High Frequency Trading and the 2008 Short Sale Ban*

Jonathan Brogaard

Terrence Hendershott

Ryan Riordan

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Abstract: We examine the effects of high frequency traders (HFTs) on liquidity and price efficiency using the September 2008 short sale ban. To disentangle the separate impacts of short selling by HFTs and non-HFTs (nHFTs) we use an instrumental variables approach exploiting differences in the ban's cross-sectional impact on HFTs and nHFTs. nHFTs' short selling improves liquidity and price efficiency, as measured by bid-ask spreads and pricing errors. HFTs' short selling has the opposite effect by decreasing liquidity and price efficiency. HFTs' negative impact is driven by liquidity demanding trades. HFTs' liquidity supply improves liquidity and price efficiency, but not enough to outweigh the negative HFT liquidity demand effect.

(for internet appendix click: http://goo.gl/XgS5ev)

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Contact: Jonathan Brogaard, Foster School of Business, University of Washington, (Email) brogaard@uw.edu , (Tel) 206-685-7822; Terrence Hendershott, University of California – Berkeley, Haas School of Business, (Email) hender@haas.berkeley.edu (Tel) 510-643-0619; and Ryan Riordan, Queen's School of Business, Queen's University (Email) ryan.riordan@queensu.ca (Tel) 705.761.8800.

Introduction

High frequency traders (HFTs) combine technology with short horizon trading strategies and now make up roughly half of all equity trading. Regulators, academics, and practitioners struggle to understand whether HFTs and high-speed automated markets improve the trading environment. With near zero monitoring, updating, and order placement costs HFTs could improve price efficiency and increase liquidity by reducing frictions in liquidity provision. However, HFTs using public information to adversely select other investors could decrease liquidity and price efficiency. Empirical studies of HFTs primarily provide evidence on correlations between HFTs and liquidity and price efficiency. Showing causality is challenging.

This paper examines the impact of HFTs' short selling on price efficiency and the price of immediacy (liquidity) using the 2008 short selling ban. In addition, the differential impact of HFTs and non-HFTs (nHFTs) short selling provides insight into heterogeneity among types of short sellers. Using the short sale ban and its differential cross-sectional impact as instruments, we find that aggregate short selling improves liquidity and price efficiency. However, HFTs' short selling that demands liquidity reduces liquidity and price efficiency.

In September 2008 the U.S. Securities and Exchange Commission (SEC) implemented a short sale ban disallowing most short selling in financial stocks. The short sale ban is a natural instrument for examining short selling's impact as the ban only targets short selling. Boehmer, Jones, and Zhang (2013) (BJZ) provide an in depth analysis of this event and conclude that short selling fell and overall market quality deteriorated. BJZ use a difference-in-differences approach to examine the ban's impact. This paper examines HFTs' short selling role in that decline and presents evidence on the impact of HFTs on markets. Doing so requires showing short selling is an important component of HFT, the ban impacts HFT, and disentangling the effect of HFTs from nHFTs short selling. To disentangle the effects of HFTs' and nHFTs' short selling we extend the difference-in-differences approach using the heterogeneity in the ban's cross-sectional impact on HFTs and nHFTs short selling as instruments.

NASDAQ provides our measures of short selling and HFTs. The HFT measure is the same as the one used in a number of other studies (Brogaard, Hendershott, and Riordan, 2013; Carrion, 2013; O'Hara, Yao, and Ye, 2013). During the ban HFTs' short selling falls from six percent of trading volume to less than one percent. nHFTs' short selling declines from 15 percent of trading volume to six percent.[1] The first-stage instrument variable (IV) regression shows differential declines in HFTs' and nHFTs' short selling based on market capitalization, options availability, and stock price. During the ban both liquidity and price efficiency decrease as measured by bid-ask spreads and the standard deviation of the pricing error component (Hasbrouck, 1993), respectively.

HFT short selling liquidity supply and demand are differentially impacted during the short sale ban. HFT liquidity demanding falls from four percent to less than one half of one percent while HFT liquidity supply shrinks from two percent to a little more than one half of one percent. By decomposing HFT into liquidity demand and liquidity supply we can provide a more nuanced discussion of the overall and individual impact of HFT on markets. Unfortunately, nHFT liquidity supply and demand fall by similar amounts, which are not statistically significantly different from each other. Thus, the IV regression cannot disentangle the ban's cross-sectional impact on nHFT short selling liquidity supply and liquidity demand. Therefore, we only examine the changes in overall nHFTs' short selling.

We examine large and small stocks separately as well as all stocks together. BJZ find the effect of the ban to be larger and more symmetric around the ban's introduction and removal in large stocks. We find that our results hold across size groups. We show that nHFTs' short selling increases liquidity and decreases pricing errors. In contrast, HFTs' short selling decreases liquidity and increases pricing errors. HFTs' negative impact is driven by liquidity demanding trades. HFTs' liquidity supply improves liquidity and price efficiency, but not enough to

[1] HFTs total trading activity, both short selling and non short selling, as fraction of trading volume declines by almost 50%.

outweigh the negative HFT liquidity demand effect. We also estimate a model that includes relative HFT (both short selling and non-short selling) and the relative short selling of nHFT. We find that overall HFT reduces liquidity and increases pricing errors. A one percent increase in relative HFT causes a 4.37 basis point increase in the quoted spread and a 0.04 increase in the standard deviation of the pricing error. The same increase in nHFT short selling causes a 5.03 basis point decrease in the quoted spread and a 0.05 decrease in the standard deviation of the pricing error.

The rest of the paper is organized as follows. Section I discusses our identification strategy and the related literature. Section II describes the data used and provides descriptive statistics. Section III details the specification and its suitability for this study. The main empirical results are presented in Section IV. Section V discusses the results. Section VI concludes.

I. Short Sale Ban, Identification, and Related Literature

HFTs' short selling and a market's liquidity and price efficiency are simultaneously determined in equilibrium leading to likely bidirectional causality. Suppose HFTs' trading increases and the bid-ask spread increases. It could be that HFTs cause the bid-ask spread to increase. Alternatively, HFTs could react to the higher bid-ask spread by increasing their participation. Therefore, we use a ban on short selling in trying to establish causal effects.

The short sale ban's differential effect on HFT is not enough to overcome endogeneity concerns. It could be that for the stocks where the short sale ban increased bid-ask spreads more HFT decreased less (e.g. was higher). One still cannot determine whether the relatively higher HFT activity resulted in the higher spreads, or whether the higher bid-ask spreads caused more HFT activity. To distinguish the causal effect of HFT on liquidity and price efficiency we use IV regressions based on the short sale ban and its cross-sectional impact on short selling activity.

The September 2008 short sale ban followed a volatility time in the financial markets. The details surrounding the ban and its institutional details are well documented in BJZ. We show the short sale ban significantly impacts the level of HFTs' shorting and overall trading activity. We use BJZ's matched group of non-banned stocks to control for how a stock with similar characteristics performs during the short sale ban. In addition, we use volatility variables, lagged stock volatility and contemporaneous financial sector volatility as measured by the XLF ETF volatility, to control for other effects possibly correlated with the ban.

For the ban to separately identify the effects of HFTs' and nHFTs' short selling we must find dimensions where the ex ante expectation is that the ban differentially impacts HFTs and nHFTs. Brogaard, Hendershott, and Riordan (2014) show that HFTs are more concentrated in larger stocks. In contrast, from a period before HFTs were prevalent, Boehmer, Jones, and Zhang (2008) show that short selling is relatively constant across market capitalization quintiles. These cross-sectional differences likely arise from HFTs' short holding periods being easier to accomplish in larger, more liquid stocks. The ban also exempted options market makers. If HFTs or nHFTs are more heavily represented in this group then whether or not options are available is another source of the ban's cross-sectional impact. O'Hara, Saar, and Zhang (2013) find evidence that, given the fixed tick size, stock price levels impact HFTs' behavior. In addition, various arbitrage strategies requiring immediate execution are more difficult in stocks where the spread is constrained by a larger tick size relative to stock price. For these reasons, in addition to the short sale ban itself, we utilize the pre-ban values of market capitalization, options listing, and stock price interacted with a short sale ban dummy variable as instruments. Because we use pre-ban cross-sectional characteristics as instruments the IV regressions are essentially a multivariate difference-in-difference approach.

For the short sale ban and its heterogenous cross-sectional effects to serve as valid instruments they must satisfy the exclusion restriction. Specifically, changes in stocks' relative short selling must not be correlated with the error term in that firm's liquidity and pricing error equation. This does not require that the cross-sectional variation occurs randomly. The market quality equation includes a firm fixed effect and a set of control variables. The instruments remain valid even if the cross-sectional variation is related to these particular explanatory variables. For instance, if the stocks with more registered market makers tend to have higher liquidity, this would be picked up by the firm fixed effect and the exclusion restriction would still hold. The exclusion restriction is violated if the heterogeneous variation in short selling is somehow related to contemporaneous changes in firm-specific, idiosyncratic liquidity or price efficiency that are not due to changes in short selling.

The ban could be correlated with liquidity and pricing errors into the future if there are sufficiently persistent but temporary shocks to liquidity and price efficiency. A natural way this could occur is if the short sale ban is correlated with other temporary changes in the informational environment of the banned stocks during the ban. This seems plausible given the state of the financial system, the rushed introduction of the ban, and the various other measures introduced at the beginning of the ban, e.g., the Troubled Asset Relief Program (TARP). BJZ address these concerns by showing that the results continue to hold if one matches by industry, only examines the end of the ban, and examine stocks banned subsequent to the initial ban. We supplement this by using lagged stock volatility and contemporaneous financial sector volatility as measured by the XLF ETF volatility as controls.

Lastly, the exclusion restriction requires the heterogeneous variation in the short sale ban to affect market quality only via short selling. The ban should be relevant for short selling as the ban does not directly affect liquidity via long trading. However, we cannot test this conjecture using the available data. Thus, it is important to emphasize that our conclusion on causality rely on the intuitively appealing but ultimately untestable assumption that the short sale ban affects liquidity and price efficiency only via its effect on short selling.

The above discussion focuses on the econometric use of the ban as an instrument. There are many possibly economic mechanisms by which HFTs can affect liquidity and price efficiency. If HFTs are informed market participants, then their removal could result in spreads decreasing as other market participants adjust for the lower probability of trading with an informed trader. On the other hand if HFTs are uninformed and simply trading as market intermediaries then their removal would cause spreads to increase.

Jones (2013) and Biais and Foucault (2014) offer reviews of the literature on HFT. A number of theoretical papers examine how fast traders can adversely select slower traders. Foucault, Hombert, and Rosu (2013) and Rosu (2014) examine how some traders trading faster on public signals increases information asymmetry. Budish, Cramton, and Shim (2014) study how fast traders impose adverse selection on each other and decrease liquidity. Our results for short selling by HFTs are consistent with these concerns.[2] Dugast and Foucault (2014) show how speculators who process information quickly and trade on it can increase the frequency of price reversals. Cartea and Penalva. (2012) provide a model where fast traders trade ahead of large orders increasing their transitory price impact. Our results on HFTs decreasing price efficiency are consistent with these models.

The informational and order anticipation effects in the above models operate through the liquidity demand channel, as do our related empirical results. On the liquidity-supply side Jovanovic and Menkveld (2012) and Hoffman (2014) study how HFTs can reduce adverse selection by updating quotes quickly, reducing adverse selection and improving liquidity. Our results showing liquidity supply by HFTs' short sales improving liquidity is consistent with these models.[3]

Empirically, technological changes have been used to examine how speed and fast trading impact markets. Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2012) show how algorithmic trading improves liquidity on the New York Stock Exchange market structure and internationally. Riordan and Storkenmaier (2012) find that a trading system upgrade at Deutsche Börse improves liquidity. Gai, Yao, and Ye (2014) find that technological

[2] The Budish, Cramton, and Shim (2014) and Biais, Foucault, and Moinas (2014) examine the social efficiency of investments in fast trading.

[3] The theoretical model by Aït-Sahalia and Saglam (2014) shows how faster market makers being better able to manage their inventory risk can improve liquidity. We find related results for the non-informational component of spread, the realized spread, falling with greater HFTs' short selling liquidity supply.

improvements at the NASDAQ are associated with decreasing depth. Menkveld and Zoican (2014) show that a new trading system introduced at NASDAQ OMX in 2010 increases spreads. Menkveld and Zoican are able to identify trading by different market participants and examine how HFTs' demanding liquidity pick off HFTs' supplying liquidity. Brogaard, Hagströmer, Norden, and Riordan (2014) use a colocation upgrade at NASDAQ OMX Stockholm to find that HFTs' supplying liquidity are able to utilize the upgrade to improve liquidity.[4]

Our results also contribute to the short selling literature. In particular, we add insight into the informedness of very short term short sellers. Saffi and Sigurdsson (2011) find that short selling improves market efficiency and Boehmer and Wu (2013) and Beber and Pagano (2013) find they improve the price discovery process. Certain types of short sellers are more informed than others. Boehmer, Jones, and Zhang (2008) find that institutional non-program short sales are the most informed. Engelberg, Reed, and Ringgenberg (2012) find that registered market maker short sellers are less informed than non-market makers. Kelley and Tetlock (2013) show that retail short sellers are informed. The findings in this paper are consistent with HFT short sellers being informed, especially HFT liquidity taking short sellers. As one would anticipate, when an informed trader is removed from the market liquidity improves due to lower adverse selection cost. These are consistent with the overall HFT short selling results and the HFT liquidity demanding short selling findings.

Comerton-Forde, Jones, and Putnins (2012) consider liquidity taking and supplying short selling separately. They find liquidity taking short selling is similar to overall liquidity taking trades, but that liquidity supplying short selling do so when spreads are wide. Our findings on HFT liquidity supply are consistent with this finding. HFT short selling liquidity supply and liquidity demand differs in their impact, and it is the liquidity supplying activity that improves liquidity and price efficiency.

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[4] Malinova, Park, and Riordan (2013) use the introduction of a message fee on the Toronto Stock Exchange to show that HFTs' liquidity supplying orders are positively related to liquidity. Menkveld (2013) show how the entry of one liquidity supplying HFT improves liquidity in Dutch stocks.

HFT firms can interact with the market through marketable or limit orders and there is an observed difference between the two types of trades (Brogaard, Hendershott, and Riordan, 2014; Hagstromer and Norden, 2014; Hagstomer, Norden, and Zhang, 2013). We find that stocks in which the ban causes HFTs liquidity demanding short selling activity to fall more, spreads increase less, consistent with HFTs being informed market participants and adversely selecting other investors. The results show that higher HFT liquidity demanding short selling activity causes liquidity to deteriorate.

II. Data and Descriptive Statistics

NASDAQ provides the HFT data used in this study to academics under a non-disclosure agreement. The measure of HFT provided by NASDAQ is used in a number of other studies (Brogaard, Hendershott, and Riordan, 2014; Carrion, 2014; O'Hara, Yao, and Ye, 2013). The dataset captures an identifier of whether a trade involved an HFT firm and specifies whether or not the HFT firm supplied and/or demanded liquidity. It also specifies whether the trade was buy- or sell-initiated. The identifier capturers firms that exclusively are HFTs. NASDAQ provides data between 08/01/2008 and 10/31/2008 for every symbol used in the BJZ study. This results in a sample of 727 banned stocks. We use the same matches as BJZ and NASDAQ also provides data on these control stocks. As in BJZ we drop observations from the first day of the ban to avoid contaminating our results with the effects of triple witching day and the TARP announcement. Because we use lagged firm volatility as a control changes in firms' information environment that could be correlated with the ban we also drop observations from the last day of the ban.

The data include trades executing against either displayed or hidden liquidity on the NASDAQ exchange, but not trades that execute on other markets including those that report on NASDAQ's trade reporting facility. Trades are time-stamped to the millisecond and identify the liquidity demander and supplier as a HFT or nHFT. Firms are categorized as HFT based on

NASDAQ's knowledge of their customers and analysis of firms' trading such as how often their net trading in a day crosses zero, their order duration, and their order to trade ratio. The HFT firms are the same as that in Brogaard, Hendershott, and Riordan (2014), so the same limitations apply.

Of the 727 stocks subject to the short sale ban, 665 were part of the initial ban, the rest were added later. There are 64 trading days. We require enough trading data to estimate our variables of interest on at least 60 of the 64 days in order for the stock to be considered. Our final sample has 422 banned stocks. We match each banned stock to its BJZ control stock.

The HFT dataset is provided by NASDAQ and contains the following data fields:

(1) Symbol
(2) Date
(3) Time in milliseconds
(4) Shares
(5) Price
(6) Buy Sell indicator
(7) Type (HH, HN, NH, NN)

Symbol is the NASDAQ trading symbol for a stock. The Buy-Sell indicator captures whether the trade was buyer or seller initiated. The type flag captures the liquidity demanding and liquidity supplying participants in a transaction. The type variable can take one of four values, HH, HN, NH or NN. HH indicates that a HFT demands liquidity and another HFT supplies liquidity in a trade; NN is similar with both parties in the trade being nHFTs. HN trades indicate that an HFT demands and a nHFT supplies liquidity, the reverse is true for NH trades. The remainder of the paper denotes HFT liquidity demand trades as HFT^D (HH plus HN) and HFT liquidity supply trades as HFT^S (NH plus HH). Total HFT trading activity (HFT^D + HFT^S is labeled as HFT^A. The nHFT trading volume variables are defined analogously.

The NASDAQ HFT dataset is supplemented with the National Best Bid and Offer (NBBO) from the SIRCA TickHistory service. The NBBO measures the best prices prevailing across all markets. We use SIRCA data as it provides millisecond time stamps, whereas the Millisecond TAQ database does not begin until after our sample period. Market capitalization data is retrieved from CRSP. We focus on continuous trading during normal trading hours by removing trading before 9:30 or after 16:00 and the opening and closing crosses, which aggregate orders into an auction. We match the data to the Regulation SHO data from NASDAQ. Because both the HFT data and the Regulation SHO data are from NASDAQ they contain the same time stamp, making matching straightforward.

Table 1 reports the descriptive statistics. All statistics are based on the time series average over the relevant interval and averaged across the cross-section of stocks. The first three columns report the descriptive statistics for banned stocks, Columns (4) – (6) report for the control group of stocks. The statistics are broken down based on the pre-ban period, the banned period, and the post-ban period.

Insert Table 1 About Here

Nasdaq Volume is the average daily dollar volume of stock *i*. On average a banned stock traded $22.6 million before the ban, $16.8 million during the ban, and $20.9 million after the ban. The corresponding volumes for the match sample are $16.4, $17.4, and $17.4 million before, during, and after the ban respectively. The internet appendix graphs the time series of total volume and short selling volume on NASDAQ, and the time series of HFT volume and short selling volume.

The first measure of liquidity is the quoted spread. The quoted spread captures the costs of simultaneously buying and selling a small amount at the quoted prices using marketable orders. This is the cost of instant immediacy. Lower costs of trading may be possible by placing limit orders, but those are more difficult to measure because many limit order do not execute. The quoted spread is defined as

$$Quoted\ Spread_{i,t} = \frac{Ask\ Price_{i,t} - Bid\ Price_{i,t}}{M_{i,t}}, \qquad (1)$$

where *Ask Price* is the lowest displayed price at which an investor will sell shares in stock i at time t, *Bid Price* is the highest displayed price at which an investor will buy shares in stock i at time t. M is the midpoint price prevailing at time t in stock i. *Quoted Spread* is the national quoted spread based on data from SIRCA from all exchanges. A higher value implies less liquidity. Quoted spread only measure visible liquidity, so hidden orders may provide additional liquidity, possibly at better prices.

For the banned stocks the quoted spread increases from 27.6 basis points in the pre-ban period to 60.1 during the ban. The non-banned stocks have lower quoted spreads, but spreads increase more during ban.

We also consider another liquidity measure the effective spread, defined as

$$Effective\ Spread_{i,t} = \frac{|P_{i,t} - M_{i,t}|}{M_{i,t}}, \qquad (2)$$

where P is the price at which the trade occurred. The *Effective Spread* only evaluates trades occurring on NASDAQ using the NBBO midpoint price. The wider the effective spread the less liquid is a stock. Note that, effective spreads are strictly lower than quoted spreads, showing that hidden liquidity is regularly available. The effective spreads before, during, and after the ban follows a similar pattern as the quoted spreads.

We evaluate the realized spread, defined for buyer-initiated trades as

$$Realized\ Spread_{i,t} = \frac{P_{i,t} - M_{i,t+5min}}{M_{i,t}}, \qquad (3)$$

where $M_{i,t+5min}$ is the midpoint price prevailing 5 minutes after the stock i trade occurring at time t. The realized spread for seller-initiated trades multiplies Equation (3) by minus one. The banned stocks experience a large increase in realized spread during and after the ban, it increases from 6.6 in the pre-ban period to 20.1 during the ban and 16.6 following the ban. For the control group the realized spread increases from the pre-ban level of 7.6 to 11.5 in the ban period and 16.33 in the post-ban period.

We evaluate the price impact, defined for buyer initiated trades as

$$Price\ Impact_{i,t} = \frac{M_{i,t+5min} - M_{i,t}}{M_{i,t}}. \tag{4}$$

Equation (4) is multiplied by minus one for seller initiated trades. For banned stocks there is a large increase in the price impact from the pre-ban (13.9) to the ban period (25.9), and the price impact remains high in the post-ban period (27.5). The price impact for the control group only moderately increases between the pre-ban (12.2) and the ban (17.6) period, but rises even more in the post-ban period (24.5).

To capture price efficiency we estimate the Hasbrouck (1993) pricing error. A number of studies use the measure to estimate price efficiency by measuring the noise in prices (e.g. Boehmer and Kelley, 2009; Boehmer and Wu, 2013; Hendershott and Moulton, 2011). We follow Hasbrouck (1993), Boehmer and Kelley (2009), and Hendershott and Moulton (2011) to compute pricing errors. Using a vector autoregression (VAR) as in Hasbrouck (1993) we calculate the transitory (pricing error). We decompose the observed (log) mid-quote price, p_t, into an efficient price, m_t, and the pricing error s_t as follows:

$$p_t = m_t + s_t,$$

m_t is assumed to be non-stationary, is defined as a security's expected value conditional on all available information, and is assumed to follow a random walk. The pricing error measures the transitory deviations of the mid-quote from the efficient (random walk) prices. The pricing error has zero mean and we use its volatility (σ(s)) to measure the size of the pricing error. By using log mid-quote returns in the VAR, we remove any direct effects of the short sale ban on spreads and focus on the efficiency of mid-quotes. We estimate the VAR for each stock and each day using all trading and mid-quotes for a stock in each second of the trading day (9:30 – 16:00). We remove all seconds in which the price doesn't change relative to the previous second's price and / or there is no trading. The standard deviation of the pricing error is increasing over the sample period and is higher for the banned stocks during the ban period.

Table 1 also provides information on the trading activity of the different market participants. We provide the short sale trading volume by trader and trade type with the suffix *_Short*. The last third of Table 1 reports the relative short selling performed by different segments of the population, identified by the prefix *RelSS*. *RelSS* is the fraction of NASDAQ volume where the seller is short selling.

HFTs and nHFTs behave quite differently during the ban. For the banned stocks HFT^{A} decreases from \$9.7 million to \$5.8 million, from the Pre-Ban to the Ban period, and increases to \$9.1 million after the ban. While for the control group HFTs' trading volume increases from \$6.3 million to \$7.0 million and drifts up to \$7.1 million from the pre, during, and post periods. The banned (control) drop (rise) during the ban followed by a recovery (decline) in activity is also seen when considering HFT^{D} or HFT^{S}. nHFTs exhibited no obvious patterns. Overall $nHFT^{A}$ remained relatively flat in dollar trading volume for the banned stocks across the time period: \$12.9, \$11.1, and \$11.8 million for the pre, during and post ban periods, respectively. The dollar volume amounts for each trader type that is a short sale is also reported.

Following BJZ most of our analysis uses relative short sales (RelSS) for each trader type, which is the fraction of total trading volume for each trade type that is short sales. As expected, relative short sales fall for all trader types during the ban period. Before the ban 21.0% of the dollar volume traded was a short sale. During the ban the fraction dropped to 6.7%. Overall, HFTs' RelSS declines from 5.9% pre-ban to 0.9% during the ban, and recovers to 4.4% post-ban. nHFTs' RelSS decreases from 15.1% pre-ban to 5.7% during the ban and increases to 13.4% post-ban. RelSS for HFTs and nHFTs exhibits little variation across time periods in the control stocks.

To more clearly examine the time series of the variables in Table 1 we provide a number of figures. Following BJZ we split the sample based on market capitalization. BJZ use quartiles, but find relatively little in the two smallest quartiles. Our data requirements reduce the number of stocks so we construct two categories, large and small. In the figures graphs on the left are for large stocks and graphs for small stocks are on the right.

Figure 1 plots overall RelSS as well as HFT and nHFT RelSS. Figure 2 shows RelSS for HFT and nHFT liquidity supply and liquidity demand separately. The figures show across categories that RelSS was fairly stable before the ban and the declines in RelSS appear immediately upon the ban's introduction and persist through the ban. The recovery in RelSS after the bans removal is immediate and constant. Figures 1 and 2 illustrate the ban's large and temporary impact on short selling.

Insert Figures 1 and 2 About Here

HFTs could have continued trading at the same level by accumulating long inventory to avoid shorting. Table 1 shows the ban did impact HFTs' activity. Figures 3 and 4 plot relative HFT and it broken down into liquidity supply and demand. As with RelSS, relative HFT falls upon the ban and recovers upon removal, although the rebound is not complete. Figures 3 and 4 establish the ban significantly impacting HFTs, although HFTs are able to continue trading to a lesser extent due to the ban's market-making exemptions or by avoiding going short. This shows that while the ban produces economically large effects, not all HFT activity is affected. Section VI discusses this further in the context of interpreting the IV results.

Insert Figures 3 and 4 About Here

Figures 5 and 6 plot the liquidity and price efficiency measures. Figure 5 shows that spreads increase immediately with the ban in the banned stocks, but not in the control stocks. Spreads drift upwards during the ban in both the ban and control stocks, indicating the importance of controlling for other market-wide factors. The level of spreads in the ban and control stocks is similar before and after the ban, particularly in the large stocks. Consistent with BJZ, this suggests that the ban had a significant temporary impact on liquidity. Figure 6 shows pricing errors react in a similar fashion around with the ban. BJZ present related results for total volatility based on the high-low price range. The pricing error results appear more precise as they isolate only the transitory component of volatility.

Insert Figures 5 - 6 About Here

III. Specification Details

The summary statistics and figures show a noticeable change in trading activity and in liquidity and price efficiency around the ban. This section formalizes the IV analysis discussed in Section II. We include four instrumental variables in the first-stage regression to identify exogenous shocks to relative short selling and relative short selling by different participants. These variables for stock i and day s are:

Instrumental Variable	Description
$Ban_{i,s}$	An indicator variable taking the value 1 during the ban for stocks subject to the ban, and zero otherwise (The Ban Indicator).
$Ban_{i,s} \times Mcap_i$	The Ban Indicator interacted with the natural log of stock i's average market capitalization during the pre-period.
$Ban_{i,s} \times Options_i$	The Ban Indicator interacted with an indicator variable taking the value 1 if stock i has options traded on it as of August 1st.
$Ban_{i,s} \times Price_i$	The Ban Indicator interacted with the average price of stock i during the pre-period.

The first variable is a dummy for the short sale ban itself that takes the value one only for those days and stocks during which the ban applied and zero otherwise. The figures show shorting activity declines during the ban. Second, we include the interaction of the short sale ban with a stock's market capitalization as August 1, 2008 as HFTs tend to trade in larger stocks (Brogaard, Hendershott, and Riordan, 2014). The third instrument is the sales ban dummy interacted with a dummy taking the value one if, in August 2008, individual stock options were traded on the stock (see Battalio and Schultz, 2011, for analysis of options trading during the short sale ban). The final instrument is the short sale ban dummy interacted with the average pre-ban period stock price. O'Hara, Saar, and Zhang (2013) find evidence that, given the fixed tick size, stock price levels impact HFTs' behavior. Acemoglu and Angrist (2000) discuss the use of multiple correlated instruments for several possible treatment variables.

Table 2 provides the correlations among the instruments discussed above and the trading variables in Figures 1-4. The ban's effect on RelSS is larger in higher market capitalization stocks, stocks with options, and higher prices stocks. While larger stocks have higher prices and are more likely to have listed options, Table 2 shows that the correlation is less than one. However, the correlations among the cross-sectional instruments range from 0.57 to 0.73, which may reduce the power when trying to disentangle the casual effects of the various types of short selling. Fortunately, the correlation among the HFT RelSS and nHFT RelSS variables is low, which provides some hope for separately identifying their effects.

Insert Table 2 About Here

In addition to our instruments and matched sample, the inclusion of time series variables related to the stocks' informational environment can improves the estimation and help isolate the ban's effect. These control variables also help to address concerns that the ban is correlated with events or conditions only affecting the banned stock and not their matched firms. The control variables are listed below. Note that an options dummy is not used because it is collinear with the firm fixed effects.

Control Variable	Description
Mcap	The natural log of the market capitalization of stock *i* on date *s*.
Price	The price of stock *i* on date *s*.
Rtn. Std. Dev.(s-1)	The average 1-second standard deviation of returns of stock *i* on the previous trading day.
XLF Rtn. Std. Dev.	The average 1-second standard deviation or returns of the Financial Select Sector exchange traded fund on date *s*.

*Ban*XLF Rtn. Std. Dev.*	The average 1-second standard deviation returns of the Financial Select Sector exchange traded fund interacted with The Ban Indicator on date *s*.
Pre Period	a time series indicator variable taking the value 1 for observations before the ban and 0 afterwards.
Post Period	a time series indicator variable taking the value 0 for observations before the end of the ban 1 for observations afterwards.

Rtn. Std. Dev. (s-1) captures potential time series variation in the information environment of a stock. We use the previous days' return standard deviation as contemporaneous measures of volatility and measures of liquidity and price efficiency are simultaneously determined. XLF is the ETF on the financial sector stocks. Under the assumption that liquidity and price efficiency in each individual stock does not cause volatility in XLF, then Rtn. Std. Dev. XLF controls for the information environment for financial sector stocks. Given that the ban targets financial sector stocks, we include an interaction term of XLF volatility with the ban indicator to allow for a different impact of XLF volatility on the ban and control stocks. Pre and post period dummies capture different market-wide conditions before and after the ban that are evident in Table 1 and Figures 1-6. Finally, stock fixed effects are included to capture any other time-invariant cross-sectional heterogeneity.

The regression analysis pools all banned stocks and their matched pairs in the analysis. The final panel includes 422 x 2 = 844 stocks. Before using our IV approach to analyze the effect of HFT, we extend BJZ's main specification to include our ban cross-sectional interaction variables and our control variables. This ensures that the data requirements for our sample do not change BJZ's main conclusions and provides insight into the ban's cross-sectional effects on liquidity and price efficiency. Table 3 performs the following regression:

$$Y_{i,s} = \alpha_i + \beta_1 \times Ban_{i,s} + \beta_2 \times Ban_{i,s} \times Mcap_i + \beta_3 \times Ban_{i,s} \times Option_i + \beta_4 \times Ban_{i,s} \times Price_i + \theta X_{i,s} + \epsilon_{i,s}, \quad (6)$$

where $Y_{i,s}$ is one of the dependent variables measuring liquidity and price efficiency discussed above. The control variables capture time-series variation in financial markets other than the short sale ban that may influence the dependent variable. The matched stock setup and banned time period dummy results in a differences-in-differences methodology that aims to isolate the effect of the short sale ban. Standard errors are clustered using the techniques of Petersen (2009) and Thompson (2011) to account for time-series and cross-sectional correlation of the regression errors, as well as heteroscedasticity.

Insert Table 3 About Here

The coefficients on the ban variable in Table 3 are consistent with BJZ's findings. For all stocks quoted spreads increase by 35.7 basis points, effective spreads increase by 31.3, realized spreads increase by 21.4, price impacts rise by 9.9, and the pricing error increases by 0.29%. All the results are statistically significant at the 1% level. The ban interaction variables show there is cross-sectional variation in the outcome variables related to our instruments as the ban has a smaller effect on larger stocks and on stocks with traded options. Quoted spreads on banned stocks with listed options increase by 24.2 basis points less during the ban. Quoted spreads on larger banned stocks increase less, with the -4.5 coefficient corresponding to a firm 2.7 times larger having spreads increase by 4.5 basis points less during the ban. While the ban interacted with stock price does not have a significant coefficient, it may be useful as it correlates differently with RelSS HFT liquidity demand and supply in Table 2. The control variables have the expected signs, e.g., the coefficients on volatility are positive.

IV. **The Effects of Short Selling and HFTs**

The correlations in Table 2 essentially provide univariate regressions of the trading variable on our instruments. To disentangle the effects of different types of short selling and trading the first-stage of our IV approach uses a specification similar to the one in Table 3 with the left-hand-side variables being measures of short selling and trading:

$$Y_{i,s} = \alpha_i + \beta_1 \times Ban_{i,s} + \beta_2 \times Ban_{i,s} \times Mcap_i + \beta_3 \times Ban_{i,s} \times Option_i + \beta_4 \times Ban_{i,s} \times Price_i + \theta X_{i,s} + \epsilon_{i,s}, \quad (7)$$

where $Y_{\text{i,s}}$ takes one of several dependent trading variables discussed below. The unit of observation is stock i for day s, where Y is one of several relative trading activity measures. In the regression we include $X_{i,s}$, a vector of the remaining controls previously mentioned. We also include stock fixed effects. The results of the first stage are reported in Table 4.

Insert Table 4 About Here

We report the results for all stocks, as well as for separate estimations for large and small stocks. Each column reports the analysis for a different dependent variable of interest. Column (1) reports the results with the dependent variable being the overall relative short selling volume, RelSS. Not surprisingly the coefficient on BAN is negative showing that short selling decreases during the ban relative to overall volume. Columns (2) and (3) separate nHFT and HFT. Columns (4) and (5) decompose HFT into liquidity demanding (RelSS HFT^{D}) and supplying (RelSS HFT^{S}). Column (6) considers relative HFT, which is the fraction of trading volume by HFTs that is both buying as well as short selling and non-short selling.

Consistent with the correlations in Table 2, the ban coefficient and ban interaction coefficients vary across RelSS HFT^{A} and RelSS nHFT^{A}. On average and in stocks with options RelSS falls more with the ban for nHFT^{A}. The opposite is true for larger stocks as the coefficient on the ban interacted with log market capitalization is negative and statistically significant for RelSS HFT^{A} while being positive and insignificant for RelSS nHFT^{A}.

The ban coefficient and ban interaction coefficients vary across RelSS HFT^{D} and RelSS HFT^{S}, showing the short sale ban's differential impact on HFT liquidity supply and demand. The coefficients on the interaction terms of the ban with options and with share price are positive and statistically significant for RelSS HFT^{S} and are not for RelSS HFT^{D}. This suggests that for high-priced stocks with options HFT relative shorting activity fell more for liquidity demand than for liquidity supply.

The estimates from the varying regressions in Table 4 are used in the second stage. Before reporting the second-stage results we examine the weak identification and underidentification tests. The bottom of each column reports the first-stage F-statistic, the Angrist-Pischke chi-squared test of underidentification, and the Angrist-Pischke F-statistic test of weak identification. The F-statistic is the standard test of instrument relevance. The Angrist-Pischke (AP) first-stage chi-squared is a test of underidentification of the individual regressors. The AP first-stage F statistic is the F form of the same test statistic, which tests whether an endogenous regressor is weakly identified. The test statistics are compared to their relevant critical values at the 1% level. We also compute overall model tests statistic of underidentification (Kleibergen-Paap 2006), weak identification (Cragg-Donald 1993, Wald F statistic) and overidentification (Hansen 1982 and Sargan 1958 J statistic) and find no evidence that the full model is mis-specified.

The level changes in RelSS $nHFT^{D}$ and RelSS $nHFT^{S}$ in Table 1 and the correlation of those trading variables with the instruments in Table 2 suggest that the instruments have little power to separately identify changes in RelSS $nHFT^{D}$ and RelSS $nHFT^{S}$. We formally confirm this in two ways. First, we run the specification in Table 4 for RelSS $nHFT^{D}$ and RelSS $nHFT^{S}$. This model specification fails the weak and under identification tests.[5] Second, we run a regression of the form in Table 4 where the dependent variable is the difference in RelSS $nHFT^{D}$ and RelSS $nHFT^{S}$ in each stock each day. In that regression none of the coefficients on the instruments are statistically significantly different from zero. Hence, our instruments cannot disentangle the effects of RelSS $nHFT^{D}$ and RelSS $nHFT^{S}$. In addition, while our instrument can identify RelSS

[5] The regression results are reported in Table A1 of the Internet Appendix.

HFT^S and RelSS HFT^D, the instrument cannot identify relative HFT^S and relative HFT^D separately (see Table A1 of the Internet Appendix).

The second-stage regression uses the estimates from the first stage regression to measure exogenous variation in different market participation types' trading and how it impacts liquidity and price efficiency. Because all the instruments are fixed in the time series the IV is similar to a multivariate difference-in-difference approach. The first specification considers how the decrease in overall short selling affects liquidity and price efficiency:

$$Y_{i,s} = \alpha_i + \beta_1 \widehat{RelSS}_{i,s} + \theta X_{i,s} + \epsilon_{i,s}, \qquad (8)$$

where $Y_{i,s}$ takes one of several liquidity and price efficiency variables discussed below. The unit of observation is stock i for day s. We include the same control variables as in Equation (6). $\widehat{RelSS}_{i,s}$ takes the value estimated from Equation (7), where the dependent variable is *RelSS*. The results are reported in Table 5. Panel A reports the overall results, and Panel B and C the results for large and small stocks, respectively.

Insert Table 5 About Here

The coefficients on RelSS in the liquidity measure regressions show the short sale ban harmed liquidity through a reduction in short selling. The coefficient on *RelSS* for the liquidity measures is negative but not statistically significant for the combined analysis. However, when considering large and small stocks separately, both groups of stocks show negative and statistically significant liquidity results; with the exception of realized spreads in small stocks. The units of *RelSS* are in percent. Therefore, the quoted spread coefficient of -0.40 on large stocks is interpreted as a one percent decrease in *RelSS* causing an increase in the quoted spread of 0.40 basis points. The sign of the coefficients are consistent with the implicit interpretation of the analysis in BJZ: when short selling decreases, spreads increase. For all, large, and small stocks, the pricing error coefficient is negative and statistically significant.

While the inclusion of control variables complicates a direct comparison of the IV estimates to the simple time-series changes observed in the figures, the magnitude of the coefficients in

Table 5 are roughly the correct size for the decline in RelSS in Figure 1 to explain the increase in quoted spreads in Figure 5. For example, Figure 1 shows a decline in RelSS of about 15% with the ban, which multiplied by the 0.40 coefficient in Table 5 explains the majority of the approximately 10 basis point increase in quoted spreads for large stocks in Figure 5.

To separately identify the impact of HFT and nHFT on price efficiency and liquidity we extend the analysis in Table 5 by separating the relative short selling into that conducted by HFT and by nHFT. The regression in Equation (8) uses the instrumented relative short selling into that done by HFT and by nHFT from the first-stage regression in Table 4:

$$Y_{i,s} = \alpha_i + \beta_1 \, \widehat{RelSS\_A\_HFT}_{i,s} + \beta_2 \widehat{RelSS\_A\_nHFT}_{i,s} + \theta X_{i,s} + \epsilon_{i,s} \tag{9}$$

Here $\widehat{RelSS\_A\_HFT}_{i,s}$ takes the value estimated in Table 4 where the dependent variable is RelSS HFT^A. $\widehat{RelSS\_A\_nHFT}_{i,s}$ comes from the RelSS $nHFT^A$ regression in Table 4. Table 6 provides the results where the dependent variables in the second stage are the measures of liquidity and price efficiency.

Insert Table 6 About Here

Table 6 shows that HFT short selling causes liquidity to decrease, whereas nHFT short selling causes liquidity to improve. The quoted spread, effective spread, realized spread, and price impact results all provide similar inference. In the quoted spread (effective spread) regression RelSS HFT has a positive coefficient of 8.53 (7.86), while nHFT has a negative coefficient of -6.05 (-5.57). The price impact and realized spread results show that these effects operate through both the informational and non-information liquidity channels. These results show that HFTs harm liquidity.

The price efficiency result shows that the standard deviation of the pricing error increases with RelSS HFT (0.07) and is statistically significant at the 1% level. The sign of the coefficient suggests that more HFT activity causes prices to be noisier. The nHFT pricing error coefficient is negative (-0.06).

To further understand how HFTs can harm liquidity and price efficiency we disaggregate RelSS HFT into HFT liquidity demanding and HFT liquidity supplying in Equation (9):

$$Y_{i,s} = \alpha_i + \beta_1\, Rel\widehat{SS\ HFT}^{D}_{i,s} + \beta_2\, Rel\widehat{SS\ HFT}^{S}_{i,s} + \beta_3 Rel\widehat{SS\ \mathrm{n}HFT}^{A}_{i,s} + \theta X_{i,s} + \epsilon_{i,s}. \tag{10}$$

The estimated RelSS HFT^{D}, RelSS HFT^{S}, and RelSS nHFT^{A} come from the regressions reported in Table 4. Because our instruments cannot separately identify changes in nHFT liquidity demand and liquidity supply we continue to use the overall level of nHFT relative short selling in the regression specification. The second-stage results are reported in Table 7. The dependent variables in the second stage are the measures of liquidity and price efficiency.

Insert Table 7 About Here

HFT short selling liquidity demand harms liquidity. For HFT^{D} the quoted spread, effective spread, realized spread, and price impact all increase, and are statistically significant. For HFT liquidity supply the effect is the opposite: quoted spread, effective spread, realized spread, and price impact decrease. However, the HFT liquidity supply results are not statistically significantly different from zero for price impacts. As in Table 6, the nHFT coefficients continue to be negative and the quoted spread and effective spread are statistically significant at the 1% level. While nHFTs' short selling causes liquidity to improve, we are unable to establish whether nHFTs' liquidity demand, liquidity supply, or both are both responsible.

We find evidence that HFTs' short selling liquidity demand harms price efficiency. The coefficient on RelSS HFT liquidity demand in the standard deviation of the pricing error regression (0.12) is statistically significant at the 1% level. HFT liquidity supply on the other hand is negative but not statistically significant. The coefficient on nHFT for the standard deviation of the pricing error remains negative and statistically significant as in Table 6.

The Internet Appendix explores strategies for incorporating changes in the information environment of the banned stocks beyond using the financial sector ETF volatility, lagged stock volatility, and a matched sample of firms as controls. While these controls are the most natural ones, Tables A2-A4 in the Internet Appendix use stock returns during the ban as controls. Table

A3 uses the first day of ban's return, which coincides with TARP's introduction, and Table A4 uses the return over the entire ban period. The inclusion of either of these stock returns has little effect on the results. It is never possible to rule out all other effects possibly correlated with the ban, but our control variables are reasonably comprehensive.

The regressions use a linear relationship between short selling and liquidity and price efficiency. While this is a natural functional form, Table A5 in the Internet Appendix explores a log-linear specification. The log of the dependent variables are used in place of the levels in Equation (10). For the liquidity regressions the signs on the trading variables remains the same and most continue to be statistically significantly different from zero.

We have focused exclusively on the impact of relative short selling coming from the short sale ban. Table 1 and Figures 3 and 4 show that HFTs' overall trading was significantly affected by the shorting ban. We next examine whether our IV results extend to overall HFTs' trading by using the relative HFT measure.[6] We perform the regression:

$$Y_{i,s} = \alpha_i + \beta_1\, Rel\_\widehat{A\_H}FT_{\iota,s} + \beta_2 RelSS\_\widehat{A\_n}HFT_{\iota,s} + \theta X_{i,s} + \epsilon_{i,s}. \tag{11}$$

The results are reported in Table 8. As before RelSS nHFT has all negative coefficients on the liquidity and price efficiency measures, supporting the earlier findings that nHFT short selling improves liquidity and price efficiency. Rel HFT has positive coefficients on the liquidity and price efficiency measures, consistent with the RelSS HFT results. A one percent increase in relative HFT causes a 4.37 basis increase in the quoted spread and a 0.04 increase in the standard deviation of the pricing error. The same increase in nHFT short selling causes a 5.03 decrease in the quoted spread and a 0.05 decrease in the standard deviation of the pricing error. The evidence suggests that including long trading by HFTs does not overturn the overall negative effects of HFTs' short selling on liquidity and price efficiency.

Insert Table 8 About Here

[6] As mentioned when discussing Table 4, our instruments are too weak to decompose Rel HFT into its liquidity demanding and supplying activity.

V. Discussion

We find a downside of HFT is that the HFTs' liquidity demanding trades decrease liquidity, an issue at the heart of much theoretical work on HFTs. We also find HFTs' liquidity demanding trades decrease price efficiency. Seemingly in contrast, Brogaard, Hendershott, and Riordan (2014) show that HFT liquidity demanding trades occur in the direction against transitory movements. The instrumental variables approach in this study overcomes the endogeneity concerns allowing us to make causal statements. Our results on pricing errors are not consistent with drawing the natural conclusion from Brogaard et al.'s (2014) finding that HFTs' liquidity demanding trades reduce pricing errors. If HFTs' trading behavior impacts other market participants in such a way as to increase the temporary price impact of their trades then more HFT liquidity demand can increase pricing errors even if the HFTs trade against pricing errors. Hirschey (2013) finds evidence that HFTs trade in the direction of future nHFT order flow. This could increase the temporary price impact of the nHFTs trades and the pricing error.[7]

The IV approach captures the local average treatment effect. The ban largely eliminates HFTs' shorting activity, but has a smaller impact on overall HFT activity. Therefore, the ban captures some large amount of trading activity, but it is difficult to know how representative it is of overall HFT activity. It is possible that HFT firms or strategies that rely on short selling are significantly different from strategies that do not use short selling. It could be that HFTs' non-short-selling HFT liquidity demand is more benign or even beneficial to liquidity and price efficiency. Hence, a conservative interpretation of the results is that we find a component of HFTs' activity which is harmful and a component that is beneficial.

[7] A related possibility is momentum ignition (SEC (2010)), where HFTs' submit an order to trigger similar orders in the same direction pushing prices away from the equilibrium price and allowing them to profit from the subsequent reversal. The difference between momentum ignition and the Hirschey (2013) story is whether the nHFT trading would have occurred without the HFTs.

Consistent with a number of theoretical papers, the results suggest that a policy response to HFT could be to limit the use of HFTs' liquidity demanding trades. In our results the only possible positive benefits of HFTs' liquidity demanding trades is their causing more information to be impounded into prices. Whether such short-lived information is socially valuable is discussed in Brogaard et al. (2014). However, in considering restrictions on HFTs' liquidity demand an important consideration is the ability of HFT to supply liquidity with less ability to demand liquidity. For example, limiting the ability of HFTs to demand liquidity may impair their ability to manage risk and thereby supply liquidity.

Limiting the ability of those closest to the markets to demand liquidity has some precedence. In the past, market-makers were limited in their use of liquidity demanding trades. The market-makers, or specialists, were also guaranteed access to incoming liquidity demanding order-flow, providing them with opportunities to balance out their inventory. Without these types of benefits, limiting HFTs' ability to demand liquidity may unnecessarily harm overall liquidity. In addition, defining who is a HFT is challenging and contentious. A simpler approach would be place limits on liquidity demand by all collocated traders.

VI. Conclusion

This paper uses the 2008 Short Sale Ban to study the effect of HFT in financial markets. We use short sale ban and its differential cross-sectional impact in an instrumental variables design to make causal statements about how HFT affect liquidity and price efficiency. We find that HFT short selling liquidity demand decreases liquidity and price efficiency. nHFT shorting activity improves liquidity and price efficiency. Our results on the overall impact of HFT are based on changes in HFT driven by the short sale ban. If HFTs' short-selling is similar to HFTs' non short-selling the results are generalizable to overall HFT.

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Figure 1: Relative shorting volume and HFT nHFT shorting volume. The top graph reports the relative shorting volume in the Banned and Control groups. Relative short trading volume is calculated as dollar volume for short sales for each stock and day on NASDAQ divided by overall trading volume. The bottom graph reports the relative trading volume by HFT and nHFT. The sample consists of the common stocks listed that appear on the initial shorting ban list and their matched control firms that are not subject to the shorting ban from 1 Aug 2008 through 31 Oct 2008. We used the same matches as BJZ. The left graph is for large stocks; the right for small stocks. The vertical lines correspond to the beginning and ending of the short sale ban.

Large Stocks **Small Stocks**

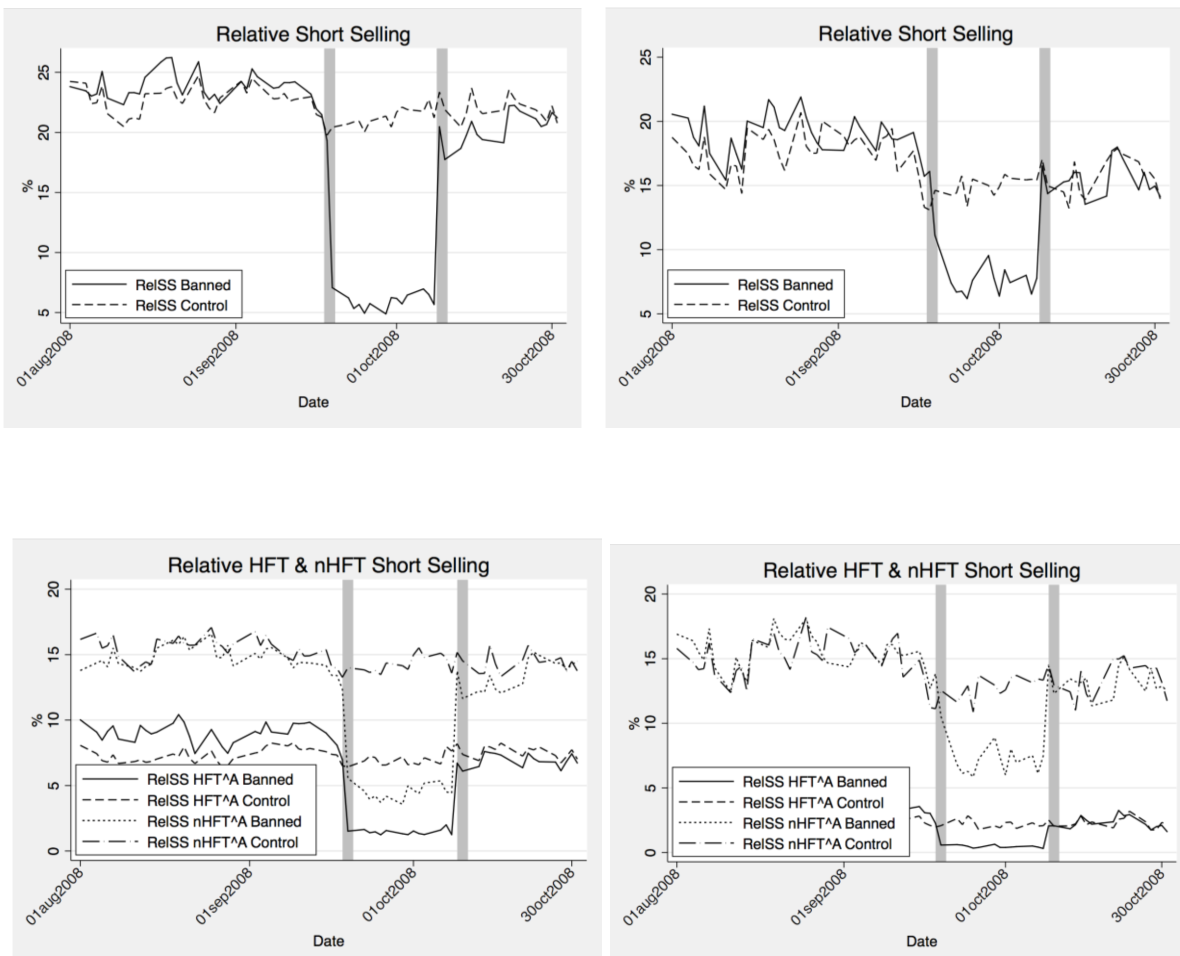


Figure 2: HFT nHFT relative liquidity demand and supply trading volume. The top graph reports the relative liquidity demand trading volume by HFT and nHFT. The bottom graph does the same for relative liquidity supply trading volume The sample consists of the common stocks that appear on the initial shorting ban list and their matched control firms that are not subject to the shorting ban from 1 Aug 2008 through 31 Oct 2008. We used the same matches as BJZ. The left graph is for large stocks; the right for small stocks. The vertical lines correspond to the beginning and ending of the short sale ban.

Large Stocks **Small Stocks**

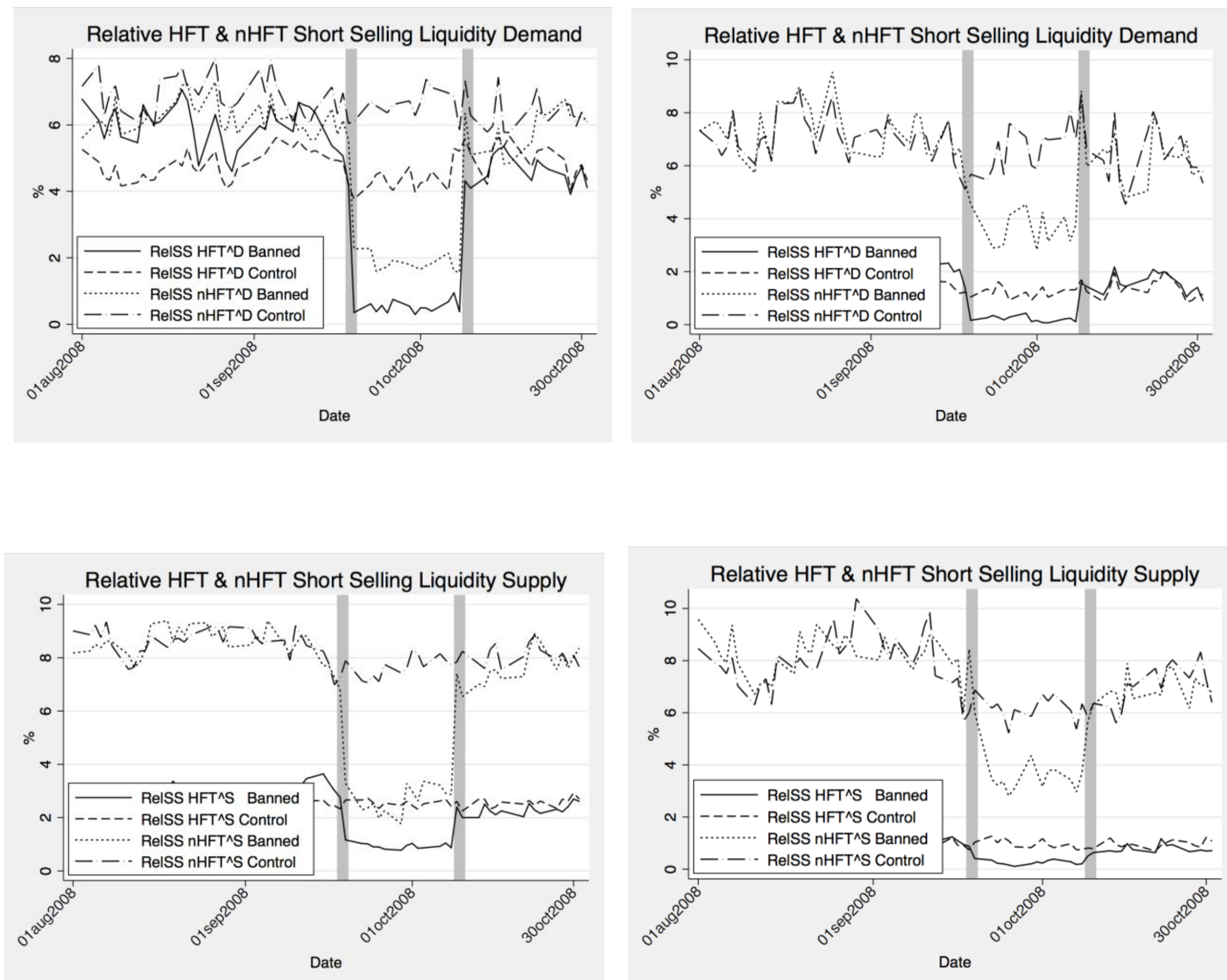
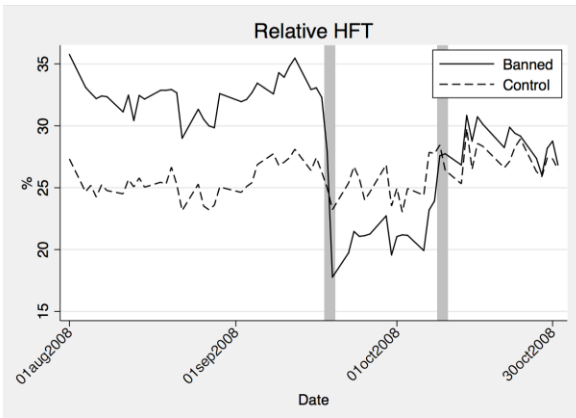


Figure 3: Relative HFT trading volume. The graph reports the relative trading volume by HFT. HFT Relative trading volume is calculated as HFT dollar volume for each stock and day on NASDAQ divided by overall trading volume. The sample consists of the common stocks that appear on the initial shorting ban list and their matched control firms that are not subject to the shorting ban from 1 Aug 2008 through 31 Oct 2008. We used the same matches as BJZ. The left graph is for large stocks; the right for small stocks. The vertical lines correspond to the beginning and ending of the short sale ban.

Large Stocks



Small Stocks

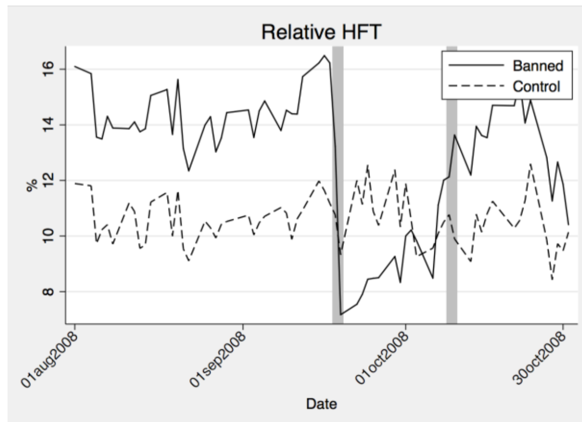


Figure 4: Relative HFT liquidity demand and supply trading volume. The top graph reports the trading volume of HFT and nHFT in the Banned and Control groups. The bottom graph reports the relative trading volume by HFT. HFT Relative trading volume is calculated as HFT dollar volume for each stock and day on NASDAQ divided by overall trading volume. The sample consists of the common stocks that appear on the initial shorting ban list and their matched control firms that are not subject to the shorting ban from 1 Aug 2008 through 31 Oct 2008. We used the same matches as BJZ. The left graph is for large stocks; the right for small stocks. The vertical lines correspond to the beginning and ending of the short sale ban.

Large Stocks **Small Stocks**

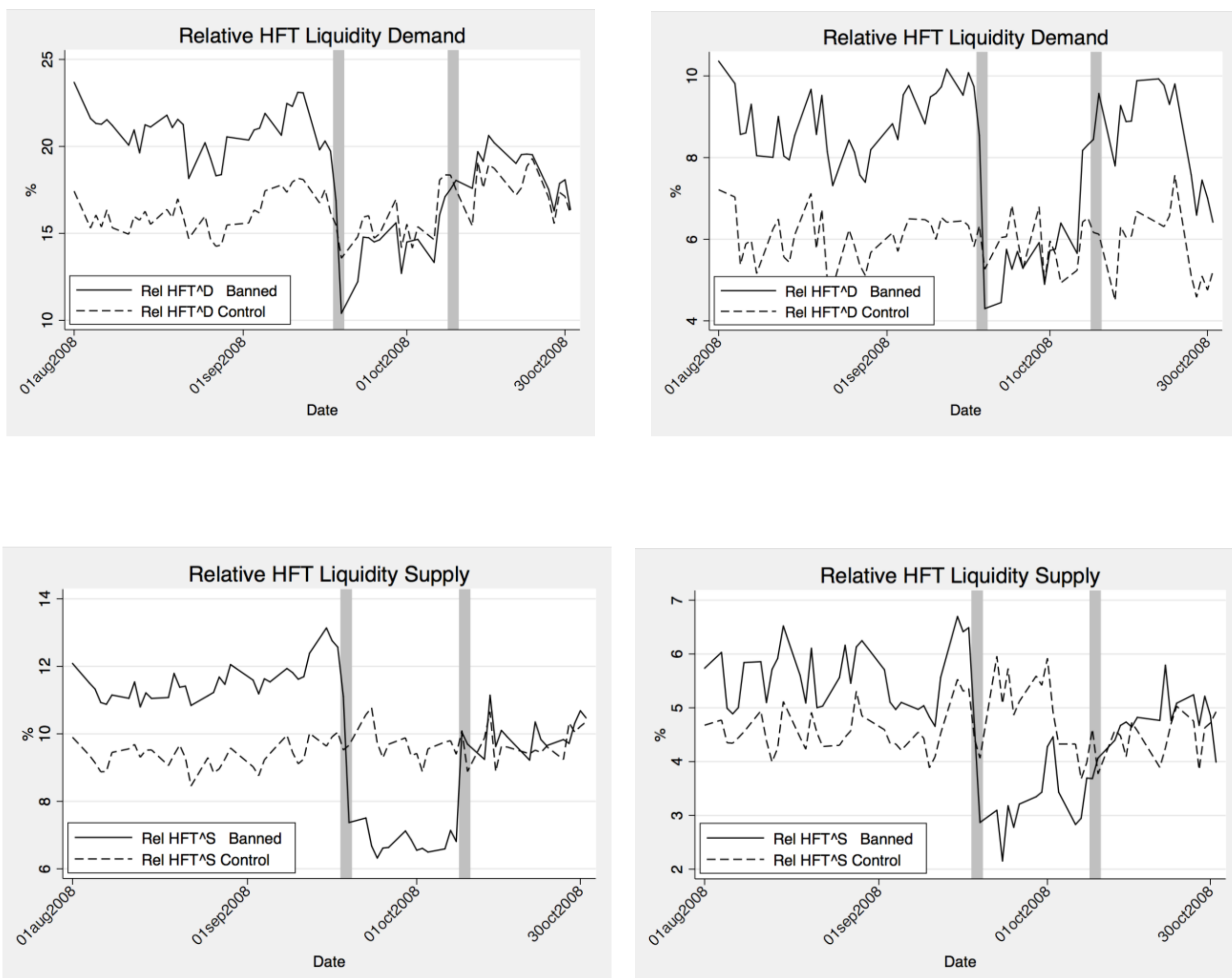


Figure 5: Liquidity Measures. The first graph reports the trade weighted quoted spread for Banned and Control stocks. The second graph reports the trade weighted effective spread. The third graph reports the trade weighted realized spread. The fourth graph reports price impacts, calculated using the National mid-point and trade price for each trade and for each stock and day. The sample consists of the common stocks that appear on the initial shorting ban list and their matched control firms that are not subject to the shorting ban from 1 Aug 2008 through 31 Oct 2008. We used the same matches as BJZ. The left graph is for large stocks; the right for small stocks. The vertical lines correspond to the beginning and ending of the short sale ban.

Large Stocks **Small Stocks**

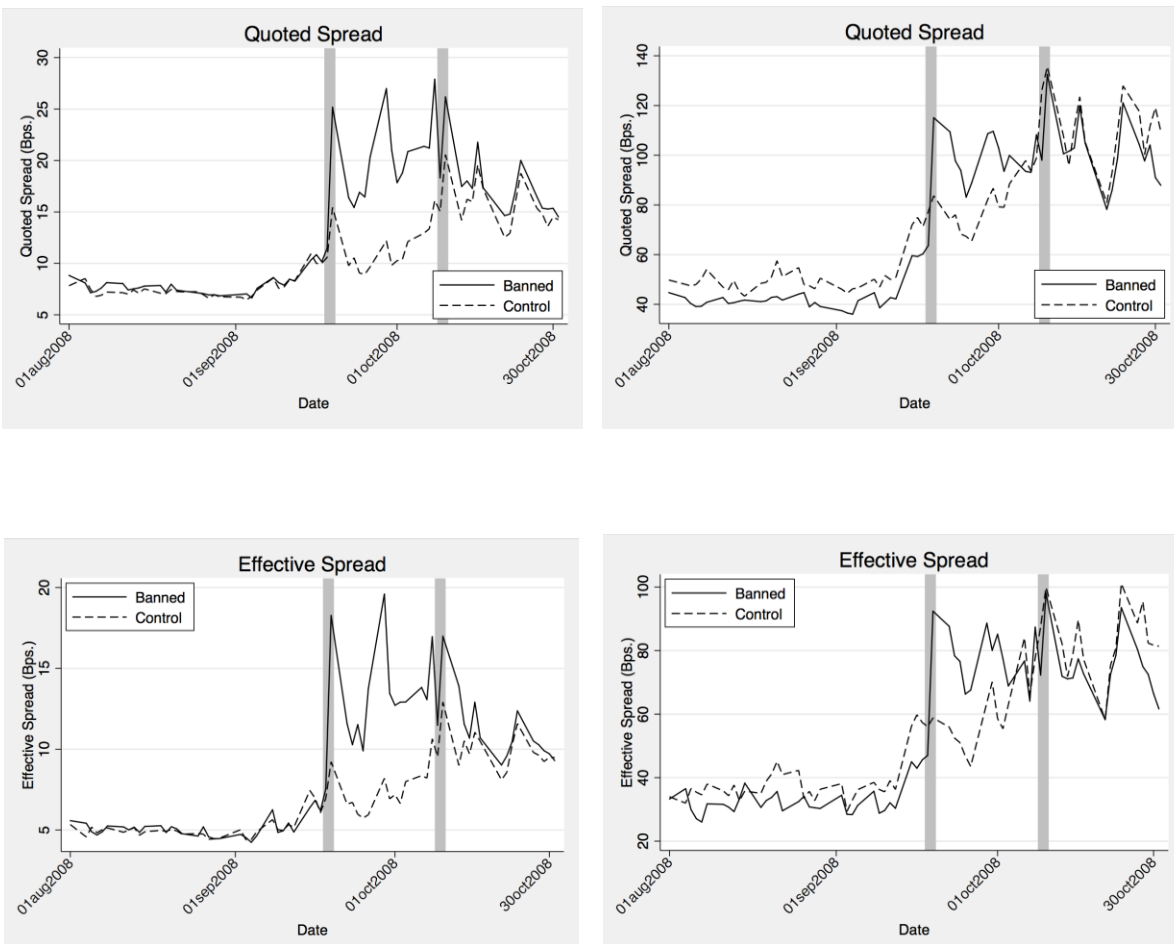
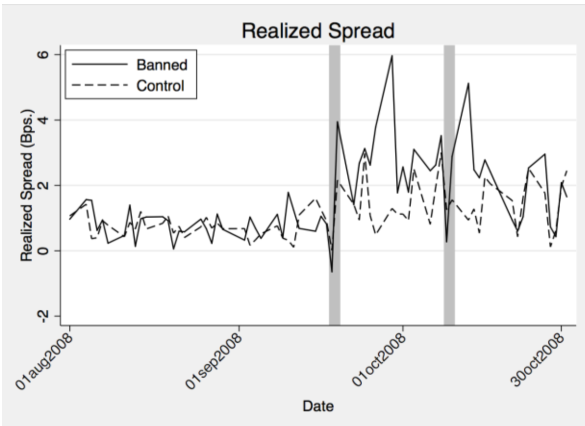
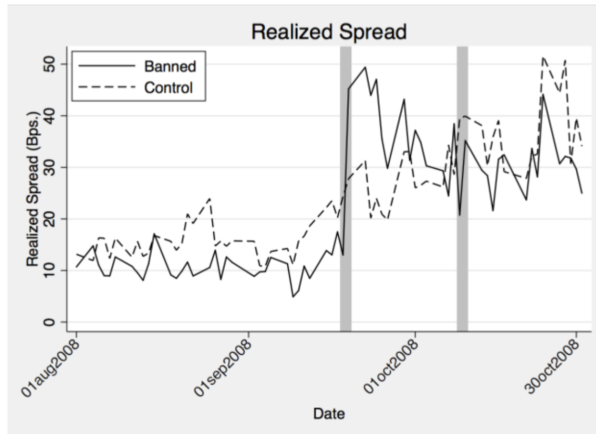
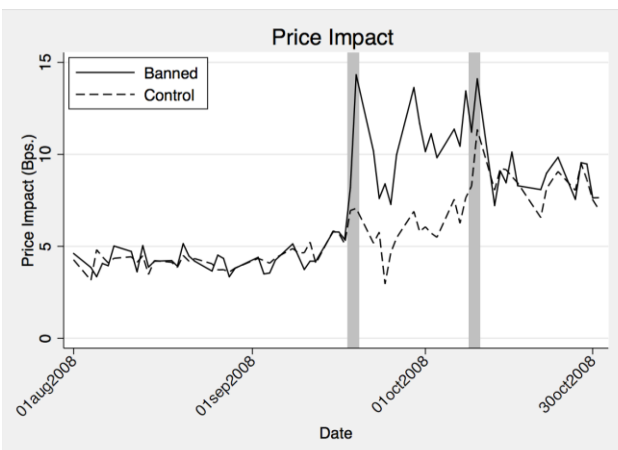


Figure 5 Continued

Large Stocks | **Small Stocks**







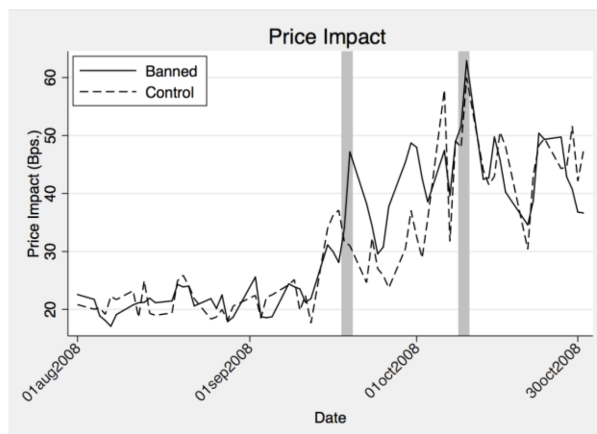
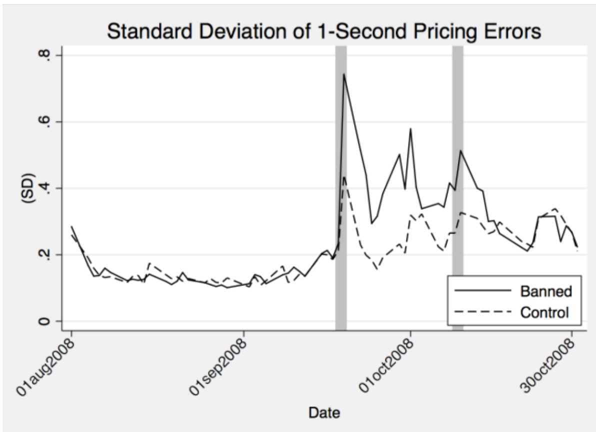


Figure 6: Price Efficiency. The graph reports the standard deviation of the pricing error (Hasbrouck, 1993). The sample consists of the common stocks that appear on the initial shorting ban list and their matched control firms that are not subject to the shorting ban from 1 Aug 2008 through 31 Oct 2008. We used the same matches as BJZ. The left graph is for large stocks; the right for small stocks. The vertical lines correspond to the beginning and ending of the short sale ban.

Large Stocks



Small Stocks

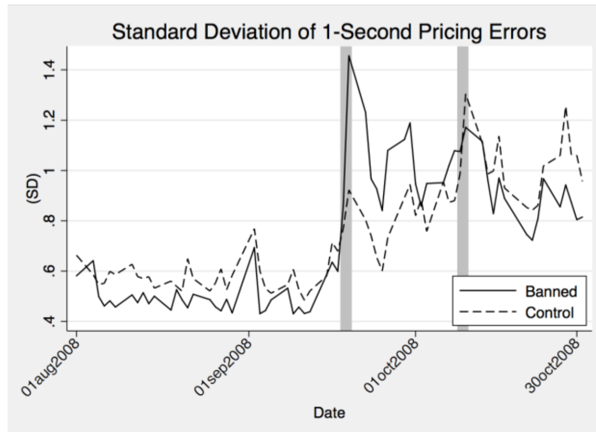


Table 1: Descriptive Statistics. This table reports descriptive statistics of the banned stocks and their non-banned (control) matches. The sample consists of 422 U.S. stocks subject to the 2008 shorting ban and a matched control sample of stocks in which shorting was not banned. Matches are the same as in BJZ. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. Quoted Spreads are time weighted; Effective Spreads, Realized Spreads, and Price Impacts are trade weighted and are proportional to the prevailing quote midpoint. Shorting and trading volume measures are based on NASDAQ trades during regular trading hours. HFT liquidity demand trades are denoted as HFT^D and HFT liquidity supply trades as HFT^s. Total HFT trading activity (HFT^D + HFT^S) is labeled as HFT^A. The nHFT trading variables are defined analogously. We provide the trading volume by trader and trade type that is a short sale. These are identified with the suffix *_Short*. The last third of the table reports the relative short selling by trader type and broken down by order type, identified by the prefix *Rel. Short Sales*. The denominator for all of the relative short selling statistics is NASDAQ volume on day *s* for stock *i*. Rel. Short Sales is shorting volume divided by dollar volume.

Table 1 Continued

Variables	Units	Banned Pre-Ban	Banned Ban	Banned Post-Ban	Control Pre-Ban	Control Ban	Control Post-Ban
No. of Stocks		422	422	422	422	422	422
Nasdaq Volume	$100,000	226.10	168.40	208.50	163.50	174.00	173.50
Quoted Spread	Bps.	27.58	60.09	61.10	27.50	39.85	55.65
Effective Spread	Bps.	20.46	45.98	44.09	19.84	29.01	40.80
Realized Spread	Bps.	6.55	20.13	16.55	7.63	11.45	16.33
Price Impact	Bps.	13.91	25.85	27.54	12.21	17.56	24.47
Std. Dev. Pricing Error	100	0.35	0.72	0.63	0.34	0.49	0.60
HFT^A	$100,000	97.03	57.61	90.94	63.00	70.28	70.67
HFT^D	$100,000	48.80	28.49	45.15	34.03	35.90	37.83
HFT^S	$100,000	48.24	29.13	45.79	28.97	34.37	32.84
$nHFT^A$	$100,000	129.10	110.80	117.60	100.50	103.70	102.80
$nHFT^D$	$100,000	64.27	55.72	59.10	47.72	51.10	48.91
$nHFT^S$	$100,000	64.83	55.09	58.46	52.78	52.63	53.91
HFT^A Short	$100,000	28.77	6.64	24.20	18.86	20.13	20.03
HFT^D Short	$100,000	14.09	1.96	12.08	10.33	10.50	10.85
HFT^S Short	$100,000	14.67	4.69	12.12	8.54	9.63	9.18
$nHFT^A$ Short	$100,000	29.19	7.67	23.79	20.77	19.68	20.60
$nHFT^D$ Short	$100,000	14.25	3.68	12.27	9.67	9.60	9.89
$nHFT^S$ Short	$100,000	14.94	3.99	11.52	11.11	10.09	10.70
Rel HFT^A	%	22.41	14.44	20.02	19.34	19.47	20.33
Rel HFT^D	%	14.07	9.64	12.88	11.86	11.45	12.62
Rel HFT^S	%	8.34	4.80	7.14	7.48	8.02	7.71
$RelSS^A$	%	21.01	6.67	17.79	20.48	18.53	19.32
$RelSS^D$	%	10.64	3.04	9.08	10.30	9.71	9.86
$RelSS^S$	%	10.38	3.63	8.71	10.17	8.82	9.47
RelSS HFT^A	%	5.89	0.93	4.37	5.29	5.02	5.37
RelSS HFT^D	%	3.82	0.37	2.88	3.37	3.06	3.43
RelSS HFT^S	%	2.07	0.57	1.50	1.91	1.96	1.93
RelSS $nHFT^A$	%	15.12	5.74	13.41	15.19	13.51	13.96
RelSS $nHFT^D$	%	6.82	2.68	6.20	6.93	6.65	6.43
RelSS $nHFT^S$	%	8.30	3.06	7.21	8.26	6.86	7.53

Table 2: Correlations. This table reports Pearson correlation coefficients of the banned stocks and their non-banned (control) matches. The sample consists of 422 U.S. stocks subject to the 2008 shorting ban and a matched control sample of stocks in which shorting was not banned. Matches are the same as inBJZ. The correlations come from the entire sample, 8/1/2008–10/31/2008 Relative Short Selling (RelSS) measures are based on NASDAQ trades during regular trading hours. HFT liquidity demand trades are denoted as HFT^D and HFT liquidity supply trades as HFT^s. Total HFT trading activity (HFT^D + HFT^S) is labeled as HFT^A. The nHFT trading variables are defined analogously. The denominator for all of the relative short selling statistics is NASDAQ volume on day *s* for stock *i*. Relative trading (Rel) considers all trading activity relative to all NASDAQ volume on day *s* for stock *i*. Ban is an indicator variable taking the value one during the short sale ban for stocks subject to the ban and zero otherwise; Ban*Mcap is the Ban indicator interacted with the average pre-ban market capitalization, Ban*Option is the ban indicator interacted with an indicator variable taking the value one if options are traded on the stock; Ban*Price is the ban indicator interacted with the average stock price in the pre-ban period. All coefficients are significant at the 1% level.

	Ban	Ban* Mcap	Ban* Option	Ban* Price	RelSS	RelSS HFT^A	RelSS HFT^D	RelSS HFT^S	RelSS $nHFT^A$	RelSS $nHFT^D$	RelSS $nHFT^S$	Rel HFT^A	Rel HFT^D	Rel HFT^S
Ban	1.00													
Ban*Mcap	0.51	1.00												
Ban*Option	0.78	0.73	1.00											
Ban*Price	0.64	0.63	0.57	1.00										
RelSS	-0.42	-0.23	-0.34	-0.29	1.00									
RelSS HFT^A	-0.29	-0.10	-0.20	-0.18	0.55	1.00								
RelSS HFT^D	-0.29	-0.13	-0.22	-0.18	0.52	0.88	1.00							
RelSS HFT^S	-0.17	-0.03	-0.11	-0.10	0.38	0.77	0.37	1.00						
RelSS $nHFT^A$	-0.33	-0.22	-0.29	-0.24	0.88	0.08	0.11	0.01	1.00					
RelSS $nHFT^D$	-0.24	-0.17	-0.22	-0.18	0.62	0.01	0.00	0.02	0.73	1.00				
RelSS $nHFT^S$	-0.26	-0.15	-0.22	-0.18	0.71	0.11	0.16	0.00	0.78	0.15	1.00			
Rel HFT^A	-0.14	0.07	-0.02	-0.03	0.36	0.84	0.74	0.64	-0.06	-0.12	0.03	1.00		
Rel HFT^D	-0.10	0.08	0.02	-0.01	0.34	0.72	0.81	0.33	-0.02	-0.16	0.12	0.88	1.00	
Rel HFT^S	-0.13	0.03	-0.06	-0.05	0.25	0.67	0.36	0.82	-0.09	-0.02	-0.11	0.78	0.40	1.00

Table 3: Effect of Short Sale Ban. This table shows the market quality regressions without instrumenting for relative short selling. It uses a daily panel of matched stock pairs from 8/1/2008 to 10/31/2008. Each sample stock subject to the shorting ban is matched to a similar stock where shorting was not banned using the same match as in BJZ. We include the following independent variables: Ban is an indicator variable taking the value one during the short sale ban for stocks subject to the ban and zero otherwise; , Ban*Mcap is the Ban indicator interacted with the average pre-ban market capitalization, Ban*Option is the ban indicator interacted with an indicator variable taking the value one if options are traded on the stock; Ban*Price is the ban indicator interacted with the average stock price in the pre-ban period; Mcap and Price alone; Rtn. Std. Dev.(s-1) is the1-second standard deviation of stock *i* on the previous trading day; XLF Rtn. Std. Dev. Is the 1-second standard deviation of the Financial Select Sector ETF, XLF. Ban* XLF Rtn. Std. Dev is the previous variable interacted with the ban indicator; Pre Period and Post Period are indicators taking the value one before and after the ban, respectively. Firm fixed effects are included. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. Dependent variables include time-weighted national quoted spreads, trade-weighted effective spreads, realized spreads, price impacts, and the standard deviation of the pricing error. Standard errors are clustered by firm and date. *, **, *** indicates significance at the 10%, 5%, and 1% respectively. Panel A reports all stocks; Panel B and C reports Large and Small stocks, respectively.

Panel A: All Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
Ban	35.67***	31.34***	21.41***	9.93***	0.29***
Ban*Mcap	-4.50***	-4.58***	-3.18***	-1.40*	-0.05***
Ban*Option	-24.17***	-18.96***	-13.66***	-5.29***	-0.09**
Ban*Price	-0.04	-0.06	-0.05	-0.01	-0.00
Mcap	-17.92***	-20.03***	-2.04	-17.99***	-0.34***
Price	0.96***	0.88***	0.16	0.71***	0.01***
Rtn. Std. Dev.(s-1)	1.28***	0.96***	0.52***	0.44***	0.02***
XLF Rtn. Std. Dev.	4.27***	3.69***	1.11**	2.57***	0.03***
Ban*XLF Rtn. Std. Dev.	1.59	0.59	-0.41	1.00*	0.02**
Pre Period	-6.57***	-4.10***	-2.12**	-1.99*	-0.07**
Post Period	10.32***	6.25***	3.61***	2.64*	-0.01
Stock FEs	Yes	Yes	Yes	Yes	Yes
N	52,111	52,111	52,111	52,111	52,111
Adj. R^2	0.64	0.54	0.24	0.27	0.28

Table 3 Continued

Panel B: Large Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
Ban	35.83***	26.42***	12.39**	14.03***	0.35***
Ban*Mcap	-2.67***	-1.90***	-0.28	-1.62***	-0.05**
Ban*Option	-24.76***	-18.51***	-9.96**	-8.55**	-0.15*
Ban*Price	0.04	0.02**	-0.00	0.03	0.00
Mcap	-3.65**	-4.78***	5.77	-10.55**	-0.16***
Price	-0.01	0.02	-0.32	0.33	0.00
Rtn. Std. Dev.(s-1)	0.18**	0.12**	0.13	-0.01	0.01**
XLF Rtn. Std. Dev.	1.35***	0.68***	-0.38	1.06**	0.00
Ban*XLF Rtn. Std. Dev.	0.89*	0.82**	0.46	0.36	0.02
Pre Period	-0.52	-0.22	1.01	-1.23	-0.06
Post Period	2.56***	1.09***	0.83	0.26	-0.05
Stock FEs	Yes	Yes	Yes	Yes	Yes
N	26,097	26,097	26,097	26,097	26,097
Adj. R^2	0.48	0.44	0.03	0.06	0.11

Panel C: Small Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
Ban	19.62***	19.75***	9.76**	9.99***	0.23***
Ban*Mcap	-16.62***	-17.72***	-16.58***	-1.14	-0.11***
Ban*Option	-16.22***	-10.43***	-5.86**	-4.57*	-0.05
Ban*Price	0.46**	0.16	0.21*	-0.04	0.00
Mcap	-17.18	-28.56***	-8.85	-19.72***	-0.45***
Price	0.44	1.32*	0.83	0.49	0.01
Rtn. Std. Dev.(s-1)	1.68***	1.27***	0.65***	0.62***	0.02***
XLF Rtn. Std. Dev.	8.29***	7.59***	3.13***	4.45***	0.06***
Ban*XLF Rtn. Std. Dev.	-0.23	-1.45	-2.15	0.70	0.02
Pre Period	-11.72***	-7.20**	-5.01***	-2.19	-0.08**
Post Period	14.74***	9.00**	5.12**	3.87	0.00
Stock FEs	Yes	Yes	Yes	Yes	Yes
N	26,014	26,014	26,014	26,014	26,014
Adj. R^2	0.60	0.49	0.26	0.26	0.26

Table 4: Relative Short Selling and the Short Sale Ban. This table shows the impact of the short sale ban on short selling activity. It uses a daily panel of matched stock pairs from 8/1/2008 to 10/31/2008. Each sample stock subject to the shorting ban is matched to a similar stock where shorting was not banned using the same match as in BJZ. We include the following independent variables: Ban is an indicator variable taking the value one during the short sale ban for stocks subject to the ban and zero otherwise; , Ban*Mcap is the Ban indicator interacted with the average pre-ban market capitalization, Ban*Option is the ban indicator interacted with an indicator variable taking the value one if options are traded on the stock; Ban*Price is the ban indicator interacted with the average stock price in the pre-ban period; Mcap and Price alone; Rtn. Std. Dev.(s-1) is the1-second standard deviation of stock i on the previous trading day; XLF Rtn. Std. Dev. Is the 1-second standard deviation of the Financial Select Sector ETF, XLF. Ban* XLF Rtn. Std. Dev is the previous variable interacted with the ban indicator; Pre Period and Post Period are indicators taking the value one before and after the ban, respectively. Firm fixed effects are included. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. We regress: $Y_{i,s} = \alpha_i + \beta_1 \times Ban_{i,s} + \beta_2 \times Ban_{i,s} \times Mcap_i + \beta_3 \times Ban_{i,s} \times Option_i + \beta_4 \times Ban_{i,s} \times Price_i + \theta X_{i,s} + \epsilon_{i,s}$, The dependent variables are different categories of relative short selling: RelSS is overall relative short selling. *RelSS HFT^A* is relative short selling by HFT. *RelSS HFT^D* is relative short selling by HFT liquidity demand trades, *RelSS HFT^S* is relative short selling by HFT liquidity supply trades, nHFT is analogously defined. Standard errors are clustered by firm and date. *, **, *** indicates significance at the 10%, 5%, and 1% respectively. Panel A reports all stocks; Panel B and C reports Large and Small stocks, respectively. At the end of each Panel we report the first-stage F-statistic, the Angrist-Pischke chi-squared test of underidentification, and the Angrist-Pischke F-statistic test of weak identification.

Panel A: All Stocks

	RelSS	RelSS HFT^A	RelSS $nHFT^A$	RelSS HFT^D	RelSS HFT^S	Rel HFT^A
Ban	-7.51***	-1.95***	-5.56***	-0.79***	-1.16***	-5.14***
Ban*Mcap	-1.06***	-1.14***	0.08	-0.54***	-0.61***	-1.72***
Ban*Option	-4.56***	-1.53***	-3.03***	-1.89***	0.36***	0.03
Ban*Price	0.00	0.01**	-0.00	-0.01	0.01***	0.01
Mcap	1.63***	0.57***	1.06**	0.39**	0.18	3.57***
Price	-0.05***	-0.01	-0.04***	0.00	-0.01***	-0.05***
Rtn. Std. Dev.(s-1)	-0.02*	0.00	-0.02**	-0.00	0.00	0.01
XLF Rtn. Std. Dev.	0.01	0.29***	-0.28	0.24***	0.05	1.14***
Ban*XLF Rtn. Std. Dev.	-0.70***	-0.61***	-0.10	-0.41***	-0.19***	-1.31***
Pre Period	2.04***	0.59***	1.45***	0.53***	0.06	0.89**
Post Period	0.66	-0.01	0.67*	0.18	-0.19***	0.24
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	52,111	52,111	52,111	52,111	52,111	52,111
Adj. R^2	0.43	0.71	0.29	0.64	0.62	0.81
F(4, 61)	393.52	273.38	218.80	205.32	108.38	86.32
Underid. AP Chi-sq(3)	1600.14	429.11	136.51	155.13	114.49	81.01
Weak Id. AP F(3, 61)	393.52	140.71	44.76	76.30	120.49	26.56

Table 4 Continued

Panel B: Large Stocks

	RelSS	RelSS HFT^A	RelSS $nHFT^A$	RelSS HFT^D	RelSS HFT^S	Rel HFT^A
Ban	-11.79***	-2.50***	-9.29***	-1.64***	-0.86***	-6.43***
Ban*Mcap	0.01	-0.88***	0.89***	-0.08	-0.80***	-1.41***
Ban*Option	-3.74***	-1.82***	-1.92*	-2.37***	0.55*	0.84
Ban*Price	0.00	0.01***	-0.00	-0.00	0.01***	0.02**
Mcap	0.37	0.72***	-0.35	0.63***	0.09	3.50***
Price	-0.02	-0.02**	0.00	0.00	-0.02***	-0.05**
Rtn. Std. Dev.(s-1)	-0.02	0.01	-0.03*	0.00	0.00**	0.02
XLF Rtn. Std. Dev.	0.04	0.39***	-0.35**	0.32***	0.08	1.47***
Ban*XLF Rtn. Std. Dev.	-0.99***	-0.89***	-0.10	-0.63***	-0.26***	-2.15***
Pre Period	1.66***	0.77***	0.89***	0.65***	0.12*	1.55***
Post Period	0.51	0.06	0.44	0.38*	-0.32***	0.87
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	26,097	26,097	26,097	26,097	26,097	26,097
Adj. R^2	0.55	0.71	0.45	0.59	0.74	0.78
F(4, 61)	374.62	232.50	202.97	164.64	115.42	68.04
Underid. AP Chi-sq(3)	1523.56	247.91	212.32	19.81	111.42	43.03
Weak Id. AP F(3, 61)	374.62	81.28	69.61	9.74	54.79	14.11

Table 4 Continued

Panel C: Small Stocks

	RelSS	RelSS HFT[A]	RelSS nHFT[A]	RelSS HFT[D]	RelSS HFT[S]	Rel HFT[A]
Ban	-7.01***	-1.59***	-5.42***	-0.75***	-0.84***	-4.06***
Ban*Mcap	-2.17***	-0.88***	-1.29**	-0.68***	-0.20**	-1.28***
Ban*Option	-3.38***	-1.33***	-2.05***	-1.36***	0.03	-0.10
Ban*Price	-0.03	-0.02*	-0.01	-0.02**	0.00	-0.10***
Mcap	3.32***	0.32	3.00***	0.22	0.09	3.55***
Price	-0.17**	-0.00	-0.17***	-0.01	0.01	-0.09
Rtn. Std. Dev.(s-1)	-0.01	-0.00	-0.01	-0.00	-0.00	0.00
XLF Rtn. Std. Dev.	-0.03	0.15*	-0.18	0.13**	0.02	0.70***
Ban*XLF Rtn. Std. Dev.	-0.46*	-0.33***	-0.13	-0.20***	-0.13***	-0.46**
Pre Period	2.50***	0.38**	2.12***	0.37***	0.00	0.05
Post Period	0.92*	-0.14	1.06**	-0.07	-0.07	-0.63
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	26,014	26,014	26,014	26,014	26,014	26,014
Adj. R^2	0.28	0.38	0.22	0.42	0.18	0.56
F(4, 61)	121.61	56.82	81.18	58.62	22.50	30.96
Underid. AP Chi-sq(3)	498.65	31.01	33.25	33.57	3.67	32.72
Weak Id. AP F(3, 61)	122.61	10.16	10.90	16.51	2.62	10.72

Table 5: Effect of Relative Short-Selling on Liquidity and Price Efficiency. This table shows the second stage regression that uses the estimates from the first stage regression, Table 4, to instrument for variation in different market participation type and how it impacts market quality. The regression is: $Y_{i,s} = \alpha_i + \beta_1 \widehat{RelSS}_{i,s} + \theta X_{i,s} + \epsilon_{i,s}$, where $Y_{i,s}$ takes one of several market quality variables: time-weighted national quoted spreads, trade-weighted effective spreads, realized spreads, price impacts, and the standard deviation of the pricing error. Control variables include: Mcap and Price alone; Rtn. Std. Dev.(s-1) is the1-second standard deviation of stock *i* on the previous trading day; XLF Rtn. Std. Dev. Is the 1-second standard deviation of the Financial Select Sector ETF, XLF. Ban* XLF Rtn. Std. Dev is the previous variable interacted with the ban indicator; Pre Period and Post Period are indicators taking the value one before and after the ban, respectively. Firm fixed effects are included. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. The unit of observation is the stock *i* for day *s*, where *Y* is the value measured for each stock. It uses a daily panel of matched stock pairs from 8/1/2008 to 10/31/2008. Each sample stock subject to the shorting ban is matched to a similar stock where shorting was not banned using the same match as in BJZ. Standard errors are clustered by firm and date. *, **, *** indicates significance at the 10%, 5%, and 1% respectively. Panel A reports all stocks; Panel B and C reports Large and Small stocks, respectively.

Panel A: All Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS	-0.23	-0.21	-0.07	-0.14	-0.01***
Mcap	-15.33***	-17.46***	-0.34	-17.12***	-0.31***
Price	0.92***	0.82***	0.13	0.69***	0.01***
Rtn. Std. Dev.(s-1)	1.32***	0.99***	0.55***	0.45***	0.02***
XLF Rtn. Std. Dev.	4.01***	3.45***	0.95*	2.50***	0.03**
Ban*XLF Rtn. Std. Dev.	1.99	0.94	-0.11	1.06*	0.02**
Pre Period	-11.72***	-8.66***	-5.43***	-3.23**	-0.10***
Post Period	5.15**	1.66	0.37	1.30	-0.05

Panel B: Large Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS	-0.40***	-0.28***	-0.12*	-0.16**	-0.01**
Mcap	-4.10***	-5.08***	5.69	-10.77**	-0.16***
Price	0.04	0.05	-0.31	0.36	0.00
Rtn. Std. Dev.(s-1)	0.19**	0.12**	0.13	-0.01	0.01**
XLF Rtn. Std. Dev.	1.38***	0.70***	-0.38	1.08**	0.00
Ban*XLF Rtn. Std. Dev.	0.50	0.55*	0.35	0.20	0.01
Pre Period	-0.26	-0.04	1.09	-1.13	-0.06
Post Period	2.60***	1.10***	0.81	0.30	-0.04

Table 5 Continued

Panel C: Small Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS	-0.85**	-0.69**	-0.20	-0.49**	-0.02***
Mcap	-14.14	-24.98***	-7.17	-17.81***	-0.38***
Price	0.34	1.14	0.74	0.40	0.00
Rtn. Std. Dev.(s-1)	1.70***	1.29***	0.67***	0.62***	0.02***
XLF Rtn. Std. Dev.	7.81***	7.13***	2.79***	4.34***	0.05***
Ban*XLF Rtn. Std. Dev.	0.22	-0.98	-1.64	0.66	0.02
Pre Period	-17.85***	-13.44***	-10.58***	-2.86	-0.10**
Post Period	7.27	1.71	-0.74	2.45	-0.04

Table 6: Effect of HFT Relative Short-Selling on Liquidity and Price Efficiency. This table shows the second stage regression that uses the estimates from the first stage regression, Table 4, to instrument for variation in different market participation type and how it impacts market quality. The regression is: $Y_{i,s} = \alpha_i + \beta_1 \widehat{RelSS\,HFT^A}_{\iota,s} + \beta_2 \widehat{RelSS\,nHFT^A}_{\iota,s} + \theta X_{i,s} + \epsilon_{i,s}$, where $Y_{\mathrm{i,s}}$ takes one of several market quality variables: time-weighted national quoted spreads, trade-weighted effective spreads, realized spreads, price impacts, and the standard deviation of the pricing error. Control variables include: Mcap and Price alone; Rtn. Std. Dev.(s-1) is the1-second standard deviation of stock i on the previous trading day; XLF Rtn. Std. Dev. Is the 1-second standard deviation of the Financial Select Sector ETF, XLF. Ban* XLF Rtn. Std. Dev is the previous variable interacted with the ban indicator; Pre Period and Post Period are indicators taking the value one before and after the ban, respectively. Firm fixed effects are included. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. The unit of observation is the stock i for day s, where Y is the value measured for each stock. It uses a daily panel of matched stock pairs from 8/1/2008 to 10/31/2008. Each sample stock subject to the shorting ban is matched to a similar stock where shorting was not banned using the same match as in BJZ. Standard errors are clustered by firm and date. *, **, *** indicates significance at the 10%, 5%, and 1% respectively. Panel A reports all stocks; Panel B and C reports Large and Small stocks, respectively.

Panel A: All Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS HFT^A	8.53***	7.86***	5.52***	2.34***	0.07***
RelSS nHFT^A	-6.05***	-5.57***	-3.79***	-1.78***	-0.06***
Mcap	-16.28***	-18.33***	-0.94	-17.39***	-0.32***
Price	0.79***	0.70***	0.04	0.66***	0.01***
Rtn. Std. Dev.(s-1)	1.14***	0.83***	0.43***	0.40***	0.01***
XLF Rtn. Std. Dev.	0.05	-0.19	-1.58	1.39*	-0.01
Ban*XLF Rtn. Std. Dev.	6.36***	4.96***	2.68**	2.29***	0.06***
Pre Period	-4.36	-1.89	-0.74	-1.15	-0.04
Post Period	12.73***	8.64**	5.20**	3.43**	0.01

Panel B: Large Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS HFT^A	2.42***	1.76***	0.49	1.27***	0.03***
RelSS nHFT^A	-2.40***	-1.73***	-0.55*	-1.17***	-0.03***
Mcap	-6.92***	-7.12***	5.08	-12.20**	-0.20***
Price	0.07	0.07	-0.30	0.37	0.00
Rtn. Std. Dev.(s-1)	0.10	0.06	0.11	-0.05	0.01**
XLF Rtn. Std. Dev.	-0.44	-0.62	-0.77	0.15	-0.02
Ban*XLF Rtn. Std. Dev.	2.82***	2.23***	0.85*	1.38***	0.04***
Pre Period	-0.54	-0.25	1.03	-1.28	-0.06
Post Period	3.24***	1.57**	0.94	0.62	-0.03

Table 6 Continued

Panel C: Small Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS HFT^A	33.98***	34.54***	26.67**	7.87*	0.25**
RelSS $nHFT^A$	-16.19***	-16.21***	-12.04**	-4.17**	-0.13***
Mcap	18.12	7.66	17.72	-10.07	-0.14
Price	-1.99	-1.22	-1.06	-0.16	-0.01
Rtn. Std. Dev.(s-1)	1.64***	1.23***	0.63***	0.61***	0.02***
XLF Rtn. Std. Dev.	0.27	-0.49	-3.02	2.53	-0.00
Ban*XLF Rtn. Std. Dev.	8.98	7.88	5.12	2.76	0.08*
Pre Period	8.92	13.64	10.08	3.57	0.11
Post Period	35.72**	30.50**	21.22*	9.28**	0.18

Table 7: Effect of HFT Relative Short Selling Liquidity Demand and Supply on Liquidity and Price Efficiency. This table shows the second stage regression that uses the estimates from the first stage regression, Table 4, to instrument for variation in different market participation type and how it impacts market quality. The regression is: $Y_{i,s} = \alpha_i + \beta_1\, \widehat{RelSS\ HFT}^{D}_{i,s} + \beta_2\, \widehat{RelSS\ HFT}^{S}_{i,s} + \beta_3 \widehat{RelSS\ nHFT}^{A}_{i,s} + \theta X_{i,s} + \epsilon_{i,s}$ where $Y_{i,s}$ takes one of several market quality variables: time-weighted national quoted spreads, trade-weighted effective spreads, realized spreads, price impacts, and the standard deviation of the pricing error. Control variables include: Mcap and Price alone; Rtn. Std. Dev.(s-1) is the1-second standard deviation of stock i on the previous trading day; XLF Rtn. Std. Dev. Is the 1-second standard deviation of the Financial Select Sector ETF, XLF. Ban* XLF Rtn. Std. Dev is the previous variable interacted with the ban indicator; Pre Period and Post Period are indicators taking the value one before and after the ban, respectively. Firm fixed effects are included. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. The unit of observation is the stock i for day s, where Y is the value measured for each stock. It uses a daily panel of matched stock pairs from 8/1/2008 to 10/31/2008. Each sample stock subject to the shorting ban is matched to a similar stock where shorting was not banned using the same match as in BJZ. Standard errors are clustered by firm and date. *, **, *** indicates significance at the 10%, 5%, and 1% respectively. Panel A reports all stocks; Panel B and C reports Large and Small stocks, respectively.

Panel A: All Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS HFT^D	18.14***	16.08***	11.36***	4.72***	0.12***
RelSS HFT^S	-8.96**	-7.12**	-5.11**	-2.01	-0.03
RelSS $nHFT^A$	-6.86***	-6.26***	-4.28***	-1.98***	-0.06***
Mcap	-17.29***	-19.19***	-1.56	-17.64***	-0.32***
Price	0.61***	0.55***	-0.06	0.61***	0.00***
Rtn. Std. Dev.(s-1)	1.17***	0.85***	0.45***	0.40***	0.01***
XLF Rtn. Std. Dev.	-1.49	-1.51	-2.52**	1.00	-0.02
Ban*XLF Rtn. Std. Dev.	6.76***	5.32***	2.93**	2.39***	0.06***
Pre Period	-6.14*	-3.41	-1.82	-1.59	-0.05
Post Period	9.62**	5.98	3.32	2.66	-0.00

Panel B: Large Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS HFT^D	8.25**	6.30**	3.42*	2.88*	0.07*
RelSS HFT^S	-1.33	-1.16	-1.40	0.24	0.01
RelSS $nHFT^A$	-4.40***	-3.29***	-1.56**	-1.73***	-0.05***
Mcap	-11.34***	-10.56***	2.86	-13.42***	-0.23***
Price	0.02	0.03	-0.33	0.36	0.00
Rtn. Std. Dev.(s-1)	0.06	0.03	0.09	-0.07	0.01**
XLF Rtn. Std. Dev.	-2.67	-2.35*	-1.89**	-0.46	-0.04
Ban*XLF Rtn. Std. Dev.	5.26**	4.13**	2.08*	2.05**	0.06**
Pre Period	-2.05	-1.42	0.27	-1.69	-0.07
Post Period	0.84	-0.30	-0.26	-0.04	-0.05

Table 7 Continued

Panel C: Small Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
RelSS HFT^D	27.59***	33.35**	27.52**	5.83	0.23**
RelSS HFT^S	-18.53	24.69	33.59	-8.90	0.10
RelSS $nHFT^A$	-7.97	-14.67	-13.12	-1.54	-0.11
Mcap	0.41	4.33	20.05	-15.72	-0.19
Price	-0.05	-0.86	-1.31	0.46	-0.01
Rtn. Std. Dev.(s-1)	1.64***	1.23***	0.63***	0.60***	0.02***
XLF Rtn. Std. Dev.	3.52	0.12	-3.45	3.57*	0.01
Ban*XLF Rtn. Std. Dev.	1.98	6.57	6.05	0.52	0.06
Pre Period	-5.70	10.90	12.00	-1.10	0.07
Post Period	23.11	28.13	22.88	5.25	0.14

Table 8: Effect of Relative Short-Selling on Liquidity and Price Efficiency. This table shows the second stage regression that uses the estimates from the first stage regression, Table 4, to instrument for variation in different market participation type and how it impacts market quality. The regression is: $Y_{i,s} = \alpha_i + \beta_1 \widehat{Rel\ HFT^A_{i,s}} + \beta_2 \widehat{RelSS\ nHFT^A_{i,s}} + \theta X_{i,s} + \epsilon_{i,s}$ where $Y_{i,s}$ takes one of several market quality variables: time-weighted national quoted spreads, trade-weighted effective spreads, realized spreads, price impacts, and the standard deviation of the pricing error. Control variables include: Mcap and Price alone; Rtn. Std. Dev.(s-1) is the1-second standard deviation of stock i on the previous trading day; XLF Rtn. Std. Dev. Is the 1-second standard deviation of the Financial Select Sector ETF, XLF. Ban* XLF Rtn. Std. Dev is the previous variable interacted with the ban indicator; Pre Period and Post Period are indicators taking the value one before and after the ban, respectively. Firm fixed effects are included. The preban period is 8/1/2008–9/18/2008; the ban period is 9/19/2008–10/8/2008; and the postban period is 10/9/2008–10/31/2008. The unit of observation is the stock i for day s, where Y is the value measured for each stock. It uses a daily panel of matched stock pairs from 8/1/2008 to 10/31/2008. Each sample stock subject to the shorting ban is matched to a similar stock where shorting was not banned using the same match as in BJZ. Standard errors are clustered by firm and date. *, **, *** indicates significance at the 10%, 5%, and 1% respectively. Panel A reports all stocks; Panel B and C reports Large and Small stocks, respectively.

Panel A: All Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
Rel HFT^A	4.37***	4.25***	2.99***	1.26**	0.04***
RelSS nHFT^A	-5.03***	-4.83***	-3.28***	-1.56***	-0.05***
Mcap	-27.36***	-29.18***	-8.58	-20.61***	-0.42***
Price	0.95***	0.85***	0.15	0.70***	0.01***
Rtn. Std. Dev.(s-1)	1.14***	0.82***	0.43***	0.39***	0.01***
XLF Rtn. Std. Dev.	-2.24	-2.62	-3.29*	0.67	-0.03
Ban*XLF Rtn. Std. Dev.	7.11**	5.94**	3.36*	2.57***	0.07***
Pre Period	-5.99	-3.27	-1.71	-1.56	-0.05
Post Period	9.76**	6.00	3.35	2.65	-0.01

Panel B: Large Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
Rel HFT^A	1.10***	0.79***	0.11	0.68***	0.02**
RelSS nHFT^A	-1.80***	-1.28***	-0.33*	-0.95***	-0.03***
Mcap	-8.80***	-8.44***	5.14	-13.58**	-0.24***
Price	0.08	0.08	-0.30	0.38	0.00*
Rtn. Std. Dev.(s-1)	0.12	0.07	0.12	-0.05	0.01**
XLF Rtn. Std. Dev.	-0.89	-0.92	-0.65	-0.27	-0.03
Ban*XLF Rtn. Std. Dev.	3.08***	2.40***	0.67	1.73***	0.06***
Pre Period	-0.83	-0.45	1.08	-1.53	-0.07
Post Period	2.30**	0.89	0.84	0.05	-0.05

Table 8 Continued

Panel C: Small Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Std. Dev. Pricing Error
Rel HFT^A	-5.30**	-1.95	-1.13	-0.82	-0.02*
RelSS nHFT^A	3.00	0.32	0.40	-0.08	-0.01
Mcap	-5.47	-20.72*	-4.66	-16.06***	-0.33***
Price	0.33	1.05	0.68	0.37	0.00
Rtn. Std. Dev.(s-1)	1.75***	1.30***	0.68***	0.62***	0.02***
XLF Rtn. Std. Dev.	12.19***	8.66***	3.72**	4.94***	0.07***
Ban*XLF Rtn. Std. Dev.	-1.64	-1.68	-2.12	0.45	0.01
Pre Period	-24.33***	-14.22***	-10.80***	-3.42	-0.11**
Post Period	1.76	1.02	-1.00	2.02	-0.05