Can AI-enabled Limit Orders Thwart Latency Arbitrage?*

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Abstract

In October 2020, Investors Exchange introduced the D-Limit order type which offers traders a bundle of a regular limit order and an autonomous cancel and resubmit decision. When the machine-learning based CQI-signal is switched 'on,' it triggers a cancellation and resubmission of the limit order. We develop a difference-in-difference estimation strategy that uses IEX's market share as the outcome variable, D-Limit as the treatment, and periods of either unstable- or stable-quotes as exposure/no-exposure periods. The average estimated treatment effect is around 1.8% reflecting that IEX is growing its market share more in stable-quote periods than in unstable ones. We confirm that price impact for 0.5 to 2 seconds after an unstable period exceeds the impacts after stable periods by around 1 basis point. A parallel dramatic improvement in the quality of IEX's displayed liquidity is reflected in an approximately eightfold increase in their market share of the quoting-based market data revenue from Q3 in 2020 to Q1 in 2021.

Keywords: Algorithms; Automated Trading; Machine Learning; Limit Orders; Limit Order Design; Market Design.

JEL Codes: G14, G18, G19, C25, O3

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1 Introduction

In U.S. equity markets changes in the national best bid and offer, the NBBO, are not an instantaneous event. Quote changes at different exchanges take place non-synchronously and as a consequence, the NBBO change unfolds over a brief time interval. This enables a well-positioned observer to make short-horizon predictions of imminent changes in the NBBO. This matters for limit order submitters who may have posted a limit order at the NBBO and in these brief intervals of instability in the NBBO their orders are about to become stale. Being able to spot these situations and cancel and resubmit the limit orders would shield the submitter from being arbitraged as her limit price is forecast to become imminently stale. A challenge is how to generate low latency signals and act upon these signals before the orders transact at soon-to-be unattractive prices. We examine empirically one such solution that offers limit orders additional protection against the risk of imminently stale prices. On October 1st, 2020, Investors Exchange (IEX), launched a new limit order type called the D-Limit order type. The order is integrated with IEX's Crumbling Quote Indicator or CQI which uses machine-learning to generate signals of imminent quote instability.

We are interested in understanding if the D-Limit order type works as intended for the target clientele, IEX's users, and also whether it is a viable solution to the general problem of adverse selection for limit orders. To our knowledge, the D-Limit is the first attempt to create a broadly available AI-enabled limit order with built-in autonomous logic for when to cancel and resubmit. Can this bundle of dynamic cancel and resubmit succeed in tilting the trading at IEX away from periods of unstable quotes towards periods of stable quotes? We are also interested in understanding whether this innovation results in rewards for the innovator. At first glance, it appears that the rewards must be modest as the D-Limit order type is associated with no change in fees collected per order.[1] However, an important channel may be indirect via the distribution of market data revenue.

[1] Here we are not talking about the discounted fee that was offered as a carrot during the first three months of D-Limit order type's existence.

Our results suggest that the D-Limit order type was received favorably by the users as IEX grew its market share overall, but the growth was systematically stronger for stable- versus unstable-quote periods. The D-Limit order type links the cancel and resubmit decision to predicting instability so our results are consistent with D-Limit order type being used by a meaningful fraction of IEX users and with the D-Limit order type working as intended. The baseline difference-in-difference estimate suggests a treatment effect of 1.8%—the difference between market share growth in stable- versus unstable-quote periods. Using price impact measured over 100 to 2000 microseconds after a trade we confirm that unstable periods are associated with about 1 basis point greater price impact than stable periods and hence liquidity suppliers benefit from the shift of their trades from unstable to stable periods that D-Limit enables.

IEX does not charge users more for using this new order type so it is reasonable to ask how this type of innovation pays off for the innovator (IEX in this case). The D-Limit order's protection against latency arbitrage encourages users to submit more competitive limit orders more often and as a result, the quality of IEX's displayed liquidity is dramatically improved. Specifically, inspired by the Reg. NMS Market Data Revenue Sharing Formula, we estimate that aside from the increased share of traded volume IEX witnessed an even more dramatic improvement in its 'quote-market-share' which determines half of the allocation of market data revenue for a given security. We estimate an average increase of IEX's 'quote-market-share' of about 20 percent from less than 1% to over 20%![2]

Our main results appear to be robust. We have re-estimated the difference-in-difference estimator for shorter time intervals — 750 microseconds versus 1000 microseconds—and we have used a higher cut-off number for the number of trades in the same direction during a period to qualify as unstable—7 trades in the same direction versus 5 trades. Our estimated treatment effects appear robust and clearly positive and economically significant across the different specifications.

[2]Consistent with this, the Unlisted Trading Plan Administration's trade and quote revenue distribution (2021) figures for 2020 and 2021 show a sharp increase for IEX.

The primary features of IEX's market mechanism at the time of the launch of the D-Limit were (i) the intentional latency delay, or 'speed bump', and (ii) the Crumbling Quote Indicator (CQI), IEX's proprietary indicator of quote instability. The CQI signal is a critical building block for the D-limit order type. The CQI signal uses the data on best quotes from eight exchanges[3] and applies a logistic regression to generate estimates of the probability that the NBBO is about to 'crumble,' i.e., change, and when that probability is high enough the CQI is switched to the 'on' state for two milliseconds. The 'speed bump' or intentional delay of 350 microseconds allows a small buffer to cancel and resubmit a limit order once the CQI signal is switched 'on.' The intentional delay is naturally important to have some time to process and react to a signal but arguably the CQI signal itself is a critical component for the D-Limit to work. Because of its critical dependence on the machine-learning-generated CQI-signal the D-Limit order is therefore in our view an AI-enabled limit order.

Limit orders face the risk of non-execution and the risk of ex-post regret. The ex-post regret arises when limit orders are executed when prices have moved against them. Weighing the probability of execution, the limit order price, and the risk of being picked off is the prototypical trade-off for liquidity suppliers. That trade-off has been analyzed by many in the large literature on optimal order submission strategies.[4] A takeaway from these studies is that a reduction in the picking-off risk will reduce the cost of submitting limit orders and improve the resulting liquidity, other things equal. More than 30 years ago, Merton Miller proposed adjustable limit orders as a solution to the problem of a massive amount of stale limit orders being picked off in the 1987 stock market crash (Miller, 1991).[5] That idea is

[3]Version 5 of the CQI is the relevant version for the time period we study.

[4]Examples of both theoretical and empirical work include Cohen et al. (1981), Copeland and Galai (1983), Biais, Hillion, and Spatt (1995), Chakrabarty and Holden (1995), Harris and Hasbrouck (1996), Harris (1998), Parlour (1998), Foucault (1999), Hollifield, Miller, and Sandås (2004) and a survey by Parlour and Seppi (2008).

[5]"A new class of orders could be introduced, for example, to be called perhaps 'contingent limit orders,' permitting standing limit orders to be marked up or down automatically by a prespecified percentage whenever a certain specified movement in the futures market occurred. [...] Automatic adjustment of limit orders need not be restricted to movements in futures prices, of course. Thanks to the wonders of electronics, the limit order book can now be programmed to handle a wide variety of new kinds of customer contingency orders." (Miller, 1991) page 191.

further developed in Brown and Holden's paper on pegged limit orders (Brown and Holden, 2005). The IEX's D-Limit order type shares properties with the adjustable or pegged limit orders, but there are key differences as well. In the D-Limit order type case, the CQI signal that triggers the cancel and resubmit (revise) decision is a prediction of quote instability as opposed to the actual observed quote change. Another difference is that the D-Limit order type's cancel and resubmit is performed natively at the exchange server and hence is faster than any trading desk-initiated cancel and resubmit decision for a few reasons. One is the IEX's speed bump of 350 microseconds. Another is the transmission of information to and from a trading desk makes that process inherently slower than the implementation of the D-Limit order type.[6]

Our empirical strategy builds on comparing 'stable' and 'unstable' periods for the NBBO before and after the introduction of the D-Limit order type for a treatment and control group. It is reasonable to assume that the risk of trading in unstable versus stable periods is best viewed as an exogenous risk. Therefore, we break a trading day into one-millisecond-long intervals. There are over 21 million such intervals in a trading day and not surprisingly, for each stock, most of the intervals display no activity (99.94%) but conditional on there being some trading of a particular symbol in a particular interval the types of intervals break down as follows.[7] In terms of trade counts less than 2% are intervals characterized as unstable intervals meaning that there are five or more trades in the same inferred direction of trade (buy or sell), 94% are stable intervals meaning there are 4 or fewer trades in the same direction, and finally around 4% are mixed with trades in both directions. If we consider the volume of trade instead of the number of trades the breakdown changes a bit. In terms of trading volume, 9–11% are unstable intervals, 76–77% are stable, and 13–14% are mixed intervals. The large difference between the number of unstable intervals versus the share

[6] The latter hurdle is naturally virtually eliminated for a co-located server in an exchange data center. IEX does not offer co-location.

[7] We realize that there is also substantial activity at the sub-millisecond level, see, for example, Menkveld (2018) but perhaps for that reason a millisecond is actually a good length of time to consider given that there is evidence of substantial activity during a millisecond.

of trading volume in unstable intervals underscores the difference between unstable and stable intervals. There is a lot more trading in unstable intervals primarily because unstable intervals feature a lot more trading as quote changes often are proceeded by a real burst of trading activity.

The key to understanding how the new order type directly benefits IEX involves the market data revenue sharing formula in the post-Reg. NMS world is structured. The updated formula features trading-volume-based and quote-based components that receive equal weights. IEX grows both post D-Limit launch but it is the growth in IEX's quote-based share that is eye-popping as it increases by eight times![8]

There is an emerging literature that focuses on alternative exchanges and exchange solutions inspired by IEX becoming an exchange featuring the much-debated intentional access delay or 'speed bump.' Our study contributes to this literature by examining a more recent decision by IEX to address an age-old problem for liquidity providers, how to deal with latency arbitrage, which used to be referred to as picking off risk. These studies belong to a broader literature that analyzes fragmented markets, differences in speed, and market liquidity and examples include Balduf and Mollner (2022), Brogaard et al. (2015), Hendershott, Jones, and Menkveld (2011), Foucault, Kozhan, and Tham (2017), and Menkveld and Zoican (2017).

Earlier studies that focus either on IEX alone or IEX among other exchanges include the following studies. Brolley and Cimon (2020)) develops a theoretical model of two competing exchanges where one exchange introduces an access delay or speed bump and implications for liquidity, price discovery, and overall welfare are explored. In Hu (2019), the focus is on the period around IEX becoming an exchange and how liquidity and price discovery potentially were influenced. Peng, Guo, and Meng (2019) develop a framework for measuring how the IEX speed bump together with the IEX signal serve to reduce the adverse selection for stock trades on IEX compared to competing venues.[9] Brolley and Zoican (2023) consider a

[8]The market data revenue formula has been studied by Caglio and Mayhew (2016) and Jones (2018)

[9]Lipson and Fernstrom (2019) presents the crumbling quote removal fee introduction in a case study that

solution based on an adjustable fee to address latency arbitrage. Our study complements the existing work by being the first to examine the launch of the D-Limit order type which with its AI-enabled limit order is a new type of defense against latency arbitrage

The remainder of the paper is organized as follows. Section 2 presents our data and some relevant institutional details. Section 3 presents our empirical methodology and results, followed by our discussion of the results in Section 4, and finally Section 5 concludes.

2 Institutional Details and Data

The first sub-section, 2.1, offers more details on the CQI signal which is a key underlying component for the D-Limit order type. A detailed presentation of the D-Limit order type follows in sub-section 2.2. Our sample is presented in sub-section 2.3. Finally we review rules and data for the sharing of market data revenue in sub-section 2.4.

2.1 The Crumbling Quote Indicator

What is known as the "Crumbling Quote Indicator" (or CQI) signal was launched by IEX in conjunction with the introduction of the Discretionary Peg order type in 2014. It is also often referred to as 'the signal' and here is how it is described on IEX's website: "...A mathematical formula developed with machine learning. The Signal is built to identify moments when a stock's price is unstable and is incorporated into a number of order types that are designed to protect orders while the price is changing." The idea behind the signal is that the official best bids and offers in the market—the National Best Bid and Offer or NBBO—do not always change as a single event; rather, they often occur as a sequence of updates over a sub-second timeframe, which is only complete when the final exchange's price changes. These sequences of updates can be used to make short-horizon predictions regarding the likelihood that the NBBO will in fact change over the next, say, a couple

also provides a nice overview of IEX's origin story and business model.

of milliseconds. When the CQI signal is switched ‘on’ it remains in the ‘on-state’ for two milliseconds.[10]

More precisely the CQI signal is built on feeding data on the number of exchanges present at the best quotes (bid and ask) currently and also the change in the number of exchanges as the best quotes from a millisecond ago. In addition, the model uses information about the dynamics of quoting over the last millisecond. These variables are fed through a logistic function and the resulting probability is compared with a threshold value that is dependent on the size of the inside spread. In other words, the threshold for switching on the CQI signal depends on the value assigned by the logistic function given the inputs and a threshold cut-off value that depends on the current bid-ask spread. The CQI signal is updated based on its past performance and periodically it is fundamentally updated as well.[11]

2.2 Discretionary Limit (D-Limit)

Discretionary Limit (D-Limit) behaves like a regular limit order, except when the IEX Signal (i.e., the Crumbling Quote Indicator or CQI) predicts the price is about to change. This triggers D-Limit orders to automatically reprice to 1 MPV (minimum NBBO variant, $0.01 for most stocks) outside that level. Note that the repricing built-in to the D-Limit is defensive in nature and it is specifically designed to provide protective order management functionality in a situation where only a natively executed algorithm has any chance to beat an opportunistic algorithm that may be reacting to the same external public signals.

In essence, the D-Limit order type is a dynamic order submission strategy that takes into account the quote instability in the market.[12] The Securities Exchange Commission’s (SEC) decision mentions that concerns about routing practices, which were raised again with respect

[10] Bishop (2017) provides detail on the evolution of the CQI signal and discussion of the different generations of the CQI signal.

[11] The CQI signal has been updated from the first version that was released in 2014 and the last update before our sample period occurred in May of 2018.

[12] In its initial implementation the D-Limit is concerned about picking-off risk and does not symmetrically make the order more aggressive if the market is running away.

to the D-Limit order type, were already addressed in its earlier decisions.[13] We take as given that the D-Limit order type and abstract from interesting market design questions[14] in what follows and focus instead on examining how and whether the new order type achieves its stated objectives of reducing picking off risk, encouraging displayed liquidity, and attracting more and better quality order flow to IEX.

2.2.1 Fee Schedule for D-Limit

Launching a new type of order presents a few challenges beyond the design and usefulness of the new order. Market participants have to make adjustments to their existing order management routines. The D-Limit order type is by design made simple to use. Nonetheless, participants still need to review their protocols as D-Limit orders may be resubmitted and repriced to avoid being 'run over by the market' but occasionally they may need to be further repriced to avoid 'the market running away from them.' The latter of the participants' responsibility for the initial version of the D-Limit. It is therefore reasonable to assume that there are some adjustment costs associated with switching to a new order type. In addition, most participants may have to be convinced to adapt to the new product and overcome any 'status quo bias' they may have.[15]

To encourage the adaption of the new D-Limit order type IEX offered the new order for free and in order to further boost the adaptation of the new order type a promotional discount of \$0.0002 per executed share was offered that was applicable to any fees incurred on D-Peg or M-Peg orders. The promotional fee component was in effect from October 1, 2020, to December 31, 2020, but starting from Jan. 1 the fees were set back to the regular limit order fees from before.[16] The fee schedule was tweaked to make the launch of the D-Limit order type more likely to succeed. Despite the fee inducements widespread adaptation

[13] "The Commission previously addressed the commenter's concern about routing an order to IEX and accounting for its access delay when the Commission approved IEX's exchange registration." Securities and Exchange Commission, Release No. 34-89686.
[14] e.g. Miller (1991) and Brown and Holden (2005)
[15] Samuelson and Zeckhauser (1988)
[16] Securities and Exchange Commission, Release No. 34-90786

of the D-Limit order type relied on the D-Limit order's ability to reduce adverse selection. Without that, any rebates and the lack of a fee associated with the new order would be a small consolation.

The revised fee schedule is important for any analysis of order submission behavior and liquidity on IEX. Thus, we exclude the period of promotional fee discount period for a fair comparison before and after the introduction of the D-Limit order type for our study. It is worth noting though those other fees were unchanged and therefore the revised fee schedule uniquely promotes the new D-Limit order type over regular limit orders. That implies that when displayed liquidity is analyzed the changes observed are quite likely to reflect more use of D-Limit orders and potentially less use of regular limit orders. Furthermore, the promotional fee discount that D-Limit order users can use against their fees incurred from submitting D-Peg and M-Peg orders does not impact displayed liquidity.

2.3 Our Sample

Our sample is collected from publicly available data sources only. We use stock market activity data from the Center for Research in Securities Prices (CRSP) and NYSE Trade and Quote (TAQ). We first select common stocks with share code (SHRCD) 10 or 11 from the CRSP database. We want to compare the changes due to the introduction of the D-Limit order by IEX, which started in October 1, 2020. However, at the same time, IEX launched the D-Limit order, IEX had a promotional discount of $0.0002 applicable to fees incurred using D-Peg and M-Peg orders until the end of 2020. To make a clean comparison, we look at January and February of 2021 as post-D-Limit orders and without the promotional period. We use August and September of 2020, 2 months before the introduction of the D-Limit order, as the observation period where there are 3,818 stocks in the universe. To obtain enough sample period (1 month pre- and post-periods) per stock, we use stocks that start trading September 1 or earlier and keep on trading for at least up to January 31, 2021, leaving us with 3,339 stocks. Since we are not interested in stocks that are rarely traded, we remove stocks that have a minimum dollar trading volume of less than \$10m during the pre- and post-period, leaving us 812 stocks. Finally, we remove penny stocks, stocks with a minimum price of smaller than \$5, during the sample period. Applying these filters leaves us with 800 stocks in our sample We also use IEX TOPS data directly downloaded from the IEX website[17] to observe the top-of-the-limit order book at IEX.

In Table 1, we report the descriptive statistics of our sample during the observation window. Market price (dollars) and market cap (billions of dollars) are day-end averages, trading volume (millions of dollars) is calculated every day by multiplying day-end price with shares outstanding, IEX market share (percentages) is trading volume initiated by IEX over total trading volume using TAQ. The quoted spread (basis points) is time-weighted relative quoted spread defined as follows:

$$Quotedspread_{it} = \frac{\sum_n [(\ln NBO_{itn} - \ln NBB_{itn}) \times time_{itn}]}{\sum_n time_{itn}}, \tag{1}$$

where for each datapoint n of National Best Bid and Offer (NBBO) updates for stock i at date t, NBO_{itn} is the National Best Offer (NBO), NBB_{itn} is the National Best Bid (NBB), and $time_{itn}$ is the time length that the NBBO is in force. That is, whenever an NBO_{itn} or NBB_{itn} changes, there is a new data point $n+1$. IEX market share and quoted spreads are measured during market hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies associated with the market open.

Table 1 about here

Our data shows that price, market cap, and trading volume are skewed to the right. The average IEX share is around 4.38 percent which seems higher than what is known to be around 1.8 percent during the observation period.[18] First, this is because we take simple averages across day and stocks, so if there's a stock-day with a relatively high IEX share mainly due to low overall volume, our average can be biased upwards. If we use weighted

[17] https://iextrading.com/trading/market-data/

[18] See https://iextrading.com/stats/ for historical IEX market share.

average using trading volumes across stocks, we show approximately 2.7 percent IEX share in the observation period. Second, since we are working with TAQ data and only between 9:35 a.m. to 4:00 p.m., we exclude trades around the open and after the close (including overnight trades). Using the full TAQ data for 800 stocks lowers the IEX share by about 0.1 percentage points. Finally, our sample excludes stocks that are less popular in terms of trading volume and these stocks tend to be traded less in IEX. Our sample has a low NBBO quoted spread with more than 75 percent of stocks averaging less than 12.42 basis points.

2.4 Regulation NMS and the Market Data Revenue Sharing

We have access to information about the Market Data Revenue Sharing Formula and Scheme from the UTP Plan Administration and we use the document entitled Summary of Market Data Revenue Allocation Formula.[19]

Quoting from the opening of the Summary of Market Data Revenue Allocation Formula document:

> Regulation NMS changed the formula for determining how market data income (revenue less administrative expenses) is allocated to individual SRO participants ("Revenue Allocation Rule"). The Revenue Allocation Rule sets forth a two-step process to allocate Plan revenue among CTA and UTP Plan Participants. · The first step is to identify the revenue attributable to each Eligible Security in the Network's data stream (the "Security Income Allocation" or "SIA"). · The second step is to identify the Participant's share of revenue in an Eligible Security based on the "Trading Share" and "Quoting Share" of each Participant. 50% of the SIA is allocated to Participants based on their respective Trading Share and 50% of the SIA is allocated to the Participants based on their respective Quoting Share.

Regulation NMS changed the formula for determining how market data income is allocated to individual SRO participants. Two aspects of the updated formula are worth

[19]See https://www.utpplan.com/ and find the "SIP Revenue Allocation Summary."

mentioning right here. The weights assigned across securities are determined based on a square-root of dollar volume formula which implies in practical terms a more even set of weights across securities. The other aspect is that an exchange's share of trading as well as the exchange time- and depth-weighted share of the NBB, and NBO determines its share of the revenue allocation for a particular security.

3 Empirical Results

In section 3.1 report event-study evidence for IEX's market share and the use of mid-quote pegged orders at IEX over our sample period, August to September 2020 and January to February 2021. In section 3.2 we present the details of our difference-in-difference empirical methodology which we apply for our main tests. In 3.3 we report results for the quality of the displayed liquidity at IEX around the launch of D-Limit and corroborate our results with data on market data revenue distributions before and after the launch.

3.1 Trading Activity on IEX Before and After the D-Limit Launch

To the extent that D-Limit order offers protection against adverse selection, we might see an increase in trading activity at IEX. Given that this is the only change it clearly makes it more attractive to submit limit orders to IEX without making any other choices less attractive. Thus, we will examine changes in IEX's market share around the launch of D-Limit omitting the three first months that feature an additional promotional discount. For each stock-day, we define IEX market share by aggregating all IEX trades (exchange code "V") and dividing all trades from 9:35 a.m. to 4:00 p.m. using TAQ.

Table 2 about here

Table 2 reports the cross-sectional averages for the IEX market share for our sample for August and September 2020, the months before the D-Limit launch, and January and February 2021, the first two months after the introductory promotional fee program ended.

There is a clear increase in the IEX market share from the before to after periods. The equally weighted market share increases by 1.8-1.9% and the volume weighted average market share increases by 1.3-1.5%. The first and third quartile and the median are reported as well and all results support the conclusion that IEX's market share increased by an economically significant amount from before to after the launch of D-Limit.

The evidence reported above suggests a net increase in trading activity at IEX but we might also observe an internal shift by traders opting to not submit, for example, mid-quote pegged orders and instead opt to submit discretionary limit orders. While we are not able to distinguish the type of the order using IEX TOPS (or IEX DEEP) or TAQ data we can observe mid-quote trades, resulting from the popular mid-quote pegged order types at IEX.

Table 3 about here

In Table 3, we report that mid-quote trades on IEX decrease significantly after the introduction of the D-Limit order, while mid-quote trades barely increase for non-IEX exchanges. Our results imply that the increase in IEX market share is not driven by mid-quote trades. On the contrary, there is some evidence that IEX customers shift away from using pegged orders and the D-Limit is one plausible alternative.

3.2 Difference-in-Difference Estimator and Results for the D-Limit Launch

We believe the nature of the distribution of trading activity over time creates a good way to structure a pseudo-experiment to study the effectiveness of the new D-Limit order type. Trading sometimes consists of sporadic trades spread across time but sometimes trading comes in tremendously packed bursts of activity. We exploit this fact by defining 'unstable', 'stable', and 'mixed' periods as follows. We break a trading day using one millisecond-long intervals. Between 9:35 a.m. to 4:00 p.m., there are 21,750,000 millisecond periods per stock-day. For each period, we categorize every millisecond of the trading period that has at least one trade into five types. i) Stable/buy: 4 or fewer buyer-initiated trades. ii) Unstable/buy: 5 or more buyer-initiated trades. iii) Stable/sell: 4 or fewer seller-initiated trades. iv) Unstable/sell: 5 or more seller-initiated trades. v) Mixed: a mix of buyer- and seller-initiated trades.[20]

Table 4 about here

Table 4 reports the percentage of intervals that are classified as unstable, stable, and mixed across our sample stocks by each of the four months of our sample period. The top versus bottom panels report the count-based versus volume-of-trade-based figures. It is clear that there are more trading unstable periods and that is reflected in the higher percentage of periods being unstable if trading volume is taken into account. It is also clear from both panels that the distribution across the three groups is quite stable over time.

We use the observation of trading in 'unstable' versus 'stable' periods as a measure of exposure versus no exposure. Intuitively, we consider IEX's D-Limit order as the treatment or intervention designed to make IEX-users, who choose D-Limits, less prone to have their orders trade in 'unstable' intervals due to the cancel, reprice, and resubmit functionality of D-Limit orders. Before versus after the launch of IEX's D-Limit order can then be compared for the treatment group (IEX) and the control group (Exchanges other than IEX). The outcome variable is trades and we care whether the trades occur in the 'unstable' or 'stable' periods. On an aggregated level the variable of interest that captures the overall outcome is the market share for IEX in 'unstable' versus 'stable' periods in in before versus after the launch period.[21] If IEX's D-Limit order type performs as expected and achieves its intended goals at least more often than not we expect to see IEX grow its market share of trading overall. Specifically, we expect the growth to be stronger for 'stable' periods compared to the IEX market share growth in 'unstable' periods. The difference-in-difference is designed

[20] We use Lee and Ready (1991) to classify trade direction, but applying methods of Ellis, Michaely, and O'hara (2000) or Chakrabarty et al. (2007) do not change our results significantly.

[21] We disregard the mixed intervals but we think that ought to have no impact as we are comparing market share measured in two different periods with each other. The critical issue is whether we have enough observations and we believe we meet that criterion easily.

to capture the difference in the growth in ‘stable’ versus ‘unstable’ periods and a positive estimate for the treatment effect is a sign that the D-Limit order type is working. Hence, in terms of testable hypothesis, our null hypothesis is that the treatment effect generated from our difference-in-difference estimator is equal to zero. In other words, if the D-Limit order type is ineffective and performs no differently than a regular limit order no difference in market share for unstable vs. stable periods is expected.

Table 5 about here

Table 5 shows the average IEX shares in trades (Panel A) and IEX share in trades excluding mid-quote trades (Panel B) per period for each period category. At the top of each panel, we show September 2020 statistics as the before D-Limit period, the middle we present January 2021 statistics as the after D-Limit period, and at the bottom of each panel we show the difference between the two periods. For all cases, we show that the IEX share increases for both ‘unstable’ and ‘stable’ periods. Further, we find that for the ‘stable’ period IEX’s share increases more than the ‘unstable’ period. This implies a positive estimated treatment effect and in turn, that is evidence against the null hypothesis of a zero treatment effect from the launch of the D-Limit order type.

We have shown that IEX grows its market share more strongly in stable versus unstable periods of trading providing support for the conclusion that the D-Limit order works we it was designed to and is used by a substantial portion of IEX users. But a skeptic may still ask how we can be so sure that unstable periods are ‘bad’ and stable periods are ‘good’? In the next table, we report evidence of the price impact measured over short intervals of time after a trade. We use 100- and 1000-millisecond time horizons and measure the changes in the mid-quote over these short periods. The results are reported in Table 6.

Table 6 about here

We calculate the price impact as follows:

$$PriceImpact_{itm} = \frac{2\left(M_{itm+\tau} - M_{itm}\right)}{M_{itm}}, \tag{2}$$

where τ is the time horizon in which we measure the future mid-quote of NBBO. We use τ to be .1 and 1 seconds.

We are particularly interested in whether there are systematic differences in the price impact following unstable and stable periods. Table 6 displays the price impact measured as the change in the mid-quote 100 and 1000 milliseconds after the trade. First, for unstable and stable intervals we observe that the mid-quote moves up after buyer-initiated trades and down after seller-initiated trades but the movement is greater in magnitude for unstable intervals across all intervals. The movement in unstable intervals is one basis point greater than the corresponding movement for stable intervals. Broadly speaking, the effect grows in magnitude from the shorter time horizons but is fairly comparable across say 1 and 2 second horizons. Furthermore, across the board, there is a tendency towards greater price impact in the post-period of January and February 2021 compared to the pre-period of August and September 2020.

For Table 5 and Table 6, we also run a robustness check by changing the period length from 1ms to 750μs. We also change the cutoff of stable and unstable periods from 5 trades to 7 trades. While we do not report the results here, we find our results to be robust and qualitatively the same across all different specifications.

3.3 Quality of Quotes and Market Data Revenue Implications

More orders initiated from IEX imply that more liquidity supplying orders are submitted to IEX. When more orders are submitted, the book on IEX is likely to have narrower spreads. Thus, it is likely that liquidity is enhanced compared to overall market liquidity after the D-limit is introduced.

Table 7 about here

Table 7 shows the IEX and market-wide (NBBO) quoted spread. After the D-Limit was introduced, IEX quoted spread decreased by about 34 percent while the market-wide quoted spread increased from September 2020 to January 2021. Our findings suggest that the introduction of D-Limit increases market liquidity at IEX.

Note that our quoted spread measures may not be an accurate way of measuring the quality of the IEX order book compared to NBBO since we do not populate samples (times) when one side of the book is not available on IEX. Also, when one side (or both sides) of the top of the book price is far away from NBBO, the quoted spread is large and these samples may contribute to the wide IEX spread despite the time that the quoted spread being large is short.

Since IEX is only one of the many exchanges in the U.S., the top of IEX order book can be different from the NBBO. When there are more traders active at IEX, it is more likely that IEX top of the order book is the same as NBBO. Thus, looking at the time that the best bid or ask at IEX is the same as NBB or NBO, respectively, and the time that the best bid and ask at IEX are the same as NBBO can be another way of measuring market quality relative to the NBBO.

Table 8 about here

We report the time that the top of IEX limit order book is at NBB and/or NBO in Table 8. In Panel A, we report the fraction of time that IEX is at the NBBO, that is, when IEX's best bid is the same as NBB and IEX's best ask is the same as NBO in price. Looking at the overall average, we find IEX to be rarely at NBBO, averaging below 2 percent before the introduction of the D-Limit order. After the D-Limit is available at IEX, we find a large increase in time at NBBO for periods after the introduction of the D-Limit order. In panel B, we report the fraction of time that IEX is either NBB or NBO. We find a similar pattern in IEX time at NBB or NBO as well. Before the launch of D-Limit order type, we found the average time to be below 16 percent in August and September. However, in January 2021 and on, we find that IEX order book meets NBB or NBO around 60 percent of trading hours. This is consistent with IEX performing well in IEX market share in Table 2 and quoted spread in Table 3 relative to the overall market.

The introduction of the D-Limit is also associated with a dramatic improvement in the quality of displayed liquidity at IEX. The IEX is much more likely to be part of the NBBO, the NBB, or the NBO than before the introduction of the D-Limit order type. These improvements can be interpreted as an economic response by IEX users to submit more aggressive limit orders more often hence causing a dramatic improvement in the quality of IEX's displayed liquidity. This response is associated with a dramatic improvement in IEX's time at the inside quotes adjusting for other venues, the depth, etc. In other words, IEX's so-called 'quote-share' improves from a low base to around 20%. This in turn implies that IEX's share of the market data revenue improves over and above what the trading volume-based share would predict.

While we show IEX's market quality improved after the introduction of the D-Limit order type, IEX has a clear incentive to make the D-Limit successful. Revenue sources of exchanges include trading fees and listing of assets, but also market data revenue should not be ignored. According to Nasdaq Economic Research,[22] SIP total revenue exceeded \$400m in 2020. 94% of the revenues were distributed for trade and quote. Exchanges gain more shares of the revenue when there is more trading activity and more quoting activity.[23]

Note that our results from Table 2 show increased trading activity so that IEX is likely to gain more shares of SIP revenue after the introduction of D-Limit order. While Table 8 shows the time IEX is at NBBO increased, it does not show how many fractions of shares at NBBO are from IEX. We recalculate IEX time-volume weighted shares at NBBO in Table 9. For each stock-day, we calculate the measure using the equation

$$\frac{\sum_t (\text{IEX Shares at NBB} + \text{IEX Shares at NBO}) \times t}{\sum_t (\text{Shares at NBB} + \text{Shares at NBO}) \times t,} \tag{3}$$

[22] https://www.nasdaq.com/articles/sip-accounting-101-2021-03-25

[23] See Caglio and Mayhew (2016), Jones (2018), and Summary of Market Data Revenue Allocation Formula for more details on market data revenue.

where the numerator is the time-weighted IEX shares at NBB and NBO and the denominator is the time-weighted shares at NBB and NBO. As we can see from Table 9, we see the quoting activity increases more than ten times when comparing pre-D-Limit (2020.08/09) to post-D-Limit (2021.01/02) periods. Since D-Limit order is an order type that is lit, attracting more lit D-Limit orders will increase revenues for IEX by having a larger share of SIP quoting activity. Our results are aligned with monetary incentives for IEX to be innovative.

Table 9 about here

Our results are also consistent with the revenues generated by IEX shown in Table 10, which is an excerpt from Unlisted Trading Plan Administration's trade and quote revenue distribution (2021). It shows 2020Q3 (pre-D-Limit) and 2021Q1 (post-D-Limit) IEX's SIP revenue share. Before the launch of D-Limit order type, IEX's SIP shares were .81% for quoting activity and 2.82% for trading activity. In 2021Q1, the shares jump to 7.89% for quoting activity and 4.09% for trading activity. We find that SIP share for IEX increases in both trading activity and quoting activity, but more in quoting activity. The results imply that IEX's innovation not only increases the market share of executed trades but also shows improvement in IEX's market quality.

Table 10 about here

4 Discussion of Results

In this section, we summarize our main results and discuss some aspects of our research design and different implications of our findings.

Recall that we use IEX's market share as the outcome variable as it summarizes in an intuitive fashion the combined effects on the treatment and control group since only IEX users have access to D-Limit they form the treatment group, and the rest of the market forms the control group. We are particularly interested in whether there are systematic differences in the IEX market share following 'unstable' and 'stable' periods. We find that IEX's market share during the ‘stable’ period increases more after the launch of D-Limit compared to ‘unstable’ periods. Our difference-in-difference results identify a positive treatment effect of between 1.8 and 1.9%. The interpretation of the positive treatment effect estimates is that IEX is growing its market share more in the ‘stable’ periods compared to the ‘unstable’ periods when the period before the introduction of the D-Limit order type, September (2020), is compared to the after-period, January (2021). The results are comparable when we use August (2020) as the pre-period and February (2021) as the post-period.[24] Similarly, the results are robust to changing the length of the time interval (1ms vs 0.75ms) and the number of trades in one direction (5 vs. 7). Our results imply that D-Limit can help limit order submitters by making their order adjust more dynamically and avoid as much as possible stale prices.[25]

We believe our difference-in-difference estimation strategy identifies the effects of the D-Limit order type introduction despite our data not identifying order types used directly. By focusing on the ‘unstable’ versus ‘stable’ periods and contrasting the period before and after the introduction of the D-Limit order type our methodology focuses directly on what the D-Limit order type is supposed to accomplish. Recall that a key component of the D-Limit order type is the CQI-signal which is supposed to switch ‘on’ when the NBBO appears to be unstable and a change in the NBBO is imminent. We do not have data on the CQI signal or the data needed to reconstruct the CQI signals. Instead, we focus on the quote instability that the CQI signal is designed to predict. We recognize that several sources of noise hinder the identification of a clean treatment effect. Firstly, the CQI signal that the D-Limit order is dependent on is a prediction itself and may be incorrect. Second, the competing trading algorithms that are the source of the orders that pick off soon-to-be stale limit orders are constantly evolving too, and hence what may have worked in the months immediately after

[24] Recall that we drop the first few months after the introduction, October to December, as a promotional fee discount fee that favored the new order type, D-Limit, would cloud the analysis. That promotion ended as of the start of 2021.

[25] With respect to the price impact, the main finding is that the price impact is larger in magnitude after ‘unstable’ versus ‘stable’ periods by about one basis point. Hence, the instability in the ‘unstable’ periods has a cost in terms of a greater price impact.

the launch may not work as well say by February 2021.

A set of results confirms that our definition of stable versus unstable intervals corresponds to differences in price stability and does not just measure more or less trading activity. Over horizons from 100 ms to 2000 ms, we confirm that price impact following trades during unstable versus stable periods are associated with about 1 basis point greater price impact. Hence the value added that D-Limit provides to liquidity suppliers is that it tends to help them avoid trading in the periods with greater price impact by shifting their executions towards more stable periods.

Do our results suggest that the case of IEX's D-Limit order type could work as a more broadly applicable solution to latency arbitrage? Perhaps, but there are some key caveats to keep in mind. Different exchanges could develop and launch order types similar to the D-Limit but it is worth keeping in mind that the D-Limit is not just a stand-alone order type but an order type that works in an integrated fashion with the IEX trading mechanism. Importantly, without the CQI signal and the intentional delay (the 'speed bump') one would imagine a D-Limit order type not working as well. It might be easier to imagine competitors developing their own version of 'the signal' and these might be even better than the IEX's CQI-signal. Naturally, the improvement in IEX's displayed liquidity was one imagines, one of the objectives. In a competitive situation, however, obtaining a bigger share of the market in terms of either 'trading volume' or in terms of the 'share' of the inside quote becomes more challenging.[26] Hence innovating exchanges would need to look for other sources of incremental revenue.

In addition to a need for periodic updates to the CQI signal to keep ahead of the competition, there is also the risk of manipulative strategies. This would be even more of a factor to take seriously if a D-Limit order type solution was adopted more broadly. With a bigger share of the market behaving in some fashion that is closely tied to the market data creates an opening to manipulate that data.

[26] Another caveat to be mindful of is co-location. It makes it even more important to have a well-performing AI-based signal to power any such new order types.

The dramatic shift in IEX's share of the market data revenue becomes clear if we compare the first three quarters of 2020 to the first three quarters of 2021. By omitting the last three quarters of 2020 the period with the promotional fee discount for D-Limit order type does not confound the inference. We use the quarterly reports posted on the Unlisted Trading Privileges website (https://www.utpplan.com/) for the figures. From the third quarter report for 2020, we see that IEX's total market data revenue share equaled $2,190,210, and that more than tripled to $6,804,096 for the first three quarters of 2021. IEX's share of the total market data revenue increased from around 2% in 2020 to over 6% in 2021. The figures above are impressive but they pale in comparison with the increase in the quoting-based share of the market data revenue. IEX collected only about $500,000 in the first three quarters from the quoting-based revenue but that increase to $4.5 million in the first three quarters of 2021. In terms of IEX's share of the total amount distributed there is an approximately eightfold increase in the share from just under 1% to above 8%. These figures are not based on our analysis but reflect the official reports from the UTP plan. Our calculations of IEX time and depth-adjusted contributions to the NBBO, NBB, and NBO reported in Section 3.3 are consistent with these broader trends in the market data revenue.

It is reasonable to ask if there are alternative solutions to the latency arbitrage problem that IEX wishes to address. In fact, an earlier effort was pursued by adopting an extra fee for liquidity-taking orders only when the CQI indicator was switched on. The fee was limited to 3 mils ($0.003) and that is the maximum allowed.[27] More generally, maker fees subsidize liquidity and one can think of that as an alternative solution in this case. The maker-fee would then act as a subsidy for the extra cost in terms of 'adverse selection' that the limit order submitter faces. In this context, the D-Limit order type is a second alternative and involves addressing the source of the problem more directly by making the order cancel and resubmissions nimbler in unstable quote environments.[28] We believe these efforts by IEX to

[27] See Appendix B for more details on the Crumbling Quote Remove Fee.

[28] Markets that apply make-take fee models in different fashion have been studied in Malinova and Park (2015) and Foucault, Kadan, and Kandel (2012) among others.

reduce their users (exposure) to latency arbitrage are examples of the type of innovation by exchanges that some observers have called for. In principle, one could imagine a future in which competing D-Limit-order-type offerings existed in many markets. Many participants may find such an option attractive, but others may choose to use other proprietary systems to manage their orders. To the extent such developments encourage displayed liquidity, they are beneficial for public markets.

5 Conclusion

D-Limit order type is one in a series of solutions that address the challenge of preventing the limit order prices from going stale. An earlier solution to address latency arbitrage involved a liquidity remove fee, which was deemed unsuccessful and ultimately terminated.[29] The Liquidity-Removal-Fee and the D-Limit-order type utilize the machine-learning-based CQI signal and the IEX-speed-bump. However, the two solutions featured different strategies for dealing with the latency arbitrage problem.

On the one hand, the 'Liquidity-Remove-Fee' sought to penalize liquidity demanding order flow in unstable-quote situations (when the CQI fires) with an extra fee and thereby discourage such orders (discourage the 'picking off'). On the other hand, the 'D-Limit-order' features no penalties for any party but instead, it helps the limit order submitters execute a nimbler cancel-reprice-resubmit strategy than they might be able to on their own. It is important to be mindful of the constraints in interpreting the outcomes of these two policies designed to address the same problem and designed to work in and with the same market mechanism. In any case, our results suggest that the D-Limit order type is a successful solution to reduce the users' exposure to latency arbitrage while leaving the latency arbitrage order flow untouched.

Is the D-Limit order type a success because it democratizes access to better technology,

[29] Our methodology applied to the liquidity remove fee episode confirms that there is no measurable effect around the introduction of the fee. See Appendix B.

and machine-learning-based signals to manage limit orders? It may offer users an edge because of the way it works with IEX's existing trading mechanism, the 'speed bump' and the CQI-signal. The trading algorithms constantly evolve and it seems fair to predict that the D-Limit order type or more precisely the CQI-signal needs to keep evolving too to allow the user to successfully cancel, reprice, and resubmit their limit orders in the future.

Is this an example of a market-based solution to the latency arbitrage problem that the former SEC chair Mary Jo White called for when she talked about the need to look for market-based solutions to equity market structure problems?[30] The AI-enabled D-Limit order type appears to be a strong candidate for such a market-based solution. There are open questions about how this alters market competition and possible barriers for a 'D-Limit order-type'-solution to be implemented more widely that we will leave for future research.

[30]Enhancing Our Equity Market Structure, Chair Mary Jo White, remarks at Sandler O'Neill & Partners, L.P. Global Exchange and Brokerage Conference, New York, N.Y., June 5, 2014.

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A Tables and Figures

Table 1: Sample Descriptive Statistics

This table shows the descriptive statistics for 800 stocks in our total sample from August to September 2020 (Panel A) and January to February 2021 (Panel B), 2 months before and after the introduction of the D-Limit order. Mean, standard deviation, 1st quartile, median, and 3rd quartile statistics of stock averages are reported. Market price and market cap are day-end averages, trading volume (millions of dollars) is calculated every day by multiplying day-end price and shares outstanding, IEX market share (percentages) is trading volume initiated by IEX over total trading volume, and quoted spread (basis points) is time-weighted relative quoted spread. IEX share and quoted spreads are measured from 9:35 a.m.–4:00 p.m. to avoid idiosyncrasies associated with the market open.

Panel A: Pre-period (2020.08–09)					
	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	IEX %	QSpread (bp)
Mean	130.10	37,072.11	343.86	4.38	9.64
SD	243.13	119,911.67	1,550.37	1.55	6.55
Q1	36.29	5,069.23	57.40	3.36	5.03
Median	76.54	11,816.21	107.81	4.33	7.93
Q3	140.72	27,862.56	239.09	5.39	12.42

Panel B: Post-period (2021.01–02)					
	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	IEX %	QSpread (bp)
Mean	156.24	43,355.69	372.06	6.30	12.42
SD	272.85	132,091.34	1,231.99	1.96	8.71
Q1	48.59	6,891.21	78.79	4.95	5.78
Median	92.55	14,894.45	141.80	6.37	9.96
Q3	171.22	34,380.86	298.43	7.68	17.40

Table 2: IEX Market Share

This table shows the monthly average IEX market share for the 800 stocks in our full sample. For each stock-day, we calculate the IEX Market share as the fraction of trades that are initiated from IEX during trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. Then we take the equal-weighted average across all days in a month for each stock to get the monthly IEX share of the stock. We report the statistics of IEX market share in percentages. Cross-sectional monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution. We also report the volume-weighted mean of IEX share (VW Mean) at the bottom.

	2020.08	2020.09	2021.01	2021.02
EW Mean	4.312	4.441	6.228	6.373
se	0.056	0.058	0.072	0.070
Q1	3.196	3.345	4.794	4.967
Median	4.233	4.408	6.302	6.430
Q3	5.357	5.463	7.623	7.712
VW Mean	2.769	2.671	3.953	4.297

Table 3: Mid-quote Execution

This table shows the monthly average fraction of mid-quote trades among all trades for the 800 stocks in our full sample. For each stock-day, we calculate the percentage of trades on IEX (non-IEX) executed at the mid-quote of the NBBO during a day. Our sample uses trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We sum the trading volume of mid-quote IEX (non-IEX) trades and divide it by all trading volume at IEX (non-IEX). Then we take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics of the IEX mid-quote fraction (Panel A) and non-IEX mid-quote fraction (Panel B) in percentages. Monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution.

Panel A: IEX mid-quote execution (%)				
	2020.08	2020.09	2021.01	2021.02
Mean	48.135	46.021	36.069	34.649
se	0.228	0.240	0.241	0.227
Q1	44.360	41.866	31.557	30.712
Median	48.219	45.910	36.345	34.743
Q3	51.892	50.304	40.800	39.082

Panel B: Mid-quote executions at other exchanges excluding IEX (%)				
	2020.08	2020.09	2021.01	2021.02
Mean	14.985	14.086	13.956	13.893
se	0.142	0.143	0.130	0.132
Q1	11.840	10.805	11.114	11.002
Median	15.056	14.114	13.833	13.689
Q3	18.313	17.355	16.637	16.828

Table 4: Statistics of 1 millisecond periods with trading

This table shows the basic statistics of one millisecond (ms) trading period during trading hours from 9:35 a.m. to 4:00 p.m. We define *unstable* period as a 1ms period with 5 or more trades and all trades in the periods coming from the same side (buy or sell). We define *stable* period as a 1ms period with less than 5 trades and all trades coming from the same side (buy or sell). We define the period to be *mixed* if we observe both buy- and sell-initiated trades within a period. Panel A shows the conditional share of periods given a trading period. Panel B shows the share of trading volume per trading group.

Panel A: Period Share (% conditional on a period with trade)				
	2020.08	2020.09	2021.01	2021.02
Unstable	1.622	1.645	1.609	1.589
Stable	94.041	94.019	94.277	94.148
Mixed	4.337	4.336	4.114	4.263

Panel B: Trading Volume (%)				
	2020.08	2020.09	2021.01	2021.02
Unstable	9.219	9.672	9.732	9.886
Stable	77.121	76.975	76.638	75.939
Mixed	13.660	13.353	13.630	14.174

Table 5: DiD – IEX Share per period

This table shows the IEX share (in percentages) by trading period type. We categorize every millisecond of the trading period that has at least one trade into five types. i) Stable/buy: 4 or fewer buyer-initiated trades. ii) Unstable/buy: 5 or more buyer-initiated trades. iii) Stable/sell: 4 or fewer seller-initiated trades. iv) Unstable/sell: 5 or more seller-initiated trades. v) Mixed: a mix of buyer- and seller-initiated trades. We present IEX share in trades (Panel A1) and IEX share in trades excluding IEX mid-quote trades (Panel A2). We provide the mean of pre-D-Limit introduction (Pre, 2020.9), post-D-Limit (Post, 2021.1), the increase from pre to post (Post−Pre), and the standard error of the change. We skip October to December 2020 sample due to the promotional fee rebate that was offered to entice users to try the new order type. Robustness checks are in Panels B and C where we vary the cutoff between stable/unstable to be 7 trades (Panel B) or change each time period to be 750 microseconds (Panel C).

Panel A1: IEX Share per period % [1ms periods, 5 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.312	6.962	5.650	1.316	7.046	5.730
Post	2.810	10.240	7.430	2.762	10.387	7.625
Post−Pre	1.498	3.278	1.780	1.447	3.341	1.894
se	0.038	0.074	0.068	0.037	0.074	0.067

Panel A2: IEX Share excluding mid-quote per period % [1ms periods, 5 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.535	6.931	5.396	1.510	6.878	5.368
Post	3.339	9.275	5.936	3.214	9.135	5.921
Post−Pre	1.804	2.344	0.540	1.704	2.257	0.554
se	0.046	0.070	0.064	0.042	0.069	0.061

Table 5 cont'd

Panel B1: IEX Share per period % [1ms periods, 7 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.167	6.695	5.528	1.200	6.777	5.577
Post	2.454	9.910	7.456	2.448	10.048	7.600
Post−Pre	1.287	3.216	1.929	1.247	3.270	2.023
se	0.040	0.071	0.068	0.046	0.071	0.070

Panel B2: IEX Share excluding mid-quote per period % [1ms periods, 7 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.334	6.737	5.403	1.332	6.687	5.355
Post	2.935	9.048	6.113	2.855	8.910	6.055
Post−Pre	1.601	2.311	0.710	1.523	2.223	0.700
se	0.047	0.068	0.065	0.050	0.067	0.067

Table 5 cont'd

Panel C1: IEX Share per period % [750μs periods, 5 trade cutoff]						
	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.081	6.909	5.828	1.089	6.992	5.903
Post	2.389	10.178	7.789	2.350	10.318	7.968
Post−Pre	1.308	3.269	1.961	1.261	3.327	2.066
se	0.037	0.073	0.069	0.037	0.073	0.069

Panel C2: IEX Share excluding mid-quote per period % [750μs periods, 5 trade cutoff]						
	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.227	6.894	5.667	1.208	6.838	5.630
Post	2.859	9.236	6.377	2.756	9.099	6.343
Post−Pre	1.632	2.342	0.710	1.548	2.261	0.713
se	0.044	0.070	0.063	0.043	0.069	0.064

Table 6: DiD – Price Impact

This table shows the price impact by trading period type. We categorize every millisecond of the trading period that has at least one trade into five types. i) Stable/buy: 4 or fewer buyer-initiated trades. ii) Unstable/buy: 5 or more buyer-initiated trades. iii) Stable/sell: 4 or fewer seller-initiated trades. iv) Unstable/sell: 5 or more seller-initiated trades. v) Mixed: a mix of buyer- and seller- initiated trades. For each millisecond period that has a trade, we calculate the price impact as $PriceImpact_{itm} = \frac{M_{itm+\tau} - M_{itm}}{M_{itm}}$, where M_{itm} is the mid-quote of NBBO, at period m, stock i, date t. We vary the time horizon τ to be 100 milliseconds (Panel A1) and 1000 milliseconds (Panel A2) in which we measure the future mid-quote of NBBO. We take the stock-day-period average by taking the equal-weighted average by period group. Then we take the equal weighted average by period group and month. We provide mean of pre-D-Limit introduction (Pre, 2020.9), post-D-Limit (Post, 2021.1), the increase from pre to post (Post−Pre), and the standard error of the change. We skip the October to December 2020 sample due to the promotional fee rebate that was offered to entice users to try the new order type. Robustness checks are in Panels B and C where we vary the cutoff between stable/unstable to be 7 trades (Panel B) or change each time period to be 750 microseconds (Panel C).

Panel A1: $\tau = 100$ milliseconds [1ms periods, 5 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.697	0.358	−1.339	−1.729	−0.374	1.355
Post	2.371	0.369	−2.002	−2.445	−0.397	2.048
Post−Pre	0.674	0.011	−0.664	−0.716	−0.023	0.693
se	0.037	0.003	0.036	0.038	0.004	0.036

Panel A2: $\tau = 1000$ milliseconds [1ms periods, 5 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	2.071	0.503	−1.568	−2.074	−0.511	1.563
Post	2.798	0.496	−2.302	−2.864	−0.530	2.334
Post−Pre	0.727	−0.007	−0.734	−0.791	−0.019	0.771
se	0.041	0.005	0.039	0.043	0.006	0.040

Table 6 cont'd

Panel B1: τ = 100 milliseconds [1ms periods, 7 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.488	0.314	−1.174	−1.523	−0.329	1.194
Post	2.055	0.316	−1.739	−2.131	−0.341	1.790
Post−Pre	0.567	0.002	−0.565	−0.608	−0.013	0.596
se	0.033	0.003	0.032	0.033	0.003	0.032

Panel B2: τ = 1000 milliseconds [1ms periods, 7 trade cutoff]

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.867	0.458	−1.409	−1.878	−0.464	1.414
Post	2.483	0.441	−2.042	−2.564	−0.472	2.092
Post−Pre	0.616	−0.017	−0.632	−0.686	−0.007	0.679
se	0.037	0.005	0.035	0.038	0.005	0.036

Table 6 cont'd

Panel C1: $\tau = 100$ milliseconds [750μs periods, 5 trades cutoff]						
	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.571	0.348	−1.223	−1.595	−0.363	1.232
Post	2.174	0.354	−1.820	−2.220	−0.382	1.838
Post−Pre	0.604	0.007	−0.597	−0.625	−0.019	0.606
se	0.032	0.003	0.030	0.032	0.004	0.030

Panel C2: $\tau = 1000$ milliseconds [750μs periods, 5 trades cutoff]						
	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.931	0.491	−1.440	−1.931	−0.498	1.433
Post	2.576	0.480	−2.096	−2.617	−0.513	2.104
Post−Pre	0.644	-0.011	−0.656	−0.686	−0.015	0.671
se	0.035	0.005	0.033	0.037	0.005	0.033

Table 7: Quoted Spread

This table shows the monthly average of quoted spreads for the 800 stocks in our full sample. For each stock-day, we calculate time-weighted market-wide quoted spreads using TAQ by $Quotedspread_{it} = \frac{\sum_n[(\ln NBO_{itn} - \ln NBB_{itn}) \times time_{itn}]}{\sum_n time_{itn}}$, where for each datapoint n of National Best Bid and Offer (NBBO) updates for stock i at date t, NBO_{itn} is the National Best Offer (NBO), NBB_{itn} is the National Best Bid (NBB), and $time_{itn}$ is the time length that the NBBO is in force. We also calculate the IEX quoted spreads using IEX TOPS data with the same formula except replacing NBO and NBB with best offer at IEX and best bid at IEX, respectively. Times when one side of the book is not available is not populated. We use trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics of IEX spreads (Panel A) and market-wide spreads (Panel B) in basis points. Monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution.

Panel A: IEX quoted spread (bps)				
	2020.08	2020.09	2021.01	2021.02
Mean	463.469	394.902	260.656	312.432
se	24.427	20.342	14.480	21.230
Q1	68.855	56.239	47.196	49.954
Median	211.573	172.283	127.083	138.768
Q3	576.778	480.869	317.760	367.716

Panel B: Market-wide quoted spread (bps)				
	2020.08	2020.09	2021.01	2021.02
Mean	9.117	10.155	12.614	12.226
se	0.230	0.237	0.309	0.310
Q1	4.675	5.430	6.003	5.701
Median	7.313	8.320	10.162	9.706
Q3	11.656	13.274	17.365	17.168

Table 8: Time IEX is at NBB and/or NBO

This table shows the monthly average fraction of trading time IEX's best bid and/or offer is at the NBB and/or NBO for the 800 stocks in our full sample. For each stock-day, we calculate the At NBBO as the fraction of trading time the stock's IEX best bid and offer matches the NBBO. At NBB or NBO is calculated as the fraction of trading times when IEX's best bid is matched with NBB or IEX's best offer is matched with NBO. Our sample uses trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics of At NBBO (Panel A) and At NBB or NBO (Panel B) in percentages. Cross-sectional monthly statistics include mean, standard error of the mean, 5th percentile, 1st quartile, median, and 3rd quartile of the distribution.

Panel A: At NBBO (%)				
	2020.08	2020.09	2021.01	2021.02
Mean	1.564	1.635	10.898	12.636
se	0.187	0.182	0.261	0.330
Q1	0.050	0.044	7.737	8.684
Median	0.101	0.095	9.335	10.413
Q3	0.290	0.337	11.375	12.713

Panel B: At NBB or NBO (%)				
	2020.08	2020.09	2021.01	2021.02
Mean	15.980	15.789	59.748	61.073
se	0.893	0.913	0.474	0.475
Q1	3.573	3.167	53.937	55.381
Median	5.487	4.847	57.412	59.216
Q3	9.697	8.861	61.327	63.495

Table 9: Time and Volume Weighted Share IEX at NBBO

This table shows the time and volume weighted fraction of IEX at NBBO for the 800 stocks in our full sample. For each stock-day, we calculate the following:

$$\frac{\sum_t (\text{IEX Shares at NBB} + \text{IEX Shares at NBO}) \times t}{\sum_t (\text{Shares at NBB} + \text{Shares at NBO}) \times t}$$

where the numerator is the time-weighted IEX shares at NBB and NBO and the denominator is the time-weighted shares at NBB and NBO. Our sample uses trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics in percentages. Cross-sectional monthly statistics include mean, standard error of the mean, 5th percentile, 1st quartile, median, and 3rd quartile of the distribution.

	2020.08	2020.09	2021.01	2021.02
Mean	1.727	1.719	20.984	21.889
se	0.013	0.015	0.060	0.062
Q1	0.633	0.580	16.225	17.135
Median	1.252	1.138	20.809	21.752
Q3	2.405	2.332	25.698	26.743

Table 10: IEX SIP Revenue Share (Source: www.utpplan.com)

This table shows the IEX and the total market SIP Revenue distributed in the quarters of 2020Q3 (pre-D-Limit) and 2021Q1 (post-D-Limit). Quote columns are revenues from the quoting activity, Trade columns are revenues from the trading activity, and the total columns are the sum of the quote and trade revenues for each quarter. The numbers are excerpted from the Unlisted Trading Plan Administration's trade and quote revenue distribution (2021).

	2020Q3			2021Q1		
	Quote	Trade	Total	Quote	Trade	Total
IEX	151,644	528,022	679,666	1,571,162	814,158	2,385,320
Total	18,707,176	18,707,176	37,414,351	19,906,632	19,906,632	39,813,264
IEX Share	0.81%	2.82%	1.82%	7.89%	4.09%	5.99%

B Analysis on Crumbling Quote Remove Fee Introduction at IEX

Note: This section of the appendix was originally circulated as a part of a separate paper circulated under the title "In Pursuit of a Level Trading Field: An Empirical Examination of IEX's Crumbling Quote Remove Fee"

In this appendix, We examine one particular market protocol change, introduction of Crumbling Quote Remove Fee (CQRF), that the Investors Exchange (IEX) implemented in 2018 to reduce liquidity makers' exposure to *crumbling quote arbitrage* on IEX and assess to what degree the change in the trading protocol was successful in achieving its goal.

When the Investors Exchange (IEX) launched as an exchange in 2016 a feature of its market design that received the most attention was the intentional access delay or the 'speed bump.' Given that the prevailing trend was towards faster and faster trading the 350-microsecond delay for all in- and out-bound messages was puzzling to many observers. Arguably the IEX Signal was another key part of IEX's trading protocol from the very beginning but it was overshadowed by the debate about the 'speed bump.' Both the 'speed bump' and the 'signal' are central to what we examine in this paper. But we focus on a more recent, 2018, change to IEX's trading protocol which involved adding a transaction fee to any order that removed liquidity during periods of 'quote instability.' The fee is also known as the *Crumbling Quote Fee* or CQ fee and it adds an extra trading fee of 3 mils or $0.30 per 100 shares that applies when the IEX Signal fires, i.e., when statistically the prevailing quotes in the market appear unstable. The idea is that the crumbling quote fee would discourage crumbling quote arbitrage strategies because it would make them less profitable and thereby encourage liquidity providers to provide more liquidity as they would face a decrease in the risk of being picked off.

The differential liquidity remove fee only applies when the crumbling quote signal is firing (switched into the on-state). When the signal is firing the signal stays in the on-state for only 2 milliseconds or 2000 microseconds. In other words, the signal stays in the on-state for about 5.7 units of the intentional access delay or speed bump. Both the intentional access delay and the liquidity remove fee work together, however, to give liquidity providers a bit more cover when the quotes are about to change in the markets. In addition to the extra fee some of the pegged orders are repriced to make them a bit less vulnerable during this brief transition period. In that respect the CQ fee and the speed bump work in tandem to make pegged orders less exposed to being picked off when the signal is firing.

In their SEC Filing[31] the IEX argued as follows: *"The Exchange (IEX) further believes that charging the Crumbling Quote Remove Fee only to the liquidity remover is equitable and not unfairly discriminatory because it is designed to incentivize order flow that enhances the quality of trading on the Exchange and disincentivize trading that does not."* The CQI signal is turned on only for around 1.2 seconds per symbol per day across all symbols that can be traded on IEX (reference the SEC filing). On a volume-weighted basis, the signal is turned on at approximately 6.5 seconds per day and symbol. All in all, the differential fee is applicable only for a brief amount of time for any symbol on any typical day. Hence one may wonder how it could possibly have any impact. To the extent trading algorithms that seek these particular trading opportunities, when quotes are unstable, they can generate a very large volume of orders and to the extent the fee, the IEX signal, and the speed bump work as intended they may discourage enough opportunistic order flow to influence liquidity.

To consider the effect of the CQRF on IEX, we work on the same main analysis that we have done for the introduction of D-Limit order on IEX. Specifically, we look at 1 or 2 months before and after the introduction of CQRF and pursue the production analogous tables from 1 to 8 in the main paper. Overall, we do not find evidence of enhanced market quality on IEX after the introduction of CQRF.

[31] Release No. 34-83048; File No. SR-IEX-2018-07. See https://www.sec.gov/rules/sro/iex/2018/34-83048.pdf.

Table A1: Sample Descriptive Statistics

This table shows the descriptive statistics for 768 stocks in our total sample from November 2017 to February 2018, a 2-month period before the introduction of the Crumbling Quote Remove Fee. Mean, standard deviation, 1st quartile, median, and 3rd quartile statistics of stock averages are reported. Market price and market cap are day-end averages, trading volume (millions of dollars) is calculated every day by multiplying day-end price and shares outstanding, IEX market share (percentages) is trading volume initiated by IEX over total trading volume, and quoted spread (basis points) is time-weighted relative quoted spread. IEX share and quoted spreads are measured from 9:35 a.m.–4:00 p.m. to avoid idiosyncrasies associated with the market open.

Panel A: Pre-period (2020.08–09)					
	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	IEX %	QSpread (bp)
Mean	95.25	30,158.47	131.49	3.06	6.86
SD	154.15	65,345.32	226.87	2.00	5.15
Q1	39.10	5,551.86	36.92	1.81	3.58
Median	65.55	11,248.04	65.95	2.64	5.35
Q3	112.58	25,350.52	124.35	3.61	8.20

Table A2: IEX Market Share

This table shows the monthly average IEX market share for the 768 stocks in our full sample. For each stock-day, we calculate the IEX Market share is the fraction of trades that are initiated from IEX during trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. Then we take the equal-weighted average (EW Mean) across all days in a month for each stock to get the monthly IEX share of the stock. We report the statistics of IEX market share in percentages. Cross-sectional monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution. We also report the volume-weighted mean of IEX share (VW Mean) at the bottom.

	2017.11	2017.12	2018.01	2018.02
EW Mean	3.834	3.651	3.635	3.462
se	0.043	0.042	0.041	0.037
Q1	3.011	2.899	2.874	2.811
Median	3.734	3.547	3.515	3.405
Q3	4.518	4.257	4.156	3.948
VW Mean	3.447	3.343	3.281	3.151

Table A3: Mid-quote Execution

This table shows the monthly average fraction of mid-quote trades among all trades for the 768 stocks in our full sample. For each stock-day, we calculate the percentage of trades on IEX (non-IEX) executed at the mid-quote of the NBBO during a day. Our sample uses trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We sum the trading volume of mid-quote IEX (non-IEX) trades and divide it by all trading volume at IEX (non-IEX). Then we take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics of IEX mid-quote fraction (Panel A) and non-IEX mid-quote fraction (Panel B) in percentages. Monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution.

Panel A: IEX mid-quote execution (%)				
	2017.11	2017.12	2018.01	2018.02
Mean	42.019	38.615	40.857	37.350
se	0.222	0.232	0.232	0.269
Q1	38.713	35.01	37.111	32.632
Median	41.702	38.087	40.385	36.585
Q3	45.109	41.860	43.615	41.237

Panel B: Mid-quote executions at other exchanges excluding IEX (%)				
	2017.11	2017.12	2018.01	2018.02
Mean	16.069	15.63	15.763	13.946
se	0.174	0.177	0.169	0.169
Q1	12.577	11.946	12.255	10.162
Median	16.552	15.608	15.852	14.008
Q3	19.519	19.305	19.019	17.450

Table A4: Quoted Spread

This table shows the monthly average of quoted spreads for the 768 stocks in our full sample. For each stock-day, we calculate time-weighted market-wide quoted spreads using TAQ by $Quotedspread_{it} = \frac{\sum_n [(\ln NBO_{itn} - \ln NBB_{itn}) \times time_{itn}]}{\sum_n time_{itn}}$, where for each datapoint n of National Best Bid and Offer (NBBO) updates for stock i at date t, NBO_{itn} is the National Best Offer (NBO), NBB_{itn} is the National Best Bid (NBB), and $time_{itn}$ is the time length that the NBBO is in force. We also calculate the IEX quoted spreads using IEX TOPS data with the same formula except replacing NBO and NBB with best offer at IEX and best bid at IEX, respectively. Times when one side of the book is not available is not populated. We use trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics of IEX spreads (Panel A) and market-wide spreads (Panel B) in basis points. Monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution.

Panel A: IEX quoted spread (bps)				
	2017.11	2017.12	2018.01	2018.02
Mean	280.710	276.798	268.904	254.986
se	3.961	4.309	4.358	4.137
Q1	215.927	197.430	185.166	163.909
Median	290.041	284.838	268.975	254.014
Q3	360.922	371.633	364.947	350.719

Panel B: Market-wide quoted spread (bps)				
	2017.11	2017.12	2018.01	2018.02
Mean	10.402	7.564	7.196	9.465
se	0.239	0.201	0.190	0.241
Q1	5.836	3.859	3.802	4.924
Median	8.705	5.982	5.604	7.496
Q3	13.441	9.175	8.749	11.769

Table A5: Time IEX is at NBB and/or NBO

This table shows the monthly average fraction of trading time IEX's best bid and/or offer is at the NBB and/or NBO for the 768 stocks in our full sample. For each stock-day, we calculate the At NBBO as the fraction of trading time the stock's IEX best bid and offer matches the NBBO. At NBB or NBO is calculated as the fraction of trading times when IEX's best bid is matched with NBB or IEX's best offer is matched with NBO. Our sample uses trading hours from 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the statistics of At NBBO (Panel A) and At NBB or NBO (Panel B) in percentages. Cross-sectional monthly statistics include mean, standard error of the mean, 1st quartile, median, and 3rd quartile of the distribution.

Panel A: At NBBO (%)				
	2017.11	2017.12	2018.01	2018.02
Mean	5.269	5.168	3.723	5.634
se	0.398	0.389	0.263	0.334
Q1	0.639	0.517	0.17	1.074
Median	1.603	1.603	1.418	3.26
Q3	4.187	4.357	4.017	7.158

Panel B: At NBB or NBO (%)				
	2017.11	2017.12	2018.01	2018.02
Mean	26.493	28.163	20.226	43.864
se	0.735	0.802	0.636	1.095
Q1	12.786	11.795	4.703	14.782
Median	19.403	20.465	15.77	36.082
Q3	32.837	37.723	29.873	72.504

Table A6: Statistics of 1 millisecond periods with trading

This table shows the basic statistics of one millisecond (ms) trading period during trading hours from 9:35 a.m. to 4:00 p.m. We first define *unstable* period as a 1ms period with 5 or more trades and all trades in the period coming from the same side (buy or sell). We define *stable* period as a 1ms period with less than 5 trades and all trades coming from the same side (buy or sell). We define the period to be *mixed* if we observe both buy- and sell-initiated trades within a period. Panel A shows the conditional share of periods given a trading period. Panel B shows the share of trading volume per trading group.

Panel A: Period Share (% conditional on a period with trade)				
	2017.11	2017.12	2018.01	2018.02
Unstable	2.054	1.900	1.807	1.657
Stable	93.473	93.817	94.042	94.046
Mixed	4.473	4.282	4.151	4.297

Panel B: Trading Volume (%)				
	2017.11	2017.12	2018.01	2018.02
Unstable	11.524	11.136	10.664	9.935
Stable	75.990	76.426	77.187	78.393
Mixed	12.486	12.438	12.150	11.672

Table A7: DiD – IEX Share per period

This table shows the IEX share (in percentages) by trading period type. We categorize every millisecond of the trading period that has at least one trade into five types. i) Stable/buy: 4 or fewer buyer-initiated trades. ii) Unstable/buy: 5 or more buyer-initiated trades. iii) Stable/sell: 4 or fewer seller-initiated trades. iv) Unstable/sell: 5 or more seller-initiated trades. v) Mixed: a mix of buyer- and seller-initiated trades. We present IEX share in trades (Panel A) and IEX share in trades excluding IEX mid-quote trades (Panel B). We provide the mean of pre-CQRF introduction (Pre, 2017.12), post-CQRF (Post, 2018.1), the increase from pre to post (Post−Pre), and the standard error of the change.

Panel A: IEX Share per period %

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	2.046	5.540	3.494	1.998	5.528	3.530
Post	1.778	5.428	3.650	1.730	5.418	3.688
Post−Pre	−0.268	−0.111	0.157	−0.268	−0.110	0.158
se	0.038	0.045	0.044	0.032	0.046	0.043

Panel B: IEX Share excluding mid-quote per period %

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.548	3.570	2.022	1.502	3.566	2.064
Post	1.343	3.412	2.069	1.315	3.408	2.093
Post−Pre	−0.205	−0.158	0.048	−0.187	−0.158	0.029
se	0.033	0.031	0.036	0.028	0.032	0.033

Table A8: DiD – Price Impact

This table shows the price impact by trading period type. We categorize every millisecond of the trading period that has at least one trade into five types. i) Stable/buy: 4 or fewer buyer-initiated trades. ii) Unstable/buy: 5 or more buyer-initiated trades. iii) Stable/sell: 4 or fewer seller-initiated trades. iv) Unstable/sell: 5 or more seller-initiated trades. v) Mixed: a mix of buyer- and seller- initiated trades. For each millisecond period that has a trade, we calculate the price impact as $PriceImpact_{itm} = \frac{M_{itm+\tau} - M_{itm}}{M_{itm}}$, where M_{itm} is the mid-quote of NBBO, at period m, stock i, date t. We vary the time horizon τ to be 100 milliseconds (Panel A) and 1000 milliseconds (Panel B) in which we measure the future mid-quote of NBBO. We take the stock-day-period average by taking the equal-weighted average by period group. Then we take the equal weighted average by period group and month. We provide means of pre-CQRF introduction (Pre, 2017.12), post-CQRF (Post, 2018.1), the increase from pre to post (Change), and the standard error of the change.

Panel A: $\tau = 100$ milliseconds

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.229	0.285	−0.944	−1.245	−0.286	0.959
Post	1.155	0.252	−0.903	−1.166	−0.252	0.914
Post−Pre	−0.074	−0.033	0.041	0.079	0.033	−0.046
se	0.014	0.003	0.012	0.015	0.003	0.013

Panel B: $\tau = 1000$ milliseconds

	Buy			Sell		
	Unstable	Stable	Stable−Unstable	Unstable	Stable	Stable−Unstable
Pre	1.466	0.386	−1.080	−1.480	−0.384	1.096
Post	1.389	0.360	−1.029	−1.383	−0.349	1.034
Post−Pre	−0.077	−0.026	0.051	0.097	0.035	−0.062
se	0.016	0.005	0.014	0.017	0.004	0.015