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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 on equity loans as a proxy for the degree of levered positions in a given stock, we find robust evidence of deleveraging risk. Stocks with a high degree of short selling experience large positive returns and a decrease in short selling around periods of funding capital scarcity.

I. Introduction

The extreme movements observed in asset prices and investment flows during the 2007–2008 financial crisis have renewed academic interest in the impact of liquidity shocks on financial markets. Gorton & Metrick (2012) analyze the events leading to the crisis and show how a run on repo markets led to a widespread increase in write-downs (i.e., "haircuts") applied to securities accepted as collateral, reducing the amount of capital available to investors. Heightened perceived stock returns risk can also lead to reduction in capital available to investors, inciting widespread selling of securities (i.e., fire sales) and creating a self-reinforcing cycle that widens mispricing (see Shleifer and Vishny (2011) for a

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comprehensive survey). Gromb and Vayanos (2002) discuss how large mispricing can generate forced deleveraging through lower collateral values. Brunnermeier and Sannikov (2014) model how financial intermediaries reduce their lending in downturns, limiting the amount of capital available to investors.[1] Together, these arguments suggest that investment strategies can face higher risk during periods of extreme market movements and capital scarcity. For example, Coval and Stafford (2007) show that unexpected withdrawals from mutual funds require the funds to suddenly close their long positions, leading to fire sales and temporarily reducing the prices of stocks held by these funds.

We name this source of uncertainty "deleveraging risk" and define it as the risk of losses due to a sudden and widespread reduction in investment positions in a given stock. This idea is central to traditional microstructure theoretical and empirical research on market impact. For example, Kyle (1985), Brennan and Subrahmanyam (1996), and Amihud (2002) emphasize how trading activity impacts prices and the extent of this relation is directly tied to the liquidity or depth of the market. Our notion of "deleveraging risk" builds on this theoretical link by noting that the presence of levered investors, sensitive to extreme market movements and reduced access to funding, are likely to have a significant effect on security prices. During periods of market volatility and reduced access to funding capital, levered investors can be forced to reduce positions or may voluntarily decrease their risk exposure. This combination of forced and voluntary reductions in investment positions can lead to sudden reduction in long positions (e.g., Coval and Stafford (2007)). It can also force investors to cover their short positions (i.e., "fire purchases").[2]

In this article, we test the impact of sudden deleveraging on prices by examining stocks with a high intensity of short selling. Short selling is employed by sophisticated investors, who often combine it with leverage to magnify returns. Thus, it is reasonable to assume that a stock with high short-selling intensity is also likely to have a high proportion of short sellers using leverage when establishing their investment positions. The price impact of a decrease in capital available to investors should affect all levered long and short positions. Long levered positions are expected to exhibit "fire sales" (e.g., Coval and Stafford (2007), Mitchell and Pulvino (2012)), and short levered ones to display "fire purchases" if investors must suddenly close their short positions. We expect that the most levered long positions exhibit extremely negative returns during periods of funding withdrawals. However, because we cannot observe which stocks are held by levered long investors, we cannot test for negative returns from sales of long positions in these stocks, especially at daily frequency. Stocks with low short selling are not necessarily those with a higher proportion of levered long investors.

[1] For alternative channels by which asset prices can be affected by liquidity shocks and trading frictions, see Shleifer and Vishny (1992), (1997), (2011), Kyle and Xiong (2001), Brunnermeier and Pedersen (2009), Geanakoplos (2010), and Hanson and Sunderam (2014).

[2] "Short squeeze" is a term used when short sellers are pressured to quickly cover their positions in an individual stock due to firm-specific shocks. These rare stock-specific events mostly occur in small-cap stocks. We use the term "fire purchases" to denote events when a systematic shock (e.g., reductions in funding capital) leads short sellers to cover their positions across different stocks, akin to an aggregate "short squeeze."

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One might expect highly shorted stocks to generate significant profits during aggregate stock market decreases. Our article shows, surprisingly, this is not the case. We find there is a relative price increase for the most shorted portfolio of stocks during periods of market shocks and reductions in funding. Consistent with past research, we identify a negative relation between short selling and future stock returns using several measures of short selling (e.g., Aitken, Frino, McCorry, and Swan (1998), Dechow, Hutton, Meulbroek, and Sloan (2001), Asquith, Pathak, and Ritter (2005), Cohen, Diether, and Malloy (2007), and Boehmer, Jones, and Zhang (2008)). However, this negative average relation is interrupted by periods in which stocks with the highest levels of short selling experience strong *positive* returns. This relation relates to events such as those around the Lehman Brothers bankruptcy in Sept. 2008, and to changes in variables such as the Chicago Board Options Exchange (CBOE) volatility index (VIX) and the credit default swap index for the U.S. banking sector, both associated with economy-wide reductions in funding. In summary, we show that fire purchases also happen on the short leg of portfolios (i.e., stocks with the highest proportion of short selling). When levered short sellers face a shock that leads to a sudden reduction of their positions, stocks with the highest levels of levered investors can even exhibit positive returns.

Given the lack of data on stock holdings at a frequency higher than quarterly, equity lending markets provide a valuable data source to identify stocks with more shorting by levered investors.[3] By using daily equity lending, we can analyze how prices move after deleveraging shocks at a much higher frequency than previous papers.[4] Our primary measure of short selling is the ratio of the value of securities on loan to the total market capitalization of that security on a given day (ON_LOAN). We also employ three other measures of short-selling intensity: i) the ratio of the number of securities on loan to the number of shares that were available to be loaned (UTILIZATION); ii) the ratio of the number of shares sold short to the total number of shares traded that day from the New York Stock Exchange's (NYSE) SuperDOT platform (SHORT_VOLUME); and iii) the monthly ratio of the number of shares shorted to the number of shares outstanding (SHORT_INTEREST).[5]

We run time-series regressions of the LOW − HIGH portfolio's daily returns based on stocks sorted by short-selling activity as a function of the standard Fama–French (1993) factors (MKT, SMB, and HML), the momentum factor, and a daily liquidity factor based on Corwin and Schultz's (2012) bid–ask spread estimator. Additionally, we include specific measures designed to capture the market-wide effects of illiquidity as reflected by i) indicator variables for large negative market returns on the previous day, ii) indicator variables to capture the periods associated with the so-called Quant crisis of Aug. 2007 (Khandani and Lo (2011)) and

[3]Long positions must be reported by institutions through 13-F filings. Short positions do not have to be reported to the U.S. Securities and Exchange Commission (SEC).

[4]The vast majority of equity loans are made for the purpose of short selling (Saffi & Sigurdsson (2011))).

[5]While SHORT_INTEREST is available only at a monthly frequency, it covers a much larger period, ranging from Jan. 1990 to Aug. 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 traded on the SuperDOT platform for the July 2006–June 2012 period.

the Lehman Brothers bankruptcy in Sept. 2008, iii) changes in the VIX index, iv) changes in the TED spread, v) changes in convertible bond spreads relative to their fair price (Mitchell and Pulvino (2012)), vi) changes in the NOISE funding illiquidity measure proposed by Hu, Pan, and Wang (2013)), and vii) changes in the 5-year credit default swap index of the U.S. banking sector (CDS5Y). We also use principal component analysis to extract a common factor for liquidity as an additional variable, obtaining similar conclusions.

Overall, we find evidence consistent with the 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. For example, during the Lehman Brothers crisis, we estimate that the daily equal-weighted abnormal returns to a portfolio that sells highly shorted stocks and buys the least-shorted ones are about −241 basis points (bps), in contrast with 10 bps during normal trading days.

We also examine the persistence of returns for highly shorted securities and the changes in quantities of securities sold short following a reduction in funding. We see a pattern of higher security prices across several of our funding measures for up to 80 trading days beyond the initial shock. This suggests that the effect is not immediately reversed. We also document a significant reduction in equity loan quantities following periods of deleveraging for most of our arbitrage capital measures, supporting our findings that a reduction in leveraged short positions drives the stock return results.

Together, these results suggest that the unwillingness or inability of levered investors to maintain their position sizes most likely explains the occasional strong positive relation between short selling and future returns and that this effect continues for some time after the initial reduction in funding. To our knowledge, we are the first to investigate the impact of funding shocks on short sellers, adding novel evidence to the literature on these types of shocks.

Our article proceeds as follows: Section II develops our hypothesis. Section III describes our data sources. Section IV explains our research design. Section V shows the empirical results and considers further alternatives for deleveraging patterns. Section VI concludes.

II. Hypothesis Development

Our primary hypothesis is that the abnormal returns of highly shorted stocks are less negative and can even become positive following periods of funding illiquidity. Because short sellers set up their strategies with widespread usage of leverage, stocks with the highest levels of short selling face higher levels of deleveraging risk when funding is suddenly withdrawn. When liquidity evaporates and short positions have to be covered, securities with a greater presence of levered investors experience a significant shock as these investors unwind their positions, voluntarily or not. These movements push the prices of highly shorted stocks upward, affecting them relatively more than those stocks with low levels of short selling.

There are at least three nonmutually exclusive explanations for why levered investors may be unable to maintain levered positions during periods of capital scarcity. First, portfolio managers may voluntarily reduce the leverage of their

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portfolios to maintain a desired ex ante risk level in response to economy-wide liquidity shocks (Kyle and Xiong (2001), Xiong (2001), Bollerslev, Hood, Huss, and Pedersen (2016), and Moreira and Muir (2017)). If market volatility increases, investors might choose to employ less leverage in their portfolio.

Second, investment funds' clients may withdraw capital during periods of economy-wide liquidity shocks (Shleifer and Vishny (1997), Coval and Stafford (2007)). Such shocks tend to happen when there is a general demand for collateral. This does not force a portfolio manager to reduce a portfolio's leverage, but it will cause a reduction in position size if she does not simultaneously increase leverage of the remaining investors' equity.

Third, prime brokers may reduce the amount of leverage they are willing to extend to portfolio managers in response to economy-wide liquidity shocks. 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 funding by unwinding their positions (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Brunnermeier and Sannikov (2014)).

Regardless of the exact reason why investors choose to reduce their investment positions during periods of capital scarcity, all of the potential explanations are consistent with our hypothesis that a sudden attempt to reduce position size can lead to aggregate short covering. If the demand by levered short sellers trying to buy shares to cover their positions is offset by levered long investors trying to exit their positions in a given stock following deleveraging events, we would not expect any pricing effects. However, if the aggregate pressure to close short positions is strong enough to have a price impact, we would expect to observe returns even being positive following liquidity shocks for stocks with the highest ex ante short-selling intensity.

Our ideal research design would require identification of the portfolio weights of all portfolios that use leverage for both long and short positions. It is not possible to obtain this information from publicly available data. Instead, we use various measures of short selling to proxy for latent leverage. Thus, we assume that short sellers use leverage in their portfolios and securities with a high level of short-selling activity have higher presence of levered investors. These are reasonable assumptions since this is how a typical levered investment strategy works. The typical long–short equity strategy employed by a market-neutral hedge fund starts with an initial investment of $\$X$. The investor will then create a portfolio with weights such that the final portfolio has a desired ex ante risk level. To achieve the target level of risk, the fund manager will typically employ leverage via a prime brokerage relationship. The fund manager will use prime brokerage financing to "borrow" $\$L^S \times X$ worth of securities and purchase $\$L^L \times X$ worth of securities. The $\$L^S \times X$ worth of securities that are sold short are captured by the short-selling data. However, we cannot uniquely identify the $\$L^L \times X$ worth of securities that are purchased by the levered long investor.

To support our assumption that short selling reflects portfolio leverage, we examine aggregate leverage measures and how they correlate with measures of short selling. Note that we must use aggregate measures because security-level leverage data for individual investors is unavailable. We examine the relation between three different measures of leverage and short selling at the aggregate level.

First, we use leverage data computed by Morgan Stanley for fundamental long–short equity hedge fund clients of the firm's prime brokerage arm. The sample includes U.S. long–short accounts with at least $50 million in equity and is rebalanced every 6–12 months to keep it representative of historical accounts. Each fund is equally weighted in the aggregate metric. Correlations between monthly aggregate measures of leverage and short interest are strongly positive and statistically significant. The correlation between changes in long–short hedge funds' leverage and changes in the market-wide mean fraction of shares lent out from July 2006 through June 2013 equals 0.24. If stocks with high short-selling activity are also associated with a large presence of levered investors, we would expect an even higher correlation than that of the average stock. If we use the top 95th percentile to compute the correlation, it is statistically significant and equal to 0.34, consistent with our hypothesis. Second, we compute the correlation between the monthly leverage of equity hedge funds estimate by Ang, Gorovyy, and van Inwegen (2011) and the monthly difference of short interest for stocks in the most- and least-shorted quintiles from Dec. 2004 to Sept. 2009, which equals 0.25. Third, using NYSE's member organizations gross (net) margin account debt leverage, we find that the correlation with short interest for stocks in the most-shorted quintile is 0.73 (0.54). Given these significant correlations in aggregate short selling and aggregate portfolio leverage, our assumption that short sellers are likely to be levered investors seems reasonable.

While we aim to assess the impact of deleveraging risk on equity securities, there is related literature exploring the impact of leverage constraints and deleveraging risk on asset pricing. For example, Garleanu and Pedersen (2011) show that binding margin constraints can create 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. 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 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" versus "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 strategies, is consistent with our analysis. We can show a far broader impact of deleveraging risk into the full cross section of equity securities, beyond traditional arbitrage strategies.

Deleveraging risk is also related to the notion of crowded trades (e.g., Greenwood and Thesmar (2011), Hanson and Sunderam (2014)). Our aim is to extend this literature by focusing on cross-sectional variation in security sensitivity to the 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 by Greenwood and Thesmar (2011)) or from aggregate measures of arbitrage capital (as by Hanson and Sunderam (2014)). Rather, we focus directly on security-specific measures of equity lending, which allow us to investigate our hypothesis using stock-level daily data.

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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 relates directly to the presence of levered investors, we can identify 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 (e.g., Daniel and Moskowitz (2016), Daniel, Jagannathan, and Kim (2012), and Barroso and Santa-Clara (2016)).

III. Data

A. Equity Lending and Short-Sale Data

We obtain our measures of short selling from three sources: Markit (previously Data Explorers), NYSE, and Compustat. Our daily measures of ON_LOAN (defined as the value of the shares lent out divided by the stock's market capitalization) and UTILIZATION (defined as the value of the shares lent out divided by the value of shares available to lend) use data sourced from Markit, which collects 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 the industry. We have ON_LOAN and UTILIZATION available for the period from July 2006 to May 2013. As of Dec. 31, 2010, there are more than $3.16 trillion worth of stocks available to borrow and $253 billion on loan from 702,826 reported transactions. We can compute an additional measure of short selling, SHORT_VOLUME, from intraday short selling for NYSE securities that trade electronically on the SuperDOT platform, where the vast majority of NYSE's trading volume is executed (see Boehmer et al. (2008)). Using the volume summary files, we compute the fraction of daily stock volume involving a short seller, which is available for the period from July 2006 to June 2012 for all stocks traded through the platform.

We also use SHORT_INTEREST from Compustat, defined as the monthly short interest reported by U.S. stock exchanges as a fraction of market capitalization, which is available from Jan. 1990 to Aug. 2013 and allows us to investigate whether our effects remain significant on a larger sample. More detailed definitions of each variable used in our article are provided in the Appendix.

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 must settle the trade and deliver the securities sold 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, Musto, and Reed (2002)). Thus, ON_LOAN observed on day t captures short sales that were initiated at $t-3$. For regressions with returns as the dependent variable, we use ON_LOAN observed at time t, since it is what is known to investors at time t, similar to the approach used by Ringgenberg (2011). Whenever the dependent

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variable is the quantity of shares shorted, we use ON_LOAN measured at $t+3$ as a proxy for short selling taking place on day t.

B. Funding Availability

We employ several variables related to funding availability and costs of financial intermediaries. 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 obtain data on the convertible bond spread relative to its fair price (HAIRCUT) used by Mitchell and Pulvino (2012), and the funding illiquidity measure (NOISE) estimated by Hu et al. (2013) based on deviations of U.S Treasury yields from a fitted term structure. Finally, we use Datastream's 5-year credit default swap index of the U.S. banking sector (CDS5Y) as a proxy for counterparty risk (Arora, Gandhi, and Longstaff (2012), Gorton & Metrick (2012)).

C. Other Data Sources

We merge the equity-lending and short-selling data with information from the Center for Research in Security Prices (CRSP), Compustat, and Thomson Reuters. From CRSP, we exclude closed-end funds, American depositary receipts (ADRs), and real estate investment trusts (REITs) and collect data on daily returns, market capitalization, stock turnover, and bid–ask spreads for common stocks. These data are further merged with Compustat for accounting variables needed to compute book-to-market (BM) ratio. 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 Wharton Research Data Services (WRDS), we download the Fama–French (1993) and momentum factors' daily portfolio returns (i.e., MKT, SMB, HML, and MOM). We also construct a daily liquidity factor (SPREAD) based on Corwin and Schultz's (2012) bid–ask spread estimators to capture the sensitivity of short selling-based portfolios to liquidity risk. Stocks are ranked on the previous month's average of daily bid–ask spreads, and the returns of the SPREAD risk factor are defined as the daily difference between the top and bottom quintiles.[6]

D. Commonality in Funding Availability

Each of our funding measures captures a different dimension of funding liquidity. Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) exploit the commonality in stock liquidity measures. A natural extension of our tests is to use principal component analysis to extract an underlying common factor for the funding liquidity variables.

In Panel A of Table 1, we display results for the five principal components using 1,611 days when all variables are jointly available. We follow the approach of Mancini, Ranaldo, and Wrampelmeyer (2013) and standardize all variables. The first principal component (PC1) can explain almost 70% of the total variance,

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

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being the only factor with an eigenvalue greater than 1. These results indicate that the other common factors are negligible. Panel B contains the factor loadings on each of the five funding liquidity variables for PC1, and one can see that the weightings are evenly distributed across the five measures, with each contributing relatively the same amount. In Panel C, we use these loadings to extract the common factor and compute its correlation with the five funding liquidity variables. As expected, PC1 is positively correlated with all variables, with the correlation being greater than 0.6 in all cases. PC1 has correlations above 0.9 with the VIX, HAIRCUT, and NOISE measures.

IV. Research Design

Our empirical approach is straightforward. For each day t, we assign stocks using various short selling measures to 1 of 5 quintiles and compute average returns on the *following* day (i.e., $t+1$) for stocks in the bottom (LOW) and top (HIGH) quintiles. 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, in line with the literature, exhibits significant *positive* average returns (i.e., securities with the highest level of short selling have lower future returns than those with the lowest levels of short selling), our focus is on whether the portfolio also shows significant *negative* returns at times of capital scarcity. In particular, we examine variables designed to capture the following adverse effects on levered

TABLE 1
Principal Component Analysis

Table 1 shows results of principal component (PC) analysis used to extract the common factor of the five funding liquidity variables used in our article. VIX is the daily implied volatility from the Standard & Poor's (S&P) 500 index, TED is the daily Treasury–Eurodollar spread. HAIRCUT is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). NOISE is the illiquidity measure used by Hu et al. (2013). CDS5Y is the 5-year credit default swap index for the U.S. banking sector from Datastream. Panel A shows the estimated eigenvalues for each of the five estimated components, the fraction of the total variance explained by each one, and the cumulative variance. Panel B shows the factor loading for each of the five funding liquidity variables. Panel C displays the correlations of the estimated first principal component (PC1) and the funding liquidity variables. Results in all panels are based on a sample of 1,611 days.

Panel A. Eigenvalues and the Proportion of Variance Explained by Principal Components

PC	Eigenvalue	% Variance Explained	Cumulative % Variance
1	3.403	68%	68%
2	0.751	15%	83%
3	0.528	11%	94%
4	0.205	4%	98%
5	0.114	2%	100%

Panel B. Factor Loadings of PC1

	VIX	TED	HAIRCUT	NOISE	CDS5Y
Loading	0.500	0.38	0.34	0.49	0.50

Panel C. Correlation between PC1 and Funding Liquidity Measures

Corr(↓,→)	PC1	VIX	TED	HAIRCUT	NOISE	CDS5Y
PC1	1.00					
VIX	0.92	1.00				
TED	0.70	0.56	1.00			
HAIRCUT	0.63	0.53	0.27	1.00		
NOISE	0.90	0.79	0.48	0.48	1.00	
CDS5Y	0.93	0.82	0.62	0.43	0.87	1.00

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investments: i) significant increases in market-wide volatility and counterparty risk, 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 Brothers' bankruptcy. While each crisis event had very different triggers, both created a need for levered investors to reduce their positions. The Quant crisis corresponds with the period described by Khandani and Lo (2011), that is, Aug. 6 to Aug. 8, 2007. The Lehman Brothers bankruptcy is defined as the period from Sept. 16 to Sept. 18, 2008.[7]

Our primary empirical specification is as follows:

$$
\begin{aligned}
(1) \quad \text{LOW} - \text{HIGH}_t = {} & \alpha + \beta_{\text{MKT}} \times \text{MKT}_t + \beta_{\text{SMB}} \times \text{SMB}_t + \beta_{\text{HML}} \times \text{HML}_t \\
& + \beta_{\text{MOM}} \times \text{MOM}_t + \beta_{\text{SPREAD}} \times \text{SPREAD}_t \\
& + \beta_{\text{RET(MKT)}<2.5\sigma} \times \text{D}_{\text{RET(MKT)}<2.5\sigma,t-1} + \beta_{\text{QUANT}} \times \text{D}_{\text{QUANT},t} \\
& + \beta_{\text{LEHMAN}} \times \text{D}_{\text{LEHMAN},t} + \beta_{\Delta\text{VIX}} \times \Delta\text{VIX}_{t-1} \\
& + \beta_{\Delta\text{TED}} \times \Delta\text{TED}_{t-1} + \beta_{\Delta\text{HAIRCUT}} \times \Delta\text{HAIRCUT}_{t-1} \\
& + \beta_{\Delta\text{NOISE}} \times \Delta\text{NOISE}_{t-1} + \beta_{\Delta\text{CDS5Y}} \times \Delta\text{CDS5Y}_{t-1} \\
& + \beta_{\Delta\text{PC1}} \times \Delta\text{PC1}_{t-1} + \varepsilon_t.
\end{aligned}
$$

LOW − HIGH is the daily (equal- or value-weighted) return from taking long (short) positions in securities in the bottom (top) quintile of a particular short-selling measure (i.e., LOW − HIGH portfolio). As control variables, we use the standard Fama–French (1993) factors (MKT, SMB, and HML), the momentum factor (MOM), and a daily liquidity factor (SPREAD) based on Corwin and Schultz's (2012) bid–ask estimator. We also add several measures to capture the market-wide effects of funding illiquidity. $D_{\text{RET(MKT)}<2.5\sigma}$ is an indicator variable for large negative market returns, being equal to 1 if the aggregate market return on the previous day is more than 2.5 standard deviations below the average, and 0 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 1 for trading days between Aug. 6, 2007, and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 for trading days between Sept. 16, 2008, and Sept. 18, 2008, and 0 otherwise. ΔVIX_{t-1} is the change in the VIX volatility index from day $t-2$ to day $t-1$. ΔTED_{t-1} is the change in the TED spread from day $t-2$ to day $t-1$. $\Delta\text{HAIRCUT}_{t-1}$ is the change in the convertible bond spread measure by Mitchell and Pulvino (2012). ΔNOISE_{t-1} is the change in the funding illiquidity measure based on Treasury yields by Hu et al. (2013). ΔCDS5Y_{t-1} is the change in Datastream's 5-year credit swap index from day $t-2$ to day $t-1$. ΔPC1_{t-1} is the change in the funding liquidity common factor using principal component analysis. We use changes in funding liquidity variables rather than their levels to capture unexpected increases, similar to the approach of Acharya and Pedersen (2005).

The timing of our various liquidity variables is important, with all being measured at the close of the previous trading day. We choose this timing convention

[7]This period is before the ban on short selling of financial stocks imposed by the SEC on Friday, Sept. 19, 2008 (http://www.sec.gov/news/press/2008/2008-211.htm).

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because we want to focus on the consequence of shocks to funding 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 immediately before that return performance.[8] We also run cross-sectional regressions using a panel of daily stock returns, allowing interactions of the various short selling and firm controls with the liquidity measures. Our inferences are robust to this alternative research design choice.

V. Empirical Results

A. Descriptive Statistics

In Table 2, we present descriptive statistics. The average (median) firm in our sample has a market capitalization of $4.2 billion ($0.5 billion) with 56% (62%) of shares being held by institutional investors. 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. ON_LOAN is

TABLE 2
Descriptive Statistics

Table 2 summarizes the characteristics of stocks over the period between July 2006 and May 2013 for 6,312,056 firm-day observations. SIZE is market capitalization measured in millions of dollars. IO is total institutional share ownership. SUPPLY is the total number of shares available to borrow divided by shares outstanding. ON_LOAN 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 (bps p.a.). SPREAD is the bid–ask spread estimated from Corwin and Schultz (2012). BM is the book-to-market ratio. RET6M is the cumulative return in the previous 6-months, skipping the most recent month. VIX is the VIX volatility index. RET(MKT) $< -2.5\sigma$ is an indicator variable equal to 1 if the market return is 2.5 standard deviations (taken from a GARCH(1,1) model) below the average. TED is the change in the Treasury–Eurodollar spread. HAIRCUT is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). NOISE is the illiquidity measure used by Hu et al. (2013). CDS5Y is the 5-year credit default swap index for the U.S. banking sector from Datastream. $\Delta(\cdot)$ 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	0.00	0.00
IO	56%	62%	31%	0%	100%	−0.29	1.78
SUPPLY	18.87%	19.51%	12.32%	0.00%	100%	0.18	2.22
ON_LOAN	4.18%	2.01%	5.51%	0.00%	27%	2.01	7.10
SHORT_INTEREST	21.91%	4.37%	36.68%	0.00%	100%	1.61	3.69
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.)	101.37	12.31	319.06	−7.13	2,275	5.05	30.66
SPREAD	1.30%	0.98%	1.22%	0.00%	67.30%	6.42	123.55
BM	0.73	0.57	0.63	−0.01	3.81	2.36	10.43
RET6M	3.47%	1.15%	38.00%	−77.06%	158.33%	1.05	5.98
RET (MKT) $< -2.5\sigma$	0.019	0.000	0.136	0.000	1.000	7.07	50.98
VIX	23.07	20.47	10.97	9.89	81.00	1.93	7.68
TED	0.63%	0.39%	0.62%	0.09%	4.58%	2.36	10.39
HAIRCUT	2.07%	1.13%	3.01%	−1.31%	13.69%	1.83	5.69
NOISE	3.99%	2.74%	3.81%	0.72%	20.47%	2.30	8.15
CDS5Y	131.14	122.58	80.80	10.20	595.99	0.76	4.70
ΔVIX	0.000	0.000	0.020	−0.170	0.170	0.52	17.87
ΔTED	0.00%	0.00%	0.08%	−0.80%	1.00%	0.66	48.18
ΔHAIRCUT	0.00%	0.00%	0.27%	−3.99%	2.25%	−1.46	46.00
ΔNOISE	0.00%	0.00%	0.30%	−2.06%	1.92%	−0.03	10.74
ΔCDS5Y	0.01	0.02	2.51	−15.92	16.69	0.25	11.69
ΔPC1	0.00%	−0.01%	0.14%	−1.17%	1.15%	0.79	16.43

[8] In unreported tests, we have recomputed our various liquidity measures using contemporaneous data from day t, and our inferences are unaffected by this alternative timing choice.

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as high as 27% in our sample. The average (median) SHORT_VOLUME equals 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) bps, showing that, on average, it is very cheap to borrow shares. But there are clearly exceptions; the cost of borrowing an equity security can be as high as 2,275 bps on an annualized basis. The remainder of Table 2 reports information on control variables and our various liquidity measures in both levels and changes.

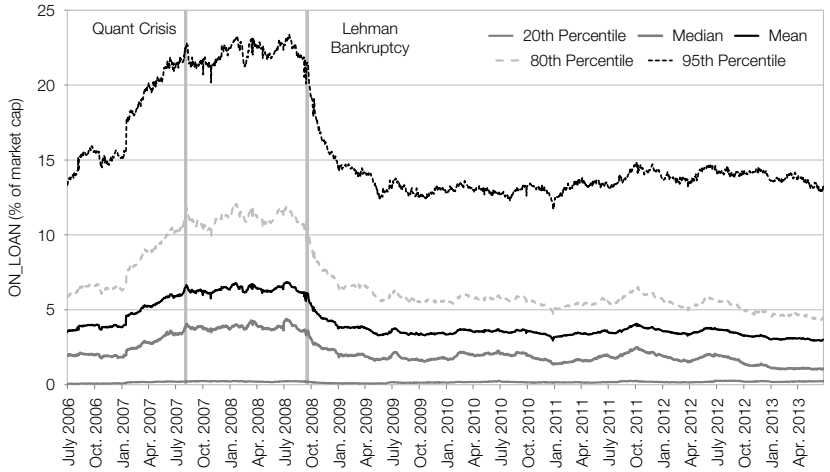
In Figure 1, we show time-series and cross-sectional variation in ON_LOAN for U.S. stocks during our sample period. For each day, we plot the mean, median, 20th, 80th, and 95th percentiles of ON_LOAN. The lower tail of ON_LOAN is relatively stable through time, but, in contrast, the right tail of ON_LOAN exhibits considerably more volatility. We have superimposed shaded areas corresponding to the Quant and Lehman Brothers crises, and 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 ON_LOAN, a consequence of aggregate deleveraging and the imposition of short-selling constraints by the SEC.

B. Relation between ON_LOAN 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 5 groups based on the breakpoints of ON_LOAN from the previous day. We then

FIGURE 1
Aggregate ON_LOAN

Figure 1 plots daily ON_LOAN of U.S. firms from July 2006 to May 2013 for various percentiles. ON_LOAN is defined as the number of shares on loan divided by the total number of shares outstanding.



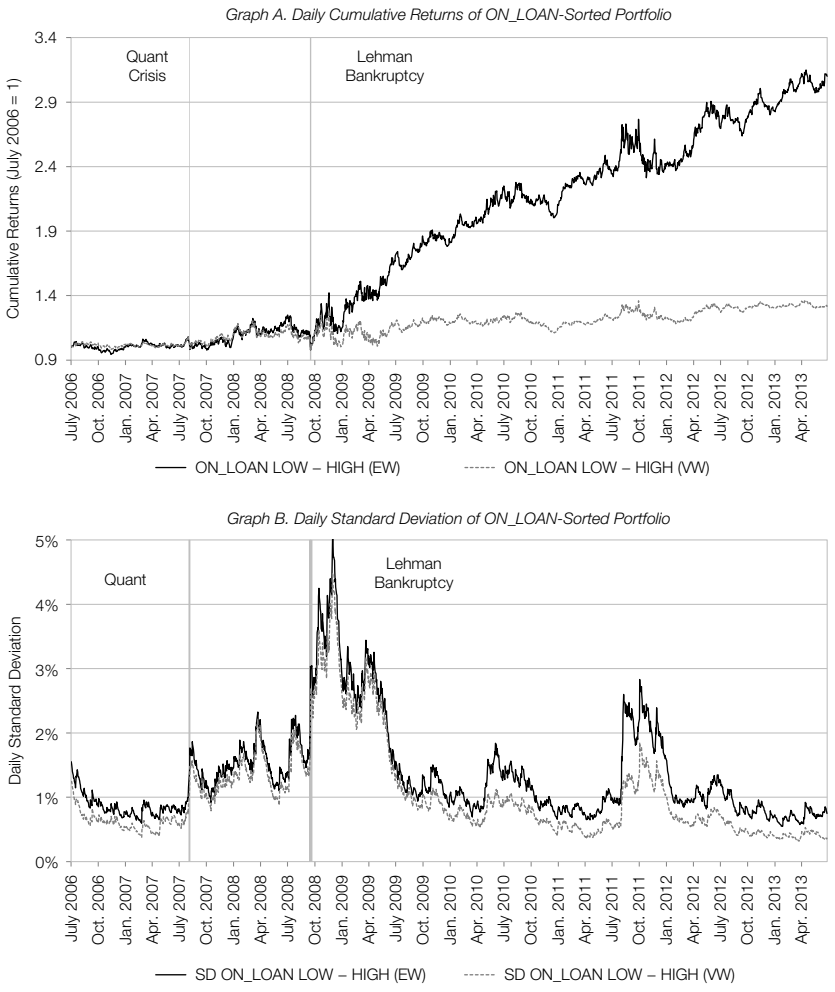
compute equal- and value-weighted returns for the lowest and highest ON_LOAN quintiles, and the difference in these quintile portfolio returns (lowest minus highest) is the hedge return from exposure to ON_LOAN. Graph A shows a strong positive return to this strategy, consistent with an extensive previous 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 on the occasional large negative returns to this strategy that happen around certain dates. Two such events occurred during the

FIGURE 2

Daily Returns and Standard Deviations of Stock Portfolios Sorted on ON_LOAN

Figure 2 plots the cumulative daily returns and the daily standard deviation of stock portfolios sorted on ON_LOAN from July 2006 to May 2013. ON_LOAN is defined as the number of shares on loan divided by the total number of shares outstanding. We rank firms into quintiles and form portfolios that take long (short) positions in securities in the LOW (HIGH) ON_LOAN quintile, using either equal weights (EW) or value weights (VW). Graph A shows cumulative daily returns for each portfolio, while Graph B displays daily standard deviations estimated from a GARCH(1,1) model.



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Quant crisis in Aug. 2007 and the Lehman Brothers bankruptcy in Oct. 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 Graph A of Figure 2. To help isolate this effect, in Graph B, 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 Brothers crises are both strongly associated with sharp increases in the return volatility of the LOW − HIGH portfolio, with daily volatility almost tripling relative to pre-event levels.

To isolate the determinants of these return realizations of a strategy mimicking levered investors, we decompose the LOW − HIGH portfolio between its long and short sides and examine the days with the largest negative return LOW − HIGH portfolio realizations. Figure 3 reports these details for the 15 (13) days in which standardized returns for the equal- (value-) weighted LOW − HIGH portfolio are more than 2.5 standard deviations below the mean. Graph A (Graph B) reports raw returns for equal (value) weighted LOW − HIGH portfolios. Our prior is that the negative realizations of the ON_LOAN hedge portfolio are 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. While the analysis in Figure 3 does not condition on explicit measures of funding, as it is based only on days with extreme negative returns for the LOW − HIGH portfolio, it shows that the extreme negative return days observed by the long–short strategy are all driven by large positive returns of the high ON_LOAN quintile. This 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 exposed to such leverage. For example, on Sept. 17, 2008, 2 days after Lehman Brothers filed for bankruptcy and the day that the U.S. Treasury announced the AIG bailout, the return of the high ON_LOAN stock portfolio equals +8.41%. If a hedge fund was shorting stocks in the top ON_LOAN quintile and had a 3:1 leverage ratio (i.e., $1 of equity for every $3 of asset value), it would have lost 25% on a single day.

In Figure 4, we examine abnormal returns around the Quant crisis (Graph A) and the Lehman Brothers' bankruptcy (Graph B) for high ON_LOAN and low ON_LOAN stock portfolios using Daniel, Grinblatt, Titman, and Wermers (DGTW) (1997) characteristic-adjusted returns. Consistent with the analysis in Figure 3, the high ON_LOAN 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 (1993) 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 (e.g., Daniel et al. (2012), Daniel and Moskowitz (2016)).

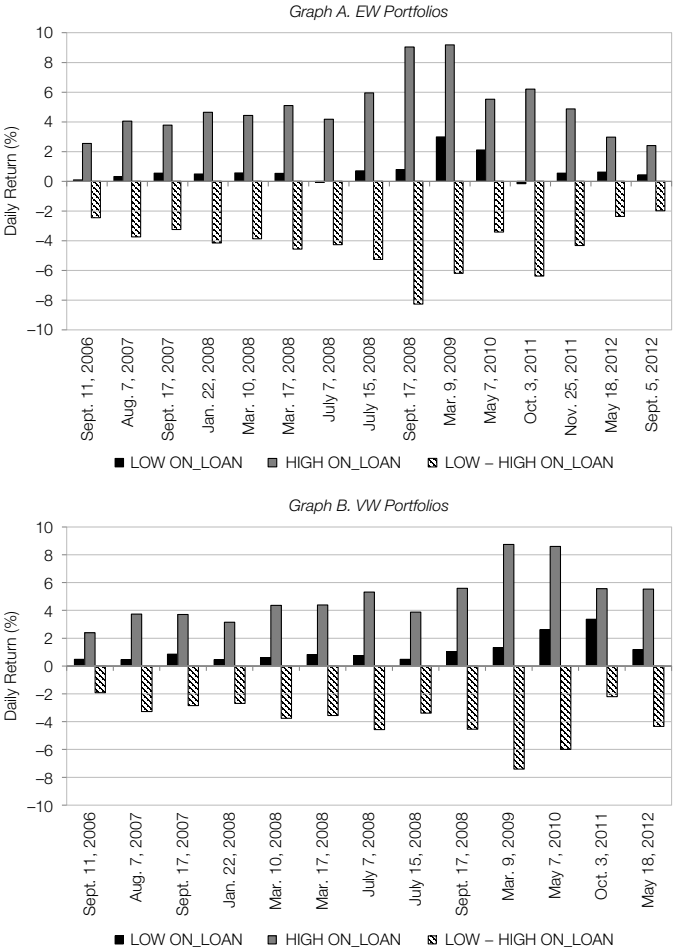
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FIGURE 3

Returns for Shorting High and Low Portfolios on Extreme Negative Realizations of (LOW – HIGH) ON_LOAN Portfolio

Figure 3 shows raw returns of stock portfolios sorted on ON_LOAN for days when the LOW – HIGH portfolio return is 2.5 standard deviations below the mean. Graph A displays returns based on equal-weighted (EW) portfolios, while Graph B is based on value-weighted (VW) portfolios. For each date, we show returns for the bottom (LOW) and top (HIGH) quintiles of firms ranked by ON_LOAN, and also for the LOW – HIGH difference. ON_LOAN 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 ON_LOAN and also for the LOW – HIGH difference.



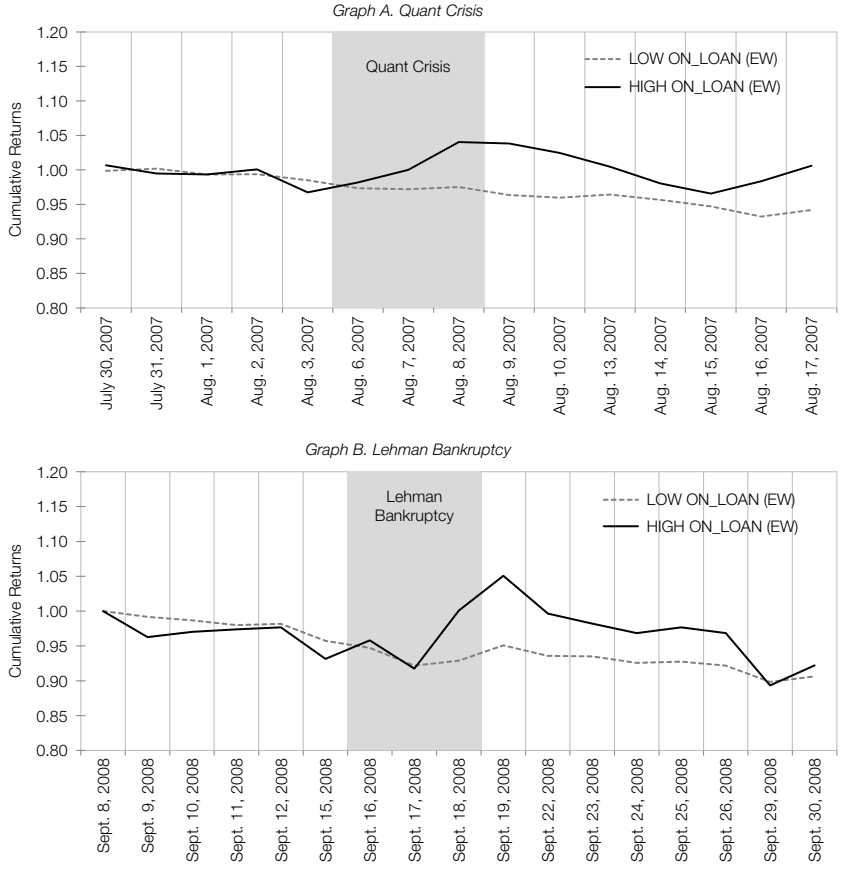
C. Calendar-Time Analysis with ON_LOAN Variable to Sort Stocks

Table 3 reports our primary regression analysis where we report nested versions of estimating equation (1) using equal-weighted portfolios based on the ON_LOAN measure as the sorting variable. For ease of interpretation, we include predicted signs for each explanatory variable. There is a reliably positive intercept, suggesting the LOW – HIGH ON_LOAN strategy generates about 10 bps of

FIGURE 4

Abnormal Returns during the Quant Crisis and Lehman Brothers' Bankruptcy

Figure 4 shows the cumulative abnormal portfolio returns of high and low ON_LOAN portfolios around the Quant crisis and the Lehman Brothers bankruptcy. Graph A displays returns around the Quant crisis in Aug. 2007, with the shaded area denoting the crisis period from Aug. 6 to Aug. 8, 2007. Graph B shows abnormal returns around Lehman Brothers' bankruptcy in Oct. 2008, with the shaded area denoting the crisis period from Sept. 16 to Sept. 18, 2008. ON_LOAN 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 return for stocks in each quintile. HIGH ON_LOAN is the abnormal returns of stocks in the top quintile of ON_LOAN, while LOW ON_LOAN is the abnormal return for stocks in the bottom quintile of ON_LOAN. Abnormal returns are computed using DGTW's (1997) characteristics-adjusted returns.



abnormal returns per day on an equal-weighted basis. Using geometric averages, this corresponds to annualized returns of about 26.7%. We find a very strong negative loading on MKT and SMB and very high R^2s for these regressions, similar to Jones and Lamont (2002). Likewise, Desai, Ramesh, Thiagarajan, and Balachandran (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 portfolio based on ON_LOAN, our negative exposure to MKT and SMB is consistent with prior research from earlier periods. We also find that the LOW − HIGH portfolio is positively exposed to

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TABLE 3

Equal-Weighted Stock Portfolio Returns Sorted on ON_LOAN

Table 3 displays regressions of stock portfolios sorted by ON_LOAN, with daily U.S. stock returns between July 2006 and May 2013. We form portfolios by ranking stocks into quintiles based on ON_LOAN in the previous day and computing equal-weighted daily returns of selling HIGH ON_LOAN stocks and buying LOW ON_LOAN stocks. ON_LOAN 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 is the return on a portfolio of prior winners minus the return on a portfolio of prior losers. SPREAD is the return on a portfolio of high-spread minus low-spread stocks. $D_{RET(MKT)<-2.5\sigma}$ is an indicator variable equal to 1 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 1 in the period between Aug. 6 and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 in the period between Sept. 16 and Sept. 18, 2008, and 0 otherwise. ΔTED is the daily change in the Treasury–Eurodollar spread in the previous day. ΔHAIRCUT is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). ΔNOISE is the illiquidity measure used by Hu et al. (2013), ΔCDS5Y the change in Datastream's U.S. banking sector credit default swap index, and ΔPC1 is the principal component from the funding liquidity variables above. Returns and risk factors MKT, SMB, HML, MOM, and SPREAD are measured at period t, while other explanatory variables are measured at period $t-1$. We report White (1980)-adjusted standard deviations in square brackets. ** and *** indicate significance at the 5% and 1% levels, respectively.

Coeff.	Predicted Sign	1	2	3	4	5	6	7	8
Intercept	+	0.094*** [0.013]	0.106*** [0.013]	0.096*** [0.013]	0.093*** [0.013]	0.093*** [0.013]	0.091*** [0.014]	0.096*** [0.013]	0.105*** [0.014]
β_{MKT}	−	−0.816*** [0.021]	−0.830*** [0.021]	−0.801*** [0.021]	−0.815*** [0.021]	−0.811*** [0.021]	−0.811*** [0.022]	−0.813*** [0.020]	−0.808*** [0.023]
β_{SMB}	−	−0.786*** [0.045]	−0.779*** [0.045]	−0.786*** [0.044]	−0.786*** [0.045]	−0.795*** [0.046]	−0.807*** [0.046]	−0.781*** [0.045]	−0.805*** [0.047]
β_{HML}	−	−0.052 [0.050]	−0.058 [0.048]	−0.046 [0.049]	−0.043 [0.050]	−0.065 [0.050]	−0.059 [0.050]	−0.052 [0.050]	−0.069 [0.050]
β_{MOM}	+	0.216*** [0.025]	0.208*** [0.024]	0.222*** [0.024]	0.215*** [0.025]	0.219*** [0.024]	0.215*** [0.025]	0.215*** [0.024]	0.215*** [0.024]
β_{SPREAD}	+	0.042** [0.019]	0.048*** [0.018]	0.034* [0.020]	0.044** [0.019]	0.045** [0.019]	0.046** [0.020]	0.039** [0.019]	0.046** [0.020]
$\beta_{RET(MKT)<-2.5\sigma}$	−		−0.354*** [0.124]						−0.320*** [0.118]
β_{QUANT}	−		−1.579*** [0.063]						−1.601*** [0.092]
β_{LEHMAN}	−		−2.511*** [0.275]						−1.885*** [0.178]
$\beta_{\Delta VIX}$	−			−4.851*** [0.921]					
$\beta_{\Delta TED}$	−				−1.267*** [0.360]				
$\beta_{\Delta HAIRCUT}$	−					−0.208** [0.092]			
$\beta_{\Delta NOISE}$	−						−0.246*** [0.075]		
$\beta_{\Delta CDS5Y}$	−							−1.294** [0.656]	
$\beta_{\Delta PC1}$	−								−0.955*** [0.153]
No. of days		1,756	1,756	1,755	1,755	1,747	1,606	1,751	1,594
Adj. R^2		0.868	0.876	0.873	0.872	0.869	0.869	0.870	0.881

MOM. (Desai et al. (2002) show a reliably negative exposure to MOM for their long highly shorted security portfolios.) The SPREAD factor to control for liquidity (Corwin and Schultz (2012)) also has the expected positive sign, suggesting that a fraction of the returns to short-selling strategies reflect compensation for general liquidity risk and ruling out the abnormal performance of short-selling strategies is due to exposure to liquidity risk.

Our primary interest, however, is the behavior of LOW − HIGH portfolio returns during periods associated with deleveraging. Columns 2–8 of Table 3

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examine the measures related to funding illiquidity. For all variables, our prior is a negative relation with respect to the daily returns of the LOW − HIGH ON_LOAN portfolio in the following day. Consistent with the evidence in Figure 4, we see very strong evidence of large negative returns to the LOW − HIGH ON_LOAN portfolio on the days of the Quant and Lehman Brothers crises. For example, in column 2, the β_{QUANT} regression coefficient is −1.579. This means that, while the LOW − HIGH ON_LOAN portfolio averages about 11 bps of returns per day, conditional on days of illiquidity crises, the returns are −147 bps. This is a strikingly large asymmetry relative to the average 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 −2.511, an even more negative effect than found for the Quant crisis. Although the economic magnitude of these indicator variables is very large, it is useful to remember that they occur for only a small number of days (3 days for each episode) due to the extreme nature of these events. Turning to the continuous measures of funding liquidity in columns 3–7, we see that all measures are negatively associated with the returns of the LOW − HIGH ON_LOAN portfolio. Finally, we compute the lagged first difference of the principal component estimated in Table 1 and include it as an additional explanatory variable in column 8 with similar results. Overall, Table 3 provides consistent evidence that the returns to the LOW − HIGH ON_LOAN portfolio are negative during periods of funding illiquidity.

1. Calendar-Time Analysis with Alternative Short-Selling Intensity Measures

Our primary analysis focuses on the equal-weighted returns of one measure of short selling: ON_LOAN. There are alternative measures to be extracted from financial markets, including UTILIZATION (measurable daily for the period July 2006–May 2013 from Markit), SHORT_VOLUME (measurable daily for the period July 2006–June 2012 from the NYSE Volume Summary Files), and SHORT_INTEREST (measurable monthly for the period Jan. 1990–Aug. 2013 from Compustat).

These measures capture different aspects of short selling, and it is important to ensure that the relation we document is robust to them. Our ideal construct is to know the extent of leverage employed by the marginal investor for every stock on 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, not easy to locate for borrowing, or both, ON_LOAN may classify the firm as having a low value of relative short selling (and hence levered investor activity), even though, at the margin, there might be a greater presence of levered investors for such securities. To address this issue, we also compute UTILIZATION, defined as the ratio of the number of shares on loan relative to the number of shares that are available to borrow.

Column 1 of Table 4 reports our regression results based on equation (1) using equal-weighted returns of ON_LOAN stock portfolios on a specification that includes all funding illiquidity measures. We can observe that the coefficients for ΔTED and ΔHAIRCUT are no longer significant, being subsumed by ΔNOISE and ΔCDS5Y. To facilitate comparison with other short-selling

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intensity measures, column 2 reports the same results shown in column 8 of Table 3 using ΔPC1. In columns 3 and 4, we change our measure of short-selling intensity and use UTILIZATION to construct LOW − HIGH portfolioreturns.Consistent with earlier results, we document a reliably positive intercept, suggesting the LOW − HIGH UTILIZATION strategy generates about 10 bps of abnormal returns per day on an equal-weighted basis. Likewise, we continue to see strong negative loadings on MKT and SMB, a strong positive loading on MOM but no statistically significant relationship to HML and SPREAD. Of more

TABLE 4

Equal-Weighted Stock Portfolio Returns
Sorted on Additional Proxies for Short-Selling Intensity

Table 4 shows regressions of equal-weighted stock portfolio returns sorted on different proxies of short-selling intensity, ON_LOAN, 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 returns of the portfolio that sells high short-selling intensity stocks and buys low short-selling intensity stocks. ON_LOAN is the total amount on loan divided by market capitalization; UTILIZATION, defined as the number of shares on loan divided by the number of shares available to borrow; and SHORT_VOLUME, 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 SPREAD are measured at period t, while other explanatory variables are measured at period $t-1$. Explanatory variables are the same as in Table 3. We report White (1980)-adjusted standard deviations in square brackets. ** and *** indicate significance at the 5% and 1% levels, respectively.

		Short-Selling Intensity Variable					
		ON_LOAN		UTILIZATION		SHORT_VOLUME	
Coeff.	Predicted Sign	1	2	3	4	5	6
Intercept	+	0.106***	0.105***	0.106***	0.107***	0.069***	0.066***
		[0.014]	[0.014]	[0.012]	[0.012]	[0.015]	[0.016]
β_{MKT}	−	−0.807***	−0.808***	−0.612***	−0.612***	−0.098***	−0.103***
		[0.022]	[0.023]	[0.020]	[0.020]	[0.021]	[0.022]
β_{SMB}	−	−0.801***	−0.805***	−0.703***	−0.702***	−0.188***	−0.201***
		[0.047]	[0.047]	[0.045]	[0.045]	[0.048]	[0.051]
β_{HML}	−	−0.068	−0.069	−0.059	−0.059	0.023	0.035
		[0.049]	[0.050]	[0.043]	[0.045]	[0.045]	[0.048]
β_{MOM}	+	0.216***	0.215***	0.213***	0.213***	0.097***	0.096***
		[0.024]	[0.024]	[0.021]	[0.021]	[0.027]	[0.028]
β_{SPREAD}	+	0.046**	0.046**	−0.014	−0.015	0.067***	0.071***
		[0.019]	[0.020]	[0.016]	[0.016]	[0.016]	[0.016]
$\beta_{RET(MKT)<-2.5\sigma}$	−	−0.285**	−0.320***	−0.152	−0.168	0.005	−0.062
		[0.116]	[0.118]	[0.119]	[0.119]	[0.149]	[0.155]
β_{QUANT}	−	−1.588***	−1.601***	−2.130***	−2.134***	−2.250***	−2.270***
		[0.087]	[0.092]	[0.348]	[0.353]	[0.628]	[0.639]
β_{LEHMAN}	−	−2.135***	−1.885***	−2.297***	−2.256***	−1.629***	−1.126***
		[0.367]	[0.178]	[0.525]	[0.468]	[0.270]	[0.252]
$\beta_{\Delta VIX}$	−	−3.897***		−2.923***		−1.898	
		[0.886]		[0.888]		[1.182]	
$\beta_{\Delta TED}$	−	−0.455		−0.520*		−0.188	
		[0.364]		[0.312]		[0.402]	
$\beta_{\Delta HAIRCUT}$	−	−0.166		−0.166*		−0.166*	
		[0.103]		[0.091]		[0.098]	
$\beta_{\Delta NOISE}$	−	−0.136**		−0.150**		0.193**	
		[0.066]		[0.061]		[0.097]	
$\beta_{\Delta CDS5Y}$	−	−1.236*		−0.698		−1.703***	
		[0.704]		[0.533]		[0.452]	
$\beta_{\Delta PC1}$	−		−0.955***		−0.808***		−0.395**
			[0.153]		[0.149]		[0.190]
No. of days		1,594	1,594	1,594	1,594	1,467	1,467
Adj. R^2		0.882	0.881	0.874	0.874	0.198	0.167

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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 regression coefficients β_{QUANT} and β_{LEHMAN} are both below −2, suggesting that the LOW − HIGH UTILIZATION strategy generates losses of more than 200 bps on days of significant deleveraging.

Both ON_LOAN and UTILIZATION are stock-based measures of short selling (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, and some researchers argue that the majority of trading on the primary stock exchanges is attributable to investors with holding periods of less than a week (e.g., Haldane (2010)). We use data from the NYSE Volume Summary files to compute SHORT_VOLUME, defined as the ratio between the number of shares that were sold short on a given day and the total number of shares traded on the SuperDOT platform for each stock. Columns 5 and 6 in Table 4 report our results using SHORT_VOLUME to construct LOW − HIGH portfolio returns. Consistent with earlier results, we find a positive intercept, with the equal-weighted LOW − HIGH SHORT_VOLUME strategy generating abnormal returns of 7 bps per day. Likewise, we continue to see negative loadings on MKT and SMB and a positive loading on MOM, but now there are much lower R^2s for these time-series regressions. The loadings we document resemble those reported by Boehmer et al. (2008). We also continue to find a negative relation between the returns for the LOW − HIGH SHORT_VOLUME strategy and the Quant and Lehman Brothers crises. For the other funding liquidity variables, results are somewhat weaker. The coefficient on ΔVIX and ΔTED are not statistically significant, but this might be caused by multicollinearity among funding liquidity variables. Using the funding liquidity factor (ΔPC1) extracted from the principal component analysis can overcome this problem and allows us to examine common variation in our funding liquidity measures. In all cases, we find that the funding liquidity factor has a negative correlation with the returns of the LOW − HIGH portfolio.

2. Calendar-Time Analysis with Alternative Portfolio Weighting Schemes

The calendar-time analyses presented in Tables 3 and 4 are based on equal-weighted stock returns to construct portfolios. Asparouhova, Bessembinder, and Kalcheva (2013) show that these weights may bias inference due to microstructure effects, which can make prices deviate from fundamental values. This spurious noise can be an issue in our tests, particularly because we use daily returns in the analysis. Thus, in Table 5 we present results using the two main weighting schemes recommended by Asparouhova et al. (2013), which are shown in simulations to have minimal bias due to noisy prices. The first one, VW, weighs stocks based on their market capitalization in the previous day. The second one, RW, computes weights based on stocks' gross returns (i.e., 1 + their return) in the previous day. For the sake of brevity, we report results using only the funding illiquidity principal component (ΔPC1) and display additional results in Table IA.1 of the Internet Appendix (available at www.jfqa.org).

For all columns, we can observe that the β_{QUANT} and β_{LEHMAN} coefficients are significant regardless of the weighting scheme employed. The funding illiquidity's

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TABLE 5

Value-Weighted and Return-Weighted Stock Portfolio Returns Sorted on Proxies for Short-Selling Intensity

Table 5 shows regressions of value-weighted (VW) and return-weighted (RW) stock portfolio returns sorted on alternative proxies of short-selling intensity, ON_LOAN, 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 returns of the portfolio that sells high short-selling intensity stocks and buys low short-selling intensity stocks. Value-weighted portfolios are constructed using a stock's market capitalization in the previous day to form weights, while return-weighted (RW) portfolios use a stock's gross return in the previous day as in Asparouhova et al. (2013)). ON_LOAN is the total amount on loan divided by market capitalization; UTILIZATION, defined as the number of shares on loan divided by the number of shares available to borrow; and SHORT_VOLUME, 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 SPREAD are measured at period t, while other explanatory variables are measured at period $t-1$. Explanatory variables are described in Table 3. We report White (1980)-adjusted standard deviations in square brackets. ** and *** indicate significance at the 5% and 1% levels, respectively.

		Short-Selling Intensity Variable					
		ON_LOAN		UTILIZATION		SHORT_VOLUME	
		Portfolio Weighting					
		VW	RW	VW	RW	VW	RW
Coeff.	Predicted Sign	1	2	3	4	5	6
Intercept	+	0.056***	0.055***	0.063***	0.065***	0.074***	0.073***
		[0.013]	[0.015]	[0.011]	[0.014]	[0.015]	[0.015]
β_{MKT}	−	−0.582***	−0.793***	−0.261***	−0.677***	−0.085***	−0.099***
		[0.024]	[0.025]	[0.019]	[0.024]	[0.025]	[0.023]
β_{SMB}	−	−0.567***	−0.630***	−0.728***	−0.611***	−0.259***	−0.195***
		[0.046]	[0.052]	[0.043]	[0.055]	[0.058]	[0.049]
β_{HML}	−	−0.020	−0.053	−0.167***	−0.093*	0.002	0.032
		[0.047]	[0.057]	[0.045]	[0.054]	[0.048]	[0.046]
β_{MOM}	+	0.247***	0.179***	0.279***	0.192***	0.154***	0.083***
		[0.022]	[0.026]	[0.019]	[0.025]	[0.024]	[0.025]
β_{SPREAD}	+	0.001	0.047**	−0.033*	0.013	0.019	0.043***
		[0.016]	[0.019]	[0.019]	[0.018]	[0.013]	[0.014]
$\beta_{RET(MKT)<-2.5\sigma}$	−	−0.210	−0.268**	−0.018	−0.204	−0.047	−0.029
		[0.134]	[0.122]	[0.111]	[0.129]	[0.162]	[0.130]
β_{QUANT}	−	−1.414***	−1.590***	−2.019***	−2.221***	−1.754***	−2.268***
		[0.143]	[0.080]	[0.445]	[0.295]	[0.418]	[0.559]
β_{LEHMAN}	−	−1.553***	−2.011***	−2.269***	−2.646***	−1.010***	−1.066***
		[0.209]	[0.182]	[0.626]	[0.485]	[0.335]	[0.273]
$\beta_{\Delta PC1}$	−	−0.818***	−0.993***	−0.220	−0.934***	−0.182	−0.403**
		[0.153]	[0.165]	[0.146]	[0.170]	[0.216]	[0.183]
No. of days		1,594	1,594	1,594	1,594	1,467	1,467
Adj. R^2		0.839	0.852	0.831	0.847	0.256	0.170

principal component (ΔPC1) coefficient is significant in most cases. In columns 1 and 2 of Table 5 we find that an increase in funding illiquidity (ΔPC1) is associated with a decrease in returns in the following period for the ON_LOAN-based portfolios, regardless of the weighting-scheme employed. Results in columns 3–6 are significant only for the return-weighted (RW) portfolios. Overall, our main results are robust to controls for noisy prices due to microstructure effects.

3. Calendar-Time Analysis with Short Interest Data

Our final supplemental measure of short selling is the traditional measure of SHORT_INTEREST, defined as the number of shares that the exchange lists as being held short relative to the number of shares outstanding. This measure has the advantage of a much longer time series, although not at daily frequency. We take SHORT_INTEREST starting in Jan. 1990 for all U.S. securities in Compustat

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and use values at the end of the previous month to sort stocks, rebalancing the portfolios once a month.

Table 6 reports our regression results using SHORT_INTEREST to construct equal-weighted 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, SMB, and HML and a positive loading on MOM and SPREAD. Over this longer 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 see a strong negative relation between the returns of the strategy and our measures of funding availability for a much longer period for all variables apart from ΔNOISE in column 6.[9] In the Internet Appendix,

TABLE 6

Equal-Weighted Stock Portfolios Sorted on SHORT_INTEREST (1990–2013)

Table 6 displays regressions of stock portfolios sorted on SHORT_INTEREST, with daily U.S. stock returns between Jan. 1990 and Aug. 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 beginning of 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 SPREAD are measured at period t, while other explanatory variables are measured at period $t-1$. Explanatory variables are the same as in Table 3 and defined in the Appendix. We report White (1980)-adjusted standard deviations in square brackets. ** and *** indicate significance at the 5% and 1% levels, respectively.

Coeff.	Predicted Sign	1	2	3	4	5	6	7
Intercept	+	0.038***	0.043***	0.038***	0.037***	0.079***	0.034***	0.078***
		[0.008]	[0.008]	[0.008]	[0.008]	[0.011]	[0.008]	[0.010]
β_{MKT}	−	−0.738***	−0.747***	−0.736***	−0.737***	−0.797***	−0.737***	−0.802***
		[0.010]	[0.010]	[0.010]	[0.010]	[0.017]	[0.010]	[0.016]
β_{SMB}	−	−0.515***	−0.514***	−0.516***	−0.515***	−0.829***	−0.521***	−0.813***
		[0.023]	[0.023]	[0.023]	[0.023]	[0.036]	[0.023]	[0.033]
β_{HML}	−	−0.277***	−0.278***	−0.276***	−0.275***	0.002	−0.282***	0.007
		[0.019]	[0.018]	[0.018]	[0.018]	[0.039]	[0.019]	[0.035]
β_{MOM}	+	0.100***	0.094***	0.100***	0.099***	0.170***	0.102***	0.159***
		[0.013]	[0.013]	[0.013]	[0.013]	[0.021]	[0.013]	[0.019]
β_{SPREAD}	+	0.062***	0.064***	0.061***	0.063***	0.050***	0.067***	0.045***
		[0.009]	[0.009]	[0.009]	[0.009]	[0.018]	[0.008]	[0.016]
$\beta_{RET(MKT)<-2.5\sigma}$	−		−0.303***					
			[0.080]					
β_{QUANT}	−		−1.610***					
			[0.311]					
β_{LEHMAN}	−		−2.160***					
			[0.208]					
$\beta_{\Delta VIX}$	−			−2.185***				
				[0.647]				
$\beta_{\Delta TED}$	−				−0.558***			
					[0.174]			
$\beta_{\Delta HAIRCUT}$	−					−0.159**		
						[0.074]		
$\beta_{\Delta NOISE}$	−						−0.038	
							[0.026]	
$\beta_{\Delta CDS5Y}$	−							−1.206**
								[0.593]
No. of days		5,964	5,964	5,963	5,963	1,965	5,689	2,427
Adj. R^2		0.756	0.761	0.757	0.757	0.877	0.753	0.879

[9]The sample size is smaller when we include ΔHAIRCUT, as this variable is available only from Oct. 2005 onward.

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we obtain similar results to those in Table 5 when computing value-weighted and return-weighted portfolio returns based on SHORT_INTEREST as a measure of short-selling intensity. In Table IA.2, we find that results for value-weighted portfolios are somewhat weaker when using similar specifications to those shown for equal-weighted portfolios in Table 6.[10]

D. Cumulative Stock Returns

So far, we have not discussed whether the impact of reductions in funding on levered securities is transitory or permanent. To address this issue, we extend the window over which we measure excess returns. This allows us to assess whether the positive returns found for stocks with high short-selling intensity immediately following illiquidity periods reverses over subsequent periods or whether they persist.

We reestimate equation (1) using cumulative returns for up to 80 trading days. The dependent variable is the cumulative returns of the LOW − HIGH ON_LOAN equal-weighted portfolios from t to $t+j$, where $j = 1, 2, 3, 4, 5, 20, 60, 80$ trading days. The risk factors (MKT, SMB, HML, MOM, and SPREAD) are also compounded over the $[t, t+j]$ window, while the illiquidity variables are held fixed at the values measured at the end of day $t-1$, so the cumulative return patterns are attributable to any reversals based on those fixed characteristics. Equation (2) summarizes our specification:

$$
\begin{aligned}
(2) \qquad \text{LOW} - \text{HIGH}_{t,t+j} = {} & \alpha + \beta_{\text{MKT}} \times \text{MKT}_{t,t+j} + \beta_{\text{SMB}} \times \text{SMB}_{t,t+j} \\
& + \beta_{\text{HML}} \times \text{HML}_{t,t+j} + \beta_{\text{MOM}} \times \text{MOM}_{t,t+j} + \beta_{\text{SPREAD}} \times \text{SPREAD}_{t,t+j} \\
& + \beta_{\text{RET(MKT)}<-2.5\sigma} \times \text{D}_{\text{RET(MKT)}<-2.5\sigma,t-1} + \beta_{\text{QUANT}} \times \text{D}_{\text{QUANT},t} \\
& + \beta_{\text{LEHMAN}} \times \text{D}_{\text{LEHMAN},t} + \beta_{\Delta\text{VIX}} \times \Delta\text{VIX}_{t-1} \\
& + \beta_{\Delta\text{TED}} \times \Delta\text{TED}_{t-1} + \beta_{\Delta\text{HAIRCUT}} \times \Delta\text{HAIRCUT}_{t-1} \\
& + \beta_{\Delta\text{NOISE}} \times \Delta\text{NOISE}_{t-1} + \beta_{\Delta\text{CDS5Y}} \times \Delta\text{CDS5Y}_{t-1} \\
& + \beta_{\Delta\text{PC1}} \times \Delta\text{PC1}_{t-1} + \varepsilon_t.
\end{aligned}
$$

In Table 7, we report the estimates found for the liquidity variables, with columns 1A, 1B, and 1C showing results for the regression with the extreme negative market return and crisis-event variables ($D_{\text{RET(MKT)}<-2.5\sigma}$, D_{QUANT}, D_{LEHMAN}); column 2 for ΔVIX; column 3 for ΔTED; column 4 for ΔHAIRCUT; column 5 for ΔNOISE; column 6 for ΔCDS5Y; and column 7 for ΔPC1. Standard errors are estimated using heteroscedasticity and autocorrelation-consistent (HAC) covariance matrices to correct for the autocorrelation in cumulative returns, and the lag order is chosen using the selection algorithm proposed by Newey and West (1994).

For $j = 1$, reported coefficients are identical to those found for next-day returns (i.e., $t+1$) of the LOW − HIGH ON_LOAN portfolios in of Table 3. As we examine larger cumulative return windows, we find that all measures of liquidity shocks are statistically significant for the first week of trading following (i.e., $j = 5$) and also for $j = 20$ trading days (i.e., a month) except for the estimate for D_{QUANT}. Even after 3 months, most estimates are still significant. It is only when

[10] Results found for the specification tested in columns 5 and 6 of Table IA.1 are also similar.

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TABLE 7

Cumulative Returns of Equal-Weighted Stock Portfolios Sorted on ON_LOAN

Table 7 displays regressions of stock portfolio returns sorted by ON_LOAN, using daily U.S. stock returns between July 2006 and May 2013 based on equation (2) in the text. The dependent variable $RET_{i,t+j}$ is the cumulative returns from t to $t+j$ after portfolio formation. We form portfolios by ranking stocks into quintiles based on ON_LOAN in the previous day and computing equal-weighted daily returns of selling HIGH ON_LOAN stocks and buying LOW ON_LOAN stocks. ON_LOAN is the total amount on loan divided by market capitalization. MKT is the 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 is the return on a portfolio of prior winners minus the return on a portfolio of prior losers. SPREAD is the return on a portfolio of high-spread minus low-spread stocks. $D_{RET(MKT)<2.5\sigma}$ is an indicator variable equal to 1 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 1 in the period between Aug. 6 and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 in the period between Sept. 16 and Sept. 18, 2008, and 0 otherwise. ΔVIX is the daily change in the VIX volatility index. ΔTED is the daily change in the Treasury–Eurodollar spread in the previous day. ΔHAIRCUT is the daily change in the spread of convertible bonds relative to their fair price from Mitchell and Pulvino (2012). ΔNOISE is the illiquidity measure used by Hu et al. (2013), ΔCDS5Y is the change in 5-year credit default swap prices for the U.S. banking sector, and ΔPC1 is the change in the first principal component of funding liquidity variables estimated in Table 3. Returns and risk factors MKT, SMB, HML, MOM, and SPREAD are measured at period t, while other explanatory variables are measured at period $t-1$. We report heteroscedasticity and autocorrelation-consistent (HAC) standard errors in square brackets using the optimum lag-selection algorithm proposed by Newey and West (1994). ** and *** indicate significance at the 5% and 1% levels, respectively.

$t+j$	$D_{RET(MKT)<-2.5\sigma}$	D_{QUANT}	D_{LEHMAN}	ΔVIX	ΔTED	ΔHAIRCUT	ΔNOISE	ΔCDS5Y	ΔPC1
Window (no. of days)	1A	1B	1C	2	3	4	5	6	7
1	−0.354***	−1.579***	−2.511***	−4.851***	−1.267***	−0.208***	−0.246***	−1.294**	−0.955***
2	−0.501***	−3.079***	−4.544***	−8.436***	−1.751**	−0.247*	−0.275**	−2.638*	−1.479***
3	−0.706***	−4.056***	−6.041***	−10.110***	−2.232***	−0.453**	−0.374**	−3.687**	−1.870***
4	−0.681**	−3.974***	−6.510***	−12.239***	−3.065***	−0.564**	−0.322*	−4.848**	−2.307***
5	−0.783**	−3.102***	−6.956***	−14.375***	−3.501***	−0.568*	−0.531**	−5.215**	−2.735***
20	−3.050***	−0.651	−5.281*	−17.012***	−4.178**	−1.423***	−0.691**	−16.617***	−4.530***
60	−3.647***	−2.729	−7.128**	−24.778***	−4.625***	−1.321***	−0.207	−17.904**	−5.602***
80	1.021	−1.803*	−6.409**	4.641	−3.768	0.123	0.817	−3.861	0.647

we examine the cumulative returns after 4 months (i.e., $j=80$) that most estimates, apart from D_{QUANT} and D_{LEHMAN}, are no longer significant. Tables IA.3 and IA.4 in the Internet Appendix show that we obtain similar results if portfolios are constructed using value-weighted and return-weighted returns.

In summary, the cumulative returns for the LOW − HIGH portfolio are consistently lower following illiquidity shocks, and these results persist for up to 3 months. Collectively, these results suggest that securities with the highest level of short selling experience *positive* returns around periods of funding illiquidity.

E. Changes in Equity Loan Quantities

A further test of our hypothesis that investors cover their positions after funding shocks is to investigate changes in equity lending *quantities*. To the extent that the levered marginal investor closes (i.e., covers) his short positions at the time of a funding shock, it should result in lower levels of short selling. Given the results in Table 7, if the price effects persist up to 80 trading days after an economy-wide liquidity shock, we should also observe a decrease in equity loans not only on the day after the shocks but also for the ensuing period.

For this analysis, we pool all stocks in our daily data, creating a panel of nearly 4.7 million daily stock return observations. We employ panel regressions similar to the specification in equation (2) but now use changes in ON_LOAN from $t+3$ to $t+3+j$ ($\Delta ON_LOAN_{i,t+3+j}$) as our dependent variable, including

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year–month fixed effects and computing standard errors clustered at the firm level. Note that $\Delta\text{ON_LOAN}_{i,t+3}$ is the cumulative change in ON_LOAN between $t+2$ and $t+3$, which is a proxy for changes in short-sale quantities between t and $t-1$ due to the mechanics of equity loans' settlement dates described in Section III.A.

Our regression specification is as follows:

$$\Delta\text{ON_LOAN}_{i,t+3+j} = \alpha_t + \beta^T X_{i,t-1} + \gamma^T X_{i,t-1} \otimes Z_{i,t-1} + \varepsilon_{i,t}. \quad (3)$$

β^T is a vector of regression coefficients and X is a vector of firm characteristics that includes BETA, SIZE, BM, RET6M, RETURN_{t-1}, ILLIQ, and SPREAD. We also include separate indicator variables (HIGH_ON_LOAN and LOW_ON_LOAN) if the stock belongs, respectively, to the highest or lowest quintiles of $\text{ON_LOAN}_{i,t-1}$ as part of X. This is meant to capture the effects of changes in equity loan quantities for the most and least shorted stocks, allowing for asymmetric effects between them. Z is a vector of funding variables that includes, respectively, $D_{\text{RET(MKT)}<-2.5\sigma}$, D_{QUANT}, D_{LEHMAN}, ΔVIX, ΔTED, ΔHAIRCUT, ΔNOISE, ΔCDS5Y, and ΔPC1. γ^T is a vector of regression coefficients capturing all interactions between all firm characteristics and the funding availability measures, including main effects for variables in Z, subjecting our hypothesis to a high hurdle rate. We report our results in Table 8 and, for the sake of brevity, report interactions only between ON_LOAN and the various funding availability measures. All variables are defined in the Appendix.

Our prior is that the removal of funding (including increased margin requirements, recall of securities lent out, client redemptions, etc.) will cause levered investors to close out short positions. This covering pressure will, in part, generate the positive return relation documented in previous tables. For example, following the Lehman Brothers bankruptcy, ON_LOAN quantities decrease even faster for stocks with the highest levels of ON_LOAN (i.e., row 1C of Panel A in Table 8), relative to the mean reversion regularly observed in normal times.[11] To provide an economic interpretation for the -0.193 value for the $\text{ON_LOAN} \times D_{\text{LEHMAN}}$ regression coefficient shown in row 1C, we can compare it to the (unreported) -0.03 regression coefficient for the high ON_LOAN dummy variable. It implies that the speed of mean reversion in short selling is much larger during the Lehman Brothers bankruptcy crisis relative to the baseline effect. The only variable in Table 8 that does not have the expected sign is ΔCDS5Y. The coefficients on ΔCDS5Y are positive rather than negative, with equity loan quantities increasing following increases in the CDS5Y index at time t and raising the issue of whether CDS5Y is a relevant measure of funding liquidity. After a month (i.e., $t+20$) the coefficients are still negative and significant, apart from ΔNOISE and ΔCDS5Y. At $t+80$, ΔNOISE and ΔCDS5Y are no longer significant, consistent with the patterns observed in Table 7. When we consider changes of the principal component factor (ΔPC1) in row 7, estimates are negative and statistically significant for all window sizes evaluated.

[11] The unreported coefficients for the level of ON_LOAN (i.e., the "main" effect) are all negative and increasing in the window length j used to measure cumulative changes in ON_LOAN quantities for all the different sets of explanatory variables used. These coefficients capture the mean reversion commonly observed for short-selling intensity.

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TABLE 8

Panel Regressions of Changes in ON_LOAN of Individual Stocks as a Function of Funding Liquidity Proxies and Crisis Indicator Variables

Table 8 displays selected coefficients of panel data regressions of changes in equity loan quantities between July 2006 and May 2013, based on equation (3) in the text. The dependent variable is $\Delta ON_LOAN_{i,t+3+j}$, defined as the difference in ON_LOAN between day $t+3+j$ and $t+3$, which captures short-selling activity between $t+j$ and $t+j-1$. Explanatory variables include ON_LOAN, defined as the total amount on loan divided by market capitalization on day $t-1$; HIGH_ON_LOAN, an indicator variable to 1 if the stock is on the top quintile of ON_LOAN, 0 otherwise; LOW_ON_LOAN, an indicator variable equal to 1 if the stock belongs to the bottom quintile of ON_LOAN, 0 otherwise; crisis-indicator variables; funding liquidity variables; and controls. We also interact all control variables, ON_LOAN, HIGH_ON_LOAN, and LOW_ON_LOAN with the crisis-indicator variables and funding liquidity variables. The control variables are BETA, SIZE, BM, RET6M, $RETURN_{t-1}$, SPREAD, and ILLIQ. Each column reports coefficients of interactions of ON_LOAN with crisis indicators or funding liquidity variable. D_{QUANT} is an indicator variable equal to 1 in the period between Aug. 6 and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 in the period between Sept. 16 and Sept. 18, 2008, and 0 otherwise. ΔVIX is the daily change in the VIX volatility index. ΔTED is the daily change in the Treasury–Eurodollar spread in the previous day. ΔHAIRCUT is the daily change in the spread of convertible bonds relative to their fair price from Mitchell and Pulvino (2012). ΔNOISE is the illiquidity measure used by Hu et al. (2013), ΔCDS5Y is the change in 5-year credit default swap prices for the U.S. banking sector, and ΔPC1 is the change in the first principal component of funding liquidity variables estimated in Table 1. All regressions include year-month fixed effects, and we report robust standard errors clustered at the firm level. ** and *** indicate significance at the 5% and 1% levels, respectively.

		Interactions of HIGH_ON_LOAN with Liquidity Variable							
	Liquidity Variable	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+20$	$t+60$	$t+80$
1A	$D_{RET(MKT)<-2.5\sigma}$	−0.004	−0.001	−0.037***	−0.040***	−0.022*	−0.176***	−0.266***	−0.223***
1B	D_{QUANT}	−0.144***	−0.309***	−0.527***	−0.693***	−0.760***	−0.792***	−0.382**	−0.306*
1C	D_{LEHMAN}	−0.193***	−0.371***	−0.535***	−0.698***	−0.841***	−1.874***	−3.476***	−3.900***
2	ΔVIX	−0.034	−0.136***	−0.191***	−0.252***	−0.416***	−0.984***	−1.761***	−1.737***
3	ΔTED	−0.034***	−0.050***	−0.067***	−0.083***	−0.098***	−0.282***	−0.618***	−0.738***
4	ΔHAIRCUT	−0.020***	−0.032***	−0.046***	−0.046***	−0.050***	−0.102***	−0.180***	−0.196***
5	ΔNOISE	−0.005	−0.010**	−0.020***	−0.008	0.005	0.013	0.017	−0.002
6	ΔCDS5Y	0.065***	0.086***	0.097***	0.129***	0.128***	0.194***	0.054**	−0.007
7	ΔPC1	−0.021***	−0.034***	−0.053***	−0.068***	−0.117***	−0.281***	−0.578***	−0.616***

Together, the results in Tables 7 and 8 suggest that the large negative returns we document for the LOW − HIGH ON_LOAN portfolios are partially attributable to the withdrawal of funding by the marginal levered investor, consistent with our hypothesis that "fire purchases" reflect liquidity shocks.

Another possibility is that negative shocks to lending supply could be driving the reduction in ON_LOAN that we document in Table 8. We have examined separately the change in lendable supply using the same approach and find a muted response. In Table 2, we see that the majority of stocks in the United States. are unconstrained, with the average UTILIZATION implying that only 18% of available supply is lent out. This is more consistent with a shock to shorting demand rather than shorting supply and supports the findings of Cohen et al. (2007).

F. Possible Causes of Deleveraging

Our empirical analysis thus far has established that securities with high levels of short selling exhibit positive returns after periods when capital is harder to obtain. There are multiple potential reasons for this observed relation. Deleveraging can be caused by a combination of voluntary actions of portfolio managers as well as involuntary actions of investors and financial intermediaries. Portfolio managers may seek to target an ex ante risk level for their fund. In response to economy-wide funding liquidity shocks or increases in risk-aversion, they 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

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risky portfolios. Such clients can be external (i.e., ultimate owners), internal (i.e., fund managers who may have internal capital allocated from a parent entity or seed capital provider), or both, and their actions would be forced upon the portfolio manager, who would then need to return capital. This would make arbitrageurs reduce their notional positions, unless they simultaneously increased their leverage, again leading to selling pressure on long positions and buying pressure on short ones. Similarly, the prime broker who provides the leverage for the portfolio manager may take direct action in response to economy-wide liquidity shocks. Such actions could include explicitly reducing the leverage extended to the portfolio manager, increasing the collateral that must be held against portfolio positions, or both. All of these outcomes would lead to selling pressure on long positions and buying pressure on short ones if portfolio managers cannot put up the required increase in margins.

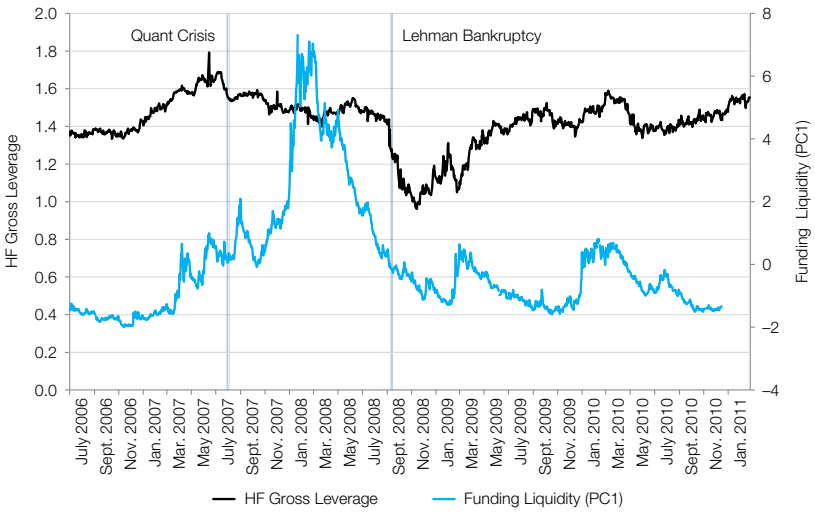
To help illuminate the voluntary deleveraging and ex ante risk targeting, in Figure 5 we analyze the daily hedge fund gross leverage and the common component of funding liquidity, finding a noticeable negative association between these two variables, with the correlation being equal to −0.79. These changes in gross leverage may be due to i) targeting constant portfolio volatility (i.e., gross leverage will decline when volatility rises, as is typical during periods of funding illiquidity) and ii) systematic internal drawdown controls that curb gross leverage during times of funding illiquidity. We spoke informally with several prime brokers, and the consensus of these discussions was 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), and 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.

To analyze client withdrawals from risky portfolios, we examine the time-series correlation between aggregate hedge fund flows and leverage. We obtain aggregate hedge fund leverage data from Ang et al. (2011), which come from a fund-of-funds provider and tracks leverage over the period Dec. 2004–Oct. 2009. The overlapping period with our sample is 42 months of data. We also compute aggregate equity hedge fund flow data from Hedge Fund Research (HFR) and Lipper TASS (https://www.thomsonreuters.com/en/resources/third-party-restrictions/tass-database.html). We use the equity market-neutral style from HFR and Lipper TASS as well as the equity long–short style from Lipper TASS. We cannot find any robust correlations between aggregate hedge fund leverage and flow data. We examine contemporaneous, leading, and lagging correlations. This lack of result is perhaps not surprising, as many hedge funds have in place so-called gates, and the redemption process often requires formal applications that occur on a set cycle. This suggests that external client redemptions are unlikely to completely explain the observed deleveraging we document. We do not have access to internal capital allocated to equity hedge funds, so we cannot directly comment on internal client redemptions as a cause of deleveraging risk. However, based on anecdotal discussions with hedge fund

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FIGURE 5
Hedge Fund Gross Leverage and Funding Liquidity

Figure 5 plots daily hedge fund (HF) gross leverage from Morgan Stanley for its fundamental long–short equity hedge fund clients of its prime brokerage arm and the first principal component of funding liquidity measures (PC1) from July 2006 to Dec. 2012. The sample includes U.S. long–short accounts with at least $50 million in equity and has been rebalanced every 6–12 months to keep it representative of historical accounts. Each fund is equally weighted in aggregate metric. We use the following funding liquidity proxies to extract the principal component. VIX is the daily implied volatility from the S&P 500 index. TED is the daily Treasury–Eurodollar spread. HAIRCUT is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). NOISE is the illiquidity measure used by Hu et al. (2013). CDS5Y is the 5-year credit default swap index for the U.S. banking sector from Datastream.



managers, especially those operating on platforms such as D. E. Shaw, Millennium, 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 only partly explains the deleveraging risk that we document. This is also consistent with the results of Ben-David, Franzoni, and Moussawi (2012).

Finally, we discussed forced reduction in positions with several prime brokers. The common assessment was that closing of short positions due to recalls is rare and stock-specific and applies mainly to small-cap stocks. Forced deleveraging by prime brokers is also unusual. Hence, forced deleveraging is unlikely to explain our results. This suggests that a voluntary reduction in leverage by portfolio managers is the most likely explanation for our observed deleveraging risk.

VI. Conclusion

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 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

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reduced capital availability. Our assumption, validated by aggregate data and institutional features of how market-neutral equity funds operate, is that short sellers employ leverage as part of their investment strategy. We can therefore identify the effects of liquidity shocks to levered positions by tracking the actions of participants in the equity lending market.

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 and future stock returns across a variety of measures. However, extending the literature, we document evidence of occasional very large positive returns to short selling. We further find that these episodes of positive returns are associated with i) discrete liquidity events, such as the Quant crisis of Aug. 2007 and the Lehman Brothers bankruptcy in Sept. 2008 and ii) reductions in capital availability as reflected in a variety of measures, such changes in TED spread, changes in convertible bond spreads relative to their fair price (Mitchell and Pulvino (2012)), and changes in the NOISE measure used by Hu et al. (2013).

The return effects following funding shocks are economically significant and persist for up to 80 trading days for all the measures employed. The effect on equity lending quantities is also persistent, and we find evidence of significantly lower quantities on loan for up to 80 trading days after deleveraging shocks. Together, the continuation of positive returns for securities with high levels of short selling after periods of reductions in funding and the reduced quantities of short selling suggest that the withdrawal of funding for the marginal levered investor is the likely explanation for the effects we document.

These results may help regulators and investors understand the risks associated with short selling and the impact of the use of leverage on their portfolios around times of reduced capital availability.

Appendix. Variable Definitions

SUPPLY: Daily total number of shares available to borrow from Markit divided by shares outstanding.

ON_LOAN: 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). *Source:* 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: Percentage of share outstanding held by institutional investors for each firm-quarter. *Source:* Thomson Reuters 13-F files in WRDS.

RET6M: Cumulative return in the previous 6 months skipping the most recent month.

BM: Compustat's CEQQ divided by MCAP, computed quarterly.

MKT: Daily excess (to risk-free rate) market return. *Source:* WRDS.

SMB: Daily factor portfolio return to the size factor. *Source:* WRDS.

HML: Daily factor portfolio return to the value factor. *Source:* WRDS.

MOM: Daily factor portfolio return to the momentum factor (UMD). *Source:* WRDS.

SPREAD: 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.

$D_{\text{RET(MKT)}<-2.5\sigma}$: Indicator variable equal to 1 for trading days where the aggregate market return is more than 2.5 standard deviations below its average value in the previous day, and 0 otherwise. This is computed using a GARCH(1,1) model on a rolling 252 trading-day basis.

D_{QUANT}: Indicator variable equal to 1 for trading days between Aug. 6, 2007 and Aug. 8, 2007, and 0 otherwise.

D_{LEHMAN}: Indicator variable equal to 1 for trading days between Sept. 16, 2008 and Sept. 22, 2008, and 0 otherwise.

VIX: Implied volatility for S&P 500 options computed by the CBOE. *Source:* Datastream (DSCODE: CBOEVIX).

TED: Difference between 3-month Treasury and Eurodollar futures middle rate. *Source:* Datastream (DSCODE: TRTEDSP).

HAIRCUT: Convertible bond spread relative to its "fair price" from Mitchell and Pulvino (2012).

NOISE: Funding illiquidity measure used by Hu et al. (2013) based on Treasury bond prices.

CDS5Y: The 5-day average of U.S. banks sector 5-year credit default swap index mid-rate price. *Source:* Datastream (DSCODE: USBANCD).

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