that, respectively. DIVYLD is the yearly sum of ordinary cash dividends divided by the price (both adjusted for splits) at the end of the year. RMSEDAY is the estimated volatility of the residuals from the BETA regression. BETA, ILLIQ, TRNOVDY, DIVYLD, and RMSEDAY are lagged for one year. RHO, ABSRET and VOLD are lagged for one month.

	Panel A: 1964-1974						Panel B: 1975-1985					
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
BETA	-0.187	-0.308	-0.014	-0.011	-0.040	-0.111	-0.412	-0.265	-0.267	-0.289	-0.243	-0.083
	(-2.04)**	(-2.34)**	(-0.16)	(-0.13)	(-0.41)	(-0.74)	(-4.27)***	(-2.43)**	(-2.76)***	(-2.87)***	(-2.26)**	(-0.69)
LNSIZE	-3.182	-3.739	-2.914	-2.892	-2.917	-3.893	-2.590	-2.519	-2.478	-2.622	-2.655	-2.746
	(-25.01)***	(-18.17)***	(-22.52)***	(-21.64)***	(-20.49)***	(-16.92)***	(-20.06)***	(-16.41)***	(-18.77)***	(-18.97)***	(-19.36)***	(-16.79)***
LNBTM	-0.387	-0.554	-0.362	-0.256	-0.223	-0.541	-0.014	-0.177	-0.065	-0.107	-0.014	-0.095
	(-3.23)***	(-2.52)**	(-3.01)***	(-2.10)**	(-1.78)*	(-2.35)**	(-0.10)	(-1.06)	(-0.46)	(-0.71)	(-0.09)	(-0.50)
RHO	-0.557	-0.427	-0.559	-0.527	-0.526	-0.419	-0.887	-0.568	-0.876	-0.867	-0.864	-0.551
	(-5.51)***	(-3.02)***	(-5.53)***	(-5.23)***	(-5.22)***	(-2.97)***	(-9.30)***	(-5.88)***	(-9.18)***	(-9.11)***	(-9.08)***	(-5.78)***
ABSRET		0.042						0.041				
		(0.05)						(0.07)				
VOLD		0.002				0.006		-0.002				-0.001
		(0.43)				(1.31)		(-2.15)**				(-1.93)*
ILLIQ			0.376	0.477	0.470	0.550			0.093	0.091	0.098	-0.215
			(4.35)***	(4.46)***	(4.52)***	(4.71)***			(3.67)***	(3.31)***	(3.53)***	(-3.11)***
TRNOVDY			-0.036	-0.035	-0.035	-0.028			-0.151	-0.170	-0.147	-0.109
			(-1.05)	(-1.01)	(-1.00)	(-0.47)			(-3.95)***	(-4.31)***	(-3.57)***	(-2.11)**
RLAG13_8				0.051	0.050	0.037				0.046	0.044	0.079
				(5.28)***	(5.18)***	(2.92)***				(4.55)***	(4.36)***	(7.47)***
RLAG7_2				-0.034	-0.035	-0.092				-0.098	-0.099	-0.095
				(-3.43)***	(-3.53)***	(-7.43)***				(-10.52)***	(-10.59)***	(-10.01)***
DIVYLD					-0.055	-0.073					-0.044	0.016
					(-1.64)	(-1.58)					(-1.89)*	(0.59)
RMSEDAY					0.030	-0.319					-0.159	-0.364
					(0.26)	(-2.20)**					(-1.77)*	(-3.62)***
CONSTANT	14.996	15.461	13.415	13.169	13.438	16.645	37.005	34.402	36.359	36.828	37.545	36.147
	(19.26)***	(14.15)***	(16.73)***	(16.02)***	(14.45)***	(11.90)***	(45.41)***	(37.55)***	(44.14)***	(43.62)***	(42.85)***	(36.54)***
Observations	117642	63717	117642	117494	117494	64015	147797	113816	147797	147227	147227	113935
Number of firms	1334	1039	1334	1332	1332	1041	1594	1296	1594	1584	1584	1297
R-squared	0.3028	0.3296	0.3036	0.3043	0.3043	0.3311	0.2720	0.2736	0.2723	0.2740	0.2741	0.2753

	Panel C: 1986-1996						Panel D: 1997-2007					
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
BETA	0.351	0.198	0.457	0.401	0.291	0.245	0.457	0.293	0.447	0.431	0.283	0.289
	(3.74)***	(1.87)*	(4.81)***	(3.88)***	(2.69)***	(2.07)**	(4.41)***	(2.40)**	(4.28)***	(3.80)***	(2.48)**	(2.24)**
LNSIZE	-2.422	-1.944	-2.389	-2.561	-2.403	-2.048	-2.915	-2.447	-2.860	-2.975	-2.887	-2.581
	(-22.50)***	(-17.09)***	(-22.18)***	(-21.79)***	(-19.44)***	(-16.07)***	(-27.72)***	(-19.63)***	(-26.66)***	(-25.14)***	(-23.24)***	(-18.20)***
LNBTM	0.384	0.218	0.372	0.336	0.326	0.178	0.351	0.135	0.346	0.203	0.238	0.062
	(3.80)***	(1.95)*	(3.66)***	(3.05)***	(2.89)***	(1.46)	(3.73)***	(1.23)	(3.72)***	(2.04)**	(2.32)**	(0.52)
RHO	-0.306	-0.261	-0.299	-0.308	-0.320	-0.281	-0.223	-0.059	-0.233	-0.272	-0.271	-0.130
	(-3.46)***	(-2.84)***	(-3.37)***	(-3.46)***	(-3.60)***	(-3.06)***	(-2.31)**	(-0.56)	(-2.41)**	(-2.81)***	(-2.80)***	(-1.26)
ABSRET		-0.459						-1.020				
		(-0.71)						(-1.60)				
VOLD		-0.001				-0.001		0.000				0.000
		(-4.19)***				(-3.04)***		(-3.15)***				(-1.55)
ILLIQ			0.006	0.005	-0.004	0.247			1.076	1.337	1.268	1.513
			(3.03)***	(3.03)***	(-1.61)	(0.71)			(3.70)***	(4.42)***	(4.16)***	(3.34)***
TRNOVDY			-0.111	-0.127	-0.166	-0.086			0.013	0.006	-0.011	0.028
			(-4.29)***	(-4.43)***	(-5.48)***	(-2.70)***			(0.89)	(0.38)	(-0.62)	(1.67)*
RLAG13_8				0.041	0.041	0.067				-0.021	-0.023	-0.013
				(4.35)***	(4.25)***	(6.28)***				(-2.43)**	(-2.70)***	(-1.22)
RLAG7_2				-0.133	-0.134	-0.130				-0.092	-0.094	-0.085
				(-14.56)***	(-14.65)***	(-12.20)***				(-9.19)***	(-9.35)***	(-6.51)***
DIVYLD					0.027	0.049					-0.114	-0.070
					(1.02)	(1.75)*					(-2.34)**	(-1.46)
RMSEDAY					0.343	-0.049					0.302	-0.174
					(3.91)***	(-0.46)					(4.08)***	(-1.93)*
CONSTANT	16.227	13.893	16.194	17.434	15.993	14.573	23.511	20.894	23.023	23.974	23.189	22.169
	(23.63)***	(18.55)***	(23.66)***	(23.18)***	(19.08)***	(16.06)***	(31.24)***	(22.51)***	(30.03)***	(28.63)***	(24.59)***	(19.71)***
Observations	146184	108434	146184	143417	143417	108589	166941	118756	166941	164705	164705	119071
Number of firms	1906	1326	1906	1867	1867	1331	2241	1642	2241	2216	2216	1647
R-squared	0.2105	0.2439	0.2107	0.2126	0.2128	0.2462	0.1624	0.1708	0.1626	0.1637	0.1640	0.1716

TABLE 4: ALPHAS OF PORTFOLIOS SORTED ON THE INFORMATION PROXY RHO

This table reports the raw and the risk-adjusted monthly returns (alphas) of decile portfolios sorted on the information proxy, RHO. Decile 10 corresponds to the highest values of RHO, indicating an informationally rich month, decile 1 just the opposite. The last column, 1-10, refers to the portfolio that is long in low RHO stocks and short in high RHO stocks. Portfolios are rebalanced every month based on the percentiles of RHO. The time period is from 1966 to 2004. Risk adjustment includes the market, size, book-to-market, momentum, and liquidity factors. White's heteroskedasticity-consistent standard errors are used to calculate the t-statistics.

	Decile Portfolio										
	1	2	3	4	5	6	7	8	9	10	1-10
					Panel A: Equal-weighted						
Raw returns	1.080	0.994	1.022	1.011	1.059	1.081	1.021	0.908	0.939	0.880	0.199
	(4.558)***	(4.198)***	(4.240)***	(4.239)***	(4.409)***	(4.406)***	(4.138)***	(3.631)***	(3.738)***	(3.437)***	(2.494)**
CAPM alpha	0.645	0.551	0.571	0.567	0.605	0.622	0.557	0.442	0.468	0.406	0.239
	(5.778)***	(5.299)***	(5.442)***	(5.326)***	(6.001)***	(5.826)***	(5.227)***	(3.953)***	(4.236)***	(3.461)***	(2.999)***
Fama-French alpha	0.329	0.237	0.258	0.249	0.301	0.306	0.255	0.109	0.148	0.060	0.269
	(3.728)***	(3.105)***	(3.201)***	(3.088)***	(4.098)***	(3.865)***	(3.163)***	(1.377)	(1.929)*	(0.749)	(3.475)***
Four-factor alpha (Momentum)	0.478	0.341	0.348	0.356	0.384	0.417	0.344	0.174	0.193	0.135	0.343
	(5.746)***	(4.577)***	(4.515)***	(4.554)***	(5.227)***	(5.466)***	(4.299)***	(2.172)**	(2.443)**	(1.697)*	(4.363)***
Five-factor alpha (PS Liquidity)	0.514	0.375	0.387	0.395	0.419	0.453	0.383	0.220	0.233	0.184	0.330
	(6.393)***	(5.210)***	(5.297)***	(5.199)***	(6.088)***	(6.268)***	(5.135)***	(2.970)***	(3.221)***	(2.546)**	(4.210)***
					Panel B: Value-weighted						
Raw returns	0.571	0.582	0.479	0.557	0.540	0.477	0.450	0.419	0.480	0.389	0.181
	(2.702)***	(2.683)***	(2.279)**	(2.673)***	(2.526)**	(2.213)**	(2.097)**	(1.917)*	(2.193)**	(1.732)*	(1.386)
CAPM alpha	0.168	0.171	0.080	0.161	0.126	0.065	0.040	0.003	0.057	-0.035	0.203
	(1.939)*	(1.963)*	(0.940)	(1.939)*	(1.619)	(0.763)	(0.475)	(0.0334)	(0.695)	(-0.370)	(1.522)
Fama-French alpha	0.141	0.089	0.005	0.115	0.070	0.037	0.017	-0.093	-0.003	-0.101	0.242
	(1.777)*	(1.069)	(0.0652)	(1.510)	(0.990)	(0.457)	(0.213)	(-1.109)	(-0.0380)	(-1.013)	(1.782)*
Four-factor alpha (Momentum)	0.172	0.086	0.016	0.144	0.069	0.063	-0.017	-0.051	-0.016	-0.046	0.218
	(2.050)**	(0.973)	(0.205)	(1.818)*	(0.950)	(0.737)	(-0.207)	(-0.561)	(-0.194)	(-0.454)	(1.549)
Five-factor alpha (PS Liquidity)	0.189	0.100	0.032	0.159	0.077	0.078	0.007	-0.029	0.012	-0.024	0.213
	(2.197)**	(1.133)	(0.408)	(1.975)**	(1.053)	(0.915)	(0.0801)	(-0.322)	(0.148)	(-0.244)	(1.483)

TABLE 5: FIVE-FACTOR ALPHAS OF PORTFOLIOS SORTED ON SIZE AND RHO

Five factors are: MKT, SMB, HML, UMD, LIQ, which represent risks associated with market, size, book-to-market, momentum, and liquidity variables, respectively. Stocks are sorted into quintiles first on their market capitalization, then on RHO, resulting in 25 double-sorted portfolios. Quintile 1 refers to lower values of market capitalization and RHO, quintile 5 the opposite. 1-5 refers to the portfolio that is long in low RHO stocks and short in high RHO stocks. Portfolios are rebalanced every month based on the percentiles of market cap and RHO. The time period is from 1966 to 2004. White's heteroskedasticity-consistent standard errors are used to calculate the t-statistics.

	Rho Quintile					
Size Quintile	1	2	3	4	5	1-5
	Panel A: Equal-weighted					
1	1.351	1.205	1.071	1.066	0.796	0.555
	(12.00)***	(10.34)***	(9.704)***	(8.783)***	(6.961)***	(4.480)***
2	0.455	0.306	0.301	0.262	0.059	0.396
	(4.466)***	(2.946)***	(2.921)***	(2.782)***	(0.593)	(3.443)***
3	0.295	0.321	0.352	0.182	0.137	0.158
	(3.039)***	(3.485)***	(3.550)***	(1.802)*	(1.339)	(1.494)
4	0.226	0.143	0.178	0.086	-0.069	0.295
	(2.453)**	(1.613)	(2.024)**	(0.974)	(-0.801)	(2.778)***
5	0.099	0.053	0.062	0.040	-0.091	0.190
	(1.308)	(0.770)	(0.939)	(0.557)	(-1.260)	(1.984)**
	Panel B: Value-weighted					
1	1.178	0.962	0.843	0.804	0.598	0.580
	(10.06)***	(7.993)***	(7.406)***	(6.876)***	(5.179)***	(4.308)***
2	0.426	0.317	0.271	0.237	0.038	0.388
	(4.126)***	(3.109)***	(2.556)**	(2.518)**	(0.376)	(3.241)***
3	0.262	0.300	0.339	0.154	0.117	0.146
	(2.657)***	(3.190)***	(3.380)***	(1.486)	(1.120)	(1.358)
4	0.194	0.123	0.173	0.102	-0.036	0.230
	(2.192)**	(1.451)	(1.991)**	(1.179)	(-0.419)	(2.158)**
5	0.106	0.077	-0.009	-0.048	0.023	0.083
	(1.357)	(1.148)	(-0.131)	(-0.646)	(0.321)	(0.744)

TABLE 6: FAMA-MACBETH REGRESSIONS OF STOCK RETURNS ON RHO AND OTHER STOCK CHARACTERISTICS

This table reports the time-series averages of the slopes obtained from individual cross-sectional regressions ran every month from 1964 to 2007. T-statistic is the average slope divided by its time-series standard error. BETA is CAPM's measure of systematic risk, estimated at a yearly frequency using daily returns. LNSIZE is the log of market value of equity on the last day of the year prior to the year returns are measured. LNBTM is the log of book-to-market ratio, calculated as the ratio of the book value of equity to the market value of equity on the last day of the year prior to the year returns are measured. RHO is the proxy for information revelation and is defined as the monthly estimate of the daily correlation between (market-adjusted) absolute returns and dollar volume. ABSRET is the firm-specific monthly absolute return and similarly, VOLD is the firm-specific monthly dollar volume. ILLIQ is Amihud's liquidity measure, which is defined as the yearly average ratio of daily absolute returns to dollar volume. TRNOVDY is the yearly average of daily turnover. RLAG7-2 and RLAG13-8 are geometric averages of lagged returns in the previous 6 months and the 6 months before that, respectively. RLAG1 is simply the previous month's return. DIVYLD is the yearly sum of ordinary cash dividends divided by the price (both adjusted for splits) at the end of the year. RMSEDAY is the estimated volatility of the residuals from the BETA regression. BETA, ILLIQ, TRNOVDY, DIVYLD, and RMSEDAY are lagged for one year. RHO, ABSRET and VOLD are lagged for one month.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BETA	0.241	0.090	0.079	0.080	0.312	0.361	0.371	0.341	0.250	0.062	0.075	0.079
	(1.547)	(0.536)	(0.469)	(0.481)	(1.986)**	(2.516)**	(2.634)***	(2.574)**	(2.061)**	(0.525)	(0.584)	(0.612)
LNSIZE	-0.277	-0.141	-0.139	-0.141	-0.158	-0.164	-0.166	-0.161	-0.146	-0.079	-0.099	-0.099
	(-6.773)***	(-3.603)***	(-3.532)***	(-3.615)***	(-3.920)***	(-4.172)***	(-4.348)***	(-4.348)***	(-4.221)***	(-2.439)**	(-3.012)***	(-3.032)***
LNBTM	0.182	0.093	0.096	0.096	0.190	0.190	0.225	0.240	0.306	0.296	0.191	0.191
	(3.037)***	(1.404)	(1.474)	(1.483)	(3.162)***	(3.204)***	(3.967)***	(4.472)***	(6.090)***	(5.967)***	(3.447)***	(3.435)***
RHO	-0.320	-0.209	-0.238		-0.346	-0.342	-0.360	-0.369	-0.389	-0.420	-0.239	
	(-5.599)***	(-3.434)***	(-3.865)***		(-6.035)***	(-6.153)***	(-6.473)***	(-6.670)***	(-7.130)***	(-7.731)***	(-4.206)***	
ABSRET		-0.325		-0.487							-0.390	-0.567
		(-0.741)		(-1.113)							(-0.973)	(-1.427)
VOLD			0.001	0.001							-0.001	-0.001
			(0.689)	(0.715)							(-0.421)	(-0.567)
ILLIQ					0.743	0.755	0.753	0.741	0.708	0.614	0.457	0.444
					(8.443)***	(8.572)***	(8.271)***	(8.120)***	(7.693)***	(6.697)***	(2.787)***	(2.706)***
TRNOVDY						-0.025	-0.030	-0.027	-0.035	-0.071	-0.055	-0.057
						(-1.078)	(-1.337)	(-1.233)	(-1.664)*	(-3.430)***	(-2.469)**	(-2.587)***
RLAG13_8							0.053	0.050	0.050	0.054	0.074	0.075
							(5.265)***	(5.196)***	(5.264)***	(5.794)***	(6.519)***	(6.566)***
RLAG7_2								0.036	0.036	0.037	0.030	0.030
								(2.729)***	(2.745)***	(2.824)***	(1.997)**	(2.005)**
DIVYLD									-0.067	-0.041	-0.034	-0.033
									(-3.661)***	(-2.366)**	(-1.749)*	(-1.701)*
RMSEDAY										0.336	0.007	0.003
										(5.257)***	(0.108)	(0.0407)
CONSTANT	2.991	2.154	2.126	2.114	2.119	2.150	2.127	2.049	2.288	1.384	1.872	1.835
	(9.435)***	(6.938)***	(6.782)***	(6.818)***	(6.713)***	(6.966)***	(7.061)***	(6.973)***	(7.100)***	(4.667)***	(5.824)***	(5.728)***
Observations	578564	404769	405610	404723	578564	578564	572859	572843	572843	572843	404723	404723
Number of months	526	479	479	479	526	526	526	526	526	526	479	479
R-squared	0.002515	0.000736	0.000109	0.000074	0.000986	0.000997	0.00097	0.000913	0.000923	0.001253	0.000731	0.000617

TABLE 7: FAMA-MACBETH REGRESSIONS OF STOCK RETURNS ON RHO AND SYSTEMATIC LIQUIDITY BETAS

This table reports the time-series averages of the slopes obtained from individual monthly cross-sectional regressions. T-statistic is the average slope divided by its time-series standard error. The sample period is 1968-2006, depending on the availability of the liquidity factor. In Panel A, BETALIQ is the systematic liquidity beta of Pastor and Stambaugh. In Panels B and C BETALIQ is one of the two liquidity component betas of Sadka. BETAMKT, BETASIZE, BETABTM are the estimated betas of stocks with respect to the market, size and book-to-market factors. These betas are estimated in the pre-sample period with a multivariate regression of monthly returns on factors using a 60-month window. Regressions are rolled over every month, hence betas are updated every month. RMSEMON is the estimate of the volatility of the residuals from those regressions. All other variables are as defined previously in the fixed-effects specification.

	Panel A: Pastor and Stambaugh (1968-2005)			Panel B: Sadka Transitory Fixed (1988-2006)			Panel C: Sadka Permanent Variable (1988-2006)		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
BETA	0.053	0.063		0.218	0.212		0.218	0.235	
	(0.389)	(0.466)		(0.967)	(0.950)		(0.967)	(1.052)	
LNSIZE	-0.100	-0.102		-0.070	-0.073		-0.070	-0.070	
	(-2.716)***	(-2.778)***		(-1.335)	(-1.400)		(-1.335)	(-1.350)	
LNBTM	0.225	0.230		0.166	0.165		0.166	0.165	
	(3.782)***	(3.886)***		(2.581)**	(2.578)**		(2.581)**	(2.586)**	
RHO	-0.279	-0.280	-0.309	-0.153	-0.153	-0.236	-0.153	-0.154	-0.237
	(-4.583)***	(-4.606)***	(-5.145)***	(-1.758)*	(-1.765)*	(-2.818)***	(-1.758)*	(-1.771)*	(-2.820)***
DIVYLD	-0.032	-0.031	-0.003	-0.029	-0.030	0.001	-0.029	-0.028	0.003
	(-1.504)	(-1.475)	(-0.140)	(-1.054)	(-1.086)	(0.0338)	(-1.054)	(-1.007)	(0.0978)
ILLIQ	0.545	0.543	0.758	0.783	0.725	0.953	0.783	0.756	0.986
	(3.166)***	(3.148)***	(4.675)***	(2.306)**	(2.131)**	(2.976)***	(2.306)**	(2.259)**	(3.145)***
TRNOVDY	-0.056	-0.055	-0.043	-0.004	-0.004	-0.002	-0.004	-0.005	-0.002
	(-2.363)**	(-2.356)**	(-1.812)*	(-0.162)	(-0.149)	(-0.0730)	(-0.162)	(-0.218)	(-0.0837)
RLAG13_8	0.077	0.078	0.062	0.060	0.059	0.043	0.060	0.057	0.041
	(6.389)***	(6.452)***	(5.222)***	(3.550)***	(3.537)***	(2.617)***	(3.550)***	(3.399)***	(2.516)**
RLAG7_2	0.022	0.022	0.021	0.001	-0.001	-0.002	0.001	0.001	0.001
	(1.394)	(1.432)	(1.380)	(0.0303)	(-0.0637)	(-0.101)	(0.0303)	(0.0509)	(0.0348)
BETALIQ		0.133	0.164		0.012	0.017		0.009	0.011
		(1.163)	(1.226)		(1.872)*	(2.328)**		(0.575)	(0.725)
BETAMKT			0.029			0.069			0.082
			(0.237)			(0.372)			(0.447)
BETASIZE			0.115			-0.011			-0.022
			(1.372)			(-0.0931)			(-0.188)
BETABTM			0.211			0.185			0.173
			(2.698)***			(1.431)			(1.331)
RMSEMON			2.722			4.908			4.811
			(1.657)*			(2.337)**			(2.254)**
CONSTANT	1.928	1.934	0.808	1.577	1.633	0.561	1.577	1.583	0.552
	(5.311)***	(5.323)***	(3.967)***	(3.376)***	(3.463)***	(2.349)**	(3.376)***	(3.384)***	(2.321)**
Observations	374302	374302	374302	184432	184432	184432	184432	184432	184432
Number of months	445	445	445	215	215	215	215	215	215
R-squared	0.000886	0.000896	0.000924	0.00066	0.000709	0.000517	0.00066	0.000725	0.000485

FIGURE 1: PRICE CHANGES AND TRADING VOLUME AROUND KNOWN INFORMATION EVENTS

RHO is the monthly estimate of the daily correlation between the absolute returns and dollar trading volume of a stock. ABSRET and VOLD are the residuals calculated from the estimated parameters of a pre-sample 60 month regression of absolute retuns and dollar volume on their market counterparts. The residuals are then divided by their corresponding estimated standard deviations to achieve cross-firm comparability. Figures plot the cross-sectional means of these variables against event time. In Panel A the information event is the earnings announcement, in Panel B, the merger announcement for a target.

Panel A: Earnings Announcements	Panel B: Merger Announcements

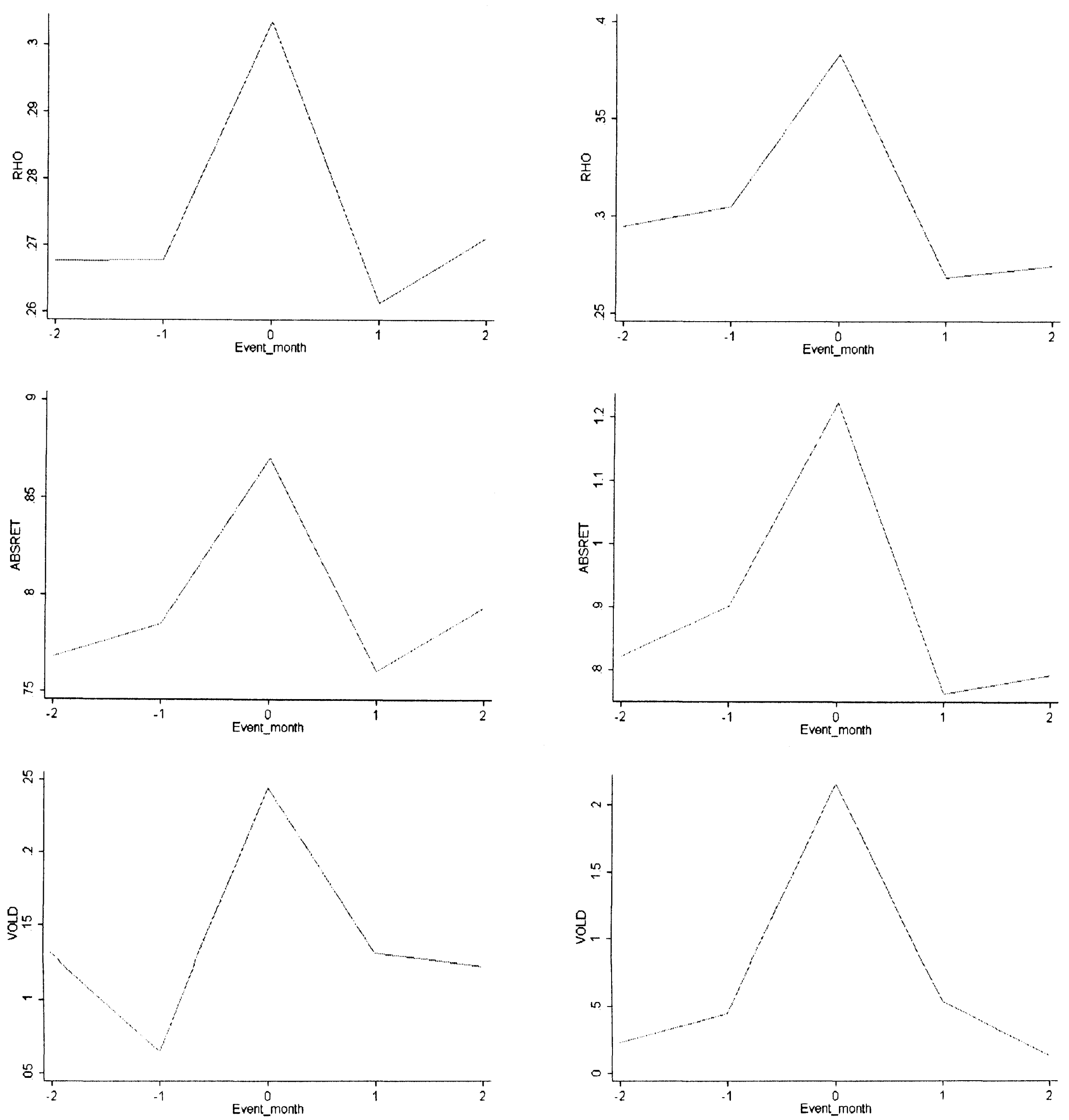
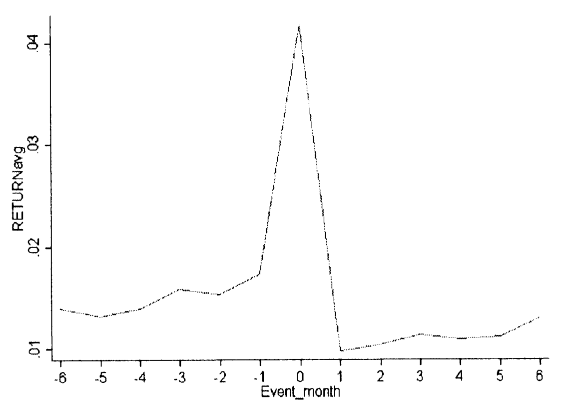


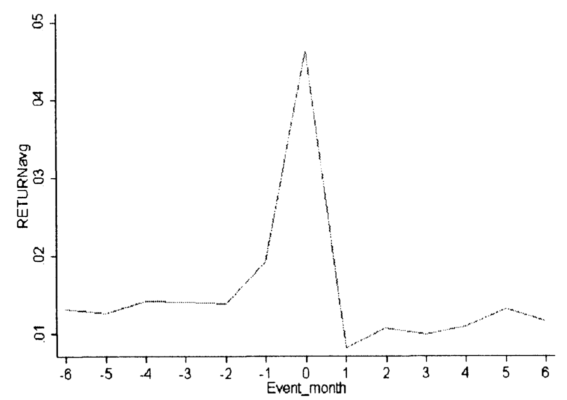
FIGURE 2: AVERAGE RETURNS OF STOCKS BEFORE AND AFTER INFORMATION REVELATION

A month in which information has been revealed (t=0) is defined as the information proxy, RHO, being above its 90th percentile value for the life of a stock. Returns for that stock in the previous and subsequent six months, along with their respective differences are then averaged cross-sectionally in event time. Below figures plot these averages against event time. Panel A uses all available data, other panels represent subsamples. Panel B excludes months in which earnings announcement were made. In Panel C, only "Bad News" events are used. "Bad News" is defined by the return in the information revelation month being negative. In Panel D only "Good News" event are used. Good News" is defined by the return in the information revelation month being positive.

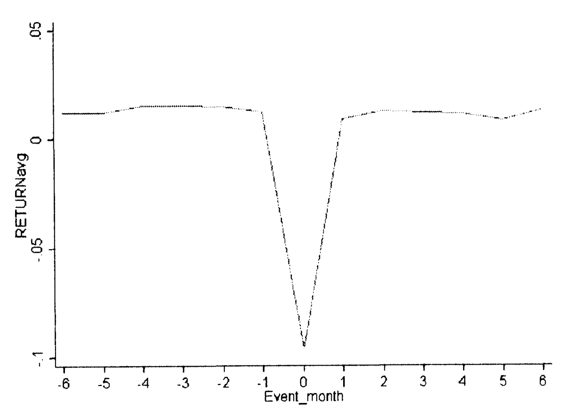
Panel A: All News



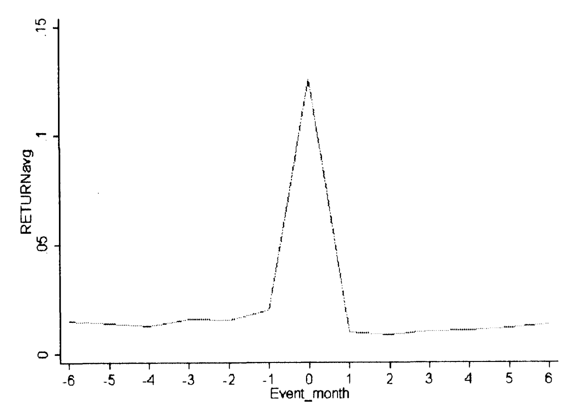
Panel B: Non-scheduled News



Panel C: Bad News



Panel D: Good News



Market Value of Banking Relationships: New Evidence from the Financial Crisis of 2008*

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Abstract

I use the financial crisis of 2008 as a natural experiment to identify the value of non-financial firms' stake in the banking system. Unrated firms underperform investment grade rated firms when Lehman Brothers fails, and overperform when the Treasury injects capital into the nine largest US banks. These differences are economically significant, around 1.5% in daily returns, and do not appear to be borne out of risk or the creditworthiness of the firm. Lenders' financial health – proxied by their capital ratios, deposits, and mortgage exposure – is also related to the borrowers' stock performance. Longer relationships and broader syndication benefit the borrowers, but greater reliance on credit lines hurt them. The findings highlight the interconnectedness of the banking system and the relevance of the "bank lending channel" even for large public corporations.

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1 Introduction

Theories of financial intermediation argue the uniqueness of banks based on their informational advantage in evaluating and monitoring borrowers (Fama (1985), Diamond (1984)) and as providers of liquidity (Holmström and Tirole (1998), Kashyap, Rajan, and Stein (2002)). If bank financing in the form of credit lines cannot easily be substituted for, then the firms that rely on them ought to have a valuable stake in the durability of the banking system. The financial crisis of 2008 provides a unique opportunity - a natural experiment - to identify the value of this stake because the shocks to the banking system did not spring from business lending, nor from monetary policy actions, both of which usually present endogeneity and reverse causality problems. I examine changes in the market value of non-financial firms in response to shocks to the banking system which I take as exogenous. I mostly focus on the market reaction to two key events that abruptly altered investors' expectations regarding bank solvency. The first event, the bankruptcy of Lehman Brothers, shook investors' perception of what "too big to fail" meant[1] and cast doubts about the durability of the entire banking system. The second, US Treasury Department's decision to use funds from the $700 billion Troubled Asset Relief Program (TARP) to invest directly in the nine largest financial institutions[2], alleviated these fears to a large extent and helped restore investor confidence.

Firms naturally differ in their utilization of bank lending and ability to access capital markets. I proxy for "bank-dependence" using the firm's credit rating and other loan characteristics when available. Following Kashyap, Lamont, and Stein (1994), I consider firms without a credit rating (but *with* short-term, or long-term, debt outstanding) to be the most bank-dependent, followed by speculative or "junk" rated firms. Investment-grade rated firms that have access to alternate sources of capital (e.g., public bonds,

[1] With $691 billion in assets, Lehman's was the largest bankruptcy in the history of the United States.

[2] These nine institutions were: JP Morgan, Citigroup, Wells Fargo, Bank of America, Merrill Lynch, Goldman Sachs, Morgan Stanley, State Street, Bank of New York Mellon.

commercial paper) are taken to be the least bank-dependent. In the universe of public Compustat firms, I find that unrated and junk rated firms underperform investment-grade rated firms by about 1.5%, and 0.9%, respectively, on the day of Lehman Brothers' bankruptcy. Investment-grade firms tend to be larger, however these differences in returns are not driven by smaller firms. Firm size is negatively related to returns in the face of a negative shock and among a subset of larger firms the underperformance of unrated and junk rated firms is even more pronounced: 2.2% and 1.6%, respectively. All returns used in the regressions are risk-adjusted using the Fama and French (1996) three factors and additional control variables are included to proxy for potentially missing risk factors (i.e. bankruptcy risk, financial distress risk, liquidity risk, etc.).

When hit by a positive shock, such as the TARP bailout of the nine largest US banks, all of the aforementioned differences in stock returns reverse signs. Unrated firms now overperform investment-grade firms by 1.5%, and junk rated firms no longer underperform. Firms with low cash flow who have underperformed in reaction to Lehman Brothers' bankruptcy, overperform with the announcement of the direct capital injections of the US Treasury to the ailing banking system. These results suggest that the TARP benefitted not only the recipient banks, but also the non-financial firms who rely on the "bank lending channel" (Bernanke and Gertler (1995)). As a more direct piece of evidence on the effects of the TARP, I show that the firms with pre-existing lending relationships with the first nine banks that received government capital further gain in market value on the announcement of the program.

In addition to Compustat, I use bank loan level data from the DealScan database to link borrowers to lenders in the pre-crisis period (2006-2007), hence define a banking "relationship". Consistent with prior studies that document the value of banking relationships such as Petersen and Rajan (1994) or Berger and Udell (1995), I find that the further back the relationship goes, higher is the stock return of the borrower on the day of Lehman Brothers' bankruptcy. These "relationships" also allow me to study the effects of lenders' financial health on the borrower. Banks with higher capital ratios and more core deposits have a positive effect on their borrowers' stock return when Lehman fails. In addition, banks' mortgage exposure has a negative effect. These effects are stronger for junk rated firms and not significant at all for investment grade firms.

DealScan breaks down each "deal" into its term loan and credit lines components. It turns out that the credit line component plays an important and an unexpected role in the borrowers' performance. Credit lines provide liquidity insurance (Holmström and Tirole (1998)) or are used as an alternative to holding costly cash (Sufi (2009)[3]); a priori, one would expect higher valuations for firms who have been able to secure more lines before the liquidity shock arrives. However, the data reveals that the level of committed credit lines before the crisis (as a fraction of the firm's assets at the end of 2007) is *negatively* related to the firm's stock performance on the day of Lehman Brothers' bankruptcy. One explanation for this result might be the risk of rolling over these lines, or making full use of them, in the wake of Lehman's collapse. Indeed, Ivashina and Scharfstein (2009) demonstrate that the new issuance of revolving credit facilities declined significantly in the last quarter of 2008, and Cornett, McNutt, Strahan, and Tehranian (2010) show that banks preference for liquid assets fueled a decline in credit origination. Huang (2009) argues that the stressed banks could ration takedown volumes on existing lines by the power of strict covenants they have set initially. Another explanation might be that the market was expecting more banks to default following Lehman and thus valued these credit lines as worthless. Whichever is the explanation, it is clear that greater endorsement of credit lines implies greater dependence on the banking system. The underperformance of such firms suggests that credit lines are not a bulletproof tool for managing corporate liquidity; they can easily become a handicap if bank durability becomes suspect due to reasons completely beyond a firms' control.

[3]Sufi (2009) details the link between cash holdings, cash flow, lines of credit and financial covenants. He shows that firms who can not access credit lines due to low cash flow choose to hold more cash instead.

The results are robust to numerous controls and estimation methods. Firstly, unrated firms that underperform significantly do not appear to be financially distressed at the end of 2007 when variables are observed. They rank similar to investment grade rated firms on leverage, cash holdings, and cash flow. Industry effects can not explain the return differences either, as I control for industry effects using dummy variables, or clustering the standard errors by industry, or by a generalized least squares approach where observations are weighted by their estimated industry variances. Weighted-least-squares estimation actually increases both the magnitude and the statistical significance of the estimates. All returns are measured over one day, hence I include the bid-ask spread in all my regressions to control for stock market liquidity. I also repeat my tests on days with banking related events other than the bankruptcy of Lehman Brothers or the TARP announcement, and find qualitatively similar, albeit weaker results. Another concern might be that these return differences do not reflect the response to the banking shocks but simply exist as unexplained patterns in the data. To address this concern, I construct a counterfactual by running the same cross-sectional regressions on every trading day from 2005 to 2007. Comparing investment grade rated firms with unrated firms as before, I find that there are *no* days in this pre-crisis period where the difference in abnormal returns were greater than the one observed on September 15, 2008, Lehman Brothers' bankruptcy. Lastly, I run a panel regression in 2008 where I interact event day dummies with the variables that were significant in the cross-sectional regressions. The interaction terms all come out significant whereas the characteristics by themselves do not. This result supports the conclusion that events such as the bankruptcy of Lehman Brothers or the TARP were highly unusual in their impact and thus fitting choices for studying the sensitivity of non-financial firms to the health of the banking system.

This paper extends the literature on banking relationships by demonstrating the universal and the interconnected nature of their value. Previous literature have focused on lender (or borrower)-specific events to infer value. I take the failures and bailouts of banks as shocks to the whole banking system and explore the repercussions for *all* non-financial firms. For example, Slovin, Sushka, and Polonchek (1993) run an event study on borrowing firms when their relationship bank fails and is later rescued by the FDIC. In their paper there is only one bank, Continental Illinois, and 53 borrowers. In contrast, I use all (public) borrower-lender pairs available in the DealScan database from 2006 to the end of 2007. Moreover, I *exclude* the failed bank: Lehman Brothers. Thus, the negative abnormal returns observed for the borrowers cannot be due to the failure of their lender, as was the case for Continental Illinois. Similarly, the positive abnormal returns on the TARP announcement day are *not* strictly limited to firms with existing relationships with the banks that were to receive the government capital; all firms benefit. These widespread effects can be interpreted as a reflection of the changes in the "cost of credit intermediation" described by Bernanke (1983) in his analysis of the great depression.

There are other approaches used in the literature to demonstrate different dimensions of the value of banking relationships. James (1987), Lummer and McConnell (1989), and Best and Zhang (1993) all find that the public announcements of new bank credit agreements generally increase the share price of a firm, hence conclude that new relationships must create value. Petersen and Rajan (1994) and Berger and Udell (1995) show that relationship's length is related to the availability and the cost of funds for the borrower. Their focus though, is on particularly small firms - firms collected from the National Survey of Small Business Finance. The results in my paper extend that value to large public corporations. Hubbard, Kuttner, and Palia (2002) show that bank characteristics affect the costs of borrowing, but they do not study the market valuations of borrowers as I do. Kang and Stulz (2000) on the other hand, study market valuations but do not link them to bank characteristics. Their main finding is that more bank-dependent firms in Japan lost more market value during the crash of the Tokyo Stock Exchange in the early 90s. Chava and Purnanandam (2008) is the closest paper to mine in terms of methodology. They too study the performance of bank-dependent and non-bank-dependent firms faced with an exogenous shock. The shock in their paper is the Russian bond crisis of 1998 and they find evidence supporting the value of banking relationships. Analogous to my finding that a bank's mortgage exposure in the recent crisis negatively affects its borrowers, they find that a bank's investment in foreign securities negatively affects its borrowers during the Russian bond crisis. The results in their paper and mine are consistent throughout however there's one important distinction: The Russian bond crisis, while having the advantage of being a truly exogenous event, does not inform us about the interconnectedness of the banking system. Lehman Brothers' bankruptcy on the other hand, was a unique event in that it has exposed just how interconnected the US banking system has become.

This paper is also related to the literature on bank lines of credit and corporate liquidity management. Demiroglu and James (2010) provide an excellent review of this literature hence I will not list all the papers here in the interest of brevity. Two papers however are worth mentioning, because the atypical nature of this financial crisis may appear in contrast to their arguments. Kashyap, Rajan, and Stein (2002) build a theoretical model to explain why it would be in the banks' interest to provide liquidity. In this model, banks have a natural hedge against liquidity shocks because of synergies in simultaneous lending and deposit taking. Gatev and Strahan (2006) provide empirical evidence for this model by showing that takedown demand on credit lines increases at times when the commercial paper market tightens. In both of these papers banks' willingness to lend *also* increases at the time of the liquidity shock because banks experience an inflow of liquid assets from investors who (presumably) perceive banks as a "safe haven". What the recent financial crisis highlights and what the Kashyap, Rajan, and Stein (2002) model does not capture is that, banks can lose that credibility – as they clearly did after the collapse of Lehman – and become liquidity constrained themselves. This in turn makes credit lines less effective as a tool for managing corporate liquidity for non-financial firms in a systemic crisis.

There is also a strand of literature which studies the real effects of the financial crisis and more generally, how shocks to the banking sector propagate to the real sector. Almeida, Campello, Laranjeira, and Weisbenner (2009), Campello, Giambona, Graham, and Harvey (2009), Campello, Graham, and Harvey (2010), Ivashina and Scharfstein (2010) all find that one reason firms were investing less during the crisis was because of credit constraints. This finding is consistent with previous studies such as Gibson (1995) who shows that in Japan firms' investment is sensitive to the credit ratings of their main banks, or Peek and Rosengren (2000) who show that an exogenous loan supply shock originating from Japan hampers investment in the U.S. One area I do not explore in this paper is the real effects of the banking events I have chosen to study. While real effects are just as important as market valuations, the proximity of the events makes it impossible to observe changes in investment and/or operating performance in such short time frames.

2 Background on the Financial Crisis

While the majority of bank failures and bailouts occurred in 2008, it is now generally understood that the financial crisis had its roots in the subprime lending practices of the previous years. Freddie Mac's statement on February 27, 2007 that it would no longer buy the most risky subprime mortgages and mortgage-related securities is marked as the first event of the financial crisis by the St. Louis Fed[4]. Rest of 2007 saw more than eighty subprime lenders either closing down their operations or declaring bankruptcy[5], some being among the largest players in the mortgage market (New Century Financial, American Home Mortgage, Countrywide Financial, etc.). Initially, these failures gave the appearance of being confined to subprime lenders in the face of declining housing prices and rising foreclosures – "[the impact of] the problems in the subprime market seems likely to be contained" told the Fed Chairman Ben Bernanke to the Congress in his testimony

[4] Source:http://timeline.stlouisfed.org

[5] The list can be found at:
http://online.wsj.com/public/resources/documents/info-subprimeloans0706-sort.html

before the Joint Economic Committee on March 28, 2007. This view turned out to be overly optimistic unfortunately; the big investment banks were also highly exposed to the mortgage market through mortgage-backed-securities and other structured products, and perhaps more dangerously so because of the complexity of these financial instruments and the lax accounting standards. Eventually, these so-called "toxic assets" would erode their balance sheets, wipe out investor confidence, and fuel the liquidity crisis[6] that would push major banks into insolvency.

In hindsight, Bear Stearns' sudden collapse in early 2008 is illustrative of how even the most reputable financial institutions can become insolvent overnight. The event is also consequential in terms of shaping market expectations on government's handling of the crisis. In early March of 2008, investors were growing increasingly uncomfortable with the quality of Bear Stearns' collateral. They started to pull out their money, putting strain on the firm's day-to-day funding ability. In what amounted to a bank run, on March 14, Bear Stearns had to call for an emergency loan from the Fed and was later sold to JP Morgan with the Fed bearing the risk of $29 billion of Bear Stearns's less liquid assets. This was a major turning point in Fed policy. Traditionally, the Fed has lent to commercial banks in financial panics, but not to investment banks. It has accepted only US Treasuries for collateral. For the first time since the Great Depression, it invoked the "unusual and exigent circumstances" clause of the Federal Reserve Act, which authorize lending by reserve banks to individuals, partnerships and corporations, practically anyone they see fit. Naturally, this set a precedent for rescuing "too big to fail" Wall Street firms. And the Fed wasn't the only regulator reinforcing the belief in "too big to fail"; FDIC took over IndyMac, one of the largest mortgage banks in California, in July of the same year, and later that September the Treasury ended up placing mortgage giants Fannie Mae and Freddie Mac into federal conservatorship.

[6]See Brunnermeier (2009) for an in-depth analysis of how the subprime mortage crisis turned into a liquidity crisis.

When Lehman Brothers reported a loss of $3.9 billion for its 3rd quarter (on top of 2.8 billion it had written down for the 2nd quarter) within the same week of Fannie and Freddie's bailout, the anticipated course of action was selling off some of its divisions to raise capital while the Fed would provide the much needed liquidity. On many occasions the Fed, as well as the Treasury, have publicly stated that big banks posed a systemic risk to the economy, therefore allowing them to fail would depress the economy even further. Timothy Geithner, the president of the New York Fed, and Henry Paulson, the secretary of the Treasury, called Lehman and two potential buyers, Bank of America and Barclays, into a meeting over the weekend to broker a deal before the markets opened on Monday, September 15. The markets were anxious but some kind of deal was expected. Neither bidder however, wanted to stand behind Lehman's liabilities without government guarantees. Fearing the public backlash over putting more taxpayer money at risk, the Fed and the Treasury balked and Lehman suddenly found itself with no other option than filing for bankruptcy.

[Figure 1 here]

On September 15, 2008, investors woke up to a world that no longer offered implicit government guarantees, a world in which no bank was "too big to fail". Counterparty risk became the foremost concern and markets began to freeze up. In Figure 1, we see this evidenced by the sharp rise in the TED spread following the bankruptcy of Lehman Brothers. The TED spread, difference between the interest rates on 3-month LIBOR and 3-month T-bills, serves as an indicator of the banks' default risk. On September 15, 2008, it rose to 201 basis points, and in the next two days it topped 300. Historically it has hovered around 50 basis points. For the rest of the month it kept rising, signaling the ever increasing fear of bank failures.

By the time the TED spread reached its peak value of 465 basis points on Friday, October 10th, the Fed's efforts to restore confidence in the markets have proven to be ineffective. The Treasury stepped in with the recently established TARP funds[7]. The top officials at the nine largest U.S. banks were called into an emergency meeting by Henry Paulson, who pressed for the government's plan to inject capital directly into these nine institutions. Under his proposal these institutions were to receive an aggregate amount of $125 billion via the sale of preferred stock to the US Treasury. A unanimous agreement was reached that day and a public announcement was made the next morning declaring the names of the nine banks and the amounts of capital they would be receiving. The markets cheered. The TED spread stopped rising after this event, dropped roughly by 100 basis points that week, and gradually settled down to normal levels within the next six months as more banks took advantage of the TARP.

3 Data and Methodology

An all-too-common problem in empirical work on banking relationships is separating demand shocks from supply shocks. Banks may be distressed because firms are distressed and have difficulty paying back their loans, or there might be latent economic factors that undermine both parties' performance. The current financial crisis presents a unique opportunity in this respect; because the crisis had its origins in subprime mortgages and the structured products derived from these mortgages, events can be viewed as exogenous shocks to the supply of credit for businesses. Assuming that the stock market immediately prices in the value implications of these shocks, the firm's daily (risk-adjusted) stock return can be used as a proxy for the value of its stake in the banking system. The variation in the firms' dependence on bank financing allows the value of the banking relationship to be pinned down when the "bank lending channel" is impaired (or repaired). This "natural experiment" approach allows me to avoid reverse causality issues that often plague similar

[7]After an initial rejection on September 29, the Congress passed the Emergency Economic Stabilization Act of 2008 on October 3, which established the $700 billion Troubled Asset Relief Program (TARP).

studies on banking relationships.

The basic methodology I use throughout the paper is cross-sectional regressions of abnormal stock returns on borrower, lender, and loan deal characteristics. The model is:

$$AR_i = \alpha + \beta X_i + \gamma B_i + \delta L_i + \lambda D_i + \epsilon_i \tag{1}$$

where AR_i is the abnormal return of stock i, X_i is a vector of firm characteristics for stock i, B_i is a vector of firm i's bank's characteristics, L_i is a vector of firm i's loan deal characteristics, and D_i is a vector of credit rating indicators. $\beta, \gamma, \delta, \lambda$ are the parameters to be estimated and ϵ_i is the residual.

For D_i, I use two dummy variables to represent three mutually exclusive categories: investment-grade rated debt, speculative-grade ("junk") rated debt, and unrated debt. Firms that have no debt (all equity) are dropped. Following Kashyap, Lamont, and Stein (1994), I assume unrated debt to be bank debt. Junk rated firms are also quite likely to be users of bank debt since it is expensive for them to issue new bonds. Including them with a dummy or excluding them altogether from the sample do not change the results in any way. In all regressions investment-grade rated firms are the reference (omitted) group. S&P Ratings for long-term debt are obtained from Compustat and matched to the month of the fiscal year end in 2007 for each firm. Covenant violation data is obtained from Amir Sufi's website[8]. All regressions also include (but do not report) industry dummies based on the Fama-French 12 industry definitions[9].

I define abnormal return as the realized minus the expected return according to the Fama and French (1996) three factor model. The parameters of the model are (pre)estimated for each firm by a multivariate regression using the time-series of daily

[8]Source: http://faculty.chicagobooth.edu/amir.sufi/data.htm . See Nini, Sufi, and Smith (2009) for the collection of this data.

[9]Source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Using finer industry classifications, such as the Fama-French 49 industry definitions, do not affect the results in any meaningful way.

returns from CRSP, in the year prior to the year in which the cross-sectional regressions are run (e.g., 2007 daily returns are used for parameter estimates for the cross-sectional regressions to be run on September 15, 2008). More specifically:

$$AR_{it} = R_{it} - (r_{ft} + b_i MKT_t + s_i SMB_t + h_i HML_t) \tag{2}$$

where R_i is the realized return of stock i on event day t, r_{ft} is the risk-free rate on day t, b_i, s_i, h_i are the pre-estimated parameters, and MKT_t, SMB_t, HML_t are the three factors of Fama and French (1996).

The first part of the analysis uses all public firms in Compustat, without taking into account the relationship between a specific firm and a bank. Unrated firms are simply considered to be dependent on the banking system as a whole. The more detailed analysis of the banking relationship requires matching borrowers to lenders. The DealScan database from Loan Pricing Corporation (LPC) acts as the centerpiece to my study in this respect. DealScan provides detailed information on loan agreements such as, the type of the loan, facility amount, lead arrangers and participants, prices, fees, etc. Most of the data originates from commercial loans filed with the Securities and Exchange Commission (SEC). The rest is collected through LPC's own research. Although the coverage is extensive, it does not represent the complete universe of loan agreements; there is a tilt towards large public companies. This bias however, is not necessarily a concern for the validity of the results. Because the value of banking relationships should be greater for smaller firms (as theory suggests), underrepresentation of these firms in the sample should make the differences smaller, making it *more* difficult to find statistically significant results.

The main identifier in DealScan is the borrower's name and I first match these to the Compustat identifier "gvkey" on a yearly basis using the link file from Michael R.

Roberts[10]. I manually go over the unmatched names to check for alternate spellings, acronyms and other errors. I hand-match the lender names in DealScan to the CRSP identifier "permco"s, which are then matched to the Call Report regulatory high holding company codes[11]. This matching process, by construction, forces both the borrower and the lender to be public companies, and the lenders to be either commercial banks or bank holding companies. To the extent that public companies should find it easier to raise capital compared to their private counterparts, the reported market values of banking relationships can be considered conservative.

I identify a firm's relationship bank as the "lead arranger" in a loan deal (in addition to "arranger" there are other labels in DealScan such as "agent", or "bookrunner", that designate this role). While most loans are syndicated, the origination falls in the hands of the lead bank[12]. I drop all other participant banks. The universe of borrowers is further narrowed by the following criteria:

- I drop all loan types other than credit lines. This is because credit lines represent commitments by the bank as opposed to amounts actually drawn, and thus may better characterize the level of dependence of a firm on banks. Credit lines are usually rolled over as well, which makes them a better proxy for the ongoing relationship than the one-time only term loans.

- Firms in the financial, insurance, real estate (SIC codes between 6000-7000), and construction (SIC codes between 1520-1600), sectors are excluded to avoid endogeneity issues.

- Deals in which Lehman Brothers is identified as the lead arranger are dropped.

[10] See Chava and Roberts (2008) for the details on the construction of the link between DealScan and Compustat identifiers.

[11] I thank Philip E. Strahan for providing me with the link between Call Report codes and CRSP permcos.

[12] There are cases when there is more than one lead bank in a deal. Using either one of the lead banks gives yields similar results.

While Lehman was not a big supplier of credit lines to businesses, its clients would be highly likely to underperform when faced with its unexpected bankruptcy.

- Firms with less than 125 days of trading in 2007 are dropped. This is simply to obtain more precise parameter estimates used in the calculation of abnormal returns.

- The firm should be trading on the two event dates: September 15, 2008 and October 14, 2008.

Some firms have multiple lines with multiple banks. To reduce the sample to a one observation per firm, I average all bank and deal characteristics in proportion to the sizes of the loans. The final sample contains 880 unique borrowers and 34 unique lenders.

4 Results

4.1 Compustat firms

Table 1 presents the summary statistics of borrower characteristics across the three long-term debt rating categories. The statistics are estimated from data in 2007, and therefore represent a snapshot of the financial conditions of the firms before the test period. The first thing to note is the size difference between rated and unrated firms. While the median unrated firm has market capitalization of $247 million, the median investment-grade rated firm has around $9 billion. This is to be expected because we know that firms gain access to public bond markets as they mature, nevertheless, it calls attention to the importance of controlling for size in the regression analyses.

[Table 1 here]

Table 1 is also helpful in eliminating financial distress as the potential driver of the underperformance of unrated firms. Compared to investment grade rated firms, unrated firms hold approximately three times as much cash (as a fraction of their assets), yet at the same time they are less levered. Under these conditions it should not be more difficult for these firms to meet their short-term obligations. The median book-to-market ratios are also similar – 0.413 for investment grade firms and 0.469 for unrated firms – another indication that the unrated group's market valuations are not on average inferior to investment grade before the crisis.

Table 2 presents eight cross-sectional regression results, four on each event date. OLS standard errors are reported. Industry dummies are included to control for heteroskedasticity. The three credit rating categories are represented by the two dummy variables, "JUNK" RATED and UNRATED (omitted group is the investment grade rating). All specifications control for size (logarithm of market value of equity), and in addition, a subset of larger firms is analyzed separately. In Column 4 of both panels I restrict the sample to firms whose market values exceed $391 million. This size cutoff is the market value of the *smallest* investment-grade rated firm in Compustat. The rationale is that any firm smaller than that carries no information on the utility of having access to public bond markets.

[Table 2 here]

On the day of Lehman Brothers' bankruptcy (Panel A), the estimated coefficient on UNRATED is -1.490 for the whole sample, and -2.157 for the larger firms subsample. The interpretation of these coefficients is that the firms with access to public bond markets significantly overperform those without, on a risk-adjusted basis. If one considers junk rated firms as also being dependent on bank lending (issuing bonds for these firms would be costly), their underperformance of 1.62% (Panel A, Column 4) provides additional support for the idea that banks provide value. These results are unlikely to be driven by small firms; not only dropping smaller firms in Column 4 makes the results stronger, but logSIZE actually comes in *negatively* significant (t=-3.57) in this specification. It might be that once certain benefits of being a large firm are taken into account with the control variables, size weights down the firm in a crisis.

Note that the differences in returns due to the firm's credit rating (or lack thereof), are over and on top of their performance related to cash flow and leverage. While in a Modigliani-Miller type of world the type of financing should have no effect on the value of the firm, in the real-world of financial frictions we expect firms with high leverage and low cash flow to be more sensitive to the shocks to the financial system. They may run into trouble servicing their debt or rolling it over, they may fall short of necessary working capital, or they may have to let go of positive NPV projects cause they can not fund them. All these factors would decrease firm value, and in fact, this is exactly what the data exhibit: EBITDA is positively, LEVERAGE is negatively related to returns. Both variables are highly statistically significant at the 1% level. One can also view these variables taken together as a rough measure of the firm's dependence on external finance; then the conclusion is that the financial crisis had adverse effects on firms who called for more external finance. COVENANT VIOLATE dummy is also significant for the whole sample, and the larger firms subsample. The negative sign implies that firms who have violated the covenants on their bank loans were hurt more by Lehman Brothers' bankruptcy. This is consistent with the idea that these firms would find it more difficult to obtain new financing from banks. In a liquidity crisis banks are likely to ration credit and covenant violations allow them to do so without breaching their loan contracts.

In Panel B, I perform the same tests on the second event date, the public announcement of the nine TARP banks who have agreed to receive government capital. Most coefficients flip signs. In particular, the unrated firms outperform investment-grade firms between 1.5% to 1.7%. This positive abnormal return indicates that the capital injections under TARP were perceived by the market to be beneficial to those firms whose primary providers of credit were banks. A further benefit can be observed by the positive coefficient on LEVERAGE in the last column. Overperformance of firms with high leverage hints at the expectation of the credit markets to function smoothly again. Overall, these results imply that the TARP was met with success, at least at its inception. It would be hasty to conclude however, that this was the right policy response to the crisis without investigating the TARP's long-term consequences.

4.2 DealScan firms

In this section I present more detailed evidence on the value of banking relationships, utilizing loan level data from DealScan. DealScan offers a comprehensive selection of loans, though it is not the complete universe. The similarity of the borrower characteristics in Table 3 to the ones in Table 1 from Compustat assures us that DealScan sample is likely to be representative. One notable difference is the median size of the unrated firm – $708 million in DealScan compared to $247 million in Compustat – but as pointed out earlier, this bias towards larger firms makes the comparisons between unrated firms and the investment grade rated firms more appropriate. Similar to the Compustat sample, unrated firms do not display any signs of financial distress. They rank similar to investment grade firms on cash holdings, cash flow, and leverage. The number of unrated firms is reduced considerably when we move onto DealScan; 346 compared to 1687 in Compustat. If anything, this should increase the standard errors and result in more conservative estimates.

[Table 3 here]

Three new variables, LEAD BANK TIER 1 CAP. RATIO, LEAD BANK DEPOSITS, and LEAD BANK MORTGAGE, are obtained from the Call Report in the last quarter of 2007. They are intended to proxy for the financial health of a bank who acts as the lead arranger in a credit line deal. All are reported as a fraction of banks' total assets. If a bank is a subsidiary of a bank holding company they are aggregated at the holding company level. If a firm has more than one credit line with different banks, they are averaged in proportion to the size of the facility. Table 3 shows that these lender characteristics are roughly similar across the borrowers' credit rating categories (median deposits is exactly the same for all three groups, for instance). This similarity makes it relatively safe to assume that when borrowers chose their banks (or banks chose their borrowers), the financial state of the bank did not factor into the decision.

Summary statistics on the deal characteristics reveal that unrated firms have, on average, shorter relationships with their banks, pay a higher price for the credit facility, rely more heavily on credit lines (as a fraction of their assets), and have access to fewer number of banks to draw on their lines. All these characteristics point to their stake in the durability of the banking system.

[Table 4 here]

In Table 4, the variables previously shown to be significant in explaining the cross-section of returns in the Compustat sample, are again shown to be significant. Coefficients in column 1 are similar to the ones in Table 2 in significance and magnitude. When new variables are introduced, the underperformance of non-investment grade firms is slightly reduced to around 1%. Some of the variation in returns is now captured up by bank and deal characteristics. LEAD BANK TIER 1 CAP. RATIO is statistically significant with a positive sign on the Lehman bankruptcy date, and a negative sign on the TARP announcement date. This means that firms who had prior relationships with banks which held more equity capital were harmed less by Lehman's failure, and firms whose relationship banks held less equity capital were helped more by the governments' recapitalization efforts. Standardized coefficients are reported for the bank ratios thus, one standard deviation in the lender's capital ratio corresponds to 0.48%, or 0.67%, daily return depending on the event day. The economic significance of this effect is quite large when one considers the fact that capital ratios of most banks are quite similar[13]. Besides the magnitude, there is yet another economic insight that can be gleaned from this variable. The positive abnormal return attributable to the bank's capital ratio on the TARP announcement date implies that the Treasury's plans for capital injections had a positive impact on *all* banks and their borrowers, regardless of whether the bank was named at the announcement or not. This is evidence of the interconnectedness nature of the banking system because on that date no money had yet changed hands and the government had no saying on how this capital were to be used.

Of course, having a prior relationship with one (or more) of these nine banks that *were* named at the TARP announcement brings in additional gains for the borrower, as attested by the positive coefficient on the 9-TARP dummy. 9-TARP is a dummy variable that takes on the value of 1 if the firm has an existing credit line with any one of the initial nine banks included in the first round of TARP. The magnitude of the coefficient in column 3, 1.8%, is substantial considering that some of these benefits are already accounted for by the LEAD BANK TIER 1 CAP. RATIO variable. The situation here echoes the positive stock price response to Continental Illinois's borrowers when it got bailed out (Slovin, Sushka, and Polonchek (1993)), and is direct evidence of the value of banking relationships. Let's assume for a moment that the previously demonstrated differences in returns were caused by some unknown economic factor unrelated to banking. There would be no reason for the firms who had borrowed from the nine TARP banks to outperform those who had not, if they did not stand to benefit from the government bailout through the bank lending channel.

Bank solvency (proxied by the capital ratio) is not the only measure of banks' ability and willingness to lend. Bank liquidity is also an important dimension. I proxy for liquid-

[13]Consider this real-world example: on the day of the Lehman Brothers' bankruptcy, an unrated firm whose main lender was Wachovia with a capital ratio of 7.8%, would have returned approximately 0.36% less than another firm whose main lender was Bank of America, whose capital ratio was 9.4%. And that same firm who had borrowed from Wachovia would have appreciated an extra 0.51% in response to the TARP announcement, compared to a borrower from Bank of America.

ity by the bank's core deposits. Deposits are a stable source of funding for banks because of the explicit guarantees offered by the FDIC. Thus, one expects banks whose deposits make up a larger fraction of their assets to be more willing to lend. The coefficient on LEAD BANK DEPOSITS is positive and significant on the day of Lehman's bankruptcy, supporting this view. Firms whose relationship banks had easier access to cash through deposits are viewed more favorable by the market in a crisis.

By the second half of 2008 it has become apparent to investors that subprime mortgages were the main culprit for the crisis, and in particular for bank failures. Yet another way to proxy for banks' financial health therefore, is to look at their mortgage exposure. LEAD BANK MORTGAGE is the value of residential mortgages as a fraction of total assets on the bank's balance sheet at the end of 2007. Higher mortgage exposure is the forerunner of future losses due to defaults, hence implies a weaker bank. Not surprisingly, this variable turns out to be negatively related to the borrower's stock return. Its economic significance is comparable to the effects of bank capital on borrower performance. One standard deviation increase in mortgage exposure reduces the borrower's returns by 0.53% on the day of Lehman's bankruptcy, and boosts returns by a similar amount on the news of the bailout. One caveat is that these estimates may not accurately reflect the true impact of mortgages, as it was common practice among banks to move mortgage products off their balance sheets.

Moving onto loan characteristics we see that they are all significant to some extent. LOAN SPREAD which controls for the creditworthiness of the borrower is significant at the 1% level in both panels. It could be said that the underperformance of unrated firms is a reflection of their credit quality, however with the LOAN SPREAD to proxy for credit quality UNRATED is more likely to be capturing bank-dependence. LENGTH of RELATIONSHIP which is measured in years, is significant at the 5% level but note that magnitude of this coefficient is quite small. It may take many years working with the same bank to observe an economically significant benefit. This is one reason why bank failures, by the nontransferable nature of relationships, impose deadweight costs. Lastly, TOTAL LINES and NUMBER of PARTICIPANTS are significant at the 5% and 10% level. In the next section I will show that this result is driven primarily by unrated firms, hence I defer their discussion till then.

Overall, the results in this section underscore the influence of bank health and durability on the whole economy. My findings complement the "borrowers as stakeholders" concept put forth in Slovin, Sushka, and Polonchek (1993), by showing that the stakeholder view applies more generally than initially assumed. Failure of major banks, or their rescue, affects *all* firms. Every firm that requires bank credit becomes a stakeholder in every bank.

4.3 Interactions

The previous section assumed that the explanatory variables did not vary in their degree of significance with the credit rating of the firm. I relax that assumption in this section and repeat my tests within each rating category. Columns 1 to 3 in the two panels of Table 5 correspond to the rating categories previously marked by the dummy variables. The regression model is estimated as a system of equations to facilitate tests of equality of the coefficients. Standard errors are clustered by the rating category.

[Table 5 here]

The first takeaway from Table 5 is that the estimated coefficients for individual rating groups are unequal. The Wald test for the equality of all three models rejects at 1% (p-value in Panel A is zero to four significant digits). The differences in the estimated coefficients are easily discernible by casual observation. For the investment grade rated group, variables which previously exhibited significance are not at all significant. This is consistent with the initial assumption that access to public debt markets makes these firms essentially non-bank-dependent. For the junk rated and unrated group, the coefficients are typically larger than their counterparts in Table 4. For example, LEAD BANK TIER 1 CAP. RATIO and LEAD BANK MORTGAGE are more strongly related to returns for junk rated firms compared to the average firm.

Compared to the regression results in Table 4, TOTAL LINES and NUMBER of PARTICIPANTS display stronger significance (t=-3.31 and t=3.26) among unrated firms. NUMBER of PARTICIPANTS measures how dispersed the loan is, and it is easy to see why having access to more than one bank in a crisis would be beneficial: syndication of the loan provide a sort of diversification benefit to borrowers. The negative coefficient on TOTAL LINES may not be immediately intuitive and requires a bit of explanation. If credit lines are a form of liquidity insurance, firms with more lines are supposed to be better shielded from liquidity shocks. However, this reasoning assumes that banks will always be ready to lend. The unique aspect of this financial crisis was that the liquidity issues emerged from the banks themselves, which made them even more hesitant to lend. Even if banks were willing to lend, Lehman Brothers' sudden bankruptcy made it seem like any bank could fail overnight. The market's concern about bank durability over this period is likely to have decreased the perceived insurance value of credit lines, giving rise to a negative relation between the amount of lines and returns.

4.4 Tests on other days

4.4.1 "Good" news and "Bad" news

In this section, I investigate the stock market responses to a wider selection of banking related events that occurred in the last half of 2008. I focus on the period after Lehman's collapse, because it happens to be extraordinarily rich in terms of banks' failures and policy responses. First, I select the banking-related events from the timeline on St. Louis Fed's website and classify them as "good" or "bad" based on the return of the Dow Jones US Financial Services Index. A positive return implies optimism about the future of the banking industry (hence "good"), a negative return implies pessimism (hence "bad"). A priori, I expect these sentiments to migrate to non-financial firms, as was the case for Lehman Brothers' bankruptcy, and the TARP bailout. Figure 2 shows the timeline of the selected events. Events in the upper half of the graph represent the "good" news, events in the lower half, the "bad" news.

[Figure 2 here]

[Table 6 here]

Table 6 presents the cross-sectional regression results. The dependent variable is the daily abnormal return of a firm *averaged* over the "good", or the "bad", event days. Lehman Brothers bankruptcy and the TARP announcement are excluded from this analysis to avoid these two major events driving the results (their inclusion makes the results reported in this section stronger). The two main variables of interest, "JUNK" RATED and UNRATED, are significant on both "bad" and "good" news days, in almost all specifications. The signs are consistent with what we have observed before. The magnitudes of the coefficients are somewhat smaller, due to the fact that some of these events may have been anticipated or the banks being less interconnected than Lehman. This may also be the reason why bank characteristics do not turn out to be significant in this set of regressions. The underperformance of non-investment grade firms on "bad" news days, and their overperformance on "good" news days supports the same conclusion reached earlier: firms that rely on bank credit have a valuable stake in the durability of the banking system.

4.4.2 Non-event days

The US stock market went through one of its most volatile periods in recent history during the financial crisis of 2008. Daily index fluctuations of 1-2% were not uncommon, so it is conceivable that the daily return differences documented in this paper are driven by the heightened volatility. It could also be the case that these differences always existed, and do not necessarily reflect the reaction to the banking events. To rule out these explanations, I try two different estimation techniques. First, I run the same cross-sectional regressions on the same set of firms from DealScan, on every trading day in 2008. I save the estimated coefficients and compare the coefficients I previously obtained on the event days to this "empirical" distribution (the methodology resembles partly the Fama-MacBeth approach, and partly bootstrapping, but is not exactly either one). I also repeat this exercise for all firms in Compustat, going further back in time to a pre-crisis period[14]. Second, I run one panel regression in 2008, interacting the event dummies with firm, bank, and loan characteristics. The aim is to show that these characteristics are not significant on an average day, but become significant on specific dates.

[Table 7 here]

Table 7 reports the time-series summary statistics of the saved coefficients, the point estimates previously reported on the day of Lehman's bankruptcy and the TARP announcement, and their corresponding non-parametric p-values calculated from the empirical distribution. In Panel A, p-value of the coefficient on UNRATED observed on September 15, 2008 (Lehman Brothers bankruptcy) is 0.036, which means that only on 9 days out of the 253 trading days were the estimated coefficients greater in magnitude than the value observed on September 15. In other words, there were only 9 days in 2008 when the performance of unrated firms relative to investment grade firms was worse than the time around Lehman Brothers' bankruptcy. Similarly, junk rated firms' relative performance was worse only on 13 days (p=0.051). P-values for LEAD BANK MORTGAGE and LEAD BANK TIER 1 CAP. RATIO are lower (0.016 and 0.024, respectively). In Panel B, I run the same tests for the Compustat sample in 2008. The p-values are 0.020

[14]The DealScan sample is not useful before 2008 for this methodogy becase the borrower-lender matching is done in 2006-2007

for UNRATED and 0.059 for "JUNK" RATED. LEVERAGE and EBITDA also exhibit p-values below 5%. Overall, there is not much evidence to warrant volatility as the driving factor behind abnormal returns.

In Panel C, I report results obtained in the pre-crisis period, 2005-2007, using the Compustat sample. The empirical p-values for both "JUNK" RATED and UNRATED turn out to be identically zero in these tests. It is possible that on some days one (or both) of these groups of firms may have underperformed investment grade firms, but there does not exist a single day in 2005, 2006, or 2007 where that difference exceeds what was observed on the day of Lehman Brothers' bankruptcy. These tests demonstrate that non-investment grade firms do *not* consistently underperform investment grade firms; hence we can rule out the explanation that the abnormal returns represent some sort of asset-pricing anomaly.

[Table 8 here]

Table 8 presents pooled OLS regressions using the DealScan sample in 2008. The dependent variable is the daily abnormal return and the same set of explanatory variables are used (only selected variables are displayed to save space). Standard errors are clustered by day. Interaction terms are included as three separate sets to avoid collinearity issues. As expected, the variables which were successful in explaining the cross-section of returns on specific event days are not significant when all trading days are included in the regressions. Interaction terms with the event dates on the other hand, are. Roughly speaking Columns 1 represent the importance of having access to capital markets , Columns 2 represent the relative ease of obtaining new bank loans, and Columns 3 represent the financial conditions of the lender, all of which become important for valuations when there is a shock to the banking industry.

4.5 Robustness

All regressions thus far were estimated using ordinary least squares (OLS). While they all included industry dummies, I employ two additional methods in this section to control for industry-level heteroskedasticity and demonstrate the robustness of the results. In Table 8 columns named "Clustered Std. Errors" represent OLS regressions with standard errors clustered at the Fama-French 12 industry level. Columns named "Weighted Least Squares" report a 2-stage generalized least squares (GLS) estimation, in which the first stage uses the regression residuals to estimate industry variances, and the second weights the observations by the reciprocal of those industry variances. Because GLS is more efficient than standard OLS theoretically, I expect more precise estimates with this approach (assuming the specifications are valid).

[Table 9 here]

The results in Table 9 confirm these expectations. T-statistics for "JUNK" RATED and UNRATED are larger than the ones found in Table 4. To illustrate, on the day of Lehman's bankruptcy the coefficient on UNRATED in Column 2 obtained using weighted least squares has a t-statistic of -5.14, whereas the same coefficient obtained using OLS has a t-statistic of -3.17. For the same variable on the TARP date, the weighted least squares returns a t-statistic of 2.29 whereas OLS returns 1.06. T-statistics of other variables of interest, such as EBITDA, LENGTH of RELATIONSHIP, 9-TARP, TOTAL LINES, among others, resemble previous findings and are higher in some cases. TOTAL LINES for example, goes from being significant at the 5% level to 1% when estimated by weighted least squares as opposed to ordinary least squares. Statistical significance aside, clustered standard errors vs. weighted least squares yield remarkably close point estimates, reaffirming that the regressions are properly specified. For example, the coefficients on UNRATED are -2.096 and -2.286, 9-TARP are -1.973 and -1.851, and NUMBER of PARTICIPANTS are identical at 0.047.

5 Conclusion

In this paper I examine the value of banking relationships by observing changes in the market valuations of non-financial firms with varying degrees of bank dependence, bank quality, and credit usage. The financial crisis of 2008 is an ideal opportunity to observe these changes because the subprime mortgages that gave rise to the crisis were not associated with business lending or the non-financial firms' performance. This allows me to treat banking related events in the crisis such as the collapse of Lehman Brothers, as exogenous shocks. I expect changes in bank durability to be reflected in the stock prices of non-financial firms if these firms cannot costlessly replace bank financing.

Even though in a perfect capital market the type of financing should not affect firm value, theory has emphasized the banks' unique ability to reduce financial frictions such as information asymmetry and moral hazard, and thus create value. My findings support this view, and in addition suggest that the value of banking relationships is not strictly limited to small firms, or to the bank's pre-existing clients. I find that generally, more bank-dependent firms were hurt more by Lehman Brothers' bankruptcy, and were helped more by the government bailouts.

Banks' financial health also plays a role in the market valuations of their borrowers in periods of market turmoil. The more deeply invested in mortgages and less adequately capitalized a bank was, the lower were the stock returns of its borrowers at the time of Lehman's collapse, and higher at the announcement of the TARP capital injections. If the borrower has an investment grade rating, they seem immune to the financial conditions at their banks, presumably as a result of their ability to substitute bonds or commercial paper for bank credit. The Fed Chairman Ben Bernanke's remark, "money was easy for a few safe borrowers, but difficult for everyone else"[15], regarding the great depression is equally apt for the current crisis.

[15] It is possible to draw more parallels between the Great Depression and the current financial crisis. See Bernanke (1983) for a detailed discussion.

Particularly among unrated firms – the group who is the most bank-dependent – higher levels of bank lines of credit contracted on before the crisis led, curiously, to lower stock performance at the time of the crisis. This result implies that credit lines may only provide a firm liquidity insurance if the banks themselves are not liquidity constrained, or insolvent. The syndication of these lines benefits the firm. Greater the number of banks that participate in a deal, higher was the firm's stock return.

Using the TARP funds to inject capital directly into the banks appears to have benefitted not only Wall Street, but also Main Street, as evidenced by the positive stock returns experienced by the more bank-dependent firms. Nevertheless, I shy away from making specific policy recommendations based on these findings. For some, empirical evidence demonstrating the interconnectedness of the banking industry and the spillover effects to outside industries provide justification for the government bailouts. For others, the same results call for a overhaul of the regulatory system and an effort to end "too big to fail". Hopefully, this paper can aid such discussions with its analysis of the current events.

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Table 1: Summary statistics on public firms in Compustat

Dataset includes public firms in the Compustat annual files in 2007 whose balance sheets record nonzero long-term debt, or debt in current liabilities, and whose stock returns are available on September 15th, 2008. Firms in the financial, real estate, insurance, and construction sectors are excluded. Compustat variables are winsorized at 1% and 99%. BID-ASK is the ask price minus the bid price on the event date, divided by the average share price over the previous three months (excluding the event date). SIZE is the market value of equity on the last day of 2007. BOOK-TO-MARKET is book value divided by market value of equity. Book value is the stockholders' book equity, plus balance sheet deferred taxes and investment tax credit, minus the redemption, liquidation, or par value (in that order) of preferred stock. If stockholders' equity is missing I substitute in the book value of common equity plus the par value of preferred stock, or the book value of assets minus total liabilities (in that order). DIVIDEND YIELD is the total common/ordinary dividends divided by market value of equity. CASH is Compustat item Cash and Short-Term Investments, EBITDA is Earnings Before Interest, LEVERAGE is Long-Term Debt plus Debt in Current Liabilities, PP&E is Property, Plant and Equipment, all normalized by total assets.

	Borrower characteristics							
Statistic	**BID-ASK**	**SIZE($M)**	**BOOK-TO -MARKET**	**DIVIDEND YIELD**	**CASH**	**EBITDA**	**LEVERAGE**	**PP&E**
	Panel A: Investment Grade Rated Firms							
Mean	0.255	24043	0.518	0.019	0.072	0.147	0.246	0.337
Median	0.100	8955	0.413	0.014	0.046	0.138	0.243	0.263
Std. Dev.	1.012	47061	0.409	0.031	0.076	0.065	0.126	0.232
Obs	381	381	381	381	381	381	381	381
	Panel B: Speculative ("Junk") Grade Rated Firms							
Mean	0.423	2924	1.319	0.038	0.087	0.125	0.419	0.347
Median	0.161	1434	0.577	0.000	0.049	0.118	0.370	0.297
Std. Dev.	1.176	4685	8.683	0.375	0.112	0.072	0.323	0.252
Obs	493	493	493	493	493	493	493	493
	Panel C: Unrated Firms							
Mean	1.865	848	1.183	0.034	0.227	0.017	0.217	0.232
Median	0.439	247	0.469	0.000	0.124	0.089	0.154	0.144
Std. Dev.	3.363	2836	8.003	0.452	0.250	0.240	0.277	0.232
Obs	1687	1687	1687	1687	1687	1687	1687	1687

TABLE 2: CROSS-SECTIONAL REGRESSIONS OF ABNORMAL STOCK RETURNS ON FIRM CHARACTERISTICS IN COMPUSTAT

The dependent variable is the firm's abnormal stock return on the event date. Abnormal return is the realized return minus the expected return according to the Fama-French three-factor model. Model parameters are estimated from daily returns in 2007 at the firm level. In Panel A, the event date is September 15, 2008, the day on which Lehman Brothers filed for bankruptcy. In Panel B, the event date is October 14, 2008, the day on which the Treasury announced the capital injections into the nine largest US banks under the Troubled Asset Relief Program (TARP). Balance sheet items and S&P credit ratings are measured at the end of the company's fiscal year in 2007. Compustat variables are winsorized at 1% and 99%. "JUNK" RATED is a dummy that takes on the value of 1 if the firm has a S&P long-term debt rating that is equal to BB+ or below, 0 otherwise. UNRATED is a dummy that takes on the value of 1 if the firm has no S&P long-term debt rating, 0 otherwise. Investment-grade rating is the omitted category. COVENANT VIOLATE is a dummy that takes on the value of 1 if the firm has a covenant violation reported in the SEC filings in 2007 or in 2008, before Lehman Brothers' bankruptcy. Firms with no debt are excluded from the sample, as well as firms in the financial, real estate, insurance, and construction sectors. In column 4 of both panels firms smaller than the smallest investment grade rated firm (measured by market value of equity) are dropped. All specifications include (but do not report) industry dummies using Fama-French 12 industry definitions. T-statistics based on OLS standard errors are in parentheses.

	Panel A: Lehman Brothers Bankruptcy				Panel B: TARP - 9 BANKS announcement			
Variables	(1)	(2)	(3)	(4) Size > $391M	(1)	(2)	(3)	(4) Size > $391M
BID-ASK	0.125	0.100	0.110	-0.158	-0.063	-0.048	-0.039	-0.896
	(2.75)***	(2.17)**	(2.39)**	(-0.95)	(-0.99)	(-0.74)	(-0.59)	(-2.43)**
logSIZE	0.318	0.123	0.107	-0.411	-0.227	-0.020	-0.036	0.111
	(4.60)***	(1.36)	(1.18)	(-3.57)***	(-2.06)**	(-0.14)	(-0.25)	(0.71)
BOOK-TO-MARKET	0.019	0.018	0.018	-0.267	0.012	0.013	0.014	-0.189
	(1.30)	(1.18)	(1.24)	(-2.37)**	(0.49)	(0.55)	(0.58)	(-1.23)
DIVIDEND YIELD	0.076	0.069	0.101	0.792	-0.650	-0.629	-0.596	-4.552
	(0.27)	(0.25)	(0.36)	(0.76)	(-1.49)	(-1.44)	(-1.36)	(-3.25)***
CASH	0.146	0.538	0.320	0.174	-0.023	-0.495	-0.710	-0.223
	(0.21)	(0.78)	(0.46)	(0.21)	(-0.02)	(-0.45)	(-0.65)	(-0.20)
EBITDA	2.985	3.256	3.220	6.027	-6.147	-6.388	-6.425	-5.694
	(4.16)***	(4.52)***	(4.47)***	(5.25)***	(-5.39)***	(-5.58)***	(-5.61)***	(-3.65)***
LEVERAGE	-1.210	-1.312	-1.306	-1.476	0.198	0.510	0.512	1.784
	(-2.90)***	(-3.06)***	(-3.04)***	(-3.22)***	(0.30)	(0.74)	(0.74)	(2.88)***
PP&E	-0.389	-0.390	-0.411	0.241	0.030	0.097	0.085	-0.764
	(-0.62)	(-0.62)	(-0.66)	(0.38)	(0.03)	(0.10)	(0.09)	(-0.88)
"JUNK" RATED		-0.868	-0.861	-1.621		0.185	0.193	0.531
		(-1.96)**	(-1.95)*	(-4.35)***		(0.27)	(0.28)	(1.05)
UNRATED		-1.514	-1.490	-2.157		1.460	1.482	1.689
		(-3.30)***	(-3.25)***	(-5.44)***		(2.03)**	(2.06)**	(3.15)***
COVENANT VIOLATE			-0.833	-1.147			-0.826	-0.220
			(-2.24)**	(-2.39)**			(-1.41)	(-0.34)
Observations	2561	2561	2561	1448	2540	2540	2540	1443
R-squared	0.073	0.077	0.079	0.147	0.060	0.063	0.064	0.104

TABLE 3: SUMMARY STATISTICS ON BORROWERS, LENDERS, AND LOANS IN DEALSCAN

Dataset is built from all public firms in the 2006 and 2007 version of DealScan, for whom balance sheet information exists in Compustat as of 2007, and whose stock returns are available on September 15th, 2008. Among those, only the firms whose lead banks (lead arranger, bookrunner, etc.) in the loan deals are commercial banks or bank holding companies that can be matched to the FDIC Call Reports at the end of 2007 are used. Borrowers in the financial, real estate, insurance, construction, and utilities sectors are excluded. Deals in which Lehman Brothers is recorded as a lead bank are excluded. Only credit line deals are used in the sample, which are identified by the "loan type" variable indicating "Revolver", "Line", or "364-Day Facility". LEAD BANK TIER 1 CAP. RATIO is data item Tier 1 Capital divided by the Risk-Weighted Assets, LEAD BANK DEPOSITS is data item Total Deposits minus Wholesale Deposits divided by Total Assets, LEAD BANK MORTGAGE is data item Mortgages Secured by 1-4 Family Residential Mortgages divided by Total Assets, in the Call Report. LENGTH of RELATIONSHIP is the time in years between the first deal and the last deal that can be found in DealScan for a given borrower-lender pair. LOAN SPREAD is the interest rate in basis points that a borrower needs to pay over LIBOR when he or she draws on the line. TOTAL LINES is the sum of all loan facility dollar amounts for a given firm, divided by the total assets of the firm. NUMBER of PARTICIPANTS is the total number of lenders in a syndicated loan deal. If multiple facilities exist for a single borrower all lender and deal characteristics are weighted by the relative size of the facility.

	Borrower characteristics								*Lender characteristics*			*Deal characteristics*			
Statistic	BID-ASK	SIZE($M)	BOOK-TO -MARKET	DIVIDEND YIELD	CASH	EBITDA	LEVERAGE	PP&E	LEAD BANK TIER 1 CAP. RATIO	LEAD BANK DEPOSITS	LEAD BANK MORTGAGE	LENGTH of RELATIONSHIP	LOAN SPREAD	TOTAL LINES	NUMBER of PARTICIPANTS
Panel A: Investment Grade Rated Firms															
Mean	0.277	25047	0.504	0.019	0.069	0.149	0.246	0.325	0.081	0.423	0.145	9.511	32.792	0.163	12.083
Median	0.100	9713	0.397	0.013	0.047	0.140	0.239	0.255	0.090	0.452	0.113	9.546	28.000	0.151	11.000
Std. Dev.	1.165	46553	0.391	0.035	0.076	0.065	0.125	0.225	0.025	0.145	0.077	6.210	24.110	0.125	6.267
Obs	283	283	283	283	283	283	283	283	283	283	283	283	283	283	283
Panel B: Speculative ("Junk") Grade Rated Firms															
Mean	0.370	2819	1.015	0.026	0.071	0.123	0.416	0.335	0.076	0.390	0.150	5.707	148.094	0.224	9.364
Median	0.148	1545	0.572	0.000	0.037	0.116	0.367	0.273	0.088	0.452	0.135	4.564	150.000	0.159	7.083
Std. Dev.	0.813	3759	3.552	0.166	0.084	0.065	0.378	0.252	0.031	0.174	0.090	5.456	73.851	0.215	7.073
Obs	251	251	251	251	251	251	251	251	251	251	251	251	251	251	251
Panel C: Unrated Firms															
Mean	0.809	1649	0.973	0.050	0.091	0.124	0.243	0.262	0.080	0.449	0.184	3.456	116.875	0.356	6.264
Median	0.199	708	0.507	0.000	0.045	0.127	0.213	0.181	0.086	0.452	0.231	1.333	100.000	0.264	6.000
Std. Dev.	2.018	4101	3.117	0.468	0.114	0.102	0.260	0.235	0.021	0.146	0.085	4.530	87.760	0.440	4.604
Obs	346	346	346	346	346	346	346	346	346	346	346	346	346	346	346

TABLE 4: CROSS-SECTIONAL REGRESSIONS OF ABNORMAL STOCK RETURNS ON FIRM, BANK, AND LOAN CHARACTERISTICS IN DEALSCAN

The dependent variable is the firm's abnormal stock return on the event date. In Panel A, the event date is September 15, 2008, in Panel B, October 14, 2008. Balance sheet items and S&P credit ratings are measured at the end of the company's fiscal year in 2007. Bank characteristics are taken from the Call Report at the end of 2007. 9-BANK is a dummy that takes on the value of 1 if the lead bank in a deal was one of the initial 9 banks which agreed to receive capital under the TARP, 0 otherwise. See Tables 1-3 for the other variable definitions. Standardized coefficients are reported for LEAD BANK DEPOSITS, LEAD BANK MORTGAGE, and LEAD BANK TIER 1 CAP. RATIO. Firms with no debt are excluded from the sample, as well as firms in the financial, real estate, insurance, and construction industries. All specifications include (but do not report) industry dummies using Fama-French 12 industry definitions. T-statistics based on OLS standard errors are in parentheses.

	Panel A: Lehman Brothers Bankruptcy				Panel B: TARP - 9 BANKS announcement			
Variables	(1)	(2)	(3)	(4) Size > $391M	(1)	(2)	(3)	(4) Size > $391M
BID-ASK	-0.065	-0.017	0.020	-0.232	-0.595	-0.660	-0.679	-0.617
	(-0.68)	(-0.18)	(0.20)	(-1.29)	(-4.29)***	(-4.74)***	(-4.87)***	(-1.33)
logSIZE	-0.197	-0.456	-0.436	-0.409	-0.020	0.291	0.277	0.270
	(-1.68)*	(-3.40)***	(-3.25)***	(-2.59)***	(-0.10)	(1.25)	(1.19)	(1.18)
BOOK-TO-MARKET	0.051	0.039	0.044	0.153	-0.046	-0.023	-0.031	-0.392
	(1.03)	(0.80)	(0.90)	(0.96)	(-0.54)	(-0.28)	(-0.36)	(-1.63)
DIVIDEND YIELD	0.412	0.382	0.379	-0.245	-2.481	-2.420	-2.401	-4.374
	(0.95)	(0.89)	(0.89)	(-0.24)	(-3.35)***	(-3.28)***	(-3.26)***	(-2.96)***
CASH	1.203	1.622	1.810	1.663	0.967	0.405	0.275	-0.496
	(0.77)	(1.04)	(1.16)	(1.00)	(0.37)	(0.15)	(0.10)	(-0.21)
EBITDA	8.198	7.303	7.237	6.279	-4.518	-2.542	-2.705	-4.380
	(4.62)***	(4.12)***	(4.08)***	(2.93)***	(-1.49)	(-0.83)	(-0.89)	(-1.39)
LEVERAGE	-1.794	-1.512	-1.476	-1.448	1.932	1.584	1.401	2.028
	(-3.48)***	(-2.93)***	(-2.85)***	(-2.77)***	(2.20)**	(1.78)*	(1.57)	(2.66)***
PP&E	-0.150	-0.262	-0.252	0.034	-0.249	-0.034	-0.083	-1.228
	(-0.20)	(-0.35)	(-0.34)	(0.04)	(-0.19)	(-0.03)	(-0.06)	(-1.04)
"JUNK" RATED	-1.454	-0.881	-0.926	-0.919	-0.104	-0.973	-0.997	-0.247
	(-3.42)***	(-1.97)**	(-2.08)**	(-1.98)**	(-0.14)	(-1.27)	(-1.30)	(-0.36)
UNRATED	-1.448	-0.967	-1.013	-1.275	0.821	0.396	0.414	0.921
	(-3.17)***	(-2.10)**	(-2.20)**	(-2.77)***	(1.06)	(0.50)	(0.52)	(1.37)
COVENANT VIOLATE	-1.187	-1.072	-1.090	-1.270	-0.631	-0.856	-0.895	-0.519
	(-2.56)**	(-2.33)**	(-2.38)**	(-2.35)**	(-0.80)	(-1.08)	(-1.13)	(-0.66)
LEAD BANK		0.433				0.056		
DEPOSITS		(2.30)**				(0.17)		
LEAD BANK		-0.529	-0.532	-0.409		0.074	0.529	0.033
MORTGAGE		(-2.77)***	(-2.91)***	(-2.04)**		(0.23)	(1.68)*	(0.11)
LEAD BANK			0.483	0.358			-0.669	-0.351
TIER 1 CAP. RATIO			(2.56)**	(1.80)*			(-2.07)**	(-1.21)
LENGTH of		0.065	0.060	0.048		-0.047	-0.029	-0.040
RELATIONSHIP		(2.53)**	(2.32)**	(1.87)*		(-1.06)	(-0.65)	(-1.06)
LOAN SPREAD		-0.007	-0.007	-0.007		0.013	0.012	0.007
		(-3.05)***	(-2.92)***	(-2.53)**		(3.32)***	(3.22)***	(1.65)*
TOTAL LINES		-1.052	-0.991	0.582		0.578	0.511	0.154
		(-2.32)**	(-2.18)**	(0.76)		(0.74)	(0.65)	(0.14)
NUMBER of		0.043	0.043	0.030		-0.036	-0.045	-0.048
PARTICIPANTS		(1.73)*	(1.73)*	(1.26)		(-0.85)	(-1.07)	(-1.38)
9-TARP		-1.252	-1.824	-1.314		1.347	2.054	0.807
		(-3.05)***	(-3.98)***	(-2.50)**		(1.89)*	(2.61)***	(1.05)
Observations	880	880	880	719	874	874	874	715
R-squared	0.186	0.223	0.224	0.224	0.084	0.103	0.107	0.127

TABLE 5: REGRESSIONS WITHIN CREDIT RATING CATEGORIES

This table reports the cross-sectional regressions of abnormal stock returns of borrowers in DealScan on firm, bank, and loan characteristics, run separately within each credit rating category (i.e., investment-grade, speculative-grade, unrated), on the two event dates: Lehman Brothers' bankruptcy and the TARP announcement. The dependent variable is the firm's abnormal stock return on the event date. See Tables 1-4 for the variable definitions. The models are estimated as a system of equations and standard errors are clustered by the ratings category. All specifications include (but do not report) industry dummies using Fama-French 12 industry definitions. Chi-squared statistic and the corresponding p-value is obtained from the Wald test that jointly tests the equality of coefficients across the three models.

	Panel A: Lehman Brothers Bankruptcy			Panel B: TARP - 9 BANKS announcement		
Variables	(1) INVESTMENT GRADE RATED	(2) SPECULATIVE GRADE RATED	(3) UNRATED	(1) INVESTMENT GRADE RATED	(2) SPECULATIVE GRADE RATED	(3) UNRATED
BID-ASK	-0.207	-0.496	0.201	-1.548	0.431	-0.822
	(-4.48)***	(-1.49)	(1.70)*	(-1.92)*	(0.61)	(-1.69)*
logSIZE	-0.089	-0.771	-0.579	-0.240	1.086	0.156
	(-0.41)	(-2.72)***	(-2.18)**	(-0.97)	(2.08)**	(0.29)
BOOK-TO-MARKET	-0.388	0.034	0.042	-1.111	0.017	0.011
	(-0.49)	(1.09)	(1.32)	(-1.42)	(0.28)	(0.11)
DIVIDEND YIELD	4.741	-0.636	0.398	-2.737	1.928	-2.647
	(1.65)*	(-0.34)	(2.69)***	(-0.51)	(1.13)	(-3.39)***
CASH	-5.262	10.973	1.483	2.827	-1.197	-0.784
	(-1.66)*	(3.39)***	(0.66)	(0.82)	(-0.18)	(-0.22)
EBITDA	2.708	8.931	9.096	-6.814	-1.647	-4.236
	(0.73)	(2.70)***	(3.78)***	(-1.69)*	(-0.25)	(-1.08)
LEVERAGE	2.231	-2.946	1.039	3.746	4.137	-4.009
	(1.27)	(-6.99)***	(1.59)	(1.78)*	(2.85)***	(-1.78)*
PP&E	-0.236	-0.308	0.059	0.853	-0.886	1.316
	(-0.22)	(-0.20)	(0.05)	(0.56)	(-0.32)	(0.51)
COVENANT VIOLATE	0.635	-1.690	-1.209	-2.409	1.653	-1.837
	(0.65)	(-1.63)	(-1.59)	(-1.90)*	(1.09)	(-1.21)
LEAD BANK	-0.389	-0.720	-0.557	-0.083	1.298	0.537
MORTGAGE	(-1.53)	(-2.09)**	(-1.91)*	(-0.27)	(1.77)*	(1.06)
LEAD BANK	-0.052	0.801	0.544	-0.025	-1.981	-0.006
TIER 1 CAP. RATIO	(-0.23)	(2.09)**	(1.93)*	(-0.10)	(-2.47)**	(-0.01)
LENGTH of	0.011	0.129	0.032	0.019	-0.027	-0.075
RELATIONSHIP	(0.42)	(2.56)**	(0.65)	(0.59)	(-0.30)	(-0.78)
LOAN SPREAD	-0.001	-0.008	-0.005	-0.003	0.014	0.011
	(-0.13)	(-1.75)*	(-1.59)	(-0.42)	(1.95)*	(1.90)*
TOTAL LINES	-2.237	0.977	-1.594	-0.485	0.002	0.984
	(-1.25)	(0.99)	(-3.31)***	(-0.27)	(0.00)	(0.90)
NUMBER of	0.008	0.016	0.162	-0.011	-0.032	-0.143
PARTICIPANTS	(0.27)	(0.45)	(3.26)***	(-0.34)	(-0.53)	(-1.54)
9-TARP	-0.768	-3.012	-1.782	0.851	3.141	1.829
	(-0.98)	(-3.04)***	(-2.64)***	(0.76)	(1.70)*	(1.49)
Observations	283	251	346	281	250	343
R-squared	0.205	0.333	0.256	0.165	0.190	0.174
Wald test: Model 1=Model 2=Model 3	164.9	164.9	164.9	81.87	81.87	81.87
Prob > chi2	0.0000	0.0000	0.0000	0.0051	0.0051	0.0051

TABLE 6: CROSS-SECTIONAL REGRESSIONS OF AVERAGE ABNORMAL STOCK RETURNS ON DAYS WITH BANKING-RELATED NEWS EVENTS

The dependent variable is the abnormal return of a borrower, averaged across days which are classified as either good news or bad news events. The events are taken from the financial crisis timeline on St. Louis Fed's website and the list is given in Figure 2. "Bad News Days" and "Good News Days" are defined by the daily return of the Dow Jones US Financial Services Index being negative, or positive, respectively, on the day of the event. Lehman Brothers' bankruptcy and the TARP announcement are excluded from the list of events. In Column 1 of each panel Compustat sample is used, in remaining columns DealScan sample is used.

	Panel A: Bad News Days				Panel B: Good News Days			
Variables	(1) Compustat	(2) DealScan	(3) DealScan	(4) DealScan	(1) Compustat	(2) DealScan	(3) DealScan	(4) DealScan
BID-ASK	0.061	-0.036	-0.016	-0.014	-0.045	-0.117	-0.146	-0.137
	(2.44)**	(-0.72)	(-0.31)	(-0.28)	(-1.06)	(-1.08)	(-1.33)	(-1.25)
logSIZE	-0.052	-0.225	-0.305	-0.303	0.367	0.297	0.351	0.357
	(-0.78)	(-2.61)***	(-3.11)***	(-3.09)***	(4.58)***	(2.62)***	(2.70)***	(2.75)***
BOOK-TO-MARKET	0.055	0.073	0.068	0.069	0.017	0.034	0.041	0.043
	(5.23)***	(2.12)**	(1.97)**	(1.99)**	(1.39)	(0.76)	(0.90)	(0.94)
DIVIDEND YIELD	-0.292	-0.271	-0.277	-0.278	-0.308	-0.164	-0.181	-0.185
	(-1.50)	(-0.90)	(-0.92)	(-0.92)	(-1.34)	(-0.41)	(-0.45)	(-0.46)
CASH	-0.066	-0.944	-0.781	-0.760	0.094	-0.543	-0.415	-0.361
	(-0.14)	(-0.88)	(-0.71)	(-0.69)	(0.16)	(-0.38)	(-0.29)	(-0.25)
EBITDA	-0.087	3.151	2.692	2.700	-1.705	-4.071	-3.672	-3.658
	(-0.17)	(2.57)**	(2.15)**	(2.16)**	(-2.85)***	(-2.51)**	(-2.22)**	(-2.22)**
LEVERAGE	0.129	-0.611	-0.525	-0.510	0.240	0.213	0.110	0.142
	(0.43)	(-1.71)*	(-1.44)	(-1.40)	(0.68)	(0.45)	(0.23)	(0.29)
PP&E	-0.574	-0.665	-0.712	-0.708	0.149	-0.289	-0.325	-0.317
	(-1.31)	(-1.27)	(-1.35)	(-1.34)	(0.29)	(-0.42)	(-0.47)	(-0.45)
"JUNK" RATED	-0.664	-1.043	-0.817	-0.818	1.222	1.033	0.914	0.910
	(-2.14)**	(-3.52)***	(-2.58)**	(-2.58)***	(3.32)***	(2.63)***	(2.17)**	(2.16)**
UNRATED	-1.448	-0.773	-0.623	-0.627	0.821	1.535	1.441	1.431
	(-3.17)***	(-2.44)**	(-1.91)*	(-1.93)*	(1.06)	(3.67)***	(3.35)***	(3.33)***
COVENANT VIOLATE	-1.187	-0.830	-0.785	-0.783	-0.631	0.266	0.278	0.281
	(-2.56)**	(-2.59)***	(-2.43)**	(-2.43)**	(-0.80)	(0.63)	(0.65)	(0.66)
LEAD BANK DEPOSITS			0.020				0.070	
			(0.15)				(0.40)	
LEAD BANK MORTGAGE			-0.100	-0.132			0.029	-0.036
			(-0.74)	(-1.03)			(0.16)	(-0.21)
LEAD BANK TIER 1 CAP. RATIO				0.073				0.181
				(0.55)				(1.04)
LENGTH of RELATIONSHIP			0.021	0.019			-0.006	-0.009
			(1.15)	(1.06)			(-0.24)	(-0.38)
LOAN SPREAD			-0.003	-0.003			0.002	0.003
			(-1.93)*	(-1.90)*			(1.19)	(1.24)
TOTAL LINES			-0.291	-0.282			0.841	0.863
			(-0.91)	(-0.88)			(1.99)**	(2.04)**
NUMBER of PARTICIPANTS			0.010	0.011			0.005	0.006
			(0.57)	(0.61)			(0.20)	(0.26)
9-TARP			-0.524	-0.604			0.546	0.344
			(-1.81)*	(-1.88)*			(1.43)	(0.81)
Observations	2557	878	878	878	2561	880	880	880
R-squared	0.034	0.078	0.089	0.089	0.027	0.067	0.076	0.077

TABLE 7: EMPIRICAL DISTRIBUTION OF THE REGRESSION COEFFICIENTS

This table reports the time-series summary statistics of the cross-sectional regression coefficients, estimated and recorded on every trading day in the 2005-2008 period. The dependent variable is the firm's daily abnormal return. See Tables 1-4 for the variable definitions. Panel A reports results for the DealScan sample in 2008, Panel B reports results for the Compustat sample in 2008, Panel C reports results for the Compustat sample from 2005 through 2007. P-values corresponding to the two events (Lehman Brothers' bankruptcy and the TARP announcement) are non-parametric estimates derived from the empirical distribution in each panel.

Panel A: DealScan firms in 2008

Variables	MEAN	STD. DEV.	1th PERCENTILE	99th PERCENTILE	COEFF. on LEHMAN BROS. BANKRUPTCY	P-VALUE on LEHMAN BROS. BANKRUPTCY	COEFF. on TARP - 9 BANKS ANNOUCEMENT	P-VALUE on TARP - 9 BANKS ANNOUCEMENT
BID-ASK	*0.069*	*0.364*	*-0.775*	*1.023*	*0.020*	*0.458*	*-0.679*	*0.012*
logSIZE	*0.045*	*0.262*	*-0.642*	*0.798*	*-0.436*	*0.032*	*0.277*	*0.146*
BOOK-TO-MARKET	*-0.003*	*0.115*	*-0.391*	*0.406*	*0.044*	*0.241*	*-0.031*	*0.368*
DIVIDEND YIELD	*0.023*	*0.909*	*-2.393*	*3.123*	*0.379*	*0.237*	*-2.401*	*0.008*
CASH	*0.017*	*1.916*	*-5.064*	*4.790*	*1.810*	*0.162*	*0.275*	*0.427*
EBITDA	*0.502*	*3.562*	*-9.214*	*8.427*	*7.237*	*0.032*	*-2.705*	*0.126*
LEVERAGE	*-0.164*	*1.069*	*-2.731*	*2.516*	*-1.476*	*0.079*	*1.401*	*0.071*
PP&E	*0.026*	*1.010*	*-2.658*	*2.651*	*-0.252*	*0.372*	*-0.083*	*0.439*
"JUNK" RATED	*0.030*	*0.699*	*-1.893*	*2.582*	*-0.926*	*0.051*	*-0.997*	*0.047*
UNRATED	*0.048*	*0.675*	*-1.591*	*2.683*	*-1.013*	*0.036*	*0.414*	*0.202*
COVENANT VIOLATE	*-0.075*	*0.620*	*-1.558*	*1.801*	*-1.090*	*0.055*	*-0.895*	*0.075*
LEAD BANK MORTGAGE	*-0.006*	*0.204*	*-0.572*	*0.637*	*-0.532*	*0.016*	*0.529*	*0.016*
LEAD BANK TIER 1 CAP. RATIO	*0.015*	*0.224*	*-0.834*	*0.547*	*0.483*	*0.024*	*-0.669*	*0.012*
LENGTH of RELATIONSHIP	*0.000*	*0.029*	*-0.077*	*0.070*	*0.060*	*0.032*	*-0.029*	*0.126*
LOAN SPREAD	*-0.084*	*1.774*	*-4.396*	*4.513*	*-0.007*	*0.462*	*0.012*	*0.451*
TOTAL LINES	*0.066*	*0.741*	*-1.940*	*2.665*	*-0.991*	*0.063*	*0.511*	*0.233*
NUMBER of PARTICIPANTS	*0.001*	*0.026*	*-0.055*	*0.067*	*0.043*	*0.055*	*-0.045*	*0.040*
9-BANK	*-0.082*	*0.706*	*-2.101*	*1.949*	*-1.824*	*0.028*	*2.054*	*0.008*

Panel B: Compustat firms in 2008

Variables	MEAN	STD. DEV.	1th PERCENTILE	99th PERCENTILE	COEFF. on LEHMAN BROS. BANKRUPTCY	P-VALUE on LEHMAN BROS. BANKRUPTCY	COEFF. on TARP - 9 BANKS ANNOUCEMENT	P-VALUE on TARP - 9 BANKS ANNOUCEMENT
BID-ASK	0.080	0.153	-0.249	0.546	0.110	0.364	-0.048	0.146
logSIZE	0.075	0.228	-0.345	0.976	0.107	0.372	-0.020	0.328
BOOK-TO-MARKET	-0.001	0.034	-0.070	0.129	0.018	0.213	0.013	0.281
DIVIDEND YIELD	-0.033	0.367	-0.904	0.989	0.101	0.285	-0.629	0.055
CASH	0.126	0.849	-2.143	2.400	0.320	0.379	-0.495	0.209
EBITDA	0.204	1.874	-6.304	4.928	3.220	0.043	-6.388	0.008
LEVERAGE	-0.054	0.769	-1.790	2.457	-1.306	0.036	0.510	0.142
PP&E	-0.010	0.814	-1.741	2.588	-0.411	0.277	0.097	0.395
"JUNK" RATED	0.067	0.720	-1.696	2.869	-0.861	0.059	0.185	0.352
UNRATED	0.106	0.847	-1.957	3.989	-1.490	0.020	0.185	0.352
COVENANT VIOLATE	-0.047	0.492	-1.315	1.097	-0.833	0.055	1.460	0.059

Panel C: Compustat firms in 2005-2007

Variables	MEAN	STD. DEV.	1th PERCENTILE	99th PERCENTILE	COEFF. on LEHMAN BROS. BANKRUPTCY	P-VALUE on LEHMAN BROS. BANKRUPTCY	COEFF. on TARP - 9 BANKS ANNOUCEMENT	P-VALUE on TARP - 9 BANKS ANNOUCEMENT
BID-ASK	0.078	0.207	-0.319	0.979	0.110	0.393	-0.039	0.267
logSIZE	0.005	0.099	-0.188	0.306	0.107	0.114	-0.036	0.336
BOOK-TO-MARKET	0.000	0.042	-0.094	0.121	0.018	0.245	0.014	0.292
DIVIDEND YIELD	-0.071	1.466	-3.641	4.218	0.101	0.439	-0.596	0.340
CASH	-0.004	0.610	-1.603	1.460	0.320	0.289	-0.710	0.117
EBITDA	0.088	0.891	-2.069	2.170	3.220	0.000	-6.425	0.000
LEVERAGE	0.008	0.402	-0.968	1.005	-1.306	0.003	0.512	0.093
PP&E	0.023	0.408	-0.902	0.986	-0.411	0.138	0.085	0.431
"JUNK" RATED	0.016	0.214	-0.477	0.575	-0.861	0.000	0.193	0.179
UNRATED	0.004	0.264	-0.538	0.659	-1.490	0.000	1.482	0.003
COVENANT VIOLATE	-0.058	0.253	-0.632	0.556	-0.833	0.004	-0.826	0.004

TABLE 8: PANEL REGRESSIONS WITH EVENT DATE INTERACTIONS

This table extends the DealScan dataset in Table 4 to every trading day in 2008, essentially forming a panel. Pooled OLS regressions are run where the dependent variable is the firm's daily abnormal stock return. Standard errors are clustered by time (day). Event days are represented by a dummy variable: In Panel A, EVENT is equal to 1 if the date of the observation is equal to September 15, 2008, 0 otherwise, in Panel B, EVENT is equal to 1 if the date of the observation is equal to October 14, 2008, 0 otherwise. Borrower characteristics from Compustat are included in the regressions but are not reported.

	Panel A: Lehman Brothers Bankruptcy			Panel B: TARP - 9 BANKS announcement		
Variables	(1)	(2)	(3)	(1)	(2)	(3)
"JUNK" RATED	0.027 (0.59)	0.025 (0.55)	0.025 (0.55)	0.014 (0.30)	0.024 (0.54)	0.024 (0.54)
UNRATED	0.062 (1.41)	0.062 (1.39)	0.062 (1.39)	0.057 (1.28)	0.061 (1.39)	0.061 (1.39)
COVENANT VIOLATE	-0.052 (-1.20)	-0.046 (-1.08)	-0.052 (-1.20)	-0.052 (-1.20)	-0.057 (-1.30)	-0.052 (-1.20)
LEAD BANK MORTGAGE	-0.004 (-0.33)	-0.004 (-0.33)	-0.003 (-0.30)	-0.004 (-0.32)	-0.004 (-0.32)	-0.003 (-0.28)
LEAD BANK TIER 1 CAP. RATIO	0.003 (0.25)	0.003 (0.25)	0.002 (0.20)	0.003 (0.25)	0.003 (0.25)	0.004 (0.34)
LENGTH of RELATIONSHIP	0.000 (-0.08)	-0.001 (-0.29)	0.000 (-0.08)	0.000 (-0.08)	0.000 (-0.13)	0.000 (-0.08)
LOAN SPREAD	0.001 (0.14)	0.001 (0.11)	0.001 (0.14)	0.001 (0.14)	0.001 (0.14)	0.001 (0.13)
TOTAL LINES	0.053 (1.15)	0.059 (1.28)	0.053 (1.15)	0.053 (1.16)	0.050 (1.04)	0.053 (1.16)
NUMBER of PARTICIPANTS	0.001 (0.35)	0.001 (0.35)	0.001 (0.35)	0.001 (0.35)	0.001 (0.35)	0.001 (0.35)
9-TARP	-0.080 (-1.62)	-0.080 (-1.62)	-0.080 (-1.62)	-0.080 (-1.62)	-0.080 (-1.62)	-0.085 (-1.73)*
"JUNK" RATEDxEVENT	-0.484 (-9.85)***			2.644 (54.76)***		
UNRATEDxEVENT	-0.183 (-6.06)***			0.999 (29.33)***		
COV. VIOLATExEVENT		-1.339 (-26.86)***			1.375 (25.30)***	
LENGTH of RELATIONSHIPxEVENT		0.098 (42.52)***			0.025 (10.84)***	
TOTAL LINESxEVENT		-1.365 (-28.00)***			0.982 (19.34)***	
LEAD BANK MORTGAGExEVENT			-0.078 (-7.04)***			-0.137 (-9.87)***
LEAD BANK TIER 1 CAP. RATIOxEVENT			0.174 (15.01)***			-0.307 (-24.11)***
9-TARPxEVENT			-0.070 (-2.24)**			1.352 (42.72)***
Observations	191407	191407	191407	191407.000	191407	191407
R-squared	0.001	0.001	0.001	0.001	0.001	0.001

TABLE 9: INDUSTRY-CLUSTERED STANDARD ERRORS AND WEIGHTED LEAST SQUARES

This table reports the cross-sectional regressions of abnormal stock returns of borrowing firms in DealScan on firm, bank, and loan characteristics. Unlike previous regressions, industry dummies are not included. Industry-level heteroskedasticity is taken account of as following: Columns 1 and 3 cluster standard errors by industry, columns 2 and 4 utilize a 2-stage GLS methodology where observations are weighted by the reciprocal of their estimated (first-stage) industry variance.

	Panel A: Lehman Brothers Bankruptcy				Panel B: TARP - 9 BANKS announcement			
Variables	Clustered Std. Errors	Weighted Least Squares	Clustered Std. Errors	Weighted Least Squares	Clustered Std. Errors	Weighted Least Squares	Clustered Std. Errors	Weighted Least Squares
BID-ASK	-0.092	-0.087	-0.002	0.037	-0.598	-0.688	-0.689	-0.600
	(-0.79)	(-0.86)	(-0.02)	(0.37)	(-1.30)	(-4.96)***	(-1.45)	(-4.11)***
logSIZE	-0.327	-0.364	-0.587	-0.618	0.114	0.170	0.443	0.512
	(-5.18)***	(-3.10)***	(-6.19)***	(-4.70)***	(0.46)	(0.91)	(1.86)*	(2.54)**
BOOK-TO-MARKET	0.035	0.045	0.021	0.021	-0.035	-0.042	-0.014	-0.019
	(1.04)	(0.83)	(1.63)	(0.41)	(-0.44)	(-0.48)	(-0.19)	(-0.22)
DIVIDEND YIELD	0.478	0.378	0.455	0.369	-2.278	-2.366	-2.189	-2.240
	(2.65)**	(0.86)	(2.46)**	(0.86)	(-2.68)**	(-3.30)***	(-2.67)**	(-3.12)***
CASH	-0.214	-0.625	0.504	0.553	4.231	4.090	3.188	1.469
	(-0.19)	(-0.41)	(0.49)	(0.37)	(1.84)*	(1.65)*	(1.62)	(0.63)
EBITDA	9.230	7.923	7.952	7.363	-6.485	-6.284	-4.213	-4.451
	(3.94)***	(4.49)***	(4.49)***	(4.36)***	(-2.38)**	(-2.25)**	(-1.67)	(-1.65)*
LEVERAGE	-1.498	-1.489	-1.114	-0.882	2.192	2.467	1.563	3.038
	(-1.54)	(-2.79)***	(-1.03)	(-1.60)	(0.82)	(2.96)***	(0.56)	(3.96)***
PP&E	-1.583	-1.298	-1.526	-1.990	-0.694	-0.570	-0.592	-1.149
	(-0.70)	(-2.19)**	(-0.81)	(-3.44)***	(-0.37)	(-0.61)	(-0.30)	(-1.28)
"JUNK" RATED	-2.055	-2.381	-1.342	-1.476	0.150	0.533	-0.991	-0.429
	(-3.88)***	(-5.81)***	(-3.07)**	(-3.35)***	(0.28)	(0.83)	(-1.73)	(-0.64)
UNRATED	-2.096	-2.286	-1.474	-1.645	1.246	1.609	0.624	1.266
	(-4.36)***	(-5.14)***	(-4.06)***	(-3.61)***	(2.15)*	(2.29)**	(1.18)	(1.84)*
COVENANT VIOLATE	-1.251	-0.971	-1.096	-0.881	-0.562	-0.267	-0.939	-1.018
	(-2.07)*	(-1.97)**	(-1.89)*	(-1.87)*	(-0.61)	(-0.34)	(-1.01)	(-1.36)
LEAD BANK			-0.345	-0.329			0.554	0.399
MORTGAGE			(-2.03)*	(-1.78)*			(1.63)	(1.40)
LEAD BANK			0.325	0.224			-0.727	-0.432
TIER 1 CAP. RATIO			(1.13)	(1.18)			(-2.40)**	(-1.51)
LENGTH of			0.082	0.074			-0.052	-0.041
RELATIONSHIP			(2.84)**	(2.86)***			(-1.56)	(-1.04)
LOAN SPREAD			-0.008	-0.009			0.014	0.012
			(-2.70)**	(-3.96)***			(2.53)**	(3.40)***
TOTAL LINES			-1.355	-1.688			0.452	0.445
			(-2.11)*	(-3.55)***			(0.59)	(0.57)
NUMBER of			0.047	0.047			-0.048	-0.052
PARTICIPANTS			(2.62)**	(1.86)*			(-1.31)	(-1.35)
9-TARP			-1.973	-1.851			2.024	1.605
			(-3.52)***	(-3.95)***			(1.99)*	(2.23)**
Observations	880	880	880	880	874	874	874	874
R-squared	0.088	0.086	0.141	0.157	0.051	0.064	0.080	0.089

FIGURE 1: INTERBANK LENDING CONDITIONS THROUGHOUT THE CRISIS

This figure shows the time-series of the daily TED spread from July 2008 to July 2009. TED spread is the difference between 3-month LIBOR and the 3-month Treasury bill rate, hence is an indicator of the willingness of the banks to lend to each other. Higher values imply higher risk of default. The two marked points refer to the bankruptcy of Lehman Brothers and the announcement of the capital injections under the TARP. The units are in percentage points. Source: Bloomberg

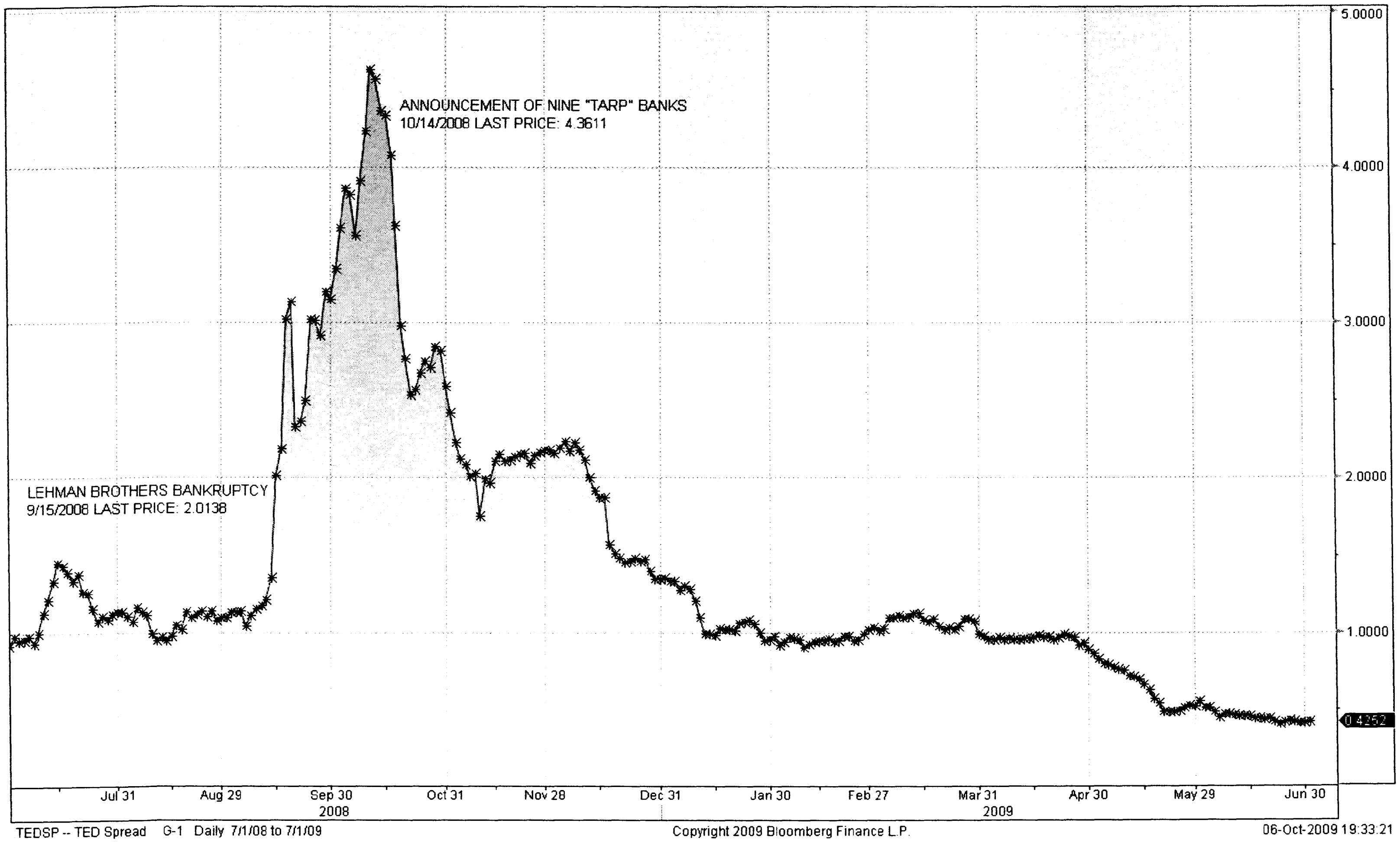

Figure 2: Timeline of the banking related events in the last quarter of 2008

This figure reports the daily returns of the Dow Jones US Financial Services Index on event dates taken from the St. Louis Fed's web site on the financial crisis.