Deleveraging Risk

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Abstract

Deleveraging risk is the risk attributable to the existence of levered positions. When funding liquidity evaporates securities with a greater presence of levered investors experience extreme return realizations as investors unwind their positions. Using unique data from equity lending markets as a proxy for the degree of leverage in a stock, we find large positive returns and reductions in short selling quantities around periods of funding illiquidity. For example, during the Quant crisis, the daily abnormal returns to a portfolio that sells highly-shorted stocks and buys lowly-shorted ones is -166 basis points, in contrast with +11 basis points during "normal" days.

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1. Introduction

Using a unique and proprietary dataset tracking the actions of participants in the equity lending market, we find strong evidence that the presence of levered investors has an effect on security prices, especially during periods associated with higher funding liquidity risk (e.g., Brunnermeier and Pedersen (2009)). Stocks held by investors who are more likely to employ leverage as part of their investment strategies carry an additional source of risk. This risk is the withdrawal of funding capital used to maintain the investors' portfolio exposures or an increase in margin requirements, forcing investors to sell their long positions and cover their short positions.[1] This forced reduction in available arbitrage capital will have a positive price impact on securities that have a relatively high degree of levered investors that are short a particular stock.

Prior research has found robust evidence that stocks with high levels of short selling activity experience poor future performance (e.g., Aitken et al. (1998); Dechow et al. (2001); Asquith et al. (2005); Boehmer et al. (2008); and Cohen et al. (2007)). However, our main focus is not on the average negative relation between short selling activity and future stock returns, but on the occasional strong *positive* relation between short selling activity and future stock returns. We use the intensity of short selling activity to capture the degree of leverage of investors that are short a particular stock. Our hypothesis is that short sellers set up their strategies with widespread usage of leverage and stocks with the highest levels of short selling activity are the ones facing the highest levels of deleveraging risk when arbitrage capital is suddenly withdrawn.

For several measures of short selling activity we find a negative relation between short selling and future stock returns, consistent with past research documenting that short sellers are on average sophisticated investors exploiting negative information about firms. However, we find robust

[1] There is no comprehensive study examining hedge fund leverage ratios due to lack of comprehensive data. A 2010 report by Hedge Fund Research (HFR) cited by Mitchell and Pulvino (2012) estimates a 2.6 leverage ratio. The report also describes that more than 70% of single-manager hedge funds say that they employ leverage. A recent research report from Credit Suisse notes that the average current leverage across hedge funds operating on their platform is 2.65 (Kinderlerer and Leonard, 2013). However, there is considerable variation in leverage across hedge fund styles with multi-strategy investment vehicles having leverage close to 4.0 and event driven strategies having leverage closer to 2.0.

evidence that this negative relation is interrupted by occasional periods of very positive returns for some stocks: those with the highest levels of short selling experience occasional periods of very strong positive returns. We further find that these occasional positive returns are attributable to economy-wide liquidity shocks such as the Quant crisis of August, 2007 and the Lehman Brothers bankruptcy in September, 2008. For example, during the Quant crisis in August 2007 we find that the daily equal (value) weighted abnormal returns to a portfolio that sells highly-shorted stocks and buys lowly-shorted ones is about -166 (-164) basis points, in contrast with 11 (5) basis points during "normal" trading days. There is a striking asymmetry to the returns of long/short portfolios that are exposed to funding leverage: the effect is almost entirely attributable to losses in those stocks with high levels of short selling activity.

The typical long/short equity investment strategy employed by a market neutral hedge fund starts with an initial equity of $X. The investor will then create a portfolio with weights such that the final portfolio has a desired *ex-ante* risk level. To achieve the target level of risk, the fund manager will typically employ leverage via a prime brokerage relationship. Specifically, the fund manager will arrange to 'borrow' $L·X worth of securities and use the proceeds from the sale of these securities to purchase $L·X worth of securities (where L > 1 is the extent of net leverage in the portfolio). This arrangement of locating and borrowing securities led to the creation of the equity lending market.

Widespread use of leverage by short sellers across securities makes equity lending markets a natural source of data to quantify the presence of levered investors and the potential effect on stock prices. We use data from Markit (previously Data Explorers), a company that collects information from the lending desks of most of the large firms in the securities lending industry. The data comprises daily security-level information on the value of shares available for lending, loan transactions and loan fees for a large sample of U.S equity securities over the July 2006 to February 2011 time period.

Our primary measure of short selling activity is the ratio of the value of securities on loan on a given day to the total market capitalization of that security, '*ONLOAN*'. We also employ other alternative measures of short selling such as (i) the ratio of the number of securities on loan on a given day to the number of shares that were available to be loaned, '*UTILIZATION*' , (ii) the ratio of the number of shares sold short on a given day to the total number of shares traded that day from NYSE's SuperDOT platform, '*SHORT VOLUME*', and (iii) the ratio of the number of shares shorted to the number of shares outstanding, '*SHORT INTEREST*'.[2]

We find a positive relation between returns to a portfolio that mimics short selling activity and systemic measures of liquidity risk such as changes in (i) the VIX index, (ii) the Treasury-Euro Dollar (TED) spread, (iii) changes in both credit spreads and equity returns of large banks that provide leverage to hedge funds, (iv) the Quant crisis of August, 2007 and (v) the Lehman Brothers bankruptcy in September, 2008. When there is evidence of a dislocation in the ability of levered investors to source levered capital, it coincides with positive returns for securities that have a greater concentration of levered short sellers.

In supplemental analyses we also examine whether these occasional positive returns for highly shorted securities are a temporary or permanent affect. When we extend the analysis out to 15 days past the initial funding liquidity shock we continue to see a pattern of increased security prices across the majority of our funding liquidity measures. This suggests that the effect is not reversed in the immediate term. We also find evidence of a significant reduction in equity loan quantities following periods of deleveraging events over the next 15 days for the majority of our funding liquidity measures. Together, these results suggest that an inability for levered investors to maintain their position sizes is the most likely explanation for the occasional strong positive relation between

[2] While *SHORT INTEREST* is only available at a monthly frequency, it spans a much larger period ranging from January 1990 to February 2011. We use the monthly Volume Summary files from the NYSE to compute *SHORT VOLUME* and compute this measure for a smaller sample of U.S. equity securities that are traded on the SuperDOT platform for the July 2006 to February 2011 time period.

short selling activity and future returns, and that this effect continues for some time after the initial funding liquidity shock.

Our analysis focuses directly on the existence of levered investors as a potential source of tail risk. We do not focus on a given anomalous return strategy such as momentum, and instead focus on a portfolio that replicates the positions of levered short sellers. Under our maintained assumption that short selling is directly related to presence of levered investors, we have a relatively clean measure of cross-sectional differences in the presence of levered invested capital. Thus, it enables us to focus on the *direct* asset pricing implications of levered positions on a particular stock. Our analysis therefore has the potential to explain tail risk across a variety of strategies, not just momentum (see e.g., Daniel and Moskowitz (2012); Daniel et al. (2012), Barroso and Santa-Clara (2013)).

While our focus is on assessing the impact of deleveraging risk on equity securities, there is a related literature exploring the impact of leverage constraints and deleveraging risk. For example, Garleanu and Pedersen (2011) show that margin constraints bind with negative shocks to fundamentals creating price gaps between securities with identical cash flows but different margin requirements. Likewise, Brunnermeier and Pedersen (2009) show that funding liquidity can have significant effects on asset prices and, in particular, funding liquidity can reinforce margin requirements leading to large and sudden moves in security prices. More generally, Duffie (2010) and Mitchell and Pulvino (2012) show that jumps in price gaps, and hence large ‘tail’ returns, are evident across a variety of ‘arbitrage’ strategies including: (i) CDS-corporate bond arbitrage, (ii) convertible debt arbitrage, (iii) merger arbitrage, (iv) closed-end fund arbitrage, (v) index arbitrage, and (vi) ‘on the run’ vs. ‘off the run’ treasury auction arbitrage. The impact of deleveraging risk, as reflected by the reduction in hedge fund capital deployed to these risky levered ‘arbitrage’ strategies, is consistent with our analysis. We are able to show a far broader impact of deleveraging risk into the full cross-section of equity securities, beyond traditional ‘arbitrage’ strategies.

Our empirical approach is also related to the notion of stock price 'fragility' described in Greenwood and Thesmar (2011), who extract measures of shared ownership from quarterly mutual fund data for US equity securities. They find that shared ownership is associated with additional co-movement across securities beyond that expected given industry membership and firm fundamentals. Such an approach could be related to the existence of levered positions but it is less likely as the data used to identify the shared ownership are from the positions of traditional long-only fund managers. These fund managers are exposed to liquidity shocks, but the common holdings of unlevered investors *cannot* be the trigger for such effects. By focussing on cross-sectional and time series differences in equity lending market activity, we are able to more directly identify securities which are most susceptible to (il)liquidity shocks due to sudden withdrawal of funding capital.

2. Research design

2.1 Data Sources

The main variables used in the paper are summarized in the Appendix. We obtain our measures of short selling activity from three sources: Markit (previously Data Explorers), NYSE and Compustat. Our daily measures of *ONLOAN* and *UTILIZATION* use data sourced from Markit, who collect data on equity loans and lendable amounts from major participants in the securities lending industry. According to Markit, the data cover more than 85% of the transactions in this industry. We are able to measure *ONLOAN* and *UTILIZATION* for the period July 2006 and February 2011. An alternative daily measure of short selling activity, *SHORT VOLUME,* is constructed from the Volume Summary files provide by the NYSE. We only have this data for the period between July 2006 and February 2011 for those securities who trade on NYSE's SuperDOT platform. Our monthly measure of *SHORT INTEREST* is obtained from Compustat who gather monthly short interest reports directly from the U.S. stock exchanges, and this measure is available from January 1990 to February 2011. As of December 31st, 2010, there are more than $3.16 trillion dollars' worth of stocks available to borrow and $253 billion on loan from 702,826 reported transactions.

We then merge our sample of securities with available short selling measures with data from CRSP, Compustat and Thomson Reuters. From CRSP, we exclude closed-end funds, American Depositary Receipts (ADRs) and real estate investment trusts (REITs) and keep only common shares, collecting data on daily returns, market capitalization, stock turnover, and bid-ask spreads. These data are further merged to Compustat for accounting variables needed to compute book-to-market (B/P), earnings-to-price (E/P) and accrual measures.[3] We obtain institutional ownership data from the Thomson Reuters CDA/Spectrum database, with quarterly holdings data reported by investment companies and money managers with assets over $100 million under management. From Datastream, we download the VIX index to proxy for changes in volatility, and use the TED spread as a proxy for the funding costs faced by leveraged investors. Furthermore, we use the mid-rate price of the five-year CDS index of the U.S. Banking Sector (CDS5y - Banks) as a proxy for counterparty risk (Arora et al. (2012); Gorton and Metrick (2012)). As reported by Gorton and Metrick (2012), during the financial crisis it was very difficult for banks to obtain repo financing using non-Treasury securities as collateral, which in turn constrained the funding capital available for hedge funds. As an additional robustness test we also employ the returns of the U.S. Banking Sector Index from Datastream. Finally, the Fama-French and momentum factors' daily portfolio returns (i.e. MKT, SMB, HML and UMD) are taken from WRDS.[4]

It is important to clarify the timing of short sales and the measurement of equity lending variables. Following a short sale on day *t*, the short seller needs to settle the trade and deliver the

[3] Accruals are computed similar to Dechow et al. (1995).

[4] In unreported analysis we have replicated all of our empirical analyses after removing securities with share price below $5. Our findings and inferences are unaffected by this filter, suggesting that the results we document are not attributable to a liquidity effect in small, illiquid securities.

securities by *t+3*. Equity loans are settled on the same day the loan is initiated, so a short seller can borrow the shares at *t+3* for delivery to the buyer and minimize his borrowing costs (Geczy et al. (2002)). Thus, *ONLOAN* observed on day *t* captures short sales that were initiated at *t-3*. For regressions with returns as the dependent variable we use *ONLOAN* observed at time *t* since it is what is available to investors at time *t*, similar to the approach followed by Ringgenberg (2011). Whenever the dependent variable is the quantity of short selling taking place on day *t* we use *ONLOAN* measured from *t+3*.

2.2 Hypothesis Development

Our ideal research design would require identification of the portfolio weights of all portfolios that use leverage for both long and short positions, which is not possible with publicly available data. Instead, we use various measures of short selling activity to proxy for latent leverage. Our maintained assumption is that short sellers set up their strategies with widespread usage of leverage and stocks with the highest levels of short selling activity are the ones facing the highest levels of deleveraging risk when arbitrage capital is suddenly withdrawn. When liquidity evaporates and short positions need to be covered, securities with greater presence of levered investors experience a significant shock as the levered investors unwind their positions. Funding capital reductions push prices of highly shorted stocks upwards, affecting stocks with high levels of short selling activity relatively more than stocks with low levels of short selling activity. Recent research has shown that during the recent financial crisis hedge funds on aggregate sold a significant portion of their portfolios and a mix of client redemptions and margin requirements associated with deleveraging were key drivers of this selling activity (Ben-David, Franzoni and Moussawi (2012)).

A potential concern is why short positions would be affected differently than long positions. The price impact of the removal of funding liquidity should affect all levered positions. However, because we cannot observe which stocks are held by levered long investors we are unable to show the negative return impact from selling of long positions. Because of data limitations, all we can do is to identify short positions of levered investors. Hence, the asymmetry arises, in part, because we are unable to measure the long side of levered investors. We would expect that the most levered long positions would also exhibit extremely negative returns during periods of funding capital withdrawals. As discussed in the introduction, a levered investor will employ leverage via a prime brokerage relationship. A dollar-neutral fund manager will arrange to 'borrow' $\$L \cdot X$ worth of securities and use the proceeds from the sale of these securities to purchase $\$L \cdot X$ worth of securities (where $L > 1$ is the extent of net leverage in the portfolio). More generally, a fund manager may 'borrow' $\$L^S \cdot X$ worth of securities and use the proceeds from the sale of these securities to purchase $\$L^L \cdot X$ worth of securities. In either case the $\$L^S \cdot X$ worth of securities that are sold short are captured by the short selling data, but we are unable to observe the $\$L^L \cdot X$ worth of securities that are purchased by the levered investor. Thus, when we aggregate our short selling data we have a clean (noisy) measure of the presence of levered investors for securities with high (low) levels of *ONLOAN*. Securities with low (or zero) short selling activity are not necessarily those securities that levered investors are long, as they will also reflect the long positions of traditional long-only investors.

Each day we assign stocks to one of five quintiles and compute average returns on the *following* day for stocks in the bottom (*LOW)* and top *(HIGH)* quintiles using various short selling measures. We then examine the returns of the strategy that buys stocks in the bottom quintile and short stocks in the top quintile to test our hypothesis, i.e. we track the returns of the *LOW-HIGH* portfolio. While this strategy exhibits significant *positive* average returns (i.e., securities with the highest level of short selling activity have lower future returns than securities with the lowest levels of short selling activity), our main focus is on whether the portfolio is also subject to significant *negative* returns at certain times. In particular, we look at measures designed to capture the following adverse effects on levered investments: (i) significant increases in market wide volatility,

(ii) sudden increases in arbitrageurs' funding costs, and (iii) sudden drops in market wide returns. We also test whether the *LOW-HIGH* portfolio faced extremely negative returns during the Quant crisis and during the Lehman Brother's bankruptcy. While each crisis event has very different triggers, both create a need for levered investors to reduce their positions. The Quant crisis event uses the period described by Khandani and Lo (2011), from August 6th to August 8th, 2007. The Lehman Brothers' event is defined as the period from September 16th to September 18th, 2008.[5]

In our main empirical analysis, we run time series regressions of the *LOW-HIGH* portfolio returns as a function of the standard Fama-French factors (MKT, SMB and HML) as well as the momentum factor. We include specific measures designed to capture the market wide effects of (il)liquidity as reflected by: (i) changes in the VIX, (ii) changes in the TED spread, (iii) changes in credit spreads and equity returns for an index of U.S. Banks, (iv) indicator variables for large negative market returns in the previous day, and (v) indicator variables to capture the designated time periods associated with the Lehman and Quant crises as described above. In supplemental empirical analysis we also run cross sectional regressions using a panel of daily data allowing interactions of the various short selling and liquidity measures.

Our primary empirical specification is as follows:

$$\begin{aligned} RET_t = {} & \alpha + \beta_{MKT} \cdot MKT_t + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \\ & \beta_{Ret(MKT)<2.5\sigma} \cdot D_{Ret(MKT)<2.5\sigma,t-1} + \beta_{QUANT} \cdot D_{QUANT,t} + \beta_{LEHMAN} \cdot D_{LEHMAN,t} + \\ & \beta_{\Delta VIX} \cdot \Delta VIX_{t-1} + \beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{BANKS} \cdot BANKS_{t-1} + \varepsilon_t \qquad (1) \end{aligned}$$

RET is the daily (equal or value weighted) return from taking long (short) positions in securities in the bottom (top) quintile of the respective short selling measure (i.e. *LOW-HIGH* portfolio). *MKT*, *SMB*, *HML*, and *MOM* are daily factor mimicking portfolio returns. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable equal to one if the aggregate market return on the *previous* day is more than 2.5 standard deviations below the average, and zero otherwise. The standard deviation is estimated from a

[5] Note that this period is before the ban on short selling of financial stocks imposed by the SEC on Friday, September 19th, 2008 (http://www.sec.gov/news/press/2008/2008-211.htm)

GARCH(1,1) model estimated on a rolling 252-day basis. D_{QUANT} is an indicator variable equal to one for trading days between August 6th, 2007 and August 8th, 2007, and zero otherwise. D_{LEHMAN} is an indicator variable equal to one for trading days between September 16th, 2008 and September 18th, 2008, and zero otherwise. ΔVIX_{t-1} is the change in the VIX from day t-2 to day *t-1*, ΔTED_{t-1} is the change in the TED Spread from day *t-2* to day *t-1*, and $BANKS_{t-1}$ is a measure of the relative health of the US banking industry on the *previous* day. Depending on the regression specification we use either $\Delta CDS5Y - BANKS,$ the change in 5 year CDS spreads for US banks (for which data is limited to 2004 onwards), or *Returns(Banks)*, the US banking sector's equity index returns (data available back to 1990).

The timing of our various liquidity variables is also important, with all being measured at the close of the previous trading day. We choose this timing convention because we want to focus on the consequence of shocks to funding liquidity on the performance of a portfolio exposed to funding liquidity risk. Our short selling mimicking portfolio is based on information available on day *t-1*. We assess the return performance of this portfolio on day *t* and, in particular, focus on the consequence of shocks to funding liquidity immediately prior to that return performance. In unreported tests we have recomputed out various liquidity measures using data from day *t*, and our inferences are unaffected by this alternative timing choice.

3. Descriptive evidence

3.1 Determinants of ONLOAN

In table 1 we present descriptive statistics of our sample. The average (median) firm in our sample has a market capitalization of \$3.5B (\$0.4B) with 59% (64%) of its shares held by institutional investors. The average (median) firm in our sample has an institutional ownership concentration of 0.12 (0.07). On average, 19.8% of a firm's market capitalization is available for lending, with 4.8% being on loan. Some stocks are heavily borrowed while others are not borrowed at all. *ONLOAN* is as high as 83% in our sample, implying that, at times, almost all of the outstanding shares are on loan. The average (median) *SHORT VOLUME* is equal to 20.3% (20.4%) suggesting that short sales of NYSE stocks on the SuperDOT platform correspond to about a quintile of trading volume. Furthermore, the average value of *UTILIZATION* is 19.2%, implying that almost one fifth of shares available to be loaned are actually on loan. The average (median) annualized lending fee is 77 (13) basis points, showing that on average it is very cheap to borrow shares. But there are clearly exceptions where the cost of borrowing an equity security can be as high as 1,662 basis points on an annualized basis. The remainder of panel A of Table 1 reports information on our various liquidity measures in both levels and changes. Panel B of Table 1 reports percentile values for our primary variables of interest: *ONLOAN*, ΔVIX, ΔTED, and $\Delta CDS5Y - BANKS$. We use these percentile values in later empirical analysis (table 10 and figure 6) to illustrate the economic significance of the impact of changes in funding liquidity on the relation between *ONLOAN* and future returns.

Table 2 reports correlations across our variables. We compute the pairwise correlation each day and then report time series averages of these daily pairwise correlations. A few results are worth noting. Large firms have greater, but less concentrated institutional ownership. The four short selling measures (*ONLOAN*, *SHORT INTEREST*, *SHORT VOLUME* and *UTILIZATION*) have a positive correlation among each other, with the weakest values observed between *SHORT VOLUME* and the other three measures. This is to be expected as *SHORT VOLUME* reflects the flow of short selling activity and the other three measures reflect the level of short selling activity. Finally, the four liquidity measures have a strong positive correlation in levels, but much weaker correlations in changes.

Figure 1 shows the cross-sectional distribution in *ONLOAN* across the set of US securities in our sample. On each day we plot the mean, median, 20^{th}, 80^{th} and 95^{th} percentiles of *ONLOAN*. The lower tail of *ONLOAN* is relatively stable through time. In contrast, the right tail of *ONLOAN* exhibits considerably more temporal volatility. In figure 1 we have super-imposed shaded areas corresponding to the Quant and Lehman crises defined in section 2.2. It is clear that these events correspond to a significant change in terms of security borrowing and hence leverage, a necessary condition for our empirical predictions. Following the Lehman Brothers' bankruptcy, in particular, there is a noticeable decrease in *ONLOAN*, a consequence of deleveraging and the imposition of short selling constraints by the SEC.

Table 3 provides some initial descriptive evidence on the characteristics of securities that have low and high levels of short selling activity. For the sake of brevity we report these descriptive differences only for two measures of short selling activity. Panel A (B) reports descriptive differences for *ONLOAN* (*SHORT INTEREST*) for the period July 1, 2006 through to February 28, 2011 (January 1990 through to February 2011) using daily (monthly) data. Our inferences are similar for other short selling measures. Each day we sort securities into five equal sized groups based on the respective short selling measure. We then report averages of various characteristics for the bottom (LOW) and top (HIGH) quintiles, with each quintile having about 525 stocks on average. In panel A (B) we see that securities with the highest level of *ONLOAN* (*SHORT INTEREST*) are smaller (larger). In both panels A and B we see that securities with higher levels of short selling activity have (i) higher levels of institutional ownership, (ii) lower concentrations of institutional ownership, and (iii) have higher security lending fees. In terms of other firm characteristics, we rank stocks into quintiles and compute the average score associated with accruals, book-to-market, earnings-to-price and momentum. Securities with higher values of *ONLOAN* are weakly positively associated with accruals, but we see no relation between accruals and *SHORT INTEREST* (see e.g., Richardson (2003)). Across both panels A and B we see that securities with higher levels of short selling activity are negatively associated with measures of 'value' and positively associated with momentum (see e.g., Dechow et al. (2001)).

In table 4 we more formally document the determinants of short selling activity. For the sake of brevity we just report results for *ONLOAN* but we note that in unreported analysis our inferences are very similar for alternative measures of short selling activity. We run two alternative regression specifications with standard errors clustered by time and include/exclude calendar fixed-effects. The results are consistent across specifications and we see that *ONLOAN* is increasing in institutional ownership, and decreasing in (i) the concentration of institutional ownership, (ii) book-to-market, (iii) the level of accruals, (iv) recent stock momentum, and (v) measures of stock illiquidity. In later analyses, we control for these determinants to help identify the unique effect of shocks to funding liquidity to the portfolio returns of *ONLOAN* (and other measures of short selling activity).

3.2 Relation between ONLOAN and future stock returns

In figure 2 we plot the cumulative returns to an investment strategy that replicates exposure to short selling intensity. Each day we sort securities into five groups based on the breakpoints of *ONLOAN* from the previous day. We then compute equal and value weighted returns for the lowest and highest *ONLOAN* quintiles, and the difference in these quintile portfolio returns (lowest minus highest) is the 'hedge' return from exposure to *ONLOAN*. The top panel of figure 2 shows a strong positive return to this strategy, consistent with an extensive previous literature examining short interest (e.g., Asquith et al. (2005)): stocks with higher (lower) short selling activity are associated with lower (higher) future stock returns.

Our main focus, however, is the occasional large negative returns to this strategy that happen around certain dates. Two such events occurred during the Quant crisis in August 2007 and the Lehman Brothers' bankruptcy in October 2008, with both exhibiting days with large negative returns in the *LOW-HIGH* portfolio. The greater volatility in the returns to the *LOW-HIGH* portfolio after these events is readily apparent in the top panel of figure 2. To help isolate this effect, in the bottom panel of figure 2 we plot the conditional daily volatility of the *LOW-HIGH* portfolios from a

GARCH(1,1) model. It is very clear that the Quant and Lehman crises are both strongly associated with sharp increases in the return volatility of the *LOW-HIGH* portfolio, with daily volatility almost tripling in size relative to pre-event levels.

To isolate the potential asymmetry in the daily returns to the *LOW-HIGH* portfolio, we plot the histogram of the portfolios standardized returns in figure 3. Akin to the analysis in the lower panel of figure 2, we scale raw returns with the conditional standard deviations estimated from a GARCH(1,1) model. There is clear evidence of an average positive return to this strategy as seen by the greater probability mass to the right of zero. What is more striking, however, is the difference in the probability mass of the left relative to the right tail: there is a higher proportion of extreme negative relative to positive returns, with the left tail being slightly thicker than the right hand tail. The estimated skewness for the equal- (value-) weighted portfolio is equal to 0.11 (0.36), but statistically significant only for the value-weighted portfolio.

To further isolate the determinants of this left tail of return realizations to a strategy mimicking levered investors, we decompose the *LOW-HIGH* portfolio into its long and short side and examine the days with the largest negative return realizations. Figure 4 reports these details for the 8 (12) days in which standardized returns for the equal (value) weighted *LOW-HIGH* portfolio are more than 2.5 standard deviations below the mean. The left (right) panel in figure 4 reports standardized returns for equal (value) weighted *LOW-HIGH* portfolios. Our prior is that the negative realizations of the *ONLOAN* 'hedge' portfolio will be attributable to liquidity shocks affecting the ability of the levered marginal investor to maintain their portfolio exposures. Thus, we expect the *short* leg of the *LOW-HIGH* portfolio to experience large positive returns on days associated with funding illiquidity, and we do not expect much movement on the long leg of the *LOW-HIGH* portfolio on these days. Consistent with these priors, figure 4 shows that the extreme negative return days are *all* driven by large positive returns of the high *ONLOAN* quintile. This is consistent with the idea that presence of levered investors causes an additional source of risk: the removal of leverage in the financial system can cause large and sudden changes in security prices, primarily for those securities that are exposed to such leverage. For example, on September 17th 2008 the return of the *HIGH ONLOAN* stock portfolio is equal to +8.41%. If a hedge fund was shorting stocks in the top *ONLOAN* quintile with a 3:1 leverage ratio (i.e. $1 of equity for every $3 of asset value), that fund would have lost 24% on a single day. On September 17th 2008, the S&P500 index lost 4.71% (the 15th highest recorded loss on its history). The behaviour of the *HIGH ONLOAN* portfolio is the more striking as one would expect that highly-shorted stocks would exhibit price decreases when the aggregate market is experiencing sharp losses.

In figure 5 we examine in more detail the days around the Quant crisis (top panel) and the Lehman Brothers' bankruptcy (bottom panel). Consistent with the analysis in figure 4, the high *ONLOAN* quintile drives extreme positive returns in both cases. Furthermore, the returns we plot in figure 5 are 'abnormal' with respect to sensitivity to the standard Fama-French factors plus momentum. To the extent that there are correlated positions across levered investors due to commonality among trading strategies with the standard risk factors used in the literature, the patterns we document in figure 5 might be understated (see e.g., Daniel and Moskowitz (2012) and Daniel et. al. (2012)).

4. Empirical analyses

4.1 Calendar time analysis with ONLOAN variable

Tables 5 and 6 report our primary regression analysis. Table 5 (6) reports nested versions of estimating equation (1) using equal (value) weighted portfolios. Across both weighting approaches there is a reliably positive intercept suggesting the *LOW-HIGH ONLOAN* strategy generates about 10-12 (4-6) basis points of abnormal returns per day on an equal (value) weighted basis. Using geometric averages these correspond to annualized returns of between 28.6-35.3 (10.6-16.3) percent respectively. In line with previous work we find a very strong negative loading on MKT and SMB and a very high explanatory power of these time series regressions. For example, Jones and Lamont (2002) report in their table 8 that excess returns to highly shorted stocks are strongly and positively related to the market. Likewise, Desai et al. (2002) find that portfolios with exposure to higher levels of short selling have high positive exposures to market returns and the SMB factor. Given that our portfolio is a *LOW-HIGH* construction of *ONLOAN*, our negative exposure to MKT and SMB is consistent with prior research from earlier time periods. In column 2 we add the MOM factor return, and both the equal and value weighted *LOW-HIGH* portfolios are positively exposed to MOM. Again this is consistent with prior research (e.g., Desai et. al. (2002) show a reliably negative exposure to MOM for their long highly-shorted security portfolios).

Our primary interest, however, is on the behaviour of *LOW-HIGH* portfolio returns during periods associated with deleveraging events. In columns 3 and 4 we add measures related to funding liquidity: (i) an indicator variable for large negative market returns in the previous day, (ii) indicator variables to capture the designated time periods associated with the Lehman and Quant crises, (iii) changes in VIX, and (iv) changes in the TED Spread. In columns 5 and 6 we use alternative measures of funding liquidity as reflected in measures related to the ease with which banks can raise financing including: (i) changes in credit spreads of a basket of US banks, and (ii) equity returns for an index of U.S. Banks. For all variables, with the exception of equity returns for US banks, our prior is for a negative relation between the daily returns of the *LOW-HIGH ONLOAN* portfolio and the changes in the respective liquidity measure for the prior day. Our liquidity measures, with the exception of equity returns for US banks, are increasing in funding illiquidity.

Consistent with the evidence in figure 5, we see very strong evidence of large negative returns to the *LOW-HIGH ONLOAN* portfolio on days around the Quant and Lehman crises. For example, in table 5 the β_{QUANT} regression coefficient is between -1.77 and -1.80. This means that while the *LOW-HIGH ONLOAN* portfolio averages about 11 basis points of returns per day, conditional on days of funding illiquidity crises events the returns are -165 basis points. This is a strikingly large asymmetry to the return profile, and is consistent with deleveraging risk having a very strong economically and statistically significant impact on security prices. Likewise, the β_{LEHMAN} regression coefficient is between -2.26 and -1.66, an even more negative effect than found for the Quant crisis. Turning to our continuous measures of funding liquidity, ΔVIX and ΔTED, we see that both are negatively associated with the returns of the *LOW-HIGH ONLOAN* portfolio. For example, in table 5 the $\beta_{\Delta VIX}$ regression coefficient is between -5.72 and -5.82 in columns 4 and 5. The standard deviation of the change in VIX is 0.02 as reported in table 1, suggesting that a one standard deviation increase in VIX is associated with a negative return of 11 basis points (0.02 x -5.72) on the following day. Finally, we see across both columns 5 and 6 that credit spread changes and equity returns for banks are reliably associated with the returns of the *LOW-HIGH ONLOAN* portfolio.

4.2 Calendar time analysis with alternative short selling measures

Our primary analysis focused on one measure of short selling activity: *ONLOAN*. There are alternative measures to be extracted from financial markets, including: (i) *UTILIZATION* (measurable daily for period July 1st, 2006 through to February 28th, 2011 from Markit), (ii) *SHORT VOLUME* (measurable daily for the period July 1, 2006 through to February 28, 2011 from the NYSE Volume Summary Files), and (iii) *SHORT INTEREST* (measurable monthly for the period January 1990 through to February 2011 from stock exchange data collected by Compustat).

These measures capture different aspects of short selling behaviour. It is important to ensure that the relation we document is robust to alternative measures of equity lending market activity. Our ideal construct is to know the extent of leverage employed by the marginal investor in every stock every day. We have used the ratio of the number of shares on loan to the total number of shares outstanding as a proxy for this construct. To the extent that a firm's shares are closely held and/or are not easy to source to borrow, then *ONLOAN* will systematically classify such firms as having a low value of relative short selling activity (and hence levered investor activity), even though at the margin there is a greater presence of levered investors for such securities. To address this issue we also compute *UTILIZATION* as the ratio of the number of shares on loan relative to the number of shares that were available to be loaned.

Table 7 reports our regression results for various nested estimations of equation (1) using *UTILIZATION* as our basis for constructing *LOW-HIGH* portfolio returns. We report results for the equal weighted specification for the sake of brevity and note that the key inferences are similar with value weighting. Consistent with earlier results, we document a reliably positive intercept, suggesting the *LOW-HIGH UTILIZATION* strategy generates about 7-9 basis points of abnormal returns per day on an equal weighted basis. Likewise we continue to see strong negative loadings on MKT and SMB, a strong positive loading on MOM, and a very high explanatory power for these time series regressions. Of more direct interest, however, is the continued strong negative relation between the returns for the *LOW-HIGH UTILIZATION* strategy and our various measures of funding liquidity. For example, the β_{QUANT} and β_{LEHMAN} regression coefficients are all below -2.0, suggesting that while the *LOW-HIGH UTILIZATION* generates an average of 7 basis points of returns per day, it experiences losses of over 220 basis points on days around significant deleveraging events. There is continued evidence that measures of the relative performance of the banking industry (providers of arbitrage capital and portfolio leverage) are associated with returns to the *LOW-HIGH UTILIZATION* portfolio. When banks are doing poorly in aggregate, funding liquidity is likely to be harder to access and this manifests itself in deleveraging risk.

Both *ONLOAN* and *UTILIZATION* are stock based measures of short selling activity (i.e., they are based on end of day positions). In recent years there has been a significant shift in the trading patterns of investors. In particular there has been an increased prevalence of so called high-frequency trading, with some arguing that the majority of trading on the primary stock exchanges is attributable to investors holding periods of less than a week (e.g., Haldane (2010)). We are able to identify intra-day patterns of short selling activity for NYSE securities that trade electronically on the SuperDOT platform, where the vast majority of NYSE trading volume is executed (see Boehmer, Jones and Zhang (2008)). Similar to Boehmer, Jones and Zhang (2008) we use data from the NYSE Volume Summary files to compute the ratio of the number of shares that were sold short on a given day to the total number of shares traded. We call this measure *SHORT VOLUME* and, as noted in table 1, the average firm in our sample period has 20.3 percent of its total volume attributable to short seller-initiated trade orders.

Table 8 reports our regression results for various nested estimations of equation (1) using *SHORT VOLUME* as our basis for constructing *LOW-HIGH* portfolio returns. Again, we report results for the equal weighted specification for the sake of brevity and note that the key inferences are similar with value weighting. Consistent with earlier results, we find a reliably positive intercept, suggesting the *LOW-HIGH SHORT VOLUME* strategy generates about 9 basis points of abnormal returns per day on an equal weighted basis. Likewise, we continue to see negative loadings on MKT and SMB, a positive loading on MOM, but now there is a much lower explanatory power for these time series regressions. The loadings we document are similar to those reported in Boehmer, Jones and Zhang (2008). We also continue to find a strong negative relation between the returns for the *LOW-HIGH SHORT VOLUME* strategy and measures of funding liquidity, most notably the indicator variables for the Quant and Lehman crises, the change in VIX and our measures for changes in the perceived riskiness of banks as providers of levered capital to arbitrageurs.

Our final supplemental measure of short selling activity is the traditional measure of *SHORT INTEREST*. This is a stock variable similar to both *ONLOAN* and *UTILIZATION*. While it has the disadvantage that it is only available once per month, it has the distinct advantage of a much longer time series. We are able to source *SHORT INTEREST* back to January 1990 for all U.S. securities in Compustat. We continue to conduct our empirical analysis at the daily frequency. To do so we simply carry forward the monthly *SHORT INTEREST* measure until the next month when the exchanges release new short interest reports, thus rebalancing our portfolios once a month. Following prior research we measure *SHORT INTEREST* as the number of shares that the exchange lists as being 'held short' relative to the number of shares outstanding. As such this measure is subject to similar limitations to the *ONLOAN* measure discussed above.

Table 9 reports our regression results for various nested estimations of equation (1) using *SHORT INTEREST* as our basis for constructing *LOW-HIGH* portfolio returns. Consistent with prior research there is a very significant positive intercept and again we find that the *LOW-HIGH SHORT INTEREST* portfolio returns have strong negative loadings on MKT and SMB and a positive loading on MOM. Over this longer time period we see that large negative aggregate market returns are associated with a significant reversal in the *LOW-HIGH SHORT INTEREST* portfolio returns. As before we continue to see a strong negative relation between the returns for the *LOW-HIGH SHORT INTEREST* strategy and the measures of funding liquidity, most notably the indicator variables for the Quant and Lehman crises, the change in VIX and our measure for changes in the perceived riskiness of banks as providers of levered capital to arbitrageurs (we do not include the change in 5 year CDS spreads for US banks over the longer time period as this data is only available post 2004).

It is also worth noting that measures of the perceived riskiness of US banks dominates the change in VIX in identifying negative returns to various short selling strategies. Across all of our tables when we include US bank returns (tables 5-9) the $\beta_{\Delta VIX}$ regression coefficient becomes less negative and is no longer significantly different from zero. This is consistent with the view that banks in particular play a powerful role in the provision of leverage in the investment management industry and concerns about their relative health can have significant consequences on the cross section of security prices.

4.3 Panel regressions

As an alternative to time series regressions of portfolio returns designed to mimic the behaviour of short sellers, we also report panel regressions. For this analysis we pool all of our daily data. This creates a panel of nearly 2 million daily return observations and we cluster standard errors by firm. Controlling for characteristics, we interact *ONLOAN* with the funding liquidity variables. Our regression specification is as follows:

$$RET_{i,t} = \alpha + \beta_{BETA} \cdot BETA_{i,t-1} + \beta_{SIZE} \cdot SIZE_{i,t-1} + \beta_{\frac{B}{P}} \cdot \frac{B}{P}_{i,t-1} + \beta_{RET6M} \cdot RET6M_{i,t-1} + \beta_{ACC} ACC_{i,t-1}$$

$$+ \beta_{ILLIQ} \cdot ILLIQ_{i,t-1} + \beta_{ONLOAN} \cdot ONLOAN_{i,t-1} + \beta_{\Delta VIX} \cdot \Delta VIX_{t-1}$$

$$+\beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{\Delta CDS5Y-BANKS} \cdot \Delta CDS5Y - BANKS_{t-1} + \beta_{QUANT} \cdot D_{QUANT} + \beta_{LEHMAN} \cdot$$

$$D_{LEHMAN} + \beta_{ONLOAN\,QUANT} \cdot ONLOAN_{i,t-1} \cdot D_{QUANT,t-1} + \beta_{ONLOAN\,LEHMAN} \cdot ONLOAN_{i,t-1} \cdot$$

$$D_{LEHMAN,-1} + \beta_{ONLOAN\,\Delta VIX} \cdot ONLOAN_{i,t-1} \cdot \Delta VIX_{i,t-1} + \beta_{ONLOAN\,\Delta TED} \cdot ONLOAN_{i,t-1} \cdot \Delta TED_{i,t-1} +$$

$$\beta_{ONLOAN\,\Delta CDS5Y-BANKS} \cdot ONLOAN_{i,t-1} \cdot \Delta CDS5Y - BANKS_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

All variables are defined in the appendix and table 10. We estimate (2) using both total daily stock returns, labelled as RAW, and characteristic-adjusted returns as defined in Daniel et al. (1997), labelled as DGTW. We repeat the estimation twice for each measure allowing for the inclusion of daily fixed-effects. The coefficients for the levels of liquidity variables and the crises indicator variables are omitted from columns 3 and 4 because they are subsumed by daily fixed effects (i.e. they have the same value for all observations on a given day).

Consistent with recent research, for our sample of firms over the 2006-2011 time period we find (i) very little evidence that BETA is associated with stock returns, (ii) SIZE is positively related with returns, (iii) B/P is positively associated with returns, (iv) RET6M (6 month momentum, skipping the most recent month) is negatively associated with returns (see Daniel et al. 2012 for the large negative returns to momentum in 2009 which are included in our sample period), (v) ACC is negatively associated with stock returns, (vi) illiquidity is positively associated with returns, and (vii) the main effect of *ONLOAN* is strongly negatively associated with future stock returns.

All of the interaction variables in table 10 are positive and strongly significant, consistent with our earlier portfolio level analysis that the relation between short selling activity and future returns is conditional on funding liquidity. To help ease the interpretation of the interaction variables we plot the effects in figure 6. Specifically, we use the regression coefficients from column (2) in table 10 and plot the relation between *ONLOAN* and future returns (labelled 'Abnormal Daily Returns'). We show this relation for different percentiles of the daily changes of liquidity variables (i.e. VIX, TED spread, CDS5y – Banks) and the event crises indicator variables. The percentile values are shown in Panel B of table 1. For example, in the upper-left panel the plotted line using P50 of ΔVIX (i.e. the median value) has the expected negative relationship between abnormal returns and short selling activity, with the forecast for stocks in the 99th percentile of *ONLOAN* being equivalent to -7.5 bps per day. As the value of ΔVIX increases we can see that the difference between P1 (i.e. *ONLOAN* equal to 0% of market capitalization) and P99 (i.e. *ONLOAN* equal to 16.85% of market capitalization) becomes less negative. For the most extreme realizations of ΔVIX above P99, the relationship becomes positive. Stocks with *ONLOAN* at the 99th percentile generate 7bps per day *more* than stocks with *ONLOAN* at the 1st percentile when ΔVIX is at its 99th percentile value. This is exactly the deleveraging risk effect that has been described throughout the paper. Sudden withdrawal of funding capital is positively associated with returns of stocks with high presence of short investors that are likely to use leverage. We find similar results for ΔTED and $\Delta CDS5Y - BANKS$. For both the Quant and Lehman Brothers' crises events we find that stocks with *ONLOAN* at the 99th percentile experience abnormal returns close to 200 bps per day relative to the 'no crises' predicted effect of -7 bps per day. The effects are similar for regressions estimated with daily fixed effects.

4.4 Temporary vs. Permanent Effects

Our empirical analysis so far has not discussed if the impact on levered securities of reductions in funding liquidity is transitory or permanent. To address this issue we perform two additional empirical analyses. First, we extend the window over which we measure excess returns to our various short selling measures. This allows us to assess if the positive returns found for stocks with high short selling intensity immediately following period of funding illiquidity reverses over subsequent periods or if they persist for some time. We re-estimate equation (1) using cumulative returns for each of the next fifteen trading days, allowing us to assess the extent to which the funding illiquidity effects are temporary or permanent. It is important to note that our explanatory variables are all held fixed at day *t*, so the cumulative return patterns are attributable to any reversals based on those fixed characteristics.

We sort stocks by *ONLOAN* on day *t-1*, rank them into quintiles and create indicator variables, $RANK\text{-}ONLOAN_k$, equal to 1 if a stock belongs to the k^{th} quintile and 0 otherwise.[6] Then, controlling for firm characteristics and daily fixed-effects, we interact each indicator variable with the proxies for funding liquidity, using the middle quintile (k=3) as the benchmark. Our baseline regression is given by:

$$CUMRET_{i,t+j} = \alpha + \beta_{BETA} \cdot BETA_{i,t-1} + \beta_{SIZE} \cdot SIZE_{i,t-1} + \beta_{\frac{B}{P}} \cdot \frac{B}{P}_{i,t-1} + \beta_{RET6M} \cdot RET6M_{i,t-1} +$$

$$\beta_{ACC} \cdot ACC_{i,t-1} + \beta_{ILLIQ} \cdot ILLIQ_{i,t-1} + \textstyle\sum_{k=1,2,4,5} \beta_{RANK-ONLOAN,k} \cdot RANK - ONLOAN_{\ k,i,t-1} +$$

$$\beta_{\Delta VIX} \cdot \Delta VIX_{t-1} + \beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{\Delta CDS5Y-BANKS} \cdot \Delta CDS5Y - BANKS_{t-1} + \beta_{QUANT} \cdot D_{QUANT,t} +$$

$$\beta_{LEHMAN} \cdot D_{LEHMAN,t} +$$

$$\textstyle\sum_{k=1,2,4,5} RANK - ONLOAN_{\ k,i,t-1} \cdot (\beta_{ONLOAN\ QUANT,k} \cdot D_{QUANT,t} + \beta_{ONLOAN\ LEHMAN,k} \cdot D_{LEHMAN,t} +$$

$$\beta ONLOAN\ \Delta VIX_{,k} \cdot \Delta VIXi,t-1 + \beta ONLOAN_{,k}\ \Delta TED \cdot \Delta TEDi,t-1 + \beta ONLOAN$$

$$\Delta CDS5Y-BANKS_{,k} \cdot \Delta CDS5Y-BANKSi,t-1+\varepsilon i,t+j, \qquad (3)$$

[6] In addition to allowing for easier interpretation, using quintiles of *ONLOAN* rather than levels also serves the purpose of a robustness test to rule out that our results are being caused by outliers in *ONLOAN*.

where $k=1,2, 4, 5$ denotes the *ONLOAN* quintile of stock i at time $t-1$.

We report our results in Table 11 for the high short selling quintile indicator variable (*RANK-ONLOAN*$_5$) and its interactions with the funding liquidity variables. The *RANK-ONLOAN*$_5$ coefficients capture the mean reversion in returns of stocks in the highest short selling activity quintiles over the next j days. Stocks with high short selling intensity at time t continue to underperform for the next 15 days. Estimated parameters are statistically significant and negative in the following 15 days, in line with results found in prior studies. The various interaction terms capture the asymmetrical degree of mean reversion in returns specifically following periods of funding illiquidity. The returns for stocks in the highest quintile of *ONLOAN* are consistently higher and statistically different that those in the middle quintile (our benchmark in the regressions) for all funding liquidity variables in the following 15 trading days but D_{LEHMAN}, which reverts back to the average after 10 days. Collectively, these results suggest that securities with the highest level of short selling activity experience positive returns around periods of funding illiquidity and these positive returns continue for at least 15 days. The impact of shocks to funding liquidity on levered investors is not a short-lived effect.

Second, we next examine changes in equity lending *quantities* following funding liquidity shocks. To the extent that the levered marginal investor is forced to close out (i.e., cover) his short position at the time of a funding liquidity shock, it should result in lower levels of short selling. Given the results in tables 10 and 11, if the price effects still persist after 15 trading days, we should also observe a decrease in short selling not only on the day after the shocks but also for the following 15 days. We employ panel regressions using changes in *ONLOAN* as our dependent variable with firm fixed-effects and robust standard deviations clustered at the firm level. Our baseline regression is specified as follows:

$$\Delta ONLOAN_{i,t+3} = \alpha + \beta_{BETA} \cdot BETA_{i,t-1} + \beta_{SIZE} \cdot SIZE_{i,t-1} + \beta_{\frac{B}{P}} \cdot \frac{B}{P}_{i,t-1} + \beta_{RET6M} \cdot RET6M_{i,t-1} +$$

$$\beta_{ACC} ACC_{i,t-1} + \beta_{ILLIQ} \cdot ILLIQ_{i,t-1} + \sum_{k=1,2,4,5} \beta_{RANK-ONLOAN,k} \cdot RANK - ONLOAN_{\ k,i,t-1} +$$

$$\beta_{\Delta VIX} \cdot \Delta VIX_{t-1} + \beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{\Delta CDS5Y-BANKS} \cdot \Delta CDS5Y - BANKS_{t-1} + \beta_{QUANT} \cdot D_{QUANT,t} +$$
$$\beta_{LEHMAN} \cdot D_{LEHMAN,t} + \sum_{k=1,2,4,5} RANK - ONLOAN_{\ k,i,t-1} \cdot (\beta_{ONLOAN*\ QUANT,k} \cdot D_{QUANT,t} +$$
$$\beta_{ONLOAN*\ LEHMAN,k} \cdot D_{LEHMAN,t} + \beta_{ONLOAN*\ \Delta VIX,k} \cdot \Delta VIX_{i,t-1} + \beta_{ONLOAN,k\ \Delta TED} \cdot \Delta TED_{i,t-1} +$$
$$\beta_{ONLOAN\ \Delta CDS5Y-BANKS,k} \cdot \Delta CDS5Y - BANKS_{i,t-1}) + \theta_i + \varepsilon_{i,t+3}, \qquad (4)$$

where *k=1,2, 4, 5* denotes the *ONLOAN* quintile of stock *i* at time *t-1*.

Note that the dependent variable $\Delta ONLOAN_{i,t+3}$, the cumulative change in *ONLOAN* between *t+3* and *t+2,* is a proxy for changes in short sale quantities between *t* and *t-1* due to the mechanics of equity lending markets described in section 2.1. Additionally, we also estimate regressions using cumulative changes in *ONLOAN* over the following 15 trading days, i.e. $\Delta ONLOAN_{i,t+3+j}$ where *j=3,…, 15*.

The results in Table 12 show a clear reduction in short selling activity for securities with the highest level of short selling activity at the start of period of funding illiquidity. Our prior is that the removal of funding liquidity (including increased margin requirements, call back of lent securities, client redemptions etc.) will force levered investors to close out pre-existing short positions. This covering pressure will, in part, generate the positive return relation documented in previous tables. For example, following the Lehman Brothers bankruptcy, *ONLOAN* decreases even faster for stocks in the highest quintile of *ONLOAN* (i.e. $RANK\text{-}ONLOAN_5 \cdot D_{LEHMAN}$ coefficient) relative to the mean reversion observed in regular times (i.e. $RANK\text{-}ONLOAN_5$ coefficient). In our sample we see a reduction in *ONLOAN* of -1.08% in terms of market capitalization in the 15 days after Lehman's bankruptcy, corresponding to a drop of almost 10% relative to the 14.03% sample average of *ONLOAN* for stocks in the highest quintile. This is an economically significant decrease in short selling. An alternative way of analyzing this effect is comparing this change to average share turnover. The average security in our sample has daily trading volume equal to 0.91% of outstanding shares, with the corresponding average turnover over fifteen days being equal to 13.61% (=0.91%*15 days). Thus, the estimated 1.08% cumulative decrease in *ONLOAN* (itself a fraction of shares outstanding) is equivalent to an eight per cent reduction on the sell side of the market. Figure 7 summarizes our results and plots marginal effects of the interaction terms assuming a three standard deviations shock for ΔVIX, ΔTED, and $\Delta CDS5Y - BANKS$ at time *t-1* for funding liquidity variables (left axis) and marginal effects after the two crisis events (right axis).

Together, the results in Table 11 on the continuation of positive returns for securities with high levels of short selling activity following periods of funding liquidity, and the results in Table 12 of reduced short selling quantities suggest that the large negative returns we document for the LOW-HIGH *ONLOAN* portfolios are attributable to the withdrawal of funding liquidity for the marginal levered investor.

5. Conclusion

In this paper we explore the impact of deleveraging events on the cross section of equity returns. We find strong evidence that deleveraging risk (i.e., the unique risk attributable to the reduction in funding liquidity necessary to maintain levered portfolio positions), affects equity returns. Using various measures of short selling activity from multiple sources for a large sample of US securities, we find that levered positions experience occasional and very large returns during periods of reduced funding liquidity.

We identify levered positions by tracking the actions of participants in the equity lending market. Given that the equity lending market aggregates the positions of short sellers across securities, it is a natural source of data to quantify the presence of levered investors and the potential effect on stock prices. Our maintained assumption is that investors engaged in short selling employ leverage as part of their investment strategy. Consistent with prior research, we find that, on average, there is a negative relation between measures of short selling activity and future stock returns across a variety of measures of short selling activity. However, contrary to past literature, we document evidence of occasional very large positive returns to short selling activity. We further find that these episodes of positive returns are associated with (i) discrete liquidity events such as the quant crisis of August 2007 and the Lehman Brothers bankruptcy in September 2008, and (ii) reductions in funding liquidity as reflected in a variety of measures such as changes in VIX, changes in TED spread, and changes in the perceived credit risk of banks that facilitate the provision of levered capital to arbitrageurs.

The return effects following funding liquidity shocks are economically significant and persist for at least ten trading days for all proxies that we use. The effect on equity lending quantities is also persistent and we find evidence of significantly lower quantities on loan for at least fifteen days after deleveraging risk events. Together, the continuation of positive returns for securities with high levels of short selling activity following periods of funding liquidity, and the reduced quantities of short selling suggest that the withdrawal of funding liquidity for the marginal levered investor is the likely explanation for the return effects we document.

These results are also helpful for investors and regulators to understand the risks associated with short-selling and the impact of the usage of leverage on their portfolios around times of funding illiquidity.

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Appendix: Variable Definitions

SUPPLY	Daily total number of shares available to borrow from Markit divided by shares outstanding.
ONLOAN	Daily total number of shares on loan from Markit divided by total number of shares outstanding.
SHORT INTEREST	Shares Held Short as of Settlement Date (SHORTINTADJ), obtained from Compustat's Monthly Updates - Supplemental Short Interest File in WRDS divided by total number of shares outstanding.
SHORT VOLUME	Daily number of shares marked as short sales on NYSE divided by total volume.
UTILIZATION	Daily number of shares on loan from Markit divided by the total number of shares available to be lent from Markit.
VW Fee	Daily loan-weighted average fee (bps p.a.), reported by Markit.
Daily Return	Daily RET reported by CRSP.
ILLIQ	Amihud (2002) daily price impact measure computed as the daily absolute returns divided by the dollar trading volume, all data obtained from CRSP.
B/P	Compustat's CEQQ divided by MCAP, computed quarterly.
E/P	Earnings to Price ratio: Compustat's IBQ divided by market capitalization. IBQ excludes income from discontinued operations or extraordinary items.
Accruals	Accruals=Δ(Current Assets)-Δ(Cash) - [Δ(Current Liabilities)-Δ(Short Term Debt)-Δ(Taxes Payable)-Depreciation as in Dechow et al. (1995)
MKT	Daily excess (to risk free rate) market return, obtained from WRDS.
SMB	Daily factor portfolio return to the size factor, obtained from WRDS.
HML	Daily factor portfolio return to the value factor, obtained from WRDS.
UMD	Daily factor portfolio return to the momentum factor, obtained from WRDS.
D_{QUANT}	Indicator variable equal to one for trading days between August 6, 2007 and August 8, 2007; and zero otherwise.
D_{LEHMAN}	Indicator variable equal to one for trading days between September 16, 2008 and September22, 2008; and zero otherwise.
$D_{Ret(MKT)<2.5\sigma}$	Indicator variable equal to one for trading days where the aggregate market return is more than 2.5 standard deviations below its average value. This is computed using a GARCH(1,1) model on a rolling 252 trading day basis; and zero otherwise.
VIX	Implied volatility for S&P500 options computed by the Chicago Board Options Exchange, obtained from Datastream (DSCODE: CBOEVIX)
TED Spread	Difference between 3-month Treasury and Eurodollar futures middle rate, obtained from Datastream (DSCODE: TRTEDSP)
CDS5y - Banks	5-day average of U.S. Banks Sector 5-year Credit Default Swap Index mid-rate Price, obtained from Datastream (DSCODE: USBANCD)
IO	% of share outstanding held by institutional investors for each firm-quarter, obtained from Thompson's 13-f files in WRDS.
IO_{HHI}	Concentration of ownership for each firm-quarter measured by the Hirschman-Herfindahl index.
Returns(Banks)	U.S. Banking Sector stock index returns from Datastream
RET6M	Cumulative return in the previous six-month period skipping the most recent month.

Figures

Figure 1: Aggregate *ONLOAN*

This figure plots the daily average *ONLOAN* of U.S. firms from July 2006 to February 2011. *ONLOAN* is defined as the number of shares on loan divided by the total number of shares outstanding.

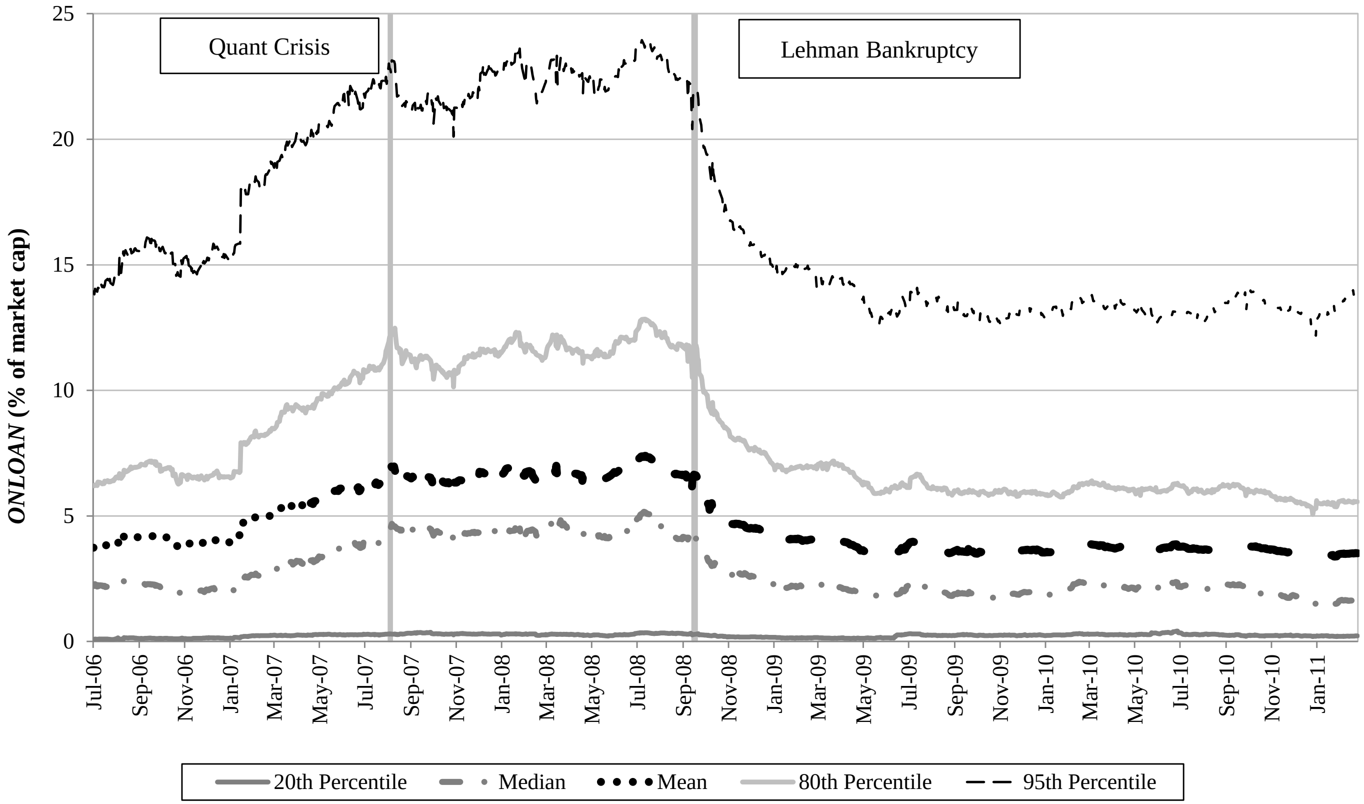
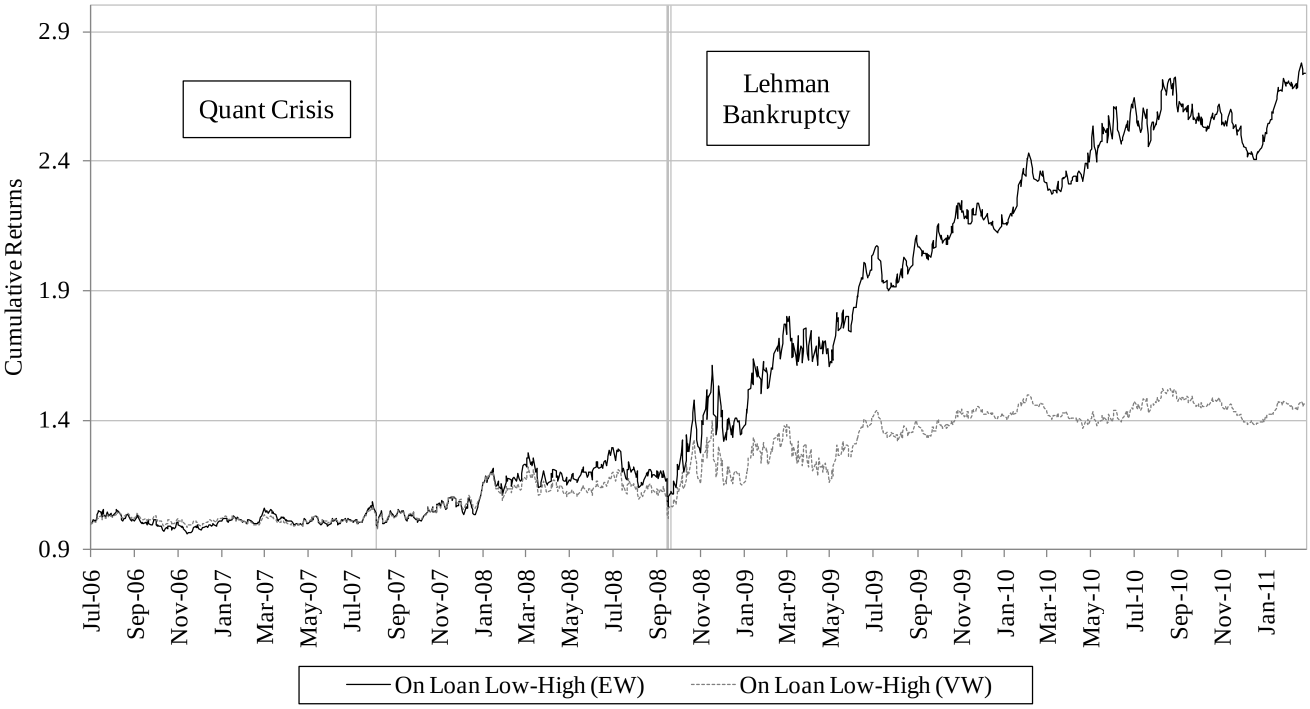


Figure 2: Daily Returns and Standard Deviations of Stock Portfolios sorted on *ONLOAN*

This figure plots the cumulative daily return of stock portfolios sorted on *ONLOAN* from January 2nd, 1990 to February 28th, 2011. *ONLOAN* is defined as the number of shares on loan divided by the total number of shares outstanding. We rank firms into quintiles and compute the equal- and value-weighted daily average returns of firms in each quintile. We plot cumulative returns of a portfolio that takes long (short) positions in securities in the LOW (HIGH) *ONLOAN* quintile. The bottom panel displays daily standard deviations estimated from a GARCH(1,1) model.



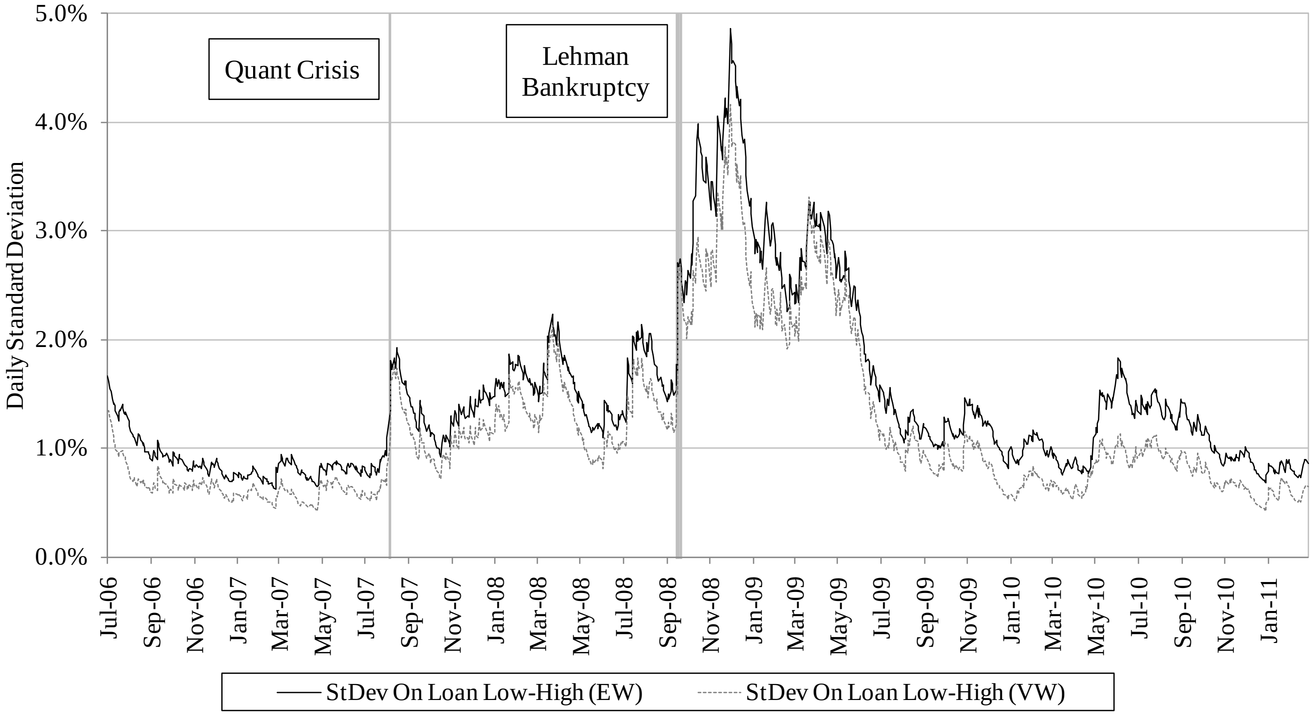


Figure 3: Histogram of Standardized Returns for *ONLOAN* Portfolios

This figure plots the histogram of daily returns of stock portfolios sorted on *ONLOAN* scaled by the volatility estimates shown in Figure 2. *ONLOAN* is defined as the number of shares on loan divided by the total number of shares outstanding. We rank firms into quintiles and compute the equal- and value-weighted daily average returns of firms in each quintile. Our portfolio takes long (short) positions in securities in the LOW (HIGH) *ONLOAN* quintile each day. Numbers above each column denote the frequency of equal-weighted standardized returns in each bin.

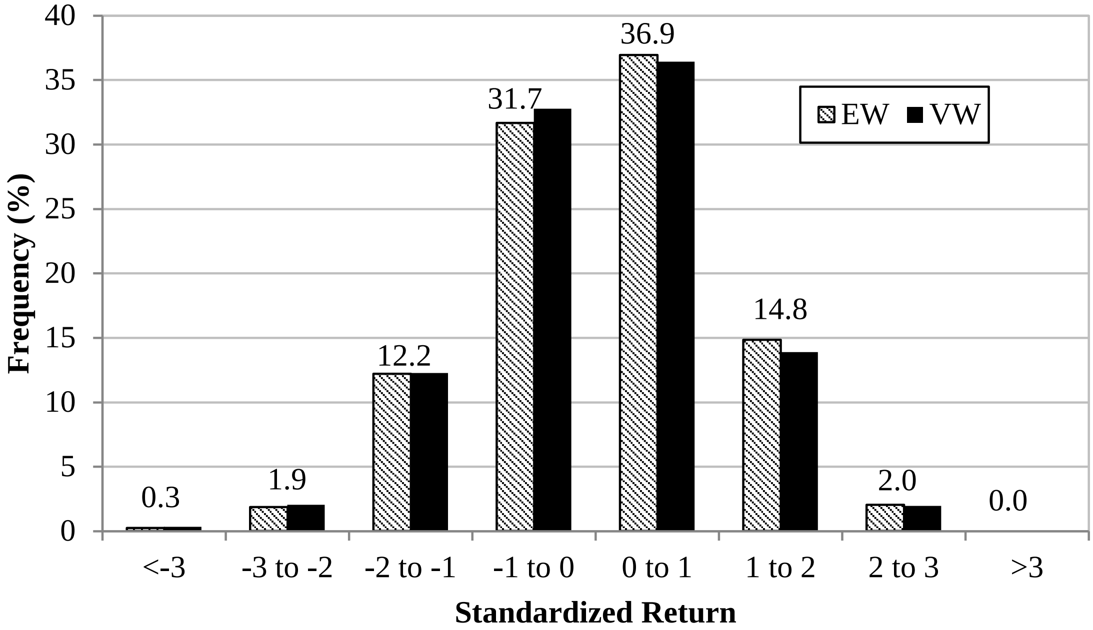
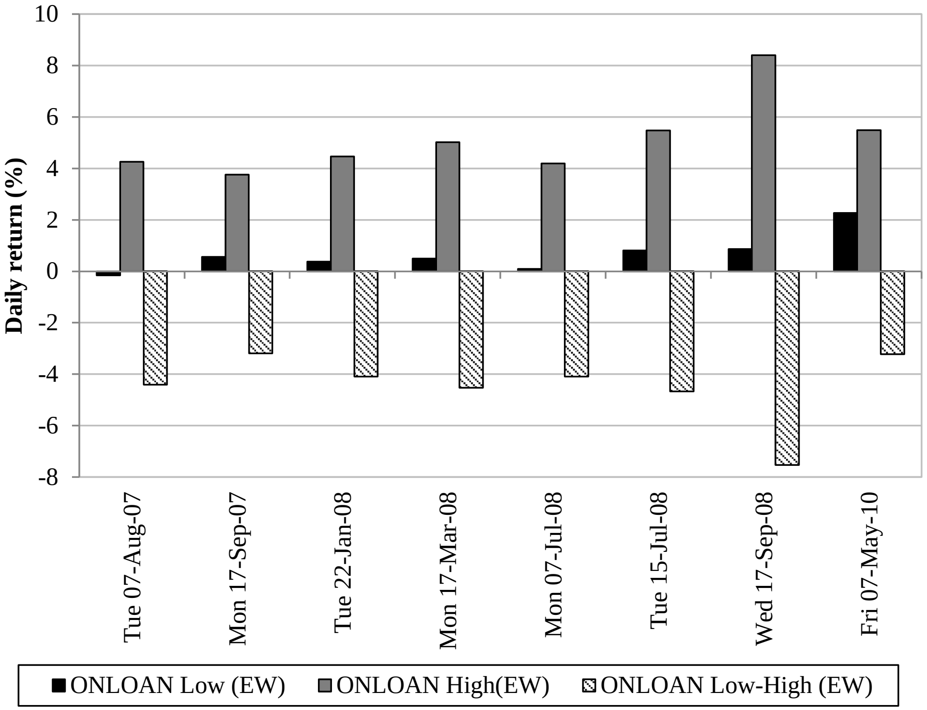


Figure 4: Extreme return days for High and Low Short *ONLOAN* portfolios

This figure shows raw returns of stock portfolios sorted on *ONLOAN* for days when the LOW-HIGH portfolio return is 2.5 standard deviations below the mean. *ONLOAN* is defined as the number of shares on loan divided by the total number of shares outstanding. Standardized returns are computed by dividing daily portfolio returns by standard deviations estimated from a GARCH(1,1) model for the period between July 1st, 2006 and February 28th, 2011. We show returns for the bottom (LOW) and top (HIGH) quintiles of firms ranked by *ONLOAN* and also for the LOW-HIGH difference. The left panel displays data for equal-weighted portfolios and the right panel for value-weighted portfolios.



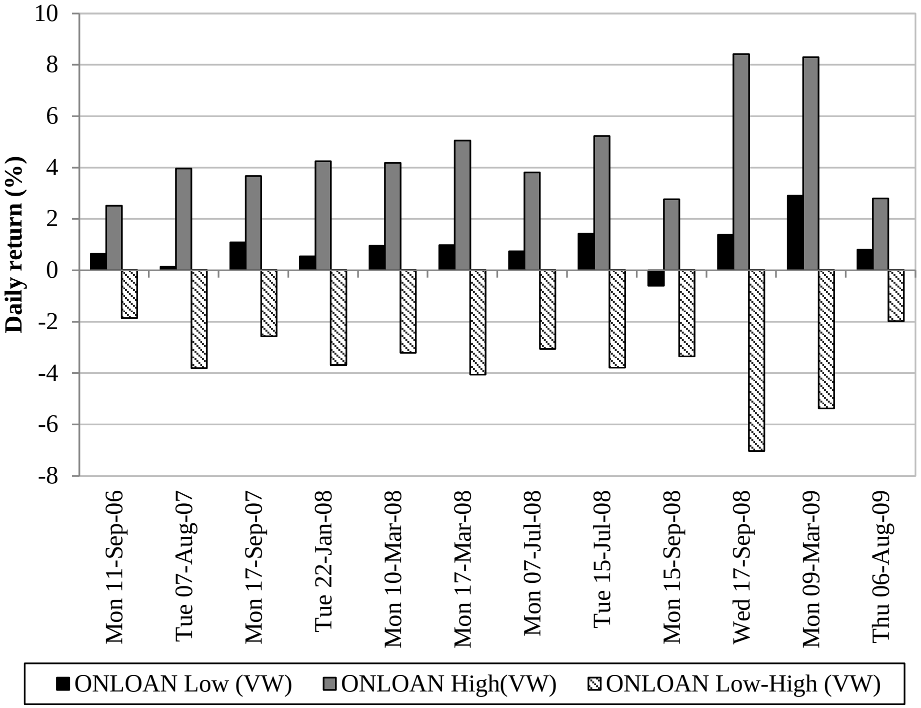
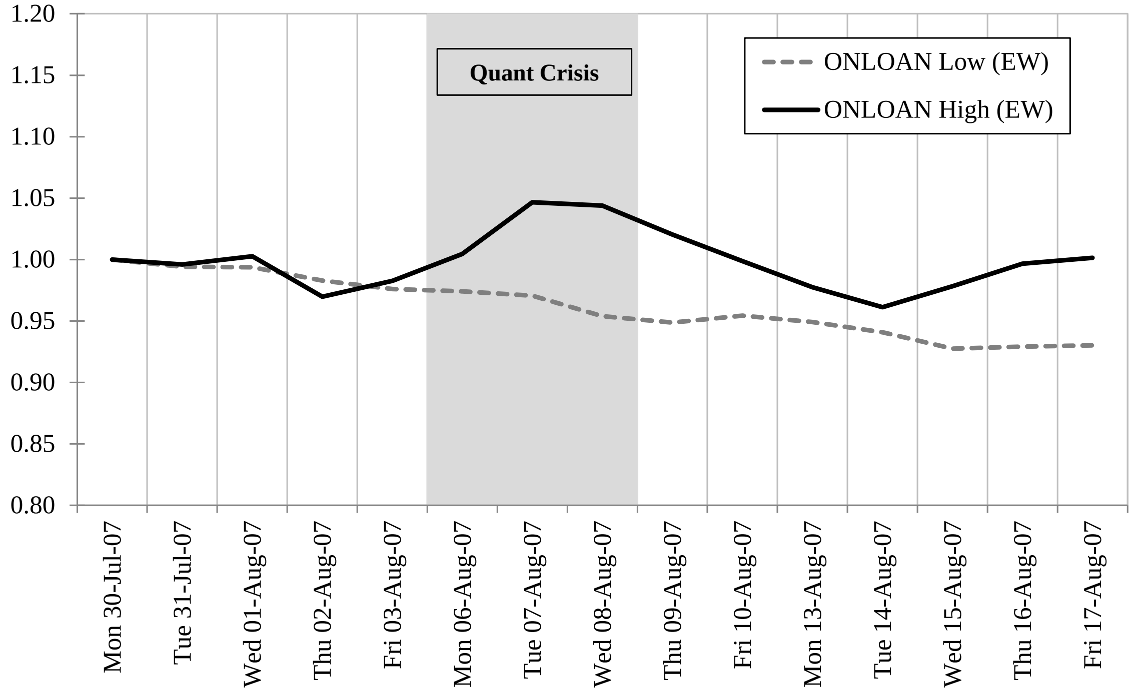


Figure 5: Abnormal Returns during the Quant crisis and Lehman Brothers' Bankruptcy
The figure show the cumulative abnormal portfolio returns of high and low *ONLOAN* portfolios around the Quant crisis and the Lehman Brothers bankruptcy. *ONLOAN* is defined as the number of shares on loan divided by the total number of shares outstanding. Each day stocks are sorted into quintiles and we compute the mean equal-weighted daily returns in each quintile. Abnormal returns are based on the Fama-French three-factor model plus momentum. The top figure displays returns around the Quant crisis in August 2007, with the shaded area denoting the crisis period from August 6th to August 8th, 2007. The lower figure shows abnormal returns around Lehman Brothers' Bankruptcy in October 2008, with the shaded area denoting the crisis period from September 16th to 18th, 2008.



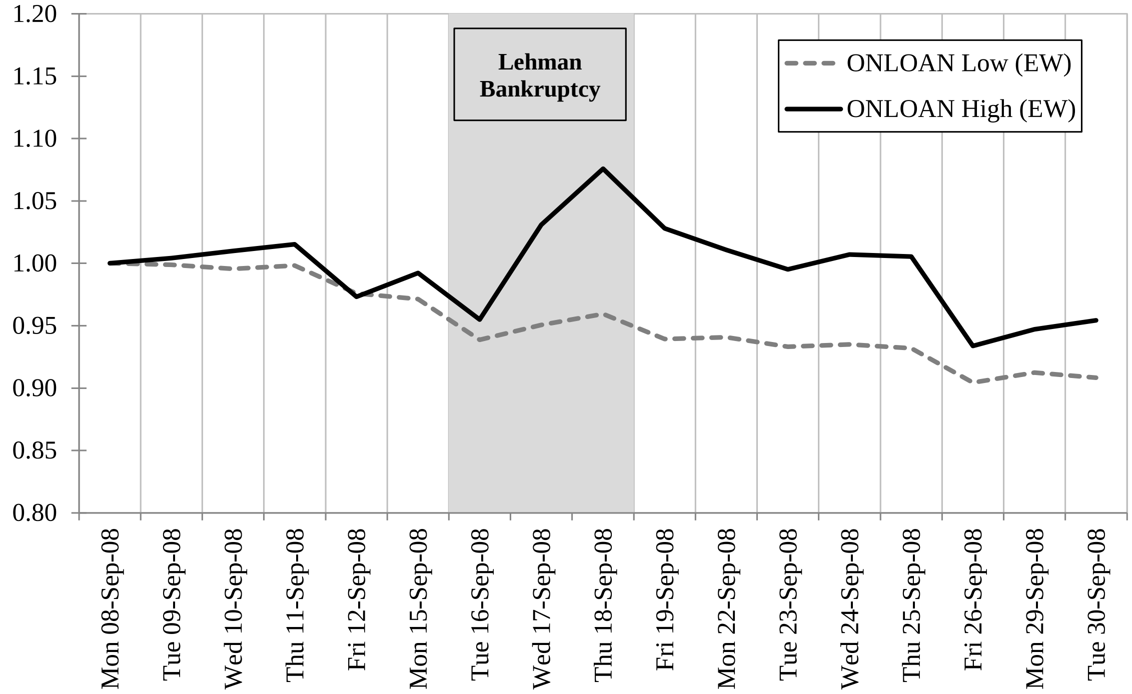


Figure 6: Association of ONLOAN and Abnormal Returns for Extreme Values of Funding Liquidity Proxies

The table displays predicted abnormal returns for different *ONLOAN* percentiles across different levels of funding liquidity variables. *ONLOAN* is the total amount on loan divided by market capitalization. The funding liquidity measures include: ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, and ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream (all measured on the previous day). D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. Parameters for levels of *ONLOAN* and interactions with funding liquidity variables are taken from Column (2) in table 10. The horizontal axis plots the 1st percentile (P1) to the 99th percentile (P99) of *ONLOAN*. Each plotted line fix a given percentile (P50, P75, P90, P95 and P99) of a funding liquidity variable to compute the predicted abnormal returns. Percentile values are taken from Panel B of Table 1. For the bottom right figure, we present the predicted effect during No Crises periods and for when a particular liquidity event indicator variable is equal to 1.

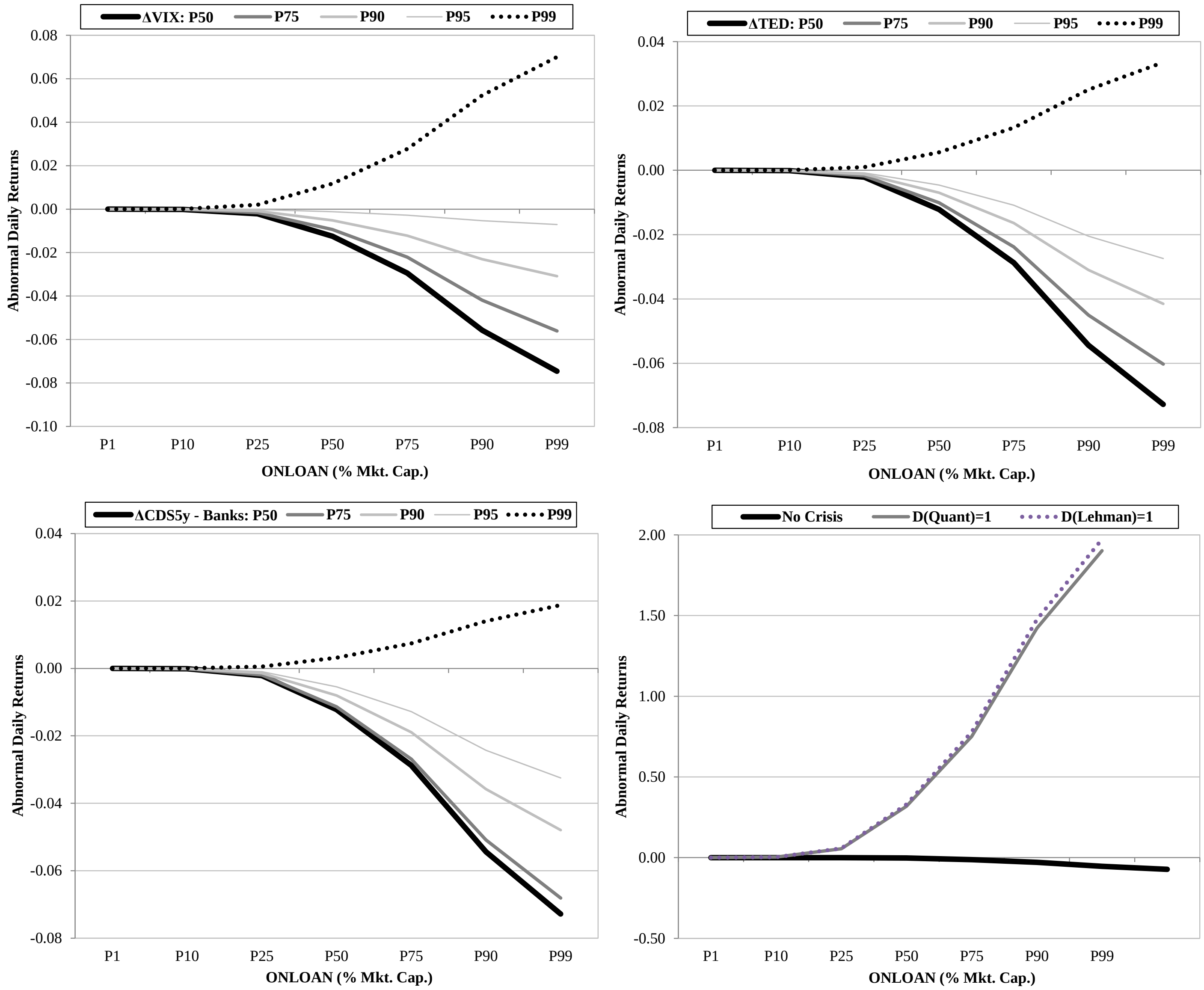


Figure 7: *ONLOAN* Quantity Predicted Changes for Extreme Values of Funding Liquidity Proxies and Crisis Indicator Variables

The figure shows the expected changes in quantities from results estimated in Table 12 assuming a 3 standard deviation increase in the funding liquidity measures (left axis) and also following the two crises events (right axis). Stocks are sorted based on *ONLOAN*, defined as the total amount on loan divided by market capitalization, on day t-1. The plotted values correspond to values of the interaction coefficients of *ONLOAN* with each funding liquidity variable between day $t+3+j$ and $t+3$, for $j=0,\ldots, 15$ shown in Table 12, which captures short selling activity between $t+j$ and t. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, and ΔCDS5Y-Banks is the change in the 5-year CDS index of financial services from Datastream (all measured on the previous day). D(QUANT) is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D(LEHMAN) is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise.

Table 1 – Descriptive Statistics

This table summarizes the characteristics of stocks over the period between July 1st, 2006 and February 28th, 2011 for 1,985,703 firm-day observations. Panel A displays summary statistics for all variables while Panel B describes key percentiles for *ONLOAN* and funding liquidity measures. Size is market capitalization measured in millions of dollars; IO is total institutional share ownership; IO_{HHI} is concentration of institutional ownership measured by the Hirschman-Herfindahl index; *SUPPLY* is the total number of shares available to borrow from Markit divided by shares outstanding; *ONLOAN* is the daily total number of shares on loan from Markit divided by shares outstanding. *SHORT INTEREST* is the number of shorted shares reported in Compustat divided by shares outstanding; *SHORT VOLUME* is the daily number of shares marked as short sales on NYSE divided by total volume; *UTILIZATION* is the number of shares on loan divided by the total number of shares available to be lent. *VW Fee* is the daily loan-weighted average annualized fee in basis points; VIX is the VIX volatility index; TED is the change in the Treasury-Eurodollar spread; CDS5Y-BANKS is the 5-year CDS index of financial services from Datastream. RETURNS(BANKS) is the equity return for an index of financial services firms. Δ(.) denotes changes between day t-2 and day t-1.

Panel A: Summary Statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Skew	Kurt
Size	3,498	412	15,230	0.26	527,172	11.78	197.69
IO	58.64%	64.34%	30.31%	0.00%	100%	-0.35	1.87
IO_{HHI}	0.12	0.07	0.14	0.01	1.00	2.86	13.09
SUPPLY	19.81%	20.46%	12.40%	0.00%	100%	0.15	2.25
ONLOAN	4.79%	2.50%	6.16%	0.00%	83%	2.32	10.91
SHORT INTEREST	5.20%	3.33%	6.33%	0.00%	216%	4.18	58.54
SHORT VOLUME	20.31%	20.37%	7.71%	0.00%	100%	0.09	3.54
UTILIZATION	19.23%	11.51%	21.10%	0.00%	87.14%	1.39	4.26
VW Fee	77.25	13.26	234.53	-7.06	1,662	5.01	30.19
VIX	24.38	22.21	12.04	9.89	81	1.75	6.58
TED	76.26	50.31	69.29	8.76	458	1.87	7.82
CDS5Y-BANKS	122.38	119.63	88.16	10.20	596	0.97	4.70
ΔVIX	0.00	0.00	0.02	-0.17	0.17	0.27	16.32
ΔTED	0.00	0.00	0.09	-0.80	1.00	0.43	33.54
ΔCDS5Y-BANKS	0.00	0.00	0.06	-0.72	0.43	-1.56	37.27
Returns (Banks)	0.00%	0.01%	2.79%	-15.92%	17%	0.28	10.38

Panel B: Percentiles of *ONLOAN* and Funding Liquidity Measures

Variable	On Loan	ΔVIX	ΔTED	ΔCDS5Y -BANKS
P1	0.000%	-0.070	-0.280	-0.187
P10	0.026%	-0.019	-0.053	-0.042
P25	0.488%	-0.008	-0.013	-0.014
P50	2.820%	-0.001	0.000	0.000
P75	6.653%	0.006	0.012	0.015
P90	12.593%	0.020	0.044	0.047
P99	16.851%	0.069	0.316	0.176

Table 2 – Correlations

This table presents the pairwise correlation tables for the main variables with pooled data between July 1st, 2006 and February 28th, 2011. Size is market capitalization measured in millions of dollars; IO is total institutional share ownership; IO_{HHI} is concentration of institutional ownership measured by the Hirschman-Herfindahl index; *ONLOAN* is the daily total number of shares on loan from Markit divided by shares outstanding. *SHORT INTEREST* is the number of shorted shares reported in Compustat divided by shares outstanding; *SHORT VOLUME* is the daily number of shares marked as short sales on NYSE divided by total volume; UTILIZATION is the number of shares on loan divided by the total number of shares available to be lent. VW Fee is the daily loan-weighted average annualized fee in basis points; VIX is the VIX index; TED is the change in the Treasury-Eurodollar spread; CDS5Y-BANKS is the 5-year CDS index of financial services from Datastream. RETURNS(BANKS) is the equity return for an index of financial services firms. Δ(.) denotes changes between day t-2 and day t-1.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Size	1														
(2)	IO	0.085	1													
(3)	IO_{HHI}	-0.135	-0.623	1												
(4)	*ONLOAN*	-0.075	0.494	-0.330	1											
(5)	*SHORT INTEREST*	-0.079	0.450	-0.321	0.820	1										
(6)	*SHORT VOLUME*	-0.059	0.041	-0.031	0.188	0.148	1									
(7)	*UTILIZATION*	-0.105	0.152	-0.165	0.745	0.659	0.194	1								
(8)	VW Fee	-0.059	-0.260	0.183	0.179	0.246	-0.029	0.487	1							
(9)	VIX	-0.028	-0.004	0.013	-0.009	0.001	0.167	-0.007	0.019	1						
(10)	TED	-0.005	0.040	-0.006	0.121	0.091	-0.045	0.107	0.048	0.591	1					
(11)	CDS5Y-BANKS	-0.019	0.004	0.010	0.022	0.036	0.243	0.004	0.027	0.596	0.350	1				
(12)	ΔVIX	0.000	0.002	-0.001	0.006	0.005	0.047	0.004	0.010	0.072	0.045	0.025	1			
(13)	ΔTED	0.002	0.003	-0.002	0.009	0.008	0.005	0.006	0.005	-0.018	0.094	0.061	0.185	1		
(14)	ΔCDS5Y-BANKS	0.001	0.003	0.000	0.014	0.008	0.045	0.009	0.002	-0.001	-0.092	0.143	0.071	0.105	1	
(15)	RETURNS(BANKS)	0.000	-0.003	0.001	-0.010	-0.008	0.010	-0.012	-0.006	-0.082	-0.037	-0.014	0.069	0.092	0.036	1

Table 3 – Descriptive Statistics for Stocks sorted on *ONLOAN* and *SHORT INTEREST*

This table summarizes the characteristics of stocks sorted by *ONLOAN* (panel A) and *SHORT INTEREST* (panel B). *ONLOAN* is the defined as the number of shares on loan from Markit divided by the number of shares outstanding, and is available daily for the period July 1, 2006 through to February 28, 2011. *SHORT INTEREST* is defined as the number of shares shorted relative to the number of shares outstanding as reported by Compustat in the previous month for the period January 1990 through to February 2011. We form equal-weighted portfolios by sorting stocks into quintiles based on each respective short selling measure and report averages for stocks in the bottom (LOW) and top (HIGH) quintiles. Size is market capitalization measured in millions of dollars, IO is total institutional share ownership relative to total market capitalization; IO_{HHI} is concentration of institutional share ownership measured by the Hirschman-Herfindahl index. The characteristics scores for Accruals, B/M, E/P and Momentum are obtained by first assigning each stock to one of five quintiles and then computing the average. The last column reports the difference between the two quintiles. ***(**)=statistical significance at the 1% (5%) level.

Panel A: *ONLOAN* (July 1st, 2006 – February 28th, 2011)

Variable	LOW	HIGH	HIGH-LOW
Average # of firms	525.30	525.78	0.037***
Size	1,772	1,550	-222***
IO	24.83%	81.10%	56.27%***
IO_{HHI}	0.28	0.06	-0.23***
ONLOAN	0.05%	14.03%	13.98%***
SHORT INTEREST	0.35%	13.09%	12.74%***
VW Fee (bps p.a.)	60.86	134.78	73.92***
Accrual Score	2.93	2.98	0.05***
B/M Score	3.79	2.60	-1.19***
E/P Score	2.97	2.84	-0.13***
Momentum Score	2.86	2.96	0.09***

Panel B: *SHORT INTEREST* (January 1st, 1990 – February 28th, 2011)

Variable	LOW	HIGH	HIGH-LOW
Average # of firms	525.29	525.70	-0.416***
Size	541	1,337	796***
IO	24.49%	79.41%	54.92%***
IO_{HHI}	0.28	0.06	-0.22***
ONLOAN	0.29%	13.03%	12.75%***
SHORT INTEREST	0.11%	13.96%	13.85%***
VW Fee (bps p.a.)	65.95	150.77	84.83***
Accrual Score	2.95	2.95	0.01
B/M Score	3.85	2.57	-1.28***
E/P Score	2.97	2.77	-0.19***
Momentum Score	2.87	2.94	0.06***

Table 4: Determinants of *ONLOAN*

The table displays regressions of *ONLOAN* as a function of lagged firm characteristics using daily U.S. stock data between July 2006 and February 2011 of U.S. firms. *ONLOAN* is the defined as the number of shares on loan from Markit divided by the number of shares outstanding. IO is total stock ownership by institutions; IO_{HHI} is the concentration of institutional ownership measured by the Hirschman-Herfindahl index; Accruals is computed as in Dechow et al. (1995); B/M the book-to-market ratio; Momentum is the cumulative return in the previous two quarters measured at the end of the previous quarter; $D_{P<5}$ is an indicator variable equal to one if the price is below five dollars, and zero otherwise and ILLIQ is Amihud's Illiquidity measure. Institutional ownership, Accruals, B/M and Momentum are taken from the previous quarter. All other variables are lagged by one day. We report standard deviations in brackets and significance levels are indicated as follows: *** (**)=statistical significance at the 1% (5%)level.

Variables	Prior	(1)	(2)
IO	+	9.683***	9.397***
		[0.095]	[0.090]
IO_{HHI}	-	0.044	-0.283***
		[0.059]	[0.057]
Accruals	+	-0.190***	-0.706***
		[0.060]	[0.046]
B/M	-	-0.468***	-0.315***
		[0.020]	[0.014]
Momentum	-	-0.276***	-0.044**
		[0.024]	[0.018]
$D_{P<5}$	-	-0.230***	-0.141***
		[0.015]	[0.012]
ILLIQ	-	-0.024***	-0.030***
		[0.001]	[0.001]
Intercept		-0.732***	
		[0.037]	
Firm-Days		1,985,703	1,985,703
Clustered St. Errors		Time	Time
Time Dummies		No	Yes

Table 5: Equal-Weighted Stock Portfolios sorted on *ONLOAN*

The table displays regressions of stock portfolios sorted by *ONLOAN*, with daily U.S. stock returns between July 2006 and February 2011. We form portfolios by ranking stocks into quintiles based on *ONLOAN* in the previous day. Our dependent variable is the equal-weighted daily return of selling High *ONLOAN* stocks and buying Low *ONLOAN* stocks. *ONLOAN* is the total amount on loan divided by market capitalization. Returns and risk factors MKT, SMB, HML and MOM are measured at period t while other explanatory variables are measured at period t-1. MKT is excess market return above the risk free rate, SMB is the return on a portfolio of Small stocks Minus the return on a portfolio of Big stocks, HML is the return on a portfolio of High book-to market (value) Minus Low book-to-market (growth) stocks, and MOM, the return on a portfolio of prior winners minus the return on a portfolio of prior losers. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream. RETURNS(BANKS) is the equity return for an index of financial services firms. $D_{Ret(MKT)<2.5\sigma}$ is a indicator variable equal to one if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.097***	0.100***	0.106***	0.113***	0.116***	0.115***
	[0.020]	[0.019]	[0.019]	[0.018]	[0.018]	[0.018]
β_{MKT}	-0.825***	-0.784***	-0.784***	-0.766***	-0.765***	-0.762***
	[0.030]	[0.030]	[0.030]	[0.030]	[0.030]	[0.027]
β_{SMB}	-0.786***	-0.800***	-0.802***	-0.800***	-0.794***	-0.791***
	[0.054]	[0.055]	[0.055]	[0.051]	[0.051]	[0.046]
β_{HML}	-0.162***	0	0.003	-0.002	-0.008	0.011
	[0.058]	[0.061]	[0.061]	[0.058]	[0.058]	[0.052]
β_{MOM}		0.190***	0.192***	0.199***	0.202***	0.215***
		[0.027]	[0.028]	[0.026]	[0.026]	[0.026]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.263*	-0.170	-0.177	-0.232**
			[0.158]	[0.125]	[0.120]	[0.117]
β_{QUANT}				-1.797***	-1.770***	-1.801***
				[0.225]	[0.220]	[0.212]
β_{LEHMAN}				-1.662***	-2.262***	-1.881***
				[0.434]	[0.357]	[0.384]
$\beta_{\Delta VIX}$				-5.718***	-5.822***	-0.191
				[1.087]	[1.126]	[1.539]
$\beta_{\Delta TED}$				-0.623*		
				[0.337]		
$\beta_{\Delta CDS5Y-BANKS}$					-1.418**	
					[0.697]	
$\beta_{RETURNS(BANKS)}$						0.066***
						[0.015]
# Days	1,172	1,172	1,172	1,171	1,171	1,171
Adj. R2	0.833	0.846	0.846	0.861	0.862	0.865

Table 6: Value-Weighted Stock Portfolios sorted on *ONLOAN*

The table displays regressions of stock portfolios sorted by *ONLOAN*, with daily U.S. stock returns between July 2006 and February 2011. We form portfolios by ranking stocks into quintiles based on *ONLOAN* in the previous day. Our dependent variable is the value-weighted daily return of selling High *ONLOAN* stocks and buying Low *ONLOAN* stocks. *ONLOAN* is the total amount on loan divided by market capitalization. Returns and risk factors MKT, SMB, HML and MOM are measured at period t while other explanatory variables are measured at period t-1. MKT is excess market return above the risk free rate, SMB is the return on a portfolio of Small stocks Minus the return on a portfolio of Big stocks, HML is the return on a portfolio of High book-to market (value) Minus Low book-to-market (growth) stocks, and MOM, the return on a portfolio of prior winners minus the return on a portfolio of prior losers. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream. RETURNS(BANKS) is the equity return for an index of financial services firms. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable equal to one if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.039**	0.043***	0.048***	0.055***	0.058***	0.057***
	[0.018]	[0.017]	[0.017]	[0.016]	[0.016]	[0.016]
β_{MKT}	-0.621***	-0.567***	-0.566***	-0.553***	-0.552***	-0.550***
	[0.034]	[0.033]	[0.033]	[0.033]	[0.033]	[0.031]
β_{SMB}	-0.666***	-0.685***	-0.686***	-0.681***	-0.675***	-0.675***
	[0.051]	[0.050]	[0.050]	[0.048]	[0.047]	[0.044]
β_{HML}	-0.227***	-0.011	-0.008	-0.01	-0.015	-0.001
	[0.062]	[0.062]	[0.062]	[0.060]	[0.058]	[0.055]
β_{MOM}		0.255***	0.257***	0.262***	0.263***	0.272***
		[0.024]	[0.024]	[0.023]	[0.023]	[0.023]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.219	-0.114	-0.113	-0.156
			[0.148]	[0.110]	[0.103]	[0.104]
β_{QUANT}				-1.720***	-1.695***	-1.723***
				[0.219]	[0.211]	[0.220]
β_{LEHMAN}				-1.897***	-2.439***	-2.037***
				[0.302]	[0.270]	[0.261]
$\beta_{\Delta VIX}$				-4.325***	-4.230***	-0.54
				[0.956]	[0.954]	[1.516]
$\beta_{\Delta TED}$				-0.407		
				[0.312]		
$\beta_{\Delta CDS5Y-BANKS}$					-1.691***	
					[0.595]	
$\beta_{RETURNS(BANKS)}$						0.045***
						[0.014]
# Days	1,172	1,172	1,172	1,171	1,171	1,171
Adj. R2	0.786	0.822	0.822	0.839	0.844	0.842

Table 7: Equal-Weighted Stock Portfolios sorted on *UTILIZATION*

The table displays regressions of stock portfolios sorted on *UTILIZATION*, with daily U.S. stock returns between July 2006 and February 2011. We form portfolios by ranking stocks into quintiles based on *UTILIZATION* in the previous day. Our dependent variable is the equal-weighted daily return of selling High *UTILIZATION* stocks and buying Low *UTILIZATION* stocks. *UTILIZATION* is defined as the number of shares on loan divided by the number of shares available to borrow (Markit). Returns and risk factors MKT, SMB, HML and MOM are measured at period t while other explanatory variables are measured at period t-1. MKT is excess market return above the risk free rate, SMB is the return on a portfolio of Small stocks Minus the return on a portfolio of Big stocks, HML is the return on a portfolio of High book-to market (value) Minus Low book-to-market (growth) stocks, and MOM, the return on a portfolio of prior winners minus the return on a portfolio of prior losers. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream. RETURNS(BANKS) is the equity return for an index of financial services firms. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable equal to one if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th 2008; and zero otherwise. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.070***	0.074***	0.080***	0.089***	0.091***	0.090***
	[0.018]	[0.016]	[0.016]	[0.016]	[0.016]	[0.015]
β_{MKT}	-0.674***	-0.624***	-0.624***	-0.611***	-0.610***	-0.608***
	[0.024]	[0.023]	[0.023]	[0.024]	[0.023]	[0.022]
β_{SMB}	-0.776***	-0.793***	-0.795***	-0.786***	-0.782***	-0.781***
	[0.055]	[0.055]	[0.055]	[0.051]	[0.051]	[0.048]
β_{HML}	-0.235***	-0.036	-0.033	-0.036	-0.042	-0.029
	[0.054]	[0.056]	[0.056]	[0.049]	[0.049]	[0.046]
β_{MOM}		0.234***	0.236***	0.237***	0.240***	0.248***
		[0.024]	[0.024]	[0.023]	[0.023]	[0.023]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.281	-0.121	-0.13	-0.166
			[0.173]	[0.126]	[0.125]	[0.126]
β_{QUANT}				-2.462***	-2.439***	-2.459***
				[0.459]	[0.449]	[0.457]
β_{LEHMAN}				-2.230***	-2.737***	-2.477***
				[0.472]	[0.527]	[0.466]
$\beta_{\Delta VIX}$				-3.752***	-3.930***	-0.453
				[1.046]	[1.098]	[1.315]
$\beta_{\Delta TED}$				-0.602**		
				[0.295]		
$\beta_{\Delta CDS5Y-BANKS}$					-1.001*	
					[0.534]	
$\beta_{RETURNS(BANKS)}$						0.041***
						[0.012]
# Days	1,172	1,172	1,171	1, 171	1,171	1,171
Adj. R2	0.833	0.853	0.874	0.875	0.877	0.865

Table 8: Equal-Weighted Stock Portfolios sorted on NYSE *SHORT VOLUME*

The table displays regressions of stock portfolios sorted on *SHORT VOLUME*, with daily U.S. stock returns between July 2006 and February 2011. We form portfolios by ranking stocks into quintiles based on *SHORT VOLUME* in the previous day. Our dependent variable is the equal-weighted daily return of selling High *SHORT VOLUME* stocks and buying Low *SHORT VOLUME* stocks. *SHORT VOLUME* is the number of shares traded short on the NYSE SuperDOT system divided by the total number of traded shares on the NYSE SuperDOT system. Returns and risk factors MKT, SMB, HML and MOM are measured at period t while other explanatory variables are measured at period t-1. MKT is excess market return above the risk free rate, SMB is the return on a portfolio of Small stocks Minus the return on a portfolio of Big stocks, HML is the return on a portfolio of High book-to market (value) Minus Low book-to-market (growth) stocks, and MOM, the return on a portfolio of prior winners minus the return on a portfolio of prior losers. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream. RETURNS(BANKS) is the equity return for an index of financial services firms. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable equal to one if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.086***	0.088***	0.087***	0.094***	0.095***	0.094***
	[0.018]	[0.018]	[0.018]	[0.017]	[0.017]	[0.017]
β_{MKT}	-0.105***	-0.088***	-0.088***	-0.073***	-0.071***	-0.071***
	[0.026]	[0.027]	[0.027]	[0.027]	[0.027]	[0.026]
β_{SMB}	-0.206***	-0.212***	-0.212***	-0.211***	-0.204***	-0.207***
	[0.051]	[0.051]	[0.051]	[0.050]	[0.050]	[0.051]
β_{HML}	-0.017	0.049	0.048	0.03	0.026	0.037
	[0.053]	[0.060]	[0.060]	[0.057]	[0.056]	[0.055]
β_{MOM}		0.077***	0.077***	0.080***	0.080***	0.086***
		[0.026]	[0.026]	[0.025]	[0.025]	[0.025]
$\beta_{Ret(MKT)<2.5\sigma}$			0.022	0.111	0.122	0.09
			[0.166]	[0.142]	[0.125]	[0.136]
β_{QUANT}				-2.485***	-2.473***	-2.493***
				[0.628]	[0.622]	[0.631]
β_{LEHMAN}				-1.044***	-1.357***	-1.020***
				[0.306]	[0.186]	[0.231]
$\beta_{\Delta VIX}$				-4.315***	-4.023***	-1.638
				[1.328]	[1.366]	[1.837]
$\beta_{\Delta TED}$				-0.042		
				[0.401]		
$\beta_{\Delta CDS5Y-BANKS}$					-1.487***	
					[0.430]	
$\beta_{RETURNS(BANKS)}$						0.030*
						[0.016]
# Days	1,172	1,172	1,171	1, 171	1,171	1,171
Adj. R2	0.819	0.846	0.846	0.867	0.867	0.868

Table 9: Equal-Weighted Stock Portfolios sorted on *SHORT INTEREST* (1990-2011)

The table displays regressions of stock portfolios sorted on *SHORT INTEREST*, with daily U.S. stock returns between January 1990 and February 2011. We form portfolios by ranking stocks into quintiles based on *SHORT INTEREST* in the previous month, and carry these ranks forward daily until the next month. Our dependent variable is the equal-weighted daily return of selling High *SHORT INTEREST* stocks and buying Low *SHORT INTEREST* stocks. *SHORT INTEREST* is the number of shares sold short divided by the total number of outstanding shares. Returns and risk factors MKT, SMB, HML and MOM are measured at period t while other explanatory variables are measured at period t-1. MKT is excess market return above the risk free rate, SMB is the return on a portfolio of Small stocks Minus the return on a portfolio of Big stocks, HML is the return on a portfolio of High book-to market (value) Minus Low book-to-market (growth) stocks, and MOM, the return on a portfolio of prior winners minus the return on a portfolio of prior losers. ΔVIX is the daily change in the VIX volatility index, and ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day. RETURNS(BANKS) is the equity return for an index of financial services firms. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable equal to one if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=statistical significance at the 1% (5%) level.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.087***	0.082***	0.085***	0.086***	0.085***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
β_{MKT}	-0.757***	-0.731***	-0.731***	-0.728***	-0.728***
	[0.012]	[0.011]	[0.011]	[0.011]	[0.010]
β_{SMB}	-0.470***	-0.477***	-0.477***	-0.477***	-0.479***
	[0.023]	[0.022]	[0.022]	[0.022]	[0.021]
β_{HML}	-0.323***	-0.270***	-0.270***	-0.265***	-0.263***
	[0.021]	[0.020]	[0.020]	[0.019]	[0.019]
β_{MOM}		0.117***	0.118***	0.118***	0.119***
		[0.013]	[0.013]	[0.013]	[0.013]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.179**	-0.163**	-0.162**
			[0.075]	[0.067]	[0.065]
β_{QUANT}				-1.796***	-1.817***
				[0.348]	[0.337]
β_{LEHMAN}				-1.977***	-2.020***
				[0.210]	[0.223]
$\beta_{\Delta VIX}$				-3.273***	-0.089
				[0.725]	[0.860]
$\beta_{\Delta TED}$				-0.218	
				[0.164]	
$\beta_{RETURNS(BANKS)}$					0.040***
					[0.008]
Obs.	5,546	5,546	5,546	5,545	5,545
Adj. R2	0.738	0.746	0.747	0.753	0.756

Table 10: Panel Return Regressions for *ONLOAN* (2006-2011)

The table displays panel data regressions of individual stock returns between July 2006 and February 2011. BETA is computed from a market model using daily data in the previous quarter, SIZE is the logarithm of market capitalization, B/P is the book-to-market ratio, and RET6M is the return in the previous six-month period skipping the most recent month. ACC is accruals as measured in Dechow et al. (1995). ILLIQ is Amihud's illiquidity measure. *ONLOAN* is the total amount on loan divided by market capitalization. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream (all measured on the previous day). D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report robust standard deviations clustered at the firm level in brackets and significance levels are indicated as follows: *** (**)=statistical significance at the 1% (5%) level.

	RAW (1)	DGTW (2)	RAW (3)	DGTW (4)
β_{BETA}	-0.002	-0.007	-0.006	-0.006
	[0.009]	[0.008]	[0.009]	[0.009]
β_{SIZE}	0.039***	0.035***	0.033***	0.034***
	[0.002]	[0.002]	[0.002]	[0.002]
$\beta_{B/P}$	0.135***	0.069***	0.093***	0.071***
	[0.012]	[0.008]	[0.010]	[0.009]
β_{RET6M}	-0.032*	-0.014	-0.022*	-0.022
	[0.017]	[0.009]	[0.013]	[0.014]
β_{ACC}	-0.250***	-0.093**	-0.117**	-0.093**
	[0.053]	[0.045]	[0.046]	[0.045]
β_{ILLIQ}	0.009***	0.013***	0.014***	0.013***
	[0.003]	[0.003]	[0.003]	[0.003]
β_{ONLOAN}	-0.977***	-0.432***	-0.491***	-0.455***
	[0.061]	[0.047]	[0.049]	[0.048]
$\beta_{\Delta VIX}$	1.995***	-3.225***		
	[0.355]	[0.347]		
$\beta_{\Delta TED}$	0.722***	-0.709***		
	[0.063]	[0.062]		
$\beta_{\Delta CDS5Y-BANKS}$	-0.099	-0.416***		
	[0.088]	[0.086]		
β_{QUANT}	-0.137	-1.229***		
	[0.088]	[0.088]		
β_{LEHMAN}	-1.279***	-1.107***		
	[0.112]	[0.112]		
$\beta_{ONLOAN*QUANT}$	14.506***	11.720***	13.995***	11.758***
	[0.974]	[0.965]	[0.974]	[0.965]
$\beta_{ONLOAN*LEHMAN}$	16.589***	12.142***	14.844***	12.165***
	[1.130]	[1.109]	[1.109]	[1.109]
$\beta_{ONLOAN*\Delta VIX}$	15.319***	17.402***	12.850***	17.744***
	[3.909]	[3.866]	[4.033]	[3.972]
$\beta_{ONLOAN*\Delta TED}$	4.153***	3.712***	5.354***	4.067***
	[0.581]	[0.555]	[0.565]	[0.557]
$\beta_{ONLOAN*\Delta CDS5Y-BANKS}$	5.476***	4.149***	7.923***	3.735***
	[0.887]	[0.850]	[0.890]	[0.863]
Time FE	N	N	Y	Y
Firm-Days	1,985,703	1,985,703	1,985,703	1,985,703

Table 11: Cumulative Returns of High *ONLOAN* Stocks as a Function of Funding Liquidity Proxies and Crisis Indicator Variables

The table displays selected coefficients of panel data regressions of cumulative stock returns between July 2006 and February 2011. Stocks are sorted based on *ONLOAN*, defined as the total amount on loan divided by market capitalization, on day *t-1* and define the dependent variable $CUMRET_{i,t+j}$ as the cumulative returns from *t* to *t+j* after portfolio formation. As explanatory variables we include indicator variables equal to one if a stock belongs to the k^{th} quintile of *ONLOAN* and zero otherwise, funding liquidity variables and firm controls. We report coefficients for $RANK - ONLOAN_5$ and interactions with funding liquidity variables. All regressions include daily fixed-effects and the same set of controls used in Table 10: BETA, SIZE, B/P, RET6M, ACC and ILLIQ. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream (all measured on the previous day). D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report robust standard deviations clustered at the firm level in brackets and significance levels are indicated as follows: *** (**)=statistical significance at the 1% (5%) level.

			Interaction of $RANK - ONLOAN_5$ with									
	$RANK - ONLOAN_5$		D_{QUANT}		D_{LEHMAN}		ΔVIX		ΔTED		$\Delta CDS5Y - BANKS$	
j	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.
0	-0.155***	[0.013]	3.144***	[0.219]	1.547***	[0.205]	8.909***	[0.834]	1.839***	[0.147]	0.02	[0.122]
1	-0.216***	[0.023]	6.060***	[0.418]	2.922***	[0.346]	14.483***	[0.976]	2.878***	[0.220]	0.743***	[0.132]
2	-0.257***	[0.034]	7.757***	[0.527]	4.142***	[0.475]	12.070***	[1.059]	3.138***	[0.265]	1.188***	[0.168]
3	-0.284***	[0.045]	6.889***	[0.536]	3.878***	[0.575]	17.974***	[1.161]	3.339***	[0.307]	1.182***	[0.179]
4	-0.309***	[0.056]	4.817***	[0.537]	3.537***	[0.623]	21.527***	[1.222]	3.313***	[0.322]	1.388***	[0.170]
5	-0.351***	[0.067]	3.377***	[0.557]	3.780***	[0.682]	21.367***	[1.175]	2.770***	[0.343]	2.356***	[0.188]
6	-0.378***	[0.078]	4.106***	[0.602]	3.520***	[0.758]	21.326***	[1.316]	2.339***	[0.372]	2.220***	[0.198]
7	-0.410***	[0.089]	5.735***	[0.646]	3.741***	[0.804]	20.603***	[1.298]	1.733***	[0.400]	2.320***	[0.203]
8	-0.436***	[0.101]	7.506***	[0.688]	2.097**	[0.848]	21.579***	[1.342]	2.089***	[0.424]	1.265***	[0.217]
9	-0.453***	[0.112]	7.916***	[0.699]	1.524*	[0.866]	18.679***	[1.353]	1.549***	[0.445]	2.422***	[0.212]
10	-0.483***	[0.123]	7.636***	[0.715]	1.317	[0.885]	21.692***	[1.394]	0.465	[0.460]	2.366***	[0.220]
11	-0.507***	[0.134]	6.731***	[0.742]	0.356	[0.931]	20.408***	[1.449]	1.244***	[0.467]	2.717***	[0.236]
12	-0.522***	[0.145]	6.064***	[0.772]	-1.156	[0.957]	21.948***	[1.468]	2.686***	[0.481]	2.231***	[0.238]
13	-0.534***	[0.156]	5.093***	[0.795]	-1.332	[1.028]	25.009***	[1.443]	3.020***	[0.496]	2.996***	[0.252]
14	-0.559***	[0.167]	4.231***	[0.826]	-1.088	[1.094]	25.222***	[1.464]	2.227***	[0.506]	2.242***	[0.261]
15	-0.591***	[0.179]	3.668***	[0.859]	-0.001	[1.147]	21.289***	[1.463]	1.180**	[0.515]	2.681***	[0.266]

Table 12: Changes in *ONLOAN* Quantities of High *ONLOAN* Stocks as a Function of Funding Liquidity Proxies and Crisis Indicator Variables

The table displays selected coefficients of panel data regressions of changes in equity loans between July 2006 and February 2011. Stocks are sorted based on *ONLOAN*, defined as the total amount on loan divided by market capitalization, on day *t-1* and define the dependent variable $\Delta ONLOAN_{i,t+3+j}$ as the difference in *ONLOAN* between day *t+3+j* and *t+3*, which captures short selling activity between *t+j* and *t-1*. As explanatory variables we include indicator variables equal to one if a stock belongs to the k^{th} quintile of *ONLOAN* and zero otherwise, funding liquidity variables and firm controls. We report coefficients for $RANK-ONLOAN_5$ and interactions with funding liquidity variables. All regressions include firm fixed-effects and the same set of controls used in Table 10: BETA, SIZE, B/P, RET6M, ACC and ILLIQ. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, ΔCDS5Y-BANKS is the change in the 5-year CDS index of financial services from Datastream (all measured on the previous day). D_{QUANT} is an indicator variable equal to one in the period between August 6th and August 8th, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16th and September 18th, 2008; and zero otherwise. We report robust standard deviations clustered at the firm level in brackets and significance levels are indicated as follows: *** (**)=statistical significance at the 1% (5%) level.

			Interaction of $RANK-ONLOAN_5$ with									
	$RANK-ONLOAN_5$		D_{QUANT}		D_{LEHMAN}		ΔVIX		ΔTED		$\Delta CDS5Y-BANKS$	
j	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.	Coeff.	StDev.
0	-0.045***	[0.001]	-0.043*	[0.025]	-0.103***	[0.023]	0.002	[0.052]	-0.02	[0.014]	0.008	[0.010]
1	-0.088***	[0.003]	-0.185***	[0.045]	-0.208***	[0.037]	-0.071	[0.059]	-0.062***	[0.019]	0.045***	[0.012]
2	-0.130***	[0.004]	-0.412***	[0.067]	-0.318***	[0.050]	-0.201***	[0.068]	-0.001	[0.022]	0.063***	[0.015]
3	-0.172***	[0.005]	-0.707***	[0.083]	-0.445***	[0.061]	-0.254***	[0.072]	-0.009	[0.024]	0.060***	[0.015]
4	-0.213***	[0.006]	-0.904***	[0.096]	-0.529***	[0.071]	-0.318***	[0.073]	-0.017	[0.026]	0.081***	[0.014]
5	-0.255***	[0.007]	-0.960***	[0.101]	-0.549***	[0.079]	-0.563***	[0.079]	-0.060**	[0.029]	0.073***	[0.016]
6	-0.297***	[0.008]	-0.960***	[0.105]	-0.676***	[0.085]	-0.164**	[0.081]	-0.05	[0.032]	-0.026	[0.017]
7	-0.338***	[0.010]	-0.989***	[0.111]	-0.625***	[0.090]	-0.579***	[0.086]	-0.008	[0.035]	0.114***	[0.018]
8	-0.379***	[0.011]	-1.011***	[0.117]	-0.668***	[0.096]	-0.487***	[0.088]	-0.039	[0.036]	0.073***	[0.018]
9	-0.421***	[0.012]	-1.027***	[0.125]	-0.763***	[0.102]	-0.546***	[0.090]	0.03	[0.038]	0.057***	[0.018]
10	-0.462***	[0.013]	-1.026***	[0.131]	-0.829***	[0.107]	-0.596***	[0.096]	0.01	[0.038]	0.088***	[0.019]
11	-0.502***	[0.014]	-0.936***	[0.137]	-0.977***	[0.114]	-0.599***	[0.099]	-0.032	[0.040]	0.053***	[0.020]
12	-0.544***	[0.015]	-0.896***	[0.144]	-0.910***	[0.121]	-0.517***	[0.102]	-0.127***	[0.043]	0.057***	[0.021]
13	-0.586***	[0.016]	-0.853***	[0.151]	-0.960***	[0.127]	-0.598***	[0.103]	-0.147***	[0.044]	0.060***	[0.021]
14	-0.627***	[0.017]	-0.887***	[0.154]	-1.042***	[0.132]	-0.585***	[0.105]	-0.059	[0.045]	0.057***	[0.022]
15	-0.668***	[0.018]	-0.909***	[0.156]	-1.083***	[0.135]	-0.902***	[0.107]	-0.095**	[0.047]	0.101***	[0.022]