Informed Trading and Co-Illiquidity

Søren Hvidkjær* Massimo Massa† Aleksandra Rzeźnik‡

November 14, 2018

Abstract

We study the link between informed trading and co-movement in liquidity. We argue that investors concerned with liquidity and fire sale shocks respond to an increase in informed trading by shifting their portfolios away from stocks with high information asymmetry. Their rebalancing results in a substitution in ownership away from the very same investors that induce financial fragility and co-movement in liquidity. This reduces co-illiquidity of the affected stocks. We exploit a unique natural experiment that increases the incentives of informed traders to trade. Our results suggest that informed traders reduce the exposure to co-movement in liquidity: one of the major problems during the latest global financial crisis.

Keywords: Short-sales constraints, liquidity, commonality, informed trading

JEL classification: G12, G14, G15

We thank Ben Sand, Michael Roberts, and brown bag participants at the Schulich School of Business.

*Copenhagen Business School, e-mail: sh.fi@cbs.dk.
†INSEAD, e-mail: massimo.massa@insead.edu.
‡Wirtschaftsuniversität Wien, e-mail: arzeznik@wu.ac.at.

Introduction

The last decades have seen the parallel rise of both informed trading and liquidity trading. The first trend – the rise of informed trading – is linked to the development of new technologies and new data that has concentrated trading power in the hands of few relatively more informed investors (e.g., short sellers, hedge funds). While their trade has made the market more efficient, still it has also increased the amount of information asymmetry due to the trade of more informed investors. For example Asquith, Pathak, and Ritter (2005) show that short interest steadily increases over time and SEC (2010) documents the rise of High Frequency Traders and attributes 50% of total trading volume to HFT. The second trend is linked to the rise of open-end investment. The amount of money intermediated by open-end structures in the US has reached \$221 trillion in 2017. This represented 25% of the US stock market capitalization, with an average growth rate of 10% over the previous 10 years. Open-end structures are not informed investors (Kacperczyk and Seru (2007)) but share many features with liquidity traders characterized by short-term view (e.g. Stein (2005), Cella, Ellul, and Giannetti (2013), Liu and Mello (2011), and Giannetti and Kahraman (2017)).

Therefore, the first trend tends to reduce the offering of liquidity, while the second tends to increase its demand. In this paper, we investigate the link between these two phenomena. We argue that they are linked and that the rise of informed trading can in fact improve one key facet of illiquidity: "co-illiquidity" – the tendency of assets to become illiquid at the same time.

We concentrate on co-illiquidity because, as the recent crisis has shown, a key concern for mutual funds is to not be exposed to fire sales when everybody else is selling the same assets. Indeed, the negative effects of fire sales are magnified in the case the fund (co)-holds the same assets as other open-end funds and the latter have (cor)related liquidity needs – due for example to common withdrawals. The need to liquidate the assets will make them stampede to sell, leading to a drop in price that will drastically reduce their performance. As it has been shown (e.g., Chen, Goldstein, and Jiang (2010), Zeng (2017), and Goldstein, Jiang, and Ng (2017)) such "strategic complementarities" may even induce investors to try to preempt each other by selling assets before others do it. This will lead to asset "runs". Mutual funds managers will try to manage co-illiquidity risk by focusing on assets that are less likely to become illiquid *when everybody in the market needs liquidity* – i.e., less "co-illiquid" assets.

The question is how the rise of informed trading affects such co-illiquidity. We start from the consideration/stylized fact that an increase of informed investors in the market raises informational efficiency and, at the same time, increases asymmetry of information (Kim and Verrecchia (1994)). The higher informational efficiency will make the stock more sensitive to stock-specific news, increasing the stock-specific (idiosyncratic) component in stock return. This will lower the tendency of the affected stock to move with the market, reducing its sensitivity to co-movement shocks and, among them, co-illiquidity shocks. This will make it co-move in liquidity less with the other stocks in the market – i.e., less co-illiquid. Moreover, the higher asymmetry of information will reduce the demand for the stock by the relatively less informed investors and, critically, by the ones among them who were holding the stock for liquidity reasons. Indeed, the very fact that such stock becomes the preferred trading avenue for specialized/informed investors will make it a less desirable source of liquidity and therefore less used by investors to buffer liquidity shocks. This will change the composition of the stock ownership, from investors who were holding it for liquidity reason – likely to be more exposed to fire sales risk – to investors who hold it either because they are more informed or simply because their longer horizon makes them less sensitive to short-term information driven swings. This shift in ownership composition from investors more subject to co-illiquid shocks to the ones less subject to them reduces the sensitivity of the stock to co-illiquidity risk and makes the stock less co-illiquid.

In this paper, we test this link between informed trading and co-illiquidity exploiting an event that exogenously increases informed trading in the market, allowing us to pin down causality. We document how such a shock shifts both the degree of co-movement in liquidity among stocks as well as the behavior of the open-end mutual funds that manage their portfolios' co-illiquidity in a way consistent with our intuition.

We focus on investors that have been traditionally identified as informed – the short sellers – and we look at an experiment that exogenously shifts their ability to trade. Short sellers have traditionally been considered informed or at least better able to process information (e.g., Boehmer, Jones, and Zhang (2008), Engelberg, Reed, and Ringgenberg (2012), Cohen, Diether, and Malloy (2007), Diether, Lee, and Werner (2009), Boehmer, Huszar, and Jordan (2010)). The shock that we exploit is the "SHO experiment" that has made it easy for short sellers to trade (Boehmer and Wu (2013), Alexander and Peterson (2008)). On July 28 2004, the SEC announced a year-long pilot program eliminating uptick rule from approximately one-third of the largest stocks and published a list of 968 randomly assigned pilot firms ("Pilot" stocks). The main goal of the program was to evaluate the impact of unrestricted short selling on market volatility, price efficiency, and liquidity. The randomized experiment split the stocks in the Russell 3000 index into the ones part of the experiment ("Pilot" stocks) and the others unaffected by the regulation, effectively splitting the stocks into a treated and a control group. We exploit the experiment to test whether – controlling for the change in the level of liquidity – the increase in short selling in the Pilot stocks reduced the liquidity co-movement of the stocks involved and how the mutual fund managers reacted to it.

We start by providing some preliminary evidence of the link between liquidity co-movement and short selling activity. We focus on the most exogenous part of the latter: the supply of shares made available to be lent to short sellers in the market ("lending supply"). A Granger analysis documents that, while lending supply Granger-causes liquidity co-movement, liquidity co-movement does not Granger-cause short selling supply. The effect is also economically relevant: one standard deviation increase in lending supply is related to a reduction in liquidity co-movement that ranges between $0.01\times$ and $0.015 \times \sigma(\mathrm{R}^2_{\mathrm{LIQ}})$, depending on our definition of short selling supply. This provides our first evidence that supports our intuition on the direction of the link between short selling and co-movement in liquidity.

Next, we focus on the SHO experiment. We document that as of July 2004 (SHO announcement) co-illiquidity for the PILOT stocks drops while no analogous drop is there for the control sample of the NON-PILOT stocks. More specifically, if we focus on different windows after the beginning of the experiment, we see that liquidity co-movement drops for all the windows considered for the experiment. The drops ranges from between $0.11 \times \sigma(\mathrm{R}^2_{\mathrm{LIQ}})$ and $0.1 \times \sigma(\mathrm{R}^2_{\mathrm{LIQ}})$ for two months ahead to between $0.05 \times \sigma(\mathrm{R}^2_{\mathrm{LIQ}})$ and $0.04 \times \sigma(\mathrm{R}^2_{\mathrm{LIQ}})$ for 11 months ahead. This drop compares to the $0.015 \times \sigma(\mathrm{R}^2_{\mathrm{LIQ}})$ of the previous estimates based on Granger causality. Similar results hold for whether we use a panel-based or event-based specification. Overall, these results support our working hypothesis that short selling negatively affects the degree of co-movement in liquidity.

Armed with these results, we investigate the channel based on mutual fund behavior and test how mutual funds reacted to SHO-induced changes in co-movement in liquidity. As we argued, we expect that the higher asymmetry will induce mutual funds – the relatively less informed traders (e.g., Kacperczyk and Seru (2007)) – to shift from PILOT to NON-PILOT stocks. The effect should increase with the fraction of PILOT stocks in their portfolios.

We find that, in line with our working hypothesis, funds holding PILOT stocks rebalance towards NON-PILOT stocks and towards previously neglected more co-illiquid stocks. The effect is not only statistically significant but also economically relevant. Funds with one standard deviation higher amount of portfolio invested in PILOT stocks reduce their investment in PILOT stock by $0.256 \times \sigma(\Delta\mathrm{PILOT}_f)$ and into more co-illiquid stocks by $0.266 \times \sigma(\Delta\mathrm{CO\text{-}ILLIQ}_f)$. The results are robust whether we use panel- or event-based specification. These results show that mutual funds, even if they are open-end and desire liquidity, still rebalance away from it towards more co-illiquid stocks in order to be away from informed trading. In other words, the Kim and Verrecchia (1994)'s effect acts in a full way.

Next, we explicitly focus on the determinants of mutual fund quest for more co-liquidity: exposure to fire sales risk and financial fragility as well as exposure to strategic complementarities. We define fire sales as per Coval and Stafford (2007), financial fragility as per Greenwood and Thesmar (2011) and strategic complementarities as per Chen et al.

(2010). Then, we assess how much shocks to these variables affect mutual funds' demand for co-illiquidity and how their behavior changes during Reg SHO pilot program.

We find that shocks to fire sales, financial fragility, and strategic complementarities reduce the investment in co-illiquid stocks, but the effect is attenuated during the SHO period. In other words, funds do manage fire sales, fragility risk and exposure to strategic complementarities by tilting towards less co-illiquid stocks. However, during the SHO experiment the desire to rebalance away from asymmetric information stocks attenuates this tilt and management of fragility risk. The effect is economically relevant. One standard deviation higher fire sale shock (shock to financial fragility, shock to strategic complementarities) reduces the investment toward more co-illiquidity stocks by $0.048 \times \sigma$ ($0.081 \times \sigma$, $0.057 \times \sigma$) of portfolio's co-illiquidity. However, this effect is reduced by $0.033 \times \sigma$ ($0.115 \times \sigma$, $0.070 \times \sigma$) during the SHO experiment. In other words, the reduction in co-illiquidity due to the SHO experiment reduces the needs to rebalance towards less co-illiquid stocks, especially for the funds more subject to the market – i.e., the ones with a greater exposure to fire sales, financial fragility, or strategic complementarities shocks.

Overall, these results suggest that mutual funds cope with the drawbacks related to the open-end structure and the issues induced by strategic complementarities by managing co-illiquidity. However, changes in the informational structure that put them at an informational disadvantage constrain this co-illiquidity management. The equilibrium implication is a change in ownership structure such that the stocks experiencing an increase in informed trading (Pilot) will now be held less by mutual funds. Consequently, investors more subject to fire sales and more likely to generate co-movement in liquidity refrain from pilot stocks, which in turn reduces the co-illiquidity of the affected stocks. This will make these stocks less fragile and less co-illiquid vis-à-vis the other (Non-Pilot) stocks towards which the mutual funds do now rebalance.

These results provide two important pieces of information for the political debate. The first is about the role played by openness for the mutual fund industry. Our results suggest that reducing its open-end structure and curtailing liquidity for the investors may not be really required as mutual funds manage co-illiquidity. The second point is about information. More informed trading by increasing informational asymmetry may in fact hampers the ability of mutual funds to manage co-illiquidity even if in equilibrium the stocks become less co-illiquid.

We relate and contribute to three distinct lines of literature. First, we contribute to the literature on fire sales, financial fragility, and strategic complementarities (Greenwood and Thesmar (2011), Coval and Stafford (2007), Chen et al. (2010), Jotikasthira, Lundblad, and Ramadorai (2012), Shleifer and Vishny (1997), Morris and Shin (2004)). This literature has focused on the strategic interaction among asset managers that face common liquidity shocks and need to sell. This generates strategic behavior in the choice of the assets to hold and may induce fragility in the underlying assets. We contribute by showing how asset managers are aware of it and manage it.

Second, we contribute to an extensive research documenting considerable co-movement in liquidity among stocks. There is a substantial empirical evidence for existence of commonality in liquidity. Chordia, Roll, and Subrahmanyam (2000) identify commonality in liquidity and show that market-wide trading activity, interpreted as inventory risk and asymmetric information, measured by the number of individual transactions have reverse influence on a stock's liquidity. Whereas Chordia et al. (2000) deal with liquidity co-movement and liquidity risk, Brunnermeier and Pedersen (2009) propose a model that interrelates assets' market liquidity and investors' funding liquidity. They explain the market liquidity and fragility co-movement across assets by changes in the funding conditions that influence market liquidity provision for all assets. Hameed, Kang, and Viswanathan (2010) find supportive conclusions about the influence of capital supply on market liquidity. Namely, there is a significant market liquidity decrease and liquidity co-movement increase subsequent to large negative market returns. Financial intermediaries fail to provide liquidity, when most needed, because of the drop in their aggregated collateral. Coughenour and Saad (2004) consider the link between funding constrains and commonality in liquidity and show lower co-variation between stocks' and market portfolio's liquidity with increasing specialist size, i.e. with fewer funding constrains. While their analysis supports the supply-side hypothesis, Karolyi, Lee, and Van Dijk (2012) argue that demand-side might be crucial for explaining variation in commonality across countries and over time. Institutional ownership, investor sentiment, and correlated trading activity seem to affect the dynamics of co-movement in liquidity. Those findings are in line with the previous work of Kamara, Lou, and Sadka (2008) and Koch, Ruenzi, and Starks (2016). Kamara et al. (2008) point out that the sensitivity of stocks' liquidity to market liquidity has increased for large stocks while it has decreased for small firms. They argue that the expansion of institutional ownership is fraught with the increase in the sensitivity of large stocks to common liquidity shocks. We contribute by showing the causal link between short selling constraints and co-movement in liquidity and providing a link between the latter and asset management behavior.

Third, we contribute to the literature on short selling. Our work is closely related to Saffi and Sigurdsson (2011) and to Beber and Pagano (2013). Saffi and Sigurdsson (2011) study the impact of short selling constrains on the price efficiency. They use equity lending data also obtained from Data Explorers and show that higher short selling constraints, proxied by low short selling supply, lead to lower price efficiency. Whereas Beber and Pagano (2013) use a "natural experiment" of imposition and removal of short selling bans on different groups of stocks in different countries in the face of the financial crisis in 2008. They document that short selling bans or regulatory constraints have a destructive influence on the market liquidity. Similarly, Kolasinski, Reed, and Thornock (2013) also take advantage of the financial crisis in 2008 and test the implications of Diamond and Verrecchia (1987) model distinguishing between constraining and prohibiting short selling. Their results suggest that the imposition of naked short selling ban on a group of stocks and short selling ban on financial stocks increased the proportion of the informed traders relative to uninformed while reducing the market quality. Finally, there are some theoretical studies (Miller (1977), Diamond and Verrecchia (1987), Bai, Chang, and Wang (2006)) linking short selling constraints with the stock market efficiency. Among others, Duffie, Gârleanu, and Pedersen (2002) derive a model explaining dynamics of stock prices, lending fees and short selling demand, in which greater divergence in investors' beliefs concerning value of a stock can lead to its overvaluation.

Also the literature has established the impact of short sellers' behavior on stock prices (Senchack and Starks (1993), Asquith and Meulbroek (1995), Aitken, Frino, McCorry, and Swan (1998), Boehmer et al. (2008), Boehmer and Wu (2013), Saffi and Sigurdsson (2011)). The literature has focused on short sellers as more informed investors (Cohen et al. (2007)), or better able to process public information (e.g., Engelberg et al. (2012)). We contribute by showing how short selling constraints affect the quality of the market by looking at liquidity risk.

2 Data Description and Main Variables

2.1 Data Sources

We use stock data from CRSP from 2005 to 2010. We collect daily returns, prices, trading volumes, and number of shares outstanding data for common stocks with share codes 10 and 11. We exclude American Depository Receipts (ADRs), Global Depository Receipts (GDRs), Exchange Traded Funds (ETFs), or any other receipts. To avoid the issue of small "penny" stocks, following Hameed et al. (2010), we impose the constraint that a stock price at the end of a previous month to be between 2 and 1000 USD. Following Karolyi et al. (2012), we also discard stock-day observations if a daily return is in the top or bottom 0.1% of the cross-sectional distribution.

The stock data are merged with short selling information data from DataExplorers (now Markit), a leading provider of security lending data. Specifically, we use the value and quantity of shares available for lending. We also proxy the lending supply by the utilisation ratio – the value of assets on loan from lenders divided by the total lendable value. The provided data are available at the security level and span the period from January 2003 to August 2010. The observation frequency varies over time. Until July 2004, the data are available at the monthly level, from August 2004 to June 2006 at the weekly level, and from July 2006 on, we observe daily short selling activity. We conduct our analysis at a monthly frequency and require non-missing information on the number of shares available for lending, thus we can use almost the entire sample from January 2005 to August 2010.

We focus on US open-ended mutual funds actively investing in US equity. We use monthly mutual fund holdings obtained from Morningstar for the period of 2003 – 2006. The Morningstar data cover both mandatory SEC filings and voluntary disclosures. Mutual funds' monthly total net assets (TNA), net returns, and net flows also come from Morningstar database. For mutual funds with multiple share classes, we calculate the TNA-weighted average of total returns net of expense ratio across all share classes to derive the net return of the fund. Mutual fund net flows are already available at the fund level and aggregated across share classes. In order to merge Morningstar holdings to CRSP stock data, we use CUSIP identification number. Our sample consists of only those mutual funds with at least 70% of their holdings value identified as a common US equity and successfully merged with CRSP dataset. We exclude funds with less than 1 million dollars of total net assets (TNA) to reduce the incubation bias.

2.2 Variables Construction

In order to construct a measure of liquidity co-movement, we follow Karolyi et al. (2012). Our liquidity measure is a logarithmic transformation of the Amihud (2002) measure:

$$\mathrm{LIQ}_{i,d} = -\log\left(1 + \frac{|\mathrm{R}_{i,d}|}{\mathrm{P}_{i,d} \cdot \mathrm{VOL}_{i,d}}\right), \tag{1}$$

where $\mathrm{R}_{i,d}$ is stock i's return on day d, $\mathrm{P}_{i,d}$ is a daily closing price, and $\mathrm{VOL}_{i,d}$ is a daily trading volume. Our liquidity measure increases with liquidity, as we multiply the standard log-transformation of Amihud measure by -1.

With the purpose of capturing the general trading activity, we introduce daily turnover measure $\mathrm{TURN}_{i,d}$ of stock i on the day d:

$$\mathrm{TURN}_{i,d} = \log\left(1 + \frac{\mathrm{VOL}_{i,d}}{\mathrm{NSH}_{i,y}}\right) - \frac{1}{\mathrm{N}}\sum_{k=1}^{100} \log\left(1 + \frac{\mathrm{VOL}_{i,d-k}}{\mathrm{NSH}_{i,y}}\right), \tag{2}$$

where $\textsc{Nsh}_{i,y}$ is a number of shares outstanding at the beginning of the year and $\textsc{Vol}_{i,d}$ is the trading volume of stock i on day d. Following Karolyi et al. (2012), we use log-transformation of turnover and detrend the daily turnover with 100-day moving average to address a non-stationarity concern.[1] We also make sure, that the daily trading volume does not exceed the number of shares outstanding.

Next, we estimate the co-movement measure for both stock's liquidity and turnover. We follow the procedure suggested by Hameed et al. (2010), which consists of two steps. First, we isolate the shocks in a stock's liquidity and trading activity from their predictable components. Then, we use the innovations in liquidity and trading activity of an individual stock to measure their co-movement. Whereas $\textsc{Turn}_{i,d}$ is a flow variable, and thus innovation computation is not necessary, it is essential to insulate variation in liquidity surprises from the forecastable component of liquidity fluctuations. In the first step, we run monthly regressions of stock i's liquidity $\textsc{Liq}_{i,d}$ on its lagged value $\textsc{Liq}_{i,d-1}$ and day-of-the-week dummy variables D_τ:[2]

$$\textsc{Liq}_{i,t,d} = \alpha_{0,i,t}\textsc{Liq}_{i,t,d-1} + \sum_{\tau=1}^{5} \alpha_{\tau,i,t}\mathrm{D}_\tau + \omega^{\textsc{Liq}}_{i,t,d}. \tag{3}$$

For the daily turnover, we run the same filtering regression. Then, we use the residuals from equation (3) to estimate the liquidity (trading activity) co-movement measure, which is defined as the coefficient of determination $\mathrm{R}^2_{\textsc{Liq},i}$ ($\mathrm{R}^2_{\textsc{Turn},i}$) from the following regression:

$$\hat{\omega}^{\textsc{Liq}}_{i,t,d} = \beta_{0,i,t} + \sum_{j=-1}^{1} \beta_{2+j,i,t}\hat{\omega}^{\textsc{Liq}}_{m,t,d+j} + \varepsilon^{\textsc{Liq}}_{i,t,d}, \tag{4}$$

where $\hat{\omega}^{\textsc{Liq}}_{m,t,d+j}$ is a lead, lagged, and contemporaneous market value-weighted innovation in liquidity. The measures of commonality in stock's liquidity and trading activity have values between 0 and 1. In order to use them as LHS variables in our OLS regression

[1]See e.g., Campbell, Grossman, and Wang (1993), Lo and Wang (2000), Griffin, Nardari, and Stulz (2007) for a similar approach in estimating the daily turnover.

[2]Chordia, Sarkar, and Subrahmanyam (2005) provide evidence for a day-of-the-week effect in liquidity.

analysis, we perform logistic transformation of the R^2 measures, $\log(\mathrm{R}^2/((1-\mathrm{R}^2)))$.[3]

To define the short selling supply, we use data from the DataExplorers dataset that provides us with the value and quantity of shares available for lending. We define lending supply for stock i in month t as a fraction of the average value of shares available for lending to its market capitalization:

$$\textsc{Supply-Value}_{i,t} = \frac{\textsc{Average Value of Shares Supplied}_{i,t}}{\textsc{Market Capitalization}_{i,t}}. \tag{5}$$

We define $\textsc{Supply-Quantity}_{i,t}$ in an analogous manner, where average number of shares available for landing is divided by the number of shares outstanding. A big advantage of our data is that it directly differentiates between short selling demand and supply. While Cohen et al. (2007) use the shifts in loan fees and number of shorted shares to proxy for lending demand and supply, we do not need a unique identification strategy, because we observe both the value of shares available for lending and the value of shares on loan. However, for the robustness purposes we also use $\textsc{Utilisation}_{i,t}$ as a proxy for short selling supply, while controlling for short selling fees.

In the second part of our paper, we focus on mutual fund management of co-illiquidity. We therefore define variables at the fund level. In particular, we define $\textsc{Co-Illiq}_f$ ($\textsc{Liq}_f$) as a fund portfolio's value-weighted average co-illiquidity (liquidity). $\textsc{Net-Flow}_f$ is a fund's monthly percentage net-flows. $\textsc{Ret}_f$ ($\textsc{Log(TNA)}_f$) is total return net of expense ratio (log of total net assets) aggregated across share classes. We define $\textsc{Pilot}_b$ and $\textsc{Non-Pilot}_b$ as the fractions of a fund's benchmark portfolio invested in SHO Regulation pilot and non-pilot stocks. $\textsc{Pilot}_f$ and $\textsc{Non-Pilot}_f$ are the fractions of a fund's portfolio invested in SHO Regulation pilot and non-pilot stocks.

In order to study how a fund's exposure to fire sales and portfolio's fragility affect fund manager decision regarding portfolio's co-illiquidity, we define fund-level measures of fire sale pressure and fragility. We proceed as follows. First, we construct $\textsc{Fire Sales Shock}_{f,t}$ measure that captures an exogenous change in fund's exposure to

[3] Karolyi et al. (2012) and Morck, Yeung, and Yu (2000) also use logistic transformation of their commonality measures.

fire sales of other mutual funds. For every holding i that belongs to a fund's portfolio f at the beginning of month t, we define $\textsc{Fire Sales}_{f,i,t}$ as in Coval and Stafford (2007):

$$\textsc{Fire Sales}_{f,i,t} = \frac{\sum_{j=1}^{N} \left(\max(0, -\Delta\textsc{Hlgs}_{j,i,t} | \textsc{Net-Flow}_{j,t} < \text{P}(10\textsc{th}))\right)}{\textsc{Number of Shares Outstanding}_{i,t}}, \quad (6)$$

where $f \neq j$ and $\Delta\textsc{Hlgs}_{j,i,t}$ is a change in number of shares of stock i held by fund j within month t. $\textsc{Fire Sales}_{f,i,t}$ increases with a reduction in shares held by mutual funds experiencing extreme outflows ($\textsc{Net-Flow}_{j,t} < \text{P}(10\textsc{th})$). We define a fund specific fire sales shock as a change in fund's fire sales exposure keeping a fund's investment decision constant:

$$\textsc{Fire Sales Shock}_{f,t} = \sum_{i=1}^{\text{S}_{f,t-1}} \text{w}_{i,f,t-1} \cdot \left(\textsc{Fire Sales}_{f,i,t} - \textsc{Fire Sales}_{f,i,t-1}\right), \quad (7)$$

where $\text{w}_{i,f,t-1}$ is a fraction of fund's portfolio f invested in stock i in month $t-1$.[4]

Next, we proceed with the estimation of a stock price fragility measure suggested by Greenwood and Thesmar (2011). The authors argue that correlated liquidity shocks of asset owners may contribute to excess asset return co-movement and volatility. Therefore, for every stock i in month t, we compute:

$$\text{G}_{i,t} = \left(\frac{1}{\theta_{i,t}}\right)^2 \text{W}'_{i,t}\Omega_t\text{W}_{i,t}, \quad (8)$$

where $\text{W}'_{i,t} = (\text{w}_{i,1,t}, \ldots, \text{w}_{i,k,t})$ is the vector of weights of each mutual fund in security i, Ω_t is the variance-covariance matrix of funds' net-flows estimated over previous 12 months, and $\theta_{i,t}$ is stock's market capitalization used as a scaling factor. Given the evidence that the fragility measure predicts greater asset return volatility and co-movement, we expect mutual funds to adjust their portfolio's co-illiquidity in response to a shock to their holdings' fragility. We use the same approach as in case of fire sales and define a

[4]The fire sales shock is obtained from the shift-share analysis of a change in a portfolio's fragility as in Rzeźnik (2017). Shift-share analysis allows to decompose the change in a weighted mean into one part that is due to a change in the weights and another part that is due to the change in the underlying variable - see Dunn (1960).

fund-specific fragility shock in the following way:

$$\textsc{Fragility Shock}_{f,t} = \sum_{i=1}^{S_{f,t-1}} \mathrm{w}_{i,f,t-1} \left(\mathrm{G}_{i,t} - \mathrm{G}_{i,t-1} \right). \tag{9}$$

We also use an additional measure that captures fund's exposure to financial fragility – i.e., strategic complementarities. Chen et al. (2010) document that funds that hold less liquid assets are more exposed to the strategic complementarities in mutual fund withdrawals, because it is more costly to meet redemption obligations when portfolio is illiquid. They measure the degree of strategic complementarities with a composition of mutual fund's investors, arguing that large investors are more likely to absorb payoff externalities. We follow their approach and, for every holding i in fund's portfolio f in month t, we construct strategic complementarities measure $\textsc{Inst Own}_{f,i,t}$:

$$\textsc{Inst Own}_{f,i,t} = \sum_{j=1}^{N} \zeta_{j,i,t} \% \textsc{Inst Investors}_{j,t}, \tag{10}$$

where $\zeta_{j,i,t} = \frac{\textsc{Number of Shares}_{j,i,t}}{\sum_{j=1}^{N} \textsc{Number of Shares}_{j,i,t}}$ and $f \neq j$. $\%\textsc{Inst Investors}_{j,t}$ is a fraction of institutional investors in fund portfolio j in month t. Finally, we compute $\textsc{Inst Own Shock}_{f,t}$ that captures an exogenous change in fund f's exposure to strategic complementarities:

$$\textsc{Inst Own Shock}_{f,t} = \sum_{i=1}^{S_{f,t-1}} \mathrm{w}_{i,f,t-1} \left(\textsc{Inst Own}_{f,i,t} - \textsc{Inst Own}_{f,i,t-1} \right). \tag{11}$$

A negative value of $\textsc{Inst Own Shock}_{f,t}$ implies that the degree of strategic complementarities of fund f has on average increased over month t, as fund's holdings are now held by other funds with higher fraction of retail investors (who are less likely to internalize redemptions).

2.3 Summary Statistics

We report descriptive statistics in Tables 1 and 2. Table 1, Panel A contains descriptive statistics for our main variables. For each variable, we report the time-series averages of cross-sectional mean, median, standard deviation, minimum and maximum, and 5th, 25th, 75th and 95th percentiles in each month from January 2005 to August 2010. Due to the log-transformation of Amihud measure and its multiplication by minus one, our liquidity variable is negative and it increases with liquidity (i.e., smaller absolute values imply greater liquidity). On average 17% of the market capitalization value (shares outstanding) is available for lending with a standard deviation of 10.5% (10.9%). The mean (median) $\mathrm{R}^2_{\mathrm{LIQ}}$ is 19.2% (16.3%). The summary statistics of short selling utilisation suggest that on average 19% of shares available for lending are indeed lent with a mean fee of 60 bps.

Finally, Panel B reports pairwise correlation coefficients of the main variables. The short selling supply is negatively correlated with the commonality in liquidity (-0.040) and stock liquidity (-0.068), whereas positively with the co-movement in trading activity measure (0.037).

Table 2 shows the summary statistics of the mutual fund sample for two periods: "Before Announcement" (July 2003 – June 2004) and "After Implementation" (May 2005 – April 2006). We report number of unique funds (N), mean, median, and standard deviation for the main variables in both sub-periods. The mutual funds in our sample generate an average total return net of expenses of 1.68% (1.77%) in the control (treatment period). The median net-flow is 0.4% (-0.056%) before Reg SHO announcement (after Reg SHO implementation). Fund's portfolio co-illiquidity decreased from 19.7% to 18.8%. While the fraction of the pilot stocks in benchmark's portfolio decreased from 26.834% to 25.647%, the percentage of the pilot stocks in a fund's portfolio remained unchanged at around 24.5% – 24.3%.

3 Short-selling and Liquidity Comovement

3.1 Preliminary Analysis

We start with a simple Granger causality analysis in which we regress our proxy of liquidity co-movement on lending supply variables, their lags as well as a set of control variables. In particular, we estimate:

$$\begin{aligned} \mathrm{R}^2_{\text{LIQ},i,t} &= \gamma_0 + \gamma_1 \mathrm{R}^2_{\text{LIQ},i,t-1} + \gamma_2 \text{SUPPLY}_{i,t-1} + \gamma_3 \text{LIQ}_{i,t-1} + \gamma_4 \text{LN}(\text{MCAP}_{i,t-1}) \\ &\quad + \gamma_5 \text{RVOL}_{i,t-1} + \gamma_6 \mathrm{R}_{\text{TURN},i,t-1} + \mathrm{D}_s + \mathrm{D}_t + \epsilon_{i,t} \end{aligned} \tag{12}$$

and

$$\begin{aligned} \text{SUPPLY}_{i,t} &= \gamma_0 + \gamma_1 \text{SUPPLY}_{i,t-1} + \gamma_2 \mathrm{R}^2_{\text{LIQ},i,t-1} + \gamma_3 \text{LIQ}_{i,t-1} + \gamma_4 \text{LN}(\text{MCAP}_{i,t-1}) \\ &\quad + \gamma_5 \text{RVOL}_{i,t-1} + \gamma_6 \mathrm{R}_{\text{TURN},i,t-1} + \mathrm{D}_s + \mathrm{D}_t + \epsilon_{i,t} \end{aligned} \tag{13}$$

where $\mathrm{R}^2_{\text{LIQ},i,t}$ is a measure of liquidity co-movement. We use three different measures for short selling supply: $\text{SUPPLY-VALUE}_{i,t}$ is a fraction of the average value of shares available for lending to its market capitalization, $\text{SUPPLY-QUANTITY}_{i,t}$ denotes a ratio of shares available for lending to the number of shares outstanding, and $\text{UTILISATION}_{i,t}$ is defined as the value of assets on loan from lenders divided by the total lendable value. In order to isolate the supply shifts in $\text{UTILISATION}_{i,t}$, we control for value-weighted average short selling fee $\text{FEE}_{i,t}$. $\text{LIQ}_{i,t}$ is a stock's log-transformed Amihud (2002) measure, $\text{LN}(\text{MCAP}_{i,t})$ is the log of market capitalization, $\text{RVOL}_{i,t}$ is the volatility of the returns of stock i in month t and $\mathrm{R}^2_{\text{TURN},i,t}$ captures a stock i's trading activity in month t. We control for industry D_s and year-month D_t fixed effects. The standard errors are clustered at stock and year-month level.

We report the results in Table 3. The coefficient estimates from regression 12 are presented in columns (1) – (3) and the estimate of equation 13 in columns (4) – (6). The results display a strong negative correlation between different measures of lending supply and liquidity co-movement (columns (1) – (3)). The effect is economically relevant: if we focus on column (1) ((2)) one standard deviation increase in lending supply is related to a $0.015 \times \sigma$ ($0.01 \times \sigma$) reduction in $\mathrm{R}^2_{\mathrm{LIQ},i,t}$.[5] Further, an increase in utilisation ratio, while controlling for short selling fees, is also associated with lower co-movement in liquidity. In contrast, there is no effect of our liquidity co-movement variable on any lending supply measures. This provides evidence that while lending supply Granger-causes liquidity co-movement, liquidity co-movement does not Granger-cause short selling supply. These results are preliminarily showing that changes in lending supply have an impact on liquidity co-movement and the impact is economically comparable to the one of Karolyi et al. (2012).

3.2 The SHO Experiment

The preliminary evidence has showed that while short selling supply reduces liquidity co-movement, it remains unaffected by stock's co-illiquidity. We now explicitly address endogeneity issues – reverse causality – by focusing on a natural experiment – the "SHO experiment". On July 28 2004, the SEC announced a year-long pilot program eliminating uptick rule from approximately one-third of the largest stocks and published a list of 968 randomly assigned pilot firms. The main goal of the program was to evaluate the impact of unrestricted short selling on market volatility, price efficiency, and liquidity.[6] The pilot group constitutes a subset of stocks from Russell 3000 index listed on NYSE, Nasdaq, and AMEX. First, SEC assigned Russell 3000 stocks to their exchanges, and then ranked them (within a single exchange) by their average daily dollar volume over the previous year. Finally, SEC allocated every third stock to the pilot group. The Reg SHO pilot program was firstly implemented on May 2, 2005 and planned to end after 12 months on April 28, 2006.

Our analysis covers the period from July 2003 (12 months before the announcement

[5] The unreported standard deviations of the short selling supply-value, supply-quantity, and utilisation are 0.125, 0.124, and 0.214, respectively.

[6] See https://www.sec.gov/spotlight/shopilot.htm.

of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was first implemented). In our study, we eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. Figure 1 depicts the definition of control, treatment, and phasing period. We obtain the list of pilot (treated) stocks from the Securities Exchange Act Release No. 50104 and 69 FR 48032. The control group constitutes the remaining part of Russell 3000 index. In order to construct our final sample, we follow Diether et al. (2009) very closely. First, we make sure that our analysis is not confounded by index inclusion and exclusions. The reconstitution of Russell 3000 index always takes place in June, thus we keep 2,352 stocks that were part of Russell 3000 index in June 2003, 2004, and 2005. We exclude 19 stocks that were listed on Nasdaq's small cap market, 53 stocks that have their ticker or listing venue changed, and 111 companies experiencing a merger between July 2003 and April 2006.[7] We discard 109 non-ordinary common stocks – with share codes different from 10 or 11. With this filtering, from total 3,727 stocks that appeared on Russell 3000 index between June 2003 and June 2005, we arrive at 2,060 stocks in the final sample, of which 686 are pilot stocks and 1,374 are non-pilot stocks.

We start by providing a graphical view of the main results in Figures 2 and 3. In the spirit of the previous results, we concentrate on the unexplained component of liquidity co-movement ("co-illiquidity") and we see how it relates to the SHO experiment. In doing this, we explicitly control for the other variables that have been identified as relevant explanatory variables in the previous analysis such as lagged liquidity, lagged co-movement in trading activity, and lagged co-illiquidity measures. All of these seem to be important predictors of a stock's co-movement in liquidity. While the regression analysis allows us to directly control for other factors affecting the liquidity co-movement, in our graphical approach we need to be sure that the effect of the SHO regulation on the co-movement in liquidity is not contaminated by other confounding variables. Thus, we focus on the effect of the SHO experiment on the part of the liquidity co-movement that cannot be explained by other predictors.

[7]We delete securities with delisting CRSP code between 200 and 299 (mergers).

In particular, we calculate the cumulative abnormal co-illiquidity which captures the unexpected component of a stock's co-illiquidity ($R^2_{\mathrm{LIQ},i}$) for Reg SHO pilot stocks and non-pilot stocks, which have been part of Russell 3000 index in June 2003, 2004, and 2005.[8] We construct it by taking the residual from a stock and time fixed effect regression, where stock's monthly co-illiquidity measure $R^2_{\mathrm{LIQ},i}$ is regressed on its lagged value, lagged liquidity, return volatility, natural logarithm of market capitalization, and co-movement in trading activity. Then, we subtract from the residual co-illiquidity the average residual co-illiquidity over the pre-SHO announcement period (from July 2003 to June 2004). This variable proxies for the part of co-illiquidity unexplained by the standard explanatory variables as well as by the past. Finally, we aggregate the abnormal co-illiquidity across two sub-groups of stocks (pilot and non-pilot) and through time, which allows us to draw inferences for our event – the SHO Regulation implementation and visually analyze its dynamics over time.

In Figure 2, we plot the cumulative abnormal co-illiquidity for Reg SHO pilot stocks and non-pilot stocks, which have been part of Russell 3000 index in June 2003, 2004, and 2005. The dark-gray solid line with diamonds depicts the cumulative abnormal co-illiquidity of non-pilot stocks, while the light-gray line with circles plots the cumulative abnormal co-illiquidity of pilot stocks. We clearly see that as of July 2004 – i.e., as of the SHO announcement – co-illiquidity for the pilot stocks drops while no analogous drop is there for the control sample of the non-pilot stocks. In particular, the SHO experiment reduces the unexpected component of stock's co-illiquidity. This suggests that, in line with our working hypothesis, the SHO experiment did in fact reduce co-illiquidity. We provide additional evidence in Figure 3. Here, we follow Gormley and Matsa (2011) and plot the coefficients of the regression of the cumulative abnormal co-illiquidity on a dummy proxying for the SHO experiment. In particular, for each month between July 2003 and April 2006, we focus on the Russell 3000 index stocks and estimate the cross-sectional

[8] We base the construction of the cumulative abnormal co-illiquidity on Grullon, Michenaud, and Weston (2015) measure of the cumulative abnormal short interest.

regression:

$$\textsc{Cum Abn } \mathrm{R}^2_{\mathrm{LIQ},i} = \alpha_0 + \alpha_1 \textsc{Pilot} + \zeta_i \tag{14}$$

where $\textsc{Cum Abn } \mathrm{R}^2_{\mathrm{LIQ},i}$ is the cumulative abnormal co-illiquidity of a stock i. Pilot is a dummy variable equal to one if a stock belongs to Reg SHO pilot stocks, otherwise zero. We plot the α_1 coefficients estimates (black line) and provide the 90% confidence intervals adjusted for heteroscedasticity around them (gray dash-dotted lines). We see that as of April 2005, the coefficients are statistically different from zero and display a negative impact of the SHO experiment on the degree of stock co-illiquidity.

Comforted with these results, next we provide a formal analysis by estimating a dif-in-dif specification:

$$\begin{aligned} \overline{\mathrm{R}}^2_{\mathrm{LIQ},i,e+m} &= \gamma_0 + \gamma_1 \text{SHO } \textsc{Period} \\ &\quad + \gamma_2 \text{SHO } \textsc{Period} \times \textsc{Pilot Stock} + \mathrm{D}_i + \epsilon_{i,e+m}, \end{aligned} \tag{15}$$

where $\overline{\mathrm{R}}^2_{\mathrm{LIQ},i,e+m}$ is the stock's i average co-illiquidity measure calculated over m months before (after) the event e – SHO Regulation announcement (implementation). SHO Period is a dummy variable equal to one, when Reg SHO pilot program was implemented, otherwise zero. SHO Period × Pilot Stock is an interaction term and equals one if a stock is a pilot stock and Reg SHO has been implemented, otherwise zero. We control for stock fixed effects D_i and the standard errors are adjusted for heteroscedasticity. The sample includes stocks that have been part of Russell 3000 index in June 2003, 2004, and 2005. We exclude stocks that changed listing venue or ticker, were delisted, or were involved in a merge or an acquisition. We also discard Nasdaq small cap stocks and non-ordinary common stock with share codes different from 10 and 11. The pilot stock group is a subset of Russell 3000 stocks that was part of SHO Regulation pilot program. Our sample covers the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented.

We report the results in Table 4. We use two regression procedures in order to estimate the effect of SHO pilot program on liquidity co-movement: weighted least squares (WLS) regression in Panel A and ordinary least squares (OLS) regression in Panel B. While OLS procedure estimates the regression coefficient by minimizing the sample equally-weighted average of squared residuals, WLS weights each term in the residual sum of squares by the natural logarithm of market capitalization at the beginning of the control period. The OLS estimates of our model ignore the differences in market capitalization sizes. By using WLS procedure, we can address a potential concern that SHO pilot program might have a heterogeneous effect on liquidity co-movement depending on the stock's size.[9] Both in Panel A and B, we report the results of the estimates for one month, 2 months, ..., till 12 months ahead.

We focus on the interaction between SHO Period and Pilot Stock. The results show that liquidity co-movement drops for all the windows considered for the experiment. In particular, the drop ranges between 0.11 (Panel A) and 0.1 (Panel B) for two months ahead and 0.035 and 0.031 for 12 months ahead. This drop translates into 15% (13%) decrease in stock's average co-illiqudity over two months period (12 months period) and compares to the $0.015 \times \sigma$ of the previous estimates based on Granger causality.[10]

Next, as a robustness check, we estimate equation 15 but using monthly sampling as opposed to averaging observations before and after event dates. Our sample covers the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented).

We report the results in Table 5. As in the previous specification, we use weighted least squares (WLS) procedure in Panel A and B, while in Panel C and D, we choose ordinary least squares (OLS) procedure to estimate the regression coefficients. In both cases, we report the results of the estimates for one month, 2 months, ..., till 12 months ahead. The results are consistent with the previous ones and of a comparable economic

[9]See e.g., Grullon et al. (2015) who argue that SHO Pilot program had stronger effect on smaller and financially constrained firms, where short selling uptick rule seemed to be more binding.

[10]The unreported standard deviation of the average stock's co-illiquidity over 2 months (12 months) is 0.7338 (0.3089). The estimated effects come from WLS regression: $-0.11/0.7338 \approx 0.15$ and $0.035/0.3089 \approx 0.13$.

magnitude. If we focus on the interaction between SHO Period and Pilot Stock, we see that it is significant and negative, suggesting that liquidity co-movement drops for all the windows considered for the experiment. In particular, the drop ranges between 0.1 (in all panels) for two months ahead and 0.047 (in Panel A and B) and 0.044 (Panel C) for 11 months ahead. In Panel C and D, the regression coefficient for 12 months horizon is negative, yet insignificant.

In our analysis we focus on the impact of the increase in informed trading on co-illiquidity. One potential confounding effect is the change in contemporaneous change in liquidity. That is, we may be worried that SHO regulation affects liquidity of the stock as:

$$\text{Liq}_{i,t} = \beta_0 + \beta_1 \text{Reg SHO} + \epsilon_{i,t}. \tag{16}$$

We want to identify the effect of SHO regulation on stock's co-illiquidity, but we are worried that co-illiquidity is determined by stock's liquidity rather than by SHO regulation. If this is the case, when we estimate:

$$\text{Co-Illiq}_{i,t} = \gamma_0 + \gamma_1 \text{Reg SHO} + \gamma_2 \text{Liq}_{i,t} + \eta_{i,t}. \tag{17}$$

We expect γ_1 to be zero and γ_2 to be significantly different from zero. We can plug equation 16 into equation 17 and have:

$$\text{Co-Illiq}_{i,t} = \gamma_0 + \gamma_1 \text{Reg SHO} + \gamma_2(\beta_0 + \beta_1 \text{Reg SHO} + \epsilon_{i,t}) + \eta_{i,t} \tag{18}$$

or

$$\text{Co-Illiq}_{i,t} = \underbrace{\gamma_0 + \gamma_2\beta_1}_{\pi_0} + \underbrace{\gamma_1 + \gamma_2\beta_1}_{\pi_1} \text{Reg SHO} + \underbrace{\gamma_2\epsilon_{i,t} + \eta_{i,t}}_{\mu_{i,t}}. \tag{19}$$

If coefficient γ_1 from equation 17 is (more or less) the same as π_1 from equation 19, this implies that either γ_2 or β_1 are zero. This is what, we observe in our data, that when we run a regression without any controls the π_1 coefficient is not very different from coefficient γ_1 when we add contemporaneous control variables.

We therefore estimate our main specifications with and without the concurrent liquidity level as a control variable. We also perform a Hausman test (Hausman (1978)) in order to formally compare the SHO Period × Pilot Stock regression coefficients in the specification with (Panel B) and in the specification without concurrent stock liquidity (Panel A). We do it using both a WLS specification (Panel B) and a OLS specification (Panel D). We present the χ^2-statistics and p-values at the bottom of the Panel B and D. All the reported p-values fail to reject the null hypothesis that the estimated SHO Period×Pilot Stock coefficients in the regressions with and without concurrent stock liquidity are the same. The fact that the coefficients do not differ either statistically or economically supports our intuition about the direct channel between Reg SHO pilot program and stock's co-illiquidity.[11]

Overall, these results document that short selling impacts the degree of co-movement in liquidity among assets. We now consider mutual fund behavior and assess whether it may be a potential explanation for the reduction in co-illiquidity for the Pilot stocks.

4 Mutual Funds and Liquidity Co-movement Management

We now focus on mutual funds and investigate how they react to the potential increase in short selling activity. We start with an event-time analysis: for each fund we look at its portfolio before and after the event. More specifically, we concentrate on the period

[11]In the Appendix, Table A1 documents that the decrease in stock's co-illiquidity due to Reg SHO pilot program is mainly predominant in the subset of stocks with a high (above the median) pre-SHO mutual fund ownership. Both the magnitude and the significance of regression coefficients on SHO Period × Pilot Stock are greater in case of stocks with high mutual fund ownership compared to a subset of stocks with low fund ownership. This finding further supports our working hypothesis that the reduction is pilot stocks' co-illiquidity is due to a change in the ownership composition from investors who were holding it for liquidity reason (mutual funds) to investors who hold it either because they are more informed or simply because their longer investment horizon makes them less sensitive to short-term information driven swings.

from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented) and eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. We look at whether the funds with a high fraction of PILOT stocks in their portfolio – i.e., the ones subject to increase in trade by informed investors – do react to this exogenous shift in informed trading by adjusting their portfolios. More specifically, we estimate the following specification:

$$\begin{aligned}\Delta \mathrm{Y}_f &= \delta_0 + \delta_1 \%\textsc{Pilot}_{f,\textsc{June 2004}} + \delta_2 \overline{\textsc{Ret}}_{f,ctr} + \delta_3 \overline{\textsc{Net-Flow}}_{f,ctr} + \delta_4 \overline{\textsc{Liq}}_{f,ctr} \\ &\quad + \delta_5 \overline{\textsc{Log(TNA)}}_{f,ctr} + \delta_6 \overline{\%\textsc{Russell 3000}}_{f,ctr} + \eta_f, \end{aligned} \tag{20}$$

where $\Delta \mathrm{Y}_f$ is a change in the fraction of pilot stocks $\Delta\textsc{Pilot}_f$ or a change in the fund portfolio's value-weighted co-illiquidity $\Delta\textsc{Co-Illiq}_f$ both constructed based on the average fraction of PILOT stocks (degree of co-illiquidity) defined over 12 months before the announcement of SHO pilot program (from July 2003 to June 2004) and 12 months after the implementation (from May 2005 to April 2006). We use $\%\textsc{Vw-Pilot}_{f,\textsc{June 2004}}$ as a measure capturing a fund's exposure to SHO pilot program. $\%\textsc{Vw-Pilot}_{f,\textsc{June 2004}}$ is defined as a percentage of pilot stocks in fund f's portfolio at the end of June 2004 – the last month before Reg SHO announcement. The intuition behind this measure is the following: funds with a greater fraction of pilot stocks in their portfolio are more exposed to the SHO pilot program.

To control for other confounding effects, we also include a full set of control variables defined over the pre-treatment period (from July 2003 to June 2004): the average fund's return $\overline{\textsc{Ret}}_{f,ctr}$, the average fund's net-flows $\overline{\textsc{Net-Flow}}_{f,ctr}$, the average portfolio's liquidity $\overline{\textsc{Liq}}_{f,ctr}$, the average of natural logarithm of fund's total net assets $\overline{\textsc{Log(TNA)}}_{f,ctr}$, and the average fraction of fund f's portfolio invested in Russell 3000 index (i.e., pilot and non-pilot stocks) $\overline{\%\textsc{Russell 3000}}_{f,ctr}$.

We report the results in Table 6. Columns (1) – (3) show that, the higher the percentage of stocks that will then become part of the SHO experiment ("PILOT"), the higher the shift of the fund away from PILOT stocks. The effect is robust across specifications and is also economically relevant. Funds with one standard deviation higher amount of portfolio invested in pilot stocks decrease their investment in them by $0.256 \times \sigma(\Delta\text{PILOT}_f)$.[12] In other words, the funds who were holding PILOT stocks do rebalance away from them. This shift away from pilot stocks seems to be unrelated to other factors, e.g., the performance of pilot stocks relative to non-pilot ones. In the Appendix (Table A2), we document that SHO regulation did not have a significant impact on stock returns. It is important to notice that this result also supports our working intuition that the channel of action is through an increase in information asymmetry as opposed to a mere increase in liquidity. Indeed, the latter would have induced an even further loading on the PILOT stocks.

This intuition is further confirmed in columns (4) – (6). Here, we document that mutual funds with a higher fraction of stocks that will then become part of the SHO experiment respond stronger to SHO pilot program, by shifting their portfolio towards more co-illiquid stocks. The magnitude of the effect is comparable to the previous case, where fund's response to SHO pilot program is measured by the change in the average percentage of PILOT stocks in a fund's portfolio. One standard deviation increase in the fraction of fund's portfolio invested in pilot stocks at the end of June 2004 is associated with $0.266 \times \sigma(\Delta\text{CO-ILLIQ}_f)$ increase in the investment in more co-illiquid assets. It is worth noting, that the coefficient on $\%\text{VW-PILOT}_{f,\text{JUNE 2004}}$ does not change much across specification, which is expected in case of a randomized experiment like Reg SHO pilot program.

Till now, the analysis was based on event-time, as a robustness check, we also consider a generalized difference-in-difference specification with the continuous exposure to the treatment – a fraction of pilot stocks in a fund's benchmark portfolio $\%\text{PILOT}_{b,t-1}$. We

[12]The unreported standard deviation of a fraction of pilot stocks in a mutual fund portfolio at the end of June 2004 is 0.0695. The unreported mean and standard deviation of a change in the average fraction of pilot stocks in the fund's portfolio calculated over two 12-months sub-periods are -0.00073 and 0.05957. We compute the effect $(0.256 \times \sigma(\Delta\text{PILOT}_f))$ of one standard deviation increase in a fraction of PILOT stocks in a mutual fund portfolio on a change in the average fraction of the pilot stocks in the following way: $\frac{0.2190 \cdot 0.0695}{0.05957} \approx 0.256$.

estimate the monthly panel regression of the form:

$$\begin{aligned}\text{Co-Illiq}_{f,t} &= \rho_0 + \rho_1\%\text{Pilot}_{b,t-1} + \rho_3\%\text{Pilot}_{b,t-1} \times \text{SHO Period} \\ &+\rho_4\text{Net-Flow}_{f,t-1} + \rho_5\text{Log(TNA)}_{f,t-1} + \rho_6\text{Liq}_{f,t-1} \\ &+\rho_7\text{Ret}_{f,t-1} + \rho_8\%\text{Russell 3000}_{b,t-1} + \text{G}_f + \text{G}_t + \nu_{f,t} \qquad (21)\end{aligned}$$

where $\%\text{Pilot}_{b,t-1} \times \text{SHO Period}$ is an interaction term between percentage of pilot stocks in fund's benchmark and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. The rest of the variables are defined as before, but the sampling is monthly. In the panel set-up, we use the composition of the benchmark's portfolio instead of fund's portfolio itself as a measure of fund's exposure to the SHO Regulation treatment, because of three reasons. First, fund's portfolio composition is an outcome variable and is very likely to change in response to SHO Regulation. Second, fund's portfolio composition and co-illiquidity are determined by time-varying fund manager's strategy, attention, or skills, thus a regression with a fraction of pilot stocks in a fund's portfolio would suffer from a potential endogeneity concern (omitted variable). Finally, mutual funds are tied to their benchmarks by e.g., tracking error. But, they also may choose to deviate from the benchmarks because of profitable investment ideas. Thus, the composition of benchmark's portfolio constitutes a good proxy for fund's exposure to SHO Regulation and at the same time is not influenced by the action of a single mutual fund.

We report the results in Table 7. They confirm the previous ones. If we focus on the interaction between $\%\text{Pilot}_{b,t-1}$ and SHO Period, we see that funds belonging to benchmarks with a higher representation of stocks that will then become part of the SHO experiment tend to shift more their investments towards co-illiquid assets. Funds assigned to a benchmark with a one standard deviation higher percentage of pilot stocks in the previous month increase their investment in more co-illiquid assets by $0.067 \times \sigma(\text{R}^2_{\text{LIQ},f})$.[13]

[13] The unreported standard deviation of portfolio's co-illiquidity (the fraction of PILOT stocks in benchmark portfolio) is 0.2196 (0.0490). We calculate the effect in the following way: $\frac{0.3039 \cdot 0.0490}{0.2196} \approx 0.067$.

These results support our working hypothesis. The next question is whether the behavior of the funds is linked to its "sensitivity to the market". This sensitivity may be related to the need to meet redemptions ("fire sales") as well as to the fund's exposure to the liquidity shocks and interaction with other mutual funds ("financial fragility"). We therefore construct proxies of fire-sales shocks as per Coval and Stafford (2007) and proxies of financial fragility shocks as per Greenwood and Thesmar (2011) and Chen et al. (2010). We refer to the data section 2.2 for a detail description of the variable definition. We construct a shock variable via a shift-share analysis.

We decompose a change in fund's fire sales exposure into two parts: shifts due to an active modification of portfolio composition – the active part and shifts due to a change in the co-illiquidity of the holdings keeping portfolio composition constant – the shock (passive) part. The second component is our fire sales shock measure, because it isolates the unexpected and exogenous component of the change in fund's fire sales exposure.[14] Then, we look at how shocks to fire sales, the financial fragility, or the strategic complementarities exposure induce a lower rebalancing away from co-illiquid stocks during the SHO period. More specifically, we estimate the following monthly panel regression:

$$\begin{aligned}\Delta\text{Co-Illiq}_{f,t} \;=\;& \theta_0 + \theta_1 \mathrm{X}_{f,t-1} + \theta_2 \mathrm{X}_{f,t-1} \times \text{SHO Period} + \theta_3 \text{Net-Flow}_{f,t-1} \\ & + \theta_4 \text{Log}(\text{TNA})_{f,t-1} + \theta_5 \text{Ret}_{f,t-1} + \theta_6 \text{Liq}_{f,t-1} + \mathrm{G}_f + \mathrm{G}_t + \nu_{f,t} \qquad (22)\end{aligned}$$

where $\mathrm{X}_{f,t-1}$ is the variable that represents the shocks to either fire sales, or financial fragility, or payoff complementarities. Our focus variables are Fire Sales Shock$_{f,t-1}$ $\times$ SHO Period (Panel A) is – i.e., the interaction between a shock to fund's fire sales exposure and Reg SHO pilot program indicator variable that equals one if the SHO Regulation has been implemented and otherwise zero, Fragility Shock$_{f,t-1}$ $\times$ SHO Period (Panel B) – i.e., the interaction between a shock to fund's portfolio fragility and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been imple-

[14]The fire sales, financial fragility, and strategic complementarities shocks are defined in equations 7, 9, and 11, respectively.

mented and otherwise zero and $\text{Inst Own Shock}_{f,t-1} \times \text{SHO Period}$ (Panel C) – i.e., the interaction between a shock to fund's strategic complementarities exposure and Reg SHO time dummy variable.

We report the results in Table 8. We find that while shocks to fund's fire sale, financial fragility, and strategic complementarities exposure reduce the investment in co-illiquid stocks, this effect is attenuated during the SHO experiment. The interaction between either fire sales or fragility shock and the SHO experiment is positive and significant. The effect is also economically relevant. In particular, one standard deviation higher shock to fire sales (financial fragility) reduces the investment toward more co-illiquidity stocks by on average between $0.044\times$ and $0.048 \times \sigma(\Delta\text{Co-Illiq}_{f,t})$ ($0.076\times$ and $0.081 \times \sigma(\Delta\text{Co-Illiq}_{f,t})$). However, this effect is reduced by between $0.058\times$ and $0.063 \times \sigma(\Delta\text{Co-Illiq}_{f,t})$ ($0.113\times$ and $0.115 \times \sigma(\Delta\text{Co-Illiq}_{f,t})$) during the SHO experiment.[15] In Panel C, we report a positive $\text{Inst Own Shock}_{f,t}$ coefficient, which implies that an increase in strategic complementarities exposure (a negative value of $\text{Inst Own Shock}_{f,t}$) is associated with a shift towards less co-illiquid assets. The interaction term is negative and significant, implying that the shift towards less co-illiquid assets is weaker when SHO Regulation is implemented. A one standard deviation increase in the shock to strategic complementarities exposure decreases the investment in more co-illiquid asset by on average $0.057 \times \sigma(\Delta\text{Co-Illiq}_{f,t})$. This effect declines by $0.070 \times \sigma(\Delta\text{Co-Illiq}_{f,t})$, when SHO experiment is implemented. In other words, the reduction in co-illiquidity due to the SHO experiment reduces the needs to rebalance towards less co-illiquid stocks, especially for the funds more subject to the market – i.e., the ones with a greater exposure to fire sales, fragility shocks, and strategic complementarities.

These results clearly show that mutual funds, far from appreciating the further reduc-

[15] The unreported standard deviation of the change in portfolio's co-illiquidity, the shock to the fire sales exposure, financial fragility, and strategic complementarities is 0.3458, 0.0164, 0.1177, and 0.9245. We calculate the main effect of the fire sales shock on the portfolio's co-illiquidity as: $\frac{1.0071 \cdot 0.0164}{0.3458} \approx 0.048$, the effect of financial fragility shock: $\frac{0.2385 \cdot 0.1177}{0.3458} \approx 0.081$, and the effect of strategic complementarities shock: $\frac{0.0214 \cdot 0.9245}{0.3458} \approx 0.057$. We compute the interaction terms in the following way: $\frac{1.3351 \cdot 0.0164}{0.3458} \approx 0.063$ (for the fire sales), $\frac{0.3388 \cdot 0.1177}{0.3458} \approx 0.115$ (for the financial fragility), and $\frac{0.026 \cdot 0.9245}{0.3458} \approx 0.070$.

tion in co-illiquidity of the PILOT stocks, they rebalance away from them and are willing to move to even more co-illiquid stocks. The desire to manage co-illiquidity – stronger in funds more subject to financial fire sales and fragility shocks – is attenuated by the event that tilts the information structure in the market. The net effect is an overall higher loading on co-illiquidity for the affected funds. That is, fund managers do not just exploit the additional leeway provided by the higher co-illiquidity of their portfolio to move to stocks that were too "risky" for them in terms of co-illiquidity, preserving the same overall degree of portfolio co-illiquidity, but increase the overall degree of portfolio co-illiquidity in order to move away from informed-trading affected stocks.

Moreover, these results do also provide a first direct evidence of how mutual funds manage co-illiquidity. The question of whether fund managers manage co-illiquidity optimally reacting to co-movement in liquidity is not easy to address as on the one hand co-movement in liquidity drives the behavior of the managers, while, on the other hand, the behavior of the managers will directly impact the degree of co-movement in liquidity of the assets themselves. Indeed, most of the determinants that have been advocated to explain co-movement in liquidity – e.g., inventory risk and asymmetric information (Chordia et al. (2000)), funding liquidity risk (Brunnermeier and Pedersen (2009)), value of collateral (Coughenour and Saad (2004)), capital supply (Hameed et al. (2010)), and demand-side shocks (Karolyi et al. (2012)) – are endogenously determined in equilibrium and therefore impacted by asset managers' behavior. For example, changes in the value of the collateral may also affect the ability of the managers to fund themselves and therefore impact both their behavior and the degree of co-movement in liquidity of the assets. This endogeneity has until now plagued the analysis and made it very difficult to provide a clear identification. These results provide a first direct evidence on this issue.

5 Robustness

In the previous section, we document that mutual funds increase the co-illiquidity of their portfolio if they had held more pilot stocks just before SHO Regulation pilot stock list was published and when they belonged to a benchmark with a higher fraction of pilot stocks. Whereas the percentage of pilot stocks at the end of June 2004 allows us to perform event study analysis, it might be noisy. We only look at a fund's (unaware) decision to select a subset of Russell 3000 stocks, which turned out to be pilot stocks, in one time point: at the end of June 2004. While the fraction of pilot stocks in the portfolio is likely to be a good proxy for a fund's regular asset allocation decision, there still might be some funds, whose average behavior may very much differ from this snapshot at the end of June 2004. This, in turn, would introduce noise into our analysis. Also, in the previous section, we proxy for the portfolio allocation of the fund in pilot stocks with the lagged percentage of pilot stocks in a fund's benchmark. Therefore, as a robustness check, we also use the actual average fraction of pilot stock in a fund's portfolio and its average diversification over the control period (July 2003 – June 2004). We estimate:

$$\begin{aligned} \text{Co-Illiq}_{f,t} &= \rho_0 + \rho_1 \overline{\%\text{Pilot}}_{f,ctr} \times \text{SHO Period} + \rho_2 \text{Net-Flow}_{f,t-1} \\ &\quad + \rho_3 \text{Log(TNA)}_{f,t-1} + \rho_4 \text{Ret}_{f,t-1} + \rho_5 \text{Liq}_{f,t-1} + \text{G}_f + \text{G}_t + \nu_{f,t} \end{aligned} \tag{23}$$

$\text{Co-Illiq}_{f,t}$ is the value-weighted co-illiquidity of fund f's portfolio in month t. In columns (1) – (3), $\%\text{Vw-Pilot}_{f,ctr} \times \text{SHO Period}$ is an interaction term between an average percentage of pilot stocks in a fund f's portfolio over the control period (from July 2003 to June 2004) and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. However, the fraction of pilot stocks in a fund's portfolio captures only one dimension of portfolio's co-illiquidity, namely stock's co-illiquidity. According to Pástor, Stambaugh, and Taylor (2017), portfolio's diversification is an important factor determining portfolio's liquidity. Consequently, we use a second measure $\%\text{Ew-Pilot}_{f,ctr}$ that captures the average degree of diversification within a subset of fund's portfolio comprising only pilot stocks. In columns (4) – (6), $\%\text{Ew-Pilot}_{f,ctr} \times \text{SHO Period}$ is an interaction term between an average diversification of pilot stocks in a fund's portfolio over the control period (from July 2003 to June 2004) and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. We denote the lagged fund's return by $\text{Ret}_{f,t-1}$, the fund's net-flows by $\text{Net-Flow}_{f,t-1}$, the portfolio's liquidity by $\text{Liq}_{f,t-1}$, and the natural logarithm of fund's total net assets by $\text{Log(TNA)}_{f,t-1}$. We control for fund G_f and year-month G_t fixed effects. t-statistics are reported in the brackets. Standard errors are clustered at a fund level.

We report the results in Table 9. They confirm the previous ones. If we focus on the interaction between $\%\text{Vw-Pilot}_{f,ctr}$ and SHO Period ($\%\text{Ew-Pilot}_{f,ctr}$ and SHO Period), we see that the funds with a higher percentage of stocks (more diversified portfolio of stocks) that will then become part of the SHO pilot program shift more their investment towards co-illiquid assets. A one standard deviation increase in the value-weighted (equally-weighted) average fraction of the fund's portfolio invested in pilot stocks results in the fund's shift towards more co-illiquid assets by $0.06 \times \sigma(\text{Co-Illiq}_{f,t})$ $(0.07 \times \sigma(\text{Co-Illiq}_{f,t}))$ during SHO Regulation period.[16]

Conclusions

We study the link between informed trading and co-illiquidity. We argue that an increase in informed trading coincides with greater informational asymmetry, which in turn reduces the demand for the stock by the relatively less informed investors and, critically, by the ones among them who are holding the stock for liquidity reasons. This changes the composition of the stock ownership, from investors who were holding it for liquidity reason – likely to be more exposed to fire sales risk – to investors who hold it either because they are more informed or simply because their longer investment horizon makes them less sensitive to short-term information driven swings. This shift in ownership reduces the sensitivity of the stock to co-illiquidity risk and makes the stock less co-illiquid.

We bring this hypothesis to the data by focusing on a specific class of informed investors – the short sellers – and on a natural experiment that exogenously changes their

[16]The unreported standard deviation of the average fraction of Pilot stocks in the fund's portfolio (average diversification of Pilot part of fund's portfolio) is 0.0624 (0.0591).

ability to trade: the SHO experiment. We document that the stocks in which the ability of short sellers to trade increased experienced a drop in co-illiquidity. The mutual funds rebalanced away from the affected stocks and toward even more co-illiquid stocks. Then, we focus on two standard proxies for the problems related to strategic complementarities: the need to meet redemptions ("fire sales") as well as the interaction with other mutual funds ("financial fragility"). We document that while shocks to fire sales and financial fragility reduce the investment in co-illiquid stocks, the effect is attenuated for mutual funds exposed to an increase in informed trading.

Overall, these results suggest that mutual funds cope with the drawbacks related to the open-end structure and the issues induced by strategic complementarities by managing co-illiquidity. However, changes in the informational structure that put them at an informational disadvantage constrain this co-illiquidity management. This will make these stocks less fragile and less co-illiquid vis-à-vis the other stocks towards which the mutual funds do now rebalance.

Our results have important policy implications as they suggest another channel by which short selling, far from destabilizing the market, does in fact help in stabilizing it reducing the exposure to co-movement in liquidity: one of the major problems during the latest global financial crisis.

References

Aitken, M. J., A. Frino, M. S. McCorry, and P. Swan (1998). Short Sales Are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange. *Journal of Finance 53*(6), 2205–2223.

Alexander, G. J. and M. A. Peterson (2008). The effect of price tests on trader behavior and market quality: An analysis of Reg SHO. *Journal of Financial Markets 11*(1), 84–111.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Asquith, P. and L. K. Meulbroek (1995). An empirical investigation of short interest. *Working Paper*, 1–27.

Asquith, P., P. A. Pathak, and J. R. Ritter (2005). Short interest, institutional ownership, and stock returns. *Journal of Financial Economics 78*(2), 243 –276.

Bai, Y., E. C. Chang, and J. Wang (2006). Asset Prices Under Short-Sale Constraints. *Working Paper, MIT Sloan School of Management*, 1–42.

Beber, A. and M. Pagano (2013). Short-Selling Bans Around the World: Evidence from the 2007-09 Crisis. *Journal of Finance 68*(1), 343–381.

Boehmer, E., Z. R. Huszar, and B. D. Jordan (2010). The good news in short interest. *Journal of Financial Economics 96*(1), 80–97.

Boehmer, E., C. M. Jones, and X. Zhang (2008). Unshackling short sellers: The repeal of the uptick rule. *Working Paper*, 1–37.

Boehmer, E. and J. J. Wu (2013). Short selling and the price discovery process. *Review of Financial Studies 26*(2), 287–322.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Campbell, J. Y., S. J. Grossman, and J. Wang (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics 108*, 905–939.

Cella, C., A. Ellul, and M. Giannetti (2013). Investors' horizons and the amplification of market shocks. *Review of Financial Studies 26*(7), 1607–1648.

Chen, Q., I. Goldstein, and W. Jiang (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics 97*(2), 239–262.

Chordia, T., R. Roll, and A. Subrahmanyam (2000). Commonality in liquidity. *Journal of Financial Economics 56*(1), 3–28.

Chordia, T., A. Sarkar, and A. Subrahmanyam (2005). An empirical analysis of stock and bond market liquidity. *Review of Financial Studies 18*(1), 85–129.

Cohen, L., K. B. Diether, and C. J. Malloy (2007). Supply and Demand Shifts in the Securities Lending Market. *Journal of Finance 62*(5), 2061–2096.

Coughenour, J. F. and M. M. Saad (2004). Common market makers and commonality in liquidity. *Journal of Financial Economics 73*(1), 37–69.

Coval, J. D. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*(2), 479–512.

Diamond, D. W. and R. E. Verrecchia (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics 18*, 277–311.

Diether, K. B., K.-h. Lee, and I. M. Werner (2009). It's SHO Time! Short-Sale Price-Tests and Market Quality. *Journal of Finance 64*(1), 1–54.

Duffie, D., N. Gârleanu, and L. H. Pedersen (2002). Securities lending, shorting, and pricing. *Journal of Financial Economics 66*(2-3), 307–339.

Dunn, E. S. (1960). A statistical and analytical technique for regional analysis. *Regional Science Association 6*, 97–112.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics 105*(2), 260–278.

Giannetti, M. and B. Kahraman (2017). Open-End Organizational Structures and Limits to Arbitrage. *Review of Financial Studies 31*(2), 773 –810.

Goldstein, I., H. Jiang, and D. T. Ng (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics 126*(3), 592 –613.

Gormley, T. A. and D. A. Matsa (2011). Growing Out of Trouble? Corporate Responses to Liability Risk. *Review of Financial Studies 24*(8), 2781–2821.

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

Griffin, J. M., F. Nardari, and R. M. Stulz (2007). Do investors trade more when stocks have performed well? Evidence from 46 countries. *Review of Financial Studies 20*(3), 905–951.

Grullon, G., S. Michenaud, and J. P. Weston (2015). The real effects of short-selling constraints. *Review of Financial Studies 28*(6), 1737–1767.

Hameed, A., W. Kang, and S. Viswanathan (2010). Stock market decline and liquidity. *Journal of Finance 65*(1), 257–293.

Hausman, J. (1978). Specification Tests in Econometrics. *Econometrica 46*(6), 1251–1271.

Jotikasthira, C., C. Lundblad, and T. Ramadorai (2012). Asset Fire Sales and Purchases and the International Transmission of Funding Shocks. *Journal of Finance 67*(6), 2015–2050.

Kacperczyk, M. and A. Seru (2007). Fund Manager Use of Public Information: New Evidence on Managerial Skills. *Journal of Finance 62*(2), 485 –528.

Kamara, A., X. Lou, and R. Sadka (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics 89*(3), 444–466.

Karolyi, G. A., K. H. Lee, and M. A. Van Dijk (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics 105*(1), 82–112.

Kim, O. and R. E. Verrecchia (1994). Market liquidity and volume around the earnings announcements. *Journal of Accounting and Economics* (17), 41–64.

Koch, A., S. Ruenzi, and L. Starks (2016). Commonality in liquidity: A demand-side explanation. *Review of Financial Studies 29*(8), 1943–1974.

Kolasinski, A. C., A. Reed, and J. R. Thornock (2013). Can Short Restrictions Actually Increase Informed Short Selling? *Financial Management 42*(1), 155–181.

Liu, X. and A. S. Mello (2011). The fragile capital structure of hedge funds and the limits to arbitrage. *Journal of Financial Economics 102*(3), 491–506.

Lo, A. W. and J. W. Wang (2000). Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory. *Review of Financial Studies 13*(7625), 257–300.

Miller, E. M. (1977). Risk, Uncertainty, and Divergence of Opinion. *Journal of Finance 32*(4), 1151–1168.

Morck, R., B. Yeung, and W. Yu (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics 58*(1-2), 215–260.

Morris, S. and H. S. Shin (2004). Liquidity Black Holes. *Review of Finance 8*, 1–18.

Pástor, u., R. F. Stambaugh, and L. A. Taylor (2017). Do Funds Make More When They Trade More? *Journal of Finance*.

Rzeźnik, A. (2017). Mutual fund flight-to-liquidity. *Working Paper*, 1–48.

Saffi, P. A. C. and K. Sigurdsson (2011). Price Efficiency and Short Selling. *Review of Financial Studies 24*(3), 821–852.

SEC (2010). Concept release on equity market structure. Release No. 34-61358; File No. S7-02-10. pp. 1–74.

Senchack, A. J. and L. T. Starks (1993). Short-Sale Restrictions and Market Reaction to Short-Interest Announcements. *Journal of Financial and Quantitative Analysis 28*(2), 177–194.

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

Stein, J. C. (2005). Why Are Most Funds Open-End? Competition and the Limits of Arbitrage. *Quarterly Journal of Economics 120*(1), 247 –272.

Zeng, Y. (2017). A Dynamic Theory of Mutual Fund Runs and Liquidity Management. *Foster School of Business Working Paper*, 1 –75.

Figure 1: Reg SHO pilot program timeline.

This figure shows the time period of the SHO analysis. We mark the main events of Reg SHO pilot program: the announcement on July 28, 2004 and the implementation on May 2, 2005. Our sample spans the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005 (the shaded area), when Reg SHO pilot program was announced but yet not implemented. We call the period from July 2003 to June 2004 (May 2005 to April 2006) the control (treatment) period.

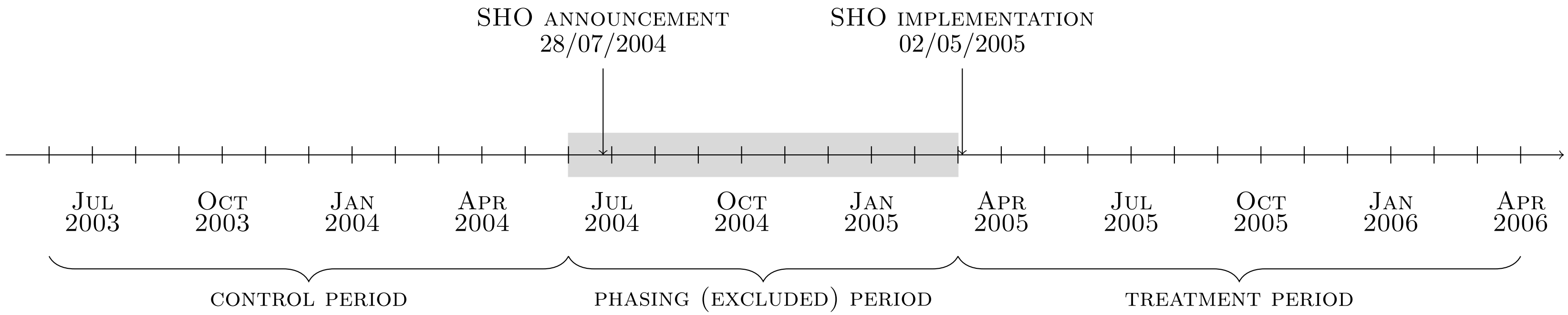

Figure 2: Cumulative abnormal co-illiquidity.

This figure shows the cumulative abnormal co-illiquidity for Reg SHO pilot stocks and non-pilot stocks, which have been part of Russell 3000 index in June 2003, 2004, and 2005. The abnormal co-illiquidity captures the unexpected component of stock's co-illiquidity. We create it by taking the residual from a stock and time fixed effect regression, where the monthly stock's co-illiquidity is regressed on its lagged value, lagged liquidity, return volatility, natural logarithm of market capitalization, and co-movement in trading activity. Then, we subtract from the residual co-illiquidity the average residual co-illiquidity over the pre-SHO announcement period (from July 2003 to June 2004). In order to subtract the average co-illiquidity over the pre-SHO announcement period, we require non-missing observation over the entire control period. The dark-gray solid line with diamonds depicts the cumulative abnormal co-illiquidity of non-pilot stocks, while the light-gray line with circles plots the cumulative abnormal co-illiquidity of pilot stocks.

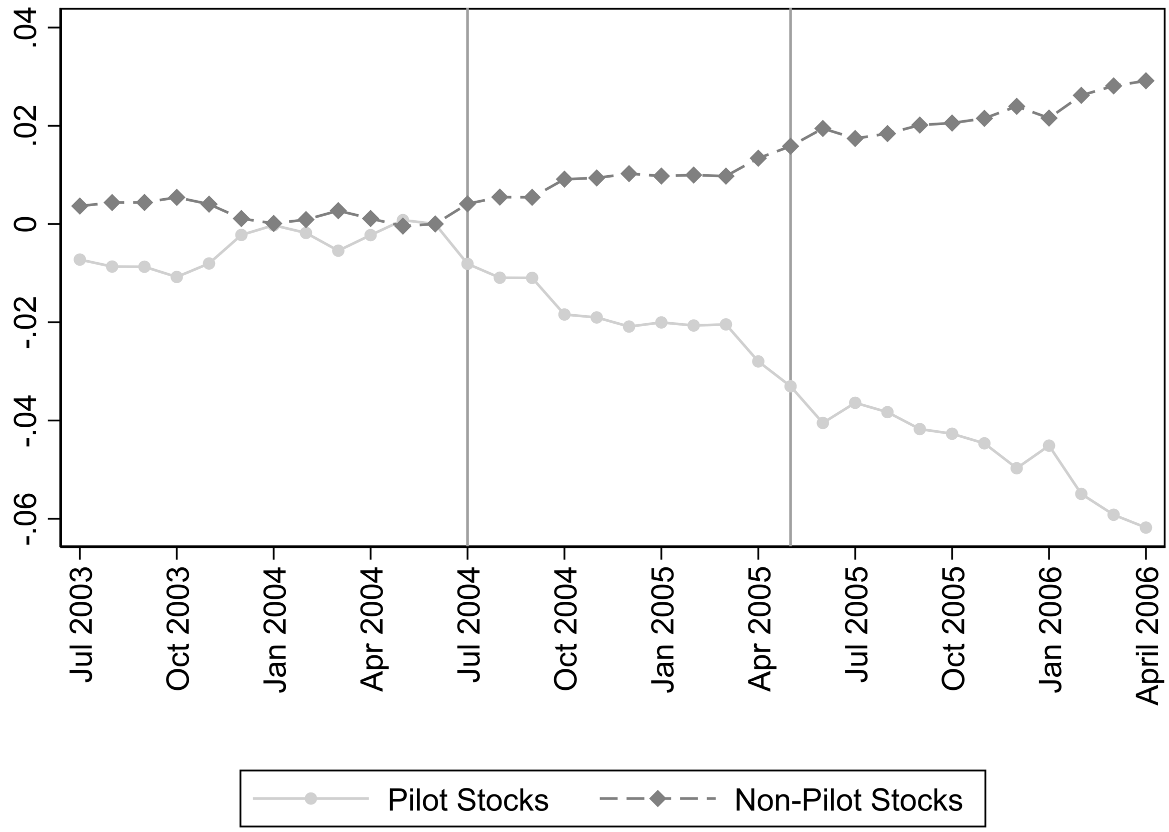

Figure 3: Commonality in liquidity impacts of Reg SHO pilot program.
This figure plots α_1 coefficients from the cross-sectional regression of the form:

$$\text{Cum Abn R}^2_{\text{LIQ},i} = \alpha_0 + \alpha_1 \text{Pilot} + \zeta_i,$$

ran for each month between July 2003 and April 2006 (overall 34 regression) only for Russell 3000 index stocks. Cum Abn $R^2_{\text{LIQ},i}$ is the cumulative abnormal co-illiquidity of a stock i. The abnormal co-illiquidity captures the unexpected component of stock's co-illiquidity. We create it by taking the residual from a stock and time fixed effect regression, where the monthly stock's co-illiquidity is regressed on its lagged value, lagged liquidity, return volatility, natural logarithm of market capitalization, and co-movement in trading activity. Then, we subtract from the residual co-illiquidity the average residual co-illiquidity over the pre-SHO announcement period (from July 2003 to June 2004). In order to subtract the average co-illiquidity over the pre-SHO announcement period, we require non-missing observation over the entire control period. Pilot is a dummy variable equal to one if a stock belongs to Reg SHO pilot stocks, otherwise zero. The black solid line depicts α_1 coefficients estimates. The gray dash-dotted lines represent 90% confidence intervals adjusted for heteroskedasticity.

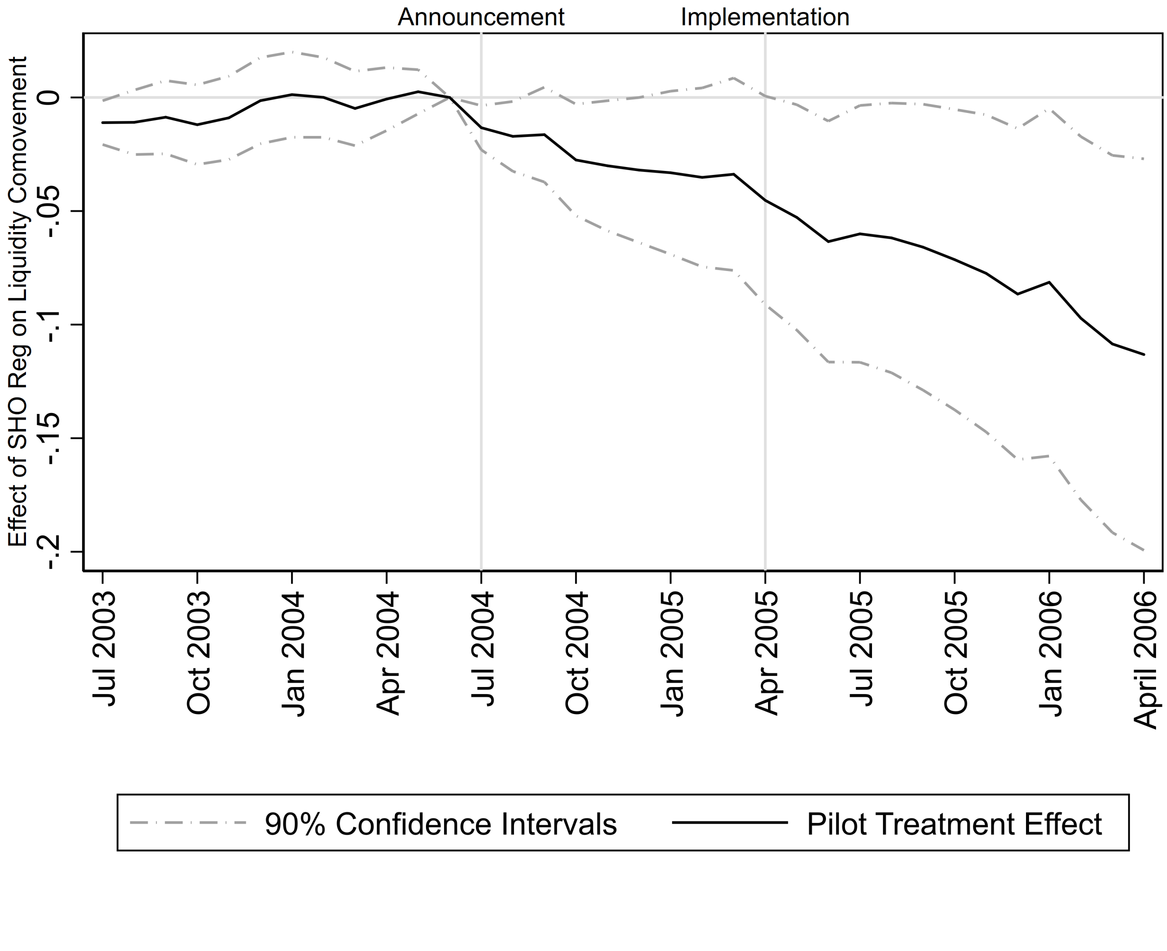

Table 1: Descriptive statistics – stock level.

Panel A shows summary statistics of the main variables used in the paper. R^2_{LIQ} is the commonality in liquidity measure constructed in a two-step procedure as in Karolyi et al. (2012). SUPPLY-VALUE (%) is a measure of short selling supply and it is defined as a fraction of a stock's average value of shares available for lending relative to its market capitalization. SUPPLY-QUANTITY (%) is an alternative measure of short selling supply and is constructed as a ratio of the average number of shares available for lending to the number of shares outstanding. UTILISATION (%) is a proxy measure for short selling supply and is defined as the value of assets on loan from lenders divided by the total lendable value. LIQ is a stock's log transformed Amihud (2002) measure. ln(MCAP) is a natural logarithm of a stock's market capitalization. R^2_{TURN} measures the commonality in trading activity and is computed in the same way as R^2_{LIQ} via the two-step procedure. FEE is a value-weighted average short selling fee. For each variable, we calculate cross-sectional mean, median, standard deviation, minimum and maximum, 5th, 25th, 75th, and 95th percentile in each month from January 2005 to August 2010. The reported values are computed from the time-series of 68 monthly cross-sectional statistics. Panel B shows pairwise correlation coefficients of the main variables computed from the time-series of cross-sectional averages for each variable.

Panel A: Descriptive statistics of main variables

	Mean	Median	St. Dev.	Min	P 5%	P 25%	P 75%	P 95%	Max
R^2_{LIQ}	0.1920	0.16282	0.1385	0.0008	0.0259	0.0870	0.2662	0.4582	0.9409
Supply-Value(%)	17.0075	17.32785	10.4859	0.0000	0.8172	8.1412	24.6907	34.1532	55.5646
Supply-Quantity(%)	16.9884	17.35631	10.8992	0.0000	0.8152	8.1578	24.6746	33.9312	84.3080
Utilisation(%)	19.3270	12.03673	20.7930	0.0000	0.1362	3.2284	28.6851	64.5074	98.4869
Liq	-0.0011	-0.00001	0.0056	-0.0523	-0.0043	-0.0001	-0.0000	-0.0000	-0.0000
ln(Mcap)	13.2033	13.08019	1.8371	8.4172	10.3907	11.8901	14.3807	16.5185	19.7780
R^2_{TURN}	0.2492	0.22246	0.1621	0.0009	0.0357	0.1200	0.3532	0.5519	0.9351
Fee (bps)	60.1163	12.59754	192.6173	-31.3669	5.3479	9.8282	23.5191	283.1580	3321.3455

Panel B: Pairwise correlations of the main variables

Variables	R^2_{LIQ}	Supply-Value(%)	Supply-Quantity(%)	Utilisation (%)	Liq	ln(Mcap)	R^2_{TURN}	Fee (bps)
R^2_{LIQ}	1.000							
Supply-Value(%)	-0.040	1.000						
Supply-Quantity(%)	-0.038	0.933	1.000					
Utilisation(%)	-0.018	0.091	0.089	1.000				
Liq	-0.068	0.131	0.124	0.080	1.000			
ln(Mcap)	-0.044	0.424	0.399	0.057	0.190	1.000		
R^2_{TURN}	0.037	0.107	0.111	0.004	-0.002	0.146	1.000	
Fee	0.011	-0.184	-0.175	0.365	-0.026	-0.168	-0.033	1.000

Table 2: Descriptive statistics – mutual fund level.

This table reports summary statistics of the mutual fund sample for two periods: "Before Announcement" (July 2003 - June 2004) and "After Implementation" (May 2005 - April 2006). Because of the focus of the paper, we select US open-ended mutual funds actively investing in US equity. The information on fund's monthly holdings, net-flows, returns, total net assets, and benchmark is obtained from the Morningstar survivorship-bias-free mutual fund database. CO-ILLIQ$_f$ (LIQ$_f$) is a portfolio's value-weighted average co-illiquidity (liquidity). NET-FLOW$_f$(%) is a fund's monthly percentage net-flows. RET$_f$ (LOG(TNA)$_f$) is total return net of expense ratio (log of total net assets) aggregated across share classes. PILOT$_b$ and NON-PILOT$_b$ are the fractions of a fund's benchmark portfolio invested in SHO Regulation pilot and non-pilot stocks. PILOT$_f$ and NON-PILOT$_f$ are the fractions of a fund's portfolio invested in SHO Regulation pilot and non-pilot stocks. FIRE SALES SHOCK$_f$ is the unexpected change in a fund's exposure to fire sales and is defined in equation 7. We use Coval and Stafford (2007) measure of fire sales. FRAGILITY SHOCK$_f$ is a change in portfolio's fragility due to a market wide change in stock's fragility and is defined in equation 9. INST OWN SHOCK$_f$ is a shock to fund's exposure to strategic complementarities and is defined in equation 11. We report number of unique funds N, mean, median, and standard deviation for the main variables in both sub-periods.

	Before Announcement				After Implementation			
	N	Mean	Median	St. Dev.	N	Mean	Median	St. Dev.
$R^2_{\text{LIQ},f}$	298	0.197	0.197	0.021	302	0.188	0.188	0.018
NET-FLOW$_f$(%)	296	1.605	0.402	5.847	300	1.435	-0.059	8.156
RET$_f$	298	1.677	1.615	1.433	302	1.773	1.673	1.424
LIQ$_f$	298	-0.003	-0.000	0.011	302	-0.003	-0.000	0.015
LOG(TNA)$_f$	298	19.115	19.179	1.859	302	19.272	19.350	1.800
PILOT$_b$	298	26.834	27.810	4.498	302	25.647	26.153	2.896
NON-PILOT$_b$	298	50.653	51.449	4.639	302	52.185	53.969	4.951
PILOT$_f$	298	24.482	24.518	6.975	302	24.331	24.347	6.631
NON-PILOT$_f$	298	50.040	50.165	7.748	302	50.162	50.732	8.892
FIRE SALES SHOCK$_f$	298	0.001	0.001	0.011	302	-0.000	-0.000	0.014
FRAGILITY SHOCK$_f$	298	0.016	0.006	0.125	302	-0.001	-0.000	0.071
INST OWN SHOCK$_f$	298	0.027	0.048	0.584	302	0.274	0.246	0.742

Table 3: The relationship between short-selling supply and liquidity comovement.
In columns (1) – (3), this table reports the coefficients of the monthly panel regression of the form::

$$\begin{aligned}\mathrm{R}^2_{\textsc{Liq},i,t} =&\gamma_0 + \gamma_1 \mathrm{R}^2_{\textsc{Liq},i,t-1} + \gamma_2 \textsc{Supply}_{i,t-1} + \gamma_3 \textsc{Liq}_{i,t-1} + \gamma_4 \ln(\textsc{Mcap}_{i,t-1}) + \gamma_5 \mathrm{R}\textsc{Vol}_{i,t-1} \\ &+ \gamma_6 \mathrm{R}^2_{\textsc{Turn},i,t-1} + \mathrm{D}_s + \mathrm{D}_t + \varepsilon_{i,t}.\end{aligned}$$

In columns (4) – (6), the table reports the coefficients of the monthly panel regression of the form:

$$\begin{aligned}\textsc{Supply}_{i,t} =&\gamma_0 + \gamma_1 \textsc{Supply}_{i,t-1} + \gamma_2 \mathrm{R}^2_{\textsc{Liq},i,t-1} + \gamma_3 \textsc{Liq}_{i,t-1} + \gamma_4 \ln(\textsc{Mcap}_{i,t-1}) + \gamma_5 \mathrm{R}\textsc{Vol}_{i,t-1} \\ &+ \gamma_6 \mathrm{R}^2_{\textsc{Turn},i,t-1} + \mathrm{D}_s + \mathrm{D}_t + \varepsilon_{i,t}.\end{aligned}$$

This sample spans the period of January 2005 to August 2010. The dependent variable in columns (1) – (3) is $\mathrm{R}^2_{\textsc{Liq},i,t}$ – the measure of liquidity co-movement and is computed in two-step procedure following Karolyi et al. (2012). We use three alternative measures of short selling supply: columns (1) and (4) – $\textsc{Supply-Value}_{i,t}$ defined as a fraction of the average value of shares available for lending to its market capitalization, columns (2) and (5) – $\textsc{Supply-Quantity}_{i,t}$ defined as an average number of shares available for landing divided by the number of shares outstanding, and columns (3) and (6) – $\textsc{Utilisation}_{i,t}$ defined as the value of assets on loan from lenders divided by the total lendable value. $\textsc{Liq}_{i,t}$ is a stock's log-transformed Amihud (2002) measure. $\ln(\textsc{Mcap}_{i,t})$ denotes the log of market capitalization. $\mathrm{R}\textsc{Vol}_{i,t}$ measures the volatility of the returns of stock i in month t. $\mathrm{R}^2_{\textsc{Turn},i,t}$ captures a stock i's trading activity in month t. $\textsc{Fee}_{i,t}$ is a value-weighted average short selling fee. We control for industry D_s and year-month D_t fixed effects. We use Kenneth French's website in order to classify stocks into 10 industries based on their Standard Industrial Classification (SIC) codes (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Datalibrary`). The t-statistics reported in the tables reflect robust standard errors that are clustered both at year-month and a stock level.

	$R^2_{\text{LIQ},i,t}$			$\text{SUPPLY}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$R^2_{\text{LIQ},i,t-1}$	0.0091 (4.60)	0.0091 (4.60)	0.0091 (4.59)	-0.0001 (-1.39)	0.0002 (0.79)	0.0001 (0.93)
$\text{SUPPLY-VALUE}_{i,t-1}$	-0.1356 (-2.20)			0.9635 (113.29)		
$\text{SUPPLY-QUANTITY}_{i,t-1}$		-0.1381 (-2.20)			0.9890 (298.65)	
$\text{UTILISATION}_{i,t-1}$			-0.0412 (-2.11)			0.9486 (216.88)
$R^2_{\text{TURN},i,t-1}$	0.0103 (3.79)	0.0103 (3.81)	0.0100 (3.64)	0.0002 (1.13)	0.0001 (1.37)	-0.0001 (-0.30)
$\text{LIQ}_{i,t-1}$	-4.2571 (-4.37)	-4.2555 (-4.37)	-4.3387 (-4.43)	0.0399 (1.37)	0.0051 (0.67)	0.1042 (3.00)
$\text{RVOL}_{i,t-1}$	-0.9110 (-2.35)	-0.9142 (-2.35)	-0.8864 (-2.36)	0.0277 (0.60)	0.0157 (1.99)	0.2631 (6.39)
$\ln(\text{MCAP}_{i,t-1})$	-0.0026 (-0.65)	-0.0025 (-0.64)	-0.0052 (-1.12)	0.0014 (8.98)	0.0007 (6.07)	0.0007 (2.94)
$\text{FEE}_{i,t-1}$			0.0000 (2.51)			0.0000 (0.39)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214625	214625	214625	214625	214625	214625
R^2	0.029	0.029	0.029	0.95	0.87	0.91

Table 4: SHO Regulation and commonality in liquidity – an event study.

This table reports the coefficients from twelve event study regressions of the form:

$$\overline{\mathrm{R}}^2_{\text{Liq},i,e+m} = \gamma_0 + \gamma_1 \text{Sho Period} + \gamma_2 \text{Sho Period} \times \text{Pilot Stock} + \text{d}_i + \varepsilon_{i,e+m}.$$

The sample includes stocks that have been part of Russell 3000 index in June 2003, 2004, and 2005. We exclude stocks that changed listing venue or ticker, were delisted, or were involved in a merge or an acquisition. We also discard Nasdaq small cap stocks, stocks with an average price blow \$2, and non-ordinary common stocks – with share codes different from 10 or 11. We control for changes in the sample composition by requiring at least 9 observations per stock in both control and treatment period. The pilot stock group is a subset of Russell 3000 stocks that was part of SHO Regulation pilot program. Our sample covers the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $\overline{\mathrm{R}}^2_{\text{Liq},i,e+m}$ is stock i's average co-illiquidity measure calculated over m months before (after) the event e – SHO Regulation was announced (implemented). Sho Period is a dummy variable equal to one, when Reg SHO pilot program was implemented, otherwise zero. Sho Period × Pilot Stock is an interaction term and equals one if a stock is a pilot stock and Reg SHO has been implemented, otherwise zero. We control for stock fixed effects d_i. In Panel A, the regression coefficients are estimated with weighted least squares (WLS) procedure. We use the natural logarithm of market capitalization at the beginning of the control period as weights. In Panel B, we use ordinary least squares (OLS) procedure to estimate the regression coefficients. t-statistics are reported in the brackets and standard errors are adjusted for heteroskedasticity.

Panel A: WLS Regression of Average Co-illiquidity.

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period	0.079	-0.23	-0.13	-0.079	-0.11	-0.11	-0.094	-0.12	-0.085	-0.056	-0.080	-0.067
	(1.91)	(-8.01)	(-5.57)	(-3.99)	(-6.08)	(-6.79)	(-6.09)	(-8.57)	(-6.24)	(-4.31)	(-6.44)	(-5.63)
SHO Period × Pilot Stock	-0.067	-0.11	-0.078	-0.050	-0.047	-0.047	-0.056	-0.058	-0.043	-0.047	-0.048	-0.035
	(-0.97)	(-2.25)	(-1.98)	(-1.50)	(-1.57)	(-1.73)	(-2.14)	(-2.35)	(-1.84)	(-2.10)	(-2.29)	(-1.73)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3999	4003	4003	4004	4004	4004	4004	4004	4004	4004	4004	4004
R^2	0.49	0.52	0.51	0.52	0.53	0.53	0.52	0.52	0.51	0.51	0.52	0.52

Panel B: OLS Regression of Average Co-illiquidity.

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period	0.078	-0.23	-0.13	-0.081	-0.11	-0.11	-0.094	-0.12	-0.085	-0.056	-0.081	-0.069
	(1.89)	(-8.10)	(-5.58)	(-4.08)	(-6.23)	(-6.99)	(-6.16)	(-8.62)	(-6.28)	(-4.37)	(-6.59)	(-5.84)
SHO Period × Pilot Stock	-0.052	-0.10	-0.077	-0.050	-0.046	-0.047	-0.056	-0.059	-0.044	-0.046	-0.046	-0.031
	(-0.75)	(-2.16)	(-1.94)	(-1.50)	(-1.55)	(-1.72)	(-2.18)	(-2.42)	(-1.88)	(-2.07)	(-2.18)	(-1.55)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3999	4003	4003	4004	4004	4004	4004	4004	4004	4004	4004	4004
R^2	0.49	0.52	0.51	0.52	0.53	0.53	0.52	0.52	0.51	0.51	0.52	0.52

Table 5: SHO Regulation and commonality in liquidity – a panel regression.

This table reports the coefficient from panel regressions of the form:

$$\mathrm{R}^2_{\textsc{Liq},i,t} = \gamma_0 + \gamma_1 \textsc{Sho Period} \times \textsc{Pilot Stock} + \mathrm{D}_i + \mathrm{D}_t + \varepsilon_{i,t}.$$

The sample includes stocks that have been part of Russell 3000 index in June 2003, 2004, and 2005. We exclude stocks that changed listing venue or ticker, were delisted, or were involved in a merge or an acquisition. We also discard Nasdaq small cap stocks, stocks with an average price blow \$2, and non-ordinary common stocks – with share codes different from 10 or 11. We control for changes in the sample composition by requiring at least 9 observations per stock in both control and treatment period. The pilot stock group is a subset of Russell 3000 stocks that was part of SHO Regulation pilot program. Our sample covers the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $\mathrm{R}^2_{\textsc{Liq},i,t}$ is stock i's co-illiquidity measure calculated over month t. Sho Period $\times$ Pilot Stock is an interaction term and equals one if a stock is a pilot stock and Reg SHO has been implemented, otherwise zero. In Panel A, theSho Period $\times$ Pilot Stock regression coefficients are estimated with weighted least squares (WLS) procedure. We use the natural logarithm of market capitalization before the treatment period as weights. In Panel B, we use WLS estimation procedure and add a set of contemporaneous control variables: a stock's log-transformed Amihud (2002) measure $\textsc{Liq}_{i,t}$, the return volatility $\mathrm{R}\textsc{Vol}_{i,t}$, the trading activity by $\mathrm{R}^2_{\textsc{Turn},i,t}$, and the natural logarithm of market capitalization by $\ln(\textsc{Mcap}_{i,t})$. In Panel C, we use ordinary least squares (OLS) procedure to estimate the Sho Period $\times$ Pilot Stock regression coefficients. In Panel D, we use OLS estimation procedure and use the same set of contemporaneous control variables as in Panel B. At the bottom of Panel B, we report the χ^2 statistics and p-values from a Hausman test (Hausman (1978)), where we compare the regression coefficients on Sho Period $\times$ Pilot Stock in Panel A to the corresponding Sho Period $\times$ Pilot Stock coefficients in Panel B. At the bottom of Panel D, we perform an analogous Hausman test, where we compare Sho Period $\times$ Pilot Stock regression coefficients from Panel C and D. t-statistics are reported in the brackets and standard errors are adjusted for heteroskedasticity.

Panel A: WLS Panel Regression Co-illiquidity.

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.066	-0.10	-0.078	-0.050	-0.047	-0.047	-0.055	-0.057	-0.042	-0.045	-0.047	-0.035
	(-0.95)	(-2.12)	(-1.94)	(-1.43)	(-1.50)	(-1.66)	(-2.04)	(-2.26)	(-1.75)	(-2.01)	(-2.18)	(-1.70)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3997	8001	12004	15999	19989	23987	27981	31971	35946	39966	43952	47954
R^2	0.49	0.27	0.19	0.14	0.12	0.098	0.091	0.083	0.076	0.071	0.067	0.062

Panel B: WLS Panel Regression Co-illiquidity with Contemporaneous Control Variables

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.068	-0.10	-0.077	-0.049	-0.046	-0.047	-0.054	-0.057	-0.042	-0.045	-0.047	-0.035
	(-0.98)	(-2.11)	(-1.91)	(-1.42)	(-1.49)	(-1.64)	(-2.02)	(-2.25)	(-1.75)	(-2.01)	(-2.20)	(-1.73)
$\text{Liq}_{i,t}$	-0.44	-0.037	0.067	-0.23	-0.26	-0.13	-0.14	-0.11	-0.11	-0.14	-0.16	-0.15
	(-1.38)	(-0.20)	(0.39)	(-2.02)	(-2.62)	(-2.11)	(-2.54)	(-2.35)	(-2.41)	(-2.91)	(-3.24)	(-3.15)
$\text{RVol}_{i,t}$	-0.099	-0.085	-0.12	2.13	2.10	2.11	0.77	0.061	0.25	0.43	0.84	0.92
	(-0.03)	(-0.03)	(-0.06)	(1.37)	(1.55)	(1.81)	(0.70)	(0.06)	(0.27)	(0.49)	(1.00)	(1.17)
$R^2_{\text{Turn},i,t}$	0.0092	-0.0024	-0.0020	-0.0058	0.0021	0.0056	0.012	0.013	0.011	0.011	0.013	0.010
	(0.41)	(-0.19)	(-0.20)	(-0.70)	(0.29)	(0.83)	(1.87)	(2.19)	(2.02)	(1.98)	(2.54)	(2.14)
$\ln(\text{Mcap}_{i,t})$	0.22	0.0018	-0.053	0.043	0.025	0.012	-0.00054	0.0062	0.011	0.019	0.040	0.043
	(2.01)	(0.03)	(-0.98)	(0.97)	(0.66)	(0.38)	(-0.02)	(0.23)	(0.43)	(0.85)	(1.91)	(2.22)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3997	8001	12004	15999	19989	23987	27981	31971	35946	39966	43952	47954
R^2	0.49	0.27	0.19	0.14	0.12	0.099	0.092	0.084	0.076	0.071	0.068	0.062
SHO Period× Pilot Stock (χ^2)	0.48	0.01	0.48	0.09	0.12	0.23	0.40	0.04	0.01	0.00	0.69	0.90
SHO Period× Pilot Stock (P-Val)	0.49	0.92	0.49	0.76	0.73	0.63	0.53	0.85	0.92	0.96	0.41	0.32

Panel C: OLS Panel Regression Co-illiquidity.

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.050	-0.10	-0.076	-0.049	-0.046	-0.047	-0.056	-0.058	-0.042	-0.044	-0.044	-0.031
	(-0.72)	(-2.04)	(-1.88)	(-1.41)	(-1.48)	(-1.65)	(-2.08)	(-2.31)	(-1.78)	(-1.97)	(-2.07)	(-1.51)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3997	8001	12004	15999	19989	23987	27981	31971	35946	39966	43952	47954
R^2	0.49	0.27	0.19	0.14	0.12	0.099	0.092	0.084	0.076	0.071	0.067	0.062

Panel D: OLS Panel Regression Co-illiquidity with Contemporaneous Control Variables.

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.051	-0.100	-0.075	-0.048	-0.045	-0.046	-0.055	-0.058	-0.042	-0.044	-0.045	-0.031
	(-0.74)	(-2.03)	(-1.85)	(-1.40)	(-1.46)	(-1.63)	(-2.04)	(-2.30)	(-1.78)	(-1.97)	(-2.09)	(-1.54)
$\text{Liq}_{i,t}$	-0.50	-0.051	0.060	-0.22	-0.25	-0.13	-0.14	-0.11	-0.11	-0.14	-0.15	-0.15
	(-1.65)	(-0.26)	(0.33)	(-1.91)	(-2.50)	(-2.11)	(-2.51)	(-2.24)	(-2.27)	(-2.78)	(-3.14)	(-3.06)
$\text{RVol}_{i,t}$	0.13	0.15	-0.0079	2.28	2.17	2.04	0.83	0.043	0.29	0.45	0.85	0.95
	(0.03)	(0.06)	(-0.00)	(1.46)	(1.61)	(1.76)	(0.76)	(0.04)	(0.31)	(0.51)	(1.02)	(1.22)
$R^2_{\text{Turn},i,t}$	0.0089	-0.0033	-0.0027	-0.0068	0.0012	0.0049	0.011	0.013	0.011	0.010	0.013	0.011
	(0.40)	(-0.27)	(-0.28)	(-0.82)	(0.17)	(0.73)	(1.78)	(2.17)	(2.01)	(1.96)	(2.53)	(2.20)
$\ln(\text{Mcap}_{i,t})$	0.22	0.0036	-0.044	0.050	0.028	0.015	0.00082	0.0087	0.014	0.021	0.041	0.044
	(2.04)	(0.05)	(-0.80)	(1.13)	(0.77)	(0.46)	(0.03)	(0.32)	(0.55)	(0.94)	(1.99)	(2.28)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3997	8001	12004	15999	19989	23987	27981	31971	35946	39966	43952	47954
R^2	0.49	0.27	0.19	0.14	0.12	0.099	0.092	0.084	0.076	0.071	0.068	0.062
SHO Period× Pilot Stock (χ^2)	0.22	0.03	0.32	0.05	0.16	0.31	0.68	0.08	0.02	0.01	0.51	0.75
SHO Period× Pilot Stock (P-Val)	0.64	0.87	0.57	0.82	0.69	0.58	0.41	0.78	0.90	0.91	0.48	0.39

Table 6: SHO Regulation and mutual fund's fraction of pilot stocks and portfolio co-illiquidity – an event study.

This table reports the coefficient from the event study regression of the form:

$$\Delta Y_f = \delta_0 + \delta_1 \%\textsc{Pilot}_{f,\textsc{June 2004}} + \delta_2 \overline{\textsc{Ret}}_{f,ctr} + \delta_3 \overline{\textsc{Net-Flow}}_{f,ctr} + \delta_4 \overline{\textsc{Liq}}_{f,ctr} + \delta_5 \overline{\textsc{Log(TNA)}}_{f,ctr} + \delta_6 \%\textsc{Russell 3000}_{f,ctr} + \eta_f,$$

where ΔY_f is a change in the average fraction of pilot stocks $\Delta\%\textsc{Pilot}_f$ in columns (1) – (3) and a change in portfolio's value-weighted co-illiquidity $\Delta\textsc{Co-Illiq}_f$ in columns (4) – (6). The sample consists of US open-ended mutual funds actively investing in US equity and spans the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. We construct $\Delta\%\textsc{Pilot}_f$ ($\Delta\textsc{Co-Illiq}_f$) by calculating the difference between portfolio's mean fraction of pilot stocks ($R^2_{\textsc{Liq}}$) over 12 months leading up to the SHO regulation announcement and after SHO Regulation implementation (we require at least 9 monthly observations for each sub-period in order to be included in the sample). $\%\textsc{Pilot}_{f,\textsc{June 2004}}$ is a percentage of pilot stocks in fund f's portfolio at the end of June 2004 – the last month before Reg SHO announcement. We denote the average fund's return over the control period (from July 2003 to June 2004) by $\overline{\textsc{Ret}}_{f,ctr}$, the average fund's net-flows by $\overline{\textsc{Net-Flow}}_{f,ctr}$, the average portfolio's liquidity by $\overline{\textsc{Liq}}_{f,ctr}$, the average of natural logarithm of fund's total net assets by $\overline{\textsc{Log(TNA)}}_{f,ctr}$, and the average fraction of fund f's portfolio invested in Russell 3000 index by $\overline{\%\textsc{Russell 3000}}_{f,ctr}$. Standard errors are corrected for heteroscedasticity. t-statistics are reported in the brackets.

	Δ Pilot Fraction			Δ Fund's Co-illiquidity		
	(1)	(2)	(3)	(4)	(5)	(6)
$\%\textsc{Vw-Pilot}_{\textsc{f,June 2004}}$	-0.3009	-0.2442	-0.2190	0.1646	0.1774	0.2161
	(-3.93)	(-2.87)	(-2.64)	(2.22)	(1.94)	(2.30)
$\overline{\textsc{Ret}}_{\textsc{f,ctr}}$			0.0071			0.0108
			(0.82)			(1.64)
$\overline{\textsc{Net-Flow}}_{\textsc{f,ctr}}$			0.2232			0.0919
			(2.43)			(1.58)
$\overline{\textsc{Liq}}_{\textsc{f,ctr}}$			-0.4780			1.0194
			(-1.52)			(2.37)
$\overline{\textsc{Log(TNA)}}_{\textsc{f,ctr}}$			0.0035			-0.0025
			(1.43)			(-0.91)
$\overline{\%\textsc{Russell 3000}}_{\textsc{f,ctr}}$		-0.0886	-0.0149		-0.0200	-0.0171
		(-1.43)	(-0.23)		(-0.31)	(-0.25)
Constant	0.0737	0.1255	-0.0209	-0.1064	-0.0947	-0.0781
	(3.79)	(2.99)	(-0.27)	(-5.44)	(-2.45)	(-1.14)
Observations	156	156	156	156	156	156
R^2	0.12	0.14	0.19	0.041	0.042	0.094

Table 7: SHO Regulation and mutual fund's portfolio co-illiquidity – a panel regression. This table reports the coefficient of the monthly panel regression of the form:

$$\begin{aligned}\textsc{Co-Illiq}_{f,t} =&\rho_0 + \rho_1\%\textsc{Pilot}_{b,t-1} + \rho_2\%\textsc{Pilot}_{b,t-1} \times \textsc{Sho Period} + \rho_3\textsc{Net-Flow}_{f,t-1} + \rho_4\textsc{Ret}_{f,t-1} \\ &+ \rho_5\textsc{Log(TNA)}_{f,t-1} + \rho_6\textsc{Liq}_{f,t-1} + \rho_7\%\textsc{Russell 3000}_{b,t-1} + \textsc{g}_f + \textsc{g}_t + \upsilon_{f,t}\end{aligned}$$

The sample consists of US open-ended mutual funds actively investing in US equity and spans the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $\textsc{Co-Illiq}_{f,t}$ is the value-weighted co-illiquidity of fund f's portfolio in month t. $\%\textsc{Pilot}_{b,t-1}$ denotes a fraction of pilot stocks in fund's benchmark portfolio and $\textsc{Pilot}_{b,t-1} \times \textsc{Sho Period}$ is an interaction term between percentage of pilot stocks in the benchmark and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. We denote the lagged fund's return by $\textsc{Ret}_{f,t-1}$, the fund's net-flows by $\textsc{Net-Flow}_{f,t-1}$, the portfolio's liquidity by $\textsc{Liq}_{f,t-1}$, and the natural logarithm of fund's total net assets by $\textsc{Log(TNA)}_{f,t-1}$. $\%\textsc{Russell 3000}_{b,t-1}$ is a fraction of fund's benchmark invested in Russell 3000 index (i.e. pilot and non-pilot stocks). We control for fund $\textsc{g}_f$ (benchmark in column (5)) and year-month $\textsc{g}_t$ fixed effects. t-statistics are reported in the brackets. Standard errors are robust – columns (1) – (3); clustered at a fund level – columns (4) and (5).

	Fund's value-weighted co-illiquidity				
	(1)	(2)	(3)	(4)	(5)
$\%\textsc{Pilot}_{b,t-1}$	0.0182	0.1106	0.0400	0.0897	0.0897
	(0.14)	(0.84)	(0.30)	(0.67)	(0.67)
$\%\textsc{Pilot}_{b,t-1} \times$ SHO Period		0.3039		0.2773	0.2773
		(2.44)		(2.04)	(2.04)
$\textsc{Net-Flow}_{f,t-1}$			-0.0145	-0.0148	-0.0148
			(-1.84)	(-1.92)	(-1.77)
$\textsc{Log(TNA)}_{f,t-1}$			-0.0152	-0.0148	-0.0148
			(-2.74)	(-2.67)	(-2.72)
$\textsc{Ret}_{f,t-1}$			0.3040	0.2910	0.2910
			(2.14)	(2.05)	(2.16)
$\textsc{Liq}_{f,t-1}$			-0.0973	-0.0967	-0.0967
			(-0.40)	(-0.40)	(-0.35)
$\%\textsc{Russell 3000}_{b,t-1}$			-0.2216	-0.0039	-0.0039
			(-0.77)	(-0.01)	(-0.01)
Constant	-1.5998	-1.6986	-1.1457	-1.4017	-1.4017
	(-46.11)	(-34.56)	(-4.72)	(-5.06)	(-4.62)
Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	
Benchmark FE					Yes
Robust SE	Yes	Yes	Yes		
Fund Cluster				Yes	Yes
Observations	7188	7188	7188	7188	7188
R^2	0.5452	0.54	0.54	0.54	0.54

Table 8: Fire sales and portfolio's fragility.

This table reports the coefficient of the monthly panel regression of the form:

$$\begin{aligned}\Delta\text{Co-Illiq}_{f,t} =&\theta_0 + \theta_1 \text{X}_{f,t-1} + \theta_2 \text{X}_{f,t-1} \times \text{Sho Period} + \theta_3 \text{Net-Flow}_{f,t-1} + \theta_4 \text{Log(TNA)}_{f,t-1} \\ &+ \theta_5 \text{Ret}_{f,t-1} + \theta_6 \text{Liq}_{f,t-1} + \rho_7 \%\text{Russell 3000}_{b,t-1} + \text{G}_f + \text{G}_t + \upsilon_{f,t},\end{aligned}$$

where $\text{X}_{f,t-1} \in$ ($\text{Fire Sales Shock}_{f,t-1}$, $\text{Fragility Shock}_{f,t-1}$, $\text{Inst Own Shock}_{f,t-1}$). The sample consists of US open-ended mutual funds actively investing in US equity and spans the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $\Delta\text{Co-Illiq}_{f,t}$ is the change in the value-weighted co-illiquidity of fund f's portfolio in month t. $\text{Fire Sales Shock}_{f,t-1}$ captures a fund's exposure to fire sales of other funds and is defined as a change in the fire sales exposure keeping fund's investment decision constant: $\text{Fire Sales Shock}_{f,t-1} = \sum_{i=1}^{S_{f,t-1}} \text{w}_{i,f,t-1} \cdot (\text{Fire Sales}_{f,i,t} - \text{Fire Sales}_{f,i,t-1})$, where $\text{w}_{i,f,t-1}$ is a fraction of fund f's portfolio invested in stock i in month $t-1$ and $\text{Fire Sales}_{f,i,t}$ is a stock's fire sale measure as per Coval and Stafford (2007). $\text{Fire Sales Shock}_{f,t-1} \times \text{Sho Period}$ is an interaction term between a fund's exposure to fire sales of other funds and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. $\text{Fragility Shock}_{f,t-1}$ is a change in the fragility of fund f's portfolio keeping fund's investment decision constant and is constructed in an analogous way. We use Greenwood and Thesmar (2011) measure of stock's fragility. $\text{Fragility Shock}_{f,t-1} \times \text{Sho Period}$ is an interaction term between a shock to fund's portfolio fragility and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. $\text{Inst Own Shock}_{f,t-1}$ is a change in fund portfolio's exposure to institutional ownership. We keep fund's portfolio composition at the beginning of month t constant and compute a change in institutional ownership of fund's holdings over that month. $\text{Inst Own Shock}_{f,t-1} \times \text{Sho Period}$ is an interaction term between a shock to fund's portfolio institutional ownership and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. We denote the lagged fund's return by $\text{Ret}_{f,t-1}$, the fund's net-flows by $\text{Net-Flow}_{f,t-1}$, the portfolio's liquidity by $\text{Liq}_{f,t-1}$, and the natural logarithm of fund's total net assets by $\text{Log(TNA)}_{f,t-1}$. $\%\text{Russell 3000}_{b,t-1}$ is a fraction of fund's benchmark invested in Russell 3000 index (i.e. pilot and non-pilot stocks). We control for fund G_f (benchmark in column (5)) and year-month G_t fixed effects. t-statistics are reported in the brackets. Standard errors are corrected for heteroscedasticity in columns (1) – (3) and clustered at a fund level in columns (4) and (5). We report the regression estimates of the fire sales shock in Panel A, fragility shock in Panel B, and institutional ownership shock in Panel C.

	Panel A: Fire Sales				
	(1)	(2)	(3)	(4)	(5)
Fire Sales Shock$_{f,t-1}$	-0.2433	-0.9201	-0.9034	-0.9034	-1.0071
	(-1.05)	(-2.97)	(-2.92)	(-2.59)	(-3.17)
Fire Sales Shock$_{f,t-1}$ $\times$ SHO Period		1.2827	1.2400	1.2400	1.3351
		(2.77)	(2.68)	(2.02)	(2.37)
Net-Flow$_{f,t-1}$			-0.0074	-0.0074	-0.0114
			(-0.42)	(-0.37)	(-0.77)
Log(TNA)$_{f,t-1}$			-0.0196	-0.0196	-0.0001
			(-2.30)	(-3.70)	(-0.07)
Ret$_{f,t-1}$			0.4228	0.4228	0.4155
			(1.97)	(1.95)	(2.23)
Liq$_{f,t-1}$			0.2252	0.2252	0.1153
			(0.66)	(0.86)	(1.01)
%Russell 3000$_{b,t-1}$			-0.9123	-0.9123	-0.8160
			(-2.21)	(-3.11)	(-3.43)
Constant	0.3256	0.3256	1.3974	1.3974	0.9413
	(23.62)	(23.61)	(3.88)	(5.50)	(5.07)
Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	
Benchmark FE					Yes
Robust SE	Yes	Yes	Yes		
Fund Cluster				Yes	Yes
Observations	7188	7188	7188	7188	7188
R^2	0.57	0.57	0.57	0.57	0.56

	Panel B: Fragility				
	(1)	(2)	(3)	(4)	(5)
Fragility Shock$_{f,t-1}$	-0.1282	-0.2249	-0.2377	-0.2377	-0.2385
	(-4.23)	(-6.56)	(-6.83)	(-5.82)	(-6.53)
Fragility Shock$_{f,t-1}$ $\times$ SHO Period		0.3328	0.3388	0.3388	0.3377
		(4.07)	(4.14)	(3.90)	(4.21)
Net-Flow$_{f,t-1}$			-0.0094	-0.0094	-0.0125
			(-0.54)	(-0.48)	(-0.86)
Log(TNA)$_{f,t-1}$			-0.0200	-0.0200	0.0001
			(-2.36)	(-3.72)	(0.07)
Ret$_{f,t-1}$			0.4937	0.4937	0.4762
			(2.32)	(2.31)	(2.59)
Liq$_{f,t-1}$			0.2376	0.2376	0.1130
			(0.69)	(0.89)	(0.96)
%Russell 3000$_{b,t-1}$			-1.1576	-1.1576	-1.0457
			(-2.79)	(-3.90)	(-4.35)
Constant	0.3245	0.3256	1.5914	1.5914	1.1143
	(23.50)	(23.51)	(4.41)	(6.22)	(5.95)
Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	
Benchmark FE					Yes
Robust SE	Yes	Yes	Yes		
Fund Cluster				Yes	Yes
Observations	7188	7188	7188	7188	7188
R^2	0.57	0.57	0.57	0.57	0.56

	Panel C: Institutional Ownership				
	(1)	(2)	(3)	(4)	(5)
Inst Own Shock$_{f,t-1}$	0.0015	0.0206	0.0213	0.0213	0.0214
	(0.38)	(1.94)	(1.99)	(2.09)	(2.37)
Inst Own Shock$_{f,t-1}$ $\times$ SHO Period		-0.0252	-0.0260	-0.0260	-0.0246
		(-2.21)	(-2.28)	(-2.36)	(-2.50)
Net-Flow$_{f,t-1}$			-0.0056	-0.0056	-0.0107
			(-0.31)	(-0.27)	(-0.71)
Log(TNA)$_{f,t-1}$			-0.0201	-0.0201	-0.0001
			(-2.36)	(-3.75)	(-0.06)
Ret$_{f,t-1}$			0.4695	0.4695	0.4704
			(2.19)	(2.20)	(2.57)
Liq$_{f,t-1}$			0.2125	0.2125	0.0986
			(0.63)	(0.83)	(0.87)
%Russell 3000$_{b,t-1}$			-0.8919	-0.8919	-0.7975
			(-2.17)	(-3.01)	(-3.33)
Constant	0.3255	0.3264	1.3913	1.3913	0.9261
	(23.61)	(23.66)	(3.87)	(5.46)	(4.95)
Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	
Benchmark FE					Yes
Robust SE	Yes	Yes	Yes		
Fund Cluster				Yes	Yes
Observations	7188	7188	7188	7188	7188
R^2	0.57	0.57	0.57	0.57	0.56

Table 9: SHO Regulation and mutual fund's portfolio co-illiquidity – a robustness analysis. This table reports the coefficient of the monthly panel regression of the form:

$$\text{Co-Illiq}_{f,t} = \rho_0 + \rho_1 \overline{\%\text{Pilot}}_{f,ctr} \times \text{Sho Period} + \rho_2 \text{Net-Flow}_{f,t-1} + \rho_3 \text{Log(Tna)}_{f,t-1} + \rho_4 \text{Ret}_{f,t-1} + \rho_5 \text{Liq}_{f,t-1} + \text{G}_f + \text{G}_t + \upsilon_{f,t}$$

The sample consists of US open-ended mutual funds actively investing in US equity and spans the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $\text{Co-Illiq}_{f,t}$ is the value-weighted co-illiquidity of fund f's portfolio in month t. In columns (1) – (3), $\overline{\%\text{Vw-Pilot}}_{f,ctr} \times$ Sho Period is an interaction term between an average percentage of pilot stocks in a fund's f portfolio over the control period (from July 2003 to June 2004) and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. In columns (4) – (6), $\overline{\%\text{Ew-Pilot}}_{f,ctr} \times$ Sho Period is an interaction term between an average equally-weighted fraction of pilot stocks in a fund's portfolio over the control period (from July 2003 to June 2004) and Reg SHO pilot program indicator variable that equals one if SHO Regulation has been implemented and otherwise zero. We denote the lagged fund's return by $\text{Ret}_{f,t-1}$, the fund's net-flows by $\text{Net-Flow}_{f,t-1}$, the portfolio's liquidity by $\text{Liq}_{f,t-1}$, and the natural logarithm of fund's total net assets by $\text{Log(Tna)}_{f,t-1}$. We control for fund G_f and year-month G_t fixed effects. t-statistics are reported in the brackets. Standard errors are robust – columns (1), (2), (4), and (5); clustered at a fund level – columns (3) and (6).

	Fund's value-weighted co-illiquidity					
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\%\text{Vw-Pilot}}_{f,ctr} \times$ SHO Period	0.2268	0.2167	0.2019			
	(2.85)	(2.36)	(2.11)			
$\overline{\%\text{Ew-Pilot}}_{f,ctr} \times$ SHO Period				0.2462	0.2560	0.2436
				(3.40)	(3.55)	(3.21)
$\overline{\%\text{Vw-Russell}}_{f,ctr} \times$ SHO Period		0.0001	0.0002			
		(0.22)	(0.25)			
$\overline{\%\text{Ew-Russell}}_{f,cntr} \times$ SHO Period					-1.8356	-1.5423
					(-0.32)	(-0.27)
$\text{Net-Flow}_{f,t\text{-}1}$			0.0058			0.0057
			(0.88)			(0.82)
$\text{Log(TNA)}_{f,t\text{-}1}$			-0.0106			-0.0105
			(-1.70)			(-1.71)
$\text{Ret}_{f,t\text{-}1}$			0.0010			0.0009
			(0.61)			(0.54)
$\text{Liq}_{f,\text{-}1}$			-0.3290			-0.3457
			(-0.74)			(-0.78)
Constant	-1.8510	-1.8509	-1.6540	-1.8502	-1.8503	-1.6547
	(-75.73)	(-75.50)	(-13.79)	(-76.15)	(-76.21)	(-13.99)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4246	4246	4246	4246	4246	4246
R^2	0.52	0.52	0.52	0.52	0.52	0.52

Appendix

Table A1: SHO Regulation, commonality in liquidity and mutual fund ownership – a panel regression.
This table reports the coefficient from panel regressions of the form:

$$R^2_{\text{LIQ},i,t} = \gamma_0 + \gamma_1 \text{SHO PERIOD} \times \text{PILOT STOCK} + \text{D}_i + \text{D}_t + \varepsilon_{i,t}.$$

estimated separately for stocks with pre-SHO Regulation mutual fund ownership above and below the median. The sample includes stocks that have been part of Russell 3000 index in June 2003, 2004, and 2005. We exclude stocks that changed listing venue or ticker, were delisted, or were involved in a merge or an acquisition. We also discard Nasdaq small cap stocks, stocks with an average price blow \$2, and non-ordinary common stocks – with share codes different from 10 or 11. We control for changes in the sample composition by requiring at least 9 observations per stock in both control and treatment period. The pilot stock group is a subset of Russell 3000 stocks that was part of SHO Regulation pilot program. Our sample covers the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $R^2_{\text{LIQ},i,t}$ is stock i's co-illiquidity measure calculated over month t. SHO PERIOD × PILOT STOCK is an interaction term and equals one if a stock is a pilot stock and Reg SHO has been implemented, otherwise zero. In Panel A, the SHO PERIOD × PILOT STOCK regression coefficients are estimated with weighted least squares (WLS) procedure for stocks with below median mutual fund ownership measure over control period. In Panel B, we report the regression coefficients estimated with WLS for a subset of stocks with above the median pre-SHO Regulation mutual fund ownership. We use the natural logarithm of market capitalization before the treatment period as weights. In Panel C, we use ordinary least squares (OLS) procedure to estimate the SHO PERIOD × PILOT STOCK regression coefficients for stocks with the below median mutual fund ownership. In Panel D, we use OLS estimation procedure for a subset of stocks with above the median mutual fund ownership. t-statistics are reported in the brackets and standard errors are adjusted for heteroskedasticity.

Panel A: Mutual fund ownership below median (WLS)

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO PERIOD × PILOT STOCK	0.045	-0.060	-0.082	-0.063	-0.040	-0.019	-0.041	-0.021	-0.0081	-0.015	-0.020	-0.0086
	(0.46)	(-0.85)	(-1.44)	(-1.29)	(-0.91)	(-0.47)	(-1.08)	(-0.60)	(-0.24)	(-0.47)	(-0.65)	(-0.30)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1998	4003	6007	8002	9982	11979	13974	15997	17976	19986	21958	23968
R^2	0.49	0.26	0.19	0.14	0.12	0.098	0.092	0.081	0.073	0.068	0.065	0.059

Panel B: Mutual fund ownership above median (WLS)

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.18	-0.15	-0.073	-0.036	-0.053	-0.077	-0.069	-0.094	-0.076	-0.076	-0.074	-0.060
	(-1.83)	(-2.17)	(-1.28)	(-0.73)	(-1.22)	(-1.90)	(-1.80)	(-2.65)	(-2.25)	(-2.37)	(-2.43)	(-2.04)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1999	3998	5997	7997	10007	12008	14007	15974	17970	19980	21994	23986
R^2	0.50	0.29	0.19	0.15	0.12	0.10	0.093	0.087	0.080	0.075	0.071	0.067

Panel C: Mutual fund ownership below median (OLS)

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	0.067	-0.056	-0.076	-0.060	-0.036	-0.016	-0.042	-0.023	-0.0083	-0.014	-0.016	-0.0046
	(0.69)	(-0.79)	(-1.33)	(-1.22)	(-0.83)	(-0.40)	(-1.11)	(-0.64)	(-0.25)	(-0.44)	(-0.54)	(-0.16)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1998	4003	6007	8002	9982	11979	13974	15997	17976	19986	21958	23968
R^2	0.49	0.26	0.19	0.14	0.12	0.098	0.092	0.082	0.074	0.069	0.066	0.059

Panel D: Mutual fund ownership above median (OLS)

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.17	-0.15	-0.075	-0.038	-0.055	-0.078	-0.069	-0.095	-0.076	-0.075	-0.072	-0.056
	(-1.72)	(-2.10)	(-1.31)	(-0.77)	(-1.26)	(-1.95)	(-1.81)	(-2.67)	(-2.27)	(-2.35)	(-2.37)	(-1.91)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1999	3998	5997	7997	10007	12008	14007	15974	17970	19980	21994	23986
R^2	0.50	0.29	0.19	0.15	0.12	0.10	0.093	0.087	0.080	0.075	0.071	0.067

Table A2: SHO Regulation and stock returns – a panel regression.

This table reports the coefficient from panel regressions of the form:

$$\text{RET}_{i,t} = \gamma_0 + \gamma_1 \text{SHO PERIOD} \times \text{PILOT STOCK} + \text{D}_i + \text{D}_t + \varepsilon_{i,t}.$$

The sample includes stocks that have been part of Russell 3000 index in June 2003, 2004, and 2005. We exclude stocks that changed listing venue or ticker, were delisted, or were involved in a merge or an acquisition. We also discard Nasdaq small cap stocks, stocks with an average price blow \$2, and non-ordinary common stocks – with share codes different from 10 or 11. We control for changes in the sample composition by requiring at least 9 observations per stock in both control and treatment period. The pilot stock group is a subset of Russell 3000 stocks that was part of SHO Regulation pilot program. Our sample covers the period from July 2003 (12 months before the announcement of Reg SHO pilot program) to April 2006 (12 months after Reg SHO pilot program was firstly implemented). We eliminate the period between July 2004 and April 2005, when Reg SHO pilot program was announced but yet not implemented. $\text{RET}_{i,t}$ is stock i's return in month t. SHO PERIOD × PILOT STOCK is an interaction term and equals one if a stock is a pilot stock and Reg SHO has been implemented, otherwise zero. In Panel A, the SHO PERIOD × PILOT STOCK regression coefficients are estimated with weighted least squares (WLS). We use the natural logarithm of market capitalization before the treatment period as weights. In Panel C, we use ordinary least squares (OLS) procedure to estimate the SHO PERIOD × PILOT STOCK regression coefficients. t-statistics are reported in the brackets and standard errors are adjusted for heteroskedasticity.

Panel A: WLS Panel Regression of Stock Returns

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.00041	-0.000079	-0.000070	-0.000019	0.000018	-0.000038	0.000026	-0.0000019	0.000057	0.000017	0.000028	0.000025
	(-1.68)	(-0.46)	(-0.47)	(-0.16)	(0.16)	(-0.36)	(0.27)	(-0.02)	(0.66)	(0.21)	(0.36)	(0.33)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3997	8001	12004	15999	19989	23987	27981	31971	35946	39966	43952	47954
R^2	0.51	0.27	0.27	0.25	0.21	0.19	0.17	0.16	0.18	0.17	0.16	0.15

Panel B: OLS Panel Regression of Stock Returns

	+/- 1M	+/- 2M	+/- 3M	+/- 4M	+/- 5M	+/- 6M	+/- 7M	+/- 8M	+/- 9M	+/- 10M	+/- 11M	+/- 12M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SHO Period × Pilot Stock	-0.00043	-0.00010	-0.000078	-0.000026	0.000019	-0.000036	0.000030	-0.0000050	0.000056	0.000015	0.000026	0.000026
	(-1.73)	(-0.58)	(-0.51)	(-0.20)	(0.17)	(-0.33)	(0.30)	(-0.05)	(0.63)	(0.18)	(0.33)	(0.33)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3997	8001	12004	15999	19989	23987	27981	31971	35946	39966	43952	47954
R^2	0.51	0.27	0.27	0.25	0.21	0.19	0.17	0.16	0.18	0.17	0.16	0.15