The Real Costs of Natural Experiments

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Abstract

The US Securities and Exchange Commission (SEC) initiated a Tick Size Pilot Program commencing on October 3, 2016 to increase the tick size from 1 cent to 5 cents for 1,200 randomly chosen firms. Tick size is the minimal price movement of a security. We find that an increase in tick size reduces liquidity and trading volume, and reduces price efficiency, leading to greater return autocorrelation, larger deviation of stock price from its fundamental value, and lower speed of market reacting to company-related news. Finally, we show that an increase in tick size leads to price drops for pilot firms, and that such a reduction is more pronounced for stocks more likely to be constrained by tick size. Our results indicate that the Tick Size Pilot Program imposes real costs on the pilot firms. Firms can reverse split their shares in order to counteract the negative effects due to the implementation of pilot program.

Keywords: market liquidity, price efficiency, news response rate, asset return

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1 Introduction

Controlled experiments are popular in main fields of study, but are rare in finance. One possibility is that controlled experiments may incur large financial costs for the subjects. Suppose that we randomly put a firm into a treatment group and another one in a control group. One possibility is that firms in the treatment group lose value through the experiment. Indeed, we find such a cost in an on-going experiment.

On October 3, 2016 the US Securities and Exchange Commission (SEC) launched a Tick Size Pilot Program, a two-year experiment to increase the tick size from 1 cent to 5 cents for 1,200 randomly chosen stocks. Tick size is the minimum price movement of a security. In 2001, SEC reduces the tick size from 1/16 of a dollar to 1 cent. A number of policy makers notice that, along with a reduction in tick size since 2001, U.S. IPOs also decrease (Weild, Kim, and Newport 2012). In 2012, the Jumpstart Our Business Startups Act ("JOBS Act") directed the Securities and Exchange Commissions (SEC) to conduct a study on how decimalization affects the market quality of small cap stocks and the number of IPOs, with the goal to enhance capital access for small companies and foster an ecosystem for the success of small companies. Proponents of increase the tick size argue that an increased tick size would encourage market participants to provide more liquidity, and analysts to cover these firms, thereby attracting more investors to invest small cap stocks. Our results using the pilot data, however, indicate the opposite. Our results show that stocks in the treatment group suffer from lower liquidity and price discovery, to the extent that they reduce the value of the treatment firm relative to firms in the control group.

First, we find that an increase in tick size reduces liquidity. Specifically, firms in the treatment group have larger quoted spread, effective spread, realized spread, and price impact after the implementation. We also find that an increase in tick size decreases trading volume. Second, an increase in tick size reduces price efficiency: return autocorrelation and temporary price deviation from the fundamental value increase. Further, we find that market response speed to company-related news decreases, suggesting that it takes longer for stock prices to incorporate information. Finally, we show that for stocks that are more likely to be constrained by tick size, experience price drops after the implementation controlling for other risk factors, implying a reduction of stocks' firm value. We observe no return reversal for these stocks, suggesting a permanent decrease in firm value.

The stock market has witnessed dramatic changes in the past decades, given the rise and proliferation of high frequency trading. The exact impact of increasing the tick size on market liquidity remains an empirical question under the current market condition [1]. On the one hand, because of the speed advantage of high frequency traders (HFTs), they can front-run slower traders by providing better terms of liquidity. The minimal price improvement to gain price priority over slower traders is one tick-size. Such an activity can result in an improvement in quoted spread, although the improvement can be an infinitesimal amount. This phenomenon can be especially prominent under a small tick size, as the cost for liquidity providers to establish price priority is lower. On the other hand, the front-running behaviors of HFTs may crowd out slower market makers, and

[1] A large body of literature, which does not directly model the role played by trading speed, has extensively studied the impact of tick size on market quality. For example, Foucault, Kadan and Kandel (2005) show that small tick size impairs market resiliency, and may have adverse effects on the spread. In their model, larger tick size increases the importance of time precedence. So investors will quote more aggressively, thus increase market resiliency and narrower spread. Jones and Lipson (2001) document that smaller tick size significantly increases realized execution costs for institutional investors. Such an increase is most significant for large liquidity taking orders. Thus, they conclude that small tick size can hurt liquidity. They find that spread decreases after the tick size reduction but market quality does not decrease. Seppi (1997) shows that larger tick size is more favorable for large traders than for small traders. Goettler et al. (2005) show that small tick size decreases the effective spread and benefit market order submitters, at the expense of limit order submitters. Following this, Werner et al. (2015) show that tick size reduction improves market quality for liquid stocks, but deteriorates market quality for illiquid stocks. They also show that widening tick size for liquid stocks causes traders use more market orders which leads to larger spread.

disincentivize them to provide liquidity, thus resulting in a decrease in market quality. Our study provides an assessment of this question.

We find that a wider tick size increases quoted spread and effective spread, which is in line with the findings in the literature on decimalization and the reduction in tick size implemented across the globe [2]. Based on the findings in the literature, the effect of a wider tick size on trading volume is less clear. For example, Harris (1994), O'Hara, Saar, and Zhong (2015) and Yao and Ye (2017) suggest that a larger tick size increases the value of time precedence, thereby increasing the value liquidity providing and enlarging market depth. Although we find a significant increase in market depth for the pilot group, trading volume experiences a significant decline.

In this paper, we provide strong empirical evidence on the causal impact of increasing tick size on price efficiency, for which the literature has yet to reach a conclusion. 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), however, argue that a wider tick size may improve price efficiency as a larger tick size reduces front-running risk for investors, which increases the profit for informed traders and motivates them to gather more information. Thus, there will be more information-based trading which improves price efficiency. Using a difference-in-difference framework, we find strong evidence that price efficiency, measured as 1)

[2] For example, Ahn, Charles, and Choe (1996) investigate the impact of tick size reduction from 1/8 to 1/16 on stock liquidity and other outcomes for low-price stocks on American Stock Exchange (AMEX). They find that smaller tick size leads to reduced effective and quoted spreads. Harris (1997) finds that smaller tick size leads to smaller spread and reduced quote size for stocks on the Toronto Stock Exchange and market orders submitted by small market order investors usually get executed at the NBBO. Goldstein and Kavajecz (2000) find that tick size reduction from 1/8 to 1/16 leads to reduced spread and depth for the stocks on NYSE, and conclude that reduced tick size mainly benefits small liquidity takers. Bessembinder (2003) shows that trade execution costs decrease and market quality improves after decimalization.

negative of the absolute value of the autocorrelation for midpoint return, and 2) negative of the pricing error in a vector moving average (VMA) model, deteriorate after an increase in the tick size.

Further, using a high-frequency news database (RavenPack), we examine the change in speed at which information is incorporated into stocks after an increase in tick size. RavenPack records detailed Dow Jones Newswire releases for worldwide companies with a high precision time-stamp to the level of milliseconds. Following Beschwitz, Keim, and Mass (2015), we measure market reaction speed by calculating the amount of two-minute price change and volume change that takes place in the first 10 seconds. Another proxy we use for market reaction speed is the ratio of the number of quote updates in the first 10 seconds over that during the two minute horizon. We find that market reaction speed to news decreases significantly, suggesting that it takes longer for stock price to incorporate information after widening the tick size.

Having established the results that a wider tick size decreases market quality, reduces price efficiency, and retards the speed that stock price incorporate information, we turn our attention to the impact of a larger tick size on asset returns. Decreased market quality reduces securities' values because rational investors discount securities more heavily in the presence of higher trading costs, holding all other things equal (Amihun and Mendelson, 1986; Amihud, Mendelson and Lauterbach, 1997). We estimate daily abnormal returns for a period from January 2016 to May 2017. We find that stocks with small quoted spread in the pilot group experience a significant 2.2% value deduction compared with stocks in the control group, although for stocks with a large quoted spread the change in stock price is insignificant. This finding can be attributed to the fact that traders who used to quote a narrower spread are now forced to enlarge the spread, which leads to an increase in transaction cost, a decrease in liquidity, and a drop in stock return. The decrease in stock return occurs most frequently in the two weeks immediately after the pilot program implementation. The change in stock value appears to be permanent rather than transitory, as we do not observe a reversal in stock return.

Given the costs imposed by the Tick Size Pilot Program, what can firms do to manage these costs? Yao and Ye (2017) show that in an environment of tick size constraint, the relative magnitude of tick size over stock price (i.e., the relative tick size) is of utmost importance. In order to counteract the negative effects of the Tick Size Pilot Program, firms can increase stock prices mechanically through reverse splitting their shares so as to keep the relative tick size constant. However, Weld et al. (2010) show that when deciding the stock price trading ranges, managers commonly take norms and customs as the main considerations, and seldom conduct split/reserve splits so as to achieve the optimal relative tick sizes[3]. Given our findings, we would encourage firm managers to revisit the relative tick size. By changing the ranges of nominal stock prices by conducting stock reserves splits, firms are able to neutralize the costs imposed exogenously by the Tick Size Pilot Program.

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, variables construction, and presents descriptive statistics. Section 4 analyzes the impact of larger tick size on market liquidity. Section 5 analyzes the impact of larger tick size on price efficiency. Section 6 investigates the impact of a larger tick size on stock returns. The paper ends with a brief summary and concluding remarks.

[3]Weld et al (2010) shows that three possible economic explanations, the Marketability Hypothesis, the Pay-to-Play Hypothesis and the Signaling Hypothesis are unable to explain the constant range of nominal stock price.

2 Institutional Background

In the US, 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.

In 2012, the Jumpstart Our Business Startups Act ("JOBS Act") directed SEC to conduct a study on how decimalization affects the number of IPOs and market quality of small cap stocks.[4] In July 2012, the SEC reported back to the Congress without reaching a firm conclusion. Following this, Congress mandated SEC to implement a pilot which would generate data to investigate the impact of tick size. In June 2014, the SEC directed the Financial Industry Regulatory Authority (FINRA) and the National Securities Exchange (NES) to act jointly in developing a tick size pilot program, which would widen the minimum tick size increment for a selection of small cap stocks. The aim of the SEC was to collect information from this pilot in order to better assess how tick size may impact trading, liquidity and market quality of those stocks from the pilot. On May 6, 2015, the SEC approved the proposed plan.

Supporters of the Tick Size Pilot Program argue that increasing tick size will motivate market makers to provide more liquidity to small cap stocks. Improving liquidity will thus make these stocks more attractive for investors. Opponents argue that increasing tick size will increase investors' execution costs, and the complexity of this pilot will reduce the efficiency of order execution. Additionally, they argue that a wider tick size would lead to wealth transfer from liquidity takers to liquidity suppliers.

The Tick Size Pilot Program consists of a control group and three pilot (test) groups.

[4]The general goal was to enhance market quality, which may encourage more small firms to go public (i.e., having an Initial Public Offering).

The control group contains approximately 1,200 stocks, and each test group contains about 400 stocks. Stocks in the control group continue quoting and trading at their current tick size increment. Stocks in test group 1 are required to quote in \$0.05 minimum increments, but are allowed to trade at their current price increment. 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 ones.

The pilot program was implemented on a staggered basis. Starting on October 3, 2016, stocks of test groups were moved into their designated test groups. On October 3, 2016, 5 stocks were activated in test groups 1 and 2. On October 10, 2016, 100 stocks were activated in test groups 1 and 2. On October 17, 2016, all 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. Starting from October 31, 2016, stocks of all three test groups were activated.

3 Data and Summary Statistics

Our sample consists of all stocks in the Tick Size Pilot Program in the period from January 2016 to May 2017. We restrict our sample to common-ordinary stocks (i.e., keeping stocks with CRSP share codes of 10 or 11). We further require the average daily stock price to be greater than \$2. We drop firms if they were delisted or experienced mergers or acquisitions during our sample period. We obtain the intraday quote and price data from the daily Trade and Quote (DTAQ), high frequency news data from

RavenPack News Analytics (RavenPack) database, and stock market data from the Center for Research in Security Prices (CRSP). We obtain Fama-French three factors and momentum factors data from the Kenneth R. French data library. Panel A of Table 1 reports the mean of key variables for all three pilot groups. Panel A shows that the mean market capitalization for the control group, pilot group 1, pilot group 2, and pilot group 3 are \$672 million, \$708 million, \$663 million, and \$648 million, respectively, indicating that all stocks in our sample are small cap stocks. In Panel B, we report the differences of key variables between each pilot group and control group, and test whether such differences are statistically different from zero. We find that the pilot groups and the control group exhibit similar total assets ($Asset$), market capitalization ($Size$), book-to-market ratio (MB), and liquidity (measured by $QuotedSpread$ and $RealizedVariance$). These results suggest that the pilot program was well designed, and ensures that stocks in the pilot groups and control group are similar over many dimensions. Table 2 reports the detailed summary statistics of key variables for the entire sample, for each pilot group, and for the control group, respectively.

3.1 RavenPack News

RavenPack covers all articles published on the Dow Jones Newswires. According to Beschwitz, Keim and Massa (2015), the latency between Dow Jones Newswires releasing an article and releasing the news to RavenPack is approximately 300 milliseconds. RavenPack identifies all companies related to each article, and a variable named "relevance score" shows how closely a company is related to the article. The relevance score ranges from 0 to 100, where 0 (100) means the firm is passively (predominately) related to the news article. In order to drop irrelevant news, we only keep news with relevance score equal to 100. RavenPack also provides an "event novelty score" which captures the "freshness" of a story. It ranges between 0 and 100. Articles capture the same story, whereby the first article is considered to be the most novel and receives a score of 100. Subsequent articles receive a decreasing novelty score. In our study, we intend to investigate the speed at which investors respond to news. Thus, we focus on stories that are first time reported by dropping news with a novelty score less than 100. RavenPack also provides a millisecond time-stamp which records the time at which each article is released.

RavenPack also provides two measures of sentiment for each article: the Composite Sentiment Score (CSS) and the Event Sentiment Score (ESS). Composite Sentiment Score (CSS) is based on several individual RavenPack sentiment measures, and it ranges from 0 to 100. 0 (100) presents the most negative (positive) news, and 50 presents neutral news. Event Sentiment Score (ESS) is similar to CSS, but is only available if the category of the article is available. Following Beschwitz, Keim and Massa (2015), we create one sentiment measure, $Sentiment$, which is equal to the value of ESS if it is non-missing or if CSS is equal to 50, and takes the value of CSS otherwise.

3.2 Liquidity Measure

Following Holden and Jacobsen (2014), we use daily TAQ data to construct the following liquidity measures: percent quoted spread, percent effective spread, percent realized spread, and price impact. We calculate the percent quoted spread as:

$$PercentQuotedSpread_t = \frac{A_t - B_t}{M_t}, \tag{1}$$

where A_t is the national best ask, B_t is the national best bid at interval t, and M_t is the midpoint equal to the average of A_t and B_t ($M_t = \frac{A_t + B_t}{2}$). Daily percent quoted spread ($QuotedSprd$) is the time weighted average percent quoted spread computed over all time intervals.

We calculate the second measure, percent effective spread for the k^{th} trade as:

$$PercentEffectiveSpread = \frac{2D_k(P_k - M_k)}{M_t}, \tag{2}$$

where D_k is an indicator which equals to 1 if the k^{th} trade is buyer-initiated, and -1 if the k^{th} trade is seller-initiated. P_k is the price of the k^{th} trade, and M_k is the midpoint. We use the Lee and Ready (1991) algorithm to determine whether a trade is buy or sell. Under this convention, trade with price above the midpoint is classified as a buy trade, and trade with price below the midpoint is classified as a sell trade. For trades that occur at the midpoint, classification based on the previous trade is used. Daily percent effective spread ($EffectiveSprd$) is the dollar-volume-weighted average of percent effective spread computed over all time intervals.

The percent realized spread on the k^{th} trade is defined as:

$$PercentRealizedSpread_k = \frac{2D_k(P_k - M_{k+5})}{M_t}, \tag{3}$$

where M_{k+5} is the midpoint five minutes after the midpoint M_k. Daily percent realized spread ($RealizedSprd$) is calculated as the dollar-volume-weighted average of percent realized spread computed over all time intervals.

For a given stock, the percent price impact on the k^{th} trade is defined as:

$$PercentPriceImpact_k = \frac{2D_k(M_{k+5} - M_k)}{M_t}, \tag{4}$$

daily price impact ($PriceImpact$) is the dollar-volume-weighted average of percent price impact computed over all trades.

We use realized variance ($Volatility$) as a measure for price variation. We calculate depth ($MarketDepth$) as the time-weighted average of displayed dollar-depth at the national best bid and offer (NBBO).

3.3 Measure of Price Efficiency

We employ two measures for price efficiency. Following Hasbrouck (1993) and Boehmer and Kelley (2009), we decompose transaction price into two components: informational (permanent) and non-informational (transitory). The informational component represents the expected value of stock, and the transitory component captures temporary deviation from the efficient price. We calculate pricing error using the following vector auto-regression (VAR) model with 5 lags:

$$\begin{aligned} r_{i,t} &= a_1 r_{t-1} + a_2 r_{t-2} + ... + b_0 x_{t-0} + b_1 x_{t-1} + b_2 x_{t-2} + ... + v_{1,t} \\ x_{i,t} &= c_1 r_{t-1} + c_2 r_{t-2} + ... + d_1 x_{t-1} + d_2 x_{t-2} + ... + v_{2,t}, \end{aligned} \tag{5}$$

where r_t is the difference in log price p_t and x_t is a three-by-one vector of trade related variables, including a trade sign indicator, signed trading volume, and signed square root of trading volume. We use Lee and Ready's (1991) algorithm to determine whether a trade is buy or sell.

Hasbrouck (1991) suggests that the quote revisions and trades can be expressed as a linear function of current and past innovations. The above VAR model can be transformed into the following vector moving average (VMA) model:

$$\begin{aligned} r_t &= v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{2,t-2} + ... + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + ... \\ x_t &= c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + ... + v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + ..., \end{aligned} \tag{6}$$

Following Boehmer and Wu (2013), we use pricing error as a measure for price efficiency. We use the return equation from Equation (6) to calculate pricing error. The pricing error can be expressed as:

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + ... + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + ..., \tag{7}$$

where $\alpha_j = \sum_{k=j+1}^{5} a_k^*$ and $\beta_j = \sum_{k=j+1}^{5} b_k^*$ The variance of the pricing error is calculated as:

$$\sigma_{(s)}^2 = \sum_{k=j+1}^{5} [\alpha_j, \beta_j] cov(v) [\alpha_j, \beta_j]'. \tag{8}$$

We estimate $\sigma_{(s)}$ on a daily basis. Following Boehmer and Kelley (2009), we keep $\sigma_{(s)}$ for a given stock on a particular day if there are more than 100 transactions on that day, and if $\sigma_{(s)}$ is no greater than the standard deviation of the transaction price ($\sigma_{(p)}$). Our measure of pricing error is standardized by the standard deviation of the log transaction price and is defined as follows:

$$Prc\_error = \frac{\sigma_{(s)}}{\sigma_{(p)}}, \tag{9}$$

where higher Prc_error indicates lower price efficiency.

Our second measure of price efficiency ($AR10$) is calculated as the absolute value of return autocorrelation. For each stock on each day, we calculate the autocorrelation for 10 second midpoint returns. Similar to Prc_error, we retain only the firm-day observation if there are at least 100 trades. If stock price is efficient, return should follow a random walk. Both positive and negative autocorrelation indicates predictability in return. Following Boehmer and Kelley (2009), we use the absolute value of the return autocorrelation ($AR10$) as our second measure of price efficiency.

3.4 Response Speed to News

We are interested in investigating the speed at which stock price responds to news, and we employ four proxies to measure how fast market reacts to news. Our first proxy is based on stock return. Following Beschwitz, Keim and Massa (2015), we define stock price response speed ($PriceResponse$) as:

$$PriceResponse = \frac{abs(return_{t-1,t+10})}{abs(return_{t-1,t+10}) + abs(return_{t+10,t+120})}, \tag{10}$$

where $abs(Return_{t-1,t+10})$ is the absolute value of stock return for an 11-second time horizon from $t-1$ to $t+10$ where t is the second that the news is released. $abs(Return_{t+10,t+120})$ is the absolute value of stock return for a 110 second time horizon from $t+10$ to $t+120$. $PriceResponse$ shows the amount of two minute return adjustment that take place in the first 10 seconds after the release of the news.

Our second measure of market reaction speed is based on trading volume. Volume response speed ($VolumeResponse$) is defined as:

$$VolumeResponse = \frac{volume_{t-1,t+10}}{volume_{t-1,t+10} + volume_{t+10,t+120}}, \tag{11}$$

where $volume_{t-1,t+10}$ is the trading volume executed from 1 second before the news announcement and 10 seconds after the news announcement. $volume_{t+10,t+120}$ represents trading volume executed 10 seconds after the news announcement to 120 seconds after the news announcement. Similar to price response speed, volume response speed captures the amount of two-minute volume adjustments that take place in the first 10 seconds after the news announcement.

Our third and fourth measures are based on quote adjustment. $QuoteResponse1$ is calculated as:

$$QuoteResponse1 = \frac{QuoteChange1_{t-1,t+10}}{QuoteChange1_{t-1,t+10} + QuoteChange1_{t+10,t+120}}, \tag{12}$$

where $QuoteChange1$ counts the number of NBBO changes and depth at NBBO changes. $QuoteResponse1$ shows the proportion of quotes adjusted in the first 10 seconds after the news announcement. Similarly, $QuoteChange2$ only counts the number of NBBO changes and ignores the depth at NBBO changes.

4 Market Liquidity

The primary goal of the SEC for this pilot study is to investigate the impact of a larger tick size on stock liquidity and the trading volume. In this section, we test the impact of a larger tick size on market quality using a difference-in-difference technique. As discussed in Section 2, the tick size pilot program was implemented on a staggered basis, with the first batch implemented on October 3, 2016, and the last batch implemented on October 31, 2016. To avoid the potential issues of contaminating factors associated with the implementation of this pilot study, we drop data in the implementation month (i.e., October 2016) from the analysis in this section.

The existing literature provides different views on the impact of larger ticker size on liquidity. On the one hand, studies show that a larger tick size may improve liquidity by reducing negotiation costs, increasing market makers' incentive to provide liquidity, or by increasing market depth. First, the larger tick size may improve liquidity by reducing negotiation costs, as it may reduce the possible bid-ask prices that can be offered, and reduce the amount of information needed to be exchanged between buyers and sellers (see, e.g., Harris (1991)). Second, as argued in Harris (1994, 1997), a wider tick size makes it more expensive for market makers to obtain price priority by improving quotes, thus they queue at the same quoted price and yield an increase in dollar-depth.[5]

On the other hand, increasing the tick size may hurt liquidity as well. For example, Harris (1996) suggests that a wider tick size leads to reduced competition among market makers (as it increases their costs to provide price improvement), which in turn leads to larger spread and reduces liquidity. Also, as discussed in Harris (1997), market orders submitted by small market order investors usually get executed at the NBBO. Therefore, a larger tick size may lead to higher transactions costs for small market order traders.

In summary, whether a larger tick size improves or damages liquidity is an empirical question. We empirically study the impact of a wider tick size on stock liquidity using the following difference-in-difference models. We run the OLS model separately for each pilot (test) group:

$$Liquidity_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta^{'} X_{i,t} + \epsilon_{i,t}, \tag{13}$$

where $Liquidity_{i,t}$ is a measure of liquidity for stock i on day t. $Pilot$ is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. As discussed earlier, we drop observations in October 2016. $Post$ 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 including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and the natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE

[5] See, also, Werner et al. (2015), who suggest that a wider tick size may encourage liquidity provision, reduce spreads, improve social welfare and increase market depth for illiquid stocks. Their model predicts that a wider tick size will reduce trading volume for illiquid stocks because investors switch from market to limit orders.

and those listed on NASDAQ. Therefore, the interaction term $Post \times Pilot$ captures the impact of widening the tick size on liquidity after the implementation of the Tick Size Pilot Program.

4.1 Impact of Widening Tick Size on Spreads

Following Holden and Jacobsen (2014), we use the quoted spread, effective spread, realized spread, and price impact as proxies for execution costs. We conduct regressions as in Equation (13), using these spread measures as dependent variables, and report the results of these regressions in Table 3.

Panel A of Table 3 reports the impact of a larger tick size on liquidity for stocks from test group 1 relative to the control group. The coefficient of interest is the interaction term ($Pilot \times Post$). Column (1) shows that the proportional quoted spread for pilot stocks increases by 0.001 after the implementation of a wider tick size. Economically, from Table 2 we know the average percent quoted spread for stocks in pilot group 1 is 0.01, thus the impact of widening the tick size on percent quoted spread is equivalent to a 10% increase ($\frac{0.001}{0.01}$). We use the effective spread and price impact to measure liquidity takers' trading costs. As reported in Column (2) and (3), both effective spreads and price impact increase about 0.001 following the implementation of a wider tick size. This is equivalent to an 12.5% and 20% increase, respective to their means. In addition, we use realized spread as a proxy for liquidity suppliers' market making profit. Column (4) shows that the realized spread increases about 0.001 or 20% relative to its mean. Our results suggest that a larger tick size induces a wealth transfer from liquidity takers to liquidity providers.

Panel B reports the impact of widening the tick size on liquidity for stocks in test group 2. The empirical results for test group 2 are consistent with those for test group 1.

Panel C reports the impact of widening the tick size on liquidity for stocks in test group 3. For stocks in test group 3, the quoted spread increases by 0.001 (equivalent to 11% of the mean quoted spread for test group 3). However, effective spread, realized spread, and price impact remain unchanged. Stocks in pilot group 3 are required both to quote and to trade with a $0.05 price increment. 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 more meaningful price improvement than the lit ones. This rule can result in a costly dark trading. According to Zhu (2014) and Comerton-Forde and Putnis (2015), orders executed in the dark tend to be uninformed. Increasing dark trading costs may squeeze uninformed investors to the lit markets and thus decrease market markers' risk of being adversely selected. As a result, market makers are willing to improve their quoted price. This may cancel out some of the impacts we discuss above.

4.2 Impact of Widening Tick Size on Depth

In the above subsection, we find that a wider tick size increases investors' trading costs. For large traders, dollar-depth can be a more relevant measure for liquidity when they build or liquidate their position and try to minimize the price impact.

As discussed earlier, a wider tick size can increase the cost price improvement. Traders, who previously differentiated on the price of the quotes they submitted, now submit quotes at the same price. This can result in a longer queue and a larger market depth. In this subsection, we examine the impact of a wider tick size on market depth by conducting regressions (13) using dollar-depth as dependent variables. We report the results of these regressions in Table 4 Column (1). Panel A (B and C) shows the impact of tick size on dollar-depth for stocks from test group 1 (2 and 3) compared to stocks from the control group. Our results show that the dollar-depth increases by $16,886 ($17,913 and $22,531) for stocks in pilot group 1 (2 and 3) after the implementation of a larger tick size. This is equivalent to 80% (85% and 94%) of the mean dollar-depth for test group 1 (2 and 3). These results are consistent with the prediction of Harris (1994, 1997), Bessembinder (2003), and Werner et al. (2015).

4.3 Impact of Widening Tick Size on Volume and Volatility

Harris (1997) argues that a larger tick size increases trading costs for investors, which results in a decreased trading volume. Werner et al. (2015) also predicts that a larger tick size may reduce the trading volume for illiquid stocks because investors switch from market to limit orders.

We use trading volume as our third measure of liquidity and study the impact of tick size on trading volume. Table 4 shows that both the number of trades (Column (2)) and trading volume (Column (3)) decreases after the implementation of a wider tick size, and that the magnitude is about 5% for pilot stocks. Column (4) shows the impact of tick size on realized volatility. From Table 4, volatility remain largely unchanged.

In this section, we examine the effect of a larger tick size on liquidity. Our results show that quoted spread, effective spread, realized spread and price impact increase while trading volume decreases following the implementation of the Tick Size Pilot Program.

5 Price Efficiency

In the previous section, we examine the effect of a larger ticker size on liquidity. In this section, we move on to study the effect of a larger ticker size on price efficiency.

5.1 Impact of Widening Tick Size on Price Efficiency

While most of the earlier studies focus on the impact of tick size on liquidity, the impact of tick size on price efficiency is less clear. Anshuman and Kalay's (1998) model suggests that a wider tick size may reduce the value of private information. In their model, informed traders invest more to acquire accurate signals under continuous pricing, and a wider tick size will discourage investors to acquire precise information about the stock value. Therefore, a larger tick size can lead to less price efficiency. Zhao and Chung (2006) propose an alternative story and argue that a wider tick size may improve price efficiency. They argue that a larger tick size reduces the front-running risk for investors as it is more expensive for front-runners to step in front of existing orders and to receive execution precedence by improving their price. Reducing front-running risk increases the profit for informed traders, which motivates them to gather more information. Thus, there will be more information-based trading which improves price efficiency. We will empirically test the above competing arguments in the rest of this subsection.

We use the following regression to investigate the impact of widening the tick size on price efficiency. We estimate the following regressions separately for each test group versus the control group.

$$PriceEfficiency_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta^{'} X_{i,t} + \epsilon_{i,t}. \qquad (14)$$

In the above regressions, $PriceEfficiency_{i,t}$ is a measure of price efficiency for stock i on day t. We use two proxies as our measure for price efficiency. The first measure follows Bris, Goetzmann and Zhu (2007), in which price efficiency is calculated as the autocorrelation of stock return ($AR10$). The second measure follows Hasbrouck (1993) and Boehmer and Kelley (2009), in which price efficiency is measured as the pricing error (Prc_error). $Pilot$ is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to reduce noise induced by the implementation of the pilot program, we drop observations in October 2016. *Post* is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. Similar to the analyses in Section 4, X is a vector of control variables including share turnover, the inverse of share price, the difference between the highest ask price and the lowest bid price, and the natural log of market cap. We also control the stock primary listed exchange and time fixed effects. We cluster the standard errors at the firm level in order to account for cross-sectional dependence.

The results of the above regressions are reported in Table 5. Columns (1) to (3) use return autocorrelation ($AR10$) as dependent variable. Columns (4) to (6) use pricing error (Prc_error) as dependent variable.

Columns (1) and (4) show the impact of a larger tick size on price efficiency for stocks from test group 1 compared to the control group, following the implementation of the pilot program. Columns (2) and (5) show the impact of a larger tick size on price efficiency for stocks from test group 2 compared to the control group. Columns (3) and (6) show the impact on stocks from test group 3. The coefficient of interest is $Post \times Pilot$. We find that for all three pilot groups, the coefficient on $Post \times Pilot$ is positive and significant (at the 1% level). These results suggest that there is a significant decrease in price efficiency following the adoption of a larger tick size for all three test groups. Combined with the results of decreasing trading volume, our empirical results indicate that a wider tick size reduces the informed investors' likelihood of trading, consistent with the prediction of Anshuman and Kalay (1998). In summary, we find strong empirical evidence that a larger tick size decreases the price efficiency for stocks in the pilot groups compared to those in the control group after the implementation of the pilot program.

5.2 Impact of Widening Tick Size on Speed of Market Responding to News

We have shown thus far that a larger tick size, as a result of the implementation of the pilot program, reduces the liquidity and price efficiency of the stocks of pilot groups compared to those of the control group. In this subsection, we investigate how the larger tick size affects the speed at which traders respond to company-related news.

As it is likely to be costly to follow news on each stock, investors who trade largely based on news need to make a significant investment in their trading technologies in order to rapidly respond to company-related news. A larger tick size, however, reduces the number of profitable trading opportunities and reduces the profit for investors who trade on news (see, e.g., Anshuman and Kalay (1998)). Given this, we would expect a decrease in the monitoring activeness or a decrease in the number of news arbitragers that follow stocks in the pilot (test) groups. Therefore, we expect that it would take longer for news to be incorporated into the price of the pilot stocks after their tick size becomes larger, as a result of the pilot program.

Following Beschwitz, Keim, and Mass (2015), we use the amount of two-minute price change that takes place within the first 10 seconds as our first measure for market reaction speed. Our second measure is based on the two-minute volume change that takes place in the first 10 seconds. As both measures are bounded between 0 and 1, we use the two-limit tobit model to investigate the impact of widening tick size on the speed of market responding to news. We estimate the following model separately for each test group.

$$Response_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}, \qquad (15)$$

where the dependent variable, $Response_{i,t}$, is the market reaction speed for stock i on day t. We drop firm-day observations if there is no news release for a particular firm on that day. $Pilot$ is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. Similar to the analysis above, we drop observations from October 2016. $Post$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. We include the same set of control variables as in earlier sections. β_3 is the coefficient of our interest, which captures the change in the news response speed for stocks in the test group after the implementation of the pilot program. We cluster the standard errors at the firm level to account for cross-sectional dependence.

We report the results of the above regressions in Table 6. Columns (1) to (3) report the results using the price response speed ($PriceResponse$) as dependent variables. Columns (1) and (2) shows that the speed of stock price reacting to news in test groups 1 and 2 decreases significantly following the implementation of the pilot program, compared to that of stocks in the control group.

The impact of widening the tick size on the speed of stock price reacting to news for stocks in pilot group 3 is less clear. Stocks in test group 3 will adhere to the requirement of the second test group, but will also be subject to a "trade-at" requirement. The trade-at rule requires execution priority to be given to lit orders, unless dark orders can provide meaningful price improvement than the lit ones. This rule makes dark trading more costly. However, the impact of this rule is less clear. As discussed in Zhu (2014) and Comerton-Forde and Putnis (2015), orders executed in the dark tend to be less informed. With increased dark trading costs, uninformed investors may migrate to the lit market. As a result of an increased amount of noise trading in the lit market, price becomes less efficient and it takes longer for the market to incorporate news. However, increased dark trading costs may significantly increase uninformed investors' execution costs, and therefore some uninformed investors may stop trading the pilot stocks completely. This may lead to a decrease in noisy trading in the lit market, thus increasing the speed of market reaction to news. On the other hand, according to Ye (2011) dark trading are more informed. Reduced dark trading may incentivize informed traders to migrate to the lit market or squeeze them completely out of the market. Therefore, which of these channel dominates is an empirical question to be tested. Column (3) reports the effect of widening the tick size on stock price response speed for stocks in pilot group 3 compared to that of stocks in the control group. We find that the speed of stock price reacting to news for stocks in pilot group 3 becomes slower after the implementation of the pilot program.

Columns (4) to (6) in Table 6 report regression results using $VolumeResponse$ (volume response speed) as dependent variables. The results are consistent with the results reported in Columns (1) to (3). We find that there is a significant drop in the volume response speed for stocks in pilot groups 1 and 2, compared to that for the control group, while there is only an insignificant drop in the volume response speed for pilot group 3.

In Table 6, we use price and volume change to measure the speed at which market reacts to news. As one may argue that market makers may respond to news differently, we also use quote change as a measure of market makers' response speed to news and faster quote changes indicate a faster reaction to news. We re-run the regressions as Equation 15 using these quote change measures as dependent variables, and report the results of these regressions in Table 7. We find results consistent with those reported in Table 6.

Overall, our results in this section demonstrate that a wider tick size decreases market efficiency for stocks in all three pilot groups in terms of decreasing the speed of their stock price reacting to news. Such decreases are most pronounced for stocks in pilot group 2, and least significant for stocks in pilot group 3.

5.3 Impact of Widening Tick Size on Probability of Informed Trading

Our results in the previous subsection show that a larger tick size hurts price efficiency and decreases the speed of stock price reacting to news. In the rest of this subsection, we study how a larger tick size affects information asymmetry using the probability of informed trading (PIN) as a measure of information-based trading. Higher probability of informed trading implies greater market inefficiency and more information asymmetry. Following Easley et al. (1996), we use PIN as a measure of information asymmetry. We estimate the following regressions separately for each test group versus the control group.

$$PIN_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}, \qquad (16)$$

where $PIN_{i,t}$ is the probability of informed trading for stock i in month t. $Pilot$ is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. Similar to the analysis above, we drop observations from October 2016. $Post$ is a dummy variable equal to 1 for dates on or after November, 2016, and 0 otherwise. We include the same set of control variables (X) as in earlier sections. β_3 is the coefficient of our interest, which captures the change in the level of information based trading for stocks in the test group after the implementation of the pilot program. We cluster the standard errors at the firm level to account for cross-sectional dependence.

The results of the above regressions are reported in Table 8. Columns (1) to (3) report the impact of widening the tick size on the level of informed trading for stocks from test groups 1, 2 and 3, respectively. The coefficient of interest is the coefficient of $Post \times Pilot$. We find that, for all three pilot groups, the coefficients on $Post \times Pilot$ are positive and significant (at the 1% level), suggesting that there is a significant increase in the probability of informed trading for stocks in the test groups compared to those of the control group. PIN can be regarded as the ratio of informed order flow over total order flow. Our paper also finds a reduction in trading volume after the implementation of the pilot program (Table 4). One plausible explanation for an increase in PIN is that the order flow from liquidity traders declines more significantly after the pilot program implementation. The combined results on PIN and volume, therefore, indicate that larger tick sizes impose larger constraints for liquidity traders than for informed traders.

6 Impact of Widening Tick Size on Stock Price

In earlier sections, we find that a larger tick size leads to a significant increase in the trading costs for stocks in the pilot groups and a significant decrease in the price efficiency of such stocks. A natural question is how the decreasing market liquidity and price efficiency affects the price of stocks in the pilot groups.

Following Amihud, Mendelson, and Lauterbach (1997), we use abnormal stock returns to measure the impact of widening the tick size on stock price. We calculate the abnormal returns using the Fama-French three factor and the momentum factor as follows:

$$R_{i,t} - R_{f_t} = \alpha_i + \beta_{i,1}(R_{m_t} - R_{f_t}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}MOM_t + \epsilon_{i,t}, \quad (17)$$

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. $R_{i,t} - R_{f_t}$ and $R_{m_t} - R_{f_t}$ represent the stock excess return and market excess return, respectively. 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. MOM_t is the momentum factor.

We estimate the model parameters using pre-sample data (i.e., the year of 2015). We then calculate the abnormal return as follows:

$$AR_{i,t} = (R_{i,t} - R_{f_t}) - (\hat{\alpha}_i + \hat{\beta_{i,1}}(R_{m_t} - R_{f_t}) + \hat{\beta_{i,2}}SMB_t + \hat{\beta_{i,3}}HML_t + \hat{\beta_{i,4}}MOM_t), \tag{18}$$

where $AR_{i,t}$ is the abnormal return for stock i on day t. $\hat{\alpha}_i$, $\hat{\beta_{i,1}}$, $\hat{\beta_{i,2}}$, $\hat{\beta_{i,3}}$, and $\hat{\beta_{i,4}}$ are the coefficients that we estimate for each firm using pre-sample data.

As the pilot program is implemented on a staggered basis, we estimate the following OLS regression to investigate the impact of widening tick size on stock return:

$$\begin{aligned} AR_{i,t} =& \alpha + \beta_1 Pilot + \beta_2 September1 + \beta_3 September2 + \beta_4 October1 + \beta_5 October2 \\ & + \beta_6 November1 + \beta_7 Novermber2 + \beta_8 Post + \beta_9 Pilot \times September1 \\ & + \beta_{10} Pilot \times September2 + \beta_{11} Pilot \times October1 + \beta_{12} Pilot \times October2 \\ & + \beta_{13} Pilot \times November1 + \beta_{14} Pilot \times Novermber2 + \beta_{15} Pilot \times Post + \epsilon_{i,t}, \end{aligned} \tag{19}$$

where $AR_{i,t}$ is the abnormal return for stock i on day t. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. $September1$ is a dummy variable equal to 1 for dates between September 01, 2016 and September 15, 2016, and 0 otherwise. $September2$ is a dummy variable equal to 1 for dates between September 16, 2016 and September 30, 2016, and 0 otherwise. $October1$ is a dummy variable equal to 1 for dates between October 01, 2016 and October 15, 2016, and 0 otherwise. $Octover2$ is a dummy variable equal to 1 for dates between October 16, 2016 and October 31, 2016, and 0 otherwise. $November1$ is a dummy variable equal to 1 for dates between November 01, 2016 and November 15, 2016, and 0 otherwise.. $November2$ is a dummy variable equal to 1 for dates between November 16, 2016 and November 30, 2016, and 0 otherwise. $Post$ is a dummy variable that equal to 1 for dates on or after December 1, 2016, and 0 otherwise. We also include all interaction terms of each date dummy and $Pilot$. We include the same set of control variables as in earlier sections. We cluster the standard errors at the firm level to account for cross-sectional dependence. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark.

We sort and divide our sample firms into terciles based on their average dollar quoted spread before the implementation of the Tick Size Pilot program. The bottom (top) tercile contains stocks with the smallest (largest) average dollar quoted spread. Columns (1) to (3) of Table 9 report regression results for stock returns with the lowest dollar quoted spread, and Columns (4) to (6) report regression results for stocks with the largest dollar quoted spread. The variables of interest here are the interaction terms between the $Pilot$ dummy and date dummy.

In Columns (1) and (2), we test the impact of widening the tick size on small spread stocks from test groups 1 and 2, respectively. We find that stocks in both pilot groups lose 0.2% in risk-adjusted return each day between November 01, 2016 and November 15, 2016. This yields about 2.2% decrease in total value. Widening the tick size leads to another 0.1% daily value decrease between October 16, 2016 and October 31, 2016, although the value deduction in October is statistically insignificant.

Column (3) reports the impact of widening the tick size on the abnormal returns of liquid stocks in test group 3. The daily abnormal returns for these stocks is -0.4% in the first half of November, and -0.1% (insignificant) in the second half of October. Similarly, Columns (4) to (6) report the impact of widening the tick size on the abnormal returns of illiquid stocks in the pilot groups. We find a insignificant value decrease from October 15, 2016 to November 15, 2016 for these stocks.

Our results suggest that a larger tick size leads to a price drop for stocks due to decreasing price efficiency and increasing trading costs. Further, such value destruction is more pronounced for stocks with tight quoted spreads as they are the most affected by binding constraints.

7 Conclusion

Does the implementation of the Tick Size Pilot Program come with real costs to a company? In 2012, the US Congress directed SEC to implement a tick size pilot which would generate data to investigate the impact of tick size. The Congress generally believes that an increased tick size would encourage market participants to provide liquidity. More market making would increase both liquidity and analyst coverage, and hence attract more investors to trade those small cap stocks resulting in more volume.

Making use of this clean and novel natural experiment, we provide strong empirical evidence on the causal impact of a larger tick size on liquidity and price efficiency using a difference-in-difference framework. We find that widening the tick size increases quoted, effective spread, realized spread, and leads to higher trading costs for investors. We also find that widening the tick size significantly reduces stock trading volume, damages price efficiency and slows market response speed to company-related news. This leads to more information asymmetry and increases general investors' risk of being adverse selected. Finally, we find that an increase in tick size leads to a value destruction as large as 2.2% for stocks with tight spreads before the program initiation. These stocks experience a significant return decrease immediately after the implementation, and the returns are not reversed in our sample period. More importantly, our paper sheds light on the real costs of implementing a natural experiment. The Tick Size Pilot Program commencing on October 3, 2016 will be in effect for a two-year period. It would be interesting to test whether the costs of the pilot program can be recovered when the program ends. We defer this for future work.

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Table 1: **Firm Characteristics of the Treatment and Control Groups**

Panel A reports the summary statistics of the firm characteristics for the treatment and control groups. Panel B reports the difference between the treatment and the control group. All characteristics are measured using December 2015. *Asset* and *Size* are measured in millions of dollars. The first row of each variable in Panel B reports the difference between Control and Treatment Group. The second row of each variable in Panel B reports the t-statistics for the difference. ***, **, and * indicate significance at the 1%, 5%, and 10% levels using two-tailed tests.

Panel A: Summary Statistics for Treatment and Control Groups

	C	G1	G2	G3
Mean				
N	954	324	317	310
Asset	1360	1278	1388	1274
Size	672	708	663	648
MB	4.72	5.90	3.04	3.87
CEQ	334	355	354	329
Volume	198995	214364	203769	211017
Quoted Spread	0.010	0.009	0.010	0.009
Realized Variance	1.34	0.85	0.99	2.06

Panel B: Difference between Treatment and Control Groups

Difference (Control - Test)			
Asset	81	-29	86
	(0.39)	(-0.13)	(0.40)
Size	-36	9	23
	(-0.73)	(0.18)	(0.47)
MB	-1.19	1.67	0.84
	(-0.61)	(1.37)	(0.64)
CEQ	-21	-19	5
	(-0.75)	(-0.68)	(0.17)
Volume	-5608	-4389	-4979
	(-0.37)	(-0.29)	(-0.33)
Quoted Spread	0.001	-0.001	0.000
	(0.92)	(-0.59)	(0.17)
Realized Variance	0.78	0.47	-0.89
	(1.44)	(0.79)	(-1.33)

Table 2: **Summary Statistics for Key Variables**

Panel A of this table reports summary statistics for the control group. Panel B (C/D) reports the summary statistics for test group 1 (2/3), 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, *RealizedSprd* is the dollar-volume-weighted average of percent realized spread, $MarketDepth$ is the time-weighted average displayed depth at the NBBO, $Volume$ is the daily volume, *no_trades* is total number of trades, $Volatility$ is the realized variance, $AR10$ and PRC_Error are our price efficiency measures. $MarketDepth$ and $Volume$ are measured in hundreds of shares. We winsorize the upper and lower 1% of each variable to avoid outliers. We also delete firm day observations if its share price is below $2.

Panel A: Summary statistics for Control Group

C	N	Mean	SD	Median	Min	Max
QuotedSprd	303176	0.010	0.014	0.004	0.001	0.081
EffectiveSprd	299943	0.009	0.018	0.003	0.000	0.128
PriceImpact	299883	0.004	0.010	0.001	-0.006	0.074
RealizedSprd	300050	0.004	0.013	0.001	-0.012	0.084
MarketDepth	303176	887	4624	493	100	925021
Volume	300282	214591	514654	100471	1	82286659
no_trades	303176	6194	7051	4443	1	223238
Volatility	302938	1.35	9.78	0.00	0.00	84.89
AR10	230318	0.30	0.14	0.29	0.00	0.94
PRC Error	189530	0.18	0.16	0.14	0.01	1.09

Panel B: Summary statistics for Test Group 1

G1	N	Mean	SD	Median	Min	Max
QuotedSprd	103561	0.009	0.012	0.004	0.001	0.081
EffectiveSprd	102867	0.008	0.015	0.003	0.000	0.128
PriceImpact	102844	0.004	0.008	0.002	-0.006	0.074
RealizedSprd	102895	0.004	0.011	0.001	-0.012	0.084
MarketDepth	103561	1626	6815	652	100	734581
Volume	102939	216967	439437	96332	1	48471109
no_trades	103561	5448	8083	3366	1	213357
Volatility	103478	0.74	7.07	0.00	0.00	84.89
AR10	78726	0.33	0.13	0.33	0.00	0.90
PRC Error	63194	0.18	0.15	0.15	0.00	1.09

Panel C: Summary statistics for Test Group 2

G2	N	Mean	SD	Median	Min	Max
QuotedSprd	101046	0.010	0.014	0.005	0.001	0.081
EffectiveSprd	100033	0.008	0.015	0.003	0.000	0.128
PriceImpact	100022	0.004	0.009	0.002	-0.006	0.074
RealizedSprd	100044	0.004	0.011	0.001	-0.012	0.084
MarketDepth	101046	1519	10271	659	159	1090737
Volume	100113	209029	384908	95508	1	24601296
no_trades	101046	5261	7653	3398	1	1012440
Volatility	100970	0.97	8.55	0.00	0.00	84.89
AR10	75247	0.33	0.13	0.33	0.00	0.95
PRC Error	60423	0.18	0.15	0.15	0.01	1.09

Panel D: Summary statistics for Test Group 3

G3	N	Mean	SD	Median	Min	Max
QuotedSprd	98732	0.009	0.013	0.004	0.001	0.081
EffectiveSprd	97960	0.009	0.019	0.003	0.000	0.128
PriceImpact	97941	0.005	0.011	0.002	-0.006	0.074
RealizedSprd	97975	0.004	0.013	0.001	-0.012	0.084
MarketDepth	98732	1742	8652	679	100	1120918
Volume	98035	219072	419452	97894	1	32196627
no_trades	98732	5612	15528	3673	1	4282615
Volatility	98667	1.91	11.33	0.00	0.00	84.89
AR10	75008	0.32	0.14	0.32	0.00	0.93
PRC Error	60641	0.20	0.19	0.15	0.01	1.09

Table 3: **Impact of Tick Size on Spreads**

This table reports OLS regression results of the following Panel OLS regressions: $Liquidity_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $Liquidity_{i,t}$ is a measure of liquidity for stock i on day t. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to avoid any contaminating effects associated with the implementation of wider tick size, we drop observations in October 2016. *Post* 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 including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. Panel A (B/C) reports the impact of widening tick size on liquidity for stocks from test group 1 (2/3) relative to the control group. We conduct the above difference-in-difference regressions separately for each test group using all control firms as a benchmark. All spread measures are winsorized at the 1 and 99 percentile to avoid outlier effects. Columns (1) to (5) report results using percent quoted spread, percent effective spread, percent price impact, percent realized spread, and volatility as a measure of liquidity. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	RealizedSprd (4)
Post	-0.000*	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Pilot	-0.001	-0.001	-0.001**	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Pilot x Post	0.001***	0.001**	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.014***	0.012***	0.004***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	406,389	402,466	402,383	402,601
Adjusted R-squared	0.160	0.117	0.066	0.075
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Table 3: **Impact of Tick Size on Spreads**

Panel B: Pilot Group 2

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	RealizedSprd (4)
Post	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Pilot	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Pilot x Post	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.013***	0.011***	0.004***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	403,868	399,627	399,556	399,745
Adjusted R-squared	0.161	0.113	0.062	0.074
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Table 3: **Impact of Tick Size on Spreads**

Panel C: Pilot Group 3

	QuotedSprd (1)	EffectiveSprd (2)	PriceImpact (3)	RealizedSprd (4)
Post	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Pilot	-0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Pilot x Post	0.001***	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.014***	0.012***	0.003***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	401,870	397,872	397,793	397,994
Adjusted R-squared	0.156	0.109	0.063	0.071
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Table 4: **Impact of Widening Tick Size on Market Depth, Trading Volume and Volatility**

This table reports OLS regression results of the following Panel OLS regressions: $Liquidity_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $Liquidity_{i,t}$ is a measure of liquidity for stock i on day t. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to avoid any contaminating effects associated with the implementation of wider tick size, we drop observations in October 2016. *Post* 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 including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. Panel A (B/C) reports the impact of widening tick size on liquidity for stocks from test group 1 (2/3) relative to the control group. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark. Columns (1) to (4) report results using dollar-depth, daily number of trades and total daily trading volume, and volatility as measures of liquidity. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1

	MarketDepth	n_trades	Volume	Volatility
	(1)	(2)	(3)	(4)
Post	0.405	0.171***	17.991***	0.247
	(0.826)	(0.031)	(3.509)	(0.155)
Pilot	0.043	0.065	10.737	-0.426
	(0.584)	(0.102)	(13.402)	(0.456)
Pilot x Post	16.886***	-0.297***	-15.004**	-0.358
	(2.475)	(0.046)	(6.391)	(0.290)
Constant	7.105*	0.295*	20.044	3.625**
	(4.215)	(0.158)	(19.608)	(1.637)
Observations	406,389	402,877	402,877	406,069
Adjusted R-squared	0.048	0.301	0.138	0.013
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Table 4: **Impact of Widening Tick Size on Market Depth, Trading Volume and Volatility**

Panel B: Pilot Group 2

	MarketDepth (1)	n_trades (2)	Volume (3)	Volatility (4)
Post	-0.018	0.156***	15.927***	0.197
	(1.235)	(0.031)	(3.555)	(0.156)
Pilot	-0.308	0.030	3.817	-0.296
	(0.504)	(0.102)	(12.833)	(0.518)
Pilot x Post	17.913***	-0.306***	-13.806**	-0.087
	(4.467)	(0.049)	(6.506)	(0.237)
Constant	7.398*	0.209	13.415	3.198**
	(4.095)	(0.156)	(17.321)	(1.526)
Observations	403,868	400,046	400,046	403,555
Adjusted R-squared	0.022	0.302	0.146	0.007
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Table 4: **Impact of Widening Tick Size on Market Depth, Trading Volume and Volatility**

Panel C: Pilot Group 3

	MarketDepth	n_trades	Volume	Volatility
	(1)	(2)	(3)	(4)
Post	-0.397	0.168***	16.942***	0.383**
	(0.888)	(0.032)	(3.539)	(0.166)
Pilot	0.316	0.041	9.627	0.783
	(0.665)	(0.102)	(12.984)	(0.684)
Pilot x Post	22.531***	-0.221***	-7.772	-0.384
	(3.926)	(0.052)	(7.193)	(0.326)
Constant	6.440*	0.296**	14.862	2.976*
	(3.400)	(0.140)	(15.574)	(1.576)
Observations	401,870	398,285	398,285	401,568
Adjusted R-squared	0.049	0.306	0.144	0.010
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Table 5: **Impact of Widening Tick Size on Price Efficiency**

This table reports OLS regression results of the following Panel OLS regressions: $PriceEfficiency_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $PriceEfficiency_{i,t}$ is a measure of price efficiency for stock i on day t. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to avoid any contaminating effects associated with the implementation of wider tick size, we drop observations in October 2016. *Post* 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 including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark. Both price efficiency measures are winsorized at the 1 and 99 percentile points to avoid outlier effect. 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. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		AR10			Prc_error	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.008***	0.008***	0.008***	-0.000	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)
Pilot	0.001			-0.005		
	(0.004)			(0.010)		
Pilot x Post	0.059***			0.016***		
	(0.005)			(0.004)		
Pilot		0.002**			-0.005***	
		(0.001)			(0.001)	
Pilot x Post		0.053***			0.019***	
		(0.001)			(0.001)	
Pilot			0.003			0.015
			(0.004)			(0.013)
Pilot x Post			0.042***			0.016***
			(0.005)			(0.005)
Constant	0.347***	0.354***	0.350***	0.326***	0.333***	0.335***
	(0.008)	(0.002)	(0.009)	(0.061)	(0.004)	(0.065)
Observations	308,768	305,464	305,322	252,595	249,924	250,168
Adjusted R-squared	0.031	0.027	0.023	0.042	0.040	0.044
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: **Trade Response Speed to News**

This table reports OLS regression results of the following Panel OLS regressions: $Response_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $Response_{i,t}$ measures how fast trade reacts to news for stock i on day t. We drop firm-day observations if there is no news release for a particular firm on that day. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to avoid any contaminating effects associated with the implementation of wider tick size, we drop observations in October 2016. *Post* 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 including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark. Both response speed measures are winsorized at the 1 and 99 percentile points to avoid outliers. Columns (1) to (3) use price response speed as dependant variable. $PriceResponse = \frac{abs(return_{t-1,t+10})}{abs(return_{t-1,t+10}) + abs(return_{t+10,t+120})}$, where $abs(Return_{t-1,t+10})$ is the absolute stock return from 1 second before news release to 10 seconds after the news announcement. $abs(Return_{t+10,t+120}$ represent the absolute stock return 10 seconds after the news announcement to 120 seconds (2 minutes) after the new announcement. Columns (4) to (6) use volume response speed as dependant variable. $VolumeResponse = \frac{volume_{t-1,t+10}}{volume_{t-1,t+10} + volume_{t+10,t+120}}$, where $volume_{t-1,t+10}$ is the trading volume executed from 1 second before news annoucement and 10 seconds after news announcement. $volume_{t+10,t+120}$ represents trading volume executed 10 seconds after news annoucement to 120 seconds after the news announcement. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Group1 (1)	Group2 (2)	Group3 (3)	Group1 (4)	Group2 (5)	Group3 (6)
Post	-0.119***	-0.093**	-0.115***	0.013	0.004	0.012
	(0.033)	(0.034)	(0.032)	(0.028)	(0.030)	(0.029)
Pilot1	0.010			0.015		
	(0.020)			(0.016)		
Pilot1 x Post	-0.195***			-0.052*		
	(0.032)			(0.021)		
Pilot2		-0.011			0.036*	
		(0.021)			(0.018)	
Pilot2 x Post		-0.209***			-0.090**	
		(0.045)			(0.027)	
Pilot3			-0.001			0.013
			(0.019)			(0.018)
Pilot3 x Post			-0.155***			-0.040
			(0.035)			(0.025)
Observations	21176	20268	20885	22325	21439	22021

Table 7: **Impact of Widening Tick Size on Quote Response Speed to News**

This table reports OLS regression results of the following Panel OLS regressions: $QuoteResponse_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $QuoteResponse_{i,t}$ represent quote reaction speed for stock i on day t. It captures the proportion of quote adjusted in the first 10 seconds after the news announcement. We drop firm-day observations if there is no news release for a particular firm on that day. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to avoid any contaminating effects associated with the implementation of wider tick size, we drop observations in October 2016. *Post* 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 including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark. Both response speed measures are winsorized at the 1 and 99 percentile points to avoid outliers. Columns (1) to (3) show the proportion of quote adjusted (including both NBBO changes and depth at NBBO changes) in the first 10 seconds after the news announcement. Columns (4) to (6) only count the number of NBBO changes and ignore depth at NBBO changes. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Group1 (1)	Group2 (2)	Group3 (3)	Group1 (4)	Group2 (5)	Group3 (6)
post	-0.031**	-0.035**	-0.037**	-0.060**	-0.053*	-0.063**
	(0.012)	(0.013)	(0.012)	(0.021)	(0.022)	(0.021)
g1	-0.001			-0.000		
	(0.007)			(0.012)		
post_g1	-0.022*			-0.086***		
	(0.009)			(0.019)		
g2		0.006			0.004	
		(0.007)			(0.013)	
post_g2		-0.035***			-0.111***	
		(0.009)			(0.026)	
g3			0.003			-0.004
			(0.006)			(0.011)
post_g3			-0.017			-0.072**
			(0.009)			(0.023)
Observations	26985	25914	26642	22302	21339	22012

Table 8: **Impact of Widening Tick Size on Informed Trading**

This table reports OLS regression results of of the following Panel OLS regressions: $PIN_{i,t} = \alpha + \beta_1 Post + \beta_2 Pilot + \beta_3 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $PIN_{i,t}$ is the probability of informed trading for stock i on month t. *Pilot* is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. In order to avoid any contaminating effects associated with the implementation of wider tick size, we drop observations in October 2016. *Post* is a dummy variable equal to 1 for dates on or after November, 2016, and 0 otherwise. X is a vector of control variables including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark. Columns (1) to (3) report the impact of widening tick size on the probability of informed trading for stocks in pilot groups 1, 2, and 3, respectively. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Group1	Group2	Group3
Post	0.002	0.007*	0.016***
	(0.004)	(0.004)	(0.005)
Pilot1	0.001		
	(0.005)		
Pilot1 x Post	0.022***		
	(0.004)		
Pilot2		0.001	
		(0.005)	
Pilot2 x Post		0.021***	
		(0.004)	
Pilot3			-0.000
			(0.005)
Pilot3 x Post			0.017***
			(0.005)
Constant	0.311***	0.308***	0.308***
	(0.008)	(0.008)	(0.008)
Observations	17,221	17,085	17,013
Adjusted R-squared	0.050	0.052	0.045
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes

Table 9: **Abnormal Return**

This table reports OLS regression results of of the following Panel OLS regressions: $AR_{i,t} = \alpha + \beta_1 Pilot + \beta_2 September1 + \beta_3 September2 + \beta_4 October1 + \beta_5 October2 + \beta_6 November1 + \beta_7 Novermber2 + \beta_8 Post + \beta_9 Pilot \times September1 + \beta_{10} Pilot \times September2 + \beta_{11} Pilot \times October1 + \beta_{12} Pilot \times October2 + \beta_{13} Pilot \times November1 + \beta_{14} Pilot \times Novermber2 + \beta_{15} Pilot \times Post + \epsilon_{i,t}$ where $AR_{i,t}$ is the abnormal return for stock i on day t. $Pilot$ is a dummy variable equal to 1 if a company belongs to the test group, and 0 otherwise. $September1$ is a dummy variable equal to 1 for dates between September 01, 2016 and September 15, 2016, and 0 otherwise. $September2$ is a dummy variable equal to 1 for dates between September 16, 2016 and September 30, 2016, and 0 otherwise. $October1$ is a dummy variable equal to 1 for dates between October 01, 2016 and October 15, 2016, and 0 otherwise. $Octover2$ is a dummy variable equal to 1 for dates between October 16, 2016 and October 31, 2016, and 0 otherwise. $November1$ is a dummy variable equal to 1 for dates between November 01, 2016 and November 15, 2016, and 0 otherwise.. $November2$ is a dummy variable equal to 1 for dates between November 16, 2016 and November 30, 2016, and 0 otherwise. $Post$ is a dummy variable that equal to 1 for dates on or after December 1, 2016, and 0 otherwise. We also include all interaction terms of each date dummy and $Pilot$. X is a vector of control variables including share turnover, the inverse of the share price, the difference between the highest ask price and the lowest bid price, and natural log of market cap. We also control for time and stock primary listed exchange fixed effects. The inclusion of month-fixed effects controls for shocks that are common to all stocks, whereas that of listing exchange fixed effects controls for the possible systematic differences between stocks listed on NYSE and those listed on NASDAQ. We cluster the standard errors at the firm level to account for cross-sectional dependence. We conduct the above difference-in-difference regressions separately for each test group using all the control firms as a benchmark. Columns (1) to (3) report regression results for stocks with lowest average dollar quoted spread, and Columns (4) to (6) report regression results for stock with highest average dollar quoted spread ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Small dollar quoted spread stocks			Large dollar quoted spread stocks		
	Group1	Group2	Group3	Group1	Group2	Group3
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot1	-0.001			0.001***		
	(0.001)			(0.000)		
September1	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
September2	0.001***	0.001***	0.001***	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
October1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
October2	0.001***	0.001***	0.001***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
November1	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
November2	0.001*	0.001*	0.001*	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post	0.001***	0.001***	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pilot1 x September1	0.000			0.000		
	(0.001)			(0.001)		
Pilot1 x September2	-0.001			-0.000		
	(0.001)			(0.001)		
Pilot1 x October1	-0.000			0.001		
	(0.001)			(0.001)		
Pilot1 x October2	-0.001			0.000		
	(0.001)			(0.001)		
Pilot1 x November1	-0.002*			-0.000		
	(0.001)			(0.001)		
Pilot1 x November2	0.000			0.000		
	(0.001)			(0.001)		
Pilot1 x Post	-0.000			-0.000		
	(0.000)			(0.000)		
Pilot2		0.001			0.000	
		(0.000)			(0.000)	
Pilot2 x September1		0.000			-0.001	
		(0.001)			(0.001)	
Pilot2 x September2		-0.001			0.000	
		(0.001)			(0.001)	
Pilot2 x October1		0.000			-0.000	
		(0.001)			(0.001)	
Pilot2 x October2		-0.001			-0.000	
		(0.001)			(0.001)	
Pilot2 x November1		-0.002*			-0.000	
		(0.001)			(0.001)	
Pilot2 x November2		0.001			-0.001	
		(0.001)			(0.001)	
Pilot2 x Post		0.000			-0.000	
		(0.000)			(0.000)	
Pilot3			0.000			0.000
			(0.000)			(0.000)
Pilot3 x September1			-0.001			-0.000
			(0.001)			(0.001)
Pilot3 x September2			-0.000			0.000
			(0.001)			(0.001)
Pilot3 x October1			-0.000			-0.001
			(0.001)			(0.001)
Pilot3 x October2			-0.001			-0.001
			(0.001)			(0.001)
Pilot3 x November1			-0.004***			0.001
			(0.001)			(0.001)
Pilot3 x November2			-0.001			-0.001
			(0.001)			(0.001)
Pilot3 x Post			-0.000			0.000
			(0.000)			(0.000)
Constant	-0.004	-0.005	-0.006	-0.001*	-0.001	-0.001*
	(0.003)	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)
Observations	133,726	127,298	129,060	134,661	134,328	133,339
R-squared	0.001	0.001	0.001	0.001	0.000	0.000
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes	Yes