Deleveraging Risk[*]

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First Draft: October 30th, 2012
This Draft: March 15th, 2013

Abstract

We assess whether deleveraging events have an impact on the cross section of stock returns. Deleveraging risk is the unique risk attributable to the existence of levered positions. When funding 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. Using a unique dataset of equity lending data as a proxy for the degree of leverage in a stock, we find strong evidence of extreme return realizations attributable to the unwinding of these levered positions. We further find that these deleveraging risk events are attributable to (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, TED spread, and the perceived credit risk of banks that facilitate the provision of levered capital to arbitrageurs.

JEL classification: G12; G14; G15

Keywords: Deleveraging, equity lending, utilization, risk, short selling, funding liquidity.

[*] We are grateful to Itzhak Ben-David, Kent Daniel, Peter Feldhutter, Francisco Gomes, Lasse Pedersen, Tapio Pekkala, Ruy Ribeiro, and Avanidhar Subrahmanyam for helpful discussions and comments.

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 be employing leverage as part of their investment strategies carry an additional source of risk. This risk is the removal of the leverage required 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 arbitrage capital will have an asymmetric impact on equity prices depending on the degree of leverage in a particular stock.

Prior research has found robust evidence that securities with high levels of short interest 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)). 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 used by investors in particular stock.

Using several measures of short selling activity we find a negative relation between each 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 evidence that this negative relation is interrupted by occasional periods of very positive returns. This breakdown in the negative relation between short selling intensity and future stock

[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.

returns is asymmetric: securities 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, around the Quant crisis in August 2007 we find that the daily equal (value) weighted returns to a portfolio that sells highly-shorted stocks and buys lowly-shorted ones is about 170 (155) basis points. There is a striking asymmetry to the returns of portfolios that are exposed to funding leverage: the effect is almost entirely attributable to those stocks with high levels of short selling activity. 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.

The typical long/short equity investment strategy starts with an initial investment 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 desired 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. Saffi and Sigurdsson (2011) show that the equity lending market is very deep and liquid for the majority of U.S. stocks, with the average value (equal) weighted annualized lending fee for equity securities in the US being equal to 10 (68) basis points and 93 percent of US securities having shares available to borrow at any point in time.

The aggregation of short selling activity 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 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 onloan 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 between the number of securities on loan on a given day and the number of shares that were available to be loaned, '*UTILIZATION*' , (ii) the ratio between the number of shares sold short on a given day relative and the total number of shares traded that day from NYSE's SuperDOT platform, '*SHORT VOLUME*', and (iii) the ratio between the number of shares shorted and the number of shares outstanding, '*SHORT INTEREST*'.[2]

More generally, we find a positive relation between the portfolio returns to a utilization strategy 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 ability of levered investors to source levered capital, this coincides with positive returns of stocks which have high presence of (short) levered investors.

Our analysis focuses directly on the existence of levered investors as a potential source of tail risk. We do not focus on the momentum strategy, or any other potential anomalous return strategy, and instead focus on a portfolio that replicates the positions of levered short sellers. Under our maintained assumption that utilization in the securities lending market is directly related to presence of levered investors, we have a relatively clean measure of cross-sectional differences in the extent of levered invested capital. This allows us to focus on the *direct* asset pricing implications of levered invested capital. Our analysis therefore has the potential to explain tail risk across a variety

[2] While SHORT INTEREST is only available at a monthly frequency, it spans a much larger period raging 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.

of strategies, not just momentum (see e.g., Daniel and Moskowitz (2012); Daniel et al. (2012), Barroso and Santa-Clara (2012).

While our focus is on assessing the impact of deleveraging risk on equity securities, there is a related literature exploring the impact of deleveraging risk in the context of other securities. 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 differing 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, (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 beyond traditional 'arbitrage' strategies to the full cross-section of equity securities.

Our empirical approach is also related to the notion of stock price 'fragility' described in Greenwood and Thesmar (2012), 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 these (il)liquidity shocks.

The rest of the paper is structured as follows. Section 2 describes our measures of the intensity of the levered investor and our sample selection procedures. Section 3 provides some descriptive evidence on the cross-sectional and time series properties of our measures of levered invested capital. Section 4 presents our main empirical analysis and section 5 concludes.

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. Our daily measures of *ONLOAN* and *UTILIZATION* are constructed from Data Explorers who collect data on equity loans and lendable amounts from major players in the securities lending industry. According to the company, they cover more than 85% of the transactions in this industry. These variables are available between July 2006 and February 2011. An alternative daily measure of *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 and then only for those securities who trade on NYSE's SuperDOT platform. Our monthly measure of *SHORT INTEREST* is obtained from Compustat who in turn gather this data directly from the U.S. stock exchanges and 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 shorting 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 also obtain institutional ownership data from the Thomson Reuters CDA/Spectrum

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

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 and the 3-month LIBOR minus the overnight interest swap rate spreads (LIBOR-OIS Spread) as proxies 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.

2.2 Hypothesis Development

Our ideal research design would require identification of the portfolio weights of all portfolios that use leverage, 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 (see e.g., Ben-David, Franzoni and Moussawi, 2011).

A potential concern is why short positions would be affected differently than long ones. The return 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.

Each day we assign stocks to one of five quintiles sorted by our various shorting measures and compute average returns on the *following* day for stocks in the bottom and top quintiles. We then examine the returns of the LOW-HIGH portfolio. While this portfolio exhibits significant *positive* alpha (i.e., securities with the highest level of short selling have lower future returns than those with the lowest levels of short selling), 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 levered portfolio faced extremely negative returns during the Quant crisis and during the Lehman Brother's bankruptcy, two periods associated with a withdrawal of arbitrage capital. The Quant crisis event uses the period described by Khandani and Lo (2011), going from August 6th to August 8th, 2007. The Lehman Brothers' event is defined as the period from September 16th to September 18th, 2008.[4]

[4] 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)

In our primary empirical analysis, we run calendar portfolio regressions on 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 the LIBOR-OIS spread, (iv) changes in credit spreads and equity returns for an index of U.S. Banks, (v) indicator variables for large negative market returns in the previous day, and (vi) 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 characteristic regressions using a panel of daily data allowing interactions of the various short selling and liquidity measures.

Our primary empirical specification is as follows:

$$RET_t =$$

$$\alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t +$$

$$\beta_{Ret(MKT)<2.5\sigma} D_{Ret(MKT)<2.5\sigma,t-1} + \beta_{QUANT} D_{QUANT,t} + \beta_{LEHMAN} D_{LEHMAN,t} + \beta_{\Delta VIX} \Delta VIX_{t-1} +$$

$$\beta_{\Delta TED} \Delta TED_{t-1} + \beta_{\Delta LIBOR-OIS} \Delta LIBOR - OIS_{t-1} + \beta_{BANKS} BANKS_{t-1} + \varepsilon_t \qquad (1)$$

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. *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 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. $\Delta LIBOR - OIS_{t-1}$ is the change in the LIBOR-OIS spread from day t-2 to day t-1. $BANKS_{t-1}$ is a measure of the relative health of the US banking industry on the *previous* day. Depending on the regression specification we use either the change in 5 year CDS spreads for US banks (data limited to post 2004) or equity returns for US banks (data available back to 1990).

It is important to note the timing of our various liquidity variables. All of our liquidity variables are measured at the close of the previous 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-1 and 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. There is considerable concentration in the pattern of institutional shareholdings. Firms with more concentrated holdings tend to have lower lending supply (e.g., Prado et al., 2012). The average (median) firm in our sample has an institutional ownership concentration of 0.12 (0.07).

On average, 19.9% of a firm's market capitalization is available for lending (untabulated), 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) 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 1662 basis points on an annualized basis. The remainder of Table 1 reports information on our various liquidity measures. 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.

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 regression specifications with clustered standard errors by time (e.g., Petersen, 2009), 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 (ii) the concentration of institutional ownership, (ii) measures of fundamental 'cheapness', (iii) the level of accruals, (iv) recent stock momentum, (v) and measures of stock illiquidity.

3.2 Relation between ONLOAN and future stock returns

In figure 2 we plot the cumulative returns to an investment strategy that replicates *ONLOAN*. Each day we sort securities into five groups based on the breakpoints of *ONLOAN* from the previous day. We then compute equal (value) weighted returns for the combined long (LOW) and short (HIGH) *ONLOAN* quintile. The difference 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 'hedge' portfolio. The greater volatility in the returns to the *ONLOAN* 'hedge' 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 *ONLOAN* 'hedge' portfolio, with daily volatility almost tripling in size relative to pre-event levels.

To isolate the potential asymmetry in the daily returns to the *ONLOAN* 'hedge' 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 *ONLOAN* 'hedge' 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 utilization 'hedge' 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 *ONLOAN* 'hedge' 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 <u>short</u> side of the *ONLOAN* 'hedge' portfolio to experience large positive returns on days associated with funding illiquidity, and we do not expect much movement on the long side of the *ONLOAN* 'hedge' 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.

In figure 5 we examine in more detail the days around the Quant crisis (top panel) and the Lehman Bankruptcy (bottom panel). Consistent with the analysis in figure 4, the high *ONLOAN* quintile drive extreme positive returns in both cases. For example, on Wednesday September 17th 2008, the return of the high *ONLOAN* portfolio was +8%. Note that this return is without any degree of leverage. If, for example, a hedge fund was shorting stocks in the high *ONLOAN* quintile with a 3:1 leverage ratio (i.e. $1 of equity for every $3 of asset value), it could lose 27% on a single day. Furthermore, it is important to note that 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 in their portfolio construction choices, the returns we document in figure 5 will be understated (see e.g., Daniel and Moskowitz, 2012 and Daniel et. al., 2012).

4. Empirical Analyses

4.1 Calendar time analysis with primary 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 (5-6) basis points of abnormal returns per day on an equal (value) weighted basis. Using geometric averages these correspond to annualized returns of between 13.5-16.3 (28.6-35.2) 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 *ONLOAN* portfolios are positively exposed to MOM. Again this is consistent with prior research (e.g., Desai et. al., 2002 have a reliably negative exposure to MOM for their long highly-shorted security portfolios).

Our primary interest, however, is on the behaviour of *ONLOAN* portfolio returns during periods associated with deleveraging events. In column 3 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 TED Spread. In columns 4 to 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 the LIBOR-OIS spread, (ii) changes in credit spreads of a basket of US banks, and (iii) 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.

Across both table 5 and 6 we see no reliable evidence of large negative market returns affecting the performance of the LOW-HIGH *ONLOAN* portfolio. However, 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 -1.74 and -1.71. This means that while the LOW-HIGH *ONLOAN* portfolio averages about 10 basis points of returns per day, on days of funding illiquidity the returns are -175 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 -2.34 and -1.73, 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 reliably negative associated with the returns of the LOW-HIGH *ONLOAN* portfolio. For example, in table 5 the $\beta_{\Delta VIX}$ regression coefficient is between -6.1 and -5.7 for columns 3 to 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 -5.7) on the following day. Finally, we see across both tables 5 and 6, that $\Delta LIBOR - OIS$ is not associated with the returns of the LOW-HIGH *ONLOAN* portfolio, but as expected, both 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 1, 2006 through to February 28, 2011 from Data Explorers), (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 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 onloan 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 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 6-8 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 a positive 6 basis points of returns per day it experiences losses of over 200 basis points on days around significant deleveraging events. As before there is no reliable evidence of large negative aggregate market returns or changes in the LIBOR-OIS spread affecting the returns to the LOW-HIGH *UTILIZATION* portfolio. But there is continued evidence that measures of the relative performance of the banking industry (providers of arbitrage capital and portfolio leverage) are positively 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). Using data from the NYSE Volume Summary files we 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 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 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 10 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, 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*. It has the disadvantage that it is only available once per month, however it has the distinct advantage of a much longer time series. We are able to source *SHORT INTEREST* back to January 1990 for all US 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 with 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 now 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 changes in 5 year CDS spreads for US banks (tables 5-8) or US bank returns (tables 5-9) the 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 Cross-sectional Return Regressions

As an alternative to time series regressions of portfolio returns designed to mimic the behaviour of short sellers, we also report a standard characteristic-based regression. For this analysis we pool all of our daily data. This creates a panel of over 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:

$$RET_{i,t+1} = \alpha + \beta_{BETA}BETA_{i,t} + \beta_{SIZE}SIZE_{i,t} + \beta_{B/P}B/P_{i,t} + \beta_{RET6M}RET6M_{i,t} +$$
$$\beta_{ACC}ACC_{i,t} + \beta_{ILLIQ}ILLIQ_{i,t} + \beta_{ONLOAN}ONLOAN_{i,t} + \beta_{\Delta VIX}\Delta VIX_t + \beta_{\Delta TED}\Delta TED_t +$$
$$\beta_{\Delta CDS5Y-BANKS}\Delta CDS5Y - BANKS_t + \beta_{QUANT}D_{QUANT} + \beta_{LEHMAN}D_{LEHMAN} +$$
$$\beta_{ONLOAN*\,QUANT}ONLOAN_{i,t} * D_{QUANT} + \beta_{ONLOAN*\,LEHMAN}ONLOAN_{i,t} * D_{LEHMAN} +$$
$$\beta_{ONLOAN*\,\Delta VIX}ONLOAN_{i,t} * \Delta VIX_{i,t} + \beta_{ONLOAN*\,\Delta TED}ONLOAN_{i,t} * \Delta TED_{i,t} +$$
$$\beta_{ONLOAN*\,\Delta CDS5Y-BANKS}ONLOAN_{i,t} * \Delta CDS5Y - BANKS_{i,t} + \varepsilon_{i,t+1} \qquad (2)$$

All variables are defined in the appendix and table 10. We estimate (2) using both total daily stock returns, labelled as RAW, and also characteristic-adjusted returns as defined in Daniel et al. (1997), labelled as DGTW. We repeat the estimation three times for each measure allowing for the inclusion of daily and firm fixed effects in various combinations. The coefficients for the levels of liquidity variables and the crises dummy variables are omitted from columns 3 to 6 because they are subsumed by the daily fixed effects.

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) 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 negative 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 shot selling activity and future returns is conditional on funding liquidity. To help ease the interpretation of the interaction variables we have plotted 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 predicted 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 dummy 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: as we increase *ONLOAN* returns are more negative, with the forecast for stocks in the 99th percentile of *ONLOAN* being equivalent to -7.5 bps per day. As we increase the value of $\Delta(VIX)$ 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 $\Delta(VIX)$ 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. This is exactly the deleveraging risk that has been described throughout the paper. We find similar results for $\Delta(TED)$ and $\Delta(CDS5y - Banks)$. For both the Quant and Lehman Brothers' 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. These effects are similar for the regressions estimated with daily and firm fixed effects.

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 short positions experience occasional and very positive returns.

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 in the equity lending market employ leverage as part of their investment strategy. This is a reasonable assumption given the institutional features of the equity lending market. Consistent with prior research, we find across a variety of measures of short selling activity that, on average, there is a negative relation between measures of short selling activity and future stock returns. However, contrary to past literature, we document evidence of occasionally 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.

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Appendix: Variable Definitions

ONLOAN	Daily total number of shares on loan from Data Explorers divided by total number of shares outstanding.
SHORT VOLUME	Daily number of shares marked as short sales on NYSE divided by total volume.
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.
UTILIZATION	Daily number of shares on loan from Data Explorers divided by the total number of shares available to be lent from Data Explorers.
VW Fee	Daily loan-weighted average fee, in basis points, as reported by Data Explorers.
Daily Return	Daily RET reported by CRSP.
ILLIQ	Amihud's daily price impact measure computed as the ratio of absolute daily returns to the absolute value of 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 6th, 2007 and August 8th, 2007; and zero otherwise.
D_{LEHMAN}	Indicator variable equal to one for trading days between September 16th, 2008 and September 18th, 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 in the previous day. 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)
LIBOR-OIS Spread	Difference between 3-month LIBOR Eurodollar rate and the Overnight Interest rate, obtained from Bloomberg (Ticker codes: US0003M and USSOC).
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

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.

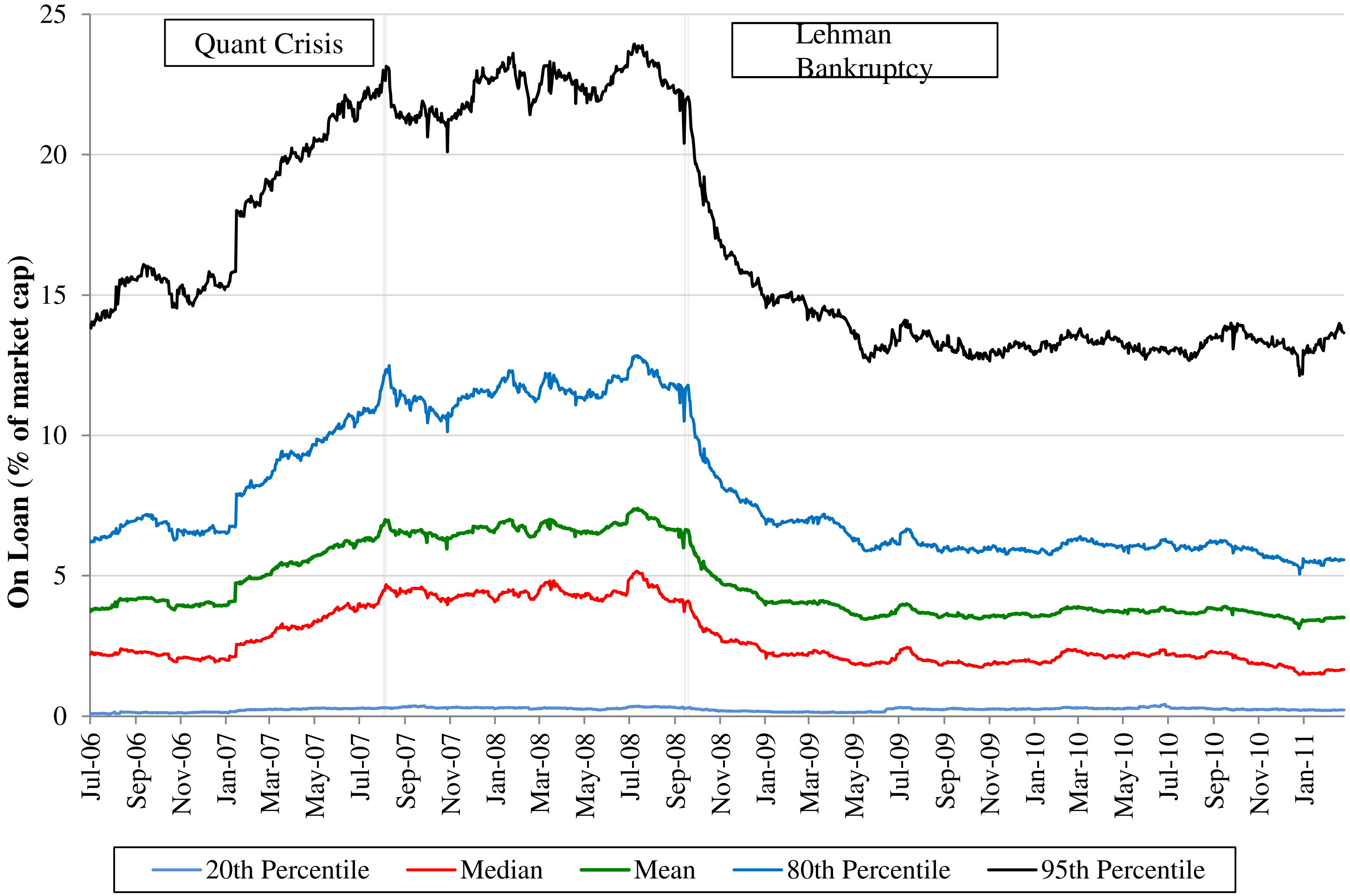

Figure 2: Daily Returns and Standard Deviations of Stock Portfolios sorted on *ONLOAN*
This figure plots the cumulative daily return of stock portfolios sorted on utilization from January 2nd, 1990 to February 28th, 2011. *ONLOAN* is defined as the number of shares on loan divided by the total number 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 to 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.

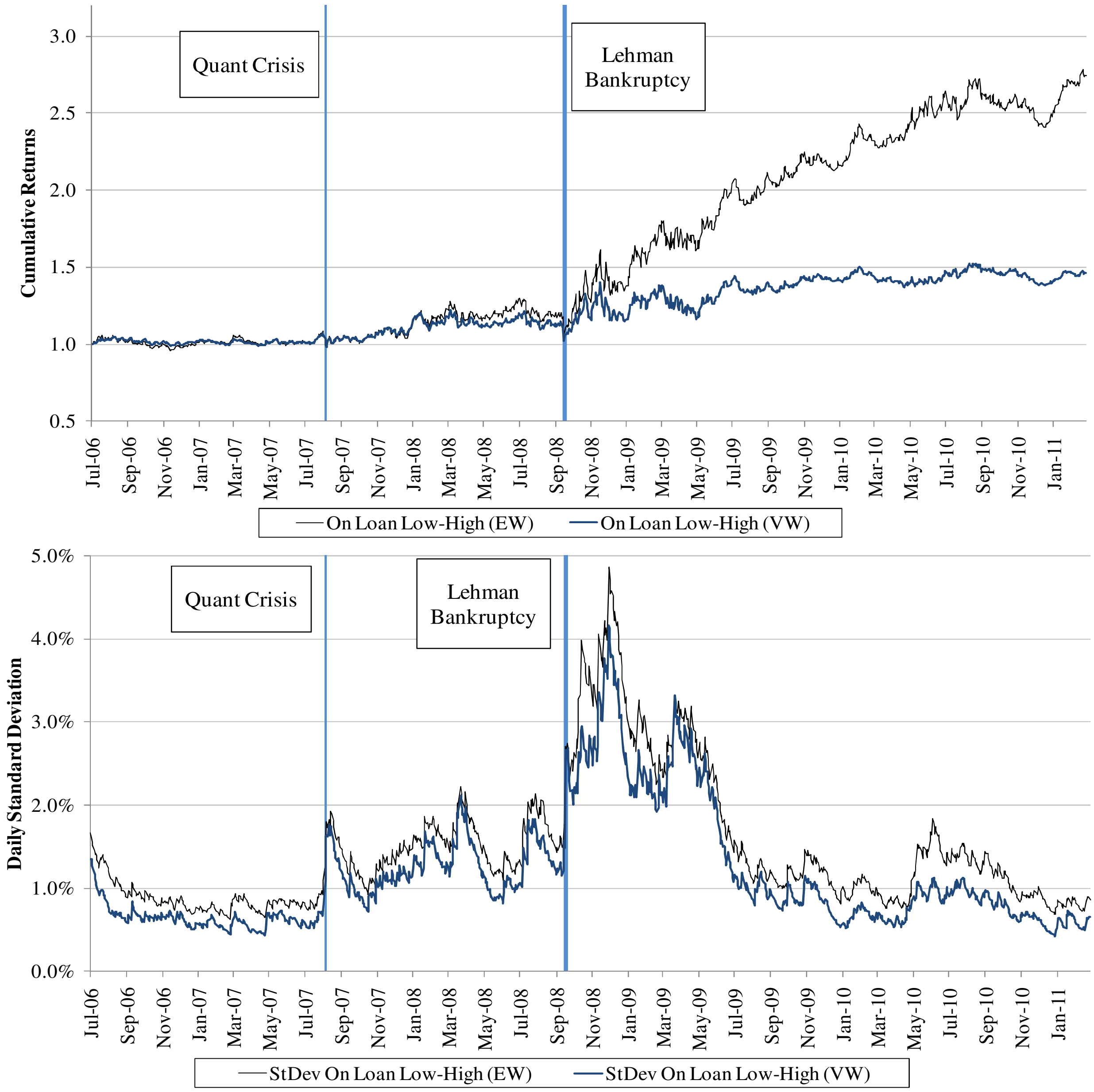

Figure 3: Histogram of Standardized Returns for *ONLOAN* Portfolios

This figure plots the histogram of daily returns scaled by the volatility 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. The portfolio returns are expressed in standard deviations that reflect the portfolio risk on each day.

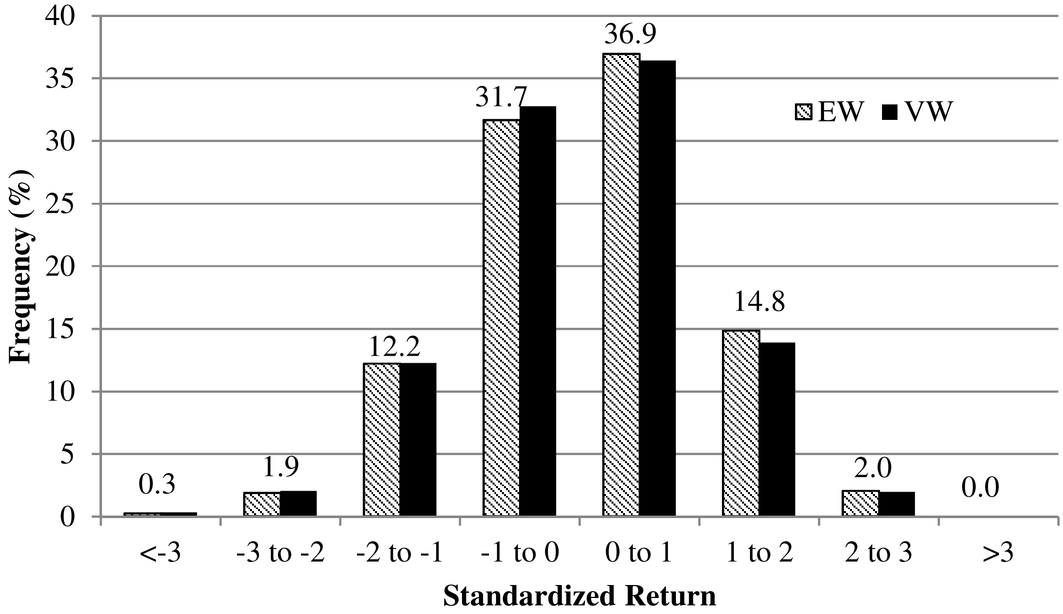

Figure 4: Extreme return days for High and Low Short *ONLOAN* portfolios

This figure shows raw returns of days when the LOW-HIGH *ONLOAN* portfolio returns are 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 returns by estimated standard deviations from a GARCH(1,1) model for the period between July 1st, 2006 and February 28th, 2011. The left panel displays data for equal-weighted portfolios and the right panel for value-weighted portfolios. For each day, we show returns for the bottom (LOW) and top (HIGH) quintiles of firms ranked by *ONLOAN* and also for the LOW-HIGH difference.

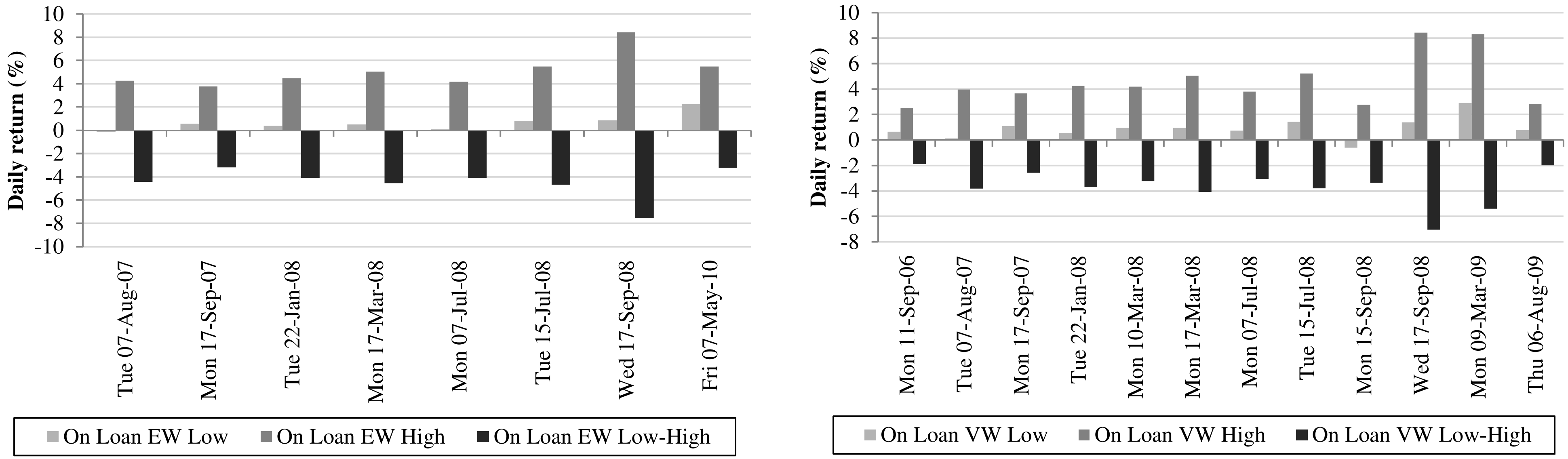

Figure 5: Abnormal Returns during the Quant crisis and Lehman Brothers' Bankruptcy
Figures show the cumulative abnormal portfolio returns of high and low *ONLOAN* portfolios. *ONLOAN* is defined as the number of shares on loan divided by the total number of shares outstanding. Abnormal returns are based 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 and August 8th, 2007. The lower panel displays returns around Lehman Brothers' Bankruptcy in October 2008, with the shaded area denoting the crisis period from September 16th to September 18th, 2008.

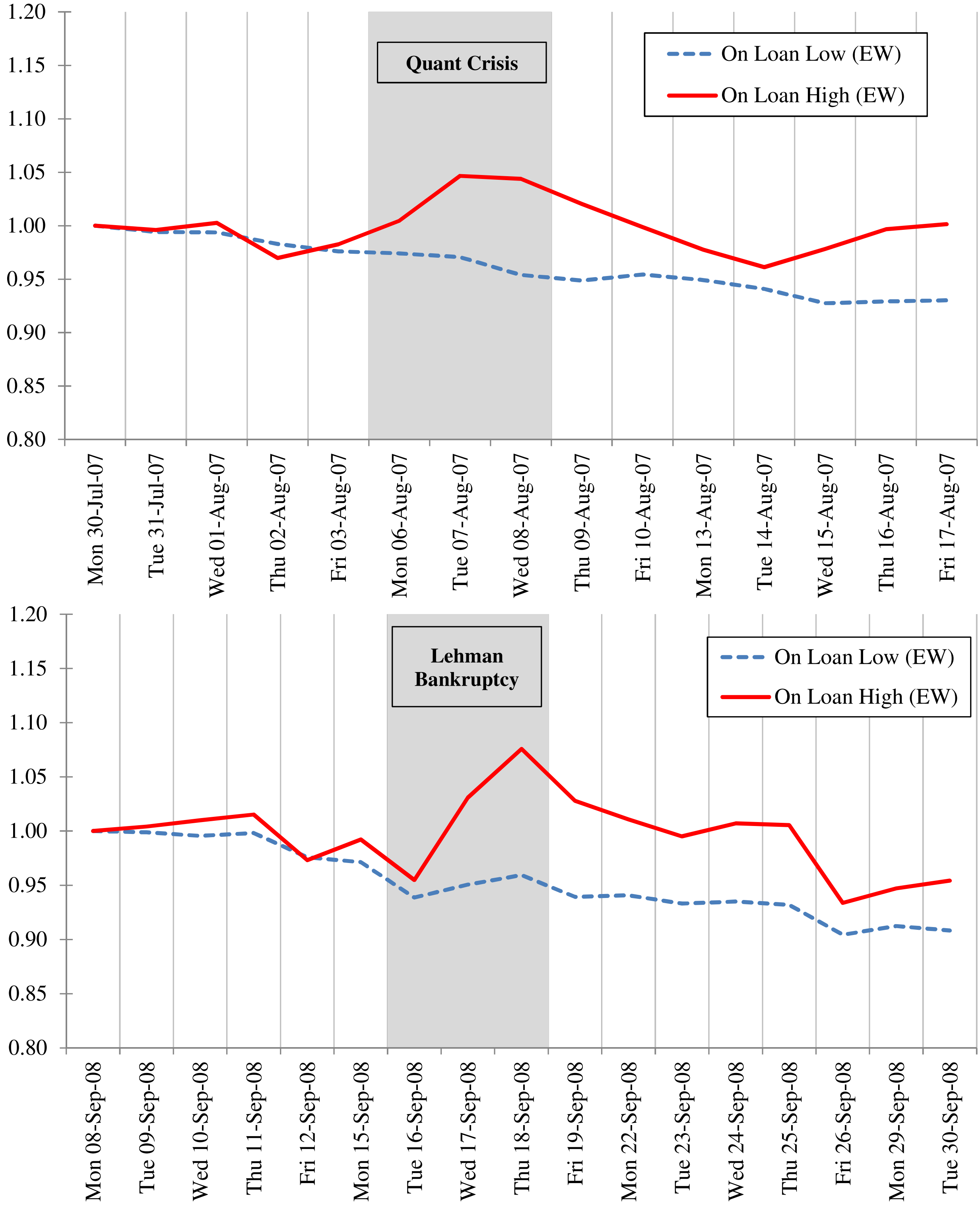

Figure 6: Asymmetric Changes of Predicted Abnormal Returns based on *ONLOAN*

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 are: 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. 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 dummy variable is equal to 1.

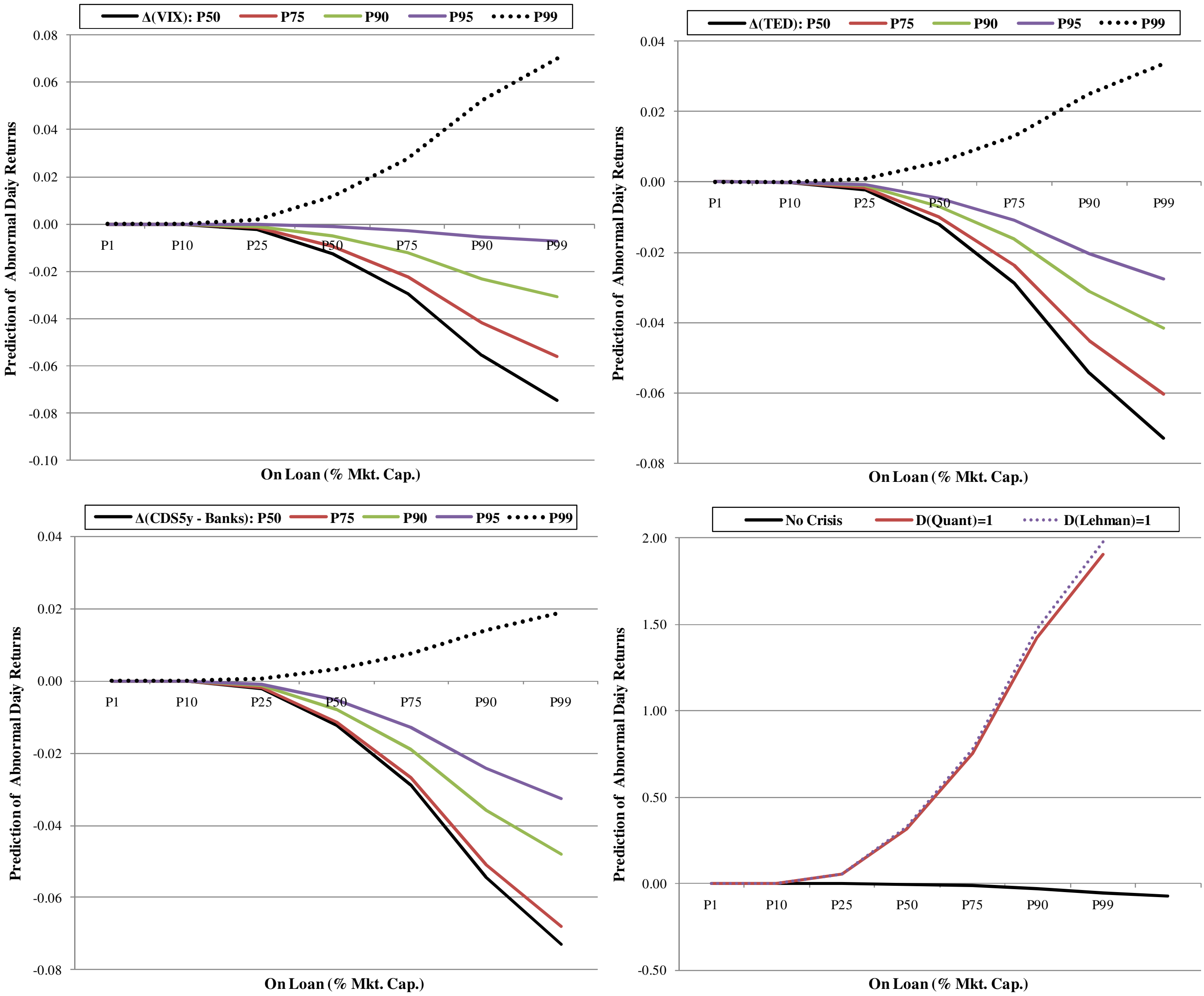

Table 1 – Descriptive Statistics

This table summarizes the characteristics of stocks over the period between July 1st, 2006 and February 28th, 2011 for 2,038,288 firm-day observations. Panel displays summary statistics for all variables while Panel B describes key percentiles for *ONLOAN* and funding liquidity measures.

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	2.86	13.09
ONLOAN	4.79%	2.50%	6.16%	0.00%	83%	2.32	10.91
VW Fee	77.25	13.26	234.53	-7.06	1,662	5.01	30.19
SHORT INTEREST	5.20%	3.33%	6.33%	0.00%	216%	4.18	58.54
VIX	24.38	22.21	12.04	9.89	81	1.75	6.58
Ted Spread	76.26	50.31	69.29	8.76	458	1.87	7.82
LIBOR-OIS Spread	0.45	0.17	0.58	-0.30	4	2.81	13.00
CDS 5y - Banks	122.38	119.63	88.16	10.20	595.99	0.97	4.70
Δ(VIX)	0.00	0.00	0.02	-0.17	0	0.27	16.32
Δ(Ted Spread)	0.00	0.00	0.09	-0.80	1.00	0.43	33.54
Δ(LOIS)	0.00	0.00	0.12	-1.07	1.07	1.19	33.70
Δ(CDS5y)	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	Δ(VIX)	Δ(TED)	Δ(CDS5y - 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 – Correlation Tables

This table presents the 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 Data Explorers 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; VIX is the VIX index; TED Spread is the change in the Treasury-Eurodollar spread; Libor-OIS is the difference between 3-month LIBOR Eurodollar rate and the Overnight Interest rate; CDS5y - Banks is the 5-year CDS index of financial services from Datastream. Δ(.) denotes changes between day t-2 and day t-1.

Panel A: Correlation

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Size	1													
(2)	IO	-0.098	1												
(3)	IO_{HHI}	-0.119	-0.229	1											
(4)	*ONLOAN*	-0.183	0.333	-0.093	1										
(5)	*SHORT INTEREST*	-0.195	0.268	-0.058	0.801	1									
(6)	*SHORT VOLUME*	-0.061	0.041	-0.031	0.188	0.149	1								
(7)	VIX	-0.044	0.002	0.011	0.011	0.030	0.167	1							
(8)	Ted Spread	-0.001	0.077	0.004	0.152	0.116	-0.045	0.588	1						
(9)	LIBOR-OIS Spread	-0.027	0.034	0.009	0.059	0.072	0.028	0.788	0.800	1					
(10)	CDS 5y - Banks	-0.033	0.013	0.008	0.054	0.083	0.241	0.593	0.350	0.480	1				
(11)	Δ(VIX)	0.000	0.003	-0.001	0.006	0.005	0.045	0.066	0.041	0.008	0.024	1			
(12)	Δ(Ted Spread)	0.003	0.004	-0.001	0.010	0.008	0.006	-0.016	0.096	-0.013	0.062	0.181	1		
(13)	Δ(LOIS)	0.002	0.004	0.000	0.009	0.007	-0.017	-0.009	0.068	0.107	0.016	-0.019	0.154	1	
(14)	Δ(CDS5y)	0.001	0.006	0.000	0.016	0.010	0.044	0.001	-0.089	-0.132	0.141	0.069	0.108	-0.103	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 Data Explorers 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, and is available monthly 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. ***(**)=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 short interest 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 Data Explorers 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; ILLIQ is Amihud's Illiquidity measure; Δ(VIX) is the daily change in the VIX index; Δ(TED Spread) is the daily change in the Treasury-Eurodollar spread; Δ(CDS5y - Banks) is the daily change inin the 5-year CDS index of financial services from Datastream. D(Quant) is a dummy variable equal to one in the period between August 6th and August 8th, 2007, 2007. D(Lehman) is a dummy variable equal to one in the period between September 16th and September 18th, 2008. 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]
Constant		-0.732***	0.895***
		[0.037]	[0.068]
Firm-Days		2,040,703	2,040,703
Clustered St. Errors		Time	Time
Time Dummies		No	Yes

Table 5: Calendar Equal-Weighted Portfolio Regressions based on *ONLOAN* (2006-2011)

The table displays a regression of 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, ΔLIBOR-OIS is the difference between the 3-month LIBOR and overnight interest swap rate, 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 dummy 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)
α	0.101***	0.104***	0.117***	0.118***	0.120***	0.119***
	[0.020]	[0.019]	[0.018]	[0.018]	[0.018]	[0.018]
β_{MKT}	-0.824***	-0.782***	-0.764***	-0.765***	-0.763***	-0.760***
	[0.030]	[0.029]	[0.030]	[0.029]	[0.029]	[0.026]
β_{SMB}	-0.793***	-0.807***	-0.806***	-0.807***	-0.800***	-0.798***
	[0.054]	[0.054]	[0.050]	[0.050]	[0.050]	[0.046]
β_{HML}	-0.177***	-0.012	-0.013	-0.016	-0.019	0.000
	[0.057]	[0.060]	[0.057]	[0.057]	[0.057]	[0.052]
β_{MOM}		0.194***	0.203***	0.206***	0.206***	0.219***
		[0.027]	[0.026]	[0.026]	[0.026]	[0.025]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.181	-0.207*	-0.189	-0.243**
			[0.124]	[0.120]	[0.119]	[0.117]
β_{QUANT}			-1.742***	-1.722***	-1.714***	-1.745***
			[0.243]	[0.239]	[0.238]	[0.228]
β_{LEHMAN}			-1.730***	-2.036***	-2.340***	-1.950***
			[0.446]	[0.365]	[0.366]	[0.398]
$\beta_{\Delta VIX}$			-5.699***	-6.097***	-5.789***	-0.299
			[1.080]	[1.115]	[1.114]	[1.518]
$\beta_{\Delta TED}$			-0.621*			
			[0.330]			
$\beta_{\Delta LIBOR-OIS}$				0.085		
				[0.326]		
$\beta_{\Delta CDS5Y(BANKS)}$					-1.475**	
					[0.677]	
$\beta_{RETURNS(BANKS)}$						0.064***
						[0.014]
# Days	1,172	1,172	1,171	1,171	1, 171	1,171
Adj. R2	0.836	0.849	0.864	0.863	0.866	0.869

Table 6: Calendar Value-Weighted Portfolio Regressions based on *ONLOAN* (2006-2011)

The table displays a regression of 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, ΔLIBOR-OIS is the difference between the 3-month LIBOR and overnight interest swap rate, 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)
α	0.045**	0.049***	0.061***	0.063***	0.064***	0.063***
	[0.018]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
β_{MKT}	-0.614***	-0.559***	-0.546***	-0.546***	-0.544***	-0.543***
	[0.034]	[0.032]	[0.033]	[0.032]	[0.032]	[0.031]
β_{SMB}	-0.667***	-0.686***	-0.681***	-0.683***	-0.674***	-0.675***
	[0.051]	[0.050]	[0.048]	[0.048]	[0.047]	[0.044]
β_{HML}	-0.240***	-0.023	-0.02	-0.019	-0.025	-0.011
	[0.061]	[0.062]	[0.059]	[0.057]	[0.058]	[0.054]
β_{MOM}		0.256***	0.263***	0.266***	0.265***	0.274***
		[0.023]	[0.022]	[0.022]	[0.022]	[0.022]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.096	-0.134	-0.095	-0.139
			[0.110]	[0.100]	[0.099]	[0.105]
β_{QUANT}			-1.550***	-1.527***	-1.524***	-1.552***
			[0.221]	[0.215]	[0.211]	[0.222]
β_{LEHMAN}			-2.072***	-2.238***	-2.639***	-2.218***
			[0.306]	[0.315]	[0.266]	[0.266]
$\beta_{\Delta VIX}$			-4.353***	-4.612***	-4.243***	-0.594
			[0.948]	[0.994]	[0.945]	[1.506]
$\beta_{\Delta TED}$			-0.417			
			[0.304]			
$\beta_{\Delta LIBOR-OIS}$				0.28		
				[0.277]		
$\beta_{\Delta CDS5Y(BANKS)}$					-1.793***	
					[0.574]	
$\beta_{RETURNS(BANKS)}$						0.045***
						[0.014]
# Days	1,172	1,172	1,171	1,171	1, 171	1,171
Adj. R2	0.787	0.823	0.841	0.841	0.847	0.845

Table 7: Calendar Equal-Weighted Portfolio Regressions based on *UTILIZATION* (2006-2011)

The table displays a regression of 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 (Data Explorers). 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, ΔLIBOR-OIS is the difference between the 3-month LIBOR and overnight interest swap rate, 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)
α	0.066***	0.070***	0.083***	0.085***	0.085***	0.085***
	[0.017]	[0.016]	[0.015]	[0.015]	[0.015]	[0.015]
β_{MKT}	-0.693***	-0.649***	-0.633***	-0.634***	-0.633***	-0.631***
	[0.024]	[0.023]	[0.023]	[0.023]	[0.023]	[0.021]
β_{SMB}	-0.742***	-0.757***	-0.752***	-0.753***	-0.748***	-0.746***
	[0.054]	[0.054]	[0.049]	[0.050]	[0.051]	[0.047]
β_{HML}	-0.228***	-0.055	-0.054	-0.057	-0.06	-0.046
	[0.054]	[0.056]	[0.050]	[0.051]	[0.050]	[0.046]
β_{MOM}		0.204***	0.209***	0.212***	0.212***	0.221***
		[0.024]	[0.023]	[0.023]	[0.023]	[0.023]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.114	-0.144	-0.125	-0.166
			[0.119]	[0.117]	[0.118]	[0.117]
β_{QUANT}			-2.187***	-2.165***	-2.161***	-2.184***
			[0.306]	[0.299]	[0.295]	[0.305]
β_{LEHMAN}			-2.149***	-2.472***	-2.702***	-2.418***
			[0.305]	[0.310]	[0.385]	[0.292]
$\beta_{\Delta VIX}$			-4.528***	-4.953***	-4.732***	-0.636
			[1.035]	[1.068]	[1.069]	[1.273]
$\beta_{\Delta TED}$			-0.666**			
			[0.290]			
$\beta_{\Delta LIBOR-OIS}$				0.12		
				[0.333]		
$\beta_{\Delta CDS5Y(BANKS)}$					-1.069*	
					[0.549]	
$\beta_{RETURNS(BANKS)}$						0.048***
						[0.013]
# Days	1,172	1,172	1,171	1,171	1, 171	1,171
Adj. R2	0.833	0.853	0.874	0.873	0.875	0.877

Table 8: Calendar Equal-Weighted Portfolio Regressions based on NYSE *SHORT VOLUME* (2006-2011)

The table displays a regression of 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, ΔLIBOR-OIS is the difference between the 3-month LIBOR and overnight interest swap rate, 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)
α	0.099***	0.100***	0.107***	0.108***	0.109***	0.108***
	[0.018]	[0.018]	[0.017]	[0.017]	[0.017]	[0.017]
β_{MKT}	-0.114***	-0.103***	-0.089***	-0.089***	-0.087***	-0.087***
	[0.025]	[0.026]	[0.027]	[0.026]	[0.026]	[0.025]
β_{SMB}	-0.173***	-0.177***	-0.176***	-0.178***	-0.170***	-0.172***
	[0.055]	[0.055]	[0.056]	[0.054]	[0.055]	[0.056]
β_{HML}	0.039	0.084	0.069	0.07	0.065	0.075
	[0.051]	[0.058]	[0.056]	[0.054]	[0.054]	[0.054]
β_{MOM}		0.053**	0.055**	0.057**	0.056**	0.062**
		[0.026]	[0.024]	[0.024]	[0.025]	[0.025]
$\beta_{Ret(MKT)<2.5\sigma}$			0.023	-0.004	0.029	-0.002
			[0.124]	[0.119]	[0.109]	[0.119]
β_{QUANT}			-2.299***	-2.283***	-2.281***	-2.302***
			[0.540]	[0.537]	[0.531]	[0.543]
β_{LEHMAN}			-0.939**	-0.998***	-1.346***	-0.995***
			[0.399]	[0.325]	[0.274]	[0.334]
$\beta_{\Delta VIX}$			-3.778***	-3.893***	-3.566**	-1.349
			[1.405]	[1.441]	[1.429]	[1.842]
$\beta_{\Delta TED}$			-0.193			
			[0.391]			
$\beta_{\Delta LIBOR-OIS}$				0.234		
				[0.416]		
$\beta_{\Delta CDS5Y(BANKS)}$					-1.566***	
					[0.395]	
$\beta_{RETURNS(BANKS)}$						0.028*
						[0.017]
# Days	1,171	1,171	1,171	1,171	1,171	1, 171
Adj. R2	0.105	0.111	0.168	0.169	0.188	0.174

Table 9: Calendar Equal-Weighted Portfolio Regressions based on *SHORT INTEREST* (1990-2011)

The table displays a regression of 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, ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day, ΔLIBOR-OIS is the difference between the 3-month LIBOR and overnight interest swap rate. 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)
α	0.087***	0.082***	0.086***	0.087***	0.085***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
β_{MKT}	-0.757***	-0.731***	-0.728***	-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***	-0.265***	-0.266***	-0.263***
	[0.021]	[0.020]	[0.019]	[0.019]	[0.019]
β_{MOM}		0.117***	0.118***	0.118***	0.119***
		[0.013]	[0.013]	[0.013]	[0.013]
$\beta_{Ret(MKT)<2.5\sigma}$			-0.163**	-0.166**	-0.162**
			[0.067]	[0.067]	[0.065]
β_{QUANT}			-1.796***	-1.792***	-1.817***
			[0.348]	[0.345]	[0.337]
β_{LEHMAN}			-1.977***	-2.101***	-2.020***
			[0.210]	[0.161]	[0.223]
$\beta_{\Delta VIX}$			-3.273***	-3.374***	-0.089
			[0.725]	[0.732]	[0.860]
$\beta_{\Delta TED}$			-0.218		
			[0.164]		
$\beta_{\Delta LIBOR-OIS}$				-0.048	
				[0.038]	
$\beta_{RETURNS(BANKS)}$					0.040***
					[0.008]
Obs.	5,546	5,546	5,545	5,545	5,545
Adj. R2	0.738	0.746	0.753	0.753	0.756

Table 10: Robustness Test - Cross-sectional 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. 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)	RAW (5)	DGTW (6)
β_{BETA}	-0.002	-0.007	-0.006	-0.006	-0.025**	-0.018*
	[0.009]	[0.008]	[0.009]	[0.009]	[0.012]	[0.011]
β_{SIZE}	0.039***	0.035***	0.033***	0.034***	0.746***	0.659***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.030]	[0.026]
$\beta_{B/P}$	0.135***	0.069***	0.093***	0.071***	0.390***	0.337***
	[0.012]	[0.008]	[0.010]	[0.009]	[0.034]	[0.030]
β_{RET6M}	-0.032*	-0.014	-0.022*	-0.022	-0.144***	-0.131***
	[0.017]	[0.009]	[0.013]	[0.014]	[0.050]	[0.047]
β_{ACC}	-0.250***	-0.093**	-0.117**	-0.093**	-0.297***	-0.249***
	[0.053]	[0.045]	[0.046]	[0.045]	[0.085]	[0.079]
β_{ILLIQ}	0.009***	0.013***	0.014***	0.013***	0.019***	0.021***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
β_{ONLOAN}	-0.977***	-0.432***	-0.491***	-0.455***	-1.587***	-1.383***
	[0.061]	[0.047]	[0.049]	[0.048]	[0.180]	[0.162]
$\beta_{\Delta VIX}$	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***	12.688***	18.432***
	[0.974]	[0.965]	[0.974]	[0.965]	[3.905]	[3.872]
$\beta_{ONLOAN*LEHMAN}$	16.589***	12.142***	14.844***	12.165***	4.660***	3.397***
	[1.130]	[1.109]	[1.109]	[1.109]	[0.597]	[0.554]
$\beta_{ONLOAN*\Delta VIX}$	15.319***	17.402***	12.850***	17.744***	1.072***	0.646
	[3.909]	[3.866]	[4.033]	[3.972]	[0.398]	[0.398]
$\beta_{ONLOAN*\Delta TED}$	4.153***	3.712***	5.354***	4.067***	14.275***	11.915***
	[0.581]	[0.555]	[0.565]	[0.557]	[0.970]	[0.961]
$\beta_{ONLOAN*\Delta CDS5Y-BANKS}$	5.476***	4.149***	7.923***	3.735***	15.534***	11.935***
	[0.887]	[0.850]	[0.890]	[0.863]	[1.198]	[1.166]
Time FE	N	N	Y	Y	Y	Y
Firm FE	N	N	N	N	Y	Y
Firm-Days	1,985,703	1,985,703	1,985,703	1,985,703	1,985,703	1,985,703