# Fails-to-Deliver, Short Selling, and Market Quality

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**Abstract**

We investigate the collective net impact on market liquidity and pricing efficiency of equity trades that result in fails to deliver ("FTDs"). Given the nature of the US electronic trade settlement system for stocks, such "FTD trades" should originate almost exclusively from short sales, and we confirm this empirically on the basis of a natural experiment arising from a regulatory event. For a sample of 1,492 NYSE common stocks over a 42-month period from 2005 to 2008, we find that such trades lead to the same beneficial impact on liquidity and pricing efficiency as short sales that result in timely delivery. We do not find evidence that such trades are causally related to subsequent price declines or distortions, or to the failure of financial firms during the 2008 financial crisis.

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## 1. Introduction

Trades in US stock markets are settled on a three-day cycle: for trades on day *t*, if the net delivery obligations of a clearing member are not fulfilled on day *t+3*, any undelivered position becomes a "failure-to-deliver" (or "FTD").[1] The total number of FTDs for a stock on any day is, *by definition*, the open interest of these undelivered positions. This paper investigates the collective net impact of equity trades that result in FTDs. We hereafter label such trades as "FTD trades". First, we analyze the effect of FTD trades on pricing efficiency and liquidity. Second, we examine whether FTD trades played a causal role in the major price declines or the demise of financial institutions during the 2008 financial crisis.

FTDs originate almost exclusively from short sales. Ownership records are ordinarily held, tracked and transferred electronically through an automated process; and if the stock ownership accounts associated with a seller with a net delivery obligation do not actually include the stock needed for delivery on the third day following a trade, the undelivered position becomes a FTD. The automated nature of the electronic process ensures that "long" sales (i.e. sales backed up by duly owned stock in relevant stock ownership accounts) do not remain undelivered; hence, the delivery shortfall in stock ownership accounts arises when the seller does not own the stock (i.e., the trade is a short sale) *and* the corresponding stock has not been borrowed in time to credit the stock ownership account by settlement day. Furthermore, the three-day settlement cycle starts only *after* trade reconciliation between buyer and seller firms for removal of purely clerical or recording errors; and hence such errors (in "long" sales) cannot be responsible for FTDs. However, processing delays with respect to share certificates *not* held electronically can occasionally cause FTDs to arise also from "long" sales (e.g., when the broker does not insist on delivery and electronic recording of any paper certificates prior to trade); but such cases should be a minuscule proportion of the total number of FTDs, since more than 99.9% of all trades involve only electronically held securities (Morris and Goldstein, 2009).[2] Therefore, the open interest of *undelivered positions* (i.e., the total number of FTDs) should be virtually the same as the open interest of *undelivered short sold positions.* This is empirically confirmed by results we document at the outset, based on a natural experiment arising from an exogenous regulatory event.

[1] Settlement is done electronically through the Depositary Trust and Clearing Corporation and its subsidiaries (hereafter collectively referred to as "DTCC"). DTCC becomes the central counterparty of all duly matched trades, electronically checks stock ownership accounts associated with all such trades, and notifies clearing brokers about their settlement day net delivery obligations.

[2] Morris and Goldstein (2009) is a publication officially endorsed by DTCC to provide details of the settlement system. The institutional conclusions here are also confirmed by our discussions with industry insiders.

The investigation of FTD trades is interesting from an economic perspective, since a short sale that fails to deliver should be associated with the same market impact as a short sale that results in timely delivery; hence, it should arguably have a positive impact on liquidity and pricing efficiency, as is well-documented of short selling in general.[3] First, the two might not differ at inception, as a short seller need not definitively know on the day *t* of the trade whether or not s/he will deliver or fail on settlement day *t+3*. This is because that decision should rationally be taken only on day *t+3* and on the basis of the rebate rates in the OTC stock-borrowing market on day *t+3.* [4] The short seller will borrow and deliver if these rebate rates are positive and fail if they are negative.[5] Second, as explained by Culp and Heaton (2008), an FTD results either in an automatic stock borrowing at zero rebate rates from a pool of voluntary lenders under the DTCC *Stock Borrow Program*, or a forced stock borrowing at zero rebate rates from a (randomly assigned and daily changing) broker with a long stock position.[6] As far as the market is concerned, since the stock is being temporarily borrowed anyway (voluntarily or otherwise), there should not be any functional consequences arising from whether a short sale ultimately results in an FTD or not.[7] In this context, we empirically analyze the impact on pricing efficiency and liquidity of short sales that fail to deliver, questioning whether that impact is any different from the impact of timely-delivered short sales.

Our investigation of FTD trades is also motivated by the enormous regulatory focus on reducing such trades.[8] Regulatory concerns have been driven by the widespread perception and the extensive litigation about at least a subset of FTD trades being used abusively or manipulatively by "naked" short sellers strategically choosing whether or not to deliver.[9] Such "naked" short sellers have also been widely alleged to have

[3] While there could be dissenting opinions, there is broad consensus behind an extensive literature finding that short selling is beneficial for pricing efficiency and liquidity (Diamond and Verrecchia, 1987; Abreu and Brunnermeier, 2002 and 2003; Miller,1977; Bris et. al.,2007; Diether et al.,2009; Boehmer et al., 2008).
[4] Clearly, since stock borrowing arrangements are ordinarily accompanied by same day delivery, it is economically not rational for short sellers to borrow prior to the delivery date and pay the extra borrowing fees involved (Geczy et al., 2002).
[5] Evans, et al. (2009) show that short sellers use the alternative to fail only when rebate rates are negative. Boni (2006) also offers evidence of correlation between fails and borrowing costs, which she interprets as indicative of "strategic" fails.
[6] The involuntary lender can enforce delivery by forcing a "buy-in" from the market, but there is little incentive to do this since the random assignment can potentially change every day (Putniņš, 2010).
[7] The majority of delivery 'fails' are just delays in delivery: Boni (2006) shows that the median age of fails is only 3 days.
[8] In January 2005, Regulation SHO introduced requirements to "locate" stocks prior to a short sale and to "close-out" FTDs for "threshold-list" stocks with high number of persistent FTDs; but the locate requirement did not eliminate FTDs since rules allowed use of "Easy to Borrow" lists without locating a specific bloc of shares (Welborn, 2008). In July/ August 2008, a temporary SEC Order mandated specific stock borrowing arrangements prior to short selling in select financial stocks. In September 2008, following Lehman's collapse, FTDs were banned (except for market-makers) by mandating a presumption of deceptive intent from a FTD, and by requiring a compulsory "close-out" of a FTD through borrowing or purchase by the broker by the morning after the failure day (through Rule 204T, later made permanent). In November 2012, new EU rules have instituted a pan-European pre-trade borrowing requirement for short sales.
[9] There is no widely accepted definition of the term "naked short selling". The SEC's use of the term appears to be confined to just implying failing-to-deliver because of not making pre-trade borrowing arrangements. However, the term is

contributed to the financial crisis by precipitating sharp price declines of financial firms.[10] Notwithstanding extensive concerns, the SEC (in Report 450, March 2009) says that *"there is hardly unanimity in the investment community or the financial media"* on associated dangers, and *"despite its assertions regarding the potential of danger..., the [SEC] Report can cite to no bona fide studies"* on the market impact associated with FTD trades. This paper accordingly investigates FTD trades.

We first empirically confirm whether FTD trades arise primarily from short sales. We utilize a natural experiment based on an exogenously-imposed temporary SEC Emergency Order (Release 58166 dated July 15, 2008) that remained in force between July 21 and August 12, 2008. The only mandate of this order was to require pre-borrowing arrangements prior to all short sales in 19 selected financial stocks in order to eliminate new FTDs. This order could not affect any FTDs arising from (processing delays in) "long" sales, since the order was only about stock-borrowing for short sales. We find that, during the temporary order validity period, reported FTDs for the affected securities reduce rapidly to only about 12% of their pre-order average within one week, to just about 2% of their pre-order average within three weeks, and finally, on the last day of the order period, reported FTDs are zero for each and every affected security. In contrast, we observe a slight increase in FTDs for control-sample securities. Given that FTDs cannot fall immediately to zero because of FTDs persisting from prior to the order, this natural experiment provides strong evidence, consistent with our understanding of settlement mechanics, that FTD trades arise overwhelmingly from short sales.

Our main sample consists of all the 1,492 NYSE ordinary common-share issues for which all relevant data is available over the period January 2005 to June 2008. For robustness, we replicate our analysis on a sample of 2,381 NASDAQ ordinary common-share issues over the same period. The first section of the empirical analysis examines whether FTD trades are followed by reductions in pricing errors, pricing error volatility, return volatility, bid-ask spreads, and order imbalances. The various tests we present allow us to control for timely-delivered short sales and to compare the impact of FTD trades and timely-delivered short sales. First, we analyze liquidity and pricing efficiency for securities in different portfolios based on the number

often inextricably linked to a pejorative mental presumption of *manipulative intent*, which we do *not* examine in this paper. This is a paper on the totality of FTD trades irrespective of any manipulative intent. It is not possible to determine *manipulative intent* with any reasonable objectivity with the data available to us. Furthermore, in spite of a flood of lawsuits, even after intensive individual case analysis within the courts' system, it has not been possible to prove manipulative intent to the extent necessary to win a judgment of damages relating to "naked" short selling (Stokes, 2009).

[10] Several investor associations and high-profile CEOs lobbied aggressively against FTDs, and the huge volume of litigation alleging associated stock price manipulation led to "naked" short selling being called the "Holy Grail ….bigger than tobacco" for plaintiffs' lawyers (Stokes, 2009). Over a two-year period leading up to the 2008 financial crisis, the SEC received more than 5,000 complaints in this regard (*Wall Street Journal Asia*, March 20, 2009), and a *Factiva* search shows over 4,600 printed English-language articles on the subject.

of FTDs. Second, we utilize OLS regressions and Granger-causality tests to investigate the link between FTD trades and market liquidity and pricing efficiency. Third, given the complex and endogenous interrelationships between market quality metrics, we fit vector autoregressive models and test the same relationships using impulse response functions. To further fully distinguish between association and causality, we utilize the imposition of the July/August 2008 SEC Emergency Order selectively targeting only FTD trades and estimate the impact of that order on pricing efficiency and liquidity. Finally, we examine whether FTD trades by market makers affect securities differently from FTD trades by other "public traders", by using a proxy based on the reduction in FTDs subsequent to SEC Rule 204T in September 2008 that selectively precluded public-trader FTDs but not market-maker FTDs.

The second section of the empirical analysis investigates whether FTD trades causally precipitated price declines of financial firms during the 2008 financial crisis. In this context, we analyze FTDs of a few high-profile financial firms that experienced dramatic stock price declines: *Bear Stearns Companies Inc.* ("Bear Stearns"), *Lehman Brothers Holdings Inc.* ("Lehman"), *Merrill Lynch & Co. Inc.* ("Merrill"), and *American Insurance Group* ("AIG"). We also analyze credit rating downgrades and large price drops during 2008 to examine if short sales that fail to deliver trigger price declines, or are responding to them and associated news.

We find that FTDs affect about 95% of NYSE securities, though on average only about 1% of short sales result in delivery failures. FTD data are reported daily: hence, all our analysis is at daily frequency. We estimate that FTD trades equivalent to 10 basis points of the number of outstanding shares lead to a 1% reduction in spreads, a 2% reduction in order imbalances, a 10% reduction in the magnitude of positive pricing errors, a 13% decline in pricing error volatility, and a 1% reduction in stock price volatility; each of these changes is statistically significant and not subject to significant subsequent corrections. These results are consistent with failing-to-deliver short sellers acting as value arbitrageurs enhancing pricing efficiency and providing liquidity as needed. Consistent with our hypotheses, we also find that the estimated impact of FTD trades and delivered short sales on our market-quality metrics is similar in both magnitude and significance. We further focus on sub-samples of securities affected by high levels of FTDs or by persistent FTDs and obtain very similar results.[11] Importantly, to control for any omitted variables, we investigate the securities affected by

[11] We thank an anonymous referee for suggesting this line of inquiry. Accordingly, we identify two data subsets. First, we isolate a sub-sample of securities with the highest average level of outstanding FTDs. Second, we isolate securities which are included, at any time between January 2005 and July 2008, in the "Threshold List" – a list published by the SEC identifying securities with high and persistent levels of outstanding FTDs.

the exogenous imposition of the July/August 2008 SEC Emergency Order mandating stock borrowing prior to a short sale and find that these securities display a significant increase in returns volatility, pricing error volatility, and spreads during the time period for which the order was in force: i.e., the pre-short sale stock-borrowing mandate designed to reduce FTDs significantly worsened pricing efficiency and liquidity. Finally, our results show that the beneficial impact on pricing efficiency and liquidity of FTD trades is driven by both market-maker FTDs and FTDs originating from public traders. Overall, we conclude that short sales that fail to deliver contribute beneficially to market liquidity and pricing efficiency, just as duly delivered short sales do.

In relation to Bear Stearns, Lehman, Merrill and AIG, we find that FTDs were too few for any significant stock price distortions for most of the days, and when FTDs did become abnormally high, it was *after* price declines, *not before*. Similarly, we find that the volume of FTDs increases *after* credit rating downgrade announcements and *after* large price drops, *not before*. In each case, failing-to-deliver short sellers were *responding to* information about the firms, rather than being responsible for triggering observed price declines. We find no evidence that FTDs played a causal role in the demise of financial institutions or in generating price distortions during the 2008 financial crisis.

This research contributes to the literature on settlement systems and delivery failures. While it is true that concerns about delivery fails are justified in the context of fair and orderly markets, it is also true that Evans, et al. (2009) show that "the alternative to fail is valuable and important to the pricing and trading of options"; and our results additionally and importantly show that the alternative to fail has a beneficial impact on liquidity and pricing efficiency of equity markets as well. We also know from Merrick, et al. (2005) that the alternative to fail is an important release valve for settlement-related pressures and manipulative distortions. Similarly, in the context of our research, the alternative to fail is an important release valve that protects traders from the extreme vagaries of the less regulated stock borrowing market: it is particularly valuable when stock-borrowing become so costly that short-selling rebate rates become negative, which is exactly when liquidity is most needed in the stock-borrowing market (Evans, et al., 2009). Hence, regulatory removal of the alternative to fail for all public traders is debatable when progressive fines for settlement delays can be effective without being an extreme solution. It is more important for regulators to focus on removing the economic incentives for delivery failures by improving the liquidity, transparency and regulation of the stock borrowing market.

This research also contributes significantly to the short selling literature. First, while there is extensive evidence on the market-quality benefits of short selling, our contribution is to show that short sales that fail to deliver are as beneficial for market quality as short sales that deliver in time. Second, our evidence shows that a blanket ban on FTDs in some stocks in July 2008, effectively an additional constraint on short selling, has predictably negative consequences on market quality; and we thereby extend the literature on the market impact of short sales restrictions.[12] Finally, our findings have important implications for the extensive media discussions on, and the regulatory response to, "naked" short sales.

The remainder of the paper is structured as follows. Section 2 establishes the link between FTDs and short sales, and develops testable hypotheses. Section 3 outlines the data, the variables and the measures utilized. Section 4 presents empirical results on the impact of FTD trades on pricing efficiency and liquidity. Section 5 investigates the role of FTD trades in creating price distortions during the 2008 financial crisis. Finally, Section 6 offers concluding remarks.

## 2. FTDs, short sales and testable hypotheses

### *2.1. FTDs and short sales*

As discussed in the introduction, the total number of FTDs (i.e., the open interest of *undelivered positions*) should ordinarily be the same as the open interest of *undelivered short sold positions,* though processing delays with respect to paper certificates can sometimes cause FTDs to arise also from "long" sales.[13] In this sub-section, we empirically examine whether FTDs arise overwhelmingly from short sales (rather than "long" sales) using a natural experiment arising from the exogenous imposition by the SEC of an Emergency Order on July 15, 2008, selectively targeting pre-short sale borrowing requirements and applicable only to the stocks of a select group of 19 publicly traded financial institutions from July 21 to August 12, 2008.

The SEC order required that "*no person may effect a short sale in these securities… unless such person or its agent has borrowed or arranged to borrow the security or otherwise has the security available to borrow in its inventory prior to effecting such short sale.*" (SEC Release 58166, 2008). The only regulatory change affecting these stocks during this period was this temporary order mandating firm stock-borrowing

[12] Several recent papers examine short selling restrictions in 2008: Boulton and Braga-Alves (2010) and Kolasinsky, et al. (2012) also examine aspects of the July/August 2008 SEC Emergency Order that we investigate in this paper; while other papers - Battalio and Schultz (2011), Boehmer, et al. (2011), Autore, et al. (2011) and Beber and Pagano (2011) - examine the subsequent September 2008 short selling ban (that we do not examine).

[13] FTDs can potentially arise from the mechanism of the offering process in price-supported IPOs (Edwards and Hanley, 2010). In this context, as indicated later in Section 3, we remove from our sample: first, all ETFs and other non-common-stock securities; second, securities that started trading during our sample interval (to avoid distorting our inferences through IPO-related FTDs); and third, securities for which we observe significant changes in the number of shares outstanding (to prevent the possibility of similar FTDs in conjunction with other share issues).

arrangements prior to executing short sales. Any FTDs arising from "long" sales cannot be affected by this order, as "long" sales do not require any stock borrowing: the effect of the SEC order on FTDs can arise only from short sales. We employ an event study methodology to investigate the variation in FTDs around this mandate requiring pre-short sale stock borrowing arrangements.

Data on FTDs have been made available by the SEC under the Freedom of Information Act (FOIA) since March 22, 2004.[14] Data for 17 of the 19 securities affected by the July 2008 SEC Emergency Order are available from CRSP. We construct a matched control sample: for each of our affected 17 affected securities, we identify the firm that is not affected by the SEC Emergency Order, but shares the same 4-digit SIC code and has the closest market capitalization as of January 1, 2008. Then, we analyze the number of reported FTDs duly scaled by the number of shares outstanding, for both event and control samples, over a pre-ban period (January 1 to July 20, 2008), for each week in the ban period (July 21 to August 12, 2008), and for the three-week period following the ban (August 13 to September 2, 2008), finishing well before the tumultuous period around the Lehman bankruptcy in mid-September 2008.[15] We report these results in Table I.

Reported FTDs (as a proportion of shares outstanding) for the 17 securities in our sample average 4.88 basis points (or 'bp') during the pre-order period. After the order, FTDs reduce rapidly to about 0.57 bp, or 12% of their pre-order average within one week; to about 0.12 bp, or 2% of the pre-order average, within three weeks; and, on the last day of the Emergency Order period, reported FTDs are zero for each and every affected security. In contrast, reported FTDs for control sample securities do not decrease over the same time frame. As soon as the temporary order period expires, reported FTDs of affected securities increase monotonically and significantly. The difference in reported FTDs between event and control firms is positive and significant prior to the mandate period, negative and significant during the mandate period, and again positive and significant after the mandate is lifted. Given that reported FTDs cannot fall immediately to zero because of the time required for fails outstanding from prior to the SEC order to clear (Boni, 2006), this "natural experiment" strongly indicates that FTDs arise almost entirely from short sales.[16]

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[14] SEC data record FTDs for a security when only when FTDs exceed 10,000 shares. Since this is a tiny fraction of the total number of shares outstanding for most securities, the underestimation due to the threshold is likely to be immaterial.

[15] Here and in the remainder of the paper, we scale the number of FTDs by the number of shares outstanding, mirroring previous literature which relied on measures of 'relative short interest' (short interest scaled by the numbers of shares outstanding) and which amply discusses the need to 'standardize' short interest data; for example, amongst others, DeChow et al. (2001), Desai et al. (2002), and Chen and Singal (2003).

[16] We also find that new FTDs on day $t+3$ are significantly ($p$-value<<0.01) and positively related only to the daily trading volume arising from short sales on day $t$, and not the daily trading volume arising from "long" sales on day $t$.

## 2.2 *FTD trades: testable hypotheses on pricing efficiency and liquidity*

Duly-delivered short sales, as well as short sales that fail to deliver in time, should both contribute similarly to the price discovery process by enabling value-traders to more quickly and easily bring the prices of overpriced securities in line with their "true value". Since FTD trades arise primarily from short sales, our first hypothesis is *H1: FTD trades have a beneficial impact on pricing efficiency.*

To test Hypothesis *H1*, we empirically investigate several aspects of pricing efficiency:

1. Short sales that fail-to-deliver, like timely-delivered short sales, should contribute to pricing efficiency to the extent that value arbitrageurs enter the market when securities are over-priced and therefore reduce the positive pricing errors of these overpriced securities. Accordingly, we test whether FTD trades, like delivered short sales, lead to a reduction in positive pricing errors next period.
2. A reduction in positive pricing errors should make the market informationally more efficient. Such a market should display lower dispersion of pricing errors (Hasbrouck, 1993). Hence, we test whether FTD trades, like delivered short sales, lead to reduced volatility of pricing errors next period.
3. Greater pricing efficiency should translate into reduced volatility of stock returns. Hence, we test whether FTD trades, like delivered short sales, lead to a reduction in stock return volatility next period.
4. If short sales that fail-to-deliver also contribute causally to pricing efficiency, an exogenous imposition of mandatory pre-short sale borrowing arrangements should lead to reduced pricing efficiency. Accordingly, we test whether the July 2008 SEC Emergency Order leads to higher volatility of pricing errors, higher spreads, and lower trading volume.

Financial intermediaries and other liquidity suppliers should provide liquidity more effectively and expeditiously in the presence of all short sales, whether delivered in time or not. Failing to deliver also offers an alternative to short sellers when rebate rates are negative (Evans, et al., 2009), i.e., when the cost of borrowing in the security-lending markets is high, which is more likely when liquidity is most needed. Hence, our second hypothesis is *H2: FTD trades have a beneficial impact on market liquidity.*

We test hypothesis *H2* in two ways. First, we test whether FTD trades, like timely-delivered short sales, lead to lower spreads and reduced order imbalances in the next period. Second, if FTD trades contribute causally to greater liquidity, the exogenous imposition of mandatory pre-trade borrowing through the July 2008

SEC Emergency Order should lead to a reduction in liquidity. Accordingly, we test whether the Emergency Order above led to higher spreads and larger order imbalances.

### *2.3. FTD trades: testable hypothesis on price distortions and the 2008 financial crisis*

As discussed in Section 1, extensive concerns have been articulated in the media and by investor groups and company CEOs about FTD trades being utilized to trigger sharp declines in stock prices, particularly during the 2008 financial crisis.[17] Accordingly, our third hypothesis is *H3: FTD Trades caused price crashes and distortions during the 2008 financial crisis*.

We empirically investigate Hypothesis *H3* in several different ways.

1. FTD trades have been often blamed for the price crashes of Bear Stearns, Lehman, AIG and Merrill.[18] Accordingly, we test for high levels of FTD trades *prior to* the large price declines in the stock prices of those companies.
2. Short sellers are often associated with "bear raids" through failing to deliver to trigger downward price spirals with the aim of achieving credit downgrades so as to also profit from potentially simultaneous positions in the CDS market. In this context, we test whether the volume of FTD trades grow *prior to* credit rating downgrades. In a similar spirit, we investigate whether volumes of FTD trades grow prior to large stock price declines, particularly for securities issued by highly levered firms.

## 3. Data, variables, and measures

### *3.1 Data and sample*

Our main sample consists of all NYSE listed common stocks in CRSP share codes 10 and 11 for which complete data are available across the various data sources listed above. By restricting analysis to CRSP share codes 10 and 11, we specifically exclude ETFs (in case FTDs are caused by delays in the creation of units), and

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[17] Such investor associations include *The Movement for Market Reform*, *National Coalition against Naked Short Selling* and *Coalition for the Reform of Regulation SHO*. Crusading high-profile CEOs include Patrick Byrne of Overstock.com (which filed lawsuits against both naked-short sellers and financial institutions accused by them of facilitating 'naked-shorting'), and Richard Fuld of Lehman Brothers who, in his October 2008 testimony before the US House of Representatives Committee on Oversight and Reform, alleged that "naked short selling .... dealt a critical, if not fatal, blow to Bear Stearns", and also contributed significantly to the collapse of Lehman Brothers. Examples of lawsuits include *The Biovail lawsuit* against Stephen Cohen, Gradient, and others; *the Overstock lawsuit* against Rocker Partners, Gradient, and others; and the *The NFI lawsuit* against *Bank of America* (the Specialist) and the Prime Brokers.

[18] For example, Robert Shapiro, Former Under Secretary of Commerce, was quoted as stating that *"Bear Stearns failed because it went bankrupt. However, the pace of the collapse of the stock price was clearly accelerated by the enormous naked short sale activity"*(*Euromoney*, December 2008). The media sentiment is exemplified by statements such as "*when Bear and Lehman made their final leap off the cliff of history, both undeniably got a push — especially in the form of a flat-out counterfeiting scheme called naked short selling*" (*Rolling Stone*, October 2009).

other securities that are not common stocks.[19] We also restrict the main sample to securities that are listed for at least six months (in order to have adequate data to estimate our vector autoregressive models), and that have been trading for at least one year prior to the start of our sample period. Having a year of trading data allows us to estimate pricing errors as discussed later in this section. We further require that the number of shares outstanding does not vary by more than 10% over any single day, thus controlling for the unusual volumes of FTDs around primary market transactions documented by Edwards and Hanley (2010).[20] In view of the potentially confounding influence of the July 2008 SEC Emergency Order and the severe restrictions on short selling and FTDs subsequently imposed in September and October 2008, we confine our analysis of FTD trades to the period up to June 30, 2008. Our main sample thus consists of 1,492 NYSE securities over the period January 2005 to June 2008. For robustness tests, we similarly construct a comparable sample of 2,381 NASDAQ securities for the same sample period. Our short interest data are from www.shortsqueeze.com, and short sales data (available from January 2005 onwards) are from the NYSE. We obtain the number of shares outstanding from CRSP. Our market quality measures are based on NYSE TAQ data.

### 3.2 *Outstanding Fails Ratio* (*OFR*) *and Outstanding Delivered Ratio* (*ODR*)

Our metric for the open interest of undelivered positions is the *Outstanding Fails Ratio* (*OFR*), defined for each day *t* as the number of outstanding FTDs as of day *t* scaled by the total number of shares outstanding of the firm (which we obtain from CRSP).[21] Our approach is similar in spirit to previous literature that relies on measures of 'relative short interest' (DeChow et al., 2001; Desai et al., 2002; Chen and Singal, 2003). We similarly estimate the *Outstanding Delivered Ratio* (*ODR*) as the open interest of timely-delivered short sales positions scaled by the number of shares outstanding. The open interest of timely-delivered short sales is computed by subtracting the open interest of undelivered positions (i.e., short sales that fail to deliver) from the contemporaneous value of open interest of all short sales. Estimates are based on total short-interest data and the total volume of daily short sales. We use the daily change in *OFR* as our measure of "FTD trades" on the same day, and the daily change in *ODR* as our measure of timely delivered short sales that day.

[19] We thereby exclude securities classified by CRSP as certificates, American trust components, ADRs, SBIs and units such as "depositary units" and "units of limited partnership interest", as well as securities issued by other types of entities such as foreign firms, closed-end funds, and REITs.

[20] That said, we also re-sample without this last constraint and find that our results are robust.

[21] Reported raw FTD data from the SEC for day *t* represents fails that have already taken place by that day. Hence, in computing outstanding FTDs, we incorporate a minor adjustment to account for the short sales executed on *t-1* and *t-2* that eventually fail to deliver on their respective settlement days, even though the failure has not yet been revealed in reported FTDs by day *t*. That said, this adjustment does not change the economic content or the significance of the results.

*3.3. Pricing error*

An important measure of pricing efficiency that we use is the "pricing error". We define the "pricing error" on any day as the difference between the observed price on that day and the estimated information-efficient price for the same day. The unobservable daily estimate of the information-efficient "random-walk" or "fundamental" price of the security, a "latent" stochastic variable, is estimated for each sample security using a Kalman-filter methodology as in Hamilton (1985). The procedure involves establishing two equations. The first equation dictates the evolution of the latent variable, and in our case we assume, in the spirit of Hasbrouck (1993), that the logarithm of the stock's underlying or information-efficient value, $F(t)$, follows a random walk with a drift, $\mu$, and a white noise innovation, $\varepsilon(t)$, with mean zero and variance $\sigma_\varepsilon^2$:

$$F(t) = \mu + F(t-1) + \varepsilon(t), \quad \varepsilon \sim N(0, \sigma_\varepsilon^2)$$

The second equation relates the observed and latent variables, i.e., specifies the pricing error process. In our case, we assume that the pricing error *Y(t)* follows a mean-reverting process around zero, with *α,* the rate of mean-reversion, ranging between 0 and 1. Pricing errors correct fully in one period when *α* is equal to one, and not correct at all when *α* is equal to zero.

$$\Delta Y(t) = -\alpha Y(t-1) + \varphi(t), \quad \varphi \sim N(0, \sigma_\varphi^2)$$

The observed log of stock price $S(t)$ is the sum of the fundamental price and pricing error:

$$S(t) = F(t) + Y(t)$$

Hence, $S(t) = \mu + (1-\alpha)S(t-1) + \alpha F(t-1) + \theta(t)$, $\quad \theta(t) = \phi(t) + \varepsilon(t)$

The *Expectation Maximization* (EM) algorithm (Dempster, et al., 1977) is employed to compute the Maximum Likelihood (ML) estimate of the unobservable variable, *F(t)*, based on data relating to the observed variable, *S(t)*. Hamilton (1985) employs such an approach to estimate expected quarterly inflation, the latent variable, based on observed actual inflation. In exactly the same way, we utilize the observed daily stock prices to infer the daily unobserved "fundamental price", and hence the daily pricing error, using daily closing price data from CRSP. The state-space representation of the system is as follows.

Measurement Equation:

$$\begin{bmatrix} S(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} S(t) \\ F(t) \\ \varepsilon(t) \end{bmatrix}$$

Transition Equation

$$\begin{bmatrix} S(t) \\ F(t) \\ \varepsilon(t) \end{bmatrix} = \begin{bmatrix} (1-\alpha) & \alpha & \mu \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} S(t-1) \\ F(t-1) \\ 1 \end{bmatrix} + \begin{bmatrix} \theta(t) \\ \varepsilon(t) \\ 0 \end{bmatrix}$$

To test the bias and efficacy of our pricing error estimation process, we run 500 simulations of both fundamental price and pricing error for a hypothetical stock over 252 trading days assuming a range of volatility parameters and mean reversion parameters. In each case, we add the fundamental price and the pricing error to arrive at the equivalent of a simulated "observed" price. Then, we run our Kalman-filter estimation procedure on this "observed" price series to determine our Kalman-filter estimate of the originally simulated fundamental price. Finally, we run a regression of changes in the originally simulated fundamental price on changes in our Kalman-filter estimate of that fundamental price. In each and every case, the regression intercept is not significantly different from zero, and the regression slope is not significantly different from one; and the root mean square error in the estimated fundamental price is economically small in magnitude.

### *3.4 Other variables and market quality measures*

Table II defines the other variables and measures we use in the paper. The liquidity and the pricing efficiency measures and the other variables in Table II are defined and estimated as commonly done in the literature and based largely on NYSE TAQ data.

## 4. Empirical results: FTDs, pricing efficiency, and liquidity

### *4.1. Preliminary descriptive analysis of overall sample*

We first sort securities into ten deciles according to mean *OFR*, computed over the entire sample period (January 1, 2005 to June 30, 2008). In Table III, we report sample means, medians, and standard deviations of the main variables, for the overall sample and for the top and bottom deciles. We find that mean *OFR* is about 6 basis points. By construction, *OFR* varies by decile: the mean is less than 1 basis point in decile 1 and about 43 basis points in decile 10. Notably, though not reported in the table, *OFR* is higher prior to the introduction of Regulation SHO in January 2005 by an average of about 9 basis points. The mean *FTDs to Total Short Interest* ratio is about 1% for the overall sample, 2.8% for decile 10, and 0.1% for decile 1. We find that *ODR* is similarly higher in decile 10 (13.4%) than in decile 1 (3.95%), which is indicative of a positive correlation between *ODR* and *OFR*. Securities in deciles 1 and 10 do not differ significantly in terms of mean pricing errors. However, securities with higher *OFR* display significantly higher positive pricing errors and pricing error volatility, which is consistent with FTDs intensifying when securities are overpriced. Similarly, higher *OFR* is associated with higher and positive order imbalances and higher stock price volatility but lower spreads.

Our analysis also reveals that FTDs are significantly more common for relatively smaller firms, as average market capitalization for firms in decile 1 (USD 12.5 billion) is almost ten times larger than for firms in decile 10 (USD 1.48 billion).

### 4.2. *Portfolio approach*

As a first test of the relationship between FTD trades and subsequent market quality, on each day *t* in our sample spanning January 2005 to June 2008, we group the 1,492 securities into nine portfolios based on changes in *OFR* and *ODR*.[22] We start by estimating the daily time-series standard deviation in *OFR* by security. On each day, we include securities with a one-standard deviation or greater decrease in *OFR* into a "Low FTD Trades" portfolio and, similarly, securities with a one-standard deviation or greater increase in *OFR* into a "High FTD Trades" portfolio. We include all remaining securities into a "Normal FTD Trades" portfolio. In order to control for the extent of timely-delivered short sales, we replicate the same procedure on the basis of timely-delivered short sales, proxied by changes in *ODR*, thus forming the portfolios "Low Delivered Short sales", "Normal Delivered Short sales" and "High Delivered Short sales". Finally, we intersect those groups of securities, forming nine final portfolios. For each portfolio, we compute average changes in our metrics of price levels, return volatility, market liquidity, pricing errors, pricing error volatility and order imbalances for the following day (*t*+1). All variables are standardized and winsorized (at three standard deviations) by security. We compute next-day average changes for the portfolios "Low FTD Trades, Normal Delivered Short sales" and "High FTD Trades, Normal Delivered Short sales" and we further test for differences between these averages.

The results of this analysis are presented in Table IV. For the portfolio "High FTD Trades, Normal Delivered Short sales", we find, on the following day, a 14 basis points decrease in pricing error, an 81 basis points reduction in pricing error volatility, a 1 basis point decrease in spreads, a 23 basis points decrease in order imbalances, and a 6 basis points decrease in stock price volatility – all results being statistically significant at the 1% level; we also find a decrease in prices, but the result is not statistically significant. For the portfolio "Low FTD Trades, Normal Delivered Short sales", we observe a statistically significant (at 10% level) 2 basis points increase in volatility. We further investigate the differences in next-day metrics between the two portfolios. The "High FTD Trades" portfolio, compared to the "Low FTD Trades" portfolio, displays lower

[22] Our interest lies in changes in *OFR*. We form portfolios on changes in *ODR* to control for the impact of duly-delivered short sales on liquidity and pricing efficiency.

pricing errors, pricing error volatilities, prices, spreads, order imbalances and volatility, with all results being statistically significant at the 1% level.

This initial analysis offers evidence consistent with Hypotheses *H1* and *H2*: high FTD trades are followed by next day improvements in both market liquidity and pricing efficiency. Given the limitations of this univariate framework, we conduct multivariate analysis in the following section, employing OLS regressions to investigate the relationship between FTD trades and subsequent market quality while controlling for timely-delivered short selling and relevant systematic factors.

### *4.3. Panel OLS regressions*

We next estimate panel regressions to investigate the relationship between FTD trades and next-day market quality metrics: pricing errors, pricing error volatility, prices, return volatility, spreads, and order imbalances. Accordingly, we estimate six separate regressions, with changes in market quality metrics as responses. Our main explanatory variables are previous-day changes in *OFR* and *ODR*, proxying for FTD trades and timely-delivered short sales respectively. As controls, we include, in each regression, lagged changes of the dependent variable, to account for possible autocorrelations. In addition, to control for systematic effects, we include market averages of the changes in the same quality metrics. Finally, when modeling changes in pricing errors, we add interaction variables between changes in *OFR* and *ODR* and a binary variable identifying positive pricing errors, to allow for an asymmetric impact of fails on pricing errors. All regressions contain security fixed-effects and standard errors are time-clustered. The models estimated are as follows:

$$\begin{aligned}\Delta PE_{i,t} = {} & \lambda_{0,i} + \lambda_1 \Delta OFR_{i,t-1} + \lambda_2 \Delta ODR_{i,t-1} + \lambda_3 \Delta OFR_{i,t-1} * Positive\_PE\_Dum_{i,t-1} + \\ & \lambda_4 \Delta OSR_{i,t-1} * Positive\_PE\_Dum_{i,t-1} + \lambda_5 \Delta PE_{M,t} + \lambda_6 \Delta PE_{i,t-1} + \varphi_{i,t}\end{aligned}$$

$$\begin{aligned}\Delta PE\_Volatility_{i,t} = {} & \gamma_{0,i} + \gamma_1 \Delta OFR_{i,t-1} + \gamma_2 \Delta ODR_{i,t-1} + \gamma_3 \Delta PE\_Volatility_{M,t} \\ & + \gamma_4 \Delta PE\_Volatility_{i,t-1} + \nu_{i,t}\end{aligned}$$

$$\Delta Volatility_{i,t} = \delta_{0,i} + \delta_1 \Delta OFR_{i,t-1} + \delta_2 \Delta ODR_{i,t-1} + \delta_3 \Delta Volatility_{M,t} + \delta_4 \Delta Volatility_{i,t-1} + \theta_{i,t}$$

$$\Delta Spread_{i,t} = \beta_{0,i} + \beta_1 \Delta OFR_{i,t-1} + \beta_2 \Delta ODR_{i,t-1} + \beta_3 \Delta Spread_{M,t} + \beta_4 \Delta Spread_{i,t-1} + \varepsilon_{i,t}$$

$$\Delta OIB_{i,t} = \kappa_{0,i} + \kappa_1 \Delta OFR_{i,t-1} + \kappa_2 \Delta ODR_{i,t-1} + \kappa_3 \Delta OIB_{M,t} + \kappa_4 \Delta OIB_{i,t-1} + \rho_{i,t}$$

$$\Delta Logmid_{i,t} = \mu_{0,i} + \mu_1 \Delta OFR_{i,t-1} + \mu_2 \Delta ODR_{i,t-1} + \mu_3 \Delta Logmid_{M,t} + \mu_4 \Delta Logmid_{i,t-1} + \sigma_{i,t}$$

We estimate the above parameters with OLS regressions using daily data. Variables definitions are included in Table II; the *'M'* subscript indicates an equally weighted average computed over our entire sample.

Results for the overall sample are presented in Table V. As reported, an increase in *OFR* is associated with a next-day decrease in pricing error volatility, spreads, order imbalances (all significant at 1%), and return volatility (at 5%). An increase in *OFR* is also associated with a decrease in pricing errors when those are positive and a much smaller increase in pricing errors when those are negative (both significant at 1%). Prices are not significantly affected.

This second set of results is highly consistent with our previous findings: FTD trades are related to improvements in liquidity and pricing efficiency. We recognize that the correlations documented in this analysis are not proof of causation. Hence, we attempt to gain insights into the direction of causality in our system by first testing for Granger causality.[23] For each metric of interest, we test both directions of Granger causality: that is, we test whether previous day FTD trades 'Granger-cause' next-period market quality metrics (*PE*, *PE Volatility*, *Volatility*, *Spread*, *OIB*, and *Logmid*). We first find that FTD trades Granger-cause *PE*, *PE Volatility*, *Volatility*, *Spread*, and *OIB*. Yet, when testing the other side of causality, we find it equally meaningful, as each of those variables Granger-causes FTD trades as well. FTD trades and market quality metrics Granger-cause each other – and the whole system displays feedback effects over time. Hence, it is necessary for us to investigate the impact of FTD trades within a statistical model that allows us to control for inter-temporal interdependency amongst all metrics. Accordingly, in the next section, we present results from a VAR model, duly accounting for endogenous interrelationships between market quality metrics, FTD trades and timely delivered short sales.

### *4.4. Vector autoregressive framework*

In a third set of tests, we control for endogenous interrelationships using three vector autoregressive (VAR) models, with additional exogenous variable(s) added as controls. The system of equations underlying each of these models is formally described in Table VI. In VAR Model 1, our VAR variables are changes in *OFR*, *ODR*, *Pricing Error*, *Volatility*, *Spread*, and *Order Imbalance*. We add, as predictors in the pricing error equation, (1) an interaction between lagged changes in *OFR* and a lagged binary variable set equal to one when pricing error is positive and (2) an interaction between lagged changes in *ODR* and a lagged binary variable set

[23] We thank an anonymous referee for suggesting this line of inquiry. Results are not included for brevity.

equal to one when pricing error is positive. Accordingly, we are able to separately estimate the impact of FTD trades and delivered short sales on pricing error when the pricing error is positive in contrast to when the pricing error is negative. We add two more predictors to each of the equations in which the change in *OFR* or *ODR* are the response variables: (3) a lagged binary variable set equal to one when order imbalance is positive and zero otherwise and (4) a lagged binary variable set equal to one when pricing error is positive and zero otherwise. Finally, in each equation we add, as an exogenous variable, the market-wide equally-weighted average of the dependent variable, to control for possible systematic effects. In VAR Model 2, we replace *Pricing Error* by *Pricing Error Volatility,* or effectively the absolute value of the *Pricing Error*; given that we do not here model pricing error, we do not include the interaction-variables described above in points (1) and (2). VAR Model 3 is similar to Model 2, but we replace *Pricing Error* by *Price*.

We estimate VAR Models 1, 2 and 3 separately for each security. The results we report in Table VI are based on estimating the models by first standardizing all variables by subtracting the security-specific mean and dividing by the security-specific standard deviation, and then winsorizing at three standard deviations from the mean.[24] Based on an analysis of the Schwarz information criteria (SIC), we determine that, for all models, it is most appropriate to use a VAR of order one. In order to draw inferences about the true population parameters, we average coefficient estimates obtained for each security as in Fama and MacBeth (1973). Similarly, we use cross-sectional estimates of standard errors. To account for possible underestimation of those standard errors due to cross-correlations, we correct standard errors as in Chordia, Roll and Subrahmanyam (2001).

We estimate VAR Models 1, 2, and 3 for both our “entire market” sample and for a subset of our sample containing only the 10% of securities with the highest FTDs based on mean *OFR* over the sample period, January 2005 to June 2008 (the same sub-sample described as ‘decile 10’ in Table II). We focus on this subset of securities with the highest FTDs to find whether the impact of FTD trades differs when they occur most frequently. We find that the sign and the significance of the various inter-relationships involved are economically reasonable for both samples. For compactness, ease of interpretation and to preserve the focus on the specific equations of interest to us, we report in Table VI only those relationships that are relevant to the issues addressed in the paper. In particular, we report, for all three models and for both samples, the coefficient

[24] For robustness, we also estimate all three models without standardizing variables, but we sometimes run into problems with the convergence of our maximum likelihood estimation algorithm, likely driven by the extreme differences in magnitude across our variables. For those securities for which we manage to obtain results without standardizing variables, our results are qualitatively similar to those reported.

estimates related to the effects of FTD trades and timely-delivered short sales on each of the market quality metrics. We present estimated coefficients and related statistical significance in Table VI, Panels A and B.

First, and most importantly, irrespective of the measure used as proxy for pricing efficiency or liquidity, FTD trades increase liquidity and improve pricing efficiency, supporting Hypotheses *H1* and *H2*. In particular, we reach the following conclusions:

1. FTD trades significantly reduce positive pricing errors, consistent with short sellers functioning as value arbitrageurs (statistically significant at 1%).
2. FTD trades significantly reduce the volatility of pricing errors, which is also consistent with an increase in pricing efficiency (statistically significant at 1%).
3. FTD trades significantly reduce stock return volatility, consistent with improved market stability (significant at 1% in five models and at 5% in the sixth).
4. FTD trades significantly reduce order-imbalances, consistent with short sellers contributing to improvement in liquidity (significant at 1%).
5. Coefficient estimates uniformly indicate that FTD trades reduce spreads but results are not statistically significant.
6. Coefficient estimates uniformly indicate that FTD trades reduce prices, but results are not statistically significant.

Second, we find that the direction and significance of all results relating to the impact of FTD trades are qualitatively similar to the direction and significance of all results relating to the impact of short sales that duly result in delivery. The main differences lie in the fact that delivered short sales appear to have a statistically significant impact on prices and spreads, while the results are not statistically significant for FTD trades (estimated coefficients, however, carry the same signs).

To further investigate the impact of FTD trades on pricing efficiency and liquidity, we compute impulse response functions based on the vector autoregressive models of Table VI. We estimate accumulated impulse response function parameters for each security and then present cross-sectional means of the parameter estimates. We employ cross-sectional standard errors. We present the results related to accumulated impulse response functions depicting the impact of one-standard deviation increase in *OFR* on pricing error volatility, return volatility, spreads and order imbalances in Figure 1.[25] For comparison, we present a similar set of impulse response functions for the impact of delivered shorts in Figure 2.[26] As the impulse response functions indicate, the impact of FTD trades on market quality metrics – pricing errors, pricing error volatility, prices, return volatility, spreads, order imbalances – documented in Table VI occur over the day following the FTD trades. On subsequent days, accumulated responses are mostly flat, indicating no further correction or reversal.

Our main analysis does not include any measure of trading volume, as trading volume is highly correlated with other market quality metrics. Nevertheless, for robustness, we add to the VAR models a measure of trading volume based on the daily number of trades for the security of interest.[27] The core results describing the relationship between FTD trades and metrics of market liquidity and pricing efficiency are unaffected. We also obtain similar results by utilizing a different metric of trading volume, based on the monetary value of shares traded daily.

### *4.5. FTD trades vs. timely-delivered short sales*

Overall, when qualitatively comparing the impact of FTD trades – or short sales that result in FTDs – to timely-delivered short sales, the direction and significance of our results are virtually identical, indicating that the impact on market quality is very similar irrespective of whether short sales are delivered or not delivered. That said, we note that the coefficients measuring the impact on market quality in Table VI, Panels A and B are, in most cases, larger in magnitude for timely-delivered short sales relative to FTD trades. This is arguably what we should expect given that the vector autoregressive models we employ are based on standardized variables, and the average standard deviation of timely-delivered short sales is much greater than that of FTD trades. Hence, a one standard deviation change in timely-delivered short selling predictably results in a much greater change in the level of overall short selling relative to a one standard deviation change in short selling that results in FTDs and a greater level of overall short selling should arguably have a greater beneficial impact on market quality. In this context, we next examine the economic significance of the impact of FTD trades and timely-

[25] We opt to utilize accumulated, rather than orthogonalized, impulse response functions because, consistent with what is expected on the basis of the general econometric literature in this regard, the latter are extremely sensitive to the ordering of variables in the model, thus adding a level of arbitrariness to the estimation procedure. In unreported analysis, we estimate orthogonalized impulse response functions for models differing in order of the variables and find the results not to be robust to the ordering of variables.

[26] For brevity, we only report impulse response functions related to the VAR models including pricing error volatility, omitting the models including pricing errors and prices; given the similarities in estimated and reported VAR coefficients, the omitted impulse response function sets are extremely similar.

[27] Results are not here included for brevity, but are available upon request.

delivered short sales by estimating the market-quality impact of FTD trades and timely-delivered short sales equal to a given fraction of shares outstanding. The results are reported in Table VI, Panels C and D for the impact of FTD trades and timely-delivered short sales respectively.

Based on the "entire market" sample, we find that FTD trades corresponding to 10 basis points of the total number of outstanding shares – approximately equal to a one-standard deviation increase in total short interest –leads to about a 1% reduction in spreads, a 1.7% reduction in order imbalances, a 9.8% reduction in the magnitude of positive pricing errors, a 12.9% decline in pricing error volatility and a 1% reduction in stock price volatility. The impact on prices, aside from not being statistically significant, is tiny, with a reduction of 0.01%. In comparison, again based on the "entire market" sample, we find that delivered short sales corresponding to 10 basis points of the total number of outstanding shares leads to about a 0.7% reduction in spreads, a 1.3% reduction in order imbalances, a 4.9% reduction in the magnitude of positive pricing errors, a 7.4% decline in pricing error volatility and a 0.7% reduction in stock price volatility. The impact on prices is similarly tiny, at 0.01%. Overall, the economic significance of the estimated impact of FTD trades and timely-delivered short sales is of roughly similar magnitude.  Inferences based on the sample with the highest FTD trades are weaker (the same quantity of FTD trades leads to smaller market-wide reactions). This suggests that a certain volume of FTD trades has a weaker impact when existing levels of outstanding FTDs are higher.

The bottom-line is that the market-quality impact of short sales that result in timely delivery, as well as those that do not, is economically significant and very similar, which is in line with our expectations, since the two are indistinguishable at the time of the trade. The impact is also in the direction of being clearly beneficial for market quality. Our results provide strong support for Hypotheses *H1* and *H2*. Short sellers, whether they deliver on time or with a delay, appear to have a positive effect on market quality, first by enhancing pricing efficiency through correction of security overvaluation and reduction of volatility, and second by providing and improving liquidity through reduction of order-imbalances and spreads.

### *4.6. Robustness Check: threshold-list securities*

The impact of FTD trades could be different when failures are persistent or long-lived. Accordingly, we focus on a sample of securities which displays persistent FTDs – securities that appear on the NYSE Threshold List. In accordance to the SEC Regulation SHO, "threshold securities" are securities for which the aggregate FTD position for five consecutive settlement days at a registered clearing house totals 10,000 shares or more and equals at least 0.5% of the total number of shares outstanding for the issuer.[28] From our sample, we identify 165 securities which appear on the NYSE Threshold List during our sample period. Accordingly, we re-estimate the VAR model for this subset of securities. Results, reported in Table VI, Panel E, are largely consistent with what previously reported: coefficient estimates are of similar magnitude to those obtained with the data subset containing the securities with the highest level of FTDs.[29]

### *4.7. Robustness check: NASDAQ securities*

As a further robustness test, we re-estimate the VAR model with a sample of securities with NASDAQ as a primary exchange. We apply the same filters in creating the sample as we did for our overall, NYSE-based, sample: we focus on securities with share codes 10 and 11 in CRSP, for which we have at least 18 months of continuous trading data and with no significant changes in the number of shares outstanding and we obtain a full sample of 2,381 securities. Results are presented in Table VI, Panel F.[30] In this data subset, similar to our NYSE results, we find that FTD trades lead to a next-day decline in positive pricing errors, return volatility, and in pricing error volatility. But, estimates display weaker statistical significance and we do not find a significant relationship between FTD trades and order imbalances. However, in this context, it is relevant to recognize that some factors have made it problematic to use time-series of market-quality metrics, particularly liquidity metrics, for NASDAQ securities.[31] Most importantly in the context of this paper, while NYSE has played the dominant role in our sample period in the supply of liquidity for stocks with NYSE as their primary exchange, this has not been so for stocks with NASDAQ as their primary exchange. For example, Diether, Lee, and Werner (2009) document that, while NYSE accounted for almost 80% of shares sold short in NYSE stocks, NASDAQ accounted for less than 35% of the shares sold short in NASDAQ securities. Hence, our estimated order-imbalances can potentially be a noisy proxy of the overall order-imbalances of NASDAQ stocks.

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[28] For the full legal definition offered by the SEC, please refer to: http://www.sec.gov/spotlight/keyregshoissues.htm.

[29] We thank an anonymous referee for suggesting that we focus our attention on Threshold Lists and also examine NASDAQ securities, which we do in the following section,

[30] The total number of securities for which we are able to estimate the models presented in Table VI, Panel F ranges from 2,381 to 2,170. For some securities, despite having the complete dataset, estimation is not possible because of inadequate number of positive pricing errors, or negative pricing errors, or order imbalances.

[31] The fragmentation of trading across several different platforms and systems on NASDAQ has led in the past to difficulty in observing and reacting to short-term changes in market variables. For example, quote adjustment has been documented to be slower (Jones and Lipson, 1999) and time stamps of trades and quotes on NASDAQ could not always be matched (Schultz, 2000). More recently, Pastor and Stambaugh (2003) and Watanabe and Watanabe (2008) do not use NASDAQ data in their pricing of liquidity studies apparently because of problems in using NASDAQ-based liquidity measures.

*4.8. The market quality impact of exogenous imposition of restrictions on FTD trades.*

In this sub-section, we report the effect on market quality of restrictions on FTD trades. While the VAR models address issues of directional causality, our inferences could be affected by possible omitted-variable bias. In this context, we utilize the exogenous event described in Section 2.1 – the temporary SEC order mandating pre-short selling borrowing arrangements for select securities in July and August 2008 – to confirm the causal relation between FTD trades and pricing efficiency or market liquidity. The temporary SEC order is an exogenous event that reduces FTD trades. In turn, if FTD trades are beneficial for market quality, the imposition of the order should *cause* deterioration in market quality metrics selectively for the securities and for the period during which the order is in force. For each of our 17 sample securities affected by the temporary SEC order, and the 17 unique control sample matches, and for each day in the interval January 1, 2008 to September 9, 2008, we compute *OFR*, *Pricing Error Volatility*, *Return*, *Volatility*, *Spread*, and *Order Imbalance*, as in Table II. We average each of these six variables across securities to obtain a daily mean for the affected and control samples. We then run six separate OLS regressions: in each regression, the response variable is the affected sample mean of either *OFR*, *Pricing Error Volatility*, *Return*, *Volatility*, *Spread*, or *Order Imbalance*, while the explanatory variables include an intercept, the control sample mean of the variable of interest and a binary variable, *Event*, set equal to 1 on all days during which restrictions were in place and equal to 0 on all other days. Our results are presented in Table VII. We observe higher return volatility and pricing error volatility during the temporary order period, both significant at the 1% level. We also document higher spreads, significant at 10%. The impact of the SEC order on returns and order imbalances is not statistically significant. Overall, our results indicate that mandating stock-borrowing arrangements prior to executing a short sale adversely impacts the stock's liquidity and hampers the price discovery process, providing strong support to Hypotheses *H1* and *H2*.[32]

*4.9. FTD trades: market makers vs. public traders*

Market-makers routinely sell-short to manage their inventory in the course of providing liquidity; such short selling does not always involve pre-arranged borrowing and occasionally leads to FTDs. The SEC has

[32] Our results are consistent with contemporaneous work of Kolasinski, et al. (2010). While their main focus is on the different impact of restrictions vs. bans on short selling, they analyze the same event (interpreting it as a temporary short selling restriction) and find that the order negatively impacted liquidity of the affected securities. Our results on this particular issue are also consistent with contemporaneous work of Boulton and Braga-Alves (2010).

regarded the use of FTD trades by market-makers as bona fide and positive for market liquidity.[33] It is therefore conceivable that the beneficial effects on market quality of FTD trades arise due to such market-making activities, and that there are no beneficial effects from FTD trades of public traders. We define the term "public trader" in this context to mean all market participants other than registered market-makers. Notably, it is these public traders that have been the primary focus of negative media and regulatory attention. If there are no beneficial effects of public-trader FTD trades, our estimated FTD-related improvement in market quality will be relatively weaker for securities that have a relatively greater proportion of public-trader FTD trades. To estimate the impact of public-trader FTD trades relative to the impact of market-maker FTD trades, we classify securities based on the proportion of FTDs originating from public traders. In order to accomplish that, we employ another exogenous event – an SEC ban in September 2008 that affected only public-trader FTD trades but not market-maker FTD trades: SEC temporary rule 204T (later made permanent).

SEC rule 204T required all market participants *other than registered market makers* to purchase or borrow securities to close out their FTD position by the beginning of day $t$+4, effectively banning FTDs for anyone other than a market maker. Hence, we compute average FTDs across our entire sample of NYSE securities for two periods: pre-204T from January 1, 2005 to June 30, 2008; and post-204T from January 1, 2009 to December 31, 2010. We intentionally omit the period July to October 2008 because of multiple short selling rule changes, and omit November and December 2008 to allow outstanding FTD positions to fully clear and thereby enable accurately gauging the impact of post-204T FTDs. Across all securities, we find a drop in average *OFR* of approximately 71%, suggesting that, on average, less than 30% of all FTDs was due to market-makers prior to September 2008.[34] For each sample security, we use the proportional change in mean *OFR* between the two sub-periods as our proxy for FTD trades by public traders. We accordingly rank securities on the basis of this proportional decline and allocate securities to terciles. We then re-estimate our VAR for January 2005 to June 2008 for the two terciles "Low Proportion of Public Traders" (i.e., securities with the lowest decline in mean *OFR*) and "High Proportion of Public Traders" (i.e., securities with the highest decline

[33] The SEC has acknowledged that the use of FTDs by market-makers could be *bonafide* positive for market liquidity. SEC Report "Key Points about Regulation SHO", April 11, 2005, updated 2008 says: "*because it may take a market maker considerable time to purchase or arrange to borrow the security, a market maker engaged in bona fide market making, particularly in a fast-moving market, may need to sell the security short without having arranged to borrow shares*". In a similar vein and context, SEC Report No. 450, March 18, 2009 states that the SEC "*has repeatedly stressed the fact that the practice can provide needed market liquidity in certain circumstances*".

[34] The SEC has also analyzed FTDs around Rule 204T removing the right to fail except for market-makers. They report an overall drop in FTDs of about 70% (as against a 100% drop in July/August 2008 when pre-trade borrowing arrangements were mandated for selected stocks), indicating that market-maker FTDs averaged about 30% of FTDs prior to Rule 204T.

in mean *OFR*). Our underlying assumption here is that the number of market-maker FTD trades is fairly constant over time and that the observed decline is a proxy for the proportion of public-trader FTD trades.

Our results are reported in Table VIII. For both samples, our coefficient estimates are of the same sign as those of the overall sample. For the "High Proportion of Public Traders" sub-sample, all previously documented results remain strong and statistically significant even though the sample size is much smaller than the overall sample. For the "Low Proportion of Public Traders" subsample, we observe statistically significant parameter estimates for the impact on pricing error volatility, returns volatility, and order imbalances. Estimates are not statistically significant for spreads and pricing errors. Our overall results indicate that, if anything, the impact of FTD trades is stronger for the subset of securities with a relatively high proportion of FTD trades from public traders, rather than the subset with a high proportion of market maker initiated FTD trades. Hence, at the very least, our results are inconsistent with the hypothesis that the beneficial effects of FTD trades arise entirely from market-makers.

## 5. Empirical results: FTD Trades and the 2008 Financial Crisis

In the wake of the 2008 financial crisis, it has been alleged that short sellers have, through FTD trades, caused or accelerated sharp declines in stock prices, particularly of financial firms, and created conditions that triggered credit downgrades in order to profit from the downward price spiral and the eventual collapse of the financial institutions involved.[35] In this context, we examine whether significant FTD trades *preceded* (and hence potentially triggered) the price crashes associated with the four major casualties of the 2008 financial crisis, i.e., Bear Stearns, Lehman, AIG and Merrill, and similarly *preceded* credit downgrades and large price decline episodes in other financial firms; or did significant FTD trades take place *after* these price crashes and *in response to* negative public news.

The first large financial casualty of the 2008 financial crisis was Bear Stearns, the fifth largest investment banking firm in the nation at the time of its demise. We analyze *OFR* on the days preceding and immediately following the dramatic loss of market value that led to the demise of the firm. Figure 3 provides a time-line about the crisis. Outstanding suspicions about liquidity problems at Bear Stearns were reported in the media from March 10 onwards, along with news that the company's management was repeatedly denying

[35] A commentary in *Euromoney* (December 2008) claimed that "Fails to deliver in the US equity market have exacerbated the sharp declines in share prices of financials". Similar opinions were expressed by *Rolling Stone* (October 2009) and *Bloomberg.com* (October 29, 2008).

rumors about such problems. The first major price-crash took place on Friday, March 14, when the price per share dropped from $57 to $30 after a 9 a.m. announcement that Bear would receive an unprecedented loan from the Federal Reserve System; and two days later, on Sunday March 16, JP Morgan Chase proposed buying Bear Stearns for $2 per share.[36] When markets opened on March 17, a second major price crash materialized, and the price dropped to a close of $4.81.

We compute *OFR* for Bear Stearns on each trading day from January 1 to March 28, 2008. We also compute, as a control variable, an equal weighted average *OFR* for four other financial institutions with the same primary SIC code as Bear Stearns, and with the closest market value as of the end of the fiscal year 2007. We test for the statistical significance each day of the difference, i.e. the "abnormal" *OFR* of Bear Stearns.[37] Our results are presented in Table IX, Panel A.

Even though negative media attention started on March 10, Table IX, Panel A and Figure 3 show that abnormal *OFR* was statistically insignificant or significantly negative up to March 11. While *OFR* did increase significantly on March 12 and 13, the increase was still relatively tiny from an economic perspective since it was tiny relative to the total number of shares outstanding, tiny relative to the typical overall short volume, and tiny relative to what took place on or after March 14: *OFR* was only 1.06% of shares outstanding until market close on March 13. *OFR* increased to 2.24% (t-stat. 20.7) on March 14, but increased massively only on March 17, reaching 12.18% (t-stat. 137.3). Importantly, given that the Fed announcement was at the start of trading on March 14, even the (relatively small) increase in *OFR* on March 14 was clearly *subsequent to* the public release of tangibly negative news in the form of the announcement and the consequent immediate precipitous price-drop. By the time *OFR* spiked on March 17, the company was already in an open distress sale. The evidence clearly shows that the abnormal incidence of FTD trades did not precede the price decline but followed it; and the decline in stock price was triggered by other well-identified negative economic news. Consistent with our previous results, short sellers appear to be facilitating price discovery, rather than increasing pricing errors. Overall, we find no support for Hypothesis *H3*.

The second notable casualty of the financial crisis of 2008 was Lehman. To investigate the link between FTD trades and Lehman's stock price crash, we employ the same method we used for Bear Stearns: we analyze

[36] See, for example, *The Wall Street Journal* (March 15, 2008) and *J.P. Morgan News Release* (March 16, 2008).
[37] The four control stocks are: *Raymond James Financial Corporation*, *Ameritrade Holdings Corporation*, *Ameriprise Financial Inc.* and *Charles Schwab Corporation*. To construct a t-statistic for the difference in means: we compute the mean and standard error of this difference over the period January 1 to February 15, 2008; we subtract this historic mean from the daily difference and divide the result by the historic estimate of the standard deviation of the difference.

*OFR* on the days surrounding the dramatic loss of market value of the firm on September 9, 2008. Our results are in Table IX, Panel B. In Figure 4A we present the relationship between *OFR* and stock price for the period from January 2008 to Lehman's bankruptcy on September 15, 2008. We present a closer look at the period surrounding Lehman's bankruptcy in Figure 4B. The above table and figures indicate abnormally low *OFR* in the days leading to September 9: only around 0.01%.[38] But, by September 9, the firm's stock price had already lost approximately 87% of its value as of the beginning of the year. The biggest single-day price drop, about 45%, occurred on September 9, following news that talks with the *Korea Development Bank* (previously rumored to be considering a 25% stake in Lehman) had failed. While *OFR* increases on that day, *OFR* is still less than 0.16% of shares outstanding. Abnormal *OFR* increased more dramatically only *after* September 10, well after widespread coverage of negative news about Lehman and the associated price crash. On September 11, as shareholders rejected a management rescue plan, the stock price fell by an additional 42% and *OFR* further increased to 3.3%. Over the following days, talks of a possible acquisition by Bank of America and Barclays failed, triggering further declines in stock price and an increase in *OFR* to 4.9%. Lehman announced its bankruptcy on September 15, and *OFR* increased beyond 8% on September 17. In sum, our analysis shows that the incidence of FTD trades, even at its peak, was too low to justify the decline in price that took place. Again, we find no support for Hypothesis *H3*.

We report the relationship between *OFR* and the stock price for Merrill and AIG in Figure 5 and Figure 6 respectively. In both cases, the stock price declines were fairly gradual through the year and were not accompanied by any significant increase in FTDs. For Merrill, *OFR* reached its highest value of *only* 0.18% on October 14, 2008, well after the Merrill had lost most of its value. AIG had also lost about 40% of its market value by the end of August 2008, and the largest single-day price drop was on September 15, 2008 when Standard & Poor's cut AIG's credit rating. Following the announcement, the company's stock price dropped by about 60%. Yet, *OFR* reached its highest value only a fortnight later on September 29, 2008, and even this highest value was *only* 0.32%. Given that *OFR* remained so low all through the financial crisis period for both Merrill and AIG, we do not engage in any further statistical testing. We find no support for Hypothesis *H3*.

[38] An article in *Bloomberg* (March 19, 2009), notes that a rumor about Barclays PLC buying Lehman for a 25% discount to market value was responsible for a 11% fall in Lehman's stock price on June 30. We find that *OFR* spikes significantly on June 27, the day preceding the rumor, but the spike is still just 0.06%, far too miniscule to conclude that FTD trades, rather than negative information, was responsible for the price decline.

We run further tests, in an attempt to find evidence of the distorting influence of FTD trades. In this context, we examine FTD trades around credit rating downgrades for a sample of financial securities. We do not report results here for brevity - however, we find that *OFR* is abnormally low in the days preceding the credit rating downgrade. This evidence is again inconsistent with our hypothesis *H3*. Similarly, we analyze whether FTD trades intensify prior to large price drops. We identify a sample of large price drops in NYSE securities during 2008 and find, overall, no evidence of spikes in *OFR* prior to such events. Further, we focus on large price drops for small-capitalization securities and for highly levered firms, as those are likely target for "bear raids". Once more, we fail to find any evidence of FTD trades preceding large price drops.

## 6. Conclusions

We investigate the collective net impact on market quality of FTD trades, i.e., trades that result in FTDs ("fails to deliver"). The total number of FTDs on any day is the "open interest" of undelivered positions on that day. Given the nature of the US electronic trade settlement system for stocks, FTDs should arise almost exclusively from short sales, and that is fully supported by our empirical evidence. Hence, FTD trades represent short sales that fail to deliver. The consensus in extant literature is that, overall, short sales are beneficial for liquidity and pricing efficiency. In this context, we analyze whether FTD trades have the same beneficial impact on liquidity and pricing efficiency as timely delivered short sales.

For a sample of 1,492 NYSE securities covering a period of 42 months, we show that FTD trades equivalent to 10 basis points of the number of outstanding shares lead to a 1% reduction in spreads, a 2% reduction in order imbalances, a 10% reduction in the magnitude of positive pricing errors, a 13% decline in pricing error volatility, and a 1% reduction in stock price volatility. Further, these results are driven not just by market-maker FTD trades, but also by public-trader FTD trades. They are also robust for securities with high levels of FTDs and those with persistent FTDs. We also show that a temporary SEC order restricting FTD trades in select financial securities in the summer of 2008 led to higher absolute pricing errors, higher spreads, and lower trading volumes. Furthermore, we find that the beneficial effects on market quality metrics of FTD trades are similar to the beneficial effects of timely-delivered short sales.

We do not also find any evidence linking FTD trades to the failures of the flagship victims of the 2008 financial crisis: Bear Stearns, Lehman, Merrill, and AIG. We find that abnormal increases in FTDs took place *after* and *not* before their major stock price declines and associated negative news; and hence the decline in stock prices of those financial institutions was not triggered by FTD trades. We also analyze FTD trades around credit rating downgrades and around the steepest stock price declines of financial firms during our 2008 financial crisis. We find, yet again, that FTD trades lag price declines, suggesting that the direction of significant causality is from steep price falls to FTD trades, not vice-versa. Overall, our results indicate that, sharply contrary to media and regulatory perceptions, short sellers did not precipitate the collapse of major financial firms in 2008 by failing to deliver.

While we focus on a sample of NYSE securities, we replicate our analysis, with consistent conclusions, also for a sample of over 2,300 NASDAQ securities over the same period. We do, however, leave a further detailed analysis of the differential impact of FTD trades on non-NYSE securities as an open issue for future research. We also note that data limitations constrain our analysis to the aggregate impact over daily time intervals. Analysis including intra-day timestamps of FTD trades could potentially provide additional insights; unfortunately, such data is, to our knowledge, not presently available.

Our findings have important implications for regulatory policy. While there clearly needs to be zero tolerance for individual cases of abusive FTD trades, we find no evidence indicating that FTD trades in aggregate systematically and manipulatively precipitated price declines, even in the extreme situation of the 2008 financial crisis. Instead, the gently regulated FTD regime that existed after Regulation SHO up to mid-2008 was net beneficial for pricing efficiency and market liquidity. In this context, the virtual removal of the alternative to fail for the vast majority of market participants appears debatable, since the alternative to fail arguably reduces stock borrowing costs at the time when such costs are the highest, and thereby protects traders from the extreme lack of liquidity sometimes seen in the less regulated stock borrowing market. This alternative to fail is valuable for markets, also because it can prevent (potentially manipulative) distortions in the stock borrowing and lending market from getting transformed into serious pricing and liquidity distortions in the mainstream stock market. Regulators could alternatively consider progressive fines for settlement delays rather than blanket removal of the alternative to fail. Further, regulation should focus on how best to generate liquidity and transparency in the stock borrowing market.

**References**


Abreu, D., Brunnermeier, M., 2002. Synchronization risk and delayed arbitrage, Journal of Financial Economics 66, 341-360.

Abreu, D., Brunnermeier, M., 2003. Bubbles and crashes, Econometrica 71, 173-204.

Autore, D., Billingsley, R., Kovacs, T., 2011. The 2008 short sale ban: Liquidity, dispersion of opinion, and the cross-section of returns of US financial stocks, Journal of Banking & Finance 35, 2252-2266.

Battalio, R., Schultz, P., 2011. Regulatory Uncertainty and Market Liquidity: The 2008 Short Sale Ban's Impact on Equity Option Markets, Journal of Finance 66, 2013-2053.

Beber, A., Pagano, M., 2011. Short selling Around the World: Evidence for the 2007-1009 Crisis, Journal of Finance, Forthcoming.

Boehmer, E., Jones, C., Zhang, X., 2008. Which shorts are informed?, Journal of Finance 63, 491-526.

Boehmer, E., Jones, C., Zhang, X., 2011. Shacking Short Sellers: The 2008 Shorting Ban, Working Paper.

Boni, L., 2006. Strategic delivery failures in U.S. equity markets, Journal of Financial Markets 9, 1-26.

Boulton, T., Braga-Alves, M., 2010. The skinny on the 2008 naked short sale restrictions, Journal of Financial Markets 13, 397-421.

Bris, A., B., Goetzmann, W., Zhu, N., 2007. Efficiency and the bear: short sales and markets around the world, Journal of Finance 62, 1029-1079.

Chen, H., Singal, V., 2003. Role of Speculative Short Sales in Price Formation: The Case of the Weekend Effect, Journal of Finance 58, 685-705.

Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity, Journal of Finance 56, 501-530.

Culp, C., Heaton, J., 2008. The Economics of Naked Shorting, Regulation 31, 46-51.

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

Dempster, P., Laird, N., Rubin, D., 1977. Maximum likelihood from incomplete Data via the EM Algorithm, Journal of the Royal Statistical Society B 39, 1–38.

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

Diamond, D., Verrecchia, R., 1987. Constrains on short selling and asset price adjustment to private information, Journal of Financial Economics 18 (2), 277-311.

Diether, K., Lee, K., Werner, I., 2009. It's SHO Time! Short sale Price-Tests and Market Quality, Journal of Finance 64, 37-73.

Diether, K., Lee, K., Werner, I., 2009. Short sale Strategies and Return Predictability, Review of Financial Studies 22, 575-607.

Edwards, A., Hanley, K., 2010. Short selling in initial public offerings, Journal of Financial Economics 98, 21-39.

Evans, R., Geczy, C., Musto, D., Reed, A., 2009. Failure is an option: impediments to short selling and options prices, The Review of Financial Studies 22 (5), 1955-1980.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests, Journal of Political Economy 81, 607-633.

Geczy, C., Musto, D., Reed, A., 2002. Stocks are special too: an analysis of the equity lending market, Journal of Financial Economics 66, 241-269.

Hamilton, J., 1985. Uncovering financial market expectations of inflation, Journal of Political Economy 93, 1224-1241.

Hasbrouck, J., 1993. Assessing the quality of a security market: a new approach to transaction- cost measurement, The Review of Financial Studies 6 (1), 191-212.

Jones, C., Lipson, M., 1999. Price Impacts and Quote Adjustment on the Nasdaq and NYSE/AMEX, Working Paper.

Kolasinski, A., Reed, A., Thornock, J., 2012. Can Short Restrictions Result in More Informed Short Selling? Evidence from the 2008 Regulations, Financial Management, Forthcoming.

Merrick, J., Naik, N., Yadav, P., 2005. Strategic trading behavior and price distortion in a manipulated market: anatomy of a squeeze, Journal of Financial Economics 77 (1), 171-218.

Miller, E., 1977. Risk, uncertainly, and divergence of opinion, Journal of Finance 32, 1151-1168.

Morris, V., Goldstein, S., 2009. Guide to Clearance & Settlement, Lightbulb Press, New York.

Pastor, L., Stambaugh, R., 2003. Liquidity Risk and Expected Stock Returns, Journal of Political Economy 111, 642-685.

Putniņš, T., 2010. Naked short sales and fails-to-deliver: An overview of clearing and settlement procedures for stock trades in the USA, Journal of Securities Operations and Custody 2 (4), 340-350.

Schultz, P., 2000. Regulatory and Legal Pressures and the Costs of Nasdaq Trading, The Review of Financial Studies 13, 917-957.

Stokes, A., 2009. In pursuit of the naked short, N.Y.U. Journal of Law and Business 5(1).

Watanabe, A., Watanabe, M., 2008. Time-Varying Liquidity Risk and the Cross Section of Stock Returns, The Review of Financial Studies 21 (6), 2449-2486.

Welborn, J., 2008. The phantom shares menace, Regulation 31 (1), 52-61.

**Table I – FTDs and Short Sales**

This table presents the average number of fails-to-deliver (FTDs) scaled by the contemporaneous number of shares outstanding for "Event Securities" and "Control Securities". "Event Securities" are 17 stocks that were subject to the imposition of the SEC Order requiring pre-short sale stock borrowing arrangements between July 21, 2008 and August 12, 2008, i.e., the "Order Period". While the order affected 19 securities, we have data for 17 of these: Bank of America Corporation, Barclays, Bear Stearns Companies Inc., Citigroup Inc., Credit Suisse Group, Deutsche Bank Group AG, Allianz SE, Goldman, Sachs Group Inc, Royal Bank ADS, HSBC Holdings PLC ADS, J. P. Morgan Chase & Co., Merrill Lynch & Co., Inc., Mizuho Financial Group, Inc., Morgan Stanley, UBS AG, Freddie Mac, and Fannie Mae. "Control Securities" are a sample of 17 market capitalization and industry matched stocks that were not subject to any relevant regulatory changes during the "Order Period". The "Pre-Order Period" refers to the interval January 1, 2008 to July 20, 2008. The "Post-Order Period" refers to the interval August 13, 2008 to September 2, 2008. The number of FTDs scaled by shares outstanding is reported in basis points and computed for "Event Securities" and "Control Securities" on a daily basis over the interval January 1, 2008 to August 12, 2008. Reported t-values are for a test of differences in mean FTDs (scaled by shares outstanding) between the indicated order sub-periods and the "Pre-Order Period" and between "Event Securities" and "Control Securities". "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively.

| | Event Securities | | Control Securities | | Difference (Event-Control) | |
|---|---|---|---|---|---|---|
| | Mean (bps) | t value | Mean (bps) | t value | Mean (bps) | t value |
| **Pre Order Period** | 4.88 | | 0.51 | | 4.37 | 9.43 *** |
| | | | | | | |
| **Order Period, 1st Week** | 0.57 | | 2.79 | | -2.23 | -4.81 *** |
| Order Period, 1st Week-Pre Order | -4.31 | -9.28 *** | 2.29 | 49.06 *** | -6.60 | -14.23 *** |
| **Order Period, 2nd Week** | 0.17 | | 0.46 | | -0.29 | -0.63 |
| Order Period, 2nd Week-Pre Order | -4.70 | -10.13 *** | -0.04 | -0.91 *** | -4.66 | -10.06 *** |
| **Order Period, 3rd Week** | 0.12 | | 0.48 | | -0.36 | -0.79 |
| Order Period, 3rd Week-Pre Order | -4.76 | -10.25 *** | -0.03 | -0.54 | -4.73 | -10.21 *** |
| **Order Period, 3rd Week, Last Day** | 0.00 | | 0.20 | | -0.20 | -0.79 |
| Order Period, 3rd Week, Last Day-Pre Order | -4.88 | -10.55 *** | 0.20 | 6.97 *** | -5.08 | -10.00 *** |
| | | | | | | |
| **Post Order Period** | 1.39 | | 0.17 | | 1.22 | 2.64 *** |
| Post Order - Order Period, 3rd Week | 1.28 | 2.75 *** | -0.31 | -0.67 | 1.59 | 3.42 *** |

**Table II - Variable Definitions**

Table II defines the variables used in our analysis. All variables are daily, unless otherwise specified.

| | |
|---|---|
| **Short Selling** | |
| *Outstanding FTD Ratio (OFR)* | Ratio of the estimated number of outstanding fails to deliver over total shares outstanding. |
| *Outstanding Delivered Short Ratio (ODR)* | Ratio of the estimated number of outstanding delivered shorted shares over total shares outstanding. |
| *FTD Trades* | Trades that result in FTDs proxied by daily changes in *OFR* |
| | |
| **Pricing Error** | |
| *Pricing Error (PE)* | The non-random walk component of a daily return series estimated using a Kalman filter methodology. |
| *Negative Pricing Error (Negative PE)* | A variable set equal to the pricing error when pricing error is negative, to zero otherwise. |
| *Positive Pricing Error (Positive PE)* | A variable set equal to the pricing error when pricing error is positive, to zero otherwise. |
| *Pricing Error Volatility (PE Volatility)* | The absolute value of the pricing error. |
| *Positive PE Dum* | A binary variable set equal to one if pricing error is positive, to zero otherwise. |
| | |
| **Liquidity Related Metrics** | |
| *Order Imbalance (OIB)* | The daily sum of the 5-minute difference between the market value of shares traded in buyer initiated trades and the market value of shares traded in seller initiated trades, divided by total daily dollar trading volume. |
| *Positive OIB Dum* | A binary variable set equal to 1 if *OIB* is positive and to zero otherwise. |
| *Spread* | The daily average of the ratio of the difference between bid and ask and the mid-quote. |
| *Volume* | Daily number of shares traded. |
| **Other** | |
| *Price* | The natural log of the daily average of the 5-minute midquote. |
| *Volatility* | The daily standard error of the 5-minute stock price return. |
| *Market Value* | The number of shares outstanding multiplied by the closing price for the day. |

**Table III - Summary Statistics**

All variables are as defined in Table II. The sample is built as follows: *OFR* is computed for all NYSE common stock of US-based firms (CRSP share codes 10 and 11) listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, and with no daily large changes (>10%) in the number of shares outstanding and for which we had all required data (n= 1,492). We rank each security by mean *OFR* and allocate securities on that basis to decile 1 (lowest) through 10 (highest). Daily statistics are computed by security, security averages are further averaged over deciles and for the entire sample. This table reports mean, median and standard deviation for the sample, means for deciles 1 and 10 and the difference between those, along with results of a t-test for differences in means across deciles 1 and 10. "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively.

| Variables | Sample Mean | Sample Median | Sample STD | Decile 1 Mean | Decile 10 Mean | Decile 10 - Decile 1 | p-value | |
|---|---|---|---|---|---|---|---|---|
| ***OFR*** | 0.06% | 0.01% | 0.22% | <0.01% | 0.43% | 0.40% | <0.01 | *** |
| ***ODR*** | 5.45% | 4.34% | 5.30% | 3.95% | 13.38% | 9.43% | <0.01 | *** |
| ***FTDs to Total Short Interest*** | 0.97% | 0.43% | 5.09% | 0.10% | 2.77% | 2.67% | <0.01 | *** |
| ***Pricing Error*** | -0.15% | 0.00% | 4.33% | 0.02% | -0.50% | -0.52% | 0.35 | |
| ***Positive Pricing Error*** | 0.51% | 0.10% | 1.47% | 0.38% | 1.11% | 0.73% | <0.01 | *** |
| ***Pricing Error Volatility*** | 1.18% | 0.21% | 4.96% | 0.74% | 2.75% | 2.01% | <0.01 | *** |
| ***Order Imbalance*** | 6.72% | 6.92% | 5.71% | 3.84% | 7.98% | 4.14% | <0.01 | *** |
| ***Spread*** | 0.18% | 0.11% | 0.27% | 0.38% | 0.26% | -0.12% | 0.01 | ** |
| ***Volatility*** | 0.21% | 0.20% | 0.08% | 0.21% | 0.29% | 0.08% | <0.01 | *** |
| ***Market Value* (US$ M)** | $8,223 | $2,088 | $2,421 | $12,500 | $1,480 | ($11,020) | <0.01 | *** |
| Number of Obs. | 1,492 | 1,492 | 1,492 | 149 | 150 | | | |

**Table IV – FTD Trades and Market Quality, Portfolio Approach**

All variables are as defined in Table II. All variables are standardized and winsorized by security. The sample is built as follows: we include all NYSE common stock of US-based firms (CRSP share codes 10 and 11) available in the CRSP and TAQ databases listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, and with no large changes (>10%) in the number of shares outstanding. The resulting sample includes 1,492 securities. On each day *t* between January 2005 and June 2008, we allocate securities from the sample with a one-standard deviation or greater decrease in *OFR* into a 'Low FTD Trades' portfolio and, similarly, securities with a one-standard deviation or greater increase in *OFR* into a 'High FTD Trades' portfolio. We include all remaining securities into a 'Medium FTD Trades' portfolio. In order to control for the extent of delivered short selling, we replicate the same procedure on the bases of the intensity of delivered short selling, proxied by changes in *ODR*, thus forming the portfolios 'Low Delivered Short sales', 'Normal Delivered Short sales' and 'High Delivered Short sales'. Finally, we intersect those groups of portfolios, forming nine final portfolios. For each portfolio, we then compute averages of changes in our measures of returns, return volatility, market liquidity, pricing errors and order imbalances for the following day (*t*+1). The table presents results for the 'High FTD Trades, Normal Delivered Short sales' and the 'Low FTD Trades, Normal Delivered Short sales' portfolios, along with results of a test for differences between them. p-values are from two-sided t-tests. "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively.

| Response Variable | High FTD Trades, Normal Delivered Short sales | p-value | | Low FTD Trades, Normal Delivered Short sales | p-value | | Difference | p-value | |
|---|---|---|---|---|---|---|---|---|---|
| *ΔPE(t+1)* | -0.14% | 0.01 | ** | 0.04% | 0.37 | | -0.18% | <0.01 | *** |
| *ΔPE Volatility(t+1)* | -0.81% | <0.01 | *** | 0.02% | 0.66 | | -0.84% | <0.01 | *** |
| *ΔPrice(t+1)* | -0.15% | 0.39 | | 0.38% | 0.33 | | -0.53% | <0.01 | *** |
| *ΔVolatility(t+1)* | -0.06% | <0.01 | *** | 0.02% | 0.07 | * | -0.08% | <0.01 | *** |
| *ΔSpread(t+1)* | -0.01% | <0.01 | *** | 0.00% | 0.63 | | -0.01% | <0.01 | *** |
| *ΔOIB(t+1)* | -0.23% | <0.01 | *** | 0.07% | 0.32 | | -0.30% | <0.01 | *** |
| *N (days)* | 845 | | | 848 | | | | | |

**Table V – FTD Trades and Market Quality, OLS Regressions**

This table presents results for panel regressions with firm fixed effects and time-clustered standard errors. Metrics of market quality (listed in column headings) are regressed on lagged values of the predictors (listed in the column labeled 'predictors'). All variables are standardized and winsorized by security, expressed in first-order differences, and defined as in Table II. The sample is built as follows: we include all NYSE common stocks of US-based firms (CRSP share codes 10 and 11) available in the CRSP and TAQ databases listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, and with no large changes (>10%) in the number of shares outstanding. The resulting sample includes 1,492 securities. The "Market" variable for a given predictor on day *t* is obtained by averaging the related variable across all securities on day *t*. All variables are differenced (subtracting the previous day's value). The *p-values* are in italics. "*", "**", and "***" indicate significance at 10%, 5% and 1% level respectively.

| Predictors | *Δ Pricing Error(t)* | *Δ Pricing Error Volatility(t)* | *Δ Price(t)* | *Δ Volatility(t)* | *Δ Spread(t)* | *Δ OIB(t)* |
|---|---|---|---|---|---|---|
| *Δ OFR(t-1)* | 0.015 | -0.020 | ~ 0.001 | -0.005 | -0.011 | -0.022 |
| | *<0.01 **** | *<0.01 **** | *0.96* | *0.05* ** | *<0.01 **** | *<0.01 **** |
| *Δ ODR(t-1)* | 0.195 | -0.275 | -0.004 | -0.070 | -0.098 | -0.261 |
| | *0.02 **** | *0.03 *** | *0.21* | *0.31* | *0.08 ** | *<0.01 **** |
| *Δ Pricing Error (t-1)* | -0.349 | | | | | |
| | *<0.01 **** | | | | | |
| *Δ OFR(t-1)*Positive PE(t-1)* | -0.033 | | | | | |
| | *<0.01 **** | | | | | |
| *Δ ODR(t-1)*Positive PE(t-1)* | 0.195 | | | | | |
| | *0.02 *** | | | | | |
| *Δ Pricing Error Volatility(t-1)* | | -0.376 | | | | |
| | | *<0.01 **** | | | | |
| *Δ Price(t-1)* | | | -0.025 | | | |
| | | | *<0.01 **** | | | |
| *Δ Volatility(t-1)* | | | | -0.194 | | |
| | | | | *<0.01 **** | | |
| *Δ Spread(t-1)* | | | | | -0.321 | |
| | | | | | *<0.01 **** | |
| *Δ OIB(t-1)* | | | | | | -0.448 |
| | | | | | | *<0.01 **** |
| *Δ Market Pricing Error(t)* | 0.856 | | | | | |
| | *<0.01 **** | | | | | |
| *Δ Market Pricing Error Volatility(t)* | | 0.836 | | | | |
| | | *<0.01 **** | | | | |
| *Δ Market Price(t-1)* | | | 0.997 | | | |
| | | | *<0.01 **** | | | |
| *Δ Market Volatility(t)* | | | | 0.915 | | |
| | | | | *<0.01 **** | | |
| *Δ Market Spread(t)* | | | | | 0.875 | |
| | | | | | *<0.01 **** | |
| *Δ Market OIB(t)* | | | | | | 0.802 |
| | | | | | | *<0.01 **** |
| Number of Firm-Days | 1,001,656 | 1,001,656 | 1,001,656 | 1,001,656 | 1,001,656 | 1,001,656 |

**Table VI - FTD Trades and Market Quality, VAR Analysis**

This table provides results for the estimation of three vector autoregressive models of order one: VAR with *Pricing Error* (Model 1), VAR with *Pricing Error Volatility* (Model 2) and VAR with *Price* (Model 3). All variables are standardized and winsorized by security, and are as defined in Table II. The 'entire market' sample is built as follows: we include all common stock of US-based firms (CRSP share codes 10 and 11) with NYSE as the primary exchange, available in the CRSP and TAQ databases listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, and with no large changes (>10%) in the number of shares outstanding. For the 'most FTDs' sample, we rank each security by mean *OFR*, and allocate securities on that basis to decile 1 (lowest) through 10 (highest); the securities included in decile 10 constitute the 'most FTDs' sample. The VAR models are defined below; the subscripts *M* and *t* indicate, respectively, the market-wide average of the variable of interest and day *t*.

$$\text{Model1}: \mathbf{\Delta Y1_t} = \mathbf{c1} + \boldsymbol{\beta}\mathbf{1}\mathbf{\Delta Y1_{t-1}} + \mathbf{M1_t} + \mathbf{S1_t} + \mathbf{S2_t} + \boldsymbol{\varepsilon}\mathbf{1_t} \qquad \boldsymbol{\varepsilon}1_\mathbf{t} \sim \text{i.i.d.}N(\mathbf{0},\boldsymbol{\Omega})$$

$$\text{Model2}: \mathbf{\Delta Y2_t} = \mathbf{c2} + \boldsymbol{\beta}\mathbf{2}\mathbf{\Delta Y2_{t-1}} + \mathbf{M2_t} + \mathbf{S1_t} + \boldsymbol{\varepsilon}\mathbf{2_t} \qquad \boldsymbol{\varepsilon}2_\mathbf{t} \sim \text{i.i.d.}N(\mathbf{0},\boldsymbol{\Omega})$$

$$\text{Model3}: \mathbf{\Delta Y3_t} = \mathbf{c3} + \boldsymbol{\beta}\mathbf{3}\mathbf{\Delta Y3_{t-1}} + \mathbf{M3_t} + \mathbf{S1_t} + \boldsymbol{\varepsilon}\mathbf{3_t} \qquad \boldsymbol{\varepsilon}3_\mathbf{t} \sim \text{i.i.d.}N(\mathbf{0},\boldsymbol{\Omega})$$

$$\mathbf{Y1_t} = \begin{pmatrix} OFR_t \\ ODR_t \\ PE_t \\ Volatility_t \\ Spread_t \\ OIB_t \end{pmatrix} \qquad \mathbf{Y2_t} = \begin{pmatrix} OFR_t \\ ODR_t \\ PE\ Volatility_t \\ Volatility_t \\ Spread_t \\ OIB_t \end{pmatrix} \qquad \mathbf{Y3_t} = \begin{pmatrix} OFR_t \\ ODR_t \\ Price_t \\ Volatility_t \\ Spread_t \\ OIB_t \end{pmatrix}$$

$$\mathbf{M1_t} = \begin{bmatrix} \psi 1 \times \Delta OFR_{M,t} \\ \psi 2 \times \Delta ODR_{M,t} \\ \psi 3 \times \Delta PE_{M,t} \\ \psi 4 \times \Delta Volatility_{M,t} \\ \psi 5 \times \Delta Spread_{M,t} \\ \psi 6 \times \Delta OIB_{M,t} \end{bmatrix} \qquad \mathbf{M2_t} = \begin{bmatrix} \psi 7 \times \Delta OFR_{M,t} \\ \psi 8 \times \Delta ODR_{M,t} \\ \psi 9 \times \Delta PE\ Volatility_{M,t} \\ \psi 10 \times \Delta Volatility_{M,t} \\ \psi 11 \times \Delta Spread_{M,t} \\ \psi 12 \times \Delta OIB_{M,t} \end{bmatrix} \qquad \mathbf{M3_t} = \begin{bmatrix} \psi 13 \times \Delta OFR_{M,t} \\ \psi 14 \times \Delta ODR_{M,t} \\ \psi 15 \times \Delta Price_{M,t} \\ \psi 16 \times \Delta Volatility_{M,t} \\ \psi 17 \times \Delta Spread_{M,t} \\ \psi 18 \times \Delta OIB_{M,t} \end{bmatrix}$$

$$\mathbf{S1_t} = \begin{bmatrix} \tau 1 \times Positive\ OIB\ Dum_{t-1} + \tau 2 \times Positive\ PE\ Dum_{t-1} \\ \tau 3 \times Positive\ OIB\ Dum_{t-1} + \tau 4 \times Positive\ PE\ Dum_{t-1} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\mathbf{S2_t} = \begin{bmatrix} 0 \\ 0 \\ \tau 5 \times (Positive\ PE\ Dum_{t-1} \times \Delta OFR_{t-1}) + \tau 6 \times (Positive\ PE\ Dum_{t-1} \times \Delta ODR_{t-1}) \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\Delta X_t = X_t - X_{t-1}$$

**Table VI Panels A and B** are extracts of estimates of the parameters in Models 1, 2 and 3 above and report results pertaining to the impact of, respectively, *OFR* and *ODR*. Reported parameter estimates are averages of parameters estimated by security. Significance is tested employing a cross-sectional estimate of the standard error of the parameter estimate, as in Chordia, Roll and Subrahmanyam (2000). The p-values from two-sided t-tests are in italics below the parameter estimate. "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively.

**Panel A - Impact of FTDs**

| | Response | | | | | | |
|---|---|---|---|---|---|---|---|
| **Sample** | *Δ PE* | *Δ PE (incremental effect when lag PE > 0)* | *Δ PE Volatility* | *Δ Price* | *Δ Volatility* | *Δ Spread* | *Δ OIB* |
| **A: Overall** | 0.046 | -0.123 | | | -0.064 | -0.016 | -0.046 |
| 1,402 Securities | *<0.01 ****** | *<0.01 ****** | | | *0.01 ***** | *0.19* | *<0.01 ****** |
| **B: Most FTDs** | 0.165 | -0.288 | | | -0.124 | -0.008 | -0.084 |
| 150 securities | *<0.01 ****** | *<0.01 ****** | | | *<0.01 ****** | *0.79* | *<0.01 ****** |
| **A: Overall** | | | -0.069 | | -0.070 | -0.015 | -0.046 |
| 1,418 Securities | | | *<0.01****** | | *0.02 ***** | *0.24* | *<0.01 ****** |
| **B: Most FTDs** | | | -0.159 | | -0.138 | -0.005 | -0.083 |
| 150 securities | | | *<0.01****** | | *<0.01 ****** | *0.88* | *<0.01 ****** |
| **A: Overall** | | | | ~-0.001 | -0.064 | -0.014 | -0.046 |
| 1,418 Securities | | | | *0.86* | *<0.01 ****** | *0.36* | *<0.01 ****** |
| **B: Most FTDs** | | | | -0.008 | -0.131 | -0.010 | -0.087 |
| 150 securities | | | | *0.28* | *<0.01 ****** | *0.73* | *<0.01 ****** |

**Panel B - Impact of Delivered Short Selling**

| | Response | | | | | | |
|---|---|---|---|---|---|---|---|
| **Sample** | Δ *PE* | Δ *PE* (incremental effect when lag *PE* > 0) | Δ *PE Volatility* | Δ *Price* | Δ *Volatility* | Δ *Spread* | Δ *OIB* |
| **A: Overall** | 0.590 | -1.494 | | | -0.996 | -0.237 | -0.819 |
| 1,402 Securities | *<0.01 ****** | *<0.01 ****** | | | *0.01 ***** | *0.19* | *<0.01 ****** |
| **B: Most FTDs** | 1.006 | -1.739 | | | -1.230 | -0.072 | -0.758 |
| 150 securities | *<0.01 ****** | *<0.01 ****** | | | *<0.01 ****** | *0.37* | *<0.01 ****** |
| **A: Overall** | | | -0.927 | | -1.040 | -0.222 | -0.808 |
| 1,418 Securities | | | *<0.01 ****** | | *<0.01 ****** | *<0.01 ****** | *<0.01 ****** |
| **B: Most FTDs** | | | -1.027 | | -1.290 | -0.065 | -0.754 |
| 150 securities | | | *<0.01 ****** | | *<0.01 ****** | *0.43* | *<0.01 ****** |
| **A: Overall** | | | | -0.023 | -0.991 | -0.219 | -0.811 |
| 1,418 Securities | | | | *<0.01 ****** | *<0.01 ****** | *<0.01 ****** | *<0.01 ****** |
| **B: Most FTDs** | | | | -0.025 | -1.254 | -0.081 | -0.765 |
| 150 securities | | | | *0.21* | *<0.01 ****** | *0.30* | *<0.01 ****** |

**Table VI Panels C and D** present the effect on the market quality metrics included in Models 1, 2 and 3 of an increase in *Outstanding FTD Ratio* (*OFR*) *and Outstanding Delivered Short Ratio* (*ODR*) equivalent to 10 basis points of the number of outstanding shares. We report the impact on the response variable as a proportion of the mean of the response variable. Percentages presented in bold are significant at 10% or lower.

**Panel C: Impact of a Change in** *Outstanding FTD Ratio* **(*OFR*) equal to 10 Basis Points of the number of outstanding shares**

| | Overall Sample | | | Most FTDs Sample | | |
|---|---|---|---|---|---|---|
| Response Variable | Model 1 (*PE*) | Model 2 (*PE Volatility*) | Model 3 (*Price*) | Model 1 (*PE*) | Model 2 (*PE Volatility*) | Model 3 (*Price*) |
| *Positive PE* | **-9.81%** | | | **-6.74%** | | |
| *PE Volatility* | | **-12.92%** | | | **-9.43%** | |
| *Price* | | | -0.01% | | | -0.04% |
| *Volatility* | **-1.04%** | **-1.14%** | **-1.04%** | **-0.84%** | **-0.94%** | **-0.89%** |
| *Spread* | -1.03% | -0.99% | -0.92% | -0.14% | -0.08% | -0.17% |
| *OIB* | **-1.75%** | **-1.72%** | **-1.73%** | **-1.80%** | **-1.79%** | **-1.87%** |

**Panel D: Impact of a Change in** *Outstanding Delivered Short Ratio* **(*ODR*) equal to 10 Basis Points of the number of outstanding shares**

| | Overall Sample | | | Most FTDs Sample | | |
|---|---|---|---|---|---|---|
| Response Variable | Model 1 (*PE*) | Model 2 (*PE Volatility*) | Model 3 (*Price*) | Model 1 (*PE*) | Model 2 (*PE Volatility*) | Model 3 (*Price*) |
| *Positive PE* | **-4.90%** | | | **-2.98%** | | |
| *PE Volatility* | | **-7.37%** | | | **-4.53%** | |
| *Price* | | | **-0.01%** | | | **-0.01%** |
| *Volatility* | **-0.69%** | **-0.72%** | **-0.69%** | **-0.62%** | **-0.65%** | **-0.63%** |
| *Spread* | **-0.65%** | **-0.61%** | **-0.60%** | -0.09% | -0.09% | -0.11% |
| *OIB* | **-1.31%** | **-1.30%** | **-1.30%** | **-1.20%** | **-1.20%** | **-1.22%** |

**Table VI Panels E and F** are extracts of estimates of the parameters in Models 1, 2 and 3 above and report results pertaining to the impact of *OFR*. Panel E presents results from a subset of the 'entire market' dataset discussed in panels A-D; the sample includes all common stock of US-based firms (CRSP share codes 10 and 11) with NYSE listed as the primary exchange, available in the CRSP and TAQ databases, listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, with no large changes (>10%) in the number of shares outstanding and that appear, for at least one day, on the NYSE-published list of Threshold Securities. Panel F presents results from a dataset including NASDAQ securities: we include all common stock of US-based firms (CRSP share codes 10 and 11) with NASDAQ listed as the primary exchange, available in the CRSP and TAQ databases, listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, and with no large changes (>10%) in the number of shares outstanding. Reported parameter estimates are averages of parameters estimated by security. Significance is tested employing a cross-sectional estimate of the standard error of the parameter estimate, as in Chordia, Roll and Subrahmanyam (2000). The p-values from two-sided t-tests are in italics below the parameter estimate. "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively.

**Panel E - Impact of FTDs, Threshold Securities**

| Sample Size | Response | | | | | | |
|---|---|---|---|---|---|---|---|
| | *Δ PE* | *Δ PE (incremental effect when lag PE > 0)* | *Δ PE Volatility* | *Δ Price* | *Δ Volatility* | *Δ Spread* | *Δ OIB* |
| 164 Securities | 0.153 | -0.258 | | | -0.117 | -0.022 | -0.083 |
| | *<0.01 ****** | *<0.01 ****** | | | *<0.01 ****** | *0.19* | *<0.01 ****** |
| 165 Securities | | | -0.135 | | -0.129 | -0.018 | -0.084 |
| | | | *<0.01****** | | *<0.01 ****** | *0.32* | *<0.01 ****** |
| 165 Securities | | | | -0.008 | -0.124 | -0.023 | -0.088 |
| | | | | *0.20* | *<0.01 ****** | *0.20* | *<0.01 ****** |

**Panel F - Impact of FTDs, NASDAQ Sample**

| Sample Size | Response | | | | | | |
|---|---|---|---|---|---|---|---|
| | *Δ PE* | *Δ PE (incremental effect when lag PE > 0)* | *Δ PE Volatility* | *Δ Price* | *Δ Volatility* | *Δ Spread* | *Δ OIB* |
| 2170 Securities | 0.076 | -0.136 | | | -0.064 | -0.014 | -0.025 |
| | *0.06** | *0.05*** | | | *0.07** | *0.76* | *0.63* |
| 2381 Securities | | | -0.095 | | -0.064 | 0.002 | 0.003 |
| | | | *<0.01****** | | *0.08** | *0.98* | *0.91* |
| 2380 Securities | | | | 0.013 | -0.056 | 0.005 | 0.020 |
| | | | | *0.06** | *0.09** | *0.95* | *0.54* |

**Table VII –The Impact of Restrictions on FTDs imposed by the SEC between July 21, 2008 and August 12, 2008.**

The following table presents parameter estimates and related two-sided p-values (in italics, grey font) from five OLS regressions, one for each variable of interest: *OFR*, *Pricing Error Volatility*, *Price*, *Volatility*, *Spread*, and *Order Imbalance*. All variables are computed daily over the interval January 1, 2008 to September 9, 2008. In each $k^{th}$ ($1 <= k <= 6$) regression, the response variable is the mean value of the $k^{th}$ variable of interest for the sample of the 17 stocks that were subject to the SEC mandate requiring pre-short sale stock borrowing arrangements. The ban affected 19 securities, but we have data for 17 of these: Bank of America Corporation, Barclays, Bear Stearns Companies Inc., Citigroup Inc., Credit Suisse Group, Deutsche Bank Group AG, Allianz SE, Goldman, Sachs Group Inc, Royal Bank ADS, HSBC Holdings PLC ADS, J. P. Morgan Chase & Co., Merrill Lynch & Co., Inc., Mizuho Financial Group, Inc., Morgan Stanley, UBS AG, Freddie Mac, and Fannie Mae. Explanatory variables include, in each regression, an intercept, the mean value of the $k^{th}$ variable of interest for the control sample, *Control*, and a binary variable, *Event*, equal to 1 between July 21, 2008 and August 12, 2008. All variables are standardized and winsorized by security, and are as defined in Table II. "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively. The OLS regression equation is as follows:

$$ResponseVariable_{k,t} = \alpha_k + \beta_{1,k} Event + \beta_{2,k} Control_{k,t} + \varepsilon_{k,t}$$

| Predictors | *OFR* | *PE Volatility* | *Return* | *Volatility* | *Spread* | *OIB* |
|---|---|---|---|---|---|---|
| *Intercept* | 0.001 | 0.197 | -0.002 | -0.038 | -0.001 | 0.017 |
| | *<0.01 **** | *<0.01 **** | *0.16* | *<0.01 **** | *<0.01 **** | *<0.01 **** |
| *Control* | 2.014 | 0.625 | 1.179 | 1.353 | 0.941 | 0.496 |
| | *<0.01 **** | *0.33* | *<0.01 **** | *<0.01 **** | *<0.01 **** | *<0.01 **** |
| *Event* | -0.001 | 0.074 | -0.006 | 0.007 | ~0.001 | -0.017 |
| | *<0.01 **** | *<0.01 **** | *0.11* | *<0.01 **** | *0.10 ** | *0.11* |

**Table VIII – Impact of FTD Trades for Securities with High/Low Proportion of FTDs by Public Traders relative to Market Makers**

This table provides results for the estimation of three vector autoregressive models of order one: VAR with *Pricing Error* (Model 1), VAR with *Pricing Error Volatility* (Model 2) and VAR with *Price* (Model 3), as described in Table VI. All variables are standardized and winsorized by security, and are as defined in Table II. The sample is built as follows: we include all NYSE common stock of US-based firms (CRSP share codes 10 and 11) available in the CRSP and TAQ databases listed for at least 18 months over the interval January 1, 2005 to June 30, 2008, and with no large changes (>10%) in the number of shares outstanding. The resulting sample includes 1,492 securities.
Mean *OFR* is computed for all securities included in the sample for the period preceding the introduction of Rule 204T (January 1, 2005 to June 30, 2008) and for a period following (January 1, 2009 to December 31, 2010). Securities are ranked according to the proportional change in Mean *OFR*. Securities are then allocated to three quantiles – those with the highest decline in Mean *OFR* are allocated to the "High Proportion of Public Traders" sample, while those with the lowest decline in Mean *OFR* are allocated to the "Low Proportion of Public Traders" sample. Reported parameter estimates are averages of parameters estimated by security. Significance is tested employing a cross-sectional estimate of the standard error of the parameter estimate, as in Chordia, Roll and Subrahmanyam (2000). p-values from two-sided t-tests are in italics below the parameter estimates. "*", "**", and "***" indicate significance at the 10%, 5% and 1% level respectively.

| | Response | | | | | | |
|---|---|---|---|---|---|---|---|
| **Sample** | *Δ PE* | *Δ PE (incremental effect when lag PE > 0)* | *Δ PE Volatility* | *Δ Price* | *Δ Volatility* | *Δ Spread* | *Δ OIB* |
| **A: Low Proportion of Public Traders** | 0.028 | -0.125 | | | -0.041 | -0.009 | -0.027 |
| 338 Securities | *0.24* | *0.34* | | | *<0.01 ****** | *0.45* | *0.04 *** |
| **B: High Proportion of Public Traders** | 0.054 | -0.117 | | | -0.073 | -0.020 | -0.063 |
| 345 Securities | *0.03 *** | *<0.01 ****** | | | *<0.01 ****** | *0.09 *** | *<0.01 ****** |
| **A: Low Proportion of Public Traders** | | | -0.038 | | -0.045 | -0.010 | -0.027 |
| 345 Securities | | | *<0.01 ****** | | *<0.01 ****** | *0.41* | *0.06 ** |
| **B: High Proportion of Public Traders** | | | -0.073 | | -0.079 | -0.020 | -0.063 |
| 352 Securities | | | *<0.01 ****** | | *<0.01 ****** | *0.10* | *<0.01 ****** |
| **A: Low Proportion of Public Traders** | | | | -0.001 | -0.043 | -0.011 | -0.029 |
| 345 Securities | | | | *0.79* | *<0.01 ****** | *0.32* | *0.07 ** |
| **B: High Proportion of Public Traders** | | | | -0.003 | -0.076 | -0.022 | -0.061 |
| 352 Securities | | | | *0.19* | *<0.01 ****** | *0.07 ** | *<0.01 ****** |

**Table IX– Outstanding FTD Ratio (*OFR*) of Bear Stearns (Ticker: BSC) and of Lehman Brothers Holdings Inc. (Ticker: LEH) in 2008.**

*OFR* is computed as the ratio of our estimate of outstanding fails to deliver and shares outstanding. *Index OFR* is calculated as the equal weighted average of *OFR* of common stock of 4 firms that are matched on primary SIC and market capitalization as of the end of the fiscal year 2007 to BSC in Panel A and to LEH in Panel B. We construct a t-statistic using the mean and standard error of the *OFR* difference over the time interval January 1, 2008 to February 15, 2008 for BSC and over the time interval January 1, 2008 and ending 20 trading days prior to September 9, 2008 for LEH; p-values are two-sided. “*”, “**”, and “***” indicate significance at the 10%, 5% and 1% level respectively.

**Panel A**: Bear Stearns

| *Date* | *BSC Stock Price* | *BSC OFR* | *Index OFR* | *Difference in OFR* | p-value | |
|---|---|---|---|---|---|---|
| 3/3/2008 | 77.32 | 0.30% | <0.01 | 0.30% | 0.21 | |
| 3/4/2008 | 77.17 | 0.14% | <0.01 | 0.14% | <0.01 | *** |
| 3/5/2008 | 75.78 | 0.14% | 0.02% | 0.12% | <0.01 | *** |
| 3/6/2008 | 69.9 | 0.24% | 0.02% | 0.22% | <0.01 | *** |
| 3/7/2008 | 70.08 | 0.12% | 0.02% | 0.10% | <0.01 | *** |
| 3/10/2008 | 62.3 | 0.12% | 0.02% | 0.10% | <0.01 | *** |
| 3/11/2008 | 62.97 | 0.28% | <0.01 | 0.28% | 0.16 | |
| 3/12/2008 | 61.58 | 1.16% | 0.06% | 1.10% | <0.01 | *** |
| 3/13/2008 | 57 | 1.06% | 0.06% | 1.00% | <0.01 | *** |
| 3/14/2008 | 30 | 2.24% | 0.08% | 2.16% | <0.01 | *** |
| 3/17/2008 | 4.81 | 12.18% | 0.08% | 12.10% | <0.01 | *** |
| 3/18/2008 | 5.91 | 11.74% | 0.04% | 11.70% | <0.01 | *** |
| 3/19/2008 | 5.33 | 11.74% | 0.04% | 11.70% | <0.01 | *** |
| 3/20/2008 | 5.96 | 11.68% | 0.08% | 11.60% | <0.01 | *** |
| 3/24/2008 | 11.25 | 12.26% | 0.04% | 12.22% | <0.01 | *** |
| 3/25/2008 | 10.94 | 14.38% | 0.08% | 14.30% | <0.01 | *** |
| 3/26/2008 | 11.21 | 10.92% | 0.08% | 10.84% | <0.01 | *** |
| 3/27/2008 | 11.23 | 11.68% | 0.06% | 11.62% | <0.01 | *** |
| 3/28/2008 | 10.78 | 12.36% | 0.06% | 12.30% | <0.01 | *** |
| 3/29/2008 | 10.49 | 12.36% | 0.06% | 12.30% | <0.01 | *** |

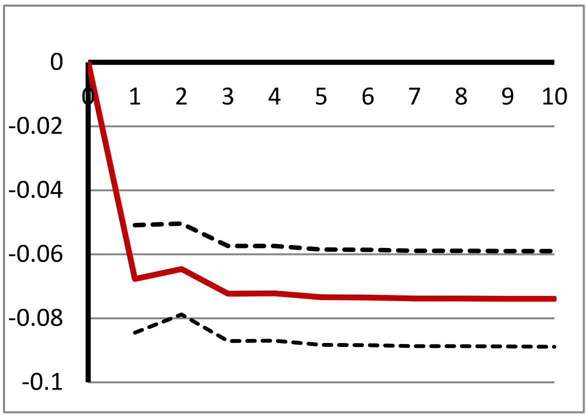
**Panel B:** Lehman Brothers Holdings Inc.

| *Date* | *LEH Stock Price* | *LEH OFR* | *Index OFR* | *Difference in OFR* | p-value | |
|---|---|---|---|---|---|---|
| 8/25/2008 | 13.45 | 0.31% | <0.01 | 0.31% | <0.01 | *** |
| 8/26/2008 | 14.03 | 0.16% | <0.01 | 0.16% | <0.01 | *** |
| 8/27/2008 | 14.78 | 0.16% | <0.01 | 0.16% | <0.01 | *** |
| 8/28/2008 | 15.87 | 0.02% | <0.01 | 0.02% | <0.01 | *** |
| 8/29/2008 | 16.09 | 0.02% | <0.01 | 0.02% | <0.01 | *** |
| 9/2/2008 | 16.13 | 0.02% | <0.01 | 0.02% | <0.01 | *** |
| 9/3/2008 | 16.94 | 0.02% | <0.01 | 0.02% | <0.01 | *** |
| 9/4/2008 | 15.17 | 0.01% | <0.01 | 0.01% | <0.01 | *** |
| 9/5/2008 | 16.2 | 0.01% | 0.02% | -0.01% | <0.01 | *** |
| 9/8/2008 | 14.15 | 0.01% | 0.02% | -0.01% | <0.01 | *** |
| 9/9/2008 | 7.79 | 0.16% | 0.03% | 0.13% | <0.01 | *** |
| 9/10/2008 | 7.25 | 0.85% | 0.04% | 0.81% | <0.01 | *** |
| 9/11/2008 | 4.22 | 3.29% | 0.04% | 3.25% | <0.01 | *** |
| 9/12/2008 | 3.65 | 4.86% | 0.03% | 4.83% | <0.01 | *** |
| 9/15/2008 | 0.21 | 4.86% | 0.05% | 4.81% | <0.01 | *** |
| 9/16/2008 | 0.3 | 5.21% | 0.16% | 5.05% | <0.01 | *** |
| 9/17/2008 | 0.13 | 8.16% | 0.18% | 7.98% | <0.01 | *** |
| 9/18/2008 | | | | | | |
| 9/19/2008 | | | DELISTED | | | |
| 9/22/2008 | | | | | | |
| 9/23/2008 | | | | | | |

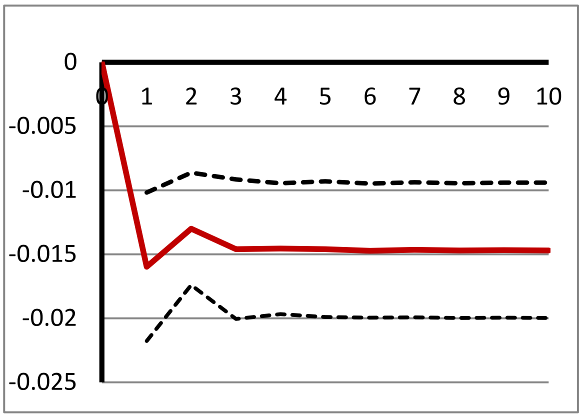
**Figure 1**

Plots of accumulated impulse response functions depicting the impact of a one-standard deviation shock in *OFR*. The VAR model used for estimation is Model 2 and the sample is the ‘overall market’, as described in Table VI. The response variables in the four panels are, respectively, *PE Volatility*, *Volatility*, *Spread* and *Order Imbalance*, as defined in Table II. The horizontal axis are time periods (days), following the initial shock (day 0). All variables are standardized and winsorized by security. Impulse response coefficients are estimated by security; mean values are depicted. 5% confidence intervals are computed using cross-sectional standard error estimates.

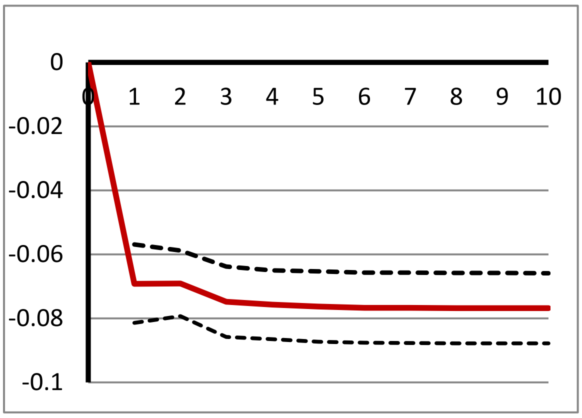
**Panel A: PE Volatility**




**Panel C: Spread**




**Panel B: Volatility**




**Panel D: Order Imbalance**

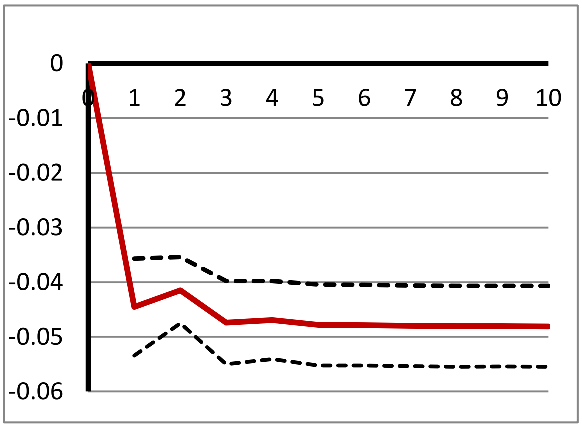
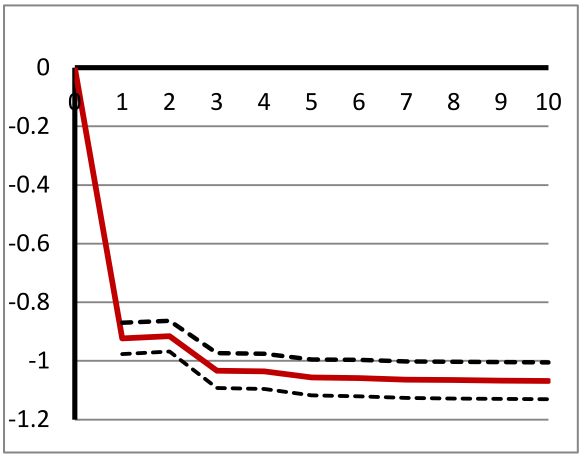


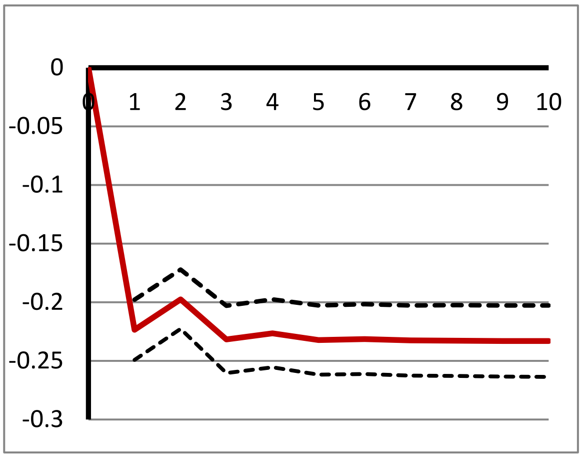
**Figure 2**

Plots of accumulated impulse response functions depicting the impact of a one-standard deviation shock in *ODR*. The VAR model used for estimation is Model 2 and the sample is the 'overall market', as described in Table VI. The response variables in the four panels are, respectively, *PE Volatility*, *Volatility*, *Spread* and *Order Imbalance*, as defined in Table II. The horizontal axis are time periods (days), following the initial shock (day 0). All variables are standardized and winsorized by security. Impulse response coefficients are estimated by security; mean values are depicted. 5% confidence intervals are computed using cross-sectional standard error estimates.

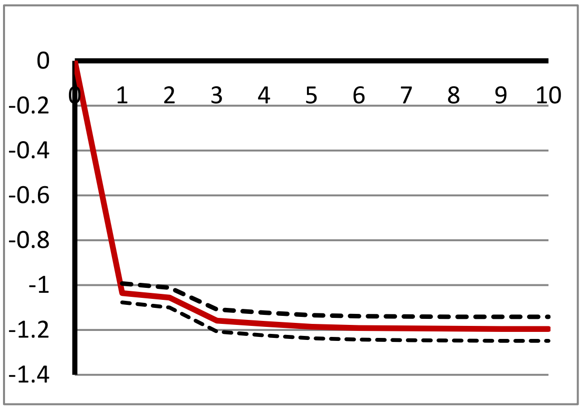
**Panel A: PE Volatility**




**Panel C: Spread**




**Panel B: Volatility**




**Panel D: Order Imbalance**

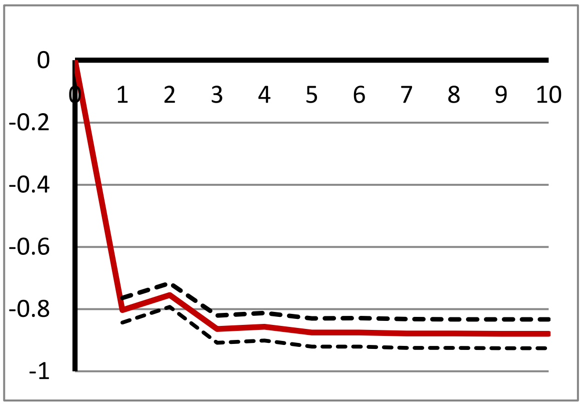


**Figure 3**

Plot of *Outstanding FTD Ratio* and *Return Index* related to Bear Sterns Companies Inc. common stock (ticker: BSC) against calendar date. The *Return Index* is set to 1 on the 1st of January, 2008; $Return\ Index_i = \sum_{j=1}^{i}(1+R_{BSC,j})$. $R_{BSC,j}$ is the observed total return for BSC on day *j*, from the CRSP database.

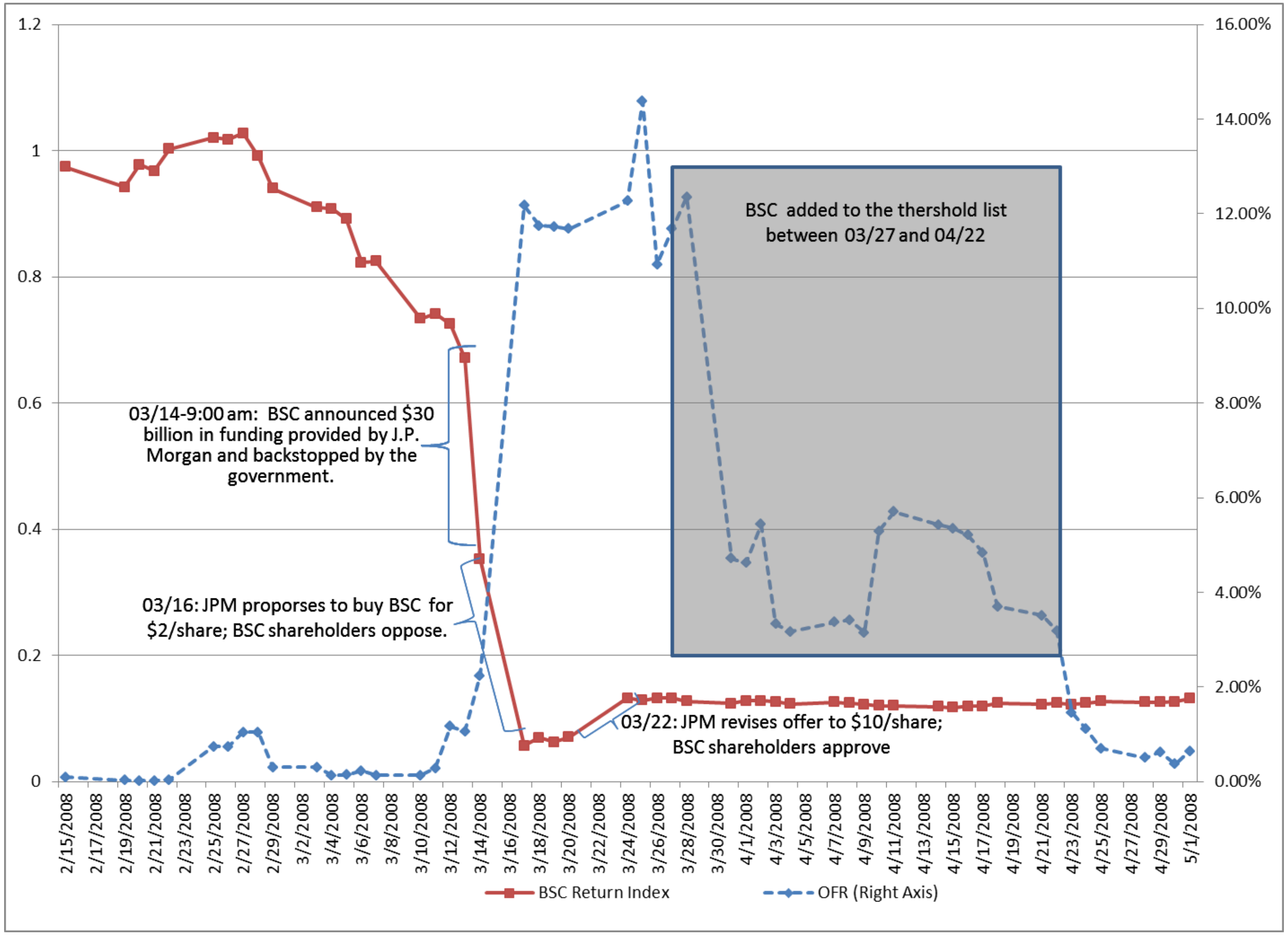


**Figure 4**

Plot of *Outstanding FTD Ratio* and *Return Index* related to Lehman Brothers Holdings Inc. (ticker: LEH) *over calendar time*. The *Return Index* is set to 1 on the 1st of January, 2008; $\mathit{Return\ Index}_i = \sum_{j=1}^{i}(1+R_{LEH,j})$. $R_{LEH,j}$ is the observed total return for LEH on day *j*, from the CRSP database.

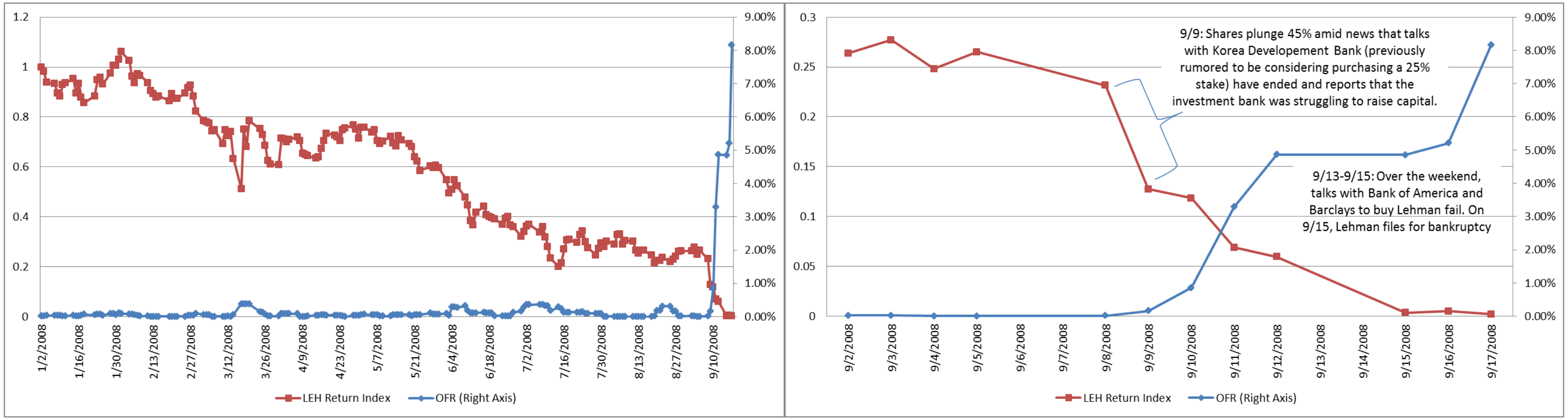


**Figure 5**

Plot of *Outstanding FTD Ratio* and *Return Index* related to Merrill Lynch & Co., Inc. (ticker: MER) *over* calendar time. The *Return Index* is set to 1 on the 1st of January, 2008; $Return\ Index_i = \sum_{j=1}^{i}(1 + R_{MER,j})$. $R_{MER,j}$ is the observed total return for MER on day *j*, from the CRSP database.

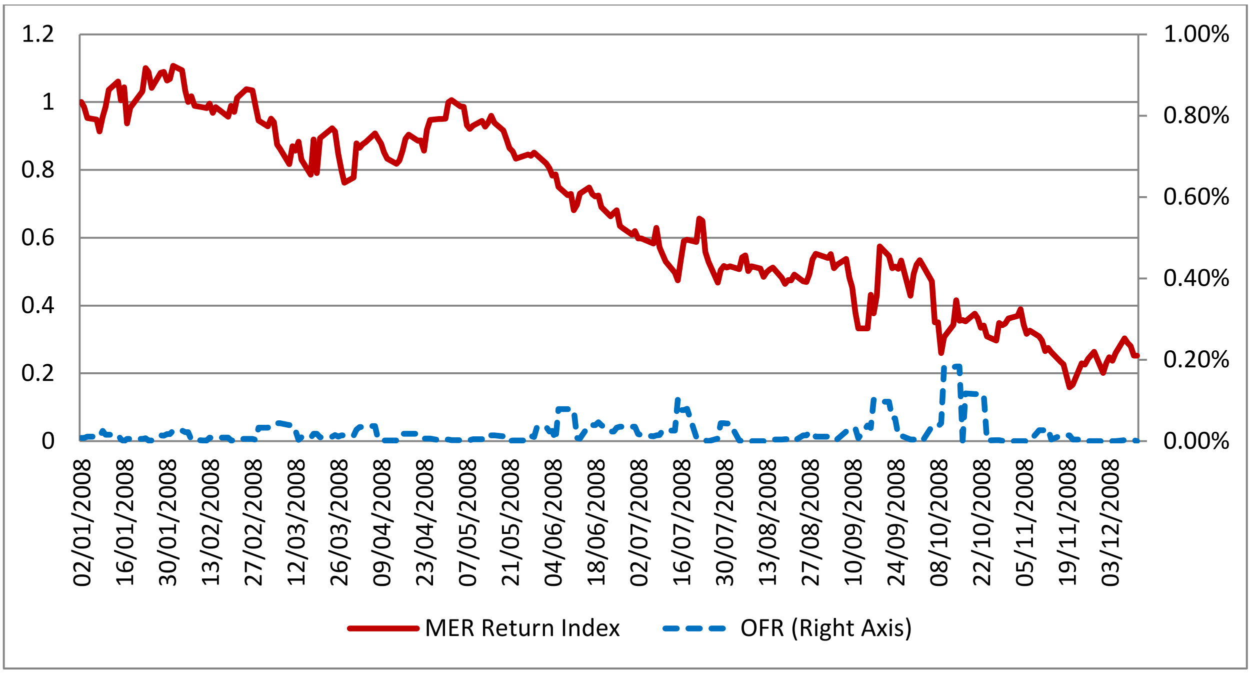



**Figure 6**

Plot of *Outstanding FTD Ratio* and *Return Index* related to American International Group (ticker: AIG) *over* calendartime. The *Return Index* is set to 1 on the 1st of January, 2008; $Return\ Index_i = \sum_{j=1}^{i}(1 + R_{AIG,j})$.

$R_{AIG,j}$ is the observed total return for AIG on day *j*, from the CRSP database.