

# The Impact of Make-Take Fees on Market Efficiency\*

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## Abstract

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# **The Impact of Make-Take Fees on Market Efficiency**

## **Abstract**

Recently, stock exchanges have altered their trading fees to subsidize liquidity by offering “make” rebates for providing liquidity through limit orders and charging “take” fees for consuming liquidity via marketable orders, leading to debate regarding the impact of these fees on market quality. Using an exogenous experiment performed by NASDAQ in 2015, I employ difference-in-differences analysis on a matched sample and find that a decrease in take fee and make rebate levels leads to greater absolute pricing error and larger variance of mispricing. This stems from widened bid-ask spreads and decreased informed trading by retail investors.

# The Impact of Make-Take Fees on Market Efficiency

## 1. Introduction

Informational efficiency in financial markets is of paramount interest to financial economists because efficient security prices result in efficient allocation of capital, which contributes to economic growth. Over the past two decades, the informational efficiency of prices has increased dramatically due to market improvements such as decimalization, tick-size reduction, and increased institutional trading (Chordia, Roll, and Subrahmanyam, 2008, 2011). One other such change to financial markets has been the introduction of the “maker-taker” pricing model of market access fees, in which traders providing liquidity receive a rebate, and those consuming liquidity pay a fee. These make-take fees, largely made possible by Reg NMS (Regulation National Market System) in 2005, have quickly become one of the most debated aspects of market design (SEC, 2016).

Angel, Harris, and Spatt (2011) call for a ban of these market access fees, citing increased agency cost between brokers and clients. Battalio, Corwin, and Jennings (2016) document that higher make-take fee levels are associated with poorer limit order execution. On the contrary, other studies – including Brolley and Malinova (2013), Malinova and Park (2015), and Anand, Hua, and McCormick (2016) – show that make-take fees result in reduced transaction costs, particularly for retail investors, and lower execution costs. However, while the existing literature examines the effect of make-take fees on the liquidity of a market, there have been no forays into the effect of make-take fees on the informational efficiency of security prices. In this paper, I investigate the empirical relationship between make-take fees and market efficiency.

Using the NASDAQ Access Fee Experiment in 2015 as a source of exogenous variation in make-take fees, I examine the resulting change in market efficiency. Utilizing propensity score matching and difference-in-differences (DiD) regressions, I find that an exogenous decrease in make-take fees causes a deterioration in market efficiency, namely an increase in absolute pricing error and an increase in the variance of mispricing. I show that this occurs because bid-ask spreads widen and fewer informative trades are executed. This suggests that make-take fees are beneficial for market efficiency.

In 2005, in hopes of further alleviating market fragmentation and creating a more cohesive national market for securities, the SEC (U.S. Securities and Exchange Commission) introduced Reg NMS, which established rules for market data, order protection (price priority), and market access fees, which were limited to \$0.0030 per share traded (or hereafter referred to as 30¢ per 100 shares traded). The “maker-taker” pricing model of market access fees has since developed due to increased competition for trading volume between stock exchanges. In this model, traders with direct market access (DMA) – namely brokers and broker-dealers – are charged a “take” fee when removing liquidity from the market via marketable orders and given a “make” rebate when providing liquidity through limit orders. For example, for the majority of orders and stocks in 2015, NASDAQ had a 30/29 fee structure in place. This meant that for every 100 shares, a trader would be assessed a 30¢ fee for consuming liquidity and credited a 29¢ rebate for providing liquidity. Meanwhile, NASDAQ itself would keep the 1¢ difference.

In February of 2015, NASDAQ – in hopes of increasing its market share (NASDAQ, 2014) – experimentally lowered its fee structure from 30/29 to 5/4 on 14 stocks for a four month

period. This change in fee structure could hypothetically have two alternative effects on informational efficiency.

First, market makers may widen their bid-ask spreads to compensate for the marginal loss of exchange rebates, as shown by Brolley and Malinova (2013), Malinova and Park (2015), and Anand, et al. (2016), which will increase transaction costs (particularly for traders without direct market access<sup>1</sup>). This increased cost of trading may, in turn, discourage informed traders from trading if they indeed prefer the immediacy of marketable orders over the uncertainty of limit orders. This would lead to a marginal decrease in the amount of information transmitted through trading. The decrease in information dissemination could then lead to a deterioration in market efficiency.

Alternatively, the lower cost of trading (lower take fees) on a public exchange like NASDAQ may encourage some orders – which would otherwise be routed to dark pools – to be routed to “lit” exchanges.<sup>2</sup> This would actually have a positive effect on information transmission, as more trades would be executed in the public eye, ultimately improving market efficiency.

In practice, it is quite possible that when the make-take fees are altered both the liquidity effect and the volume effect simultaneously impact the informational efficiency of a stock’s price, leading to conflicting *ex ante* hypotheses. In addition, Skjeltorp, Sojli, and Tham (2013) as well as Chung and Hrazdil (2010) conclude that the effect of make-take fees depends

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<sup>1</sup> Many traders, including retail and numerous institutional investors, do not have direct market access, but rather trade through a broker. This is an important point raised by Brolley and Malinova (2013) because, in practice, these traders have the bid and ask prices from the exchange passed on to them, but not the volume-based market access fee. They instead pay a flat fee. While this flat fee will also change in the long run, the authors show that in equilibrium, the higher flat fee does not offset the reduced bid-ask spread, and thus overall transaction costs reduce.

<sup>2</sup> In fact, this is what NASDAQ hypothesizes in its Dec. 12, 2014 SEC filing (NASDAQ, 2014).

largely on the degree of adverse selection occurring in the market, further increasing the ambiguity of the impact of make-take fees on market efficiency.

To answer the empirical question “How do make-take fees affect market efficiency?” I exploit the changes to make-take fees during the 2015 NASDAQ Access Fee Experiment. Using propensity score matching on pre-shock variables to alleviate concerns of selection bias, I create a control sample for a baseline comparison to the 14 treated stocks before, during, and after the NASDAQ Access Fee Experiment using difference-in-differences (DiD) regression specifications. Following Fotak, Raman, and Yadav (2014), I use a Kalman filter to estimate both the latent pricing error variable every minute as well as the latent variance of pricing error innovations parameter on a daily basis, while controlling for the bid-ask bounce. I find that when the NASDAQ reduces its access fee structure the treated stocks suffer an increase in mean absolute pricing error, as well as an increase in the variance of pricing error innovations, vis-à-vis the control stocks. This effect is in addition to, and cannot be explained simply by, widened bid-ask spreads during the experiment.

Furthermore, I show that during the access fee experiment, NASDAQ was less likely to possess the quote at the national best bid and/or the national best offer. I show that before and after the access fee experiment, the national best bid (ask) quote is on the NASDAQ 45.7% (46.1%) of the time. For stocks in the treatment group during the experiment, NASDAQ possessed the national best bid (ask) 13.3% (13.1%) less relative to the control stocks. I also find that the time NASDAQ possessed either/both of the NBBO (National Best Bid and Offer) quotes decreased during the access fee experiment, suggesting wider bid-ask spreads resulting from reduced make-take fees, at least on the NASDAQ. This is consistent

with Malinova and Park (2015) who document that bid-ask spreads narrow with higher make-take fees.

Chordia, et al. (2008) suggest that one reason liquidity and market efficiency may be associated is the increased incorporation of private information into market prices during more liquid regimes. To test this in regards to the access fee experiment, I examine the changes in adverse selection costs and find that for treatment group stocks, market makers lost less capital to informed traders during the lower make-take fee regime. This suggests that less private information was being incorporated into prices during this time, possibly explaining the steep increase in mispricing.

Finally, I consider the effect of the access fee experiment on trade volumes. While NASDAQ reports that they lost 1.5% market share on the treated stocks (relative to control stocks) during the low make-take fee regime, I find that NASDAQ lost 2.4% of the market share relative to the control group in this study. Delving further into the changes in volume, I find that overall volume actually increased during the experiment for treated stocks by 12% more than control stocks. However, this increase occurred on exchanges other than NASDAQ. This may suggest that the reduction in make-take fees actually did entice dark pool volume on to lit exchanges, however, brokers still routed marketable orders to the exchanges with higher rebates when possible.<sup>3</sup> Clearly, more data is needed to make conclusions in this area. The potential SEC-proposed market-wide access fee pilot program may allow further research to be conducted along this vein.

Overall, the empirical analysis suggests that an exogenous decrease in make-take fees is detrimental to market efficiency. Taken in conjunction with the recent literature's claims

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<sup>3</sup> For example, the BATS exchange had the next-highest rebates, with a 25/24 make-take fee structure.

that make-take fees are beneficial to market liquidity, it would not be altogether outlandish to conclude that make-take fees, while still highly debated, are actively improving market quality.

The remainder of the paper is organized as follows. In Section 2, I give a brief review of the relevant literature. In Section 3, I describe the NASDAQ Access Fee Experiment, as well as describe the data, matching process, and research methods. In Section 4, I complete the empirical analysis of the NASDAQ Access Fee Experiment. Finally, Section 5 contains my concluding remarks.

## **2. Literature Review**

Research in the area of make-take fees is still in its relative infancy. While analyzing new features of equity markets in the 21<sup>st</sup> century, Angel, et al. (2011) recommend that the SEC either require access fees to pass through to end-users, stipulate that fees be included in the order protection (price priority) rule, or simply ban access fees outright. They cite the increased agency costs between brokers and clients that arise from the maker-taker pricing model.

Since this recommendation, several theoretical works have analyzed aspects of market access fees. Colliard and Foucault (2012) emphasize the importance of distinguishing net fee and the breakdown between take fees and make rebates. They further show that an increase in net fee can either increase or decrease volume, based on several parameters. Empirically, Cardella, Hao, and Kalcheva (2015) find that an exchange's trading volume is decreasing in its net access fee. Hence, one very important aspect of this paper is that the net fee is held constant in the NASDAQ Access Fee Experiment.

Skjeltorp, et al. (2013) posit that make-take fees actually create a positive liquidity externality unless adverse selection is sufficiently high, in which case make-take fees may actually cause a negative liquidity externality because market makers are averse to trading opposite informed traders.

After recognizing that the choice between market and limit orders arises from a trader's inherent value of speed, Foucault, Kadan, and Kandel (2013) endogenize the demand for speed, and propose a model which shows that the breakdown of make and take fees becomes economically significant when the minimum tick size restricts bid-ask spread adjustment. Since markets now permit trades to be executed up to 4 decimal places, and access fees are in the 3 to 4 decimal range, this is of less concern, at least in US markets.

However, Brolley and Malinova (2013) show that because make-take fees are not, in practice, passed through brokers to end-use traders<sup>4</sup>, make-take fees should improve market quality in numerous aspects - lowering transaction costs, increasing trading volume, and improving welfare. These theoretical predictions are confirmed by Malinova and Park (2015). They use a change in make-take fees on the Toronto Stock Exchange to show that raw bid-ask spreads improve, but after adjusting for the fees, total transaction costs remain unaffected. However, since access fees are not passed to non-DMA traders, overall liquidity improves.

Similarly, Anand, et al. (2016) find that overall execution costs for liquidity demanders decline following the introduction of the make-take fee structure in options markets,

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<sup>4</sup> Rather than make-take fees, brokers typically charge a flat trade fee to its customers, which include retail traders, as well as other institutional traders not structured as brokers with direct market access. While these flat fees may increase in the long run, Brolley and Malinova (2013) show that in equilibrium, the increased fee does not offset the narrowed bid-ask spread, therefore overall transaction costs reduce.

consistent with increased quote competition. Lutat (2010), on the other hand, finds that spreads aren't affected by make-take fees, but depth at the best bid and ask quotes improves. Also related, Battalio, et al. (2016) document a negative relationship between limit order execution and rebate/fee levels.

This study builds upon Malinova and Park (2015) and Anand, et al. (2016) by showing that not only are bid-ask spreads improved by higher make-take fees, but that make-take fees also reduce mispricing. I show that this occurs through the information channel. Interestingly, Malinova and Park (2015) find that adverse selection costs actually decline as make-take fees increase while I show that adverse selection costs decline as make-take fees *decrease*.

This paper is also related to the vein of literature which relates liquidity to market efficiency. Particularly, Chordia, et al. (2008) find a positive correlation between liquidity and market efficiency. While they hypothesize that this could be because liquidity stimulates greater arbitrage activity, enhancing market efficiency, no causal evidence is explored. Chung and Hrazdil (2010) reinforce these findings, also documenting that the liquidity-efficiency relationship is amplified when adverse selection spread is higher (more informative trading).

While this paper does not provide direct evidence of a causal relationship between liquidity and informational efficiency due to confounding economic mechanisms, the results of this paper are consistent with both Chordia, et al. (2008) and Chung and Hrazdil (2010), as I find informational efficiency is improved by make-take fees because transaction costs are reduced and trades become more informative.

This study also increases our understanding of the liquidity-efficiency relationship because even during a decrease in make-take fee level, and subsequent widening of the bid-ask spread, I document an increase in trading volume, suggesting that liquidity is defined by more than just transaction costs. Additionally, whereas Chordia, et al. (2008) define market efficiency as the inverse of short-horizon return predictability from order flows, I define market efficiency following Fotak, et al. (2014), by removing the random walk component of intraday stock prices (specifically NBBO midpoints) to find mispricing, and the variance thereof.

### **3. Sample and Methodology**

#### *3.1. NASDAQ Access Fee Experiment*

In November of 2014, NASDAQ announced its intention to change its make-take fee structure for select stocks in order to analyze the changes' effect on market share, displayed liquidity, effective spreads, and volatility. In NASDAQ's filing with the SEC the exchange stated that it believed take fees had grown to a level which was discouraging certain traders from directing their trades to one of the 14 "lit" exchanges, opting instead to trade in dark pools. NASDAQ hypothesized that by reducing its take fees and make rebates that it would be able to increase its market share. In the SEC filing, the exchange requested permission to experimentally change its market access fee structure to charge a \$0.0005 fee per share to remove liquidity (from \$0.0030), and to credit a \$0.0004 rebate per share to add displayed liquidity (from \$0.0029)<sup>5</sup> (NASDAQ, 2014).

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<sup>5</sup> There were further alterations to the fee structure which included rebates for non-displayed liquidity, non-displayed midpoint liquidity, and several other obscure order types, but in general, the make-take fee structure was reduced by 25¢ per 100 shares. Also important to the validity of the results in this study, the net fee remained 1¢.

Late in 2014, NASDAQ announced the 14 stocks included in its access fee experiment: American Airlines (AAL), Micron Technology (MU), FirEye (FEYE), GoPro (GPRO), Groupon (GRPN), Sirius XM (SIRI), Zynga (ZNGA), Bank of America (BAC), General Electric (GE), Kinder Morgan (KMI), Rite Aid (RAD), Transocean (RIG), Sprint (S), and Twitter (TWTR). The NASDAQ Access Fee Experiment commenced on February 2, 2015 and was set to run for a term of four months, though wording seemed to indicate that an extended timeframe would be possible if it was deemed valuable later on.

Throughout the course of the experiment, NASDAQ reported on various aspects of the market for these stocks. The exchange had seen a small uptick in liquidity consumption (marketable orders), but it was not offset by the major losses in liquidity provision (executed limit orders), “time at the inside” of the NBBO, and market share. Therefore, NASDAQ elected to cease the experiment after the initial four month term.

### *3.2. Data and Research Design*

The majority of the data used in this study is collected from NYSE TAQ (Trade and Quotation). The data represents the consolidated tape, which covers virtually all trades and quotes on the 14 U.S. public stock exchanges. The NASDAQ experiment ran for four months, from February through May of 2015. In order to obtain a baseline sample outside of the experiment period, I collect TAQ data on all stocks spanning October 2014 through September 2015. For each day, I calculate the total volume, volume on the NASDAQ, price, NASDAQ market share, percentage bid-ask spread, dollar bid-ask spread, adverse selection cost, the percentage of time NASDAQ spent on the inside of the NBBO, and multiple mispricing measures.

Specifically, I calculate volume as the sum of the trade size (in shares) for all trades on every exchange. Similarly, NASDAQ volume is the sum of the shares traded on the NASDAQ exchange. I divide the NASDAQ volume by the total volume to measure NASDAQ's market share. In later regressions, use the natural logarithm of both of the volume variables to address the skewness of the distribution of volumes (because volume has a lower bound of 0, volume is positively skewed). Actual transaction prices are often executed at the bid or ask price. Therefore, to eliminate the bid-ask bounce, I use a volume-weighted average of the NBBO midpoint of each trade as a proxy for stock price. Similarly, I calculate the daily percentage bid ask spread as the mean of the NBBO bid-ask spread scaled by the midpoint taken after each new quote. I multiply this by the daily midpoint to calculate the dollar bid-ask spread<sup>6</sup>.

In order to estimate the level of informed trading, I calculate adverse selection costs, which represent the money that market makers lose to informed traders on average. In order to calculate this, I first sign the trades using the Lee and Ready (1991) algorithm. I calculate adverse selection costs  $AS_k$  as

$$AS_k = \frac{1}{T} \sum_{t=1}^T \frac{d_t(m_{t+k} - m_t)}{m_t}, \quad (1)$$

where  $m_t$  is the NBBO midpoint at trade  $t$ ,  $d_t$  equals 1 for a buy and -1 for a sell (according to the Lee and Ready (1991) algorithm),  $T$  is the number of trades in a given day, and  $k$  is the number of minutes after the initial trade. I calculate the adverse selection spread using a  $k$  of 1, 15, 30, and 60 minutes.

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<sup>6</sup> A differentiation between percentage and dollar bid-ask spreads is important because the make-take fees are "volume-based," rather than "value-based," which means the fees and rebates are assessed on a dollars-per-share basis, rather than a percent-of-value basis, therefore the fee structure will affect the bid-ask spreads, and ultimately the market efficiency, of low and high priced shares differentially.

In order to calculate the amount of time the NASDAQ has a quote on the inside of the NBBO, I first create two binary variables at the quote level: one which equals 1 when the national best bid is located on the NASDAQ exchange (and 0 otherwise), and one which equals 1 when the national best ask is located on the NASDAQ exchange. From these, I create two more quote-level binary variables: one which equals 1 when the NASDAQ has the best bid *and* offer (represented mathematically as  $bestbid \times bestask$ ), and another which equals 1 when the NASDAQ has *either* the best bid or ask (represented mathematically as  $max(bestbid, bestask)$ ). Next, I calculate the daily averages of these four binary variables (Best Bid, Best Ask, Best Both, and Best Either) to find the amount of quote-time the NASDAQ is at the inside of the NBBO.

Later, in order to construct a proper control sample, I collect industry (NAICS and SIC) and listing exchange data from CRSP over the same time frame. All continuous variables were then winsorized at the 1<sup>st</sup> and 99<sup>th</sup> percentiles.

### 3.2.1 Market Efficiency Measures

Because a stock's true fundamental value, and therefore pricing error cannot be directly observed, further assumptions must be made to estimate fundamental value and pricing error. Since at least Fama (1965) the random walk model, or the weak form of market efficiency, has been widely accepted in the financial economics literature. Following Hasbrouck (1993), I assume that the logarithm of a stock's observed transaction price  $p_t$  follows the equation

$$p_t = f_t + s_t \quad (2)$$

where  $s_t$  is the pricing error of the stock on day  $t$ , and the stock's fundamental value,  $f_t$ , follows a random walk with a drift  $\mu$ , and white noise innovation  $\varepsilon_t$ ,

$$f_t = \mu + f_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2). \quad (3)$$

If pricing error is assumed to follow mean-reverting process

$$\Delta s_t = -\alpha s_{t-1} + \phi_t, \quad \phi_t \sim N(0, \sigma_\phi^2) \quad (4)$$

with mean reversion parameter  $\alpha$  and white noise innovation  $\phi_t$ , then combining equations (2), (3), and (4), we get:

$$p_t = \mu + (1 - \alpha)p_{t-1} + \alpha f_{t-1} + \theta_t, \quad \text{where } \theta_t = \varepsilon_t + \phi_t. \quad (5)$$

Following Fotak, et al. (2014), I use Kalman filter estimation methodology with the transition equation:

$$\begin{bmatrix} p_t \\ f_t \\ 1 \end{bmatrix} = \begin{bmatrix} 1 - \alpha & \alpha & \mu \\ 0 & 1 & \mu \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} p_{t-1} \\ f_{t-1} \\ 1 \end{bmatrix} + \begin{bmatrix} \theta_t \\ \varepsilon_t \\ 0 \end{bmatrix}, \quad (6)$$

and the measurement equation:

$$p_t = [1 \quad 0 \quad 0] \begin{bmatrix} p_t \\ f_t \\ 1 \end{bmatrix}, \quad (7)$$

Elsewhere in the economics literature, the Kalman filter is used to observe otherwise latent variables, i.e. mispricing, from observable variables, given an assumed structure. In this case, I am removing the random-walk component from stock midpoint prices to observe mispricing. If a time-series was indeed a random walk, I would find no mispricing<sup>7</sup>.

Because the actual transaction price tends to “bounce” due to the bid-ask spread, and Malinova and Park (2015) show that make-take fees directly affect the bid-ask spread, I use the log of the midpoint of the bid-ask spread as a proxy for log price,  $p_t$ , in this estimation. Omitting the first 5 minutes of trading to eliminate the opening noise, I collect  $p_t$  from each stock at every minute from 9:35 to 16:00 over the entire sample. Using BFGS maximum

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<sup>7</sup> For more information on the Kalman filter smoothing-estimation procedure, see chapter 13 of Hamilton (1994).

likelihood optimization, I obtain estimates of  $\mu$ ,  $\alpha$ ,  $\sigma_{\phi}^2$ , and  $\sigma_{\varepsilon}^2$  for every stock, each day. I further calculate the mean absolute pricing error (MAPE) each day by averaging  $|s_t|$  over the day. I use  $\sigma_{\phi}^2$  to measure the variance of pricing error innovations on each day. These two variables were also winsorized at the 1<sup>st</sup> and 99<sup>th</sup> percentiles.

### *3.2.2 Matching Procedure*

In a laboratory setting, the treatment and control groups would be randomly selected. However, in the NASDAQ experiment, the 14 treated stocks were said to be chosen based on the estimated proportion of “off-exchange” (dark pool) trading (NASDAQ, 2014). We also know that the effect of a make-take fee reduction will differ based on the share price of a stock since make-take fees are based on shares traded, and not dollar value. Therefore, to assuage concerns over selection bias, I created a matched control sample of firms using nearest neighbor propensity score matching. To measure the propensity of being selected into the NASDAQ Access Fee Experiment, I employ a probit model using pre-experiment data (from October 2014 through January 2015).

I omit stocks which have less than 80 trading days in the 4 month window (out of 84 possible), have a missing or unclassifiable industry (SIC 9999), are listed as Financial Vehicles (NAICS 525990), or are missing the outcome variables in the study (pricing error, adverse selection spread, volume, etc.). This results in 7,573 stocks (14 of which are treated). I then take the 4-month average of the variables in the propensity score model to estimate the probit model on a firm level.

Because the firms being NASDAQ- or NYSE-listed was seemingly a criteria for inclusion (seven of each were included), I include binary variables for each in the model. Ideally, the

proportion of off-exchange volume would be a key component to the matching process, however, since dark pools do not disseminate any comprehensive transaction data, I instead substitute the NASDAQ volume into the model. I also match on dollar bid-ask spread and midpoint price, as well as average MAPE, to attempt to get the control sample close to the treatment sample on these pre-shock characteristics. The results of the probit model, along with marginal effects are displayed in Table 1.

Next, to select the control sample, for each of the 14 treated stocks I eliminate untreated stocks with a difference in average price greater than 10 percent as potential matches. I then select the 5 untreated stocks with the closest propensity score, based on the above probit, allowing for replacement. This creates a control sample of 70 stocks – 64 of which are unique. The means and medians of the pre-shock variables of interest for treatment and control groups are displayed in Table 2.

The sample means are statistically different at the 10% significance level or above for each variable in the table. This is partially due to the large sample sizes reducing the standard errors, as the means are usually economically very similar. However, we do see some economically significant differences in a few key variables, namely the adverse selection costs, MAPE, variance of mispricing, and the dollar bid-ask spread. While this raises a concern that perhaps the control and treatment samples will behave differently, violating the parallel trend assumption of DiD analysis, the difference in means is controlled for by the binary *Treated Dummy* variable in the DiD regressions, therefore, the difference in means are only problematic if they suggest that the treatment stocks and control stocks will behave differently.

#### 4. Empirical Results

To determine the effect of make-take fees on market efficiency, I regress the two (inverse) measures of market efficiency, MAPE and variance of pricing error innovations ( $\sigma_{\phi}^2$ ) in panel DiD regressions. I include a binary *Treated Dummy* variable, which equals 1 if the stock is 1 of the 14 in the NASDAQ Access Fee Experiment and 0 if it is in the control stock, a binary *Experiment Dummy* variable, which equals 1 if the lower access fees were in effect (Feb. 2015 – May 2015) and 0 for all other dates, and finally, an interaction of the two, which will produce the regression coefficient representing the difference in differences in the means. To correct the standard errors for autocorrelation and heteroskedasticity between stocks, I use robust standard errors clustered two-ways, by day and stock, as suggested by Pedersen (2009). The results of these regressions are represented in Table 3.

In the first regression in Panel A, we see that there is no statistical difference in MAPE between treatment and control samples before and after the access fee experiment, however, when NASDAQ lowers its access fees to the 5/4 structure, the MAPE increases by 0.23% of the stock price<sup>8</sup>. When I include linear controls for the price, percentage bid-ask spread, and volume, this result holds. Relative to the control stocks, the mean absolute pricing error of treated stocks increased 0.22%, roughly \$0.0546 taken at the mean – far in excess of the \$0.0025 difference in access fees.

When regressing the variance of mispricing innovations in the DiD model, I find that the access fee experiment increased the variance 0.0307 for treated stocks relative to control stocks (an increase of 17.5% in standard deviation). When including controls in the regression model, the DiD effect remains at 0.0301, with strong statistical significance.

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<sup>8</sup> Since  $p_t$  is the log of the midpoint price,  $|s_t|$ , and therefore MAPE, are also measured in the same units.

It is possible that somehow trader behavior changed after the access fee experiment, even though the make-take fees returned to the previous price structure. To ensure this wasn't driving the DiD results, Panel B of Table 3 includes regressions which exclude observations after May 2015, the end of the NASDAQ experiment. When excluding these observations, the DiD results remain largely unchanged. The DiD coefficients on the MAPE regressions increase slightly relative to the full sample, but those of the variance regressions reduce slightly. Regardless, we can conclude that the mispricing increases when make-take fees are reduced.

Subsequently, I confirm the findings of Malinova and Park (2015) that make-take fees affect bid-ask spreads. However, where their sample involves the entire market switching to a make-take fee structure, this sample involves only one exchange, NASDAQ, changing its make-take fees. Consequently, since the other 13 public exchange did not change their fee structure, the bid-ask spread may not have necessarily altered since other exchanges had make rebates as high as 24¢ and take fees as low as -6¢ (a rebate of 6¢)<sup>9</sup>. Therefore I instead examine the amount of time that NASDAQ quotes are at the inside of the NBBO. I use the same DiD regression framework as in the previous tests, with the constructed *Best Ask*, *Best Bid*, *Best Either*, and *Best Both* proportion variables.

The results of these regressions are displayed in Table 4. It's important to note, that the time at the inside of the NBBO did not differ between treatment and control groups prior to the experiment, according to the *Treated Dummy* coefficient. But when NASDAQ lowered its

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<sup>9</sup> Inverted "taker-maker" pricing structures are located on the NASDAQ Boston Exchange and Direct Edge EDGA Exchange. This pricing structure has been argued to be an alternative to dark pools since it is cheap (due to the rebate) to execute trades taking liquidity on these exchanges. This structure has also been promulgated as a hot bed for predatory high frequency traders who are essentially being charged a "make" fee by the exchange to have access to the information provided by these fee-sensitive traders.

fee structure, we see a significant differential reduction in time at the inside of the NBBO for NASDAQ quotes. For treated stocks, NASDAQ spends 13.3%, 13.1%, 17.3%, and 8.9% less time possessing the best bid, best ask, either the best bid or ask, and both the best bid and ask, respectively. As Brolley and Malinova (2013) would posit, the decrease in rebates for limit orders results in less time inside the NBBO as market makers submitting orders on the NASDAQ widen their spreads to compensate. These results hold in Panel B, when I include *price* and *volume* and linear controls. I don't include the bid-ask spread as a control, since it is mechanically related to the NASDAQ's time inside the NBBO.

Because market makers are posting limit orders in a way that is widening the bid-ask spread – due to the smaller rebates – one would expect less information to be transmitted by retail and other non-DMA traders due to the marginal increase to transaction costs. Therefore, I examine the changes in adverse selection costs to determine how the make-take fee reduction affected the incorporation of private information into security prices. The DiD analysis is presented in Table 5, without controls in Panel A and with controls in Panel B. When examining the average 1-minute and 15-minute profits of liquidity takers ( $AS_1$  and  $AS_{15}$ ), we see a significant decrease for treated stocks, relative to the control stocks, during the experiment. We also see a decrease in average 30-minute and 60-minute profits of liquidity takers, however the difference is not statistically significant. This evidence, in conjunction with prior results, suggests that the widened bid-ask spreads resulting from the make-take fee reduction led to fewer informative trades being made by non-DMA traders, which made markets less informationally efficient.

NASDAQ hypothesized that by lowering their make-take fees, they would garner more volume onto the exchange by luring away “off-exchange” trading to the NASDAQ. This

increase in volume could also arguable lead to an increase in market efficiency – because more trades take place on lit exchanges, leading to more incorporation of private information into stock prices. We can see from the above results that this was not the case, but that doesn't necessarily preclude that the treatment stocks experienced an increase in volume.

In Table 6, I investigate the changes in volume propagated by the access fee experiment. Looking at the DiD interaction coefficient, I find that NASDAQ's market share reduced by 2.4% relative to the control sample during the experiment – a slightly higher loss than the 1.5% NASDAQ estimated against its own control sample. However, interestingly, I find that the level of the volume on the NASDAQ didn't change relative to control stocks, but that the volume of the treated stocks actually increased by an average of 12.4% on all exchanges, in comparison with control stocks (13.7% when price is included as a linear control).

These results suggests that while NASDAQ did not benefit from the reduction in make-take fees, other exchanges did. This is quite possible if market makers were still apt to submit limit orders to the exchanges with the higher rebates (for example, BATS, with a 25/24 fee structure), and the reduction from 30¢ to 25¢ to execute these orders was enough to entice more traders to take liquidity, whether they would have otherwise not traded or traded in dark pools. While I've shown that this increase in volume did not result in an overall increase in trade informativeness, or a decrease in pricing error, without a more complex structural model, the volume effect of make-take fees on market efficiency is not possible to estimate, due to make-take fees' simultaneous effect on the bid-ask spread. However, these results suggest that a market-wide experiment on make-take fees – such as the SEC proposed in the summer of 2016 (SEC, 2016) – may lend valuable data to extend this line of research.

## 5. Concluding Remarks

While market efficiency is a paramount assumption in markets, directly affecting every trader and investor, the effect of market access fee level on market efficiency has not been addressed in the literature until this paper. While *ex ante* predictions range from an increase in efficiency via subsidized liquidity to a decrease in efficiency due to the prohibitive costs of trading using market orders, I find that a decrease in take fees and make rebates causes greater absolute pricing error and larger variance of mispricing, stemming from the widened bid-ask spreads and decreased informed trading by retail investors and other traders without direct market access. This suggests that higher levels of make-take fees lead to greater market efficiency. However, further research may be necessary to document the effect of make-take fees on dark pool trading volume and the market share of lit exchanges.

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**Table 1: Propensity Score Matching Probit**

This table displays the regression coefficients and (mean) marginal effects of the probit model used for propensity score matching. Stock data is from TAQ and CRSP. Stocks are excluded from this the regression if they are missing data on mispricing, time inside the NBBO, adverse selection, volume, price, bid-ask spread, or industry (SIC code). Stocks were also excluded if the pre-shock window contained less than 80 trading days, or was classified as a financial vehicle (NAICS 525990). Variables are averaged over the 4-month pre-experiment period. *Treated Dummy* is a binary variable equal to 1 if the stock was affected by the NASDAQ Access Fee Experiment, and 0 otherwise. *NASDAQ-listed* and *NYSE-listed* are binary variables equal to 1 if the stock is listed on the NASDAQ or NYSE, respectively. Other variables are described in Section 3. \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

	<b>Treated Dummy</b>	<b>Marginal Effects</b> (× 100,000)
Constant	-5.663*** (0.000)	-7.127
NASDAQ-listed	1.527*** (0.000)	1.922
NYSE-listed	1.305*** (0.000)	1.643
Nasdaq Volume	2E-06*** (0.000)	3.0E-06
Bid-ask Spread (\$)	0.1058 (0.430)	0.133
Price	-0.005*** (0.000)	-0.007
MAPE	1.212* (0.070)	1.525
Pseudo R <sup>2</sup>	0.586	
Treated Firms	14	
Untreated Firms	7559	

**Table 2: Matched Sample Pre-shock Comparison**

This table contains comparisons of the means and medians of the treated and matched-control pre-shock samples on a stock-day level. Potential match stocks are dropped from the sample if they are missing data on mispricing, time inside the NBBO, adverse selection, volume, price, bid-ask spread, or industry (SIC code). Potential matches were also dropped if the pre-shock window contained less than 80 trading days, or was classified as a financial vehicle (NAICS 525990). Each treated stock is then matched with five untreated stocks, with replacement, based on price and propensity score – the fitted value of the probit displayed in Table 1.

Variable	Treated			Control		
	N	Mean	Med.	N	Mean	Med.
<b>Best Ask is on Nasdaq</b>	1,176	0.4889	0.4395	5,876	0.4609	0.4012
<b>Best Bid is on Nasdaq</b>	1,176	0.4890	0.4377	5,876	0.4574	0.3964
<b>Best Bid and Ask are on Nasdaq</b>	1,176	0.2396	0.1321	5,876	0.1995	0.0628
<b>Best Bid or Ask are on Nasdaq</b>	1,176	0.7332	0.7416	5,876	0.7163	0.7223
<b>Adverse Selection Cost (1 min)</b>	1,176	0.0017	0.0003	5,876	0.0006	0.0002
<b>Adverse Selection Cost (15 min)</b>	1,176	0.0017	0.0003	5,876	0.0005	0.0002
<b>Mean Absolute Pricing Error (MAPE)</b>	1,176	0.0219	0.0003	5,876	0.0040	0.0003
<b>Variance of Mispricing (<math>\sigma_{\phi}^2</math>)</b>	1,176	0.0452	0.0000	5,876	0.0027	0.0000
<b>Nasdaq Volume Share</b>	1,176	0.3659	0.3411	5,876	0.3601	0.3411
<b>Log(Nasdaq Volume)</b>	1,176	14.103	14.280	5,876	13.807	13.976
<b>Log(Volume)</b>	1,176	15.127	15.356	5,876	14.865	15.068
<b>Price</b>	1,176	24.832	25.336	5,876	24.520	22.868
<b>Bid-ask Spread (\$)</b>	1,176	0.0228	0.0119	5,876	0.0128	0.0107
<b>Bid-ask Spread (%)</b>	1,176	0.0014	0.0009	5,876	0.0013	0.0005

**Table 3: Pricing Efficiency Effect**

This table displays results for the multivariate difference-on-differences analysis on the effect of a shock to make-take fee level. The sample in Panel A contains observations from Oct. 2014 – Sept. 2015. The dependent variables are the mean absolute pricing error (MAPE) and variance of pricing error innovations on a stock-day level. The dependent variables are regressed on a dummy variable equaling 1 for treated stocks, a dummy variable equaling 1 for observations during the experiment, and an interaction of the two dummy variables as well as control variables described in Section 3. Panel B omits observations after the NASDAQ experiment (June 2015-Sept.2015). Standard errors for these panel regressions are clustered by stock and date. Two-tailed  $p$ -values are in parenthesis below the corresponding coefficients. \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Panel A: Full Sample**

	MAPE	MAPE	$\sigma_{\phi}^2$	$\sigma_{\phi}^2$
Constant	0.0040* (0.070)	-0.0111 (0.108)	0.0027** (0.026)	-0.0213*** (0.001)
Treated Dummy	0.0179 (0.210)	0.0176 (0.215)	0.0426*** (0.000)	0.0422*** (0.000)
Experiment Dummy	0.0008** (0.043)	0.0020* (0.086)	0.0016 (0.281)	0.0038** (0.014)
<b>Treated × Experiment</b>	<b>0.0023** (0.012)</b>	<b>0.0022** (0.046)</b>	<b>0.0307*** (0.000)</b>	<b>0.0301*** (0.000)</b>
Price		-2.1E-05 (0.846)		-1.5E-05 (0.698)
Bid-ask Spread (%)		0.2656 (0.610)		-0.5250 (0.255)
Log(Volume)		0.0010 (0.119)		0.0017*** (0.000)
R <sup>2</sup>	0.048	0.051	0.066	0.067
Obs.	21,058	21,023	21,058	21,023

**Panel B: Oct. 2014 – May 2015 (Before and During Pilot)**

	MAPE	MAPE	$\sigma_{\phi}^2$	$\sigma_{\phi}^2$
Constant	0.0040* (0.070)	-0.0885 (0.217)	0.0027*** (0.000)	-0.1263*** (0.000)
Treated Dummy	0.0007** (0.035)	0.0014 (0.212)	0.0013*** (0.005)	0.0023*** (0.000)
Experiment Dummy	0.0179 (0.210)	0.0161 (0.416)	0.0426*** (0.000)	0.0400 (0.000)
<b>Treated × Experiment</b>	<b>0.0027*** (0.000)</b>	<b>0.0030** (0.025)</b>	<b>0.0236*** (0.001)</b>	<b>0.0239*** (0.001)</b>
Price		4.8E-05 (0.707)		1.1E-04** (0.011)
Bid-ask Spread (%)		1.9395 (0.202)		2.3658*** (0.007)
Log(Volume)		0.0060 (0.226)		0.0083*** (0.000)
R <sup>2</sup>	0.049	0.062	0.070	0.074
Obs.	13,921	13,921	13,921	13,921

**Table 4: Time NASDAQ quotes are at NBBO**

This table displays results for the multivariate difference-on-differences analysis on the effect of a shock to make-take fee level. Panel A contains no controls, while Panel B contains controls described in Section 3. The samples for all regressions include observations from Oct. 2014 – Sept. 2015. The dependent variables are the amount of volume-time that quotes on the NASDAQ were the best bid, ask, either, or both. The dependent variables are regressed on a dummy variable equaling 1 for treated stocks, a dummy variable equaling 1 for observations during the experiment, and an interaction of the two dummy variables. Standard errors for these panel regressions are clustered by stock and date. Two-tailed  $p$ -values are in parenthesis below the corresponding coefficients. \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Panel A: Without Controls**

	<b>Best Bid</b>	<b>Best Ask</b>	<b>Best Either</b>	<b>Best Both</b>
Constant	0.4573*** (0.000)	0.4608*** (0.000)	0.7162*** (0.000)	0.1994*** (0.000)
Treated Dummy	0.0316 (0.577)	0.0281 (0.613)	0.0170 (0.730)	0.0402 (0.524)
Experiment Dummy	-0.0504*** (0.000)	-0.0498*** (0.000)	-0.0528*** (0.000)	-0.0452*** (0.000)
<b>Treated × Experiment</b>	<b>-0.1330*** (0.000)</b>	<b>-0.1311*** (0.000)</b>	<b>-0.1731*** (0.000)</b>	<b>-0.0885** (0.012)</b>
R <sup>2</sup>	0.052	0.050	0.084	0.025
Obs.	21,067	21,067	21,067	21,067

**Panel B: With Controls**

	<b>Best Bid</b>	<b>Best Ask</b>	<b>Best Either</b>	<b>Best Both</b>
Constant	0.5523*** (0.000)	0.5547*** (0.000)	0.7984*** (0.000)	0.3039*** (0.000)
Treated Dummy	0.0334 (0.559)	0.0298 (0.594)	0.0186 (0.710)	0.0421 (0.504)
Experiment Dummy	-0.0589*** (0.000)	-0.0582*** (0.000)	-0.0610 (0.000)	-0.0537*** (0.000)
<b>Treated × Experiment</b>	<b>-0.1314*** (0.000)</b>	<b>-0.1293*** (0.000)</b>	<b>-0.1705*** (0.000)</b>	<b>-0.0876** (0.014)</b>
Price	0.0007 (0.424)	0.0008 (0.381)	0.0014 (0.104)	0.0001 (0.912)
Log(Volume)	-0.0075 (0.109)	-0.0076 (0.115)	-0.0078 (0.106)	-0.0072 (0.151)
R <sup>2</sup>	0.059	0.058	0.102	0.028
Obs.	21,032	21,032	21,032	21,032

**Table 5: Information Asymmetry Effect**

This table displays results for the multivariate difference-on-differences analysis on the effect of a shock to make-take fee level. Panel A contains no controls, while Panel B contains controls described in Section 3. The samples for all regressions include observations from Oct. 2014 – Sept. 2015. The dependent variables are the 1-, 15-, 30-, and 60-minute adverse selection costs (average losses of market makers due to private information). The dependent variables are regressed on a dummy variable equaling 1 for treated stocks, a dummy variable equaling 1 for observations during the experiment, and an interaction of the two dummy variables. Standard errors for these panel regressions are clustered by stock and date. Two-tailed  $p$ -values are in parenthesis below the corresponding coefficients. \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Panel A: Without Controls**

	<b>AS<sub>1</sub> (×1000)</b>	<b>AS<sub>15</sub> (×1000)</b>	<b>AS<sub>30</sub> (×1000)</b>	<b>AS<sub>60</sub> (×1000)</b>
Constant	0.6273*** (0.000)	0.4963*** (0.000)	0.4863*** (0.000)	0.4760*** (0.000)
Treated Dummy	1.0227*** (0.000)	1.1799*** (0.000)	0.6866*** (0.009)	0.7416*** (0.005)
Experiment Dummy	0.0099 (0.870)	0.1241* (0.052)	0.0961 (0.110)	0.0524 (0.387)
<b>Treated × Experiment</b>	<b>-0.6872** (0.039)</b>	<b>-0.7045** (0.043)</b>	<b>-0.2020 (0.533)</b>	<b>-0.4794 (0.139)</b>
R <sup>2</sup>	0.002	0.003	0.002	0.001
Obs.	21,029	21,027	21,024	21,025

**Panel B: With Controls**

	<b>AS<sub>1</sub> (×1000)</b>	<b>AS<sub>15</sub> (×1000)</b>	<b>AS<sub>30</sub> (×1000)</b>	<b>AS<sub>60</sub> (×1000)</b>
Constant	1.9705*** (0.000)	1.5373*** (0.000)	1.7381*** (0.000)	1.3983*** (0.000)
Treated Dummy	1.0446*** (0.000)	1.1967*** (0.000)	0.7071*** (0.002)	0.7565*** (0.003)
Experiment Dummy	-0.0834 (0.210)	0.0540 (0.419)	0.0086 (0.888)	-0.0104 (0.869)
<b>Treated × Experiment</b>	<b>-0.6987** (0.025)</b>	<b>-0.7160** (0.026)</b>	<b>-0.2120 (0.480)</b>	<b>-0.4886 (0.116)</b>
Price	-0.0145*** (0.000)	-0.0128*** (0.000)	-0.0128*** (0.000)	-0.0107*** (0.000)
Log(Volume)	-0.0665*** (0.000)	-0.0489** (0.020)	-0.0631*** (0.001)	-0.0444** (0.045)
R <sup>2</sup>	0.006	0.005	0.005	0.003
Obs.	21,029	21,027	21,024	21,025

**Table 6: Volume Effect**

This table displays results for the multivariate difference-on-differences analysis on the effect of a shock to make-take fee level. Panel A contains no controls, while Panel B contains controls described in Section 3. The samples for all regressions include observations from Oct. 2014 – Sept. 2015. The dependent variables are the NASDAQ market share, log of NASDAQ volume, and log of total volume. The dependent variables are regressed on a dummy variable equaling 1 for treated stocks, a dummy variable equaling 1 for observations during the experiment, and an interaction of the two dummy variables. Standard errors for these panel regressions are clustered by stock and date. Two-tailed  $p$ -values are in parenthesis below the corresponding coefficients. \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5% and 10% levels, respectively.

**Panel A: Without Controls**

	<b>NASDAQ Vol. Share</b>	<b>Log(NASDAQ Vol.)</b>	<b>Log(Vol.)</b>
Constant	0.3600*** (0.000)	13.807*** (0.000)	14.865*** (0.000)
Treated Dummy	0.0059 (0.761)	0.2963*** (0.000)	0.2620** (0.014)
Experiment Dummy	-0.0143*** (0.001)	-1.2851*** (0.000)	-1.2444*** (0.000)
<b>Treated × Experiment</b>	<b>-0.0238** (0.013)</b>	<b>0.0301 (0.667)</b>	<b>0.1243** (0.024)</b>
R <sup>2</sup>	0.010	0.125	0.114
Obs.	20,994	20,994	21,032

**Panel B: With Controls**

	<b>NASDAQ Vol. Share</b>	<b>Log(NASDAQ Vol.)</b>	<b>Log(Vol.)</b>
Constant	0.3401*** (0.000)	13.5161*** (0.000)	14.6393*** (0.000)
Treated Dummy	0.0056 (0.756)	0.2926*** (0.008)	0.2591* (0.052)
Experiment Dummy	-0.0137*** (0.002)	-1.2772*** (0.000)	-1.2375*** (0.000)
<b>Treated × Experiment</b>	<b>-0.0226** (0.018)</b>	<b>0.0470 (0.535)</b>	<b>0.1367** (0.023)</b>
Price	0.0008* (0.098)	0.0118*** (0.002)	0.0092** (0.041)
R <sup>2</sup>	0.032	0.142	0.124
Obs.	20,994	20,994	21,032