The Price Effects of Liquidity Shocks: A Study of SEC's Tick-Size Experiment*

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Abstract

Do stock prices of publicly listed companies respond to changes in transaction costs? Using the SEC's pilot program that increased the tick size for approximately 1,200 randomly chosen stocks, we find a stock price decrease between 1.75% and 3.2% for small spread stocks affected by the larger tick size relative to a control group. We find that the increase in the present value of transaction costs accounts for a small percentage of the price decrease. We study channels of price variation due to changes in expected returns: information risk, investor horizon, and liquidity risk. The evidence suggests that trading frictions affect the cost of capital.

Keywords: tick size pilot, liquidity, information risk, price efficiency, news response, investor horizon, liquidity risk, liquidity premium, cost of capital, JOBS Act, SEC.

JEL Code: G10, G14.

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1. Introduction

The question of whether transaction costs affect stock prices of publicly listed companies, in the intersection of market microstructure and asset pricing, has no supportive causal evidence to this date, which may explain the omission of transaction costs in mainstream asset pricing. Previous event-study tests that can potentially identify a causal relation between transaction costs and firm-level stock prices find either no evidence (e.g., Barclay, Kandel and Marx, 1998) or are silent about the relationship (Bessembinder, 2003, and Chakravarty, Wood and Van Ness, 2004). The lack of evidence on the relation between transaction costs and stock prices is consistent with asset pricing theories that predict that transaction costs have a second order effect on prices. In these theories, investors respond to higher transaction costs by trading less often (e.g., Constantinides, 1986, Aiyagari and Gertler, 1991, Heaton and Lucas, 1996, and Vayanos, 1998). However, these theories also generate too little trading volume. Not surprisingly, transaction costs that limit volume must have a small effect on prices.

We revisit this question within the context of a laboratory-like experiment called Tick-Size Pilot Program conducted by the Securities and Exchange Commission (SEC).[1] The pilot, with implementation starting on October 2016, is a field experiment that temporarily increased the tick size from 1 cent to 5 cents for a number of randomly chosen ("treated") stocks with capitalization under \$3 billion. This field experiment provides the best opportunity to date to study the hypothesis that exogenous shocks to transaction costs affect stock prices. To test this hypothesis, we estimate daily abnormal returns from September 1, 2016 to November 30, 2016 using a variety of risk-adjustment

[1] In the U.S., tick size (i.e., the minimum quoting and trading increment) is regulated under the Securities and Exchange Commission (SEC) rule 612 of Regulation National Market System (Reg NMS). This rule prohibits market participants from displaying, ranking, or accepting quotations, orders, or indications of interest in any NMS stock priced in an increment smaller than \$0.01, unless the stock is priced less than \$1.00 per share.

models.

Our main finding is that treated stocks with small pre-experiment dollar quoted spreads experience a significant stock price decrease between 1.75% and 3.2% after the tick-size change, compared to stocks in the control group. These price changes are equivalent to a loss of about $2.6 billion of market capitalization. We focus on stocks with small pre-experiment dollar quoted spreads because the tick size change is likely to be an active constraint for them. We do not find any price effects on the treated stocks with large pre-experiment dollar quoted spreads relative to the control group.

The experiment conducted by the SEC is unique in that it allows us to make causal statements about stock price changes due to shocks to liquidity. First, the SEC's stratified random sampling procedure creates a laboratory-like experiment in an actual financial market that eliminates selection issues. The procedure provides a control group of stocks built as part of the random assignment of securities to the pilot program, thus removing any discretion from the econometrician. Second, the large size of the program, with 1,200 test stocks and an equal number of control stocks, gives greater power to detect price effects. When the NYSE lowered the minimum tick size from 1/16 of a dollar to 1 cent it also implemented a pilot program, but this program involved a small number of common stocks (Chakravarty et al., 2004).[2] Third, the two-year duration of the program means that the price is unlikely to change due to policies that firms might undertake to reverse some of the unintended consequences from the tick size program such as by engaging in reverse stock split programs (Angel, 1997, Lipson and Mortal, 2006, and Weld et al., 2009).

The Tick Size Pilot Program consists of 2,400 small capitalization stocks divided into three groups with 400 treated stocks each and a control group with 1,200 stocks.

[2] In addition, in this earlier event, the control group were all the other firms in the NYSE and at the time of the pilot program implementation, these firms were known to have to move also to the lower tick size after the pilot period.

Stocks in groups 1 through 3 are all subject to an increase in the minimum quote increment from \$0.01 to \$0.05. Group 2 and 3 stocks must additionally trade in 5-cent increments. Finally, group 3 stocks are also subject to a "trade-at" prohibition. The trade-at prohibition increases the cost of trading for non-displayed liquidity in lit exchanges and for dark pool trades. Stocks in the control group continue quoting and trading at their current tick size increment of \$0.01.

The rest of the paper provides evidence on direct and indirect mechanisms that can explain the observed stock price effects. In Amihud and Mendelson (1986) and others, transaction costs have a *direct effect* on stock prices, holding expected returns (net of transaction costs) constant. We therefore analyze the effect of the tick size change on stock spreads, and liquidity more generally. We find that liquidity decreases for all stocks as proxied by a variety of measures: quoted spreads, effective spreads and price impact increase and trading volume decreases as compared to stocks in the control group after the increase in tick size. For example, the proportional quoted spread is higher by the equivalent of about 0.45 cents on a \$1 stock. The qualitative nature of the spread results was largely expected in the design of the program and is observed also in concurrent work (FINRA and NSE, 2018, Hu et al., 2018, Rindi and Werner, 2019, and others). We also find that the response across all treated groups is similar with the exception that we observe a significant drop in volume in dark trading venues for group 3 stocks, consistent with the trade-at rule imposing an additional cost on off-exchange transactions.

Using a back of the envelope calculation à la Amihud and Mendelson (1988) and Foucault et al. (2013), the present value of the increase in transaction costs is responsible for about 18% of the observed change in prices for groups 1 and 2 stocks, but only 10% for group 3 stocks, holding the expected return (net of transaction cost) constant. While these are arguably rough estimates of the direct effect of transaction costs on prices, their small size suggests that a significant portion of the observed change in prices comes from an *indirect effect* of transaction costs on expected returns (net of transaction costs). In other words, the *liquidity premium*, i.e., the change in returns due to the increase in costs, is large and several times the size of the transaction costs.

We consider three possible *indirect channels* to explain the remaining price effect: Easley and O'Hara (2004) and O'Hara (2003) information risk; Amihud and Mendelson (1986) investor horizon clientele; and Acharya and Pedersen (2005) liquidity risk.[3] In Easley and O'Hara (2004) and O'Hara (2003), prices are noisier and information risk increases in the presence of relatively more uninformed investors. Whether price efficiency increases or decreases with the increase in tick size is an empirical question. On the one hand, Anshuman and Kalay (1998) predict that investors' willingness to acquire information is reduced with a wider tick size. In addition, for group 3 stocks and due to the trade-at prohibition, we predict volume to move out of dark pools and into lit exchanges. Because volume in dark pools is primarily by uninformed investors (see Zhu, 2014, and Comerton-Forde and Putnins, 2015), we predict that the additional volume in lit exchanges from dark pools is composed primarily of uninformed trades. On the other hand, a larger tick size leads to greater analyst coverage and more information production (Weild et al., 2012), and creates a bigger gap between the competitive price and the expected asset value, prompting dealers to adjust prices more quickly (Cordella and Foucault, 1999). We find that the treated stocks experience higher pricing error and higher price delay, as measured by Hou and Moskowitz (2005) consistent with a decrease in price efficiency. In addition, we trace the market response to news using RavenPack, a high-frequency news database, and find slower market response speeds to company-related news in all treated groups. We repeat the exercise using only macro news, as the content and frequency of company news itself may have changed after the

[3]There are other asset pricing theories with transactions costs that can deliver large price effects (e.g., Huang, 2003, Garleanu and Pedersen, 2004, Lo, Mamaysky, and Wang, 2004, and Jang et al., 2007).

program started, and we obtain similar results. Our evidence is consistent with Hu et al. (2018) who find that the decrease in price efficiency is due to the change in quoting requirements. The evidence that price efficiency decreased is consistent with an increase in information risk as in Easley and O'Hara (2004) and O'Hara (2003). Our evidence is also consistent with Hou and Moskowitz (2005) that show that firms with higher price delay in response to news have higher expected returns, and with Easley, Hvidkjaer, and O'Hara (2002) and Albuquerque, de Francisco and Marques (2008) who show that proxies for private information correlate with stock returns.

Amihud and Mendelson (1986) argue that stocks with higher transaction costs attract a clientele of investors with longer investor horizons that in equilibrium require higher expected rates of return (net of transactions costs). We test the prediction that the treated firms are now held by investors with longer horizons. We use 13F data on turnover of institutional investors' portfolios to construct a proxy for investment horizon (see Gaspar, Massa and Matos, 2005, and Cella, Ellul and Giannetti, 2013). We find evidence in support of Amihud and Mendelson's model: the investment horizon of institutional investors increases by 2% (4%) for the small quoted spread stocks in groups 1 and 2 (group 3) relative to the control group after the tick size increased.

Following Acharya and Pedersen (2005), we construct several firm betas that capture liquidity risk including a beta describing how firm liquidity co-moves with aggregate liquidity. We find a statistically insignificant increase in liquidity risk for treated stocks.

As argued above, the hypothesis that discount rates increased during the pilot implies that firm cash flows are discounted at higher rates during the pilot, which leads to lower stock prices at impact. In addition, this hypothesis predicts that if investors expect discount rates to decrease to their pre-pilot level once the pilot is over, then prices should slowly reverse as the pre-determined end of the pilot approaches. That is, there should not be any price effect at the end of the pilot. We find evidence consistent with this prediction.

There are two main approaches to test the hypothesis that higher transaction costs impact stock prices negatively. One uses event studies and is better equipped to address causality, but up to now has lacked a proper random sample with a large number of test stocks. Barclay, Kandel and Marx (1998) use a sample of stocks that move from Nasdaq to the NYSE or Amex and stocks that move from Amex to the NYSE. While they observe changes in spreads for stocks moving to and from Nasdaq consistent with our findings, they find no significant relation between changes in bid-ask spreads and changes in stock prices. Elyasiani, Hauser and Lauterbach (2000) conduct a portfolio-level study of stocks that move from Nasdaq to the NYSE and attribute some of the listing excess return to liquidity changes in those portfolios (Elyasiani et al. review the literature and document the absence of evidence at the firm level).

The studies that are closest to ours, in the sense of using a laboratory-like experiment in actual financial markets, are conducted using the change to decimalization. The NYSE changed the trading requirements via a phased pilot program, implicitly giving researchers a control group for contemporaneous events. Bessembinder (2003) and Chakravarty, Wood, Van Ness (2004) who investigate the effects of decimalization do not, however, report on stock price-level effects. Fang, Noe and Tice (2009) find a positive effect of decimalization on the market-to-book value of assets from one year prior to decimalization to one year after decimalization, which they attribute to better price informativeness and improved ability to incentivize management. In a cross-country analysis of the introduction of electronic trading, that lowers trading costs, Jain (2005) shows an increase in liquidity, informativeness of stock markets, and higher prices.

The other approach uses panel regressions of stock returns on liquidity measures. This second approach is limited in its ability to identify causal relations, because of omitted variables and endogeneity concerns, but has the benefit of large panels with time series and cross sectional sources of variation. Amihud and Mendelson (1986, 1991) and Brennan and Subrahmanyam (1996) show that risk-adjusted stock and bond returns correlate positively with illiquidity measures (see, in addition, Pastor and Stambaugh, 2003, Amihud, 2002, Sadka, 2010, Beber, Driessen, and Tuijp, 2012, and Foucault, Pagano and Roell, 2013). The findings in this literature may be confounded by the fact that liquidity is affected by and affects firm policies (e.g., Chen, Goldstein, and Jiang, 2006, Ellul and Pagano, 2006, and Sadka, 2011) and that liquidity may also proxy for other risk factors.

The rest of the paper is organized as follows. Section 2 describes the institutional details of the Tick Size Pilot Program. Section 3 describes the data, gives the variable definitions, and presents some descriptive statistics. Section 4 presents the main result on price effects. Section 5 investigates sources of changes in prices including direct costs of trading and indirect costs through changes in expected returns. Section 6 discusses related literature, and Section 7 concludes.

2. Pilot design and background

The Tick Size Pilot Program consists of three treatment, or pilot groups, each with about 400 stocks, and a control group with about 1,200 stocks. Stocks in the control group continue quoting at their current tick size increment of \$0.01. Stocks in groups 1 through 3 are all subject to an increase in the minimum quote increment from \$0.01 to \$0.05, with some exceptions.[4] Group 1 stocks continue to trade at their current price increment, whereas group 2 stocks are required to trade in \$0.05 minimum increments.[5]

[4]Examples of exempted trades for all groups are negotiated trades in OTC, and midpoint peg orders that trade at the mid-point between the bid and ask price.

[5]The distinction between group 1 and 2 stocks is relevant for example for retail improving orders: for a stock in group 1 the price can be set in 1/10 cent increments, for a stock in group 2 the price has to be set in at least 1/2 cent increments. Also, for brokered cross trades–when a brokerage firm receives

Group 3 stocks adhere to the requirements of the second test group, and in addition are subject to a "trade-at" prohibition. The trade-at prohibition grants execution priority to displayed orders unless non-displayed liquidity in quoting trading centers can provide a price improvement of at least 5 cents. The trade-at prohibition also imposes a cost on non-quoting trading centers, so-called dark pools, by prohibiting them from price matching protected quotations (see FINRA and NSE, 2018).

An important feature of the pilot program is the stratified random sampling procedure used to determine the stocks to be allocated to each group. The stratification is over three variables: share price, market capitalization, and trading volume and yields 27 possible categories (e.g., low price, medium market capitalization and high volume). The pilot securities were randomly selected from the 27 categories to form the three test groups and the control group. In the next section, we preform some simple tests of the validity of the random procedure.

The pilot program was implemented on a staggered basis. Between the end-of-business day on September 3, 2016, and the beginning of trading on September 6, 2016, the list of stocks to be included in the tick size pilot program was announced as well as their group assignments. On October 3, 2016, 5 stocks were activated in each of the test groups 1 and 2. On October 10, 2016, 95 stocks were activated in each of the test groups 1 and 2. On October 17, 2016, all remaining stocks in groups 1 and 2 were activated and 5 stocks were activated in test group 3. On October 24, 2016, 95 stocks were activated in group 3, with the rest of the stocks in group 3 activated on October 31, 2016.

The pilot program results from an initiative under the Jumpstart Our Business Startups Act ("JOBS Act") signed in April of 2012. The JOBS Act directed the SEC to conduct a study on how decimalization affects the number of IPOs and market quality of

buy and sell orders on the same stock from its clients it can cross the trades without sending them to the market–while for a stock in group 1 the price can be set in 1/2 cent increments, for a stock in group 2 the price has to be set in 5 cent increments.

small capitalization stocks. In July of 2012, the SEC reported back to Congress without reaching a firm conclusion on the question. Following this study, Congress mandated the SEC to implement a pilot program to investigate the impact of increasing the tick size. In June of 2014, the SEC directed the Financial Industry Regulatory Authority and the National Securities Exchanges to develop a tick size pilot program to widen the minimum tick size increment for a selection of small-cap stocks. On May 6, 2015, the SEC approved the proposed plan.

Supporters of the Tick Size Pilot Program argue that increasing tick size (i) motivates market makers to provide more liquidity to small-cap stocks, thus making these stocks more attractive to investors (Grant Thornton, 2014) and (ii) leads to greater analyst coverage and more information production (Weild et al., 2012). In fact, the pilot program was lobbied by some investment banks and former stock exchange officials (Wall Street Journal, 2016). Opponents argue that increasing tick size (i) increases investors' execution costs, and the complexity of the pilot reduces order execution efficiency, (ii) leads to a wealth transfer from liquidity takers to liquidity suppliers (e.g., Wall Street Journal, 2016), and (iii) decreases information production (e.g., Bessembinder et al., 2015). Bessembinder et al. (2015) go on to argue that the decrease in liquidity and information production lower IPO prices and lead to fewer IPOs.[6] With the exception of Bessembinder et al. (2015), and to our knowledge, neither supporters nor opponents of the tick size program comment explicitly on the potential price and cost of capital effects of the program, which could hurt the very firms that the program wish to help.

[6]Using data from 1980-2011, Ritter (2013) finds no evidence supporting the hypothesis that the volume of small-company IPO dropped due to decimization.

3. Data description

Our sample consists of all stocks in the Tick Size Pilot Program. We drop from the sample stocks that are delisted or experience a merger and acquisition during the sample period, stocks whose prices drop below $1, stocks that are not common-ordinary stocks (i.e., keeping only stocks with CRSP share code of 10 or 11), and stocks without daily TAQ data.[7] The first two filters trigger the SEC to move stocks out of their treatment groups. These filters are consistent with those used in Rindi and Werner (2019) and Lin et al. (2017). We also drop a firm-day observation if the average daily price for that firm and day is below $2. Otherwise, we follow Holden and Jacobsen (2014) in cleaning the daily TAQ data set. We obtain the intraday quote and price data from the daily Trade and Quote (DTAQ), stock market data from the Center for Research in Security Prices (CRSP), Fama-French and momentum factors data from the Kenneth R. French data library, institutional investor holdings from Factset, and high-frequency news data from RavenPack News Analytics (RavenPack) database. Following Kaniel, Saar, and Titman (2008), we use the TAQ database to create a return series from end-of-day quote midpoint to mitigate the effect due to bid-ask bounce and nonsynchronous trading. We also use CRSP daily return as an alternative and obtain similar results. Across most of our tests, we use data from January 1, 2016 to December 31, 2018. End of pilot results use data from April 1, 2018 to April 30, 2019.

[Table 1 about here.]

[7]Dropping firms that are delisted or that experience a merger and acquisition during our sample period yields 1,139 stocks in the control group, a drop from 398 to 383 stocks (396 to 384, and 395 to 382) in group 1 (2, and 3, respectively). Dropping firms that are removed from the test group and added to the control group by the SEC due to a price decline below $1, group 1 (2 and 3, respectively) stocks decrease to 377 stocks (375 and 374, respectively). Keeping only common equity stocks leaves 979, 330, 323, and 315 stocks in our sample in the control, group 1, group 2 and 3, respectively. Finally, after dropping stocks without daily TAQ data, we obtain our final sample of 954, 323, 316, and 310 stocks in the control, group 1, group 2 and 3, respectively.

Table 1 reports the mean of key variables for all three pilot groups for the pre-experiment period starting March 1, 2016 and ending August 31, 2016. Please refer to the appendix for complete data definitions.[8] For each test group and the control group, we split stocks between small and large dollar quoted spread. We take all stocks with pre-experiment average dollar quoted spread of 3 cents or lower to be the small-spread stock sample. We take all stocks with pre-experiment average dollar quoted spread above 7 cents (approximately equal to the median) as our large-spread stock sample.[9] This results in sample cut-offs that are plus or minus 2 cents from the new tick size. The reason for the sample split is that the increased tick size may be binding only for some stocks, those that are more liquid and have small bid-ask spreads. In fact, in the pre-experiment period, the percentage of days that a stock in the small-spread stock sample has an average dollar quoted spread above 5 cents (see the mean of the *BindingTickSize* dummy variable) is under 0.3%, whereas for a stock in the large-spread stock sample that number is 95%.[10]

Panel A of Table 2 shows that there are 46 (154) small (large) spread stocks in group 1; 47 (147) small (large) spread stocks in group 2; 54 (146) small (large) spread stocks in group 3; and there are 154 (430) small (large) spread stocks in the control group. Table 1 shows that the average pre-experiment dollar quoted spread for the small (large) quoted

[8] In some cases, the quoted spread is smaller than the effective spread but this is an artifact of the different weighting schemes.

[9] We first split all stocks, treated plus control, into small and large dollar quoted spread. This procedure ensures similar pre-experiment average dollar quoted spread in each of the subsamples across all three groups and control, but may create unbalanced panels if the experiment is not well randomized. As it turns out, the size of each sample is quite homogeneous across groups. By using pre-experiment data to construct the subsamples, we do not induce any selection bias since firms and investors do not know which stocks are in the program.

[10] Griffith and Roseman (2019) and Rindi and Werner (2019) separate the treated stocks into two groups based on whether the quoted spread is larger than or equal to \$0.05. Lin et al. (2017) also use the \$0.05 cut-off to identify the most constrained stocks (they use three subsamples). We note that for stocks with pre-experiment average daily dollar quoted spread between 3 and 5 cents there is a 20% chance of having a day with an average daily quoted spread above 5 cents (untabulated). Our first draft adopted the median spread as the cutoff. The results from this earlier draft are available on an Online Appendix.

spread stocks in group 1 is \$0.02 (\$0.24); the average dollar quoted spread for the small (large) quoted spread stocks in group 2 is \$0.02 (\$0.23); the average dollar quoted spread for the small (large) quoted spread stocks in group 3 is \$0.02 (\$0.26); and the average dollar quoted spread for the small (large) quoted spread stocks in the control group is \$0.02 (\$0.27). The significant differences in spreads between small spread stocks and large spread stocks, and the differences in the frequency with which each group is likely to have spreads above 5 cents in the pre-experiment data noted in the previous paragraph, suggest that the large-spread stock sample is a good placebo sample: we do not expect the change in tick size to affect the liquidity of these stocks.

Table 2, Panel A, reports additional descriptive statistics on several key variables during the pre-implementation period.[11] The mean market capitalization in each of the groups for small spread stocks is around \$800 million (the maximum market capitalization to participate in the pilot program is \$3 billion); these stocks are larger than those in the sample of large pre-experiment quoted spreads. The mean daily volume of the small quoted spread stocks is about 400 thousand shares, versus 90 thousand shares for the large quoted spread stocks (the maximum volume to participate in the pilot program is 1 million shares). Overall, the total daily trading volume of treated and control firms in the experiment accounts for about 6.2% of total market trading volume, in approximately equal shares between treated and control firms.

Table 2, Panel B, reports the differences of key variables between each pilot group and the control group, and tests whether such differences are statistically different from zero. We find that stocks in each pilot group and in the control group exhibit similar total assets, market capitalization (with the exception of group 1 versus the control

[11] We winsorize all spread measures, market depth, volume, dark pool volume, the inverse of price, daily high minus low, turnover, AR10, and PrcError at 1% and 99%. We winsorize return at 0.05% and 99.5%. Because we winsorize these variables pooling all firms together, in some cases the minimum or maximum values are the same across test groups.

group for small spread stocks), book-to-market ratio, and spreads, as well as the inverse of price, daily high minus low and share turnover. The last three variables are used as controls in our regressions, and these tests show that they exhibit similar means in the pre-sample across treated and control groups as required. These results validate the randomization of the pilot program and ensure that stocks in the pilot and control groups are similar over several dimensions (for similar analyses see Hansen et al., 2017, and Bartlett and McCrary, 2018).

[Table 2 about here.]

4. Impact of tick size on stock prices

We study price effects around the implementation date of the pilot stocks (through October 2016). We expect price effects at the implementation dates to reflect actual investor behavior changes derived from the tick size change. We also study price effects around the announcement date of the group assignments (in early September 2016). We expect some price effect at announcement if investors are able to anticipate the price effect at implementation. We expect the announcement effects to be small compared to the implementation effects for two reasons. First, there is a lack of evidence on price effects from prior changes in the tick size. Second, the discussion surrounding the Pilot Program vastly omitted price effects.

Our study of the impact of a larger tick size on stock prices uses a difference-in-differences technique. Following Amihud, Mendelson, and Lauterbach (1997), and a large event study literature, we use abnormal stock returns to measure the impact of widening the tick size on the stock price. We calculate abnormal returns using three models: the CAPM, the Carhart (1997) four-factor model that extends the Fama-French three factors to include the momentum factor, and the Fama-French 5-factor model. In addition, we display results using raw returns to evaluate if the price effects detected with any of these three risk-adjustment models is due to changing betas. As an example, the Carhart model is

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - R_{f,t}\right) + \beta_{i,s} SMB_t + \beta_{i,h} HML_t + \beta_{i,o} MOM_t + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ is stock i's raw return on day t, $R_{f,t}$ and $R_{m,t}$ represent the risk free rate and market return on day t, SMB_t is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, HML_t is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks, and MOM_t is the momentum factor. We estimate the model parameters using pre-sample data (i.e., from September 2015 to August 2016). We then calculate the abnormal return as $AR_{i,t} = \hat{\alpha}_i + \hat{\varepsilon}_{i,t}$.

In our tests, we combine treated stocks in groups 1 and 2 together and call that 1&2. We do this for three reasons. First, Rindi and Werner (2019) show that the changes in market quality in groups 1 and 2 are mostly driven by the quote requirement. Second, the stocks in the two groups are activated concurrently. Third, to increase the power of the test by increasing the size of the treated group. Across all tests, small (large) spread stocks in the control group are assigned to small (large) spread stocks in each treated group.[12]

[12] We have repeated all our tests for group 1 stocks and for group 2 stocks separately. The results using the non-staggered implementation design are similar both in economic and statistical significance. The results using the staggered implementation design are similar in economic significance, but the statistical significance of group 1 stocks results is weaker.

4.1. Price effects at implementation: non-staggered test design

In the non-staggered test design, we assume group 1&2 (group 3) stocks are treated on October 17 (October 31), the day that three quarters of the stocks in this group are activated. Our main result is depicted in Figure 1. The figure plots the price difference between group 1&2 stocks versus the control (top panels), and the price difference between group 3 stocks versus the control (bottom panels). Prices are calculated as the cumulative raw returns (left panels), and the cumulative Fama-French 5-factor abnormal returns (right panels), excluding day and stock fixed effects. The figure plots the price from 10 trading days prior to treatment to 40 trading days post treatment. The price difference is normalized to one at the start of the period. The figure shows a significant decline in price following the full implementation of the tick size program for each group.[13] The figure also suggests that the parallel-trends assumption is satisfied, which is confirmed at the bottom of Panel B in Table 2 for raw returns (the hypothesis that there is no difference for the large-spread stocks in group 1 cannot be rejected). In untabulated results, we confirm the test of difference in mean returns in the pre-period for abnormal returns.

[Figure 1 about here.]

Table 3 reports the OLS regression results of the impact of the larger tick size on

[13] We plot the price difference because the difference-in-differences analysis can only resolve differences in behavior across treated and control groups. However, Ayiagari-Gertler (1991) and Vayanos (1998) predict that there may be a spillover effect from the less liquid assets to the more liquid assets with similar characteristics and Rindi and Werner (2019) find evidence of such spillovers in liquidity in the tick-size pilot. We do not offer a test of the spillover effect, but the possibility of such a spillover means that some of the price effects that we find may not be attributable to an absolute price drop of the treated firms but rather to a relative price drop.

stock returns controlling for firm characteristics,

$$
\begin{aligned}
AR_{i,t} =& \alpha + \gamma_1 Week1_t + \gamma_2 Week2_t + \gamma_3 Post_t + \gamma_4 Pilot_i \times Week1_t \\
& + \gamma_5 Pilot_i \times Week2_t + \gamma_6 Pilot_i \times Post_t + \gamma_7 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}.
\end{aligned} \tag{2}
$$

The results for group 1&2 stocks are reported in panel A and for group 3 stocks in panel B. For groups 1&2, $Week1_t$ is a dummy variable equal to 1 for days between October 17 and October 21, and 0 otherwise, and $Week2_t$ is a dummy variable equal to 1 for days between October 24 to October 28, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2$, and 0 otherwise. For group 3, we define these dummies similarly starting on October 31. In panel A (panel B), $Pilot_i$ is a dummy variable that equals 1 if stock i belongs to test group 1&2 (group 3) and 0 otherwise. We include all interaction terms of each date dummy with $Pilot$. The sample period is September 1, 2016 to November 30, 2016, one month prior to the implementation month and one month after the implementation month. While we use a shorter window for the return regressions than for the remaining tests in our exercise, we have replicated the return regressions with the same event window as in our other tests with similar results.

Following Angrist and Pischke (2009), we include in the regression several control variables, $X_{i,t}$. To capture factors that may be associated with microstructure effects such as the speed of incorporation of information, we include share turnover, the inverse of the share price, and the high minus low daily trading price.[14] We also include day and stock fixed effects to control for time-invariant differences in stocks such as the exchange where they trade (because of the stock fixed effects, the dummy $Pilot_i$ drops from the regression and because of the day fixed effects, the dummies $Week1_t$, $Week2_t$, and $Post_t$

[14] Abdi and Ranaldo (2017) have showed that bid-ask spreads are related to daily high minus low prices. The results without this control variable are virtually unaffected.

also drop from the regressions) and macro effects not already captured by the control group or via the risk-adjustment. These controls are not systematically related to the treatment as was shown in Panel B of Table 2, but they have explanatory power, which by reducing the variance of the residuals, has the potential to increase efficiency and to lower the standard errors of the coefficient estimates (Angrist and Pischke, 2009, section 2.3). Macroeconomic shocks occurring at the implementation date can also introduce correlation in the residuals. We deal with this issue by clustering on stock and day. By clustering on day, we effectively increase the standard errors if this correlation is present.

[Table 3 about here.]

In each panel of Table 3, Columns (1) and (2) present the results with raw returns, Columns (3) and (4) present the results for the CAPM model, Columns (5) and (6) present the results for the Carhart model, and Columns (7) and (8) present the results for the Fama-French 5-factor model. We are interested in the coefficient associated with $Pilot_i \times Week1_t$ to detect the effect of the tick size program. The coefficient associated with $Pilot_i \times Week2_t$ may be significant if investors take time to adjust and the market cannot fully anticipate their slower adjustment.

The results can be summarized in three points: i) there are large negative price effects on the small spread stocks that are invariant to the risk adjustment used, though for group 1&2 the significance of the effect is somewhat better with the Carhart and Fama-French 5-factor models; ii) the effect on raw returns is similar to that on adjusted returns, and thus it is unlikely that the price effect occurs via changes in the betas associated with the risk factors; and, iii) there are no effects on the large spread stocks. For group 1&2 (panel A), the coefficient associated with $Pilot_i \times Week1_t$ is approximately -0.35% significant at the 10% level or better, which translates into a drop in prices of $0.35\% \times 5 = 1.75\%$, compared to the control group (note that the dummy $Week1_t$

is activated over 5 days). There is a continued price decline measured with abnormal returns using the Carhart and FF5 models as $Pilot_i \times Week2_t$ is significantly negative. The cumulative price effect after the first two weeks according to the Fama-French 5-factor model is a drop in prices of $(0.362 + 0.387) \times 5 = 3.75\%$; the drop in price doubles if we include the $Pilot_i \times Post_t$ effect $(7.52\% = 3.75\% + 0.164\% \times 23)$.

For test group 3 (panel B), as for group 1&2, the effect on raw returns is of the same magnitude and significance as that on adjusted returns suggesting that the price drop is not due to changing betas. There is also no evidence of a price effect for stocks with large dollar quoted spread. The coefficient associated with $Pilot_i \times Week1_t$ is approximately -0.64%, with significance at 5% or better. These returns translate into a drop in prices of about $0.64\% \times 5 = 3.2\%$ over the first week compared to the control group. Overall, the results for group 3 are stronger in both economic magnitude (considering only $Week1$) and statistical significance than for group 1&2.

The observed drop in prices is a liquidity premium that we are able to identify given the construction of the pilot program. For group 1&2 stocks, whose total market capitalization is \$78.6 billion, a 1.75% price drop is equivalent to a loss of \$1.38 billion (market capitalization is from Table 2 using the number of stocks and the average capitalization per stock). For group 3 stocks, whose total market capitalization is \$36.2 billion, a 3.2% price drop is equivalent to a loss of \$1.2 billion. The total cost of the pilot as measured by the effect on our sample of small spread stocks is thus \$2.6 billion.

We have conducted several placebo tests reported on our Online Appendix. In one test, we shift the implementation date one month earlier, and in another, we shift the implementation date two months forward. We do not find any significant price effects. The sample of large spread stocks is also a placebo group. As the results in Table 3 demonstrate, there is no evidence of a price effect on these firms. Finally, the finding of a negative price reaction is not mechanically driven by stale prices of treated stocks–that just saw their bid-ask spreads increase–contemporaneous to a booming stock market. If this were the case, we should see a similar effect on the large spread stocks, which we do not.

4.2. Price effects at implementation: staggered test design

In the staggered test design stocks are treated at their own date of implementation. We estimate the following model with OLS

$$AR_{i,t} = \alpha + \gamma_1 Week1_{i,t} + \gamma_2 Week2_{i,t} + \gamma_3 Post_{i,t} + \gamma_4 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}, \qquad (3)$$

where the notation is as in equation (2), except that $Week1_{i,t}$ is a stock-specific dummy that equals one during the days of the first week of implementation for stock i and zero otherwise, and $Week2_{i,t}$ and $Post_{i,t}$ are also stock specific and are defined similarly. In this regression, as in Jayaratne and Strahan (1996) and Bertrand and Mullainathan (2003), control firms are not assigned to any group so $Week1_{i,t}$, $Week2_{i,t}$ and $Post_{i,t}$ are set to zero for these firms. The sample period is September 1, 2016 to November 30, 2016, one month prior to the implementation month and one month after the implementation month. We report robust standard errors clustered by stock and day.

One benefit of the staggered implementation test design over the non-staggered design is that it potentially increases the power of the test by using the actual implementation date of each stock as the treatment date. Another benefit is that it allows us to run regressions where we include treated stocks from all three groups. A cost of the staggered implementation test design relative to the non-staggered implementation, however, is that it may not capture the slow adjustment by investors that is not fully anticipated by the market. It is possible that market participants take time to adjust early in the pilot. For example, investors may take time to decide on how to rebalance their portfolios in light of the new tick size, or on how to respond to the change in information risk. Under this assumption, the dummy $Week1$ may be suitable to capture the effect on the firms treated later in the program, but not on those treated earlier. In fact, as shown next, we find some evidence of slow adjustment by market participants for the stocks treated in the beginning of the pilot.

[Table 4 about here.]

The results are displayed in Table 4. Panel A (B and C) contains the results for pilot groups 1, 2 and 3 (groups 1&2 and 3, respectively). In each panel, Columns (1) and (2) present the results with raw returns, Columns (3) and (4) present the results for the CAPM model, Columns (5) and (6) present the results for the Carhart model, and Columns (7) and (8) present the results for the Fama-French 5-factor model. We are interested in the coefficient associated with $Week1_{i,t}$ to detect the effect of the tick size program.

We find a statistically significant and negative effect when we run the regression for all three groups (panel A). The coefficient on $Week1_{i,t}$ across regressions in Panel A of Table 4 is about -0.25%, with significance better than 5%. We find somewhat weaker results under the staggered implementation test when we study stocks in group 1&2 alone (panel B of Table 4) as compared with the results under the non-staggered implementation test (panel A of Table 3). The weaker results are mostly due to a smaller coefficient, which impacts the statistical significance. Only when using the Fama-French 5-factor model do we observe the statistical significance of the coefficient associated with $Week1_{i,t}$ for stocks in group 1&2. We find similar results for group 3 under the staggered implementation (panel C of Table 4) relative to the non-staggered implementation (panel B of Table 3) albeit with smaller economic magnitude.

To understand the nature of the weaker results for group 1&2, we re-run separate regressions for stocks implemented on different days (i.e., run a regression for stocks in group 1&2 activated on October 3, and then another regression for those stocks activated on October 10, and finally another for those activated on October 17). In untabulated results (see our Online Appendix), we find that the most significant effect for stocks activated on October 3 is in the *Post* dummy (that starts on October 17, two weeks after they are implemented), the most significant effect for stocks activated on October 10 is in the $Week2$ dummy (that starts on October 17, one week after they are implemented), and the most significant effect for stocks activated on October 17 is in the $Week1$ dummy (that starts on October 17). These results show a delayed response to treatment in the early part of the pilot. This delayed response may explain the differences between Table 3 and Table 4 to the extent that Table 3 uses a single implementation date of October 17 at which point all stocks in group 1&2 seem to have experienced some price effect. Interestingly, if we repeat this exercise for group 3 stocks, which are all activated after group 1&2, we observe that most of the effect comes in the respective $Week1$ of activation. We conclude that because stocks in group 3 are implemented later, market adjustment for these stocks is immediate.[15]

In a robustness exercise, we have re-estimated the models in equations (2) and (3) using a pre-window of six months and a post-window of six months. The results are broadly consistent with the existence of a price effect as reported when using a shorter window: across models, in the regressions that combine all groups, the economic significance of the price effect decreases slightly, but the coefficients are still statistically

[15]There is a separate question of whether the market could anticipate by October 17 the price effect on firms treated on October 24 and on October 31. We estimate equation (2) for group 3 stocks assuming a single treatment date of October 17. The results show a significant effect on $Week1$ with an estimated coefficient of -0.34 to -0.37 depending on risk adjustment (slightly higher than half the effect in Table 3). Likewise, the market could anticipate by October 3 the price effect on firms in group 1&2 treated on October 17. We estimate equation (2) for group 1&2 stocks assuming a single treatment date of October 3. The results show an insignificant effect on $Week1$. The results are in the Online Appendix.

significant, and the coefficient on $Post \times Pilot$ is statistically significant as well. The results are reported in the Online Appendix.

4.3. Price effects at announcement of group assignments

Treated stocks were announced in early September 2016, which allows us to study the announcement effect separately from the implementation effect. According to Pachare and Rainer (2018), the timing of the various announcements is the following: NASDAQ posted the group assignment file for NASDAQ-listed stocks on September 2, 2016 at 6:46pm (a Friday after the market close). It subsequently published a trader alert–used by the exchanges to communicate with market participants in a timely manner–on September 6, 2016 at 12:27pm (the markets were closed on September 5 for Labor day). NYSE posted the group assignment file for NYSE- and NYSE MKT-listed stocks on September 6, 2016 at 9:03am. It subsequently published a trader alert on September 6, 2016 at 3:04pm. Additionally, FINRA posted the combined group assignment file on September 6, 2016 at 1:29pm.

In Panel A of Table 5, we present results from estimating the following regression using OLS

$$\begin{aligned} AR_{i,t} = {} & \alpha + \gamma_1 September6_t + \gamma_2 September7_t + \gamma_3 Post_t + \gamma_4 Pilot_i \times September6_t \\ & + \gamma_5 Pilot_i \times September7_t + \gamma_6 Pilot_i \times Post_t + \gamma_7 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $Pilot_i$ is a dummy variable that equals 1 if stock i belongs to any of the test groups, $September6_t$ and $September7_t$ are dummies for September 6 and 7, respectively, $Post_t$ is a dummy that equals one for days after September 7, and the rest of the variables are defined as in equation (2). The sample period is August 1, 2016 to September 30, 2016, about one month before and one month after the announcement. We report robust standard errors clustered by stock and day.

[Table 5 about here.]

The coefficient estimate associated with $September7_t$ shows a significant negative price decline on September 7, both economically and statistically. The price decline that we estimate is about 1/3 of a percent; it is 1/5 of what we find for all stocks at implementation as reported in Table 4 (see panel A and note that the dummy $Week1$ is activated over five days). We note that this analysis includes day fixed effects, much like our study of the price effects at implementation. Day fixed effects control for unobserved shocks affecting all firms that are not already controlled for in the abnormal returns.

We find no price effects on September 6. This may be due to the fact that information about the group assignments percolated slowly to the market. For example, the NYSE's trader alert only came at 3:04pm that day. To understand further what happens on September 6, in Panel B of Table 5, we repeat the regression in equation (4) splitting the September 6 dummy into two parts, before the trader alerts and after the trader alerts, and measuring returns also before and after the trader alerts on September 6. This test shows that there was a negative response through September 6, with the market responding significantly before the trader alerts, but not after. In any case, September 7 continues to deliver a significantly negative price effect.[16]

Pachare and Rainer (2018) study the price response to the announcement of group assignments and find no effect. They measure the announcement return from the market close on Friday, September 2, to the end of the trading day on September 6. The announcement-day return therefore includes the potentially confounding effects arising from volatility induced by overnight returns and weekend effects. Also, the treated

[16]Table 5 also shows that large spread stocks experience a price decline on both September 6 and September 7. This price decline could have resulted from a market overreaction, since there is no subsequent effect for these firms at implementation.

NYSE- and NYSE MKT-listed stocks were only disclosed on the morning of the 6th and including the return prior to disclosure is paramount to measuring noisier returns. Finally, they estimate a cross-sectional regression and cannot control for day fixed effects.

4.4. The end of the pilot program

To conclude the analysis of the price effects associated with the pilot, we conduct a difference-in-differences estimation at the end of the pilot on September 28, 2018. We estimate the same model as in equation (2) (mimicking Table 3), with a pre-period from September 1, 2018 to September 27, 2018, a post-period from September 28, 2018 to November 30, 2018, and with the timing of the variables appropriately adjusted. Again, we use ordinary least squares and report robust standard errors clustered by stock and day.

[Table 6 about here.]

The results are in Table 6. The coefficient estimates for $Week1$ interacted with $Pilot$ and for $Week2$ interacted with $Pilot$ are not significant for group 1&2 stocks or group 3 stocks, showing no price effects. There is a negative price effect associated with $Post$ interacted with $Pilot$ for group 1&2 stocks, but no corresponding price effect associated with $Post$ interacted with $Pilot$ for group 3 stocks.

Collecting our results on price effects, we find a price reduction at announcement and implementation of the pilot for treated stocks compared to the control group, but no price change at the end of the pilot. To explain the combined findings, our main hypothesis is that the change in tick size associated with the pilot caused changes in spreads and that these changes in spreads lead to higher risk premia and thus higher expected returns for the treated stocks. This means that cash flows are discounted at higher rates during the pilot, which leads to lower prices at impact. Furthermore, if investors expect discount rates to decrease once the pilot is over (back to their pre-pilot level), then prices should slowly reverse as the pre-determined end of the pilot approaches. This hypothesis then predicts that there should not be any price effect at the end of the pilot. The next section expands on the nature of changes in risk premia and provides evidence consistent with an increase in risk premia associated with the treated stocks.

One alternative interpretation for our findings is that the treated stocks were subject to a shock contemporaneous to both the announcement and implementation of the pilot. Such one-time shock at the beginning of the pilot would not cause any price effect at the end of the pilot. The 2016 U.S. presidential election and the events surrounding it are a potential candidate. For example, somewhat contemporaneous to the start of the pilot is the "Comey Surprise." We find these contemporaneous events unlikely. First, our regressions contain day and stock fixed effects and clustering of the standard errors at day and stock level. Second, the "Comey Surprise" happened at the end of October (on the 28th), which should not contaminate the tests, especially those using the staggered implementation of the program. Third, it would be difficult to argue an alternative story given the difference-in-differences approach to explain why only the small-spread stocks in the treated group were affected leaving the rest of the stock market unaffected.

5. Sources of price effects

This section provides evidence on the potential causes behind the observed price decline at the start of the pilot: a direct channel via the present value of increased transaction costs, and three indirect channels acting through expected return changes. The indirect channels that we study are information risk, investor horizon, and liquidity risk.

5.1. Direct effect of transaction costs

We document that the increased tick size produced an increase in spreads. The present value of the increased spreads is a measure of the direct effect of transaction costs.

5.1.1. Changes in market liquidity

We study the effect of the higher tick size on several measures of market liquidity using a difference-in-differences approach similar to that of subsection 4.2. We estimate the following model using OLS

$$Liquidity_{i,t} = \alpha + \gamma_1 Pilot_i + \gamma_2 Post_{i,t} + \delta^{'} X_{i,t} + \varepsilon_{it}, \tag{5}$$

where $Liquidity_{it}$ is a measure of liquidity for stock i on day t, and $Post_{i,t}$ is a stock-specific dummy that equals one every day after implementation for that stock and zero otherwise. $Post_{i,t}$ equals zero everywhere for control firms. Table 7 presents the results for group 1&2 (panel A for small spread stocks and B for large spread stocks) and group 3 (panel C for small spread stocks and D for large spread stocks). In panels A and B (C and D), $Pilot_i$ is a dummy variable that equals one if stock i belongs to group 1&2 (group 3), and zero otherwise. The sample period is April 1, 2016 to April 30, 2017, six months prior to the implementation month and six months after the implementation month. We report robust standard errors clustered by stock and day.

[Table 7 about here.]

For group 1&2 (group 3) small spread stocks, *QuotedSprd* (column 1) increases by 0.482 (0.435). This is an increase of 174% (172%) relative to the pre-treatment average *QuotedSprd* reported in Table 1 of 0.277 (0.253) for group 1&2 (group 3); this increase is mostly a reflection of the increase in dollar quoted spread from $0.02 from before the pilot (see Table 1) to \$0.05 after the pilot. The changes are statistically significant at the 1% level. Large and statistically significant changes in the *EffectiveSprd* (column 2) and *PriceImpact* (column 3) also occur for all groups. There are no statistically significant effects on spreads for stocks with large dollar spread. The evidence presented here is consistent with that of other papers that also study the tick size pilot program, such as FINRA and NSE (2018), Griffith and Roseman (2019), Hansen et al. (2017), Hu et al. (2018), Lin et al. (2017), and Rindi and Werner (2019), and with evidence from studies of prior tick size changes (see Biais, Glosten and Spat, 2005, for a review). The observed increase in spreads is likely to be the net effect of several forces. On the one hand, Harris (1996) argues that an increase in tick size is followed by reduced competition among liquidity providers with a consequent increase in transactions costs for market orders that generally get executed at the NBBO (Harris, 1997). On the other hand, a larger tick size improves liquidity by reducing negotiation costs (Harris, 1991), or by encouraging liquidity provision for illiquid stocks if investors switch from market to limit orders (Werner et al., 2015).[17]

Market depth (column 4) increases for group 1&2 (group 3) small dollar spread stocks by about 35 (52) thousand shares daily, compared to the control group, which represents an almost three (four) fold change relative to pre-experiment levels. These results are consistent with the hypothesis that a wider tick size reduces price competition among liquidity providers that are forced to queue at the same quoted price, limiting their ability to obtain price priority by submitting more aggressive limit orders (see Harris, 1994, 1997, and Bessembinder, 2003, O'Hara, Saar, and Zhong, 2019, and Yao and Ye, 2018). The increased depth also does not appear to lessen price impact among liquidity takers as discussed earlier. A somewhat stronger effect for group 3 stocks is consistent with the increased cost in dark venues for these stocks attracting more trades to lit

[17]For other mechanisms, see Foucault, Kadan and Kandel (2005), Kadan (2006), and Seppi (1997).

pools. Consistent with Goldstein and Kavajecz (2000), there is an increase in market depth for the more illiquid stocks as well, though the effect is economically smaller.

Total trading volume (column 5) declines by a statistically significant $84,299$ shares in group 1&2 and by $38,515$ shares in group 3, representing 18% and 9.5% of the respective group means. This evidence is consistent with Harris (1997) and Goettler, Parlour and Rajan (2005) who argue that volume decreases in response to the increase in trading costs associated with the larger tick size. We note that Ahn, Charles and Choe (1996), Porter and Weaver (1997) and Rindi and Werner (2019) find no effect of tick size changes on volume. Column 6 in Table 7 reports the change in volume in dark venues. There is no change in dark venue volume for group 1&2, but there is a significant decline of roughly 49 thousand shares for group 3 stocks.[18] In summary, the loss in total trading volume in group 1&2 occurs in lit markets. The loss in total trading volume in group 3 stocks occurs in dark venues. Group 3 stocks also lose volume in lit markets (to be expected since group 3 treatment is equal to group 2 treatment plus the trade-at rule), but that volume is compensated by volume that moves away from dark venues and into lit markets.[19]

5.1.2. A back-of-the-envelope calculation

We use a back-of-the-envelope present value calculation as in Amihud and Mendelson (1988) and Foucault et al. (2013) to translate the change in spreads into a direct price effect. First, the direct effect is only over the two-year period of the duration of the pilot. Second, we use the horizon of institutional investors as a benchmark. In our sample, the

[18] It is conceivable that investors in groups 1 and 2 stocks may want to circumvent the wider tick size by trading in dark venues, thus offsetting the higher cost brought by the wider tick size. Indeed, the market share of dark venues appears to have increased: dark trading volume for group 1&2 decreases by 10 thousand shares but total trading volume decreases by 84 thousand shares. This result is consistent with Comerton-Forde, Gregoire, and Zhong (forthcoming).

[19] Lin, Swan and Mollica (2017) study the allocation of investors and volume across exchanges.

average institutional investors' holding period horizon for the treated stocks is 5 years (using data from Table 1, the investor horizon is calculated as $1/(2 \times ChurnRatio)$). Thus, assuming that investors churn their portfolio continuously over time, after 2 years they will have churned 2/5 of their portfolio and paid transaction costs on those trades. We take the quoted spread as the measure of transaction costs.[20] Table 7 reports a change in proportional quoted spreads equivalent to 0.45 cents on a \$1 stock across all treated stocks, which implies that 0.45/2 cents are the increased transaction cost paid on a one-way trade. The value (ignoring discounting) of these costs given average turnover is $0.45/2 + \frac{2}{5} \times 0.45/2 = 0.32$ cents. For a \$1 stock, the observed change of -1.75% (-3.2%) in prices for stocks in group 1&2 (group 3) equals 1.75 (3.2) cents, meaning that the change in transaction costs represents 18% (10%) of the change in prices. These numbers are somewhat smaller if we use effective spreads. We omit at least two forces that would reduce the direct effect of transaction costs: discounting, and increases in investor horizon in response to higher transaction costs. We also omit forces that would increase the direct effect of transaction costs: higher trading intensities perhaps associated with shorter-term investors, and convexity of cost as a function of trade size. Nonetheless, these rough calculations suggest that a substantial portion of the observed change in prices across all groups is due to indirect effects via expected returns.[21]

[20] Jones and Lipson (2001) construct a measure of execution costs by adjusting transactions costs to trade and stock characteristics. In our difference-in-differences regressions of changes in *QuotedSprd* in subsection 5.1.1, by controlling for the inverse price, the day high minus low, and trading volume, some of which are also variables that help determine the trading cost residual in Jones and Lipson, we are implicitly calculating an adjusted transaction cost measure.

[21] Another way to assess the magnitude of the price response is to compare with the change in dollar value of transaction costs. The small spread stocks in our sample jointly have a daily trading volume of about 62 million shares (from data in Table 2). A one-cent tick size applied to daily volume is \$620,000 and over 250 trading days in a year equals about \$155 million. Since the treated firms had an average dollar spread of \$0.02 that increased to \$0.05, a three-cent tick size increase equals about \$465 million. This number is 18.6% of the loss in market capitalization found in subsection 4.1, about the same as our back-of-the-envelope calculation above.

The calculation above has a parallel in the asset pricing literature: the liquidity premium. The liquidity premium is the ratio of the change in returns to the change in proportional spreads. The treated stocks in group 1&2 (3) experienced a return of -1.75% (-3.2%) and a change in proportional quoted spreads of 0.48% (0.44%), which gives a liquidity premium of 3.6 (7.3). Our finding of a liquidity premium that is a multiple of the change in transaction costs contrasts with many theories of asset pricing with transaction costs. In these theories, investors use assets with lower transactions costs for their hedging needs and limit trading in equities that have higher transaction costs. Not surprisingly, increasing transaction costs for equities has a second order equilibrium effect because it does not significantly affect volume. Examples of such models are Ayiagari and Gertler (1991), Beber et al. (2012), Buss, Uppal, and Vilkov (2011), Constantinides (1986), Heaton and Lucas (1996), Vayanos (1998), and Vayanos and Vila (1999). Huang (2003) summarizes the predictions from some of these models stating that under reasonable calibrations they generate liquidity premia substantially lower than unity. While our evidence rejects these theories, it is consistent with other theories discussed next.

5.2. Indirect effect of transaction costs

We explore three channels through which transaction costs affect expected returns: information risk; investor horizon; and, liquidity risk.[22]

[22] While we interpret our findings as driven by expected return changes, it is possible that firms change their policies in response to changes in price informativeness due to the tick size increase so that cash flows of firms also change (e.g., Chen, Goldstein, and Jiang, 2007, and Fang, Noe, and Tice, 2009). We do not have any means of separating between these hypotheses at this point, but we note that the temporary nature of the program suggests that it is unlikely that firms would change investment plans, governance practices, or dividend policies.

5.2.1. Information risk

Changes in the quality of information in the marketplace, can create information risk and lead to changes in expected returns. In Easley and O'Hara (2004) and O'Hara (2003), a relatively higher fraction of uninformed traders leads to higher expected returns for two reasons. On the one hand, the stock is riskier for uninformed investors, and thus the average risk borne by investors increases. On the other hand, the price is less informative and uninformed investors face greater adverse selection.

We study how price efficiency changes with the tick size as a way to assess changes in the quality of information in the market. On the one hand, in Anshuman and Kalay (1998), informed traders invest more to acquire accurate signals under continuous pricing than under discrete tick size trading. The larger tick size thus leads to less information acquisition and a reduction in price efficiency. For group 3 stocks there is an added cost of trading in dark venues that sends volume to lit markets (see Table 7 for evidence on the decline in dark trading volume for group 3 stocks). Based on Zhu (2014) and Comerton-Forde and Putnins (2015), we predict that the additional volume in lit markets from dark pools is composed primarily of uninformed trades, which increases noise in prices, and reduces price efficiency. On the other hand, Weild et al. (2012) predict that the wider tick size leads to greater analyst coverage and more information production, and Cordella and Foucault (1999) argue that the larger tick size creates a bigger gap between the competitive price and the expected asset value and prompts dealers to adjust prices more quickly. We evaluate empirically whether price efficiency increases or decreases with the change in tick size.

As proxies for quality of information, we use the absolute value of the ten-second mid-point return autocorrelation (*AR10*), a price efficiency measure from Hasbrouck (1993) and Boehmer and Kelley (2009) (*PrcError*), the Hou and Moskowitz's (2005) price delay

(*PrcDelay*), and the speed of market response to news (*PriceResponse*, *VolumeResponse*, and *QuoteResponse*) (the definition of these variables can be found in the Appendix). We estimate the specification in equation (5), with the same sample period, for group 1&2 and group 3 using the same right-hand side variables, but with the price efficiency variables as the dependent variable.

[Table 8 about here.]

The results for *AR10*, *PrcError*, and *PrcDelay* are displayed in Table 8. The models in Table 8 are estimated using ordinary least squares and we report robust standard errors clustered by stock and day. For small spread stocks, there is evidence indicating a worsening in price efficiency. For example, return autocorrelation increases by 0.143 for group 1&2 (column 1) and by 0.128 for group 3 (column 2), compared to the control group, which represent increases of about 50% relative to mean. Measured using *PrcError*, the changes in price efficiency are somewhat smaller percentage-wise relative to those for *AR10*. *PrcDelay* increases by 0.214 for group 1&2 and by 0.247 for group 3 relative to the control group for small spread stocks. These changes represent about a 50% increase relative to the mean price delay before the pilot program. For large spread stocks, there is an increase in *AR10*, in *PrcError*, and in *PrcDelay* for group 1&2 stocks and a decrease in *AR10* for group 3 stocks, but the effects are significantly smaller relative to those for small spread stocks.

[Table 9 about here.]

[Table 10 about here.]

Table 9 presents the results for the market response speed to firm-specific news and Table 10 for macro news. The models are estimated using Tobit regression to account for the fact that the variables *PriceResponse*, *VolumeResponse*, and *QuoteResponse* are bounded between 0 and 1. We are not able to estimate the models using stock fixed effects and instead use industry fixed effects.[23] The tables show three main results. First, the market response speed declined for both firm-specific and macro news for all treated firms relative to the control group. Second, response speed to group 1&2 declined slightly more for all news than the response speed to group 3. Third, there is some evidence of the slower speed of market response also for the large spread stocks, but, and especially for firm-specific news, the change is weaker.

We document price efficiency changes caused by the Tick Size Pilot Program using a comprehensive set of standard proxies for price efficiency. The results from Tables 8 through 10 suggest a decrease in price efficiency for the small spread stocks following the adoption of a larger tick size. Taken together, our finding is consistent with an increase in information risk à la Easley and O'Hara (2004) and O'Hara (2003). Our evidence is consistent with other studies on market efficiency and transaction costs. Chordia et al. (2008) find that short-horizon return predictability increases with market inefficiency, and using liquidity to assess the degree of informativeness of prices, Kerr, Sadka, and Sadka (2017) find that earnings growth predictability increases when the market becomes more liquid after the NYSE's 1997 reduction in tick size. Zhao and Chung (2006) show an increase in the probability of informed based trading (PIN measure) after decimalization. Thomas, Zhang and Zhu (2019) provide evidence consistent with trading noise increasing for treated firms in the SEC's tick size pilot program. Hu et al. (2018) also find evidence that price efficiency decreased for the treated stocks in the SEC's pilot program and that the main driver is the change in quoting requirements.[24]

[23] We have more observations in Table 9 than in Table 8, because we can measure the market response to a piece of macro news for every firm in our sample. From RavenPack, the mean number of news per company is 32.5 and the median is 19, and there are 1,693 macro news in our sample.

[24] Lee and Watts (2018) find evidence that information acquisition prior to quarterly earnings announcements increases for treated firms in the pilot program. It is possible that to overcome the

5.2.2. Investor horizon

Amihud and Mendelson (1986) predict that assets with higher transaction costs are held by long term investors, i.e., investors with a lower churn ratio, and have higher expected returns (net of transaction costs). The intuition is that, all else equal, long term investors hold assets with higher expected returns (net of transaction costs). In equilibrium, these must also be the assets with higher transaction costs, so that the extra return earned by the long term investors is a rent from economizing on transaction costs. Short term investors, who trade more frequently, find these assets too expensive to hold.

We test the prediction from Amihud and Mendelson (1986) that the investor horizon increases for the treated firms. The proxy for (the inverse of) investor horizon is the weighted average of portfolio turnover ratios by institutional investors that own stock on the firm (*ChurnRatio*) (see the appendix for the definition). We estimate the specification in equation (5), with the same sample period, for group 1&2 and group 3 using the same right-hand side variables, but with *ChurnRatio* as the dependent variable. The models are estimated using ordinary least squares and we report robust standard errors clustered by stock and quarter.

[Table 11 about here.]

Table 11 presents the results. We find that small spread stocks experience a decrease in investor churn after the implementation of the tick size program compared to the control group. We find no effect for large spread stocks. To interpret the size of the coefficient estimates, note that the average small spread stock's churn ratio is about 0.11, implying an average holding period of 4.5 years ($1/(0.11 \times 2)$). The churn ratio for stocks in group 1&2 is reduced by 0.005 (see column (1)). So, the holding period

decrease in price informativeness, investors start to collect more information, hoping to get a better estimate of the true fundamental price.

becomes 4.76 years. This is equivalent to a 2% increase. The churn ratio for small spread stocks from group 3 decreases by 0.003 (see column (2)) from 0.109. So the average churn ratio becomes 0.105 and the holding period increases to 4.72 years $(1/(0.106 \times 2))$. This change is equivalent to a 4% increase in the holding period.

Many asset pricing models with transaction costs predict that holding periods increase with higher transaction costs, for a given investor (e.g., Constantinides, 1986, and Vayanos, 1998). Our measure captures a different dimension that is more in spirit with Amihud and Mendelson's model. Our turnover ratio holds constant the investor's horizon and asks instead how much more of the holdings of each stock are now in the hands of short- versus long-term institutional investors. Omitting the effect from the models of Constantinides and Vayanos is likely to result in an underestimation of the true effect that changes in investor horizon have on prices.

5.2.3. Liquidity risk

In this subsection, we ask whether the change in tick size induces a change in liquidity risk. Acharya and Pedersen (2005) build on work by Chordia et al. (2000) and Huberman and Halka (2001) and others to construct a liquidity-adjusted capital asset pricing model where the required return on a stock depends on the covariances between the stock's return, the stock's liquidity, the market return, and the market liquidity.

Following Acharya and Pedersen (2005), we calculate the liquidity beta for stock i at day t as a combination of four different betas (the appendix contains the details). β_1 is similar to the CAPM beta, β_2 prices co-movement in liquidity, and β_3 captures the possibility that the stock can be a hedge against aggregate liquidity shocks, and β_4 captures the possibility that the stock is liquid when the market is doing poorly.

We estimate the specification in equation (5), with the same sample period, for group 1&2 and group 3 using the same right hand side variables, but with beta $(\beta_{i,t} =$

$\beta_{i1,t} + \beta_{i2,t} - \beta_{i3,t} - \beta_{i4,t}$) and liquidity beta ($\beta_{liq,t} = \beta_{i2,t} - \beta_{i3,t} - \beta_{i4,t}$) as the dependent variable. The models are estimated using ordinary least squares and we report robust standard errors clustered by stock and day.

Table 12 presents the results. In panel A, we find that for stocks with small quoted spread, beta falls by 0.1 (0.126) after the start of the pilot program for the treated stocks in group 1&2 (group 3) relative to the control group (see columns (1) and (2)). Panel B shows evidence of an increase in liquidity beta, indicating a higher liquidity risk premium after the start of the Pilot program, but the changes are not statistically significant.

[Table 12 about here.]

6. Conclusion

We provide causal evidence on an old question in the intersection of asset pricing and market microstructure. We find that an increase in tick size impacts stock prices negatively. The estimated liquidity premium is large. We show that the decline in stock prices is associated with an increase in quoted and effective spreads and in price impact, a reduction in total trading volume, and for stocks subject to the trade-at prohibition, a reduction in dark volume.

We study the sources of price variation. We show that treated stocks with small quoted spreads experience a decline in price efficiency consistent with an increase in information risk and thus higher expected returns (Easley and O'Hara, 2004, and O'Hara, 2003). We show that there is an increase in investor horizon consistent with Amihud and Mendelson's (1986) prediction that assets with larger transaction costs are held by long term investors and carry higher expected returns. We find no evidence that the price change is due to a change in liquidity risk à la Acharya and Pedersen (2005).

Overall, our evidence is consistent with firms' cost of capital being affected by market microstructure features.

The experiment conducted by the SEC was mandated by the 2012 JOBS Act. The main motivation for the experiment was to study how a higher tick size affects the liquidity of emerging stocks, and whether it increases analyst coverage and information production, and encourages more small firms to go public. Given the large theoretical literature arguing that liquidity has second order effects on prices, and given an existing sizable empirical literature arguing similarly, it is reasonable to assume that the regulator did not expect that the very companies the JOBS Act meant to help would lose value through the experiment.

Appendix: data definitions

A.1. Stock liquidity variables Following Holden and Jacobsen (2014), we use daily TAQ data to construct several liquidity measures. Percent quoted spread is the difference between the national best ask and the national best bid (NBBO) at any time interval divided by the midpoint of the two. The daily percent quoted spread (*QuotedSprd*) is the weighted average percent quoted spread computed over all time intervals, where each weight is the length of the time interval for which the percent quoted spread is available.

The quoted spread is calculated by taking the daily average of all quotes every time the NBBO is updated. It does not require any trade to take place. Arguably, the information contained in updates of the NBBO is more relevant in the study of the speed of market response to news, than in describing execution costs since traders may choose to execute orders when bid-ask spreads are narrower (Bessembinder, 2003). We therefore, consider an alternative measure of spreads that is calculated "conditional on" trade executions. The daily percent effective spread (*EffectiveSprd*) is the dollar-volume-weighted average of the percent effective spread computed over all trades in the day. The percent effective spread for each trade is twice the signed difference ('+' for buyer-initiated and '-' for seller-initiated) between the price of the trade and the midpoint between the national best ask and the national best bid at the time of the trade, divided by the midpoint at the time of the trade. We use the Lee and Ready (1991) algorithm to determine whether a trade is buyer- or seller-initiated. The daily price impact (*PriceImpact*) is the dollar-volume-weighted average of percent price impact computed over all trades during the day. For a given stock, the percent price impact on each trade is twice the signed difference between the midpoint available five minutes after the trade and the midpoint at the time of the trade, divided by the midpoint at the time of the trade.[25] For ease of reading the results, we measure *QuotedSprd*, *EffectiveSprd*, and *PriceImpact* in percent. *Binding Tick Size* is equal to 1 if the average daily quoted spread is higher than 5 cents and 0 otherwise.

In addition, we study market depth (*MarketDepth*) (in thousands of dollars) defined as the average of displayed dollar-depth at the NBBO, daily total trading volume (*Volume*) (in thousands of shares), and daily number of shares executed in dark venue (*Dark*

[25] We also study the realized spread that equals the effective spread minus price impact. The results are consistent with both the effective spread and price impact variables.

Volume) (in thousands of shares). We winsorize the bottom 1% and top 1% of quoted spread, effective spread, price impact, daily volume and daily dark volume. For these variables, the difference between the 99th percentile and the mean in the unwinsorized samples is more than 5 times the standard deviation of the respective winsorized series.

A. 2. Investor horizon The proxy for investor horizon is the inverse of the *ChurnRatio* borrowed from Gaspar, Massa and Matos (2005) and Cella, Ellul and Giannetti (2013). Investor horizon is calculated as $1/(2 \times ChurnRatio)$ (see Gaspar et al., 2005, for details). Note that churn ratio is between 0 and 2, so investor horizon is between a quarter and infinity.

To calculate the churn ratio, we use institutional investor data from Factset for the sample period Q1:2015–Q2:2017. Turnover for each institution is pre-determined in the sense that we use 2015 turnover data (pre-pilot program data) to calculate it. Therefore, our results are not tainted by changes in volume during implementation. For each quarter, the *ChurnRatio* of any stock is measured as the weighted average of the portfolio turnover ratios. The weight is the proportion of shares held by an investor to total shares outstanding in the quarter. Cella et al. suggest that this weighting gives a more precise estimate of the selling pressure experienced by each stock as compared to the proportion of shares held by an investor to total institutional investor shares in the quarter. An increase in this weighted average signals a relatively greater presence of short-term investors, who churn their portfolios more frequently.

A. 3. Price efficiency variables $AR10$ is the absolute value of the ten-second midpoint return autocorrelation for each stock on each day (Boehmer and Kelley, 2009). We retain only the firm-day observations for which there are at least 100 trades. A high value of $AR10$ is indicative of inefficiency under the assumption that with efficient prices, the high-frequency return should follow a random walk. Both positive and negative autocorrelation indicates predictability in returns.

Our second price efficiency measure is from Hasbrouck (1993) and Boehmer and Kelley (2009). This measure assumes that the transaction price can be decomposed into an informational component that represents the expected value, or the efficient price, of the stock, and a non-informational component that captures transitory deviations from the efficient price, such as tick size or inventory effects. This decomposition is done using a vector auto-regression model with 5 lags with the following variables: the difference in log price, a trade sign indicator, signed trading volume, and signed square root of trading volume. The variability (measured by the standard deviation) of the non-informational component as a percentage of the variability of transaction prices is a measure of the information (in)efficiency in prices (see the appendix in Boehmer and Wu, 2013, for details). We denote this measure by pricing error (*PrcError*).

Our third price efficiency measure, *PrcDelay*, is based on Hou and Moskowitz (2005). For each stock on each day, we run the following regression:

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{4} \delta_i^{(-n)} R_{m,t-n} + \epsilon_{i,t}$$

where $r_{i,t}$ is the return of stock i at the one-minute interval t, and $R_{m,t}$ is the return of SPY market index at the one-minute interval t. Following Hou and Moskowitz (2005), price delay (*PrcDelay*) is defined as one minus the ratio of the (constrained) R^2 from regression above restricting $\delta_i^{(-n)} = 0$, $\forall_n \in [1, 4]$, over the R^2 from the equation above with no restrictions, that is, $PrcDelay = 1 - R^2_{const}/R^2_{unconst}$. A larger *PrcDelay* represents that more return variation is captured by lagged returns and a stronger delay in response to return innovations. We winsorize the bottom 1% and top 1% of $AR10$, *PrcError*, and *PrcDelay*.

Our other measures of price efficiency capture the speed with which stock prices respond to news (see Beschwitz, Keim and Massa, 2015). We calculate stock price response to company-specific news and to macroeconomic news. We study macro news because firms may be heterogeneous in the volume and significance of company-specific news, which may affect the inference, and also because the flow and content of firm-specific news may change as a consequence of the tick size program. None of these concerns affect our inference when we use macro news. We define stock price response speed as $PriceResponse = \frac{|return_{t-1,t+10}|}{|return_{t-1,t+10}|+|return_{t+10,t+120}|}$. $|return_{t-1,t+10}|$ is the absolute value of the stock return over an 11-second time horizon from $t-1$ to $t+10$, t is the second that the news is released, $|return_{t+10,t+120}|$ is the absolute value of the stock return over an 110-second time horizon from $t+10$ to $t+120$. *PriceResponse* gives the amount of two-minute return adjustment that takes place in the first 10 seconds after the release of the news. Volume response speed (*VolumeResponse*) is defined similarly to *PriceResponse*, but uses volume instead of the absolute return, and captures the amount of two-minute volume adjustments that take place in the first 10 seconds after the news announcement. The third measure is based on quote adjustment. *QuoteResponse* is the proportion of quotes adjusted in the first 10 seconds over a two-minute interval after the news announcement. The variable is calculated as the number of NBBO price updates in the first 10 seconds over the number of NBBO price updates in the first two minutes.

RavenPack covers all articles published on the Dow Jones Newswires providing a millisecond time stamp of release of the article. According to Beschwitz, Keim and Massa (2015), the latency between Dow Jones Newswires releasing an article and releasing it to RavenPack is approximately 300 milliseconds. We collect both firm-specific news and U.S. macroeconomic news. We keep the news that is more related to our companies (i.e., RavenPack's "relevance score" above 90) and that are reported for the first time (i.e., RavenPack's "freshness score" of 100). For both company news and macroeconomic news, RavenPack provides two measures of sentiment on each article: the Composite Sentiment Score (CSS) and the Event Sentiment Score (ESS). Both measures range from 0 to 100, with 0 (100) representing the most negative (positive) news and 50 representing neutral news. We define the absolute value of the sentiment score as the absolute value of ($ESS - 50$) if ESS is non-missing or if CSS is equal to 50, or the absolute value of ($CSS - 50$) otherwise. Following Beschwitz, Keim, and Massa (2015), we use the absolute value of the sentiment score as a control in Tables 9 and 10.

A. 4. Liquidity risk betas We use thirty-minute stock and market returns, $r_{i,s}$ and $r_{M,s}$, and liquidity, $c_{i,s}$ and $c_{M,s}$, to get

$$\begin{aligned}
\beta_{i1,t} &= \frac{cov\left(r_{i,s}, r_{M,s} - E_{s-1}\left(r_{M,s}\right)\right)}{var\left(r_{M,s} - E_{s-1}\left(r_{M,s}\right) - \left(c_{M,s} - E_{s-1}\left(c_{M,s}\right)\right)\right)}, \\
\beta_{i2,t} &= \frac{cov\left(c_{i,s} - E_{s-1}\left(c_{i,s}\right), c_{M,s} - E_{s-1}\left(c_{M,s}\right)\right)}{var\left(r_{M,s} - E_{s-1}\left(r_{M,s}\right) - \left(c_{M,s} - E_{s-1}\left(c_{M,s}\right)\right)\right)}, \\
\beta_{i3,t} &= \frac{cov\left(r_{i,s}, c_{M,s} - E_{s-1}\left(c_{M,s}\right)\right)}{var\left(r_{M,s} - E_{s-1}\left(r_{M,s}\right) - \left(c_{M,s} - E_{s-1}\left(c_{M,s}\right)\right)\right)}, \\
\beta_{i4,t} &= \frac{cov\left(c_{i,s} - E_{s-1}\left(c_{i,s}\right), r_{M,s} - E_{s-1}\left(r_{M,s}\right)\right)}{var\left(r_{M,s} - E_{s-1}\left(r_{M,s}\right) - \left(c_{M,s} - E_{s-1}\left(c_{M,s}\right)\right)\right)}.
\end{aligned}$$

We use the proportional quoted spread as a measure of liquidity for stock i at the thirty-minute interval s, $c_{i,s}$.[26] We use the equally-weighted average of $c_{i,s}$ for all stocks in the market as a measure of market liquidity, $c_{M,s}$. Similarly, we compute the market return as the equally-weighted average of all $r_{i,s}$ in the market.[27] We use thirty-minute intervals

[26]Results using Amihud's measure as a proxy for c_{is} are similar.

[27]This market return series has correlation of 0.8 with the daily stock return of the S&P 500.

because these stocks may not trade often during the day (see Rindi and Werner, 2019). We model the conditional expectations of all variables using the mean of five lagged values observed during the same thirty-minute interval in previous days. Acharya and Pedersen's net beta is defined as

$$\beta_{i,t} = \beta_{i1,t} + \beta_{i2,t} - \beta_{i3,t} - \beta_{i4,t}.$$

A. 5. Control variables Our control variables include the following: *Inverse of Price* is defined as 1 over the end of day stock price; *Daily High Minus Low* is defined as the difference between the highest daily stock price and the lowest daily stock price; and *Turnover Ratio* is the daily stock trading volume divided by the number of shares outstanding.

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Figure 1: **Cumulative Abnormal Return**

The figure plots the differences in cumulative raw returns and cumulative abnormal returns between treated groups and the control group. The top two panels plot the difference in cumulative raw returns (left) and cumulative abnormal returns (right) between stocks in test group 1&2 versus stocks in the control group. The bottom two panels plot the difference in cumulative raw returns (left) and cumulative abnormal returns (right) between stocks in test group 3 versus stocks in the control group. For group 1&2 stocks, date 0 is October 17, 2016. For group 3 stocks, date 0 is October 31, 2016.

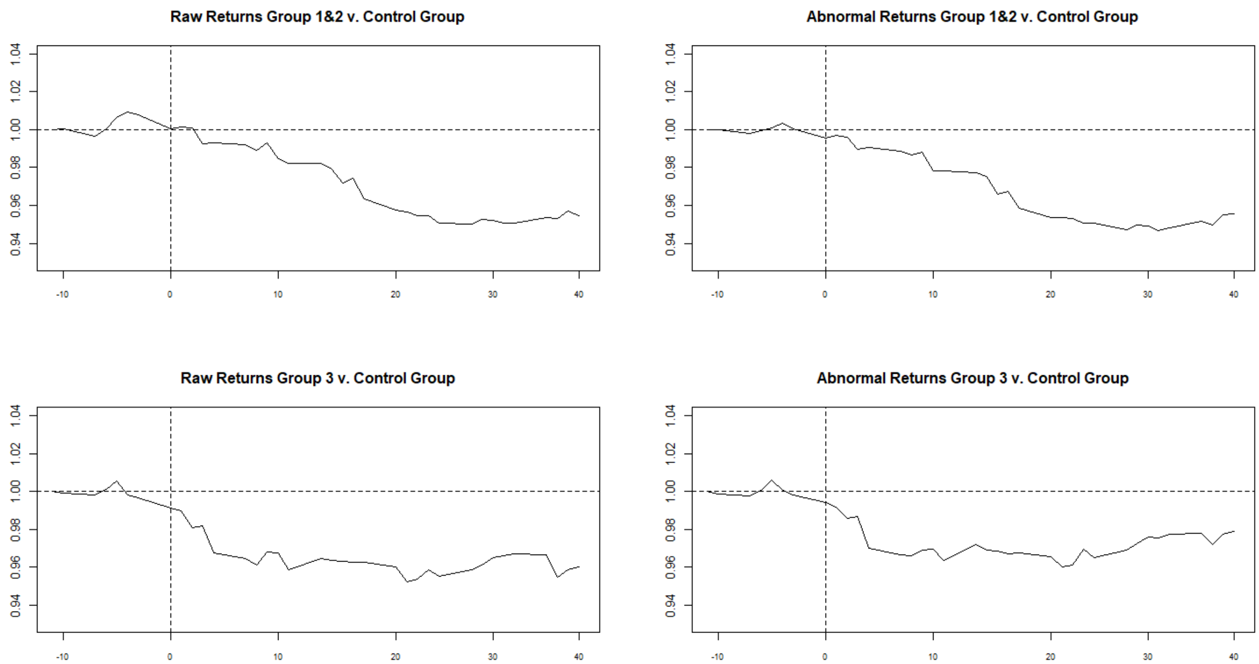

Table 1: **Summary Statistics for Key Variables**

The table presents descriptive statistics for each test group from March 1, 2016 to August 31, 2016. Panel A reports summary statistics for the control group. Panels B to D report summary statistics for test groups 1 to 3, respectively. $QuotedSprd(\$)$ is the time-weighted average of dollar quoted spread, $QuotedSprd(\%)$ is the time-weighted average of percent quoted spread, $EffectiveSprd(\$)$ is the dollar-volume-weighted average of dollar effective spread, $EffectiveSprd(\%)$ is the dollar-volume-weighted average of percent effective spread, $PriceImpact$ is the dollar-volume-weighted average of percent price impact, $MarketDepth$ is the average displayed dollar depth at the NBBO, $Volume$ is the daily volume, $DarkVolume$ is the daily number of shares executed in dark venues, identified by those with exchange code "D" in TAQ, $InverseofPrice$ is the inverse of share price, $DailyHighMinusLow$ is the difference between the highest daily trading price and lowest daily trading price, $TurnoverRatio$ is the daily share turnover, $AR10$ and $PrcError$ are price efficiency measures. $ChurnRatio$ is measured as the weighted average of the total portfolio turnover ratios of stock i's investors in quarter t. $BindingTickSize$ is a dummy variable that equals 1 every day that the average dollar quoted spread is above 5 cents. $Return$ is daily stock return in percent. $PriceResponse$, $VolumeResponse$ and $QuoteResponse$ are measures of market reaction speed to news. All spread measures are multiplied by 100 for ease of reading. $Volume$ and $DarkVolume$ are measured in thousands of shares. We divide sample stocks into two groups based on their average quoted dollar spread before September 2016. We winsorized all spread measures, $MarketDepth$, $Volume$, $DarkVolume$, $InverseofPrice$, $DailyHighMinusLow$, $TurnoverRatio$, $AR10$ and $PrcError$ at 1% and 99%. We winsorize $Return$ at 0.05% and 99.5%. We report the summary statistics for small and large dollar quoted spread stocks separately.

Panel A: Control Group

	Small Quoted Spread Stocks						Large Quoted Spread Stocks					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd($)	21942	0.020	0.009	0.019	0.011	0.706	61296	0.268	0.380	0.140	0.011	2.298
QuotedSprd(%)	21942	0.290	0.255	0.209	0.073	6.264	61296	1.577	1.923	0.777	0.073	9.073
EffectiveSprd($)	21942	0.025	0.080	0.015	0.009	2.360	59781	0.202	0.359	0.090	0.009	2.360
EffectiveSprd(%)	21942	0.337	0.857	0.182	0.047	14.693	59781	1.288	2.309	0.486	0.047	14.693
PriceImpact	21942	0.228	0.568	0.129	-0.721	8.117	59754	0.508	1.210	0.170	-0.721	8.117
Market Depth	21942	10.972	8.104	9.118	1.629	103.625	61282	14.192	13.694	10.497	1.629	103.625
Volume	21942	391.54	309.48	308.29	7.69	1452.26	60002	83.91	150.12	29.50	0.09	1452.26
Dark Volume	21942	152.56	238.32	96.80	0.64	12165.83	60002	30.87	91.09	10.01	0.00	5364.15
Inverse of Price	21942	0.143	0.101	0.112	0.023	0.435	61282	0.083	0.088	0.048	0.007	0.435
Daily High Minus Low	21942	0.366	0.269	0.300	0.020	3.580	61282	0.826	0.878	0.550	0.000	4.670
Turnover Ratio	21942	7.843	7.044	5.655	0.169	38.002	61282	4.254	5.874	2.177	0.000	38.002
AR10	21689	0.272	0.131	0.263	0.029	0.683	34127	0.342	0.143	0.336	0.029	0.683
PrcError	20406	0.155	0.113	0.133	0.045	1.035	23826	0.190	0.149	0.156	0.045	1.035
PrcDelay	18219	0.39	0.30	0.29	0.00	1.00	50228	0.60	0.30	0.62	0.00	1.00
ChurnRatio	559	0.102	0.043	0.107	0.001	0.214	1401	0.072	0.048	0.067	0.000	0.214
Binding Tick Size	21942	0.003	0.054	0.000	0.000	1.000	61296	0.955	0.208	1.000	0.000	1.000
Return	22114	0.158	2.822	0.117	-9.868	12.319	61779	0.144	2.547	0.044	-9.868	12.319
PriceResponse	1468	0.183	0.306	0	0	1	3026	0.229	0.332	0	0	1
VolumeResponse	1963	0.119	0.233	0	0	1	2581	0.126	0.277	0	0	1
QuoteResponse	1581	0.125	0.240	0	0	1	3160	0.154	0.258	0.024	0	1

Panel B: Pilot Group 1

	Small Quoted Spread Stocks						Large Quoted Spread Stocks					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd($)	7021	0.019	0.007	0.018	0.011	0.120	21385	0.241	0.329	0.139	0.011	2.298
QuotedSprd(%)	7021	0.277	0.233	0.200	0.073	2.903	21385	1.348	1.709	0.645	0.073	9.073
EffectiveSprd($)	7021	0.078	0.344	0.014	0.009	2.360	21058	0.174	0.312	0.086	0.009	2.360
EffectiveSprd(%)	7021	0.650	2.226	0.171	0.047	14.693	21058	1.037	1.873	0.399	0.047	14.693
PriceImpact	7021	0.285	0.921	0.115	-0.721	8.117	21049	0.412	0.987	0.152	-0.721	8.117
Market Depth	7021	13.818	11.137	10.872	1.629	103.625	21385	14.536	12.469	11.376	1.629	103.625
Volume	7021	470.84	367.71	385.98	8.16	1452.26	21102	88.24	144.40	35.86	0.09	1452.26
Dark Volume	7021	194.12	336.24	117.87	2.63	12395.73	21102	31.55	95.09	11.94	0.00	6953.17
Inverse of Price	7021	0.151	0.105	0.120	0.028	0.435	21385	0.074	0.085	0.042	0.007	0.435
Daily High Minus Low	7021	0.341	0.263	0.270	0.020	3.690	21385	0.842	0.822	0.610	0.000	4.670
Turnover Ratio	7021	7.618	6.466	5.928	0.248	38.002	21385	4.368	5.496	2.587	0.000	38.002
AR10	6911	0.273	0.131	0.263	0.029	0.683	12804	0.340	0.143	0.335	0.029	0.683
PrcError	6477	0.174	0.177	0.130	0.045	1.035	9093	0.184	0.138	0.155	0.045	1.035
PrcDelay	5858	0.39	0.31	0.30	0.00	1.00	17613	0.57	0.31	0.57	0.00	1.00
Binding Tick Size	7021	0.003	0.055	0	0	1	21385	0.952	0.213	1.000	0.000	1.000
Return	7077	0.104	2.758	0.087	-9.868	12.319	21554	0.088	2.243	0.036	-9.868	12.319
ChurnRatio	184	0.102	0.051	0.098	0.002	0.214	485	0.080	0.048	0.086	0.001	0.214
PriceResponse	521	0.186	0.299	0	0	1	1270	0.208	0.317	0	0	1
VolumeResponse	730	0.115	0.220	0	0	1	1069	0.116	0.256	0	0	1
QuoteResponse	569	0.118	0.219	0	0	1	1320	0.133	0.227	0.024	0	1

Panel C: Pilot Group 2

	Small Quoted Spread Stocks						Large Quoted Spread Stocks					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd($)	6630	0.018	0.007	0.017	0.011	0.068	20866	0.231	0.287	0.138	0.011	2.298
QuotedSprd(%)	6630	0.277	0.238	0.206	0.073	2.900	20866	1.543	1.840	0.784	0.073	9.073
EffectiveSprd($)	6630	0.028	0.066	0.014	0.009	2.360	20409	0.173	0.294	0.087	0.009	2.360
EffectiveSprd(%)	6630	0.325	0.494	0.195	0.047	12.095	20409	1.243	2.098	0.488	0.047	14.693
PriceImpact	6630	0.223	0.400	0.138	-0.721	8.117	20407	0.517	1.204	0.175	-0.721	8.117
Market Depth	6630	13.125	12.018	9.786	1.629	103.625	20860	13.447	11.927	10.127	1.629	103.625
Volume	6630	434.00	339.00	339.75	8.06	1452.26	20457	90.99	173.21	29.59	0.09	1452.26
Dark Volume	6630	162.32	243.98	103.39	2.29	11164.07	20457	34.11	88.63	9.96	0.00	2596.62
Inverse of Price	6630	0.153	0.106	0.120	0.026	0.435	20860	0.082	0.083	0.055	0.007	0.435
Daily High Minus Low	6630	0.321	0.227	0.265	0.010	3.273	20860	0.781	0.801	0.530	0.000	4.670
Turnover Ratio	6630	7.626	6.637	5.809	0.082	38.002	20860	4.692	6.818	2.331	0.000	38.002
AR10	6573	0.280	0.135	0.267	0.029	0.683	11805	0.341	0.144	0.337	0.029	0.683
PrcError	6221	0.181	0.181	0.137	0.045	1.035	7872	0.194	0.173	0.153	0.045	1.035
PrcDelay	5533	0.41	0.31	0.33	0.00	1.00	17117	0.60	0.30	0.62	0.00	1.00
Binding Tick Size	6630	0.001	0.037	0	0	1	20866	0.955	0.207	1.000	0.000	1.000
Return	6683	0.187	2.791	0.115	-9.868	12.319	21031	0.124	2.522	0.045	-9.868	12.319
ChurnRatio	171	0.113	0.047	0.118	0.000	0.209	470	0.070	0.048	0.068	0.000	0.210
PriceResponse	415	0.176	0.307	0	0	1	927	0.221	0.323	0	0	1
VolumeResponse	655	0.116	0.236	0	0	1	817	0.141	0.287	0	0	1
QuoteResponse	467	0.123	0.252	0	0	1	969	0.147	0.244	0.036	0	1

Panel D: Pilot Group 3

	Small Quoted Spread Stocks						Large Quoted Spread Stocks					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd($)	7445	0.020	0.007	0.019	0.011	0.117	20327	0.262	0.383	0.145	0.011	2.298
QuotedSprd(%)	7445	0.253	0.175	0.202	0.073	2.640	20327	1.415	1.653	0.764	0.073	9.073
EffectiveSprd($)	7445	0.027	0.085	0.015	0.009	2.360	19953	0.228	0.418	0.096	0.009	2.360
EffectiveSprd(%)	7445	0.310	0.798	0.171	0.047	14.693	19953	1.384	2.653	0.503	0.047	14.693
PriceImpact	7445	0.229	0.583	0.123	-0.721	8.117	19943	0.591	1.442	0.165	-0.721	8.117
Market Depth	7445	11.230	8.252	8.999	1.629	103.625	20324	15.489	16.216	11.024	1.629	103.625
Volume	7445	401.97	305.28	310.69	12.00	1452.26	20004	82.93	154.22	29.10	0.09	1452.26
Dark Volume	7445	157.28	215.90	101.92	4.23	6324.22	20004	31.19	80.38	10.29	0.00	2676.71
Inverse of Price	7445	0.133	0.091	0.102	0.027	0.435	20324	0.078	0.077	0.051	0.007	0.435
Daily High Minus Low	7445	0.371	0.281	0.300	0.020	4.020	20324	0.809	0.893	0.530	0.000	4.670
Turnover Ratio	7445	7.974	6.492	6.153	0.222	38.002	20324	4.019	5.872	2.168	0.000	38.002
AR10	7436	0.272	0.129	0.263	0.029	0.683	11372	0.350	0.145	0.345	0.029	0.683
PrcError	7272	0.167	0.136	0.137	0.045	1.035	7659	0.237	0.237	0.165	0.045	1.035
PrcDelay	6192	0.37	0.29	0.28	0.00	1.00	16751	0.62	0.29	0.65	0.00	1.00
Binding Tick Size	7445	0.002	0.048	0	0	1	20327	0.949	0.221	1	0	1
Return	7509	0.180	2.738	0.149	-9.868	12.319	20483	0.133	2.319	0.053	-9.868	12.319
ChurnRatio	178	0.109	0.046	0.111	0.002	0.214	469	0.073	0.046	0.065	0.001	0.214
PriceResponse	512	0.177	0.296	0	0	1	1058	0.215	0.317	0	0	1
VolumeResponse	686	0.111	0.223	0	0	1	910	0.139	0.288	0	0	1
QuoteResponse	549	0.118	0.228	0	0	1	1113	0.145	0.245	0.023	0	1

Table 2: **Pre-implementation Characteristics of Treated and Control Firms**

The table presents descriptive statistics of treated stocks ('G1' - 'G3') and control stocks ('C'). Panel A reports average firm characteristics for each group. Panel B reports the differences between the treatment and the control group. Total assets ($Assets$), market capitalization ($Size$), and market-to-book ratio (MB) are measured on December 2015. Daily trading volume ($Volume$), percent quoted spread ($QuotedSprd$), the inverse of share price ($InverseofPrice$), the difference between the highest daily trading price and lowest daily trading price ($DailyHighMinusLow$), share turnover ($TurnoverRatio$), and daily stock return ($Return$) are based on data from March 1 to August 31, 2016. $Assets$ and $Size$ are measured in millions of dollars. $QuotedSprd$ and $Return$ are measured in percentage. The first (second) row of each variable in Panel B reports the difference (t-statistics for the difference) between Control and Treatment Group. Small-spread stocks have pre-experiment average dollar quoted spread less than or equal to 3 cents, and large spread stocks have pre-experiment average dollar quoted spread above 7 cents. We report summary statistics for small and large dollar quoted spread stocks separately. ***, **, and * indicate significance at the 1%, 5%, and 10% levels using two-tailed tests.

Panel A: Sample Mean for Treatment and Control Groups

	Small Quoted Spread Stocks				Large Quoted Spread Stocks			
	C	G1	G2	G3	C	G1	G2	G3
Number of Stocks	154	46	47	54	430	154	147	146
Assets	1985.80	2065.20	2179.54	1343.54	1048.49	1189.73	904.03	1193.73
Size	713.79	916.62	775.43	670.31	574.88	647.81	540.65	563.34
MB	6.46	3.92	1.81	2.71	3.79	8.07	2.66	3.12
Volume	392.54	451.13	434.32	387.42	88.14	89.09	93.12	79.86
QuotedSprd (%)	0.30	0.28	0.28	0.26	1.55	1.35	1.57	1.48
Inverse of Price	0.15	0.15	0.16	0.14	0.08	0.08	0.08	0.08
Daily High Minus Low	0.36	0.35	0.32	0.36	0.86	0.83	0.80	0.82
Turnover Ratio	7.93	7.57	7.77	7.68	4.42	4.41	4.85	4.05
Return	0.16	0.10	0.18	0.18	0.14	0.09	0.12	0.13

Panel B: Difference between Treatment and Control Group

Difference (Control - Test)

	G1	G2	G3	G1	G2	G3
Assets	-79.40	-193.74	642.25	-141.24	144.46	-145.25
	(-0.11)	(-0.25)	(0.92)	(-0.65)	(0.68)	(-0.67)
Size	-202.83*	-61.64	43.47	-72.93	34.23	11.54
	(-1.82)	(-0.56)	(0.45)	(-1.07)	(0.50)	(0.17)
MB	2.54	4.65	3.75	-4.28	1.13	0.67
	(0.54)	(1.00)	(0.87)	(-1.34)	(1.17)	(0.68)
Volume	-58.58	-41.78	5.12	-0.95	-4.98	8.28
	(-1.60)	(-1.20)	(0.16)	(-0.08)	(-0.40)	(0.70)
QuotedSprd (%)	0.02	0.02	0.04	0.19	-0.02	0.07
	(0.52)	(0.46)	(1.18)	(1.33)	(-0.12)	(0.46)
Inverse of Price	0.00	-0.01	0.01	0.01	0.00	0.00
	(0.17)	(-0.53)	(0.80)	(0.85)	(0.07)	(0.63)
Daily High Minus Low	0.01	0.04	0.00	0.03	0.06	0.04
	(0.22)	(1.46)	(-0.16)	(0.45)	(0.85)	(0.58)
Turnover Ratio	0.36	-0.04	0.04	0.02	-0.42	0.38
	(0.49)	(-0.05)	(0.06)	(0.04)	(-0.94)	(0.88)
Return	0.06	-0.03	-0.02	0.05***	0.02	0.01
	(1.43)	(-0.72)	(-0.63)	(2.78)	(0.99)	(0.45)

Table 3: **Price Effects at Implementation of the Pilot: Non-staggered Test Design**

The table reports OLS regression results of the following model using a sample period from September 1, 2016 to November 30, 2016: $AR_{i,t} = \alpha + \gamma_1 Week1_t + \gamma_2 Week2_t + \gamma_3 Post_t + \gamma_4 Pilot_i \times Week1_t + \gamma_5 Pilot_i \times Week2_t + \gamma_6 Pilot_i \times Post_t + \gamma_7 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $AR_{i,t}$ is the abnormal return in percent for stock i on day t. Panel A (panel B) contains the results for pilot group 1&2 (group 3). In panel A (panel B) $Pilot_i$ is a dummy variable equals 1 if stock i belongs to test group 1&2 (group 3) and 0 otherwise. In panel A (panel B), $Week1_t$ is a dummy variable equal to 1 for dates between October 17 and October 21 (between October 31 and November 4), and 0 otherwise. $Week2_t$ is a dummy variable equal to 1 for dates in the week following $Week1_t$, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2_t$; and 0 otherwise. We include all interaction terms of each date dummy and $Pilot_i$. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Columns (1) and (2) present the results using raw returns as the dependent variable. Columns (3) and (4) present the results using the CAPM model. Columns (5) and (6) present the results using the Carhart model. Columns (7) and (8) present the results using the Fama-French 5-Factor model. Odd (even) number columns report results for small (large) spread stocks. Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1&2

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Pilot1&2 x Week1	-0.329*	-0.017	-0.336*	-0.019	-0.365**	-0.052	-0.362**	-0.027
	(0.173)	(0.073)	(0.172)	(0.072)	(0.168)	(0.055)	(0.162)	(0.088)
Pilot1&2 x Week2	-0.234	-0.000	-0.234	-0.004	-0.367*	-0.104	-0.387**	-0.079
	(0.178)	(0.076)	(0.178)	(0.074)	(0.197)	(0.119)	(0.191)	(0.107)
Pilot1&2 x Post	-0.101	-0.088	-0.112	-0.101*	-0.132	-0.070	-0.164*	-0.120*
	(0.100)	(0.058)	(0.099)	(0.059)	(0.084)	(0.071)	(0.098)	(0.063)
Observations	17,244	50,396	17,244	50,396	17,244	50,396	17,244	50,396
R-squared	0.207	0.130	0.093	0.076	0.035	0.045	0.040	0.040
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 3

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Pilot3 x Week1	-0.643***	0.153	-0.645***	0.123	-0.644**	0.119	-0.591**	0.109
	(0.225)	(0.100)	(0.223)	(0.103)	(0.262)	(0.079)	(0.273)	(0.094)
Pilot3 x Week2	-0.221	-0.158	-0.220	-0.124	-0.212	0.056	-0.121	0.074
	(0.197)	(0.159)	(0.183)	(0.133)	(0.228)	(0.200)	(0.220)	(0.199)
Pilot3 x Post	0.041	-0.015	0.038	-0.004	0.059	-0.003	0.093	0.019
	(0.103)	(0.086)	(0.107)	(0.084)	(0.120)	(0.083)	(0.103)	(0.088)
Observations	14,171	39,610	14,171	39,610	14,171	39,610	14,171	39,610
R-squared	0.218	0.129	0.099	0.078	0.036	0.048	0.043	0.041
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: **Price Effects at Implementation of the Pilot: Staggered Test Design**

The table reports OLS regression results of the following model using a sample period from September 1, 2016 to November 30, 2016: $AR_{i,t} = \alpha + \gamma_1 Week1_{i,t} + \gamma_2 Week2_{i,t} + \gamma_3 Post_{i,t} + \gamma_4 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $AR_{i,t}$ is the abnormal return in percent for stock i on day t. Panel A (B and C) contains the results for all pilot groups (pilot groups 1&2, and 3 respectively). For pilot stocks, $Week1_{i,t}$ is a dummy variable equal to 1 for dates in the week of implementation of stock i, and 0 otherwise, and $Week2_{i,t}$ is a dummy variable equal to 1 for dates in the week after $Week1_{i,t}$, and 0 otherwise. $Post_{i,t}$ is a dummy variable that equals 1 for dates following $Week2_{i,t}$; and 0 otherwise. For stocks in the control group, $Week1_{i,t}$, $Week2_{i,t}$ and $Post_{i,t}$ always equal to 0. In panel A, $Pilot_i$ is a dummy variable that equals 1 if stock i belongs to any of the test groups. In panel B (panel C), $Pilot_i$ is a dummy varibale that equals 1 if stock i belongs to test group 1&2 (group 3) and 0 otherwise. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Columns (1) and (2) present the results using raw returns as the dependent variable. Columns (3) and (4) present the results using the CAPM model. Columns (5) and (6) present the results using the Carhart model. Columns (7) and (8) present the results using the Fama-French 5-Factor model. Odd (even) number columns report results for small (large) spread stocks. Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stocks from Pilot Group 1, 2 & 3

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Week1	-0.238**	-0.006	-0.236**	-0.009	-0.259**	-0.026	-0.258**	-0.039
	(0.112)	(0.054)	(0.114)	(0.052)	(0.118)	(0.062)	(0.115)	(0.062)
Week2	-0.098	-0.040	-0.096	-0.039	-0.156	-0.043	-0.131	-0.021
	(0.111)	(0.068)	(0.109)	(0.060)	(0.121)	(0.069)	(0.118)	(0.066)
Post	-0.117	-0.063	-0.122	-0.065	-0.152*	-0.046	-0.167*	-0.067
	(0.087)	(0.041)	(0.087)	(0.041)	(0.083)	(0.051)	(0.090)	(0.045)
Observations	20,933	60,305	20,933	60,305	20,933	60,305	20,933	60,305
R-squared	0.206	0.128	0.092	0.076	0.034	0.045	0.039	0.039
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 1&2

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Week1	-0.150	0.008	-0.147	0.012	-0.193	0.003	-0.231*	-0.005
	(0.136)	(0.067)	(0.141)	(0.065)	(0.130)	(0.070)	(0.126)	(0.065)
Week2	-0.151	-0.036	-0.157	-0.043	-0.214	-0.108	-0.228	-0.092
	(0.150)	(0.062)	(0.152)	(0.061)	(0.152)	(0.078)	(0.148)	(0.083)
Post	-0.127	-0.078	-0.132	-0.088	-0.177**	-0.065	-0.212**	-0.106*
	(0.096)	(0.056)	(0.095)	(0.057)	(0.084)	(0.067)	(0.095)	(0.062)
Observations	17,244	50,396	17,244	50,396	17,244	50,396	17,244	50,396
R-squared	0.206	0.130	0.093	0.076	0.035	0.045	0.039	0.040
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Pilot Group 3

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Week1	-0.538**	-0.010	-0.538**	-0.030	-0.526**	-0.081	-0.481**	-0.106
	(0.209)	(0.097)	(0.208)	(0.100)	(0.232)	(0.128)	(0.239)	(0.136)
Week2	-0.121	-0.108	-0.107	-0.106	-0.108	0.002	-0.036	0.017
	(0.194)	(0.147)	(0.179)	(0.125)	(0.209)	(0.147)	(0.208)	(0.131)
Post	-0.098	-0.014	-0.104	0.003	-0.076	0.018	-0.037	0.041
	(0.128)	(0.089)	(0.134)	(0.086)	(0.147)	(0.086)	(0.143)	(0.092)
Observations	14,171	39,610	14,171	39,610	14,171	39,610	14,171	39,610
R-squared	0.218	0.129	0.099	0.078	0.036	0.048	0.042	0.041
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **Price Effects at Announcement of the Pilot**

The table reports OLS regression results of the following models using a sample period from August 1, 2016 to September 30, 2016:
Panel A: $AR_{i,t} = \alpha + \gamma_1 September6_t + \gamma_2 September7_t + \gamma_3 Post_t + \gamma_4 Pilot_i \times September6_t + \gamma_5 Pilot_i \times September7_t + \gamma_6 Pilot_i \times Post_t + \gamma_7 Pilot_i + \delta^{'} X_{i,t} + \epsilon_{i,t}$
Panel B: $AR_{i,t} = \alpha + \gamma_1 \text{September6 pre-alert}_{i,t} + \gamma_2 \text{September6 post-alert}_{i,t} + \gamma_3 September7_t + \gamma_4 Post_t + \gamma_5 Pilot_i \times \text{September6 pre-alert}_{i,t} + \gamma_6 Pilot_i \times \text{September6 post-alert}_{i,t} + \gamma_7 Pilot_i \times September7_t + \gamma_8 Pilot_i \times Post_t + \gamma_9 Pilot_i + \delta^{'} X_{i,t} + \epsilon_{i,t}$,
where $AR_{i,t}$ is the abnormal return in percent for stock i on day t. $Pilot_i$ is a dummy variable equal to 1 if stock i belongs to a test group, and 0 otherwise. In Panel A, $September6_t$ is a dummy variable equal to 1 for date September 6, 2016, and 0 otherwise. In Panel B, $September6$ *pre-alert*$_{i,t}$ is a dummy variable equal to 1 for date September 6, 2016 and before the stock's exchange publishes the trader alert, and 0 otherwise. $September6$ *post-alert*$_{i,t}$ is a dummy variable equal to 1 for date September 6, 2016 and after the exchange publishes the trader alert, and 0 otherwise. $September7_t$ is a dummy variable equal to 1 for date September 7, 2016, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $September7_t$; and 0 otherwise. We also include all interaction terms of each date dummy and $Pilot_i$. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Columns (1) and (2) present the results using raw return as the dependent variable. Columns (3) and (4) present the results using the CAPM model. Columns (5) and (6) present the results using the Carhart model. Columns (7) and (8) present the results using the Fama-French 5-Factor model. Odd (even) number columns report results for small (large) spread stocks. Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Day Effects

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Pilot x September6	0.056	-0.184***	0.055	-0.188***	0.113	-0.174***	0.151*	-0.128**
	(0.087)	(0.038)	(0.086)	(0.039)	(0.077)	(0.040)	(0.083)	(0.054)
Pilot x September7	-0.325***	-0.175***	-0.323***	-0.176***	-0.233**	-0.109***	-0.259***	-0.109**
	(0.100)	(0.037)	(0.099)	(0.038)	(0.094)	(0.040)	(0.091)	(0.048)
Pilot x Post	0.030	-0.049	0.031	-0.046	0.044	-0.032	0.047	-0.039
	(0.095)	(0.042)	(0.095)	(0.043)	(0.090)	(0.040)	(0.096)	(0.038)
Observations	14,823	42,276	14,823	42,276	14,823	42,276	14,823	42,276
R-squared	0.221	0.132	0.081	0.075	0.057	0.065	0.056	0.064
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Investor Alerts Effects

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Pilot x September6 pre-alert	-0.220**	-0.475***	-0.226**	-0.480***	-0.148	-0.472***	-0.252*	-0.297***
	(0.103)	(0.059)	(0.102)	(0.059)	(0.099)	(0.059)	(0.147)	(0.078)
Pilot x September6 post-alert	-0.101	-0.023	-0.097	-0.024	-0.074	-0.048	0.229**	-0.198***
	(0.079)	(0.037)	(0.078)	(0.037)	(0.077)	(0.037)	(0.088)	(0.050)
Pilot x September7	-0.242**	-0.215***	-0.240**	-0.216***	-0.171	-0.168***	-0.194**	-0.127**
	(0.102)	(0.041)	(0.101)	(0.042)	(0.105)	(0.038)	(0.093)	(0.056)
Pilot x Post	0.011	-0.068*	0.012	-0.066	0.021	-0.051	0.022	-0.064
	(0.091)	(0.040)	(0.091)	(0.041)	(0.087)	(0.039)	(0.093)	(0.041)
Observations	14,515	39,549	14,515	39,549	14,515	39,549	14,515	39,548
R-squared	0.226	0.137	0.080	0.076	0.055	0.066	0.055	0.066
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: **Price Effects at the End of the Pilot**

The table reports OLS regression results of the following model using a sample period from September 1, 2018 to November 30, 2018: $AR_{i,t} = \alpha + \gamma_1 Week1_t + \gamma_2 Week2_t + \gamma_3 Post_t + \gamma_4 Pilot_i \times Week1_t + \gamma_5 Pilot_i \times Week2_t + \gamma_6 Pilot_i \times Post_t + \gamma_7 Pilot_i + \delta^{'} X_{i,t} + \epsilon_{i,t}$, where $AR_{i,t}$ is the abnormal return in percent for stock i on day t. Panel A (panel B) contains the results for pilot group 1&2 (group 3). In panel A (panel B) $Pilot_i$ is a dummy variable equal to 1 if stock i belongs to test group 1&2 (group 3) and 0 otherwise. $Week1_t$ is a dummy variable equal to 1 for dates between October 1 and October 7, and 0 otherwise. $Week2_t$ is a dummy variable equal to 1 for dates in the week following $Week1_t$, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2_t$; and 0 otherwise. We include all interaction terms of each date dummy and $Pilot_i$. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Columns (1) and (2) present the results using raw returns as the dependent variable. Columns (3) and (4) present the results using the CAPM model. Columns (5) and (6) present the results using the Carhart model. Columns (7) and (8) present the results using the Fama-French 5-Factor model. Odd (even) number columns report results for small (large) spread stocks. Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1&2

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Pilot1&2 * Week1	0.149	-0.035	0.147	-0.029	-0.020	-0.040	-0.098	-0.056
	(0.092)	(0.095)	(0.105)	(0.099)	(0.211)	(0.105)	(0.191)	(0.112)
Pilot1&2 * Week2	0.022	-0.128**	-0.048	-0.111*	-0.064	-0.109	-0.083	-0.119
	(0.195)	(0.052)	(0.178)	(0.066)	(0.096)	(0.069)	(0.123)	(0.073)
Pilot1&2 * Post	-0.270***	-0.004	-0.280***	-0.007	-0.240**	-0.010	-0.265**	-0.014
	(0.091)	(0.049)	(0.092)	(0.050)	(0.116)	(0.048)	(0.125)	(0.046)
Observations	14,034	43,163	14,034	43,163	14,032	43,163	14,032	43,163
R-squared	0.197	0.126	0.074	0.050	0.038	0.029	0.038	0.032
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 3

	Raw Return		CAPM		Carhart		FF5	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)	Small Spread (7)	Large Spread (8)
Pilot3 * Week1	-0.050	0.027	-0.096	-0.005	0.021	0.013	-0.003	0.030
	(0.226)	(0.064)	(0.224)	(0.070)	(0.231)	(0.084)	(0.218)	(0.094)
Pilot3 * Week2	0.146	-0.099	0.033	-0.134**	-0.008	-0.154**	-0.010	-0.161*
	(0.187)	(0.083)	(0.146)	(0.065)	(0.174)	(0.076)	(0.181)	(0.093)
Pilot3 * Post	-0.119	-0.008	-0.113	-0.024	-0.040	-0.017	-0.049	-0.008
	(0.106)	(0.063)	(0.116)	(0.063)	(0.122)	(0.066)	(0.121)	(0.062)
Observations	10,922	34,279	10,922	34,279	10,920	34,278	10,920	34,278
R-squared	0.213	0.129	0.085	0.052	0.042	0.034	0.041	0.036
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Market Liquidity**

The table reports OLS regression results of the following model using a sample period from April 1, 2016 to April 30, 2017: $Liquidity_{i,t} = \alpha + \gamma_1 Pilot_i + \gamma_2 Post_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}$, where $Liquidity_{i,t}$ is a measure of liquidity for stock i on day t, identified at the top of each column. Columns (1) to (6) report results using percent quoted spread, percent effective spread, percent price impact, dollar-depth, total daily trading volume, and total daily trading volume executed in the dark pool. Panels A and B give results for group 1&2 stocks, Panels C and D give results for group 3 stocks. In panels A and B (C and D), $Pilot_i$ is a dummy variable equal to 1 if stock i belongs to test group 1&2 (group 3), and 0 otherwise. For pilot firms, $Post_{i,t}$ is a dummy variable equal to 1 for dates on or after the implementation date, and 0 otherwise. For control firms, $Post_{i,t}$ always equal to 0. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Small Quoted Spread Stocks from Pilot Group 1&2

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	MarketDepth (4)	Volume (5)	Dark Volume (6)
Post	0.482***	0.221**	0.128**	35.854***	-84.299***	-10.471
	(0.033)	(0.109)	(0.051)	(8.558)	(16.864)	(7.497)
Observations	74,128	74,128	74,128	74,128	74,128	74,128
Adjusted R-squared	0.837	0.595	0.391	0.095	0.581	0.452
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Large Quoted Spread Stocks from Pilot Group 1&2

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	MarketDepth (4)	Volume (5)	Dark Volume (6)
Post	-0.019	0.052	0.023	8.123***	-5.442	-1.038
	(0.040)	(0.053)	(0.021)	(0.682)	(3.327)	(1.387)
Observations	216,547	212,526	212,444	216,547	212,890	212,890
Adjusted R-squared	0.671	0.567	0.290	0.398	0.668	0.526
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Small Quoted Spread Stocks from Pilot Group 3

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Dark Volume
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.435***	0.239***	0.134***	52.053***	-38.515*	-49.228***
	(0.040)	(0.088)	(0.044)	(15.297)	(20.253)	(8.152)
Observations	60,854	60,854	60,854	60,854	60,854	60,854
Adjusted R-squared	0.821	0.543	0.405	0.196	0.557	0.427
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Large Quoted Spread Stocks from Pilot Group 3

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Dark Volume
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.008	-0.076	-0.002	8.265***	-4.381	-9.329***
	(0.047)	(0.073)	(0.041)	(0.875)	(4.785)	(1.921)
Observations	170,088	166,760	166,695	170,088	167,073	167,073
Adjusted R-squared	0.660	0.601	0.325	0.488	0.648	0.492
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: **Price Efficiency**

The table reports OLS regression results of the following model using a sample period from April 1, 2016 to April 30, 2017: $PriceEfficiency_{i,t} = \alpha + \gamma_1 Pilot_i + \gamma_2 Post_{i,t} + \delta^{'} X_{i,t} + \epsilon_{i,t}$, where $PriceEfficiency_{i,t}$ is a measure of price efficiency, $AR10$, $PrcError$, and $PrcDelay$, for stock i on day t. Columns (1) to (6) report regression results for stocks with small dollar quoted spread, and Columns (7) and (12) report regression results for stock with large dollar quoted spread. $Pilot_i$ is a dummy variable equals 1 if stock i belongs to a test group, and 0 otherwise. For pilot firms, $Post_{i,t}$ is a dummy variable equal to 1 for dates on or after the implementation date, and 0 otherwise. For control firms, $Post$ always equal to 0. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Odd (even) number columns report results for stock in pilot group 1&2 (3). Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Small Dollar Quoted Spread Stocks						Large Dollar Quoted Spread Stocks					
	AR10	AR10	PrcError	PrcError	PrcDelay	PrcDelay	AR10	AR10	PrcError	PrcError	PrcDelay	PrcDelay
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post	0.143***	0.128***	0.035***	0.039***	0.214***	0.247***	0.008**	-0.012***	0.015***	-0.005	0.012**	-0.000
	(0.006)	(0.006)	(0.006)	(0.008)	(0.014)	(0.017)	(0.003)	(0.004)	(0.004)	(0.009)	(0.005)	(0.006)
Observations	72,837	60,254	68,143	57,082	73,871	60,764	126,554	98,420	87,589	67,818	213,929	168,309
Adjusted R-squared	0.333	0.274	0.743	0.659	0.538	0.541	0.100	0.103	0.728	0.737	0.395	0.379
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: **Trade Response Speed to Firm Specific News**

This table reports tobit regression results of the following model using a sample period from April 1, 2016 to April 30, 2017: $Response_{i,t} = \alpha + \gamma_1 Pilot_i + \gamma_2 Post_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}$, where $Response_{i,t}$ measures how fast trade reacts to firm specific news for stock i on day t. $PriceResponse$ shows the amount of two minute return adjustment that takes place in the first 10 seconds after the release of the news. $VolumeResponse$ captures the amount of two-minute volume adjusted in the first 10 seconds after the news announcement. $QuoteResponse$ is calculated as the proportion of quote adjusted in the first 10 seconds after the news announcement. In Panels A and B, we report results for groups 1&2 and 3, respectively. Columns (1) to (3) report regression results for stocks with small dollar quoted spread, and Columns (4) to (6) report regression results for stock with large dollar quoted spread. In panel A (panel B), $Pilot_i$ is a dummy variable equals 1 if stock i belongs to test group 1&2 (group 3), and 0 otherwise. For pilot firms, $Post_{i,t}$ is a dummy variable equal to 1 for dates on or after the implementation date, and 0 otherwise. For control firms, $Post$ always equal to 0. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, sentiment score of the news, and day and industry fixed effects. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Groups 1 and 2

	Small Quoted Spread Stocks			Large Quoted Spread Stocks		
	PriceResponse	VolumeResponse	QuoteResponse	PriceResponse	VolumeResponse	QuoteResponse
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot1&2	0.089	0.047*	0.048	-0.016	0.020**	-0.016
	(0.050)	(0.023)	(0.031)	(0.024)	(0.007)	(0.014)
Post	-0.267**	-0.078*	-0.169**	-0.183***	-0.054***	-0.057*
	(0.089)	(0.031)	(0.055)	(0.039)	(0.008)	(0.023)
Observations	3718	5900	4040	8752	8148	9216
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 3

	Small Quoted Spread Stocks			Large Quoted Spread Stocks		
	PriceResponse	VolumeResponse	QuoteResponse	PriceResponse	VolumeResponse	QuoteResponse
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot3	-0.020	-0.004	-0.024	-0.035	0.066	-0.021
	(0.063)	(0.029)	(0.038)	(0.031)	(0.044)	(0.018)
Post	-0.255*	-0.038	-0.145*	-0.136**	-0.102	-0.058*
	(0.123)	(0.039)	(0.071)	(0.050)	(0.059)	(0.029)
Observations	3181	4753	3440	7125	6455	7511
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: **Trade Response Speed to Macro News**

This table reports tobit regression results of the following model using a sample period from April 1, 2016 to April 30, 2017: $Response_{i,t} = \alpha + \gamma_1 Pilot_i + \gamma_2 Post_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}$, where $Response_{i,t}$ measures how fast trade reacts to macro news for stock i on day t. $PriceResponse$ shows the amount of two minute return adjustment that takes place in the first 10 seconds after the release of the news. $VolumeResponse$ captures the amount of two-minute volume adjusted in the first 10 seconds after the news announcement. $QuoteResponse$ is calculated as the proportion of quote adjusted in the first 10 seconds after the news announcement. In Panels A and B, we report results for groups 1&2, and 3, respectively. Columns (1) to (3) report regression results for stocks with small dollar quoted spread, and Columns (4) to (6) report regression results for stock with large dollar quoted spread. In panel A (panel B), $Pilot_i$ is a dummy variable equals 1 if stock i belongs to test group 1&2 (group 3), and 0 otherwise. For pilot firms, $Post_{i,t}$ is a dummy variable equal to 1 for dates on or after the implementation date, and 0 otherwise. For control firms, $Post$ always equal to 0. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, sentiment score of the news, and day and industry fixed effects. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Groups 1 and 2

	Small Quoted Spread Stocks			Large Quoted Spread Stocks		
	PriceResponse	VolumeResponse	QuoteResponse	PriceResponse	VolumeResponse	QuoteResponse
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot1&2	0.012***	0.010***	0.000	0.009***	0.008*	0.004**
	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.001)
Post	-0.242***	-0.040***	-0.122***	-0.187***	-0.039***	-0.105***
	(0.001)	(0.003)	(0.006)	(0.004)	(0.005)	(0.002)
Observations	326735	505744	352061	824806	725885	880228
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 3

	Small Quoted Spread Stocks			Large Quoted Spread Stocks		
	PriceResponse	VolumeResponse	QuoteResponse	PriceResponse	VolumeResponse	QuoteResponse
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot3	-0.009	-0.001	-0.004	0.006	0.013*	0.002
	(0.006)	(0.003)	(0.004)	(0.003)	(0.005)	(0.002)
Post	-0.192***	-0.018***	-0.105***	-0.182***	-0.051***	-0.099***
	(0.012)	(0.004)	(0.008)	(0.005)	(0.007)	(0.003)
Observations	283199	415266	303674	653032	558682	696093
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: **Investment Horizon**

The table reports OLS regression results of the following model using a sample period from Q1, 2016 to Q2 2017: $ChurnRatio_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot_i + \gamma_3 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $ChurnRatio_{i,t}$ is measured as the weighted average of the total portfolio turnover ratios of stock i's investors in quarter t. Columns (1) and (2) report regression results for stocks with small dollar quoted spread, and Columns (3) and (4) report regression results for stock with large dollar quoted spread. In Columns (1) and (3) (columns (2) and (4)) $Pilot_i$ is a dummy variable equals 1 if stock i belongs to test group 1&2 (group 3), and 0 otherwise. $Post_t$ is a dummy variable equal to 1 for dates in or after Quarter 4, 2016, and 0 otherwise. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and quarter fixed effects. Standard errors are clustered by quarter and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Small Quoted Spread Stocks		Large Quoted Spread Stocks	
	(1)	(2)	(3)	(4)
Pilot1&2	0.008		0.001	
	(0.004)		(0.003)	
Pilot1&2 x Post	-0.005***		0.001	
	(0.001)		(0.001)	
Pilot3		0.005		0.001
		(0.005)		(0.003)
Pilot3 x Post		-0.003*		0.001
		(0.002)		(0.000)
Observations	1,576	1,279	4,798	3,804
Adjusted R-squared	0.608	0.618	0.364	0.344
Controls	Yes	Yes	Yes	Yes

Table 12: **Liquidity Risk**

The table reports OLS regression results of the following model using a sample period from April 1, 2016 to April 30, 2017: $\beta_{i,t} = \alpha + \gamma_1 Post_{i,t} + \gamma_2 Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $\beta_{i,t}$ is a measure of liquidity risk for stock i on day t. Panel A (B) reports results using β_i ($\beta_{liq,i}$) as measures of liquidity risk. These are defined as:

$\beta_{1i} = \frac{cov(r_{is}, r_{Ms} - E_{s-1}(r_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_{2i} = \frac{cov(c_{is} - E_{s-1}(c_{is}), c_{Ms} - E_{s-1}(c_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_{3i} = \frac{cov(r_{is}, c_{Ms} - E_{s-1}(c_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_{4i} = \frac{cov(c_{is} - E_{t-1}(c_{is}), r_{Ms} - E_{s-1}(r_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_i = \beta_{1i} + \beta_{2i} - \beta_{3i} - \beta_{4i}$

$\beta_{liq,i} = \beta_{2i} - \beta_{3i} - \beta_{4i}$

We use the proportional quoted spread (c_{is}) as a measure of liquidity for stock i at thirty-minute s. c_{Ms} is the equally-weighted average of c_{is} for all common stocks traded in the US. r_{is} is stock i's thirty-minute return in interval s, and r_{Ms} is the equally-weighted average of r_{is} for all common stocks traded in the US. In panel A (panel B), $Pilot_i$ is a dummy variable equals 1 if stock i belongs to test group 1&2 (group 3), and 0 otherwise. For pilot firms, $Post_{i,t}$ is a dummy variable equal to 1 for dates on or after the implementation date, and 0 otherwise. For control firms, $Post_{i,t}$ always equal to 0. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and day and stock fixed effects. Columns (1) and (2) report regression results for stocks with small dollar quoted spread, and Columns (3) and (4) report regression results for stock with large dollar quoted spread. Odd (even) number columns report results for stocks in pilot group 1&2 (3). Standard errors are clustered by day and stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Impact of Widening Tick Size on βi

	Small Quoted Spread Stocks		Large Quoted Spread Stocks	
	(1)	(2)	(3)	(4)
Post	-0.100***	-0.126***	-0.021	-0.085
	(0.033)	(0.030)	(0.029)	(0.057)
Observations	72,890	59,489	205,615	161,252
Adjusted R-squared	0.076	0.081	0.057	0.063
Controls	Yes	Yes	Yes	Yes

Panel B: Impact of Widening Tick Size on $\beta liq, i$

	Small Quoted Spread Stocks		Large Quoted Spread Stocks	
	(1)	(2)	(3)	(4)
Post	0.063	0.033	-0.034	-0.099*
	(0.046)	(0.040)	(0.052)	(0.058)
Observations	72,890	59,489	205,615	161,252
Adjusted R-squared	0.025	0.027	0.021	0.022
Controls	Yes	Yes	Yes	Yes