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

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Abstract

This paper studies the SEC's pilot program that increased the tick size for approximately 1,200 randomly chosen stocks. We provide causal evidence of a negative impact of a larger tick size on stock prices equivalent to roughly $7 billion investor loss. We investigate direct and indirect effects of the tick size change on stock prices. We find that treated stocks experience a reduction in liquidity, but find no significant change in liquidity risk. Test stocks experience a decline in price efficiency consistent with an increase in information risk. The evidence suggests that trading frictions affect the cost of capital.

Keywords: tick size pilot program, liquidity, price efficiency, news response rate, liquidity risk, liquidity premium, information risk, investor horizon, JOBS Act.

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1 Introduction

This paper investigates the stock price effects of the Tick Size Pilot Program, a two-year experiment launched on October 3, 2016 by the U.S. Securities and Exchange Commission (SEC) as mandated by the U.S. Congress to increase the tick size from 1 cent to 5 cents for a number of randomly chosen stocks. This field experiment provides a unique opportunity to study the effect of exogenous shocks to liquidity on stock prices and to estimate the liquidity premium. Stock prices may change as a result of changes in transactions costs *directly* through an effect on the present value of future trading costs as in Amihud and Mendelson (1986), Constantinides (1986), Vayanos (1998), Vayanos and Vila (1999) and others, as well as *indirectly* due to changes in expected returns caused by changes in liquidity risk as in Acharya and Pedersen (2005) or by changes in information risk as in Easley and O'Hara (2004) and O'Hara (2003). In this paper, we ask how large is the liquidity premium in response to the tick size change and what are its sources of variation.

The Tick Size Pilot Program consists of three pilot (treated) groups, each with about 400 stocks, and a control group with about 1,200 stocks. Stocks in groups 1 through 3 are all subject to an increase in the minimum *quote* increment from \$0.01 to \$0.05. Group 1 stocks are allowed to trade at their current price increment of \$0.01, whereas stocks in group 2 are required to *trade* in \$0.05 minimum increments, although with some exceptions. Stocks in group 3 adhere to the requirement of the second group, but are also subject to a "trade-at" requirement whereupon non-displayed orders can only trade at the bid or offer prices after all displayed liquidity in all lit venues has been filled at those prices. The trade-at requirement increases the cost of trading outside lit venues with potential consequences for liquidity, acquisition of information, and prices. Stocks in the control group continue quoting and trading at their current tick size increment of \$0.01. The pilot program was implemented on a staggered basis over the month of October 2016 starting with groups 1 and 2 and ending with group 3.

The main hypothesis of this paper is that the larger tick size leads to lower stock prices. To test this hypothesis, we estimate daily abnormal returns from September 1, 2016 to November 30, 2016 using a variety of return models. We study stocks with smaller, pre-experiment spreads separately from stocks with larger, pre-experiment spreads. Our results apply only to the former because the increase in tick size is more likely to be an active constraint for them. We find that stocks with small dollar quoted spread in groups 1 and 2 (group 3) experience a significant 1% (4%) value reduction compared to stocks in the control group after the tick change. These price changes imply a loss to investors of about \$7 billion. The decrease in stock prices occurs in the two weeks immediately after the pilot program implementation and appears to be permanent rather than transitory as we do not observe a subsequent reversal in stock returns. We do not find any significant price effect for stocks with a large quoted spread. These findings are consistent with Amihud and Mendelson (1986). The findings are not consistent with Vayanos (1998) who predicts that the price effect should be smaller for the more liquid stocks. Bessembinder, Hao and Zheng (2015) predict that the increase in tick size may lead to lower IPO prices, a conclusion that is consistent with our findings.

The experiment conducted by the SEC is unique because of the stratified random sampling procedure applied to the construction of the groups, the large size of the program, which involves about 1,200 test stocks and an equal amount of control stocks, and the limited duration of the program, which ends after two years. These characteristics create an ideal setting to study the stock price response to exogenous shocks to liquidity. First, the SEC's randomization creates a laboratory-like experiment in an actual financial market, eliminates any selection issue, and at the same time 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 in the implementation of the difference-in-differences methodology. Second, the large size of the program 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 only 79 common stocks (Chakravarty, Wood, Van Ness, 2004).[1] Third, the limited 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, but also Weld, Michaely, Thaler, and Benartzi, 2009).

The rest of the paper studies sources of variation, direct and indirect, that can explain the observed stock price changes. In Amihud and Mendelson (1986) and others, transactions costs have a *direct effect* on stock prices, holding expected returns (net of transactions 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 stocks in groups 1 and 2 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 effective spread, arguably the most relevant of these measures regarding trade execution costs (Bessembinder, 2003) is higher by an average of 0.15 (0.17 and 0.09) for group 1 stocks (groups 2 and 3), representing an amount equal to roughly 28% (39% and 15%) of the mean effective spread. The change in quoted spread is about twice as large. The qualitative nature of the spread results was largely expected in the design of the program. We also find that the response of group 2 stocks is very similar to that of group 1 stocks, suggesting that the main binding constraint in group 2 stocks is the requirement to quote in 5 cent

[1]In addition, in this earlier experiment the control goup were all the other firms in the NYSE and these firms were known to have to move also to the lower tick size.

increments. There is a marked difference in response of liquidity measures to the tick size change for group 3 stocks. These stocks experience a statistically significant increase in quoted spread, but not on the effective spread and only significant at 5% on price impact, and they do not experience a statistically significant decrease in trading volume. The evidence for group 3 stocks is consistent with the trade-at rule having countervailing liquidity effects to the change in tick size. Finally, market depth increases for all groups, particularly for group 3 stocks though we argue that this is largely a mechanical effect.

Amihud and Mendelson (1986) argue that stocks with higher transactions costs attract a clientele of investors with longer investor horizons, thus slowing the impact of trading costs on stock prices. We test this additional prediction using 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 some evidence in support of Amihud and Mendelson's model: the investment horizon of institutional investors increases by 3% (5%) for the small quoted spread stocks in groups 1 and 2 (group 3) relative to the control group after the tick size increased.

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 transactions costs is responsible for about 22% of the observed change in prices for groups 1 and 2 stocks, and 3.25% for group 3 stocks, holding the expected return (net of transactions cost) constant. While these are arguably very rough estimates of the direct effect of transactions costs on prices, their small size suggests that a significant portion of the observed change in prices should come from an *indirect effect* of transactions costs on expected returns (net of transactions costs), either through priced liquidity risk (Acharya and Pedersen, 2005) or through priced information risk (Easley and O'Hara, 2004, and O'Hara, 2003).

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 decrease in liquidity risk for all test stocks. The sign of the point estimate suggests that the price level change attributable to changes in spreads is larger than the estimated price drop.

In Easley and O'Hara (2004) and O'Hara (2003), the presence of more uninformed investors or lower precision of private information decrease information quality and increase information risk and expected returns. We then ask if the increase in tick size caused changes in proxies related to price efficiency and speed of market response to news as a way to capture changes in the quality of information. We find that the treated stocks experience higher return autocorrelation and higher pricing error relative to the control stocks, suggesting a relative 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 program started, obtaining similar results. Our evidence is 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.

We conclude by calculating a point estimate for the liquidity premium. The liquidity premium is equal to the ratio between the change in the expected return and the change in spreads. For a stock with expected rate of return of 5%, the liquidity premium measured with respect to the *effective spread* change is equal to 0.31 (2.2) for groups 1 and 2 (group 3) stocks. As argued by Huang (2003), many asset pricing models with transactions costs (Constantinides, 1986, Aiyagari and Gertler, 1991, Heaton and Lucas, 1996, Vayanos, 1998, and ayanos and Vila, 1999) predict liquidity premia substantially lower than 0.2 under reasonable calibrations (see also Buss, Uppal, and Vilkov, 2011).

There are however models that generate large liquidity premia. For example, in Garleanu and Pedersen (2004) bid-ask spreads do not impact prices when agents are symmetric, but can have large effects otherwise, in Huang (2003) borrowing constraints can lead to large liquidity premia, and in Lo, Mamaysky, and Wang (2004) transactions costs hinder risk sharing and lead to lower prices. In a partial equilibrium setting, Balduzzi and Lynch (1999) show that transactions costs can have large utility costs for investors that behave myopically.

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 Institutional Background

The Jumpstart Our Business Startups Act ("JOBS Act") signed in April of 2012 directs the SEC to conduct a study on how decimalization affects the number of IPOs and market quality of small cap stocks.[2] In July of 2012, the SEC reports back to Congress without reaching a firm conclusion on the question. Following this study, Congress mandates the SEC to implement a pilot program which would generate data to investigate the impact of increasing the tick size. In June of 2014, the SEC directs the Financial Industry Regulatory Authority and the National Securities Exchange to develop a tick

[2] 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.

size pilot program to widen the minimum tick size increment for a selection of small cap stocks. On May 6, 2015, the SEC approves the proposed plan.

The Tick Size Pilot Program consists of a control group and three pilot (test or treatment) groups. The control group contains approximately 1,200 stocks that continue quoting and trading at the current tick size increment. Each of the test groups contains approximately 400 stocks. Stocks in test group 1 are required to quote in \$0.05 minimum increments, but are allowed to trade at their current price increment. For example, Retail Price Improving orders are qualified stock orders that offer price improvement over the current best bid and offer. These orders can still be entered and executed in \$0.01 increments. Negotiated Trades, common in OTC, may also trade in increments less than \$0.05. Stocks in test group 2 are required to both quote and trade in \$0.05 minimum increments, but allow certain exemptions for midpoint executions, retail investors executions and negotiated trades. Stocks in test group 3 adhere to the requirement of the second test group, but are also subject to a "trade-at" requirement. The trade-at rule grants execution priority to lit orders, unless a dark order can provide a meaningful price improvement over the lit order and as such group 3 stocks are imposed an additional cost on trading outside lit venues with potential consequences for liquidity, acquisition of information, and prices. Certain exemptions to the rule apply. For example, trading centers are permitted to execute an order for a pilot security at a price equal to a protected bid or protected offer using both displayed and non-displayed liquidity if the order is of Block Size, that is of at least 5,000 shares and market capitalization of $\$100,000$.

The pilot program was implemented on a staggered basis. On September 6, 2016, the final list of 2,398 stocks to be included in the tick size pilot program is announced. Disclosure of which group a stock would belong to happens in October coinciding with the stock's activation date. On October 3, 2016, 5 stocks were activated in each of the test groups 1 and 2. On October 10, 2016, 100 stocks were activated in each of the test groups 1 and 2. On October 17, 2016, all remaining stocks in test groups 1 and 2 were activated. On October 17, 2016, 5 stocks were activated in test group 3. On October 24, 2016, 100 stocks were activated in test group 3, with the rest of the stocks in group 3 activated on October 31, 2016.

An important feature of the SEC's pilot program is the use of a stratified random sampling procedure in determining 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 three test groups with the remaining securities forming the control group.

Supporters of the Tick Size Pilot Program argue that increasing tick size motivates market makers to provide more liquidity to small cap stocks and thus making these stocks more attractive to investors (Grant Thornton, 2014). 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 increases investors' execution costs, and the complexity of this pilot reduces the efficiency of order execution. Additionally, they argue that a wider tick size leads to wealth transfer from liquidity takers to liquidity suppliers (e.g., Wall Street Journal, 2016). Surprisingly, neither supporters nor opponents of the tick size program commented on the potential price and cost of capital effects of the program, which could hurt the very firms that the program wished to help (one exception is Bessembinder et al., 2015). Below, we present evidence on stock price changes following the implementation of the program, and on liquidity changes as well as changes on liquidity risk and information risk.

3 Data Description

Our sample consists of all stocks in the Tick Size Pilot Program in the period from January 2016 to May 2017. We drop from the sample stocks that are delisted or experience a merger and acquisition during the sample period, stocks that are removed from the test group and added to the control group by the SEC due to a price decline below $1, stocks that are not common-ordinary stocks (i.e., keeping stocks with CRSP share codes of 10 or 11), and stocks without daily TAQ data.[3] 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 (2017) and Lin et al. (2017). We also drop firm-day observations when 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. 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 news that is most related to our companies (i.e., RavenPack's maximum "relevance score" of 100) and that are reported for the first time (i.e., Raven-

[3]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.

Pack's maximum "freshness score" of 100). The mean number of news per company is 32.5 and the median is 19. In addition, we collect from RavenPack U.S. macroeconomic news published on DowJones Newswire. We keep news that are first reported and with a relevance score of at least 90. There are 1,693 macro news in our sample. Table 1 reports the mean of key variables for all three pilot groups for the whole sample.

[Table 1 about here.]

For each test group, we report results for two subsamples, stocks with small dollar quoted spread (below median spread), and stocks with large dollar quoted spread (above median spread). We also split the stocks in the control group between small versus large dollar quoted spread. The reason for doing so is that the increased tick size requirement may not be binding for all stocks, especially those that are less liquid and already have large bid-ask spreads. To split each group into two samples, we use pre-experiment data, measuring the median spread with daily data from January 1, 2016 to September 30, 2016.[4] 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, 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.[5] Panel A of Table 2 shows that there are 159 (164) small (large) spread stocks in group 1; 156 (160) small (large) spread stocks in group 2; 152 (158) small (large) spread stocks in group 3; and, there are 484 (470) small (large) spread stocks in the control group. Table 2 also shows that the average pre-experiment dollar

[4]By using pre-experiment data to construct the subsamples we also do not induce any selection bias since firms and investors did not know who would be in the program.

[5]Griffith and Roseman (2017) and Rindi and Werner (2017) 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). Our cutoff is equivalent to splitting firms at $0.07 spread.

quoted spread for the small (large) quoted spread stocks in group 1 is \$0.0374 (\$0.2506); the average dollar quoted spread for the small (large) quoted spread stocks in group 2 is \$0.0392 (\$0.2413); the average dollar quoted spread for the small (large) quoted spread stocks in group 3 is \$0.0380 (\$0.2624); and, the average dollar quoted spread for the small (large) quoted spread stocks in the control group is \$0.0392 (\$0.2734). We discuss in the paper but do not tabulate results for each group as a whole. We note in advance that almost all of our results apply only to the more liquid stocks in each group, those with small quoted spreads. Thus, the results that use each group as a whole are generally economically and statistically weaker.

Panel A of Table 2 reports the mean of several key variables for all three pilot groups in the pre-implementation period.[6] The mean market capitalization in each of the groups for small spread stocks is close to \$800 million, indicating that the stocks in our sample are small cap stocks (the maximum market capitalization to participate in the pilot program is \$5 billion), but that these stocks are larger than those in the sample of large pre-experiment quoted spreads. In Panel B, we report the differences of key variables between each pilot group and the control group, and test whether such differences are statistically different from zero. We find that stocks in each of the pilot groups and in the control group exhibit similar total assets, market capitalization, book-to-market ratio, and liquidity (measured by *QuotedSprd* and *Volatility*). These results validate the randomization of the pilot program and ensure that stocks in the pilot groups and in the control group are similar over many dimensions.

[Table 2 about here.]

[6] We winsorize the quoted spread, effective spread, price impact and volatility at 1 and 99 percent. For these variables, the difference between the 99th percentile and the mean in the unwinsorized sample is more than 5 times the standard deviation of the respective winsorized series.

4 Impact of Tick Size on Stock Prices

This section presents results of the impact of a larger tick size on stock prices using a difference-in-differences technique. In this section, we group test stocks in groups 1 and 2 together. We do this for three reasons. First, we will show below that the various effects we study are quite similar for both groups. Second, the stocks in the two groups are activated concurrently. Third, to increase the power of the test by increasing the size of both the treated and control groups.

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. As an example, the Carhart model is

$$R_{it} - R_{ft} = \alpha_i + \beta_i \left(R_{mt} - R_{ft}\right) + \beta_{is} SMB_t + \beta_{ih} HML_t + \beta_{io} MOM_t + \varepsilon_{it}, \qquad (1)$$

where $R_{i,t}$ is the return on stock i 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 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., using 2015 data). We then calculate the abnormal return from September 1, 2016 to November 30, 2016 as

$$AR_{it} = R_{it} - R_{ft} - \left(\hat{\beta}_i \left(R_{mt} - R_{ft}\right) + \hat{\beta}_{is} SMB_t + \hat{\beta}_{ih} HML_t + \hat{\beta}_{io} MOM_t\right), \qquad (2)$$

where $AR_{i,t}$ is the abnormal return for stock i on day t, and $\hat{\beta}_i$, $\hat{\beta}_{is}$, $\hat{\beta}_{ih}$ and $\hat{\beta}_{io}$ are the coefficients that we estimate for each firm using the pre-sample data.

Our main result is depicted in Figure 1. The figure plots the equally-weighted cumulative abnormal return for the combined groups 1 and 2 versus control (top panel) and group 3 versus control (bottom panel) from one month before full implementation of the program for each group to one month following full implementation (full implementation for groups 1 and 2 is October 17 and for group 3 is November 1). The cumulative abnormal return for each group is set to zero at the full implementation date in each case. The average abnormal return on each test group experienced a decline in price relative to the control group following the full implementation of the tick size program that occurred on Monday, October 17, 2016 for groups 1 and 2 and on Monday, October 31 for group 3. This decline appears permanent. Note that even though the list of firms was announced in early September, they were not assigned to the test groups until they were activated and we do not expect any differential anticipatory effect on treated versus control stocks.

[Figure 1 about here.]

To obtain point estimates and standard errors of the impact of the larger tick size on stock returns controlling for firm characteristics, we estimate the following OLS regression that accounts for the staggered implementation of the program,

$$\begin{aligned} AR_{i,t} = &\alpha + \gamma_1 Pilot_i + \gamma_2 Week1_t + \gamma_3 Week2_t + \gamma_4 Post_t + \gamma_5 Pilot_i \times Week1_t \\ &+ \gamma_6 Pilot_i \times Week2_t + \gamma_7 Pilot_i \times Post_t + \delta' X_{it} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where we denote by $Pilot_i$ a dummy variable that equals 1 if a stock belongs to the test group $i = 1\&2, 3$ and 0 otherwise, and where for groups 1 and 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 dates between October 24 to October 28, and 0 otherwise, and for group 3, $Week1_t$ is a dummy variable equal to 1 for days between October 31 and November 4, and 0 otherwise, and $Week2_t$ is a dummy variable equal to 1 for dates between November 7 and November 11, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2$, and 0 otherwise, and thus depends on the treated group being considered. For example, for groups 1 and 2, $Post_t$ equals 1 after October 31. We also include all interaction terms of each date dummy and $Pilot$. We include in X_{it} a set of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and the lowest daily trading price, as well as month fixed effects and stock fixed effects that control for invariant differences in stocks such as the exchange where they trade. We use robust standard errors clustered at the firm level. We winsorize the bottom 0.5% and top 99.5% abnormal return observations (the winsorized value is larger than the winsorized mean by 3.4 times the standard deviation of the winsorized return distribution).

[Table 3 about here.]

Table 3 reports the regression results. Panel A (B) contains the results for pilot groups 1 and 2 (3). In each panel, Columns (1) and (2) present the results for the CAPM model, Columns (3) and (4) present the results for the Carhart model, and Columns (5) and (6) 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 and perhaps also with the coefficient associated with $Pilot_i \times Week2_t$ if there is some learning by the market. We do not expect that the learning will continue past $Week2_t$. The results are largely invariant to the risk adjustment used. For groups 1 & 2, the coefficient associated with $Pilot_i \times Week1_t$ is -0.002 significant at the 5%

level or better, which translates into a drop in risk-adjusted prices of $0.002 \times 5 = 1\%$, compared to the control group (note that the dummy $Week1_t$ is activated over 5 days). The effect on groups 1 and 2 appears permanent as the coefficients on $Pilot_i \times Week2_t$ and $Pilot_i \times Post_t$ are not significant.

As for test group 3, the sum of the coefficients associated with $Pilot_i \times Week1_t$ and $Pilot_i \times Week2_t$ is -0.008 in the Carhart model and -0.007 in the Fama French 5 factor model, with p-values below 1% (untabulated). These returns translates into a drop in risk-adjusted prices of about $0.008 \times 5 = 4\%$ if using the Carhart model, compared to the control group. The effect on group 3 also appears permanent as the coefficient on $Pilot_i \times Post_t$ is not significant. There is no price effect for stocks with large dollar quoted spread, i.e., the more illiquid stocks, in any of the test groups. The result of no effect for the more illiquid stocks is consistent with Amihud and Mendelson (1986), but not with Vayanos (1998) who predicts that the price effect should be smaller for the more liquid stocks. Bessembinder et al. (2015) predict that IPO stock prices will be lower with the increased tick size in the pilot program, consistent with our findings. In untabulated results we find no price drop when estimating the model above using the whole sample of stocks (small and large spread stocks) in each test group.

This drop in prices is a liquidity premium that we are able to identify given the construction of the program. Using the Carhart model, this premium represents a \$7 billion loss to investors (using the average market capitalization values from Table 2, panel A, the loss to groups 1 and 2 stocks is $0.01 \times (788 \times 159 + 792 \times 156)$ and the loss to group 3 stocks is $0.04 \times 746 \times 152$).

5 Sources of Price Variation

This section studies three potential sources of price variation that can explain the results above. A direct channel through which transactions costs increase prices, and indirect channels through changes in expected returns, liquidity risk changes, and information risk changes.

5.1 Changes in Transactions Costs

We consider several measures of transactions costs, and more generally of liquidity. We shall consider groups 1, 2 and 3 separately. From now on we drop observations in October 2016 to avoid potential contaminating factors associated with the staggered implementation of the pilot study through the implementation month and use the full sample from January 2016 to May 2017. We denote by $Post_t$ a dummy variable that equals 1 for dates on or after November 1, 2016, and 0 otherwise.[7] $Pilot_i$ is a dummy variable that equals 1 if a stock belongs to the test group $i = 1, 2, 3$ and 0 otherwise. We estimate the model

$$Liquidity_{it} = \alpha + \gamma_1 Post_t + \gamma_2 Pilot_i + \gamma_3 Post_t \times Pilot_i + \delta^{'} X_{it} + \varepsilon_{it}, \tag{4}$$

separately for each test group using ordinary least squares. $Liquidity_{it}$ is a measure of liquidity for stock i on day t, and X_{it} is the same vector of control variables as before including among other variables month fixed effects and stock fixed effects. We report robust standard errors, clustered by firm. We are interested on the sign and size of the coefficient associated with $Post_t \times Pilot_i$ that captures the impact of widening the tick

[7] This is a conservative approach for groups 1 and 2 as some of the change in market quality variables may have already occurred. Griffith and Roseman (2017) and Rindi and Werner (2017) also exclude the month of October.

size on liquidity after the implementation of the Tick Size Pilot Program.

[Table 4 about here.]

Table 4 presents the results with group 1 (2 and 3) stocks in Panel A (B and C, respectively). Consider first the effect of the tick size change on spreads and price impact. *QuotedSprd* increases by about 0.31 for group 1 small dollar quoted spread stocks, and by 0.27 for groups 2 and 3 stocks, compared to the respective control groups. The changes are statistically significant at 1% level and represent 73% (62% and 66%) of the mean quoted spread for group 1 (groups 2 and 3, respectively). Statistically significant changes in the *EffectiveSprd* occur only for groups 1 and 2, but with smaller magnitude relative to the *QuotedSprd* change, and in the *PriceImpact* for all groups, with groups 1 and 2 with a magnitude that is about one fourth that of the *QuotedSprd* change. There are no statistically significant effects on spreads for stocks with large dollar quoted spread. In untabulated results we find that the realized spread, a proxy for liquidity suppliers' market-making profit, changes by about the same magnitude as the price impact. Also, we find that the results when using the full sample within each group are qualitatively the same, but economically and statistically weaker.

The results so far suggest that the tick size program induced a wealth transfer from liquidity takers to liquidity providers, especially for group 1 and 2 stocks. These results are generally consistent with those expected by the proponents of the Pilot Program. The results are also consistent with Harris (1996) and others that argue that an increase in tick size is followed by reduced competition among market makers with a consequent increase in transactions costs for small market order traders that usually get executed at the NBBO (Harris, 1997). It is also possible that the tick size program causes some liquidity takers to switch to become liquidity providers, in which case the increase in effective spread is an upper bound to the increase in transactions costs of liquidity takers.

The results are inconsistent with models where a larger tick size improves liquidity by reducing negotiation costs (Harris, 1991), or where a larger tick size encourages liquidity provision for illiquid stocks if investors switch from market to limit orders (Werner et al., 2015).

Recall that stocks in pilot group 3 are required both to quote and to trade with a \$0.05 price increment, just like stocks in group 2. In addition, stocks in test group 3 are subject to the trade-at rule, which requires execution priority to be given to lit orders, unless dark orders can provide a meaningful price improvement over the lit orders. This additional requirement is costly for traders in dark exchanges. Theory (Zhu, 2014) and empirical evidence (Comerton-Forde and Putnis, 2015) suggest that orders executed in the dark are predominantly uninformed. Hence, increasing dark trading costs may force uninformed investors to the lit markets and decrease market markers' adverse selection costs. As a result, market makers reduce bid-ask spreads. Our results of broadly no effects on group 3 stocks, contrast with group 2 stocks, are consistent with a flow of uninformed traders back to lit markets.

We now turn to market depth, which can be a more relevant measure for liquidity for large traders when they build or liquidate their position and try to minimize their price impact. We find that market depth increases for all test groups, particularly for group 3 stocks. For smaller dollar quoted spread stocks the increase is of $\$25,145$ ($\$28,882$ and $\$36,657$) for group 1 stocks (2 and 3, respectively), compared to the control group, which represents an increase of 242% (281% and 365%) of the mean dollar-depth for test group 1 (2 and 3, respectively). These results are consistent with the notion that a wider tick size makes it more expensive for liquidity providers to obtain price priority by submitting more aggressive limit orders. A wider tick size impedes price competition and forces the liquidity providers to queue at the same quoted price, which results in an increase in dollar-depth (see Harris, 1994, 1997, and Bessembinder, 2003, O'Hara, Saar, and Zhong 2015, and Yao and Ye 2017). A stronger effect for group 3 stocks is consistent with an almost mechanical effect that increased costs in dark pools attract more trades to lit pools and increase market depth. There is an effect also for the more illiquid stocks, with larger dollar quoted spreads, but the effect is economically much smaller contrary to predicted by Werner et al. (2015).

[Figure 2 about here.]

Trading volume declines by a statistically significant $4,865,800$ shares in group 1 and $5,521,000$ shares in group 2, representing 14% and 15% of the respective group means. There is no statistically significant change in volume for group 3 stocks and for the large dollar quoted spread stocks. 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 that investors face with the larger tick size. Finally, we find almost no change in volatility across all test groups. The results for depth, volume and volatility are qualitatively similar to those when we estimate the models for the each of the test groups as a whole.

Figure 2 summarizes these results by plotting the time series of average effective spreads, volume and market depth for each of the test groups and the control group, skipping the month of October 2016. The changes in spreads are easy to detect as are the changes in depth. There does not appear to be a spillover effect of the tick size change to the control group in terms of spreads, volume or depth. Volatility of market depth appears to have increased significantly for the treated stocks; there is also an increased volatility of market depth towards the end of the sample period for the control stocks, but it appears significantly smaller.

5.1.1 Liquidity Premium

We now provide a point estimate to the liquidity premium, i.e., the ratio between the change in the expected return and the change in spreads. Assume that the percent change in prices equals the negative of the change in the expected rate of return divided by the expected rate of return (as would be the case if the stock is a perpetuity with no growth). If the expected rate of return is 5%, then the groups 1 and 2 (3) stocks experience an increase in expected returns equal to $0.05\% = 0.01 \times 0.05$ ($0.20\% = 0.04 \times 0.05$). The liquidity premium measured with respect to the percent *quoted spread* change is thus equal to $0.16 = 0.05/0.31$ ($0.19 = 0.05/0.27$, and $0.74 = 0.20/0.27$) for group 1 (2 and 3, respectively) stocks. The liquidity premium measured with respect to the percent *effective spread* change is about $0.31 = 0.05/0.16$ ($2.2 = 0.20/0.09$) for group 1 and 2 (3) stocks.

The significantly larger liquidity premium for group 3 stocks suggests a multiplicative effect from the "trade-at" requirement given that the effect of the tick size change on quoted spreads was close in magnitude for group 1 and 2 stocks versus group 3 stocks. However, recall that for group 3 stocks there was no statistically significant difference in effective spreads before and after the Tick Size Program started and only a modest increase in price impact–hence the liquidity premium relative to the effective spread may not be well defined. This points to the possibility that the driver of the price decline for group 3 stocks has less to do with a liquidity premium and more to do with the costs associated with the "trade-at" requirement and its consequences in terms of the distribution of informed versus uninformed investors across lit versus dark venues. As discussed in the introduction, a liquidity premium of $0.16-0.31$ for groups 1 and 2 is large relative to calibrated values in many asset pricing models with transactions costs. In these models investors reduce their trading of illiquid assets with high transactions costs and require a low liquidity premium (see the papers cited above including Amihud and Mendelson, 1986, and Constantinides, 1986). Hence, the liquidity premium represents a second order effect on prices even if transactions costs have a first order impact over spreads and trading volume.

To convert the drop in prices into elasticities, note that the Tick Size Program entailed a 400% change in tick size. Therefore, the stock price elasticity to tick size equals -0.25% for the stocks in groups 1 and 2, and about -1% for the stocks in group 3, though recall group 3 stocks were additionally subject to a "trade-at" requirement. The stock price elasticity to the *QuotedSpread* is $-0.01/0.31 = -3.3\%$ for the stocks in group 1, it is $-0.01/0.27 = -3.7\%$ for the stocks in group 2, and $-0.04/0.27 = -15\%$ for the stocks in group 3.

5.1.2 Changes in Investor Horizon

Amihud and Mendelson (1986) predict that in the face of higher transactions costs a clientele effect arises where only the investors with longer investment horizons choose to trade. Here, we test this additional prediction.

[Table 5 about here.]

Table 5 presents the results for *ChurnRatio*, our proxy for (the inverse of) investor horizon. Without loss, we estimate the specification in the regression model (4) for groups 1 & 2, and group 3, with respective control groups, using the same control variables but with *ChurnRatio* as dependent variable. The models are estimated using ordinary least squares and we report robust standard errors clustered by firm. Because we are using quarterly data, we do not drop October 2016 data. We winsorize the dependent variable at 1% and 99%.

We find that small spread stocks experience a decrease in investor churn, or an increase in investor horizon, 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 0.105, implying an average holding period of 4.76 years ($1/(0.105 \times 2)$). The churn ratio for stocks in groups 1 & 2 is reduced by 0.003 (see column (1)) to 0.102. So, the holding period becomes 4.9 years. This is equivalent to a 3% increase. The churn ratio for small spread stocks from group 3 decreases by 0.005 (see column (2)). So the average churn ratio becomes 0.104 and the holding period increases to 4.81 years ($1/(0.104 \times 2)$). This change is equivalent to a 5% increase in holding period. Recalling that effective spreads do not appear to have changed significantly for group 3 stocks, this change in investor horizon is likely to have been induced by specific restrictions imposed on group 3 stocks.

Note that many asset pricing models with transactions costs predict that holding periods increase with higher transactions 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.

5.1.3 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 note that the pilot program is active only for two years, so we look for a price effect from higher spreads over a two year period. Second, we use the investor horizon of institutional investors as a benchmark. The institutional investors holding the treated stocks have an average holding period of about 5 years (in group 1 the average holding period is 4.7 years, and in groups 2 and 3 it is 4.6 years). Thus, assuming that investors churn their portfolio continuously over time, after 2 years they will have churned 2/5 or 40% of their portfolio and they will have paid 40% of the transactions costs involved in turning over their portfolio. Taking transactions costs as measured by quoted spreads, a change in quoted spreads of 0.31 cents for a $1 stock, has a present value of about $0.31 + 0.4 \times 0.31 = 0.43$ cents or 0.43% of $1, ignoring discounting, for group 1 stocks. Taking transactions costs as being measured by effective spreads, a change in effective spreads of 0.16 (0.09) for groups 1 and 2 (group 3) has a present value of about 0.22% (0.13%) of $1, ignoring discounting. Either way, these rough calculations suggests that there may be a substantial portion of the observed change in prices across all groups that is due to the indirect effect that transactions costs have on prices via expected returns (net of transactions costs).

5.2 Changes in Liquidity Risk

In this subsection we ask whether the change in tick size may have induced a change in liquidity risk that induced the observed price decline. 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 of its own return and liquidity with the market return and liquidity.

Following Acharya and Pedersen (2005), we calculate the liquidity beta for stock i at day t as a combination of four different betas. We use thirty-minute stock and market returns, r_{is} and r_{Ms}, and liquidity, c_{is} and c_{Ms}, to get

$$\beta_{i1t} = \frac{cov\left(r_{is}, r_{Ms} - E_{s-1}\left(r_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)},$$
$$\beta_{i2t} = \frac{cov\left(c_{is} - E_{s-1}\left(c_{is}\right), c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)},$$
$$\beta_{i3t} = \frac{cov\left(r_{is}, c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)},$$
$$\beta_{i4t} = \frac{cov\left(c_{is} - E_{s-1}\left(c_{is}\right), r_{Ms} - E_{s-1}\left(r_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)}.$$

We use the proportional quoted spread as a measure of liquidity for stock i at the thirty-minute interval s, c_{is}. We use the equally-weighted average of c_{is} for all stocks in the market as a measure of market liquidity, c_{Ms}. Similarly, we compute the market return as the equally-weighted average of all r_{is} in the market.[8] We use thirty-minute intervals because these stocks may not trade often during the day (see Rindi and Werner, 2017). 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

$$\beta_{it} = \beta_{i1t} + \beta_{i2t} - \beta_{i3t} - \beta_{i4t}.$$

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.

Table 6 presents the results of running the difference-in-differences specification in model (4) for groups 1& 2, and group 3, with respective control groups, using the same control variables but with net beta as the dependent variable. We also run the same

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

regressions for β_{1t} and for the beta that captures liquidity components $\beta_{i2t} - \beta_{i3t} - \beta_{i4t}$ (panels B and C). We find that for stocks with small quoted spread, net-beta falls by 0.072 (0.076) after the start of the pilot program for the treated stocks in groups 1 and 2 (group 3) relative to the control group (see columns (1) and (2) of panel A). Moreover, most of the decline in net-beta comes from a decline in β_1 (see panel B). Finally, panel C shows that there does not appear to be a change in $\beta_{i2t} - \beta_{i3t} - \beta_{i4t}$. While the point estimate of the change in $\beta_{i2t} - \beta_{i3t} - \beta_{i4t}$ is negative, indicating a *lower* liquidity risk premium after the start of the Pilot program, this estimate is not statistically significant.[9]

[Table 6 about here.]

5.3 Changes in Price Efficiency

Information risk can contribute to changes in stock prices through the quality of information in the marketplace. To assess this possibility, in this subsection we use measures of price efficiency and of the speed of market response to news as proxies for quality of information. We estimate the specification in the regression model (4) for each group, with the respective control groups, using the same control variables but with price efficiency variables as dependent variables. Our price efficiency proxies are *AR10*, *PrcError*, and the speed of market response to news variables *PriceResponse*, *VolumeResponse*, *QuoteResponse1*, and *QuoteResponse2*. We again are able to separate groups 1 and 2 due to the larger number of observations.

[Table 7 about here.]

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

The results for the absolute value of return autocorrelation (*AR10*) and Hasbrouck's (1993) pricing error (*PrcError*) are displayed in Table 7. The models are estimated using ordinary least squares and we report robust standard errors clustered by firm. Starting with Panel A for small dollar quoted spread stocks, we note the robust evidence indicating a worsening in price efficiency. For example, return autocorrelation increases by 0.101 as shown in column (1) (0.090 and 0.082, as shown in columns (2) and (3)) for test group 1 stocks (2 and 3, respectively), compared to the control group, representing an increase of 36% (32% and 30%) for test group 1 stocks (2 and 3, respectively) relative to their mean. This evidence is consistent with Chordia et al. (2008) that study price efficiency with decimalization. Measured using *PrcError*, the changes in price efficiency are somewhat smaller percentage wise relative to those for *AR10*. For large dollar quoted spread stocks, there is only an increase in *PrcError* for group 1 and 2 stocks and a decrease in return autocorrelation for group 3 stocks, but the effects are significantly smaller relative to the effect on the small dollar quoted spread stocks of the respective groups. The online appendix shows that the results when we estimate the model for both *AR10* and *PrcError* for each group as a whole shows economic magnitudes smaller by about 40%.

[Table 8 about here.]

[Table 9 about here.]

Table 8 presents the results for the market response speed to company-specific news and Table 9 for macro news. We use the two-limit Tobit model to account for the fact that the variables *PriceResponse*, *VolumeResponse*, *QuoteResponse1*, and *QuoteResponse2* are bounded between 0 and 1. We are not able to estimate these models using stock fixed effects and instead use stock primary listed exchange fixed effects.

By and large our evidence regarding company-specific news is consistent with that of Table 7, with small dollar quoted spread stocks in test groups 1 and 2 having a greater reduction in response speed than those in test group 3, compared to the control group (coefficients −0.233 and −0.244 versus −0.207 for groups 1 through 3 reported in column (1) of panels A through C). Volume and quote response speed change by less in test groups 1 and 2, whereas in group 3 their change loses significance. There is some evidence of slower speed of market response also for the large dollar quoted spread stocks, but it is weaker both in economic magnitude and statistical significance. The evidence for the changing speed of market response due to a changing tick size is stronger for macro news as documented in Table 9 and shows up in both small and large dollar quoted spreads. This stronger evidence could be caused by the greater statistical power of the tests coming from the significantly larger number of observations.[10]

Overall, the results from both tables suggest a decrease in price efficiency following the adoption of a larger tick size for all three test groups, though only for the small dollar quoted spread stocks.[11] Our empirical results for groups 1 and 2 stocks are consistent with the prediction of Anshuman and Kalay (1998) that a wider tick size reduces informed investors' likelihood of trading. Anshuman and Kalay's (1998) model suggests that informed traders invest more to acquire accurate signals under continuous pricing than under discrete tick size trading and larger bid-ask spreads. Therefore, a larger tick size can lead to less price efficiency and lower quality of information. Likewise, in Goettler, Parlour and Rajan (2005), a larger tick size makes liquidity traders less aggressive and reduces price efficiency.[12]

[10]We have more observations than in the regressions with company specific news, because we can measure a market response to a piece of macro news for every firm in our sample.

[11]The results are consistent with Kerr, Sadka and Sadka (2017) who study the effect of liquidity on the predictability of earnings growth using prices where the shock to liquidity is the1997 reduction in tick size from one eighth to one sixteenth.

[12]Our results are inconsistent with Zhao and Chung's (2006) proposed alternative that a larger tick size may improve price efficiency by making it more expensive to front-runners to step in front of

For group 3 stocks, recall that we do not find a significant change in effective spreads or in price impact measures. So, it is unlikely that the price drop in group 3 is a consequence of an increase in transactions costs and thus a consequence of less information acquisition as in Anshuman and Kalay (1998). Instead, it is possible that the trade-at requirement that group 3 stocks are subject to caused a shift of uninformed investors from dark pools to lit exchanges that kept spreads low (see Zhu, 2014, and Comerton-Forde and Putnis, 2015).

The decrease in price efficiency and the slower price discovery are consistent with an increase in information risk. In the models of Easley and O'Hara (2004) and O'Hara (2003) information risk, the risk that exists of trading in assets with privately informed investors, increases with a decrease in information quality, either through an increase in uninformed traders or a decrease in the precision of private information because prices end up revealing less information to the uninformed traders in equilibrium. Thus we conjecture that information risk may have increased for all groups, at least partly explaining the stock price response.

6 Related Literature

Several papers have tried to detect the effect of shocks to bid-ask spreads on stock prices. Barclay, Kandel and Marx (1998) study this question within the context 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. Our field experiment has the advantage of eliminating the selection issue–arising because the choice of exchange venue is not

existing orders and to receive execution precedence. Reducing front-running risk increases the profit for informed traders, which motivates them to gather more information.

exogenous–that can impact causal inference of stock price effects. Elyasiani, Hauser and Lauterbach (2000) also study stocks that move from Nasdaq to the NYSE and attribute some of the listing excess return to liquidity changes in those stocks. The studies that are closest to ours, in the sense of using a laboratory-like experiment in actual financial markets, are Bessembinder (2003) and Chakravarty, Wood, Van Ness (2004) who investigate the effects of decimalization on a sample of NYSE common stock initially trading in decimals.[13] Because the NYSE changed the trading requirements via a phased pilot program, they are able to form a sample of unaffected stocks that controls for other contemporaneous events. Both papers find that quoted spreads declined after decimalization and Chakravarty et al. also finds that stock return volatilities decline over the long term. Neither paper reports on stock price effects. Muscarella and Piwowar (2001) find a price increase for frequently traded stocks in the Paris Bourse that move from call trading to continuous trading, but theirs is not a randomized sample like ours, nor do they study expected return effects. Relative to this literature we also innovate by finding supportive evidence that microstructure shocks, such as a tick size change, can have consequences for firms' cost of capital.

We conjecture that the lack of clear causal evidence of changes in the tick size on stock prices in the literature and the many theoretical arguments pointing to a second order effect of transactions costs on stock prices may explain the absence of a discussion of price effects from either proponents and opponents of the tick size program. However, our evidence suggests that the program may have hurt the very firms that the study wished to help.

There is a long empirical literature starting with Amihud and Mendelson (1986, 1991) and Brennan and Subrahmanyam (1996) that shows that risk-adjusted stock and

[13] Fang, Noe and Tice (2009) study the effect of decimalization on the change in market to book value of assets from one year prior to decimalization to one year after decimalization.

bond returns correlate positively with liquidity 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. Moreover, the lack of more direct evidence to date on the link between exogenous measures of transactions costs and prices raises a concern that these confounding aspects may be of first order. Our paper suggests otherwise as it is the first paper that shows that exogenous shocks to transactions costs have price effects.

The JOBS Act envisioned the study conducted by the SEC in order to collect information to better assess how tick size may impact liquidity and price efficiency. The scant literature studying how stock prices are affected by bid-ask spreads contrasts with the large body of literature studying the impact of tick size on liquidity.[14] See for example Harris (1994, 1997), Ahn, Charles and Choe (1996), Goldstein and Kavajecz (2000), Jones and Lipson (2001), and Bessembinder (2003), among others. More recently, Griffith and Roseman (2017) and Hansen et al. (2017), Lin et al. (2017), and Rindi and Werner (2017) also make use of the SEC's Tick Size Pilot Program to study the effect of bid-ask spreads on liquidity, including spreads, price impact, volume and depth.[15]

[14]Theoretical studies have been developed to examine the effect of tick size changes in different market structures. Foucault, Kadan and Kandel (2005) investigate a dynamic limit order book populated by strategic liquidity traders of varying impatience, and predict that a reduction in tick size can result in higher spread by impairing market resiliency and enabling traders to trade less aggressively. By modeling the competition between a specialist with market power and a competitive limit order book, Seppi (1997) shows that larger tick size is more favorable for large traders than for small traders. Werner et al. (2015) model order submission strategies of rational trades and show that tick size reduction improves market quality for liquid stocks, but deteriorates market quality for illiquid stocks. Kadan (2006) studies the welfare effects of a change in tick size in a dealer marker and argues that an increase in tick size benefits dealers while hurting investors when the number of dealers is large, and vice versa when the number of dealers is small. The JOBS Act specifically acknowledged the possibility that increasing the tick size encourages market participants to provide more liquidity, and analysts to cover these firms, thereby attracting more investors to invest in small cap stocks.

[15]Comerton-Forde, Gregoire and Zhong (2017) uses the tick size pilot program as an exogenous shock to the market share of inverted exchanges to study market quality of inverted fee models, and Lin, Swan

These papers all conclude, like we do, that increasing tick size increases spreads, price impact and depth especially for the more constrained stocks. The effect of a larger tick size on trading volume is less clear. Though the literature generally documents a negative relationship between trading volume and bid-ask spreads, Porter and Weaver (1997) and Rindi and Werner (2017) find no effect of tick size on volume. We find that trading volume experiences a significant decline for pilot groups 1 and 2 stocks and no change for group 3 stocks. Griffith and Roseman (2017), Hansen et al. (2017) and Lin et al. (2017) also find a significant drop in consolidated volume for treated firms after the tick size pilot program.

Our paper is the first to show price efficiency changes using the tick size pilot program, which are consistent with changes in information risk. We provide empirical evidence on the causal effect of a reduction in price efficiency due to an increase in tick size. Anshuman and Kalay's (1998) model suggests that a larger tick size reduces the value of private information, thus decreasing price efficiency. In their model, informed traders invest more to acquire accurate signals under continuous pricing, while a wider tick size would discourage investors from acquiring accurate information about stock value. Zhao and Chung (2006) find evidence supporting the Anshulan and Kalay (1998) model, though they consider an alternative hypothesis where a larger tick size may improve price efficiency by reducing the likelihood of front-running, which increases the profit for informed traders and motivates them to gather more information. Likewise, 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 find that after widening the tick size, market reaction speed to news decreases, suggesting that it takes longer for stock price to incorporate information, thus a decrease in price efficiency.

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and Mollica (2017) study the allocation of investors across exchanges.

7 Conclusion

We provide empirical evidence of a causal negative impact of a larger tick size on stock prices and calculate the liquidity premium implied by the change in tick size. The sources of stock price variation appear different across the various treated stocks in the program. We show that the decline in stock prices is associated with an increase in spreads and in price impact, and with a reduction in volume for groups 1 and 2 stocks. For these stocks, we show that there is an increase in investor horizon consistent with the view that transactions costs have a direct effect over stock prices holding expected returns constant, as in Amihud and Mendelson (1986). However, for group 3 stocks, we show that there is a change in quoted spreads but no change in effective spreads or in trading volume.

We also study the indirect effect on stock prices through expected returns (net of transactions costs) of the change in tick size. We show that there is no statistically significant change in liquidity risk across all test groups. However, we show that all stocks experience a decline in price efficiency suggesting that information risk and thus expected returns increased for the treated stocks. This evidence is consistent with firm's 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 different tick size trading requirements affect the liquidity of emerging stocks to perhaps encourage more of these firms to go public. Given the large theoretical literature arguing that liquidity has second order effects on prices, and given an existing sizeable empirical literature arguing similarly as discussed above, 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

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.[16] For ease of reading the results, we measure *QuotedSprd*, *EffectiveSprd*, and *PriceImpact* in percent.

In addition, we study market depth (*MarketDepth*) defined as the average of displayed dollar-depth at the NBBO and measures the number of shares (in hundreds) that must be traded before the stock price moves, daily volume (*Volume*) (in hundreds of shares) (results are similar if using the number of trades during the day), and realized variance (*Volatility*) is the sum of squared intraday five-minute returns. We winsorize the bottom

[16] 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.

1% and top 1% of quoted spread, effective spread, price impact and volatility. 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.

Investor Horizon Our proxy for investor horizon is the (inverse of the) $ChurnRatio$ borrowed from Gaspar, Massa and Matos (2005) and Cella, Ellul and Giannetti (2013). 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, which churn their portfolios more frequently (see Cella et al., 2013, for details). Investor horizon (in years) can be calculated as $1/(2 \times ChurnRatio)$.

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 of the stock, or efficient price, and a non-informational component that captures transitory deviations from the efficient price, such as tick size or inventory effects. 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 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. The reasons to look at macro news are that firms may be heterogeneous in the volume and significance of company-specific news and this may affect our inference, and that the flow and content of firm specific news may also have changed 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 $PriceResponse = |return_{t-1,t+10}| \,/\, (|return_{t-1,t+10}| + |return_{t+10,t+120}|)$. $|return_{t-1,t+10}|$ 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 and fourth measures are based on quote adjustment. *QuoteResponse1* 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 and NBBO depth updates in the first 10 second over those that are updated in the first two-minutes. Finally, *QuoteResponse2* is defined analogously to *QuoteResponse1*, but it only counts the number of NBBO price updates.

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 in the news response speed regressions as a control.

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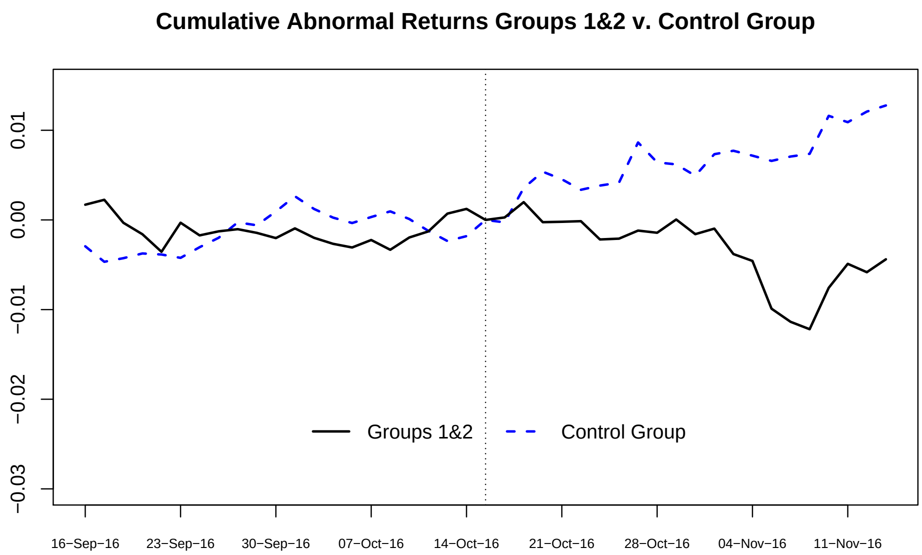
Figure 1: **Cumulative Abnormal Return**

The figure plots the daily cumulative abnormal return of treated groups and control group from September 01, 2016 to November 30, 2016. The top panel plots the cumulative abnormalreturn of test stocks in groups 1 and 2 versus the control group (test stocks in groups 1 and 2 are activated fully into the program on October 17, 2016). The bottom panel plots the cumulative abnormal return of test stocks in group 3 versus the control group (test stocks in group 3 are activated fully into the program on November 1, 2016).



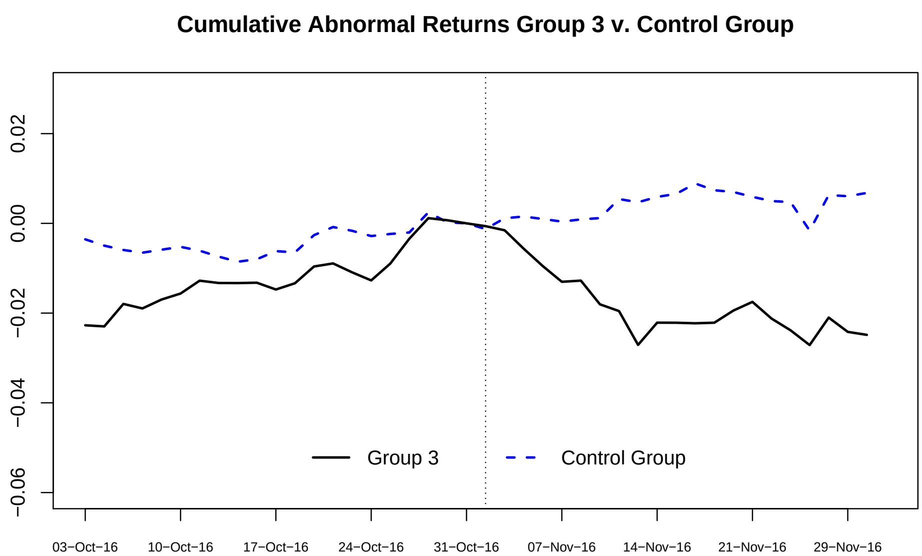


Figure 2: **Market Liquidity**

The figure plots the daily percent effective spread (top panel), trading volume (mid panel), and dollar market depth (bottom panel) for stocks in test groups 1 to 3 versus the control group. The month of October 2016 is the implementation month and is dropped.

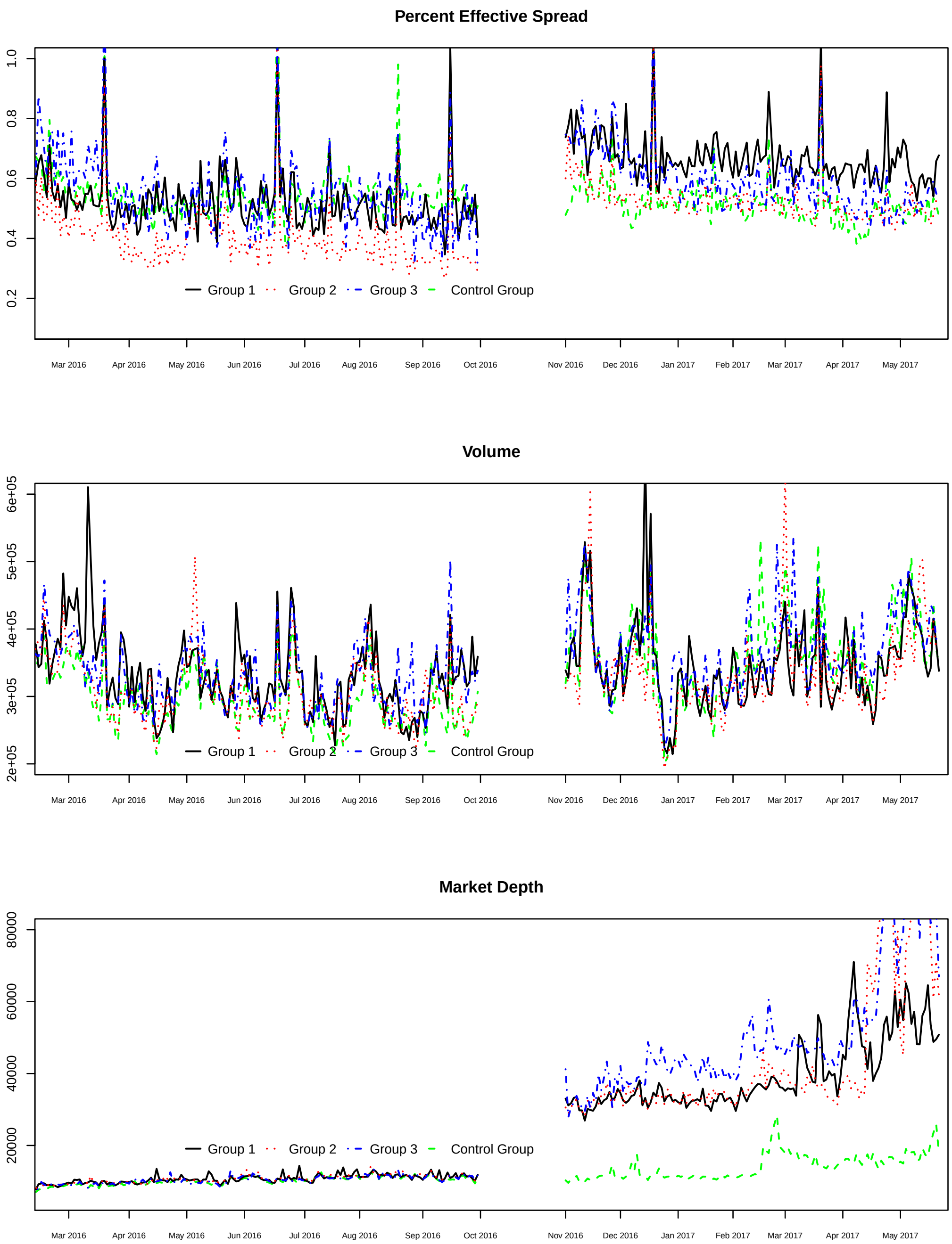


Table 1: **Summary Statistics for Key Variables**

The table presents descriptive statistics for each test group from January 01, 2016 to May 31, 2017. 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 percent quoted 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, $Volatility$ is the realized variance, $AR10$ 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. All spread measures are multiplied by 100 for ease of reading. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. 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	90144	0.412	0.474	0.275	0.073	8.111	87288	1.613	1.882	0.818	0.073	8.111
EffectiveSprd	90135	0.556	1.509	0.213	0.044	12.834	85170	1.291	2.137	0.514	0.044	12.834
PriceImpact	90135	0.338	0.889	0.142	-0.609	7.418	85137	0.519	1.152	0.181	-0.609	7.418
Market Depth	90143	9806	8083	8052	515	423462	87269	15163	31707	10405	420	2023329
Volume	90138	303684	439069	194231	2	23292925	85465	88586	211302	28523	1	16489984
Volatility	90144	0.151	1.118	0.000	0.000	9.292	86863	0.146	1.119	0.000	0.000	9.292
AR10	84017	0.280	0.140	0.267	0.000	0.914	47936	0.338	0.145	0.330	0.000	0.940
PrcError	75021	0.176	0.162	0.138	0.011	1.090	33314	0.186	0.145	0.154	0.022	1.093
ChurnRatio	1417	0.103	0.043	0.107	0.001	0.291	1382	0.072	0.049	0.066	0.000	0.255

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	29487	0.415	0.477	0.272	0.073	8.111	30334	1.380	1.671	0.677	0.073	8.111
EffectiveSprd	29487	0.520	1.418	0.206	0.044	12.834	29888	1.016	1.634	0.421	0.044	12.834
PriceImpact	29487	0.291	0.737	0.135	-0.609	7.418	29878	0.420	0.915	0.164	-0.609	7.418
Market Depth	29487	10425	10566	8482	646	551854	30334	14553	17935	10982	443	1022462
Volume	29487	340705	547945	199923	102	30938197	29951	90862	202521	35810	1	14585454
Volatility	29487	0.070	0.785	0.000	0.000	9.292	30206	0.030	0.379	0.000	0.000	9.292
AR10	27142	0.278	0.138	0.264	0.000	0.897	18104	0.337	0.145	0.329	0.000	0.893
PrcError	23932	0.168	0.150	0.134	0.008	1.088	12826	0.182	0.133	0.155	0.022	1.087
ChurnRatio	469	0.105	0.046	0.101	0.003	0.245	478	0.080	0.048	0.081	0.001	0.229

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	28915	0.400	0.477	0.234	0.073	7.694	29700	1.607	1.863	0.819	0.073	8.111
EffectiveSprd	28915	0.412	0.869	0.185	0.044	12.834	29034	1.273	2.021	0.515	0.044	12.834
PriceImpact	28915	0.264	0.578	0.130	-0.609	7.418	29031	0.525	1.156	0.186	-0.609	7.418
Market Depth	28915	10411	8716	8935	605	348372	29694	13482	15820	10022	573	1203311
Volume	28915	317339	432827	200700	4	23503988	29096	92051	202002	29437	1	6686550
Volatility	28915	0.014	0.256	0.000	0.000	9.292	29591	0.126	0.996	0.000	0.000	9.292
AR10	26689	0.280	0.141	0.264	0.000	0.890	16706	0.337	0.145	0.332	0.000	0.949
PrcError	23688	0.162	0.131	0.135	0.019	1.086	11279	0.194	0.173	0.153	0.017	1.087
ChurnRatio	458	0.109	0.047	0.113	0.001	0.223	464	0.068	0.047	0.067	0.000	0.210

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	28115	0.397	0.523	0.238	0.073	8.111	29435	1.439875	1.652	0.776	0.073	8.111
EffectiveSprd	28114	0.561	1.556	0.186	0.044	12.834	28933	1.35141	2.392	0.518	0.044	12.834
PriceImpact	28114	0.325	0.871	0.129	-0.609	7.418	28917	0.596208	1.355	0.178	-0.609	7.418
Market Depth	28115	10116	7621	8557	627	223357	29428	15848.39	21797	10727	484	530352
Volume	28114	337537	453780	224742	2	15910008	28998	88358.86	194878	30199	1	8356901
Volatility	28115	0.123	0.903	0.000	0.000	9.292	29322	0.317104	1.658	0.000	0.000	9.292
AR10	26536	0.277	0.139	0.263	0.000	0.916	16624	0.344387	0.146	0.338	0.000	0.931
PrcError	23919	0.172	0.158	0.135	0.012	1.089	11306	0.235118	0.235	0.165	0.009	1.090
ChurnRatio	445	0.109	0.045	0.114	0.001	0.220	466	0.073	0.046	0.064	0.001	0.235

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

The table presents descriptive statistics of treated stocks (‘G1’ - ‘G3’) and control stocks (‘C’) from January 01, 2016 to September 30, 2016. Panel A reports average firm characteristics for each group. Panel B reports the differences between the treatment and the control group. Total asset (*Asset*), Market Capitalization (*Size*), and market-to-book ratio (*MB*) are measured on December 2015. Daily trading volume (*Volume*), dollar quoted spread (*QuotedSprd*), and realized volatility (*Volatility*) are based on data from January 1 to September 30, 2016. *Asset* and *Size* are measured in millions of dollars. *QuotedSprd* is measured in cents. The first (second) row of each variable in Panel B reports the difference (t-statistics for the difference) between Control and Treatment Group. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. 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	484	159	156	152	470	164	160	158
Asset	1664	1390	1828	1366	1033	1188	912	1189
Size	770	788	792	746	574	640	532	560
MB	6.06	3.59	3.52	4.67	3.37	8.16	2.61	3.14
Volume	303023	338862	316710	334715	86479	88824	89491	86561
QuotedSprd ($c)	3.92	3.74	3.92	3.80	27.34	25.06	24.13	26.24
Volatility	0.15	0.07	0.01	0.13	0.19	0.03	0.15	0.33

Panel B: Difference between Treatment and Control Group

Difference (Control - Test)	C	G1	G2	G3	C	G1	G2	G3
Asset		275	-164	365		-154	121	-156
		(0.78)	(-0.43)	(0.82)		(-0.71)	(0.56)	(-0.71)
Size		-18	-22	25		-66	42	15
		(-0.25)	(-0.31)	(0.35)		(-0.95)	(0.61)	(0.21)
MB		2	3	1		-5	1	0
		(1.06)	(1.07)	(0.54)		(-1.51)	(1.22)	(0.36)
Volume		-35838	-13686	-31692		-2345	-3012	-82
		(-1.59)	(-0.63)	(-1.45)		(-0.20)	(-0.24)	(-0.01)
QuotedSprd ($c)		0.18	-0.01	0.12		2.28	3.20	1.10
		(1.18)	(-0.04)	(0.77)		(0.83)	(1.20)	(0.39)
Volatility		0.09	0.14*	0.02		0.16*	0.04	-0.14
		(1.03)	(1.73)	(0.26)		(1.82)	(0.44)	(-1.22)

Table 3: **Abnormal Returns**

The table reports OLS regression results of the following model: $AR_{i,t} = \alpha + \gamma_1 Week1 + \gamma_2 Week2 + \gamma_3 Post_t + \gamma_4 Pilot_i \times Week1 + \gamma_5 Pilot_i \times Week2 + \gamma_6 Pilot_i \times Post_t + \delta^{'} X_{i,t} + \epsilon_{i,t}$, where $AR_{i,t}$ is the abnormal return for stock i on day t. Panel A (B) contains the results for pilot groups 1&2 (3). $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. For groups 1 and 2, $Week1$ is a dummy variable equal to 1 for dates between October 17 and October 21, and 0 otherwise, and $Week2$ is a dummy variable equal to 1 for dates between October 24 to October 28, and 0 otherwise, and for group 3, $Week1$ is a dummy variable equal to 1 for dates between October 31 and November 4, and 0 otherwise, and $Week2$ is a dummy variable equal to 1 for dates between November 7 and November 11, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2$; and 0 otherwise, and thus depends on the treated group being considered. 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 time and stock fixed effects. Columns (1) and (2) present the results using the CAPM model. Columns (3) and (4) present the results using the Carhart model. Columns (5) and (6) present the results using the Fama French 5 Factor model. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. Odd (even) number columns report results for small (large) spread stocks. We cluster the standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Groups 1&2

	CAPM		Carhart		Fama French 5 Factor	
	Small Spread (1)	Large Spread (2)	Small Spread (3)	Large Spread (4)	Small Spread (5)	Large Spread (6)
Week1	0.004***	0.000	0.002***	-0.001	0.002***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week2	-0.001*	-0.000	0.001**	0.001**	0.002***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post	0.003***	0.002***	0.001**	0.001	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pilot1&2 x Week1	-0.002**	0.000	-0.002**	0.000	-0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot1&2 x Week2	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot1&2 x Post	-0.000	-0.001*	-0.000	-0.001*	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	48,060	47,847	48,049	47,797	48,049	47,797
R-squared	0.042	0.046	0.026	0.043	0.023	0.040
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 3

Week1	0.000	-0.001	0.002***	-0.000	0.001**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week2	0.015***	0.011***	0.002*	0.002**	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post	-0.001	0.000	0.000	0.000	-0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot3 x Week1	-0.003**	0.001	-0.003**	0.001	-0.003*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot3 x Week2	-0.004**	-0.001	-0.005**	-0.001	-0.004**	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pilot3x Post	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	38,207	37,469	38,133	37,313	38,133	37,313
R-squared	0.059	0.061	0.027	0.047	0.023	0.041

Table 4: **Market Liquidity**

The table reports OLS regression results of the following model: $Liquidity_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, 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 volatility as measures of liquidity. Panels A and B give results for group 1 stocks, Panels C and D give results for group 2 stocks, and Panels E and F give results for group 3 stocks. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. We drop observations in October 2016. 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 time and stock fixed effects. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Small Quoted Spread Stocks from Pilot Group 1

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.029***	0.015	-0.011	1.422	39.699**	0.057*
	(0.011)	(0.048)	(0.024)	(1.686)	(16.139)	(0.031)
Pilot1 x Post	0.311***	0.154**	0.082***	25.145***	-48.658***	-0.041
	(0.024)	(0.071)	(0.025)	(4.703)	(14.857)	(0.039)
Observations	205,432	205,419	205,419	205,432	205,422	205,432
Adjusted R-squared	0.582	0.635	0.408	0.157	0.466	0.716

Panel B: Large Quoted Spread Stocks from Pilot Group 1

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.258***	-0.267***	-0.171***	4.147***	9.990	0.020
	(0.043)	(0.041)	(0.023)	(0.586)	(6.523)	(0.020)
Pilot1 x Post	-0.042	0.064	0.031	8.797***	-4.514	0.002
	(0.057)	(0.063)	(0.024)	(1.253)	(3.561)	(0.013)
Observations	202,204	198,288	198,203	202,204	198,697	201,514
Adjusted R-squared	0.669	0.561	0.252	0.440	0.743	0.763
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Small Quoted Spread Stocks from Pilot Group 2

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.027**	-0.010	-0.025	0.408	30.292**	0.041
	(0.011)	(0.045)	(0.024)	(2.882)	(15.089)	(0.029)
Pilot2 x Post	0.267***	0.173***	0.088**	28.882***	-55.210***	-0.005
	(0.025)	(0.064)	(0.035)	(9.070)	(16.807)	(0.047)
Observations	204,011	203,998	203,998	204,011	204,001	204,011
Adjusted R-squared	0.576	0.618	0.406	0.105	0.455	0.718
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Large Quoted Spread Stocks from Pilot Group 2

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.291***	-0.285***	-0.156***	4.426***	9.604	0.009
	(0.044)	(0.046)	(0.026)	(0.551)	(6.993)	(0.025)
Pilot2 x Post	-0.008	0.036	0.013	7.673***	-0.104	0.021
	(0.054)	(0.068)	(0.028)	(0.807)	(4.722)	(0.051)
Observations	201,096	196,860	196,788	201,096	197,277	200,424
Adjusted R-squared	0.672	0.562	0.270	0.489	0.720	0.752
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Small Quoted Spread Stocks from Pilot Group 3

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	MarketDepth (4)	Volume (5)	Volatility (6)
Post	-0.029***	-0.006	-0.017	0.635	33.297**	0.048
	(0.011)	(0.045)	(0.024)	(1.458)	(15.939)	(0.030)
Pilot3 x Post	0.272***	0.090	0.067**	36.657***	-22.172	-0.068*
	(0.025)	(0.073)	(0.028)	(7.753)	(18.202)	(0.039)
Observations	202,723	202,709	202,709	202,723	202,712	202,723
Adjusted R-squared	0.589	0.627	0.417	0.173	0.455	0.712
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel F: Large Quoted Spread Stocks from Pilot Group 3

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	MarketDepth (4)	Volume (5)	Volatility (6)
Post	-0.302***	-0.286***	-0.161***	4.322***	6.545	0.027
	(0.043)	(0.044)	(0.026)	(0.542)	(6.330)	(0.027)
Pilot3 x Post	-0.006	-0.066	-0.013	8.718***	3.012	-0.103
	(0.051)	(0.075)	(0.041)	(0.948)	(3.670)	(0.075)
Observations	200,379	196,388	196,307	200,379	196,799	199,718
Adjusted R-squared	0.663	0.587	0.299	0.510	0.794	0.729
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **Investment Horizon**

The table reports OLS regression results of the following model: $ChurnRatio_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, 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 smallest dollar quoted spread, and Columns (3) and (4) report regression results for stock with largest dollar quoted spread. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 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 time and stock fixed effects. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. We cluster the standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
	(1)	(2)	(3)	(4)
Post	-0.105***	-0.106***	-0.079***	-0.077***
	(0.002)	(0.002)	(0.002)	(0.002)
Pilot1&2 x Post	-0.003*		0.000	
	(0.002)		(0.001)	
Pilot3 x Post		-0.005**		0.001
		(0.002)		(0.002)
Observations	4,566	3,630	4,493	3,575
Adjusted R-squared	0.873	0.876	0.861	0.854
Controls	Yes	Yes	Yes	Yes

Table 6: **Liquidity Risk**

The table reports OLS regression results of the following model: $\beta_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $\beta_{i,t}$ is a measure of liquidity risk for stock i on day t. Panel A (B and C) reports results using β_i (β_{1i} and $\beta_{liq,i}$) 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. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 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 time and stock fixed effects. Columns (1) and (2) report regression results for stocks with smallest dollar quoted spread, and Columns (3) and (4) report regression results for stock with largest dollar quoted spread. We cluster the standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Impact of Widening Tick Size on β_i

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
	(1)	(2)	(3)	(4)
Post	-0.498***	-0.494***	-0.053	-0.040
	(0.024)	(0.027)	(0.036)	(0.039)
Pilot1&2 x Post	-0.072***		-0.058**	
	(0.021)		(0.029)	
Pilot3 x Post		-0.076***		-0.086
		(0.026)		(0.055)
Observations	252,680	200,558	241,905	190,884
Adjusted R-squared	0.044	0.042	0.044	0.051
Controls	Yes	Yes	Yes	Yes

Panel B: Impact of Widening Tick Size on β_{1i}

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
Post	-0.569***	-0.567***	-0.381***	-0.378***
	(0.023)	(0.026)	(0.028)	(0.031)
Pilot1&2 x Post	-0.052**		-0.004	
	(0.021)		(0.022)	
Pilot3 x Post		-0.074***		0.001
		(0.024)		(0.039)
Observations	252,680	200,558	241,905	190,884
Adjusted R-squared	0.048	0.046	0.053	0.059
Controls	Yes	Yes	Yes	Yes

Panel C: Impact of Widening Tick Size on $\beta_{liq,i}$

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
Post	0.071***	0.073***	0.329***	0.338***
	(0.013)	(0.016)	(0.026)	(0.029)
Pilot1&2 x Post	-0.020		-0.054***	
	(0.013)		(0.019)	
Pilot3 x Post		-0.002		-0.088***
		(0.019)		(0.031)
Observations	252,680	200,558	241,905	190,884
Adjusted R-squared	0.028	0.031	0.020	0.022
Controls	Yes	Yes	Yes	Yes

Table 7: **Price Efficiency**

The table reports OLS regression results of the following model: $PriceEfficiency_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $PriceEfficiency_{i,t}$ is a measure of price efficiency, $AR10$ and $PrcError$, for stock i on day t. Panel A (B) reports regression results for stocks with smallest (largest) dollar quoted spread. Columns (1) to (3) use return autocorrelation as a measure of price efficiency. Columns (4) to (6) use pricing error as measure of price efficiency. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to the test group (i = 1, 2, 3), and 0 otherwise. $Post$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. We drop observations in October 2016. 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 time and stock fixed effects. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Small Dollar Quoted Spread Stocks

	AR10			PrcError		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.047***	0.047***	0.046***	0.003	0.004	0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Pilot1 x Post	0.101***			0.021***		
	(0.005)			(0.005)		
Pilot2 x Post		0.090***			0.024***	
		(0.005)			(0.004)	
Pilot3 x Post			0.082***			0.027***
			(0.005)			(0.005)
Observations	191,619	190,920	190,622	170,981	170,922	171,187
Adjusted R-squared	0.184	0.170	0.174	0.744	0.754	0.755
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Large Dollar Quoted Spread Stocks

	AR10			PrcError		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.035***	0.037***	0.036***	-0.007**	-0.004	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Pilot1 x Post	0.003			0.012*		
	(0.004)			(0.006)		
Pilot2 x Post		0.005			0.016***	
		(0.004)			(0.005)	
Pilot3 x Post			-0.015***			-0.004
			(0.004)			(0.009)
Observations	117,985	115,368	115,526	82,044	79,434	79,408
Adjusted R-squared	0.093	0.096	0.095	0.686	0.718	0.725
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: **Trade Response Speed to Firm Specific News**

This table reports tobit regression results of the following model: $Response_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Pilot_i + \gamma_3 Post_t \times Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, 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. $QuoteResponse1$ is calculated as the proportion of quote adjusted (including both NBBO changes and depth at NBBO changes) in the first 10 seconds after the news announcement ($QuoteResponse1$). $QuoteResponse2$ only counts the number of NBBO changes and ignores depth at NBBO changes. In Panels A, B and C, we report results for groups 1, 2 and 3, respectively. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. Columns (1) to (4) report regression results for stocks with smallest dollar quoted spread, and Columns (5) and (8) report regression results for stock with largest dollar quoted spread. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. We drop observations in October 2016. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 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, sentiment score of the news, and time and stock primary listed exchange fixed effects. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.110*	0.021	-0.011	-0.037	-0.113*	0.045	-0.044	-0.068*
	(0.043)	(0.029)	(0.012)	(0.027)	(0.048)	(0.064)	(0.023)	(0.031)
Pilot1	0.011	0.012	0.002	0.001	-0.012	0.036	-0.009	-0.008
	(0.022)	(0.017)	(0.006)	(0.012)	(0.031)	(0.036)	(0.015)	(0.020)
Pilot1 x Post	-0.233***	-0.057*	-0.022*	-0.129***	-0.160***	-0.044	-0.013	-0.048
	(0.052)	(0.022)	(0.010)	(0.029)	(0.042)	(0.049)	(0.018)	(0.026)
Observations	12517	15403	16768	13237	9685	8621	11555	10140
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 2

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.063	0.009	-0.005	-0.023	-0.106*	0.064	-0.059*	-0.063
	(0.043)	(0.030)	(0.012)	(0.027)	(0.051)	(0.064)	(0.024)	(0.033)
Pilot2	-0.012	0.009	0.006	0.000	-0.021	0.073	0.002	-0.008
	(0.024)	(0.017)	(0.007)	(0.015)	(0.033)	(0.043)	(0.017)	(0.021)
Pilot2 x Post	-0.244***	-0.066*	-0.031***	-0.143***	-0.176**	-0.103	-0.030	-0.078*
	(0.067)	(0.027)	(0.009)	(0.037)	(0.057)	(0.062)	(0.020)	(0.037)
Observations	12265	15107	16535	12962	9037	8056	10720	9461
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Pilot Group 3

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.085*	0.036	-0.015	-0.039	-0.129**	0.011	-0.050*	-0.073*
	(0.042)	(0.029)	(0.012)	(0.026)	(0.048)	(0.070)	(0.024)	(0.032)
Pilot3	0.018	0.008	0.010	0.011	-0.034	0.050	-0.003	-0.018
	(0.025)	(0.018)	(0.006)	(0.014)	(0.026)	(0.037)	(0.014)	(0.018)
Pilot3 x Post	-0.207***	-0.030	-0.016	-0.102**	-0.132**	-0.073	-0.024	-0.054
	(0.051)	(0.027)	(0.010)	(0.032)	(0.047)	(0.052)	(0.019)	(0.032)
Observations	12426	15125	16469	13119	9372	8367	11267	9835
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: **Trade Response Speed to Macro News**

This table reports tobit regression results of the following model: $Response_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Pilot_i + \gamma_3 Post_t \times Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, 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. $QuoteResponse1$ is calculated as the proportion of quote adjusted (including both NBBO changes and depth at NBBO changes) in the first 10 seconds after the news announcement ($QuoteResponse1$). $QuoteResponse2$ only counts the number of NBBO changes and ignores depth at NBBO changes. In Panels A, B and C, we report results for groups 1, 2 and 3, respectively. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. Columns (1) to (4) report regression results for stocks with smallest dollar quoted spread, and Columns (5) and (8) report regression results for stock with largest dollar quoted spread. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. We drop observations in October 2016. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 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, sentiment score of the news, and time and stock primary listed exchange fixed effects. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.052***	-0.006	-0.008***	-0.015***	-0.048***	0.009	-0.005*	-0.010**
	(0.005)	(0.005)	(0.002)	(0.003)	(0.006)	(0.009)	(0.002)	(0.003)
Pilot1	0.002	0.012	0.003	0.000	0.005	-0.004	0.002	0.001
	(0.006)	(0.007)	(0.003)	(0.003)	(0.006)	(0.013)	(0.003)	(0.003)
Pilot1 x Post	-0.226***	-0.031***	-0.009***	-0.110***	-0.176***	-0.034***	-0.039***	-0.097***
	(0.010)	(0.005)	(0.002)	(0.006)	(0.009)	(0.009)	(0.003)	(0.005)
Observations	1325399	1600058	1762163	1394940	1037394	882263	1293977	1101006
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 2

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.053***	-0.006	-0.009***	-0.014***	-0.054***	0.003	-0.009***	-0.015***
	(0.006)	(0.005)	(0.002)	(0.003)	(0.006)	(0.009)	(0.003)	(0.003)
Pilot2	0.004	0.003	0.002	-0.001	0.002	0.008	0.002	0.002
	(0.006)	(0.007)	(0.002)	(0.003)	(0.007)	(0.013)	(0.003)	(0.003)
Pilot2 x Post	-0.227***	-0.035***	-0.012***	-0.115***	-0.165***	-0.040***	-0.037***	-0.092***
	(0.012)	(0.005)	(0.002)	(0.006)	(0.010)	(0.009)	(0.003)	(0.005)
Observations	1334212	1595560	1764044	1404278	1014636	860891	1271277	1077517
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Pilot Group 3

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.058***	-0.007	-0.011***	-0.019***	-0.049***	-0.003	-0.006*	-0.010**
	(0.005)	(0.005)	(0.002)	(0.003)	(0.006)	(0.010)	(0.003)	(0.003)
Pilot3	-0.008	0.005	0.001	-0.004	0.000	-0.005	0.000	-0.002
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.014)	(0.003)	(0.003)
Pilot3 x Post	-0.187***	-0.022***	-0.004*	-0.099***	-0.171***	-0.037***	-0.034***	-0.091***
	(0.009)	(0.005)	(0.002)	(0.005)	(0.009)	(0.009)	(0.003)	(0.005)
Observations	1330619	1596422	1755728	1401470	1012806	860969	1270894	1077969
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes