Deleveraging Risk

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Abstract

Deleveraging risk is the risk attributable to investing in a security held by levered investors. When there is an aggregate negative shock to the availability of funding capital, securities with a greater presence of levered investors experience extreme return realizations as these investors unwind their positions. Using data from equity lending markets as a proxy for the degree of levered positions, we find large positive returns and reductions in short selling quantities around periods of funding capital availability for highly shorted stocks. For example, during the Quant crisis, the daily abnormal returns to a portfolio that sells highly-shorted stocks and buys the least-shorted ones is -147 basis points, in contrast with +11 basis points during "normal" days.

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1. Introduction

1.1 Introduction

Stocks held by investors who are more likely to employ leverage as part of their investment strategies face an additional source of uncertainty: deleveraging risk. It is the risk of losses due to a sudden and widespread reduction in investment positions in a given stock brought about by events such as withdrawal of funding capital by underlying investors (Shleifer and Vishny (1997); Coval and Stafford (2007); Hanson and Sunderam (2014)), voluntary reductions in leverage (Brunnermeier and Sannikov (2013)) and increases in margin requirements (Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009); Geanakoplos (2010)).

This combination of voluntary and forced reductions in arbitrage capital may lead investors to suddenly close their long positions (i.e. "fire sales" as in Coval & Stafford (2008)) and, as shown in our paper, to cover their short positions (i.e. "fire purchases").[1] Hence, stocks with a greater presence of levered investors should experience more extreme returns as these investors decide, or are forced, to react to a reduction in arbitrage capital by unwinding their positions. Mitchell and Pulvino (2012) show how arbitrageurs use significant leverage to ensure that arbitrage opportunities are eliminated. In equity markets, while there is rarely a clear arbitrage, investors often set up long-short portfolios to exploit perceived mispricing (e.g., short 'growth' vs. long 'value, short 'losers' vs. long 'winners') extensively using of leverage and short selling.

In this paper, we test the impact of sudden deleveraging on stock prices by examining stocks with a high intensity of short selling activity. Our assumption is that short selling is a strategy used by sophisticated investors who often combine it with leverage to magnify their returns. If so, examining security lending activity allows us to identify at a daily frequency those securities with a relatively high proportion of levered investors. Consistent with that idea, for the 2004 to 2009

[1] "Short squeeze" is a term used for when short sellers are pressured to quickly cover their positions in an individual stock due to firm-specific shocks. We use the term "fire purchases" to denote events when a systematic shock (e.g. reductions in funding capital) lead short sellers to cover their positions across different stocks.

period the correlation between the monthly margin accounts debt of NYSE member organizations - a proxy for leverage - and short interest of the stocks in the most-shorted quintile is 0.731.[2] Similarly, this correlation is 0.286 using Ang. et al. (2011)'s equity hedge fund leverage estimate as an alternative proxy for leverage. When these levered short-sellers face a shock to funding capital they cover their short positions, causing stocks with the highest levels of levered investors to exhibit positive returns following these shocks. The price impact of the removal of funding capital should affect all levered positions, both short and long. 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 levered long positions.

We find that periods associated with reductions in arbitrage capital exhibit a strong positive correlation between short selling activity and future stock returns. Consistent with past research showing robust evidence that highly shorted securities 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)), we identify a negative relationship between short selling and future stock returns using several measures of short selling activity. However, this negative average relationship is interrupted by occasional periods of very positive returns for certain 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 reduction in arbitrage capital 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 weighted abnormal returns to a portfolio that sells highly-shorted stocks and buys the least-shorted ones is about -147 basis points, in contrast with 11 basis points during "normal" trading days. There is a striking asymmetry to the returns of long/short portfolios that are exposed to reduction of arbitrage

[2] We define leverage as the total amount of debt held (or "Securities Market Credit" extended) in all margin accounts at NYSE member organizations, scaled by NYSE stocks' total market capitalization. The NYSE margin debt data can be found at http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=278&category=8

capital: the effect is almost entirely attributable to losses in those stocks with high levels of short selling activity rather than to those with low short selling activity.

Widespread use of leverage by short sellers across securities makes equity lending markets a natural source of data. Our primary measure of short selling activity and therefore the presence of levered investors 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, $SHORT\ INTEREST$.[3]

We find a reliable positive relation between returns to a portfolio mimicking short selling intensity and systemic measures associated with reduction in arbitrage capital such as (i) changes in credit spreads of large banks that provide leverage to hedge funds, (ii) the Quant crisis of August, 2007 and (iii) the Lehman Brothers bankruptcy in September, 2008. As alternative measures associated with reduction in arbitrage capital we also examine changes in (i) the VIX index and (ii) the Treasury-Euro Dollar (TED) spread, finding consistent results for the latter but mixed evidence for the former. Overall, this is consistent with our hypothesis that a dislocation in the ability of levered investors to maintain their positions coincides with positive returns for stocks that have a greater concentration of short sellers.

In supplemental analyses we explore the potential mechanisms by which deleveraging risk affect stock returns. There are at least three non-mutually exclusive explanations for why levered investors may be unable to maintain levered positions. First, portfolio managers may voluntarily

[3] While $SHORT\ INTEREST$ is only available at a monthly frequency, it spans a much larger period ranging from January 1990 to August 2013. 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 June 2012 time period.

reduce the leverage of their portfolio to maintain a desired *ex-ante* risk level in response to economy-wide liquidity shocks. Second, investment funds' clients may withdraw capital during periods of aggregate shocks. While this does not force a portfolio manager to reduce its portfolio's leverage, it will cause a reduction in position size if she does not simultaneously increase leverage. Third, prime brokers may reduce the amount of leverage they are willing to extend to portfolio managers in response to economy-wide liquidity shocks. Thus, there is a combination of voluntary and involuntary reasons for observing deleveraging by portfolio managers in response to shocks. Matching the aggregate monthly data of equity hedge fund leverage in Ang et al. (2011) to our equity lending data over the July 2006 to December 2009 period, we find some evidence of reductions in hedge fund leverage contemporaneous with (i) the Quant crisis of August, 2007 and (ii) the Lehman Brothers bankruptcy in September, 2008, but no reliable evidence of a contemporaneous or lagged response with other measures of reduction in arbitrage capital. We are also unable to identify any reliable evidence of contemporaneous or leading associations between client redemptions (as measured by aggregate equity market neutral or equity long-short hedge fund flows) and changes in hedge fund leverage. In private discussions with the prime brokerage community we were did not hear about systematic reductions in leverage or large-scale recalls of shorted securities being forced upon equity hedge funds. Together, these results suggest the possibility of voluntary reductions in leverage by portfolio managers as the most likely explanation for the observed deleveraging.

We also examine the persistence of the occasional positive returns for highly shorted securities and additionally the changes in quantities of securities sold short. When we extend the return analyses for up to 60 days beyond the initial shock to arbitrage capital we continue to see a pattern of increased security prices across several of our arbitrage capital measures. This suggests that the effect is not reversed in the immediate term. We also document a significant reduction in equity loan quantities following periods of deleveraging events over the next 60 days for the majority of our measures of reduction in arbitrage capital. Together, these results suggest that unwillingness by levered investors to maintain their position sizes is the most likely explanation for the occasional strong positive relation between short selling activity and future returns, and that this effect continues for some time after the initial reduction in arbitrage capital.

1.2 Literature Review

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 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 following liquidity shocks. 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, it 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 withdrawal of funding capital.

What we call deleveraging risk is related to the notion of 'crowded' trades (e.g., Hanson and Sunderam (2014), Greenwood and Thesmar (2013). Our aim is to extend this literature by focussing on cross-sectional variation in security sensitivity to tail risk attributable to the presence of levered investors. The 'trigger' that creates the tail risk we document is not measured from correlation in infrequently measured portfolio holdings (as in Greenwood and Thesmar, 2013) or from aggregate measures of arbitrage capital (as in Hanson and Sunderam, 2014). Rather, we focus directly on security specific measures of security lending.

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 May 2013. 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 June 2012 for those securities trading on NYSE's SuperDOT platform. We also use $SHORT\ INTEREST$ from Compustat, defined as monthly short interest reported by U.S. stock exchanges scaled by market capitalization and available from January 1990 to August 2013. 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) and earnings-to-price (E/P). 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. 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 securities by $t+3$. Equity loans are settled on the same day that a 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. Correlations between aggregate measures of hedge fund leverage and aggregate short interest are strongly positive. For the 2004 to 2009 period, the correlation between Ang. et al. (2011)'s equity hedge fund leverage and short interest of the stocks in the most-shorted quintile is 0.286. If we use the leverage of investment banks the correlation is 0.238 and with the leverage of financial sector firms 0.132. Using NYSE's member organizations gross (net) margin account debt leverage has an even higher correlation with the short interest quantity of the most-shorted stocks, being equal to 0.729 (0.543). It is therefore reasonable to assert that short sellers set up their strategies with

[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.

widespread usage of leverage and stocks with the highest levels of short selling activity face high levels of deleveraging risk when arbitrage capital is suddenly withdrawn. When liquidity evaporates and short positions need to be covered, securities with a greater presence of levered investors experience a significant shock as these investors have to 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 have sold a significant portion of their portfolios and a mix of client redemptions and margin requirements increases associated with deleveraging were key drivers of this selling activity (Ben-David, Franzoni and Moussawi (2012)).

A potential concern is why short positions are affected differently than long positions. The price impact of a decrease in funding capital should affect all levered positions. However, because we cannot observe what 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 which are highly associated with usage of leverage. 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.

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. 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 long 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 and a liquidity factor. We include specific measures designed to capture the

[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)

market wide effects of (il)liquidity as reflected by: (i) changes in the VIX, (ii) changes in the TED spread, (iii) changes in credit default swap rates 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 Quant and Lehman 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 firm controls with the liquidity measures.

Our primary empirical specification is as follows:

$$LOW-HIGH_t = \alpha + \beta_{MKT} \cdot MKT_t + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \beta_{SPREAD} \cdot SPR_t +$$
$$\beta_{Ret(MKT)<2.5\sigma} \cdot D_{Ret(MKT)<2.5\sigma,t-1} + \beta_{QUANT} \cdot D_{QUANT,t} + \beta_{LEHMAN} \cdot D_{LEHMAN,t} +$$
$$\beta_{\Delta VIX} \cdot \Delta VIX_{t-1} + \beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{\Delta CDS5Y-BANKS} \cdot \Delta CDS5Y - BANKS_{t-1} + \varepsilon_t \qquad (1)$$

$LOW-HIGH$ 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, MOM are daily factor mimicking portfolio returns for the Fama-French factors and for momentum. SPR controls for liquidity and is based on Corwin and Schultz (2012)'s bid-ask spread estimators. We rank stocks based on the previous month's average of daily bid-ask spreads and define SPR as the daily difference between the top and bottom quintile's 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*, and $\Delta CDS5Y - BANKS_{t-1}$ is a measure of the relative health of the US banking industry defined as the change in 5 year CDS spreads for US banks (for which data is limited to 2004 onwards).

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 capital on the performance of a portfolio exposed to deleveraging 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 capital 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 \$4.2B (\$0.5B) with 56% (62%) of its shares held by institutional investors. The average (median) firm in our sample has an institutional ownership concentration of 0.13 (0.07). On average, 18.9% of a firm's market capitalization is available for lending, with 4.2% being on loan. Some stocks are heavily borrowed while others are not borrowed at all. $ONLOAN$ is as high as 27% in our sample. The average (median) $SHORT\ VOLUME$ is equal to 21% (21.1%) suggesting that short sales of NYSE stocks on the SuperDOT platform correspond to about one fifth of trading volume. Furthermore, the average value of $UTILIZATION$ is 18.2%, implying that almost one fifth of shares available to be loaned are actually on loan. The average (median) annualized lending fee is 101 (12) 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 2,275 basis points on an annualized basis. The remainder Table 1 reports information on control variables and our various liquidity measures in both levels and 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, 20th, 80th and 95th percentiles of $ONLOAN$. The lower tail of $ONLOAN$ is relatively stable through time but, in contrast, the right tail of $ONLOAN$ exhibits considerably more 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 aggregate deleveraging and the imposition of short selling constraints by the SEC.

Table 2 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 $ONLOAN$ for the period July 1, 2006 through to May 31, 2013 using daily 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. Securities with the highest level of $ONLOAN$ (i) are smaller, (ii) have higher levels of institutional ownership, (ii) have lower concentrations of institutional ownership, (iii) have higher values of alternative measures of short selling, (iv) have higher security lending fees, and (v) lower bid-ask spreads (using the measure from Corwin and Shultz (2012)). In terms of other firm characteristics, 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)).

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 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 $LOW - HIGH$ portfolio realizations. Figure 3 reports these details for the 15 (14) 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 3 reports raw 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, and we do not expect much movement for the long leg of the $LOW - HIGH$ portfolio. Whilst the analysis in figure 3 does not condition on explicit measures of funding capital (it is based only on days with extreme negative returns for the $LOW - HIGH$ portfolio), it should be viewed as a necessary condition for our hypothesis. Consistent with these priors, figure 3 shows that the extreme negative return days are *all* driven by large positive returns of the high $ONLOAN$ quintile. It is also worth noting that the extreme positive returns for the high $ONLOAN$ quintile coincide with negative market return days. Together the analysis in figure 3 is consistent with the idea that the 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, two days after Lehman Brothers filed for bankruptcy and the day that the U.S. Treasury announce the AIG bailout, 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 in 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 4 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 3, the high $ONLOAN$ quintile drives extreme positive returns in both cases. Furthermore, the returns we plot in figure 4 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 4 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

Table 3 reports our primary regression analysis where we report nested versions of estimating equation (1) using equal weighted portfolios. In unreported analysis we also consider value-weighted portfolios and find very similar results. For the sake of brevity we do not report these results but they are available upon request. For ease of interpretation we include predicted signs for each explanatory variable. There is a reliably positive intercept suggesting the $LOW - HIGH\ ONLOAN$ strategy generates about 11 basis points of abnormal returns per day on an equal weighted basis (a value weighted $LOW - HIGH\ ONLOAN$ strategy generates about 5 basis points of abnormal returns per day). Using geometric averages this corresponds to annualized returns of about 32 percent. 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, a $SPREAD$ factor mimicking portfolio return based on high minus bid-ask spread to control for liquidity (using the bid-ask spread measure from Corwin and Schultz (2012)), and an indicator variable for extreme negative market returns. We find that the $LOW - HIGH$ portfolio is positively exposed to MOM, consistent with prior research (Desai et. al. (2002) show a reliably negative exposure to MOM for their long highly-shorted security portfolios). Consistent with the patterns in figure 3, we see a reliably negative association between returns for the $LOW - HIGH$ portfolio and days with extreme negative market returns. We also find that the $LOW - HIGH$ portfolio is positively exposed to SPR, suggesting that part of the returns to short selling strategies reflect compensation for general liquidity risk..

Our primary interest, however, is on the behaviour of $LOW - HIGH$ portfolio returns during periods associated with deleveraging events. In column 3 we include all the measures related to funding capital: (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 (ΔVIX), (iv) changes in the TED Spread (ΔTED), and (v) changes in credit spreads of a basket of US banks ($\Delta CDS5Y - BANKS$) reflecting the ease by which banks can raise financing. For all variables 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 are increasing in funding illiquidity.

Consistent with the evidence in figure 4, 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 3 the β_{QUANT} regression coefficient is -1.58. 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 -147 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 -2.27, even more negative effect than found for the Quant crisis. Turning to the continuous measures of funding liquidity, we see that ΔVIX and ΔTED are negatively associated with the returns of the $LOW - HIGH\ ONLOAN$ portfolio but the latter is not significant at conventional levels. Finally, as expected we see credit spread changes for banks are negatively associated with the returns of the $LOW - HIGH\ ONLOAN$ portfolio. Overall, the evidence in table 3 provides consistent evidence that the returns to the $LOW - HIGH\ ONLOAN$ portfolio are negative during periods of funding (il)liquidity.

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 2006 through to May 2013 from Markit), (ii) $SHORT\ VOLUME$

(measurable daily for the period July 2006 through to June 2012 from the NYSE Volume Summary Files), and (iii) $SHORT\ INTEREST$ (measurable monthly for the period January 1990 through to August 2013 from 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.

Column (1) of Table 4 reports our regression results 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 11 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 both below -2.0, suggesting that while the $LOW - HIGH\ UTILIZATION$ generates an average of 11 basis points of returns per day, it experiences losses of more than 200 basis points on days around significant deleveraging events. We now see that ΔTED is significantly negatively associated with the returns of the $LOW - HIGH\ ONLOAN$ portfolio. There is continued evidence that changes in the funding levels of banks are negatively associated with returns to the $LOW - HIGH\ UTILIZATION$ portfolio. When credit spreads for banks widen, funding capital 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 30 percent of its total volume attributable to short seller-initiated trade orders.

Column (2) of table 4 reports our regression results 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 7 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 capital availability, most notably the indicator variables for the Quant and Lehman crises 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 not available daily, it has the distinct advantage of a much longer time series. We are able to obtain $SHORT\ INTEREST$ back to January 1990 for all U.S. securities in Compustat. We continue to conduct our empirical analysis at the daily frequency. We simply carry forward $SHORT\ INTEREST$ measured at the end of the previous month until the next end-of-month values are released by the exchanges, thus rebalancing our portfolios once a month. Following prior research we define $SHORT\ INTEREST$ 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 5 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 and SPR. 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 capital availability, most notably the indicator variables for the Quant and Lehman crises, the change in TED spread 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 variable is only available post 2004).

4.3 Panel regressions of stock returns

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 4.7 million daily return observations and we cluster standard errors by firm and include daily fixed effects. We interact $ONLOAN$ and other firm controls with all of the proxies for funding capital availability. Our regression specification is as follows:

$$RET_{i,t} = \alpha_t + B^T X_{i,t-1} + C^T X_{i,t-1} \otimes Z_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

RET is the daily return for a security as reported in CRSP. B^T is a vector of regression coefficients. X is a vector of firm characteristics that includes $BETA$, $SIZE$, B/P, $RET6M$, $RETURN_{t-1}$, $ILLIQ$, $SPREAD$ and $ONLOAN$. Z is a vector of funding capital variables that includes D_{QUANT}, D_{LEHMAN}, ΔVIX, ΔTED and $\Delta CDS5Y - BANKS$. C^T is a vector of regression coefficients capturing all interactions between firm characteristics and funding capital availability measures, including main effects for variables in Z. For the sake of brevity we only report interactions between $ONLOAN$ and the various funding capital availability measures. All variables are defined in the appendix.

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 $DGTW$. For our sample of firms over the 2006-2013 time period we find (i) that $BETA$ is negatively associated with stock returns (e.g., Frazzini and Pedersen, 2014), (ii) $SIZE$ is positively related to returns, (iii) B/P is positively associated with returns, (iv) $RET6M$ (6 month momentum, skipping the most recent month) is positively associated with returns, (iv), strong evidence of short–term reversal, (v) illiquidity is positively associated with returns (using both Amihud and Corwin and Schultz (2012)'s $SPREAD$ measure), and (vi) the main effect of $ONLOAN$ is negatively associated with future stock returns. Inferences are similar for both measures of returns, although the explanatory power of the panel regression using $DGTW$ returns is far lower, attributable to the fact that characteristics explain much of the variation in stock returns.

With the exception of ΔVIX, the interaction variables have the expected relation, i.e., the returns to $ONLOAN$ in table 6 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 capital availability. This is the deleveraging risk effect that has been described throughout the paper. Withdrawal of funding capital is positively associated with returns of stocks with high presence of short investors that are likely to use leverage. The effects are similar for regressions estimated with or without daily fixed effects.

4.4 Possible causes of deleveraging

Our empirical analysis thus far has established that securities with high levels of short selling activity (measured in a variety of ways) have very positive returns around periods where funding capital is harder to obtain. There are multiple possible reasons for this observed relation. Deleveraging can be caused by a combination of voluntary actions of portfolio managers as well as involuntary actions of multiple parties in the financial intermediation business. First, portfolio managers may seek to target an ex ante risk level for their fund. In response to economy-wide liquidity shocks, managers may voluntarily reduce the risk of their portfolios, primarily through a decrease in leverage. This would cause selling pressure on long positions and buying pressure on short positions. Second, clients of the portfolio manager may take direct actions in response to economy-wide liquidity shocks and withdraw capital from risky portfolios. Such clients could include external clients (i.e., ultimate owners) and/or internal clients (i.e., fund managers may have internal capital allocated from a parent entity or seed capital provider) and their actions are forced upon the portfolio manager who would then need to return capital. While these involuntary actions do not necessarily force arbitrageurs to reduce their portfolios' leverage, it will cause a reduction in position sizes if they do not simultaneously increase their leverage, again leading to selling pressure on long positions and buying pressure on short positions. Third, the prime broker who provides the leverage for the portfolio manager may take direct action in response economy-wide liquidity shocks. Such actions could include explicitly reducing the leverage extended to the portfolio manager and/or increasing the collateral that must be held against portfolio positions. Both outcomes would lead to selling pressure on long positions and buying pressure on short positions if portfolio managers are unable to put up the required increase in margins.

To help discriminate between these alternative explanations we examine time series correlations between (i) measures of aggregate equity hedge fund flows and aggregate equity hedge fund leverage, and (ii) measures of aggregate equity hedge fund leverage and general funding capital availability. If we identify a positive relation between aggregate equity hedge fund flows and aggregate hedge fund leverage this would suggest that external client redemptions were partially responsible for the observed deleveraging of equity hedge funds. If we identify systematic patterns in changes of aggregate hedge fund leverage around periods of funding (il)liquidity this would suggest that voluntary actions by portfolio managers and/or involuntary actions by prime brokers were partially responsible for the observed deleveraging of equity hedge funds. It is important to note that these analyses are at best descriptive as we only have (i) aggregate equity hedge fund leverage data, (ii) aggregate equity hedge fund flow data across 'broad' styles, and (iii) all of the data is only available at a monthly frequency. Ideally, we would like leverage at the individual portfolio level at a daily frequency but regrettably it is not available.

We obtain aggregate hedge fund leverage data from Ang et al. (2011). They obtain hedge fund leverage data from a fund-of-funds provider and are able to track hedge fund leverage over the period December 2004 to October 2009. The over-lapping period with our sample is 42 months of data from July 2006 to December 2009. We also compute aggregate equity hedge fund flow data from HFR and Lipper-TASS. We use the equity market neutral style from HFR and Lipper-TASS, as well as the equity long/short style from Lipper-TASS.

For the sake of brevity we simply discuss the resulting empirical analysis in the text. Across the 42 months we are unable to find any robust correlations between aggregate hedge fund leverage and aggregate hedge fund flow data. We examined contemporaneous, leading and lagging correlations.

This lack of result is perhaps not surprising as many hedge funds have in place ‘gates’ and the redemption process often requires formal applications that occur on a set cycle. Together this suggests that external client redemptions are unlikely to be a complete explanation of the observed deleveraging we document. We do not have access to internal capital allocated to equity hedge funds, so we are unable to directly comment on internal client redemptions as a cause of deleveraging risk. However, based on anecdotal discussions with equity hedge fund managers, especially those operating on ‘platforms’ such as D. E. Shaw, Milennium, Citadel, and SAC, there are clear procedures in place to mitigate losses in periods of market stress (e.g., ‘stop-loss’ rules). Thus, it is likely that involuntary internal capital withdrawal is a partial explanation for the deleveraging risk that we document.

Turning to portfolio leverage decisions directly, we find some evidence of reductions in hedge fund leverage contemporaneous with (i) the Quant crisis of August, 2007 and (ii) the Lehman Brothers bankruptcy in September, 2008, but no reliable evidence of a contemporaneous or lagged response with other measures of funding illiquidity. Ang et al. (2011) also document a lowering of hedge fund leverage in 2007 and 2008 coincident with our crisis periods. Given the infrequent nature of the data (i.e., monthly) we are unable to determine if the reduction in leverage is leading, contemporaneous with, or lagging the crisis periods. At the monthly frequency it appears that aggregate hedge fund leverage does respond to, or with, economy-wide liquidity shocks. As described above, the cause of this deleveraging is a combination of voluntary actions by portfolio managers as well as involuntary actions from prime brokers.

To help shed some light on the voluntary and involuntary deleveraging we spoke informally with several prime brokers. The general consensus of these discussions were: (i) hedge fund leverage has indeed fallen from the pre-2008 period (as reported by Ang et al. (2011), (ii) during the Quant period there were several examples of significant deleveraging (i.e., some funds were running at up to 15x gross leverage and relatively small, but correlated, price movements precipitated sudden deleveraging), (iii) during the Lehman period known arbitrage relationships broke down (e.g., convertible bond arbitrage and basis trades) which precipitated significant deleveraging for the funds with large exposures to these strategies, (iv) closing of short positions due to recalls are rare stock specific events mainly in small cap stocks and (v) forced deleveraging by prime brokers is unusual. The last point is most relevant for us. Within the categories of equity hedge funds prime brokers generally make a distinction between ‘statistical arbitrage’ and ‘fundamental’ managers. ‘Statistical arbitrage’ fund managers have high turnover and are therefore able to respond very quickly to economy-wide shocks to liquidity. A direct consequence of this is that ‘statistical arbitrage’ fund managers are allowed to operate at significantly higher levels of leverage (up to 8 times) and it is unusual for prime brokers to force reductions in portfolio leverage of ‘statistical arbitrage’ fund managers. In contrast, prime brokers view ‘fundamental’ managers as operating relatively safer portfolios with 2-3 times leverage and as such there is less need to directly intervene on portfolio leverage choices as these accounts are well within collateral bounds. Together this suggests the possibility of voluntary reductions in leverage by portfolio managers as the most likely explanation for our observed deleveraging risk.

4.5 Temporary vs. Permanent Effects

Our empirical analysis so far has not discussed if the impact on levered securities of reductions in funding capital 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 periods 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 sixty 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, $RANK - ONLOAN_k$, 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 capital, using the middle quintile (*k*=3) as the benchmark. Our baseline regression is given by:

$$CUMRET_{i,t+j} = \alpha_t + B^T X_{i,t-1} + C^T RANK_{ONLOAN_{k,i,t-1}} + D^T X_{i,t-1_{k,i,t-1}} \otimes Z_{i,t-1} + E^T RANK_{ONLOAN_{k,i,t-1}} \otimes Z_{i,t-1} + \varepsilon_{i,t+j} \quad (3)$$

$CUMRET$ is the cumulative daily return for a security as reported in CRSP. $B^T$is a vector of regression coefficients. X is a vector of firm characteristics that includes $BETA$, $SIZE$, B/P, $RET6M$, $RETURN_{t-1}$, $ILLIQ$, and $SPREAD$. Z is a vector of funding capital variables that includes D_{QUANT}, D_{LEHMAN}, ΔVIX, ΔTED and $\Delta CDS5Y - BANKS$. D^T (E^T) is a vector of regression coefficients capturing all interactions between firm characteristics ($RANK\_ONLOAN_k$) and funding capital availability measures, including main effects for the Z variables. For the sake of brevity we only report main effects and interactions between $RANK\_ONLOAN_5$ and the various measures of funding capital availability. All variables are defined in the Appendix.

We report our results in Table 7. The $RANK - ONLOAN_5$ coefficients capture the well-known negative relation between short selling activity and future stock returns. Stocks with high short selling intensity at time *t* continue to underperform for the next *t+60* days. The various interaction terms capture the effect of deleveraging risk following periods of funding illiquidity. Across our five measures of funding capital availability, we see that for four measures (D_{QUANT}, D_{LEHMAN}, ΔTED and $\Delta CDS5Y - BANKS$), 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) as found in our calendar time regressions in Tables 3-5. This positive return pattern is relatively short lived for the Quant and Lehman crisis periods, but is relatively longer lived for

[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 $ONLOAN$.

period following increases in TED spreads and widening of credit spreads for banks. Similar to the findings reported in Table 6, the coefficient of the interaction with ΔVIX has unexpected sign. 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 up to 60 days for some measures of funding capital. The impact of shocks to funding capital availability on stocks held by levered investors does not appear to be a short-lived effect.

Next, we examine changes in equity lending *quantities* following funding capital shocks. To the extent that the levered marginal investor closes out (i.e., cover) his short position at the time of a funding capital shock, it should result in lower levels of short selling. Given the results in tables 6 and 7, if the price effects still persist up to 60 trading days after the economy wide liquidity shock, we should also observe a decrease in short selling not only on the day after the shocks but also for the ensuing period. Thus, examining changes in quantities provide us with an alternative way to test whether funding illiquidity shocks are associated with decreases in short selling. 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 the same as equation (3) but with $\Delta ONLOAN_{i,t+3+j}$ as dependent variable. Note that the $\Delta ONLOAN_{i,t+3}$, is 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 loans' settlement described in section 2.1.

For the majority of our funding capital availability measures, the results in Table 8 show a 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 capital (including increased margin requirements, call back of lent securities, client redemptions etc.) will cause 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. $RANK-ONLOAN_5 \cdot D_{LEHMAN}$ coefficient) relative to the mean reversion observed in regular times (i.e. $RANK - ONLOAN_5$ coefficient). In our sample we see a reduction in $ONLOAN$ of -3.15% in terms of market capitalization in the 60 days after Lehman's bankruptcy, corresponding to a drop of 22.5% 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 60 days being equal to 54.6% (=0.91%*60 days). Thus, the estimated 3.15% cumulative decrease in $ONLOAN$ (itself a fraction of shares outstanding) is equivalent to a 5.8% reduction on the sell side of the market.

Together, the results in Table 7 on the continuation of positive returns for securities with high levels of short selling activity following periods of funding capital, and the results in Table 8 of reduced short selling quantities suggest that the large negative returns we document for the $LOW - HIGH\ ONLOAN$ portfolios are partially attributable to the withdrawal of funding capital 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 evidence that deleveraging risk - the risk of losses due to a sudden and widespread reduction in stocks held by levered investors - affects equity returns. Using various measures of short selling activity from multiple sources for a large sample of U.S. securities, we find that stocks with high short selling activity experience occasional and very large positive returns during periods associated with reduced funding capital availability. Our maintained assumption is that investors engaged in short selling employ leverage as part of their investment strategy. Thus, we can identify the degree of levered positions by tracking the actions of participants in the equity lending market. Consistent with that idea, between 2004 and 2009 the correlation between the monthly margin accounts' debt of NYSE member organizations as a proportion of NYSE stocks market capitalization - a proxy for leverage - and short interest of the stocks in the most-shorted quintile is 0.731. Similarly, this correlation is 0.286 using Ang. et al. (2011)'s equity hedge fund leverage estimate as an alternative proxy for leverage. The equity lending market is a natural source of data to quantify the presence of levered investors and the potential effect on stock prices since it aggregates the positions of short sellers across securities. 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, extending the 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 capital availability as reflected in a variety of measures such 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 capital shocks are economically significant and persist for up to 60 trading days for the majority of measures employed. The effect on equity lending quantities is also persistent and we find evidence of significantly lower quantities on loan for up to 60 trading days after deleveraging risk events. Together, the continuation of positive returns for securities with high levels of short selling activity after periods of reductions in funding capital and the reduced quantities of short selling suggest that the withdrawal of funding capital for the marginal levered investor is the likely explanation for the return effects we document.

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

References

Aitken, M. J., A. Frino, M. S. McCorry, and P. Swan, 1998, Short sales are almost instantaneously bad news: Evidence from the Australian stock exchange, *Journal of Finance* 53(6), 2205-2223.

Amihud, Y. (2002) "Illiquidity and stock returns: cross-section and time-series effects" *Journal of Financial Markets*, 5, 31-56.

Ang, A., S. Gorovyy,and G. B. van Inwegen, , 2011, Hedge fund leverage, *Journal of Financial Economics*, vol. 102(1), pages 102-126.

Asquith, P., P. A. Pathak, and J. R. Ritter, 2005, Short Interest, Institutional Ownership and Stock Returns, *Journal of Financial Economics* 78(2), 2005, 243–276.

Arora, N., P. Gandhi, and F. A. Longstaff, 2012, Counterparty credit risk and the credit default swap market, *Journal of Financial Economics* 103(2), 280-293.

Barroso, P., and P. Santa-Clara, 2013, Momentum has its moments, Working paper, NBER and Nova School of Business and Economics.

Ben-David, I., F. Franzoni, and R. Moussawi, 2012. Hedge fund stock trading in the financial crisis of 2007-2009. *Review of Financial Studies*, 25, 1-54.

Boehmer, E., C. M. Jones, and X. Zhang, 2008, Which Shorts Are Informed?, *Journal of Finance* 63, 491–527.

Brunnermeier, M., and L. H, Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Brunnermeier, M., and Y. Sannikov, 2013, The I-Theory of Money, Working Paper, Princeton University.

Cohen, L., K. B. Diether, and C. J. Malloy, 2007, Supply and Demand Shifts in the Shorting Market, *Journal of Finance* 62, 2061–2096.

Corwin, S. A., and P. Schultz, 2012, A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance*, 67 (2), 719-759.

Coval, J. D., and E. Stafford, 2007, Asset Fire Sales (and Purchases) in Equity Markets, *Journal of Financial Economics,* 86(2): 479–512.

Daniel, K., M. Grinblatt, S. Titman and R. Wermers, 1997, Measuring mutual fund performance with characteristic based benchmarks. *Journal of Finance*, 52, 1035-1058.

Daniel, K., R. Jagannathan, and S. Kim, 2012, Tail risk in momentum strategy returns, Working paper, Columbia Business School.

Daniel, K. D., and T. J. Moskowitz, 2012, Momentum Crashes, Working Paper, Columbia Business School.

Dechow, P., A. P. Hutton, L. Meulbroek, and R. G. Sloan, 2001, Short-sellers, fundamental analysis, and stock returns, *Journal of Financial Economics* 61, 77–106.

Desai, H., K. Ramesh, S. R. Thiagarajan, and B. V. Balachandran, 2002, An investigation of the informational role of short interest in the Nasdaq market, *Journal of Finance* 57, 2263-2287.

Duffie, D., 2010, Presidential address: Asset price dynamics with sow moving capital, *Journal of Finance* 65, 1237-1267.

Frazzini, A., and L. H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics*, 111, 1-25.

Garleanu, N., and L. H. Pedersen, 2011, Margin-based asset pricing and deviations from the Law of One Price, *Review of Financial Studies* 24(6), 1980-2022.

Geczy, C., D. Musto, and A. Reed, 2002, Firms are special too: an Analysis of the Equity Lending Market, *Journal of Financial Economics,* 66, 241-269.

Geanakoplos, J., 2010, The Leverage Cycle, Cowles Foundation Discussion Papers 1715, Cowles Foundation for Research in Economics, Yale University.

Greenwood, R., and D. Thesmar, 2011, Stock price fragility, *Journal of Financial Economics* 102(3), 471-490.

Gorton, G. and A. Metrick, 2012, Securitized banking and the run on repo, *Journal of Financial Economics* 104 (3), 425–451.

Gromb, D., and D. Vayanos, 2002, Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs, *Journal of Financial Economics*, 66(2–3): 361–407.

Haldane, A. G., 2010. Patience and Finance. Oxford China Business Forum, Bank of England.

Hanson, S. G., and A. Sunderam, 2014, The growth and limits of arbitrage: Evidence from short interest. Review of Financial Studies, 27, 1238-1286.

Jones, C. M., and O. A. Lamont, 2002, Short-sale constraints and stock returns. *Journal of Financial Economics*, 66, 207-329.

Khandani, A. E., and A. Lo, 2011, What happened to the quants in August 2007? Evidence from factors and transactions data, *Journal of Financial Markets* 14 (1), 1-46.

Mitchell, M., and T. Pulvino, 2012, Arbitrage crashes and the speed of capital, *Journal of Financial Economics* 104(3), 469–490.

Ringgenberg, M., 2011, When Short Sellers Agree to Disagree: Short sales, Volatility, and Heterogeneous Beliefs, Working Paper, Washington University in St. Louis.

Shleifer, A., and R. W. Vishny, , 1997, The Limits of Arbitrage, *Journal of Finance,* 52 (1), pages 35-55.

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.
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.
$RET6M$	Cumulative return in the previous six-month period skipping the most recent month.
RET	Daily stock return 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.
$SPREAD$	Bid-ask spread based on Corwin and Schultz (2012)'s estimation method.
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.
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.
MOM	Daily factor portfolio return to the momentum factor (UMD), obtained from WRDS.
SPR	Daily factor portfolio return to the bid-ask spread factor, based on Corwin and Schultz (2012). Stocks are sorted according to their average bid-ask spread in the previous month.
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 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	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)

Figure 1: Aggregate $ONLOAN$

This figure plots daily $ONLOAN$ of U.S. firms from July 2006 to May 2013 for various percentiles. $ONLOAN$ is defined as the number of shares on loan divided by the total number of shares outstanding.

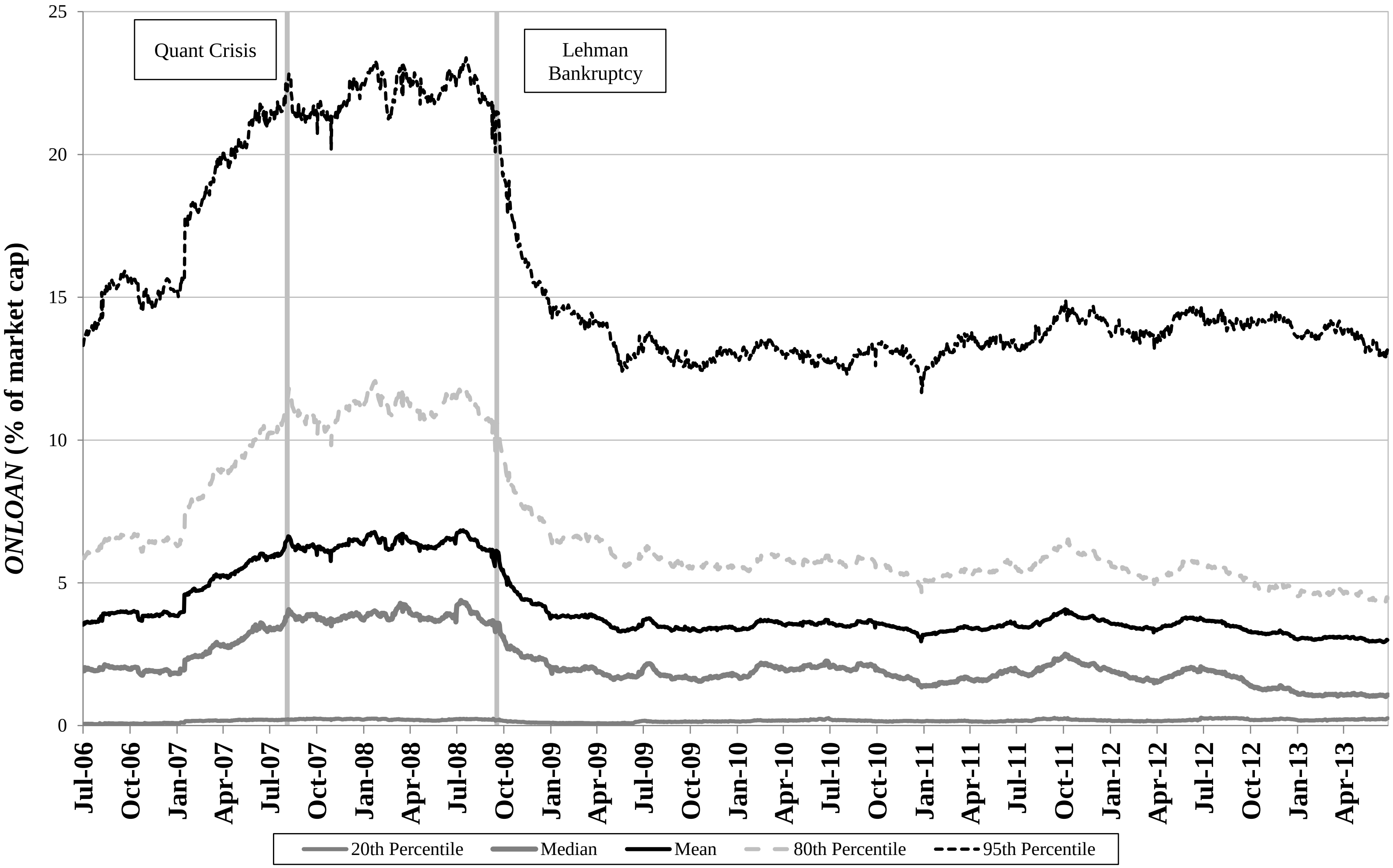
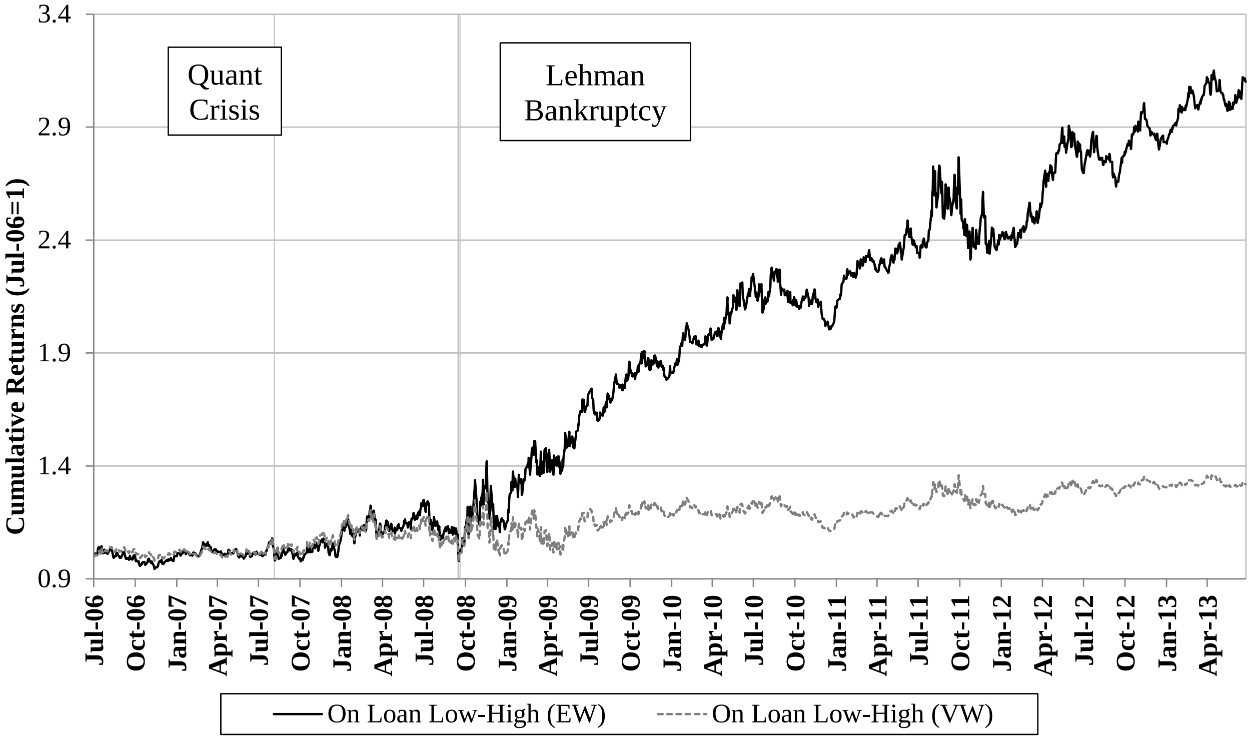


Figure 2: Daily Returns and Standard Deviations of Stock Portfolios sorted on $ONLOAN$
This figure plots the cumulative daily return of stock portfolios sorted on $ONLOAN$ from July 2006 to May 2013. $ONLOAN$ is defined as the number of shares on loan divided by the total number of shares outstanding. 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.



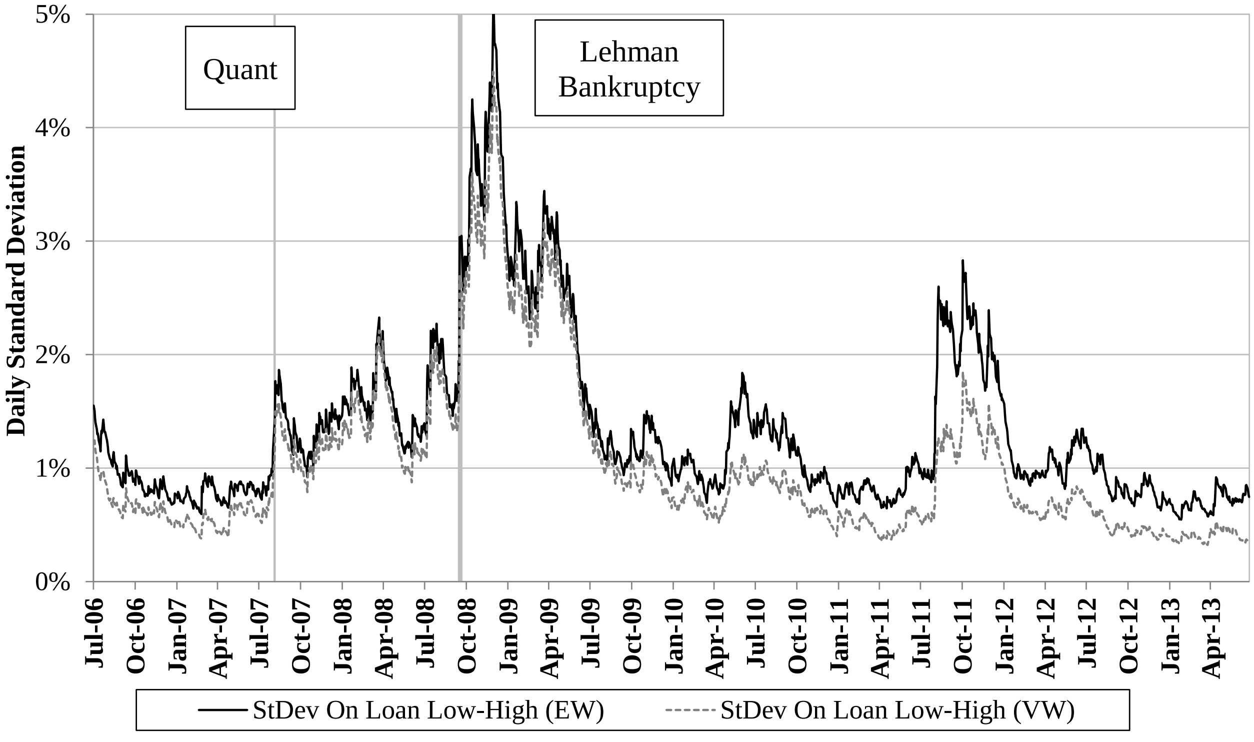


Figure 3: Extreme return days for High and Low Short $ONLOAN$ portfolios

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 2006 and May 2013. We show returns for the bottom (LOW) and top ($HIGH$) quintiles of firms ranked by $ONLOAN$ and also for the $LOW - HIGH$ difference. We also plot the CRSP VW index return for each corresponding day. The left panel displays data for equal-weighted portfolios and the right panel for value-weighted portfolios.

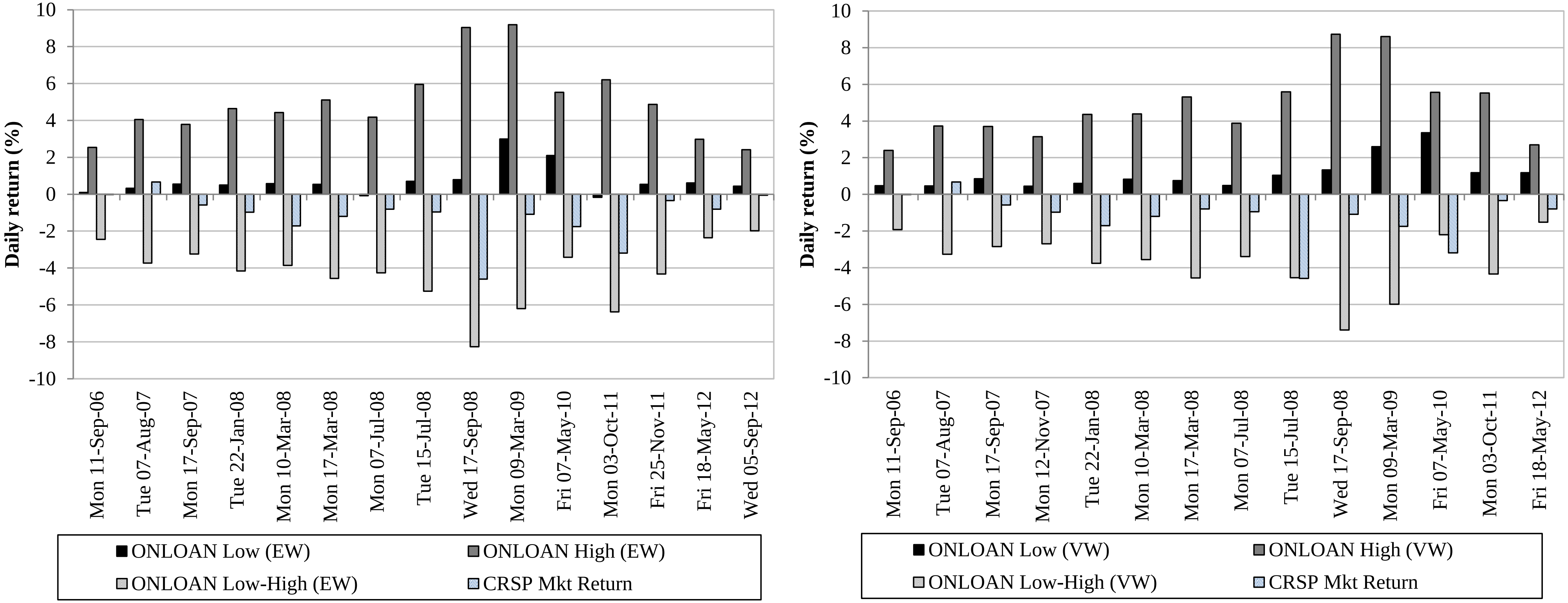
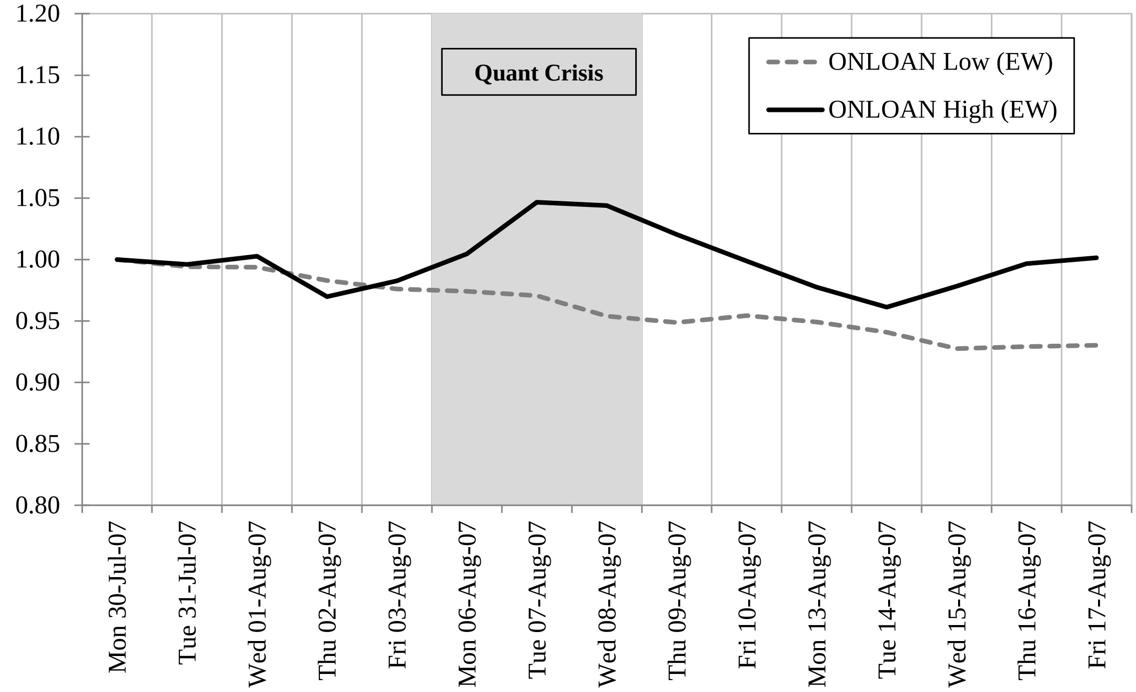


Figure 4: Abnormal Returns during the Quant crisis and Lehman Brothers' Bankruptcy
The figure show the cumulative abnormal portfolio returns of high and low $ONLOAN$ portfolios around the Quant crisis and the Lehman Brothers bankruptcy. $ONLOAN$ is defined as the number of shares on loan divided by the 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 DGTW's characteristics-adjusted returns. 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.



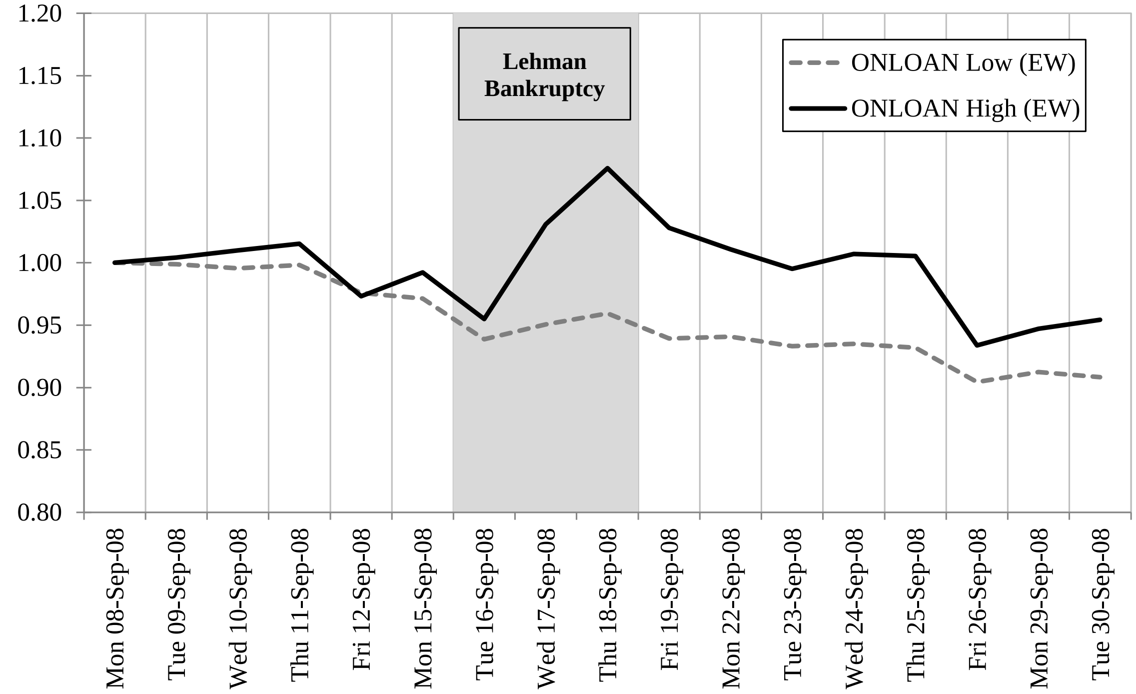


Table 1 – Descriptive Statistics

This table summarizes the characteristics of stocks over the period between July 2006 and May 2013 for 4,698,847 firm-day observations. $Size$ 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 divided by shares outstanding; $ONLOAN$ is the daily total number of shares on loan 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 per annum; $SPREAD$is the bid-ask spread estimated from Corwin & Schultz (2012); B/P is the book-to-market ratio; E/P is the earnings to price ration; $RET6M$ is the cumulative return in the previous six-months skipping the most recent month; 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. Δ(.) denotes changes between day t-2 and day t-1.

Variable	Mean	Median	Std. Dev.	Min	Max	Skew	Kurt
$Size$	4,191	510	18,300	0.26	658,000	12.44	226.71
IO	56.38%	61.61%	30.84%	0.00%	100%	-0.29	1.78
IO_{HHI}	0.13	0.07	0.15	0.01	1	2.75	11.98
$SUPPLY$	18.92%	19.52%	12.46%	0.00%	100%	0.32	3.11
$ONLOAN$	4.18%	2.01%	5.51%	0.00%	27%	2.01	7.10
$SHORT\ INTEREST$	21.95%	4.37%	36.71%	0.00%	100%	1.60	3.68
$SHORT\ VOLUME$	20.96%	21.11%	7.98%	0.00%	100%	0.11	4.42
$UTILIZATION$	18.16%	9.67%	21.30%	0.00%	88.73%	1.53	4.66
$VW\ Fee\ (bps\ p.a.)$	101.38	12.32	319.03	-7.13	2,275	5.05	30.66
$SPREAD$	1.30%	0.98%	1.22%	0.00%	67.30%	6.42	123.55
B/P	0.73	0.57	0.63	-0.01	3.81	2.36	10.42
E/P	-0.01	0.01	0.10	-0.74	0.10	-5.44	36.37
$RET6M$	3.45%	1.14%	38.01%	-77.06%	158.33%	105	598
VIX	23.07	20.47	10.97	9.89	81	1.93	7.68
TED	63.28	39.36	62.31	8.76	458	2.36	10.39
$CDS5Y - BANKS$	131.14	122.58	80.80	10.20	595.99	0.76	4.70
ΔVIX	0.00	0.00	0.02	-0.17	0.17	0.52	17.87
ΔTED	0.00	0.00	0.08	-0.80	1.00	0.66	48.18
$\Delta CDS5Y - BANKS$	0.01	0.02	2.51	-15.92	16.69	0.25	11.69

Table 2 – Descriptive Statistics for Stocks sorted on $ONLOAN$

This table summarizes the characteristics of stocks sorted by $ONLOAN$, 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 2006 through to May 2013. 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; IO_{HHI} is concentration of institutional ownership measured by the Hirschman-Herfindahl index; $SUPPLY$ is the total number of shares available to borrow divided by shares outstanding; $ONLOAN$ is the daily total number of shares on loan 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; $SPREAD$ is the bid-ask spread estimated from Corwin & Schultz (2012); B/P is the book-to-market ratio; E/P is the earnings to price ratio, and $RET6M$ is the cumulative return in the previous six-months skipping the most recent month. The last column reports the difference between the two quintiles. ***(**)=statistical significance at the 1% (5%) level.

Variable	LOW	HIGH	HIGH-LOW
Average # of firms	525.30	525.78	0.037***
$Size$	1,824	1,662	162***
IO	23.40%	85.93%	62.53%***
IO_{HHI}	0.300	0.061	-0.239***
$SUPPLY$	5.70%	27.60%	21.90%***
$ONLOAN$	0.40%	13.29%	13.25%***
$SHORT\ INTEREST$	0.46%	13.71%	13.24%***
$SHORT\ VOLUME$	15.09%	23.37%	8.28%***
$UTILIZATION$	2.46%	43.54%	41.08%***
$VW\ Fee\ (bps\ p.a.)$	76.18	177.42	101.24***
$SPREAD$	1.82%	1.15%	-0.66%***
B/P	1.09	0.59	0.49***
E/P	0.022	0.017	-0.005***
$RET6M$	1.48%	2.33%	0.85***

Table 3: Equal-Weighted Stock Portfolio Returns sorted on $ONLOAN$

The table displays regressions of stock portfolios sorted by $ONLOAN$, with daily U.S. stock returns between July 2006 and May 2013. We form portfolios by ranking stocks into quintiles based on $ONLOAN$ in the previous day and computing equal-weighted daily returns of selling High $ONLOAN$ stocks and buying Low $ONLOAN$ stocks. $ONLOAN$ is the total amount on loan divided by market capitalization. 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, MOM, the return on a portfolio of prior winners minus the return on a portfolio of prior losers, and SPR, the return on a portfolio of high-spread minus low-spread stocks. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day, $\Delta CDS5Y - BANKS$ is the change in the 5-year CDS index of financial services from Datastream. $D_{\mathrm{Ret(MKT)}<2.5\sigma}$ 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 6^{th} and August 8^{th}, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16^{th} and September 18^{th}, 2008; and zero otherwise. Returns and risk factors MKT, SMB, HML, MOM and SPR are measured at period t while other explanatory variables are measured at period t-1. We report White-adjusted standard deviations in brackets and significance levels are indicated as follow: ***(**)=significant at the 1% (5%) level.

	Predicted Sign	(1)	(2)	(3)
$Intercept$	+	0.105***	0.102***	0.108***
		[0.014]	[0.013]	[0.013]
β_{MKT}	-	-0.838***	-0.830***	-0.810***
		[0.023]	[0.022]	[0.021]
β_{SMB}	-	-0.749***	-0.785***	-0.774***
		[0.045]	[0.045]	[0.045]
β_{HML}	-	-0.183***	-0.063	-0.050
		[0.049]	[0.050]	[0.049]
β_{MOM}	+		0.205***	0.213***
			[0.025]	[0.024]
β_{SPREAD}	+		0.042**	0.038**
			[0.019]	[0.019]
$\beta_{Ret(MKT)<2.5\sigma}$	-		-0.440***	-0.283**
			[0.138]	[0.118]
β_{QUANT}	-			-1.576***
				[0.085]
β_{LEHMAN}	-			-2.271***
				[0.368]
$\beta_{\Delta VIX}$	-			-3.920***
				[0.880]
$\beta_{\Delta TED}$	-			-0.591
				[0.374]
$\beta_{\Delta CDS5Y-BANKS}$	-			-1.281*
				[0.687]
# Days		1,756	1,756	1,751
Adj. R2		0.855	0.870	0.882

Table 4: Stock Portfolio Returns sorted on Additional Proxies for Short-Selling

The table shows regressions of equal-weighted stock portfolio returns sorted on two alternative proxies of short-selling intensity, $UTILIZATION$ and $SHORT\ VOLUME$ using daily U.S. stock returns between July 2006 and May 2013. We rank stocks into quintiles based on values of short-selling proxies in the previous day and compute the equal-weighted returns of the portfolio that sells high short-selling intensity stocks and buying low short-selling intensity stocks. Our proxies for short-selling are: $UTILIZATION$ is defined as the number of shares on loan divided by the number of shares available to borrow, and $SHORT\ VOLUME$ is the number of shares traded short divided by the total number of traded shares on the NYSE SuperDOT system. $SHORT\ VOLUME$ is only available for the July 2006 to June 2012 period. Returns and risk factors MKT, SMB, HML, MOM and SPR are measured at period t while other explanatory variables are measured at period *t-1*. The explanatory variables are defined in the Appendix. We report White-adjusted standard deviations in brackets and significance levels are indicated as follow: ***(**)=significant at the 1% (5%) level.

	Predicted Sign	$UTILIZATION$	$SHORT\ VOLUME$
$Intercept$	+	0.106***	0.071***
		[0.012]	[0.015]
β_{MKT}	-	-0.613***	-0.105***
		[0.019]	[0.021]
β_{SMB}	-	-0.680***	-0.194***
		[0.044]	[0.049]
β_{HML}	-	-0.037	0.048
		[0.043]	[0.046]
β_{MOM}	+	0.216***	0.099***
		[0.021]	[0.028]
β_{SPREAD}	+	-0.018	0.072***
		[0.016]	[0.015]
$\beta_{Ret(MKT)<2.5\sigma}$	-	-0.136	-0.004
		[0.121]	[0.149]
β_{QUANT}	-	-2.114***	-2.239***
		[0.352]	[0.634]
β_{LEHMAN}	-	-2.447***	-1.594***
		[0.554]	[0.279]
$\beta_{\Delta VIX}$	-	-3.206***	-1.856
		[0.895]	[1.176]
$\beta_{\Delta TED}$	-	-0.663**	-0.129
		[0.318]	[0.391]
$\beta_{\Delta CDS5Y-BANKS}$	-	-0.725	-1.742***
		[0.519]	[0.455]
# Days		1,751	1,495
Adj. R2		0.874	0.188

Table 5: Equal-Weighted Stock Portfolios sorted on $SHORT\ INTEREST$ (1990-2013)
The table displays regressions of stock portfolios sorted on $SHORT\ INTEREST$, with daily U.S. stock returns between January 1990 and August 2013. We form portfolios by ranking stocks into quintiles based on $SHORT\ INTEREST$ at the end of the previous month, and carrying 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, MOM and SPR are measured at period *t* while other explanatory variables are measured at period *t-1*. Explanatory variables are defined in the Appendix. We report White-adjusted standard deviations in brackets and significance levels are indicated as follow: ***(**)=statistical significance at the 1% (5%) level.

	Predicted Sign	(1)	(2)	(3)
Intercept	+	0.075***	0.042***	0.043***
		[0.007]	[0.008]	[0.008]
β_{MKT}	-	-0.731***	-0.749***	-0.745***
		[0.011]	[0.010]	[0.009]
β_{SMB}	-	-0.430***	-0.516***	-0.515***
		[0.022]	[0.023]	[0.023]
β_{HML}	-	-0.290***	-0.281***	-0.276***
		[0.020]	[0.018]	[0.017]
β_{MOM}	+		0.095***	0.094***
			[0.013]	[0.013]
β_{SPREAD}	+		0.063***	0.063***
			[0.009]	[0.009]
$\beta_{Ret(MKT)<2.5\sigma}$	-		-0.333***	-0.295***
			[0.085]	[0.079]
β_{QUANT}	-			-1.615***
				[0.338]
β_{LEHMAN}	-			-1.904***
				[0.247]
$\beta_{\Delta VIX}$	-			-1.842***
				[0.630]
$\beta_{\Delta TED}$	-			-0.343**
				[0.150]
Obs.		5,546	5,546	5,545
Adj. R2		0.738	0.747	0.756

Table 6: Panel Return Regressions for $ONLOAN$ (2006-2013)

The table displays panel data regressions of individual stock returns between July 2006 and May 2013. Dependent variables in columns (1) and (2) are daily raw returns and $DGTW$ characteristic-adjusted abnormal returns respectively. $BETA$ 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. $RETURN_{t-1}$ is the previous day's return; $ILLIQ$ is Amihud's illiquidity measure; and $SPREAD$ is the bid-ask spread estimated from Corwin & Schultz (2012);. $ONLOAN$ is the total amount on loan divided by market capitalization. The funding liquidit any variables are: ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, $\Delta CDS5Y - BANKS$ 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. All regressions have day fixed-effects, which is why we only display the coefficients of interactions of funding liquidity variables and $ONLOAN$. We report robust standard deviations clustered at the firm level in brackets and significance levels are indicated as follow: *** (**)=statistical significance at the 1% (5%) level.

	Predicted Sign	RAW (1)	$DGTW$ (2)
β_{BETA}	+	-0.064*	-0.001*
		[0.036]	[0.000]
β_{SIZE}	+	0.045***	0.000***
		[0.005]	[0.000]
$\beta_{B/P}$	+	0.068***	0.001***
		[0.014]	[0.000]
β_{RET6M}	+	0.490***	0.005***
		[0.108]	[0.001]
$\beta_{RETURNt-1}$	-	-0.072***	-0.001***
		[0.005]	[0.000]
β_{ILLIQ}	+	5.041***	0.049***
		[1.287]	[0.013]
β_{SPREAD}	+	8.992***	0.083***
		[0.837]	[0.008]
β_{ONLOAN}	-	-0.213**	-0.002**
		[0.085]	[0.001]
$\beta_{ONLOAN*\,QUANT}$	+	4.321***	0.033***
		[0.681]	[0.007]
$\beta_{ONLOAN*LEHMAN}$	+	14.726***	0.118***
		[1.353]	[0.013]
$\beta_{ONLOAN*\,\Delta VIX}$	+	-22.746***	-0.159***
		[3.427]	[0.034]
$\beta_{ONLOAN*\,\Delta TED}$	+	4.960***	0.036***
		[0.663]	[0.007]
$\beta_{ONLOAN*\,\Delta CDS5Y-BANKS}$	+	2.157	-0.003
		[2.416]	[0.024]
Firm-Days		4,698,847	4,698,847
Adj. R^2		0.158	0.019
Time FE		Y	Y

Table 7: 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 May 2013. 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. Explanatory variables 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 plus interaction terms of the indicator variables with the controls, shown in equation (4) in the text. We report coefficients for $RANK - ONLOAN_5$ and $RANK - ONLOAN_1$ interacted with the funding liquidity variables. All regressions include firm fixed-effects and the same set of controls used in Table 6: $BETA$, $SIZE$, B/P, $RET6M$, $RETURN_{t-1}$, $SPREAD$, and $ILLIQ$. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, $\Delta CDS5Y - BANKS$ 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 6^{th} and August 8^{th}, 2007; and zero otherwise. D_{LEHMAN} is an indicator variable equal to one in the period between September 16^{th} and September 18^{th}, 2008; and zero otherwise. We report robust standard deviations clustered at the firm level in brackets and significance levels are indicated as follow: *** (**)=statistical significance at the 1% (5%) level.

		Interaction of $RANK - ONLOAN_5$ with:				
$t+j$	$RANK$ $ONLOAN_5$	D_{QUANT}	D_{LEHMAN}	ΔVIX	ΔTED	$\Delta CDS5Y$ $-BANKS$
1	-0.034***	0.960***	2.091***	-5.032***	0.457***	0.615***
2	-0.056***	2.757***	3.905***	-5.275***	0.439***	1.849***
3	-0.072***	3.157***	4.919***	-3.748***	0.131	2.711***
4	-0.082***	2.446***	4.444***	-4.107***	0.608***	3.432***
5	-0.091***	0.743*	4.064***	-3.891***	0.774***	3.946***
10	-0.167***	0.741	2.968***	-3.483***	0.136	4.402***
20	-0.295***	-0.483	-0.019	-4.914***	0.759**	6.267***
40	-0.436***	0.005	-0.885	-6.207***	1.213***	6.624***
60	-0.674***	-1.631	-1.536	-5.325***	1.563***	4.489**

Table 8: 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 May 2013. 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 $\Delta \mathrm{ONLOAN}_{i,t+3+j}$ as the difference in ONLOAN between day t+3+j and t+3, which captures short selling activity between t+j and t-1. Explanatory variables include indicator variables equal to one if a stock belongs to the kth quintile of ONLOAN and zero otherwise, funding liquidity variables and firm controls plus interaction terms, given in equation (4) in the text. We report coefficients for $RANK - ONLOAN_5$ and $RANK - ONLOAN_1$ interacted with the funding liquidity variables. All regressions include firm fixed-effects and the same set of controls used in Table 6: $BETA$, $SIZE$, B/P, $RET6M$, previous day return, $SPREAD$ and $ILLIQ$. ΔVIX is the daily change in the VIX volatility index, ΔTED is the daily change in the Treasury-Eurodollar spread, $\Delta CDS5Y - BANKS$ 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 follow: *** (**)=statistical significance at the 1% (5%) level.

		Interaction of $RANK - ONLOAN_5$ with:				
t+j	$RANK$ $ONLOAN_5$	D_{QUANT}	D_{LEHMAN}	ΔVIX	ΔTED	$\Delta CDS5Y$ $-BANKS$
0	-0.017***	-0.013	0.026	0.132***	0.007	0.089***
1	-0.016***	-0.014	-0.006	-0.007	-0.041***	0.187***
2	-0.032***	-0.121***	-0.088**	-0.117***	-0.087***	0.346***
3	-0.047***	-0.298***	-0.334***	-0.253***	0.002	0.321***
4	-0.062***	-0.560***	-0.500***	-0.290***	-0.000	0.416***
5	-0.078***	-0.739***	-0.651***	-0.361***	-0.005	0.445***
10	-0.093***	-0.815***	-0.766***	-0.524***	-0.040*	0.448***
20	-0.174***	-0.921***	-1.095***	-0.609***	0.034	0.527***
40	-0.340***	-0.986***	-1.857***	-0.986***	-0.085**	0.590***
60	-0.676***	-0.732***	-3.151***	-1.036***	0.057	0.039