Do Smart Limit Orders Powered by Algorithms Encourage Liquidity Provision?

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Abstract

In October 2020, Investors Exchange (IEX) launched a smart limit order called *D-Limit*, which, powered by an algorithmic quote instability signal, automatically cancels, reprices, and resubmits limit orders. The signal, which is evaluated every 100 microseconds, helps submitters avoid stale quotes and executions in unstable markets. Our empirical analysis quantifies the improvements in displayed liquidity at IEX around the D-Limit launch date. IEX's share of the aggregate depth at the NBBO increases from under 2% before to over 20% after the launch thereby attaining IEX's main objective of improving the quantity and quality of displayed liquidity at IEX.

Keywords: Automated Trading; Algorithms; Algorithmic Trading; Limit Orders; Limit Order Design; Liquidity; Adverse Selection

JEL Codes: C25, G14, O30

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1 Introduction

In U.S. equity markets, a change in the national best bid and offer, the NBBO, is not an instantaneous event. Quote changes at different exchanges take place non-synchronously, and as a consequence, an NBBO change may be preceded by a series of quote changes that are indicative of the upcoming NBBO change. This enables a well-positioned observer to utilize public information to generate a low-latency signal of the imminent change in the NBBO. This matters for limit order submitters who may have posted limit orders at the NBBO, and in these brief intervals of instability in the NBBO, their orders are predicted to become stale. Being able to anticipate these situations and cancel and resubmit their limit orders would shield the submitters from being picked off as their limit prices are forecast to become imminently stale. This in turn would motivate potential liquidity providers to submit limit orders to the order book in the first place. A challenge is how to generate low-latency signals and act upon these signals before the orders are picked off, i.e., transact at very-soon-to-be unattractive prices.[1] We examine empirically one such solution that offers limit orders protection against the risk of being picked off due to the limit price being predicted to become stale imminently. On October 1st, 2020, Investors Exchange (IEX), launched a smart limit order called the *D-Limit order type* (D-Limit). The D-Limit employs an algorithm that generates a signal of imminent quote instability and then automatically cancels, reprices, and resubmits limit orders.

We are interested in understanding if the D-Limit succeeds in improving the quality, and, lowering the cost of monitoring limit orders for the target clientele, current and new IEX's

[1] Aquilina, Budish, and O'Neill (2015) utilize stock exchange message data to quantify the cost equity markets incur from latency arbitrage. They arrive at an estimate that is equivalent to a 0.5 basis point tax on trading.

users, and thereby stimulating liquidity provision at IEX. To our knowledge, the D-Limit is the first broadly available smart limit order with an automatic cancel, reprice, and resubmit logic. Can this bundle of regular limit order with a built-in dynamic cancel, reprice, and resubmit functionality succeed in encouraging current and new IEX users to submit more limit orders?

We start by asking whether there is evidence that the launch of D-Limit changed trading and displayed liquidity at IEX. There are no other rule changes or other innovations at IEX around the launch of the D-Limit that would have changed the incentives for supplying displayed liquidity at IEX.[2] We estimate that for a median stock, in our sample of 800 stocks, IEX's market share increased from before to after the launch by about two percentage points. Additionally, there was an even more dramatic improvement in IEX's time- and depth-weighted share of the aggregated depth of the NBBO. Our results show an average increase in IEX's time- and depth-weighted share of the NBBO from less than 2% to over 20%. This dramatic increase in the supply of displayed liquidity is consistent with submitters of limit orders at IEX facing sharply lower cost of monitoring limit orders after the launch of the D-Limit order type. A sharp drop in the cost of monitoring limit orders and possible increase in the accuracy of monitoring are consistent with a much lower required profit margin for limit orders, which provides an economic explanation for the large observed increase in displayed liquidity at IEX.

Our empirical evidence provides strong support for the conclusion that the cost of monitoring limit orders at IEX decreased significantly with the launch of D-Limit order type.

[2] The one exception is the promotional fee discount that accompanied the launch of D-Limit and was in effect, October to December, 2020. We provide more details on this fee discount and how we adjust our empirical approach to deal with it in section 2.2.1

In principle, there could also be changes to the execution quality of limit orders as the automated cancel-reprice-resubmit may have a positive impact, holding other things equal. Measuring the execution quality of limit orders directly is not possible because we lack order-level data. Putting that limitation aside, traditional measures of quality, like the fill ratio or time-to-fill, may be misleading because the D-Limit differs from a regular limit order. Given its autonomous cancel-reprice-resubmit logic, one would expect that the smart limit order may take a bit longer to fill, and it may not always fill in situations in which a traditional limit order would fill, despite the smart one outperforming the regular one along some important dimensions. However, the smart limit order should make the price at which the order fills more attractive, holding other things equal, relative to a benchmark shortly after the execution.[3] For a sub-sample of 100 stocks we match the IEX executions with non-IEX executions. We examine the price impact and the realized spread for the period before and after the launch of D-Limit over periods of between 100 milliseconds to up to 10 seconds after executions. Our results do not document any statistically significant differences between the treatment group, IEX, and the control group, non-IEX executions related to the launch of D-Limit. One interpretation is that any significant difference would invite additional order submissions to equalize the realized spread earned across different venues until the expected realized spreads are equalized across venues.

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

[3] See, for example, the ex-post performance measure used in Harris and Hasbrouck (1996).

many in the large literature on optimal order submission strategies.[4] A takeaway from this literature 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. The smart limit order that we examine can through better and cheaper cancellation decisions reduce the adverse selection cost the limit orders face, thereby reducing the cost of submitting limit orders in the first place leading to improvements in liquidity. We focus on the limit orders submitted at the NBB and NBO, and abstract from the classical order submission problem of choosing the optimal order price, and focus on the cancel and resubmit decision instead.[5]

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).[6] That idea is further developed in Brown and Holden's paper on *pegged* limit orders (Brown and Holden, 2005). Fischer Black ((Black , 1995)) predicted that future exchanges may feature indexed limit orders that would be *indexed* to trader's level of urgency as well as to market conditions. The IEX's D-Limit shares properties with the *adjustable* or *pegged* or *indexed* limit orders, but there are key differences as well. In the D-Limit case, the quote instability signal that triggers the cancel and resubmit (revise) decision is a *prediction* of quote instability as opposed to an *observation* of quote instability (quote change).[7]

[4]Examples include Parlour (1998) and Foucault (1999) who develop theoretical models of this trade-off and Harris and Hasbrouck (1996) who provide empirical evidence on the trade-off.

[5]Dahlström and Nordén (2024) study limit order cancellations.

[6]"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 pre-specified 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.

[7]These issues are discussed in more detail in Foucault, Pagano, and Röell (2023), section 6.4.4. on 'Indexed Limit Orders, Monitoring, and Algorithmic Trading,' and developed further in Liu (2009).

In the setting studied by Foucault, Röell, and Sandås (2003) with market makers facing noise traders as well as opportunistic traders who monitor market makers' quote changes for a signal of stale quotes, the launch of the smart limit order (D-Limit) is like a technological shock that would lower the cost of monitoring the news and the quotes and as a result, there would be more liquidity supplied in equilibrium and less profits for the opportunistic day traders.

The analogy between limit orders and options is discussed in Foucault, Pagano, and Röell (2023), pages 235–236, where the main point is that the limit order is like a free American-style option.[8] Technological innovations like the D-Limit lower the cost incurred in writing these options as they lower the adverse selection cost they bear and hence provide an incentive to supply more liquidity.

There is an ongoing debate in the literature on whether faster trading is beneficial for the market performance. Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2021) report evidence supporting the view that faster trading is associated with increased liquidity and more informative prices. Chaboud et al. (2014) and Foucault, Kozhan, and Tham (2017) report evidence that the price efficiency gain of high-frequency trading comes at a cost of greater adverse selection risk. Biais, Foucault, and Moinas (2015) theoretically analyzes this question and takes into account the negative externality that the rise in high-frequency trading brings in terms of increased adverse selection cost. Our study relates to this discussion in that we study a solution offered by one exchange to reduce the adverse selection costs that arise from fast trading.

The remainder of the paper is organized as follows. Section 2 presents our data and some

[8] See also, Copeland and Galai (1983).

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 quote-instability signal or Crumbling Quote Indicator (CQI) signal which is the key algorithm powering the smart limit order (D-Limit). A detailed presentation of the D-Limit follows in sub-section 2.2. Our sample is presented in sub-section 2.3 some initial empirical findings on IEX's market share around the launch of D-Limit. Finally, we review rules and data for the sharing of market data revenue in sub-section 2.4.

2.1 The Quote Instability Signal

What is known as the "Crumbling Quote Indicator" (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 of milliseconds. The CQI signal is reevaluated every 100 microseconds and when the CQI signal is switched 'on,' it remains in the 'on-state' for two milliseconds.[9]

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 algorithm 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.[10]

It is also clear that the data used for the CQI signal is public information that is available and presumably used by sophisticated participants to generate signals using different approaches. At the same time, there are many participants who do not utilize this information at all.[11]

2.2 Discretionary Limit (D-Limit)

Discretionary Limit (D-Limit) behaves like a regular limit order, except when the quote instability signal (i.e., the Crumbling Quote Indicator or CQI) predicts the price is about

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

[10] 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.

[11] Lipson and Fernstrom (2019) provide a detailed discussion of IEX's origin story and business model.

to change. This triggers D-Limits to automatically cancel and reprice the order to 1 MPV (minimum NBBO variant, $0.01 for most stocks) outside that level. Another difference is that the D-Limit'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.[12] Another is the transmission of information to and from a trading desk makes that process inherently slower than the implementation of the D-Limit.[13] 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 is a dynamic order submission strategy that takes into account the quote instability in the market. The Securities Exchange Commission's (SEC) decision mentions that concerns about routing practices, which were raised again with respect to the D-Limit, were already addressed in its earlier decisions.[14] We take as given that the D-Limit has been approved and implemented, and abstract from interesting market design questions 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.

[12] Brolley and Cimon (2020) provides an equilibrium analysis of an exchange with and one exchange without a speed bump.

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

[14] "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).

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 is, by design, made simple to use. Nonetheless, participants still need to review their protocols as D-Limits 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 was 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 to ensure a successful launch.

To encourage the adoption of the new D-Limit, IEX offered the new order for free, and in order to further boost the utilization 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 January 1, 2021, the fees were set back to the regular limit order fees from before.[15] The fee schedule was tweaked to make the launch of the D-Limit type more likely to succeed. Despite the fee inducements, widespread and lasting use of the D-Limit relied on the D-Limit'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 creates a confounding effect for any analysis of order submission behavior and liquidity on IEX. It is worth noting that other fees were unchanged, and

[15] Securities and Exchange Commission (Release No. 34-90786).

therefore, the revised fee schedule uniquely promotes the new D-Limit over regular limit orders. That implies that when displayed liquidity is analyzed, the changes observed are quite likely to reflect more use of D-Limits and potentially less use of regular limit orders. The promotional fee rebates earned from October to December 2020 could only be applied to fees for D-Peg and M-Peg orders and hence would not influence 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 by IEX, which occurred on October 1, 2020. Due to the promotional fee discount from the launch date (Oct. 1st) until the end of 2020, we use January and February 2021 as the primary *post*-period. We use August and September of 2020, 2 months before the launch of the D-Limit, as the *pre*-period. Results for the two months immediately after the launch of D-Limit, that is, October and November 2020, are also reported, and we refer to this period as the *promo*-period. Recall that the impact of the D-Limit is exaggerated due to the promotional fee discounts during these months.

Figure 1 about here

To secure enough trading days per stock, we use stocks that start trading September 1 or earlier and are traded on January 31, 2021, or later, leaving us with 3,339 stocks. Given IEX's relatively low market share, actively traded stocks are needed to ensure a sufficient sample size for any stock and any day. Therefore, a minimum daily trading volume of $10m is imposed, generating a sample of 812 stocks. Finally, we remove low-priced stocks, stocks with a minimum price below $5. Applying these filters leaves us with 800 stocks in our sample. We use IEX TOPS data directly downloaded from the IEX website[16] to observe the top-of-the-limit order book at IEX.

In Table 1, we report the descriptive statistics for our sample including the following statistics: price; market capitalization; trading volume; and IEX's market share of trading. The table has four panels; panel A reports statistics for the first two months before the launch date of Oct. 1 2020 (*pre-period*); panel B reports the statistics for the two months immediately after the launch date of Oct. 1st 2020 (*promo-period*); panel C report the statistics for the first two months of 2021 which was right after the termination of the promotional fee discounts (*post-period*); finally, panel D reports the regression results for a linear regression of the IEX market share using the *pre* and either the *promo* or *post* across stocks on a constant and an indicator for the *promo* or *post* period.

By comparing figures in panel A with panels B or C, we observe that the IEX mean or median market share increased significantly around the launch of D-Limit. Using the figures from panels A and C, show an increase of more than forty percent in the mean and median market share. With the promotional period (panel B) as the second period, the same figures are around sixty percent. This economically significant increase in IEX's market share right around the launch of the D-Limit is indicative of a major shift in the attractiveness of IEX as a trading platform. The regression result reported in panel D confirms that there is a major shift in the market share for IEX around the launch of the D-Limit order type (Oct.

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

1st 2020) with a mean increase of 1.9% and median of 1.6%.

The average IEX market share is around 4.38 percent, which seems higher than what is known to be around 1.8 percent during the observation period. First, we take simple averages across days and stocks, which can explain the difference. A weighted average using trading volumes across our sample stocks produces an IEX market share of approximately 2.7 percent. Second, since we are working with TAQ data for the 9:35 a.m. to 4:00 p.m. interval, 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 have lower trading volume, and these stocks tend to be traded less on IEX.

To the extent that D-Limit offers protection against adverse selection, we might see an increase in trading activity at IEX. Given that the D-Limit 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 interpret the increase in IEX's market share around the launch of D-Limit using the two months before the launch on Oct. 1st as the *pre*-period, and either the two months right after the launch (the *promo*-period) or the first two months of 2021 (*post*-period) as the after sample evidence consistent with widespread adoption of the D-Limit order type.

2.4 Regulation NMS and the Market Data Revenue Sharing

Our discussion in this section is based on 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.[17] We include this seemingly unrelated discussion of the market data revenue sharing formula as we believe it provide a relevant background for understanding the incentives for exchanges to develop new solutions like the D-Limit order type.

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.[18] Two aspects of the updated formula are worth 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 than if the share of aggregated trading volume were used. The other aspect is that

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

[18] The market data revenue practice has been studied by Caglio and Mayhew (2016) and Jones (2018).

an exchange's (i) share of trading (trading volume), as well as the exchange time- and depth-weighted (ii) share of the NBB, and NBO determines (quoted depth), with equal weights, its share of the revenue allocation for a particular security.

3 Empirical Results

In section 3.1, we report results on the trade and quote dynamics at IEX around the launch of the D-Limit. In section 3.2, we report results on the execution quality for a matched sample of IEX and non-IEX execution before and after the launch of D-Limit.

3.1 Trade and Quote Dynamics Around the Launch of D-Limit

In this section, we report event-study results for the trading activity, the use of mid-quote pegged orders, and the quality of displayed liquidity at IEX around the launch of D-Limit. The goal is to establish empirical results that can be used to assess whether what was observed around Oct. 1 2020 reflects a widespread adoption of the D-Limit order type or if some alternative interpretation ought to be considered.

To the extent that D-Limit offers protection against adverse selection, we might see an increase in trading activity at IEX. Given that the D-Limit is the only change, it clearly makes it more attractive to submit limit orders to IEX without making any other choices less attractive. Next we examine the number of trades across three periods of the trading day across the six months of our sample. We also examine the number of trades excluding all trades that have trade prices equal to the mid-quote and hence likely do not reflect any displayed liquidity.

Table 2 about here

Table 2 reports the trading activity across IEX and other exchanges (IEX′) for different periods of the day. Take the first row of the table, which reports the average number of trades during the morning half-hour of trading (9:35–10:05) for the *pre*-period months, the *promo*-period months, and the *post*-period months. Panel B reports the average number of non-mid quote trades for the same three times of the day, and the three two-month periods, for IEX and for IEX′.

Panels C and D of Table 2 show the growth rates implied by the number of trades and the number of non-mid trades corresponding to different pairings of the monthly figures in panels A and B. The left side of panel C combines Jan-21 and Sept-20, whereas the right side of panel C combines Feb-21 with Aug-20. Panel D repeats Panel C while using Oct-20 and Nov-20 as the end months.

The growth rates for IEX and IEX′ are then subtracted to generate a difference-in-difference estimate that is reported in the '*Diff%*' column. Statistical significance with respect to a null hypothesis of a zero difference is indicated with *** for 1% level of significance. By comparing the difference-in-difference columns for the upper rows and lower rows of each of the quadrants of Panel C, we can infer that the growth is stronger when we restrict the trades to be non-mid-quote pegged trades. As an example, consider the left side of panel C, where the difference-in-difference estimates increase from +94% to +134% for the morning interval, from 82% to 108% for the mid-day interval, and from 66% to 84% for the closing interval when we compare the case of (i) all trades with the case of (ii) only non-mid-quote trades.

By comparing the upper two sub-panels of Panel C, we can deduce that the increases are robust across using August or September as the *pre*-month, and using January to February as the *post*-months. The lower two sub-panels of panel C tell us that the increases are quite comparable if we examine the *promo* period, October and November, versus the *post* period, January and February.

Finally, by top row of each sub-panel we observe that the difference, the increase in IEX's trading activity relative to the increase at control exchanges, is largest for the open period (9:35-10:05). This is consistent with the fact that the opening period for the market typically shows the highest volatility and the D-Limit order's capabilities are especially suited to support liquidity providers in high volatility periods.

Table 3 about here

In Table 3, the proportion of mid-quote trades on IEX is reported for the months before the launch (pre period), the two months directly after the launch (promo period), and the first two months of the next year (post period). The proportion of mid-quote executions is reported overall, for the open (9:35–10:05), the midday (10:05–15:30), and the close (15:30–16:00). Panel B reports the changes in the proportion of executions (trades) pegged to the mid-quote. Overall there is decrease regardless of which periods (different sub-panels) or whether we consider IEX or the control exchanges (IEX′). The magnitude of the decrease, however, clearly shows a greater decrease across all combinations of periods and intervals, oveall, open, midday or close, for IEX. The average difference is for most pairings between -5% and -10%.

The negative difference reported in panel B, indicate that the shift away from using mid-quote pegged orders is stronger at IEX. It is worth noting, however, that the base level of use of mid-quote pegged orders is much higher at IEX, so that even after the launch of D-Limit, it is far more common to observe mid-quote pegged orders at IEX compared to other exchanges. Therefore, the drop in the use of mid-quote pegged orders is telling a part of the story. The decline in the observed use of pegged orders is not contradicting the interpretation that the D-Limit order type was widely adopted but in itself it mainly reminds us that many traders who interact with the market using the IEX platform continue to submit orders pegged to the mid-quote.

Since IEX is only one of many exchanges in the U.S., the top of IEX's limit order book can be different from the NBBO, which represent the global best bids and ask quotes. When there are more traders active at IEX, it is more likely that the top of IEX's limit the order book is the same as NBBO. Thus, looking at the fraction of 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 4 about here

In Table 4, the percent of time that IEX is at either the NBB/NBO or the NBBO. In Table 5, parallel results for the time- and volume-weighted share of the NBB/NBO or the NBBO are reported. In Table 4, Panels A and B report the fraction of time that IEX is at the NBBO, or at the NBB or NBO for the two months before the launch of D-limit (pre), the two months directly after the launch (promo), and the two months after the expiration of the promotional fee discounts associated with the launch (post). Overall, there is a dramatic shift when we the first two columns of Table 4 are compared with the four columns on the right consistent with a clear shift upwards for the quality of the displayed liquidity at IEX. The strong shift up is confirmed by the regression results reported in panel C with the left-half showing results for the NBBO and the right-half results for the NBB or NBO. There are two sets of results for each case, depending on the time period used for the post-launch period, the post-period (Jan-Feb '21) or the promo period (Oct-Nov '20). Both the post and the promo periods exhibits a strong shift upwards in the proportion of time IEX is at the NBB or NBO or the NBBO. Take the post-period where we observe the proportion of time at the NBBO go from below 2% to above 10%, on average, across our sample of stocks, a fivefold increase in he proportion of time that IEX is at the NBBO. This huge increase is made possible because the base level was rather low. For the portion of time at either the NBB or the NBO the starting point is a bit below 16% and it increases after the launch to almost 45%, an increase by a factor of 1.8. The dramatic increase in the proportion of time that IEX is present at the NBBO or the NBB/NBO is suggesting that a dramatic shift in the incentives to submit limit orders at IEX occurred right around the time of the launch of the D-Limit order type.

While Table 4 reports the proportion of time that IEX is at NBBO increased, it does not show the fraction of shares at the NBBO that originated from IEX. We recalculate IEX's time-volume-weighted share of the depth at the NBBO in Table 5. For each stock-day, we calculate the measure using the equation

$$\frac{\sum_t (\text{IEX Shares at NBB} + \text{IEX Shares at NBO}) \times t}{\sum_t (\text{Shares at NBB} + \text{Shares at NBO}) \times t,} \tag{1}$$

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 5, 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, the overall share of the depth at the NBBO increased from 1.72% in September to 20.98% in January. The increases are even more dramatic for the promo period with the Sept. to Oct. figures for the open period reflecting a twentyfold increase; 1.49% in September to 33.02% in October. The figures for the promo period are best viewed with caution as it may reflect order submission strategies driven primarily by the promotional fee discount which did effectively offer a rebate usable for other order types to user of D-Limit. The figures for the post-period are a more reliable benchmark where we still observe a dramatic shift upwards. Note also that the shift is the strongest for the open period with IEXs share of the depth at the NBBO increasing fifteen times; from 1.49% (Sept.) to 23.9% (Jan.) for the open period.

Table 5 about here

IEX is much more likely to be part of the NBBO, the NBB, or the NBO after the launch of D-Limit than before the launch. These improvements can be interpreted as an economic response by existing and new 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 substantial 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 of around 2% to around 20%. This implies that IEX's share of the market data revenue improves over and above what the trading volume-based share would predict.[19] It is worth noting that any market data revenue argument is not relevant for the IEX users who choose to submit limit orders to a far greater extent after the launch of D-Limit. The market data revenue increase, however, may be relevant for IEX as it provides a steady stream of additional revenue that can be attributed to the development of the D-Limit order type.

We documented a substantial increase in IEX trading activity and IEX's market share of trading earlier, but the increases were a lot more modest than what we observe for the quoted depth in Tables 4 and 5. These findings are consistent with a world in which the cost of monitoring limit orders that have a relatively low probability of execution has been lowered so much thanks to the automated monitoring service provided by the D-Limit order type design via the CQI signal that is economically attractive to provide much more displayed liquidity.

The observations reported above demonstrate that economically big changes occurred at IEX in terms of trading activity, use of mid-quote pegged orders, and the quality of displayed liquidity around the time of the launch of the D-Limit. We next examine the price impact and the realized spread before and after the launch of D-Limit.

3.2 Execution Quality Before and After Launch of D-Limit

In this section we construct a matched sample of the 'treatment group', IEX executions, and a 'control group,' non-IEX executions. Section 3.2.1 details the matching procedure and review some statistics on the matched sample. Section 3.2.2 then reports regression results

[19] Note that the market data revenue sharing rules do not take into account in which order an exchange joined the NBB or NBO but it takes into account the size of each quote and the time for which the quote matches the NBB or the NBO. Since D-Limit is an order type that is lit, attracting more lit D-Limits will increase revenues for IEX by having a larger share of SIP quoting activity.

for the realized spread and the price impact for the matched sample.

3.2.1 Matching procedure

While looking at overall trades in the sample is helpful in understanding the overall market quality and market share, comparing market liquidity measures across exchanges can be problematic, as the order flow characteristics can differ. Thus, we approach the problem using a quasi-natural experiment setting using trade matching to achieve a more precise benchmark. We first distinguish all non-midquote trades in TAQ to IEX and non-IEX initiated trades using the exchange symbol "V" for IEX. The treated IEX trades are matched to a non-IEX controlled sample using the time of the transaction, size (volume), and trade direction.[20] We require an exact match on the stock (symbol), day of the transaction, and inferred trade direction using three buy-sell indicator methods of Lee and Ready (1991), Ellis, Michaely, and O'Hara (2000), and Chakrabarty et al. (2007), and whether the trade is a mid-quote trade or not. We use the Mahalanobis distance measure as the matching algorithm to get the closest match using time and size. Mahalanobis matching uses a Mahalanobis distance metric

$$||X_i - X_j|| = \sqrt{(X_i - X_j)' \, \Sigma_X^{-1} \, (X_i - X_j)}, \tag{2}$$

where Σ_X^{-1} is the covariance matrix. The Mahalanobis method matches directly on the covariates, so our matched samples are likely to have similar covariate values.[21]

[20] The matched sample approach we apply differs from the one studied by Davies and Kim (2009) as we are comparing trade executions for the same stocks across different market centers as opposed to differences in overall trade executions for different stocks.

[21] See Rosenbaum and Rubin (1985) and King and Nielsen (2019) for examples using Mahalanobis matching.

Table 6 about here

Since we are working with intraday data and the matching procedure takes a lot of time, we randomly select 100 stocks for computational efficiency. Table 6 reports the descriptive statistics of the sub-sample stocks. We find that our randomly chosen stocks are similar to the population in Table 1. Since odd-lot and mix-lot trades can distort the Mahalanobis distance, we only work with round-lot trades in TAQ. After we match each IEX trade with non-IEX trades, we exclude matched pairs that differ in trade time by more than 60 seconds and trade size larger than 100 of IEX trades to minimize the differences between the treated and controlled group. We reported the matched and cleaned sample in Table 7.

Table 7 about here

Table 7 shows that almost all the matched pairs are exact matches. Also, more than half of the matches are traded within one second of each other.

3.2.2 Price Impact and Realized Spread Results

For each trade m, of stock i, at date t, we calculate the price impact as follows:

$$PriceImpact_{itm} = \frac{D_{itm}\left(M_{itm+\tau} - M_{itm}\right)}{M_{itm}}, \tag{3}$$

where P_{itm} is the traded price, and M_{itm} is the mid-quote of NBBO, D_{itm} is the trade direction using the Lee-Ready algorithm. τ is the time horizon in which we measure the future mid-quote of NBBO. We use values of $\tau \in \{.1s,\ 1s,\ 5s,\ 10s\}$. We have a trade direction variable D_{itm} that is 1 if it is a buy period and -1 if it is a sell period.

For each stock-day-time of day (open, mid, close), we take the equal weighted averages of the price impact. Then for each stock-period (pre, promo, post), we take the simple averages across days and across different time horizons, 100 milliseconds, 1, 5, and 10 seconds.

Table 8 about here

Panel A of Table 8 reports the regression results for panel regression with stock fixed effect for the price impact over different time periods after each trade, 100ms, 1s,, 5s, 10s. The results are consistent across the four specifications with the estimate for the constant increasing from 3.07 to 4.50 basis points. The indicator for the post launch period is positive indicating that the post period price impact is greater. The open and close periods of the day are associated with positive coefficient estimates for the open (2 to 3 b.p.s.) and negative for the close (-1 to -2 b.p.s.). The coefficient estimate for the indicator for IEX executions has coefficient estimates around -1 b.p. suggesting lower price impact for IEX executions, unrelated to the D-Limit order introduction. Similarly the interacted term that interacts IEX with the open has a negative coefficient estimate around -1 b.p. The lower price impact for the close period interacted with the post period is around negative coefficient estimate below 0.5 b.p.

$$RealizedSpread_{itm} = \frac{D_{itm}\left(P_{itm} - M_{itm+\tau}\right)}{M_{itm}}, \tag{4}$$

Panel B in Table 8 reports the results for the realized spread across different four time horizons, 100 milliseconds, 1,5, or 10 seconds. The results are consistent across the time horizons and aide from the constant only three regressors have significant coefficient estimates, Post, Open and Post interacted with Open indicators. This implies that the realized spreads are higher in the post-launch period but that is true across the treatment and control samples. The higher realized spread is higher for the open which makes sense given the greater volatility and price impact during the period after the open. The Post and Open interacted term also has a positive coefficients that implies that the is a additional increase for the realized spreads for the open period in the period after the launch of the D-Limit.

4 Discussion of Results

In this section, we provide some discuss aspects of our research design and the different implications of our findings.

The smart limit order that we study relies on the quote-instability signal which in turn builds on applying machine learning to real-time quote updates in the market over time intervals shorter than a millisecond. It therefore provides another example of how big data is changing the nature of trading in financial markets. See, for example, Goldstein, Spatt, and Ye (2021) and Hendershott et al. (2021) for overview of big data in finance and the fintech revolution. The smart limit order launch by IEX is an example of an investment in technology that provides possibly more accurate and lower cost monitoring limit orders, reducing adverse selection costs for liquidity suppliers.[22] The smart limit order being developed and launched by an exchange illustrates the blurring of the line between financial and IT firms.

We believe our analysis identifies the effects of the D-Limit type introduction despite our data not identifying order types used directly. The changes in the time IEX is present at

[22] Foucault, Pagano, and Röell (2023), section 9.4, pages 334–344, entitled 'Investment in Speed as an Arms Race,' presents a framework for thinking about the investment in speed by fast traders and market makers and the resulting market outcomes. IEX's D-Limit order is an example of an innovation that allows liquidity suppliers to react more quickly than before and no extra cost.

the NBBO, and NBB or NBO increasing dramatically and the time- and volume-weighted share of IEX of the total NBBO and or NBB/NBO depth are all impossible to rationalize without acknowledging the widespread adoption of the D-Limit order type.

Do our results suggest that the case of IEX's D-Limit could work as a more broadly applicable solution to reduce costs associated with picking-off risk or latency arbitrage? Yes, under the current set of rules, it might. 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.[23] There is clearly a need for periodic updates to the quote-instability signal to keep ahead of the competition.

A potential danger with more use of smart limit orders like the D-Limit is that market liquidity may become more dependent on signals extracted from the same data. This trend could produce more correlated changes in overall liquidity, possibly making liquidity more fragile. A counterpoint would be that provided there is (i) an order resubmission built into the smart limit order, and to the extent it (ii) encourages more liquidity supply, the net effect could be a deeper and more stable market.

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.[24] The fee was limited to 3 mils ($0.003) and that is the maximum allowed.[25] More generally, maker fees

[23]One example of another exchange applying a quote-instability signal is NYSE American LLC. NYSE American makes use of a quote instability signal similar to IEX's CQI for its Discretionary Peg Orders. See SEC filing No. 34–94487 for more details (March 2022).

[24]See also Brolley and Zoican (2023) for an alternative implementation of a dynamic fee solution.

[25]See Appendix B for our analysis related to this change.

subsidize liquidity and one can think of that as an alternative solution to the picking off risk problem. The maker fee would then act as a subsidy for the extra cost in terms of adverse selection that the limit order submitter faces.[26] In this context, the D-Limit 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.[27] We believe these efforts by IEX to reduce their users' exposure to latency arbitrage are examples of the type of innovation by exchanges that some observers have called for. 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.

As mentioned above, the smart limit order is one in a series of solutions to address the challenge of limit orders being exposed to the risk of being picked off based on predictions of imminent staleness. An earlier solution to address the risk of being picked off involved a liquidity remove fee, which was deemed unsuccessful and ultimately terminated. The Liquidity-Removal-Fee and the D-Limit-order type utilize the machine-learning-based CQI signal and the IEX-speed-bump. The two solutions, however, featured different strategies for dealing with the picking off risk problem.

On the one hand, the 'Liquidity-Remove-Fee' sought to penalize liquidity demanding order flow in unstable-quote situations (when the CQI is switched on) with an extra fee and thereby discourage such orders (discourage the 'picking off'). On the other hand, the smart limit order (D-Limit) features no penalties for any party, but instead, it helps the limit order

[26] Jørgensen, Skjeltorp, and Ødegaard (2018) studies a related policies that target the order-to-trade ratio with fees for excessive ratios.

[27] Markets that apply make-take fee models in different fashion have been studied in Foucault, Kadan, and Kandel (2012), Malinova and Park (2015) and Comerton-Forde, Grégoire, and Zhong (2019), among others.

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 type is a successful solution to reduce the users' exposure to the risk of being picked off by making the limit order smarter.

We examine data from a different source, the Consolidated Tape Association (CTA) and Unlisted Trading Plan (UTP), to shed some light on the change in displayed liquidity and trading activity at IEX. This data covers market data revenue distribution for Nasdaq-listed securities. The Table in the appendix provides the quarterly figures for IEX's share of the dollar-value of market data revenue distributed, broken down into categories for quoting and trading, as well as the total amount. The parallel figures are reported for the aggregate, and the IEX percentage share is computed based on these numbers. In the appendix, we plot the same information in Figure A1. There is a clear shift up that peaks around the first quarter of 2021, but the level of revenue appears to have shifted up for the whole post-launch period. Of course, other events may contribute to these fluctuations, so it is not possible to attribute all of them to the launch of D-Limit. Nonetheless, the higher level of market data revenue clearly appears to be driven by quoting, suggesting that the level of displayed liquidity at IEX is permanently altered with the introduction of the D-Limit in the last quarter of 2020.

5 Conclusion

We document that IEX's smart limit order—D-Limit—which was introduced in 2020, does succeed in encouraging a substantial increase in the quantity and quality of displayed liquidity at IEX. We do not find any evidence that order executions at IEX differ systematically from order executions at other exchanges related to the launch of D-Limit. One way to interpret the latter is that competition among potential liquidity suppliers competes away any surplus and that involved a large increase in displayed liquidity at IEX following the launch of the D-Limit.

The D-Limit order lowers the cost for accessing better technology, by offering the machine-learning driven smart limit order to all IEX clients. It is worthwhile noting that the signal is based on public information only. It therefore works by reducing frictions that arises in our fragmented equity market structure. 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 and the CQI-signal needs to keep evolving too to allow the user to successfully auto-cancel, reprice, and resubmit their limit orders in the future. Other exchanges may develop their own smart limit orders and some may ultimately outperform IEX's D-Limit. There is room for everyone to succeed in reducing the losses due to picking off risk and encouraging liquidity provision.

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?[28] The D-Limit, IEX's smart

[28] 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.

limit order, appears to be a strong candidate for such a market-based solution. There are open questions about how this alters market competition, price discovery, and possible barriers for a 'D-Limit-type'-solution to be implemented more widely that we will leave for future research.

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Figures and Tables

Figure 1: Timeline of the launch of the D-Limit Order Type

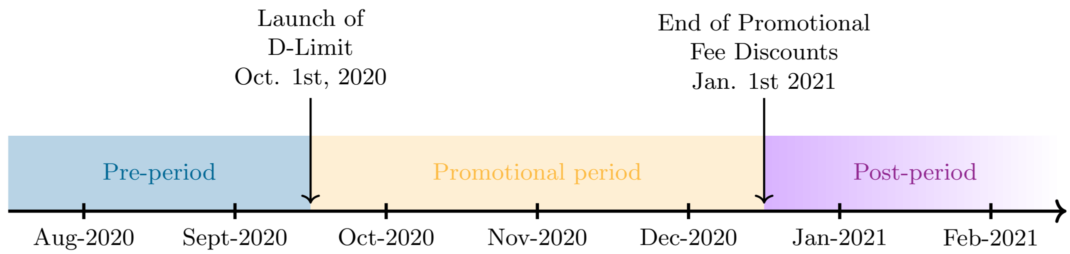

Table 1: Sample Descriptive Statistics

This table presents descriptive statistics for 800 stocks in our sample across three periods. Panel A shows results for two months before the launch of D-Limit (pre-period); Panel B shows results for the two months immediately after the launch (promo-period); and Panel C shows the results for the first two months after the launch and the launch-related promotional fee discounts expired (post-period). We report the mean, standard deviation, first quartile, median, and third quartile of stock-level averages. Price and market capitalization are measured as day-end averages. Daily trading volume (in millions of dollars) is computed by multiplying the day-end price by the number of shares traded. IEX passive market share (Mkt. Shr. %) is defined as IEX's share of the total volume. IEX's market share is computed from 9:35AM to 4:00PM. Panel D reports statistical difference on IEX Market Share comparing pre-period vs. either the promo or the post-period using paired t-test and Wilcoxon signed ranked test. Statistical significance at the 1% levels is denoted by ***.

Panel A: Pre-period (2020.08–09)

	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	Mkt.Shr. %
Mean	130.81	37,072.11	343.86	4.38
SD	245.85	119,911.67	1,550.37	1.55
Q1	36.82	5,069.23	57.39	3.35
Median	76.51	11,816.21	107.81	4.33
Q3	141.88	27,862.56	239.08	5.39

Panel B: Promo-period (2020.10–11)

	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	Mkt.Shr. %
Mean	137.20	38,562.84	317.86	7.00
SD	251.95	120,836.87	1,077.20	2.13
Q1	39.32	5,534.32	64.34	5.81
Median	81.49	12,532.55	116.73	7.22
Q3	145.26	30,563.11	243.41	8.39

Panel C: Post-period (2021.01–02)

	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	Mkt.Shr. %
Mean	156.24	43,355.69	372.06	6.30
SD	272.85	132,091.34	1,231.99	1.96
Q1	48.59	6,891.21	78.79	4.94
Median	92.55	14,894.45	141.80	6.37
Q3	171.22	34,380.86	298.43	7.68

Panel D: Statistical Difference on IEX Market Share

		Pre vs Promo	Pre vs Post
paired t-test	t-statistic	61.91	49.06
	p-value	0.00	0.00
Wilcoxon signed-rank test	z-score	24.447	24.122
	p-value	0.00	0.00

Table 2: Changes in Intraday Trading Activity

This table shows the average number of trades and non-mid trades, on IEX and IEX′ exchanges for the 800 stocks in our full sample. For each stock-day, we calculate the number of trades (Panel A) and number of non-mid trades (Panel B) from IEX and IEX′ exchanges during three intraday intervals: 9:35–10:05 (open), 10:05–15:30 (mid-day), and 15:30–16:00 (close). We then calculate the equal-weighted average across all trading days in a month for each stock to obtain the monthly averages presented in the table. Panel C shows results from paired t-tests comparing the change in trade counts between IEX and non-IEX exchanges. Panel D shows the Statistical significance of difference in growth rates at the 10%, 5%, and 1% levels is denoted by *, **, ***, respectively.

Panel A: Number of trades ('00s)							
		2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
IEX	Overall	8.22	9.56	14.12	15.20	15.39	14.87
	Open	0.79	0.90	1.44	1.68	1.53	1.53
	Mid-day	5.70	6.72	9.98	10.70	11.06	10.61
	Close	1.73	1.94	2.70	2.98	2.80	2.73
IEX′	Overall	100.07	119.65	102.76	109.21	111.12	104.93
	Open	11.30	13.14	10.45	12.54	12.19	12.06
	Mid-day	69.30	83.32	72.02	75.63	78.19	73.52
	Close	19.48	23.18	20.29	22.14	20.74	19.35

Panel B: Number of non-mid trades ('00s)							
		2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
IEX	Overall	4.45	5.28	9.31	9.89	9.72	9.72
	Open	0.45	0.52	1.01	1.15	1.06	1.08
	Mid-day	3.05	3.68	6.56	6.89	6.91	6.88
	Close	0.95	1.09	1.74	1.94	1.75	1.76
IEX′	Overall	89.82	108.09	93.49	99.23	100.74	95.17
	Open	10.32	12.04	9.61	11.56	11.23	11.17
	Mid-day	62.28	75.37	65.65	68.82	71.04	66.84
	Close	17.22	20.68	18.23	19.85	18.47	17.16

Table 2 cont'd

Panel C: Paired t-test							
		2021.01–2020.09			2021.02–2020.08		
		ΔIEX	ΔIEX$'$	ΔIEX $-\Delta$IEX$'$	ΔIEX	ΔIEX$'$	ΔIEX $-\Delta$IEX$'$
Reg.	Overall	15.39	9.56	5.83***	14.87	8.22	6.65***
	Open	91.75	−2.45	94.20***	129.89	13.13	116.76***
	Mid-day	79.06	−3.39	82.45***	103.70	8.05	95.65***
	Close	56.06	−9.98	66.03***	73.49	−0.07	73.57***
N-mid.	Overall	9.72	5.28	4.44***	9.72	4.45	5.27***
	Open	132.38	−1.33	133.71***	180.41	14.44	165.97***
	Mid-day	105.41	−2.14	107.55***	145.30	9.78	135.52***
	Close	74.85	−9.54	84.39***	102.02	0.58	101.45***

		2020.10–2020.09			2020.11–2020.08		
		ΔIEX	ΔIEX$'$	ΔIEX $-\Delta$IEX$'$	ΔIEX	ΔIEX$'$	ΔIEX $-\Delta$IEX$'$
Reg.	Overall	14.12	9.56	4.56***	15.20	8.22	6.98***
	Open	76.45	-15.94	92.39***	135.81	15.06	120.74***
	Mid-day	58.14	-10.86	68.99***	101.79	10.64	91.15***
	Close	49.18	−11.65	60.82***	86.30	10.37	75.93***
N-Mid.	Overall	9.31	5.28	4.02***	9.89	4.45	5.44***
	Open	112.54	−15.25	127.80***	177.25	16.18	161.06***
	Mid-day	87.41	−9.64	97.05***	141.07	12.64	128.43***
	Close	69.61	−10.57	80.18***	119.81	12.37	107.45***

Table 2 cont'd

Panel D: Wilcoxon signed rank test					
		2021.01–2020.09		2021.02–2020.08	
		z-score	p-value	z-score	p-value
Reg.	Overall	23.12	0.00	23.82	0.00
	Open	22.13	0.00	23.51	0.00
	Mid-day	23.29	0.00	23.88	0.00
	Close	21.51	0.00	22.94	0.00
N-mid.	Overall	23.56	0.00	23.97	0.00
	Open	22.41	0.00	23.41	0.00
	Mid-day	23.65	0.00	24.04	0.00
	Close	22.82	0.00	23.78	0.00

		2020.10–2020.09		2020.11–2020.08	
		z-score	p-value	z-score	p-value
Reg.	Overall	22.22	0.00	23.59	0.00
	Open	21.56	0.00	23.06	0.00
	Mid-day	22.18	0.00	23.62	0.00
	Close	21.23	0.00	22.91	0.00
N-Mid.	Overall	23.86	0.00	24.10	0.00
	Open	23.62	0.00	23.87	0.00
	Mid-day	23.86	0.00	24.09	0.00
	Close	23.80	0.00	24.15	0.00

Table 3: Mid-Quoted Executions

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 (stock-time period), we calculate the percentage of trades on IEX (IEX′) executed at the mid-quote of the NBBO during a day (time period). Our sample uses trading between 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We sum the number of trades at the mid-quote at IEX (IEX′) divided by the sum of all number of trades at IEX (IEX′). Then we take the equal-weighted average across all days in a month for each stock to get the monthly average. In panel B, we report the change in the mid-quote execution percentages for IEX and IEX′ in the first two columns and columns 4 and 5. We then report the difference of the change (difference-in-difference) for IEX and IEX′ using paired t-test. In panel C, we report the signed rank test result of the change difference. In Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, ***, respectively.

Panel A: mid-quote execution (%)							
		2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
IEX	Overall	44.33	43.49	34.71	34.77	35.53	33.56
	Open	40.58	41.48	31.17	31.30	29.08	27.56
	Mid-day	45.08	44.00	34.97	35.44	36.11	34.02
	Close	42.37	41.64	34.72	33.08	34.78	33.11
IEX′	Overall	9.72	9.20	8.05	8.11	8.23	8.53
	Open	6.96	6.95	6.15	6.06	5.76	5.84
	Mid-day	9.64	9.10	7.88	8.00	7.97	8.25
	Close	10.88	10.25	9.17	9.28	9.87	10.46

Panel B: Paired t-test						
	2021.01–2020.09			2021.02–2020.08		
	IEX change %p	IEX′ change %p	Diff %	IEX growth %	IEX′ growth %	Diff %
Overall	−7.96	−0.97	−6.99***	−10.78	−1.18	−9.59***
Open	−12.40	−1.20	−11.21***	−13.06	−1.11	−11.96***
Mid-day	−7.89	−1.14	−6.75***	−11.06	−1.40	−9.66***
Close	−6.86	−0.38	−6.48***	−9.26	−0.42	−8.84***

	2020.10–2020.09			2020.11–2020.08		
	IEX change %p	IEX′ change %p	Diff %	IEX change %p	IEX′ change %p	Diff %
Overall	−8.78	−1.15	−7.62 ***	−9.56	−1.61	−7.95***
Open	−10.31	−0.81	−9.50 ***	−9.27	−0.90	−8.37***
Mid-day	−9.03	−1.22	−7.81 ***	−9.64	−1.65	−7.99***
Close	−6.92	−1.08	−5.84 ***	−9.30	−1.61	−7.69***

Table 3 cont'd

Panel C: Wilcoxon signed rank test				
	2021.01–2020.09		2021.02–2020.08	
	z-score	p-value	z-score	p-value
Overall	−22.10	0.00	−24.20	0.00
Open	−23.75	0.00	−23.97	0.00
Mid-day	−20.85	0.00	−23.94	0.00
Close	−22.10	0.00	−23.84	0.00

	2020.10–2020.09		2020.11–2020.08	
	z-score	p-value	z-score	p-value
Overall	−23.43	0.00	−23.40	0.00
Open	−22.92	0.00	−21.45	0.00
Mid-day	−23.07	0.00	−23.03	0.00
Close	−22.00	0.00	−23.22	0.00

Table 4: Time at NBBO, or at the NBB or the NBO

This table shows the monthly average fraction of trading time IEX's best bid and/or offer matches NBB and/or NBO. 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 matches NBB or IEX's best offer matches NBO. Our sample uses trading between 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. An equal-weighted average across all days in a month is computed for each stock, and the average across stocks is computed to obtain the reported figures in the table. We report the mean of *At NBBO* (Panel A) and *At NBB or NBO* (Panel B) in percentages. In panels C and D, we report the paired t-statistics and signed rank test result of the change difference, respectively.

Panel A: At NBBO %						
	2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
Overall	1.56	1.63	21.61	13.84	10.90	12.64
Open	0.56	0.74	21.02	11.69	11.42	11.06
Mid-day	1.50	1.57	21.49	13.82	10.76	12.66
Close	3.29	3.23	23.53	16.36	11.87	13.91

Panel B: At NBB or NBO %						
	2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
Overall	15.98	15.79	77.29	65.78	59.75	61.08
Open	11.64	12.35	76.58	63.48	60.23	60.36
Mid-day	15.88	15.65	77.27	66.11	59.68	61.17
Close	21.40	20.75	78.14	65.24	60.02	60.71

Table 4 cont'd

Panel C: Paired t-test							
		2021.01–2020.09			2021.02–2020.08		
		%p Change	t-stat	p-value	Change	t-stat	p-value
NBBO	Overall	9.26	61.67	0.00	11.07	52.68	0.00
	Open	10.68	57.81	0.00	10.50	61.78	0.00
	Mid-day	9.19	59.63	0.00	11.17	50.88	0.00
	Close	8.64	49.39	0.00	10.63	39.58	0.00
NBB or NBO	Overall	43.96	71.11	0.00	45.09	71.05	0.00
	Open	47.88	66.98	0.00	48.72	70.86	0.00
	Mid-day	44.03	71.71	0.00	45.29	71.00	0.00
	Close	39.27	62.27	0.00	39.32	61.43	0.00

		2020.10–2020.09			2020.11–2020.08		
		Change	t-stat	p-value	Change	t-stat	p-value
NBBO	Overall	19.97	91.55	0.00	12.27	58.42	0.00
	Open	20.27	83.97	0.00	11.14	58.27	0.00
	Mid-day	19.92	90.58	0.00	12.32	57.36	0.00
	Close	20.30	88.03	0.00	13.08	55.84	0.00
NBB or NBO	Overall	61.50	71.70	0.00	49.80	60.12	0.00
	Open	64.23	76.54	0.00	51.83	63.76	0.00
	Mid-day	61.63	71.77	0.00	50.23	60.17	0.00
	Close	57.39	62.78	0.00	43.85	52.51	0.00

Table 4 cont'd

Panel D: Wilcoxon signed rank test					
		2021.01–2020.09		2021.02–2020.08	
		z-score	p-value	z-score	p-value
NBBO	Overall	24.48	0.00	24.30	0.00
	Open	24.49	0.00	24.23	0.00
	Mid-day	24.48	0.00	24.31	0.00
	Close	24.00	0.00	24.14	0.00
NBB or NBO	Overall	24.49	0.00	24.20	0.00
	Open	24.50	0.00	24.34	0.00
	Mid-day	24.49	0.00	24.19	0.00
	Close	24.11	0.00	23.95	0.00

		2020.10–2020.09		2020.11–2020.08	
		z-score	p-value	z-score	p-value
NBBO	Overall	24.49	0.00	24.49	0.00
	Open	24.49	0.00	24.49	0.00
	Mid-day	24.50	0.00	24.49	0.00
	Close	24.48	0.00	24.48	0.00
NBB or NBO	Overall	24.50	0.00	24.45	0.00
	Open	24.49	0.00	24.48	0.00
	Mid-day	24.50	0.00	24.45	0.00
	Close	24.42	0.00	24.21	0.00

Table 5: Time- and Volume-Weighted Share of the NBBO, or of either the NBB or the NBO

Panel A reports the time-weighted average number of shares at the NBBO (NBB and NBO), for each stock-day:

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

Panel B reports the time-weighted average number of shares on IEX that are at NBBO:

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

Panel C shows the time and volume-weighted fraction of depth at the NBBO that comes from IEX:

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

We take the equal-weighted average across all days in a month for each stock to get the monthly average. We report the mean of the Average number of shares at NBBO (Panel A) and the average number of IEX shares at NBBO (Panel B). Panel C shows the time- and volume-weighted share of the aggregate depth at the NBBO that is represented by depth at IEX. In panels D and E, we report the paired t-statistics and signed rank test result of the change difference (from Panel C), respectively.

Panel A: Average numbers of shares at NBBO

	2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
Overall	1991.41	1982.12	1840.18	1728.02	1243.08	1058.94
Open	1123.56	1195.56	1140.48	1023.15	809.32	684.16
Mid-day	1953.85	1945.98	1794.26	1673.06	1205.61	1027.74
Close	3265.29	3159.81	3036.81	2947.58	2082.59	1771.06

Panel B: Average number of IEX shares at NBBO

	2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
Overall	38.81	38.43	211.74	162.55	136.17	148.43
Open	21.90	24.03	198.54	146.39	120.36	125.35
Mid-day	37.44	37.28	211.14	162.80	135.27	148.75
Close	70.46	65.19	231.39	178.08	161.71	168.04

Table 5 cont'd

Panel C: IEX proportion of shares at NBBO (%)						
	2020.08	2020.09	2020.10	2020.11	2021.01	2021.02
Overall	1.73	1.72	30.14	22.67	20.98	21.89
Open	1.46	1.49	33.02	24.99	23.90	24.48
Mid-day	1.72	1.69	31.03	23.43	21.46	22.48
Close	2.06	2.19	23.91	18.02	16.65	16.98

Panel D: Paired t-test							
		2021.01–2020.09			2021.02–2020.08		
		%p Change	t-stat	p-value	Change	t-stat	p-value
NBBO %	Overall	19.26	90.72	0.00	20.16	95.60	0.00
	Open	22.41	91.74	0.00	23.02	91.77	0.00
	Mid-day	19.76	92.84	0.00	20.77	97.72	0.00
	Close	14.46	76.19	0.00	14.93	82.50	0.00

		2020.10–2020.09			2020.11–2020.08		
		Change	t-stat	p-value	Change	t-stat	p-value
NBBO %	Overall	28.41	66.99	0.00	20.94	57.71	0.00
	Open	31.53	74.26	0.00	23.53	62.36	0.00
	Mid-day	29.34	68.31	0.00	21.71	58.23	0.00
	Close	21.72	55.59	0.00	15.96	51.60	0.00

Table 5 cont'd

Panel E: Wilcoxon signed rank test

		2021.01–2020.09		2021.02–2020.08	
		z-score	p-value	z-score	p-value
NBBO %	Overall	24.50	0.00	24.50	0.00
	Open	24.50	0.00	24.47	0.00
	Mid-day	24.50	0.00	24.50	0.00
	Close	24.49	0.00	24.50	0.00

		2020.10–2020.09		2020.11–2020.08	
		z-score	p-value	z-score	p-value
NBBO %	Overall	24.49	0.00	24.48	0.00
	Open	24.49	0.00	24.47	0.00
	Mid-day	24.49	0.00	24.48	0.00
	Close	24.45	0.00	24.49	0.00

Table 6: Matched Sample Descriptive Statistics

This table presents descriptive statistics for 100 stocks in our matched sample across three periods. Timeline of the launch of the D-Limit Order Type: the two months prior to the introduction of D-Limit (Panel A), the first two months after its introduction with a promotional fee (Panel B), and the first two months without the promotional fee (Panel C). We report the mean, standard deviation, first quartile, median, and third quartile of stock-level averages. Price and market capitalization are measured as day-end averages. Daily trading volume (in millions of dollars) is computed by multiplying the day-end price by the number of shares traded. IEX passive market share (as a percentage) is defined as IEX's share of the total volume. IEX's market share is computed from 9:35AM to 4:00PM.

Panel A: Pre-period (2020.08–09)				
	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	Mkt.Shr. %
Mean	135.63	49,634.45	484.16	4.24
SD	335.65	178,548.43	1802.54	1.57
Q1	31.23	4,205.38	52.11	3.12
Median	59.59	8,397.62	102.58	4.08
Q3	118.10	20,180.06	294.00	5.40

Panel B: D-Limit with promotional fee-period (2020.10–11)				
	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	Mkt.Shr. %
Mean	142.51	51,415.69	455.43	6.92
SD	337.01	178,863.74	1709.74	2.19
Q1	36.50	4,746.83	65.38	5.85
Median	67.29	8,965.10	111.25	7.27
Q3	140.64	22,905.04	214.26	8.14

Panel C: D-Limit without promotional fee period (2021.01–02)				
	Price ($)	Mkt Cap ($m)	Trd Vol ($m)	Mkt.Shr. %
Mean	159.27	55,160.12	481.06	6.30
SD	342.81	181,555.75	1418.82	1.98
Q1	47.09	5,940.38	71.52	4.83
Median	81.61	10,794.45	126.50	6.40
Q3	163.86	27,400.32	286.53	7.87

Table 7: Matched Sample (≤ 60 seconds, ≤ 100 size)

This table shows matched sample characteristics of trades based on time and trade size differences. For each IEX trades (treated) from the randomly selected 100 stocks, we find non-IEX trades (controlled) by the matching algorithm. We require an exact match on the stock (symbol), the day of the transaction, and inferred trade direction using three buy-sell indicator methods, and whether the trade is a mid-quote trade or not. Then we use the Mahalanobis distance to select the closest matching trade based on the transaction time and size. We only use round-lot trades to enhance the quality of matching. After matching, we exclude matched pairs that exceed 60 seconds of clock time or trade size difference larger than 100 of the IEX trade. Panel A shows trade time differences and Panel B shows size differences of matched pairs. The time (size) differences are measured by subtracting non-IEX trade time (size) from IEX trade time (size).

Panel A: Trade time difference (in seconds)

Month	N	Avg	SD	P5	Q1	Median	Q3	P95
2020.08	563,307	0.01	11.86	-17.87	-0.28	0.00	0.36	17.81
2020.09	599,492	-0.03	12.24	-19.11	-0.46	0.00	0.49	18.85
2021.01	872,526	0.05	12.77	-20.33	-0.46	0.00	0.57	20.60
2021.02	882,187	0.06	12.92	-20.70	-0.57	0.00	0.75	20.91

Panel B: Trade size difference

Month	N	Avg	SD	P5	Q1	Median	Q3	P95
2020.08	563,307	0.09	3.77	0.00	0.00	0.00	0.00	0.00
2020.09	599,492	0.10	3.77	0.00	0.00	0.00	0.00	0.00
2021.01	872,526	0.05	2.99	0.00	0.00	0.00	0.00	0.00
2021.02	882,187	0.06	2.92	0.00	0.00	0.00	0.00	0.00

Table 8: Matched Sample Regression – Price Impact, Realized Spread

This table reports panel regression results for the price impact, Panel A, and realized spread, panel B. For each of the two cases four regression are estimated the regressions are estimated for the price impact (Panel A) and realized spread (panel B) for four different time horizons, 100 ms, 1s, 5s, and 10s. The coefficient estimates are reported with standard errors below in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, ***, respectively.

Panel A: Price Impact				
	(1)	(2)	(3)	(4)
Post	0.75***	0.82***	0.84***	0.94***
	(0.11)	(0.13)	(0.13)	(0.14)
IEX	−1.03***	−1.07***	−1.15***	−1.16***
	(0.11)	(0.11)	(0.14)	(0.16)
$Post \times IEX$	0.16	0.15	0.23	0.22
	(0.15)	(0.18)	(0.20)	(0.23)
Open	2.00***	2.21***	2.77***	3.14***
	(0.20)	(0.22)	(0.27)	(0.27)
Close	−1.30***	−1.37***	−1.58***	−1.78***
	(0.13)	(0.14)	(0.16)	(0.19)
$Post \times Open$	0.63*	0.58	0.46	0.51
	(0.36)	(0.38)	(0.46)	(0.51)
$Post \times Close$	−0.47***	−0.49**	−0.39*	−0.33
	(0.17)	(0.20)	(0.22)	(0.26)
$IEX \times Open$	−1.00***	−1.03***	−1.22***	−1.31***
	(0.25)	(0.28)	(0.33)	(0.35)
$IEX \times Close$	0.45**	0.47**	0.56**	0.54*
	(0.21)	(0.23)	(0.27)	(0.32)
$Post \times IEX \times Open$	0.17	0.21	0.57	0.67
	(0.42)	(0.46)	(0.57)	(0.62)
$Post \times IEX \times Close$	0.01	0.02	−0.13	−0.13
	(0.27)	(0.30)	(0.35)	(0.41)
Constant	3.07***	3.56***	4.15***	4.50***
	(0.06)	(0.06)	(0.07)	(0.08)
adjusted R^2	0.73	0.74	0.72	0.73
Interval	100ms	1s	5s	10s
Stock FE	Yes	Yes	Yes	Yes

Table 8 cont'd

Panel B: Realized Spread				
	(1)	(2)	(3)	(4)
Post	1.00***	0.94***	0.92***	0.82***
	(0.23)	(0.23)	(0.21)	(0.21)
IEX	−0.16	−0.11	−0.03	−0.03
	(0.30)	(0.28)	(0.25)	(0.24)
$Post \times IEX$	0.24	0.26	0.17	0.18
	(0.33)	(0.33)	(0.29)	(0.29)
Open	2.62***	2.46***	1.89***	1.52***
	(0.29)	(0.31)	(0.28)	(0.25)
Close	−0.44	−0.37	−0.15	0.03
	(0.30)	(0.29)	(0.26)	(0.25)
$Post \times Open$	2.50***	2.49***	2.23***	2.22***
	(0.62)	(0.61)	(0.63)	(0.62)
$Post \times Close$	−0.43	−0.42	−0.53*	−0.58*
	(0.35)	(0.35)	(0.31)	(0.31)
$IEX \times Open$	0.04	0.02	0.25	0.34
	(0.44)	(0.46)	(0.40)	(0.38)
$IEX \times Close$	0.12	0.10	−0.00	0.03
	(0.42)	(0.41)	(0.36)	(0.34)
$Post \times IEX \times Open$	0.27	0.25	0.16	0.05
	(0.87)	(0.87)	(0.85)	(0.83)
$Post \times IEX \times Close$	−0.30	−0.30	−0.13	−0.14
	(0.50)	(0.49)	(0.43)	(0.42)
Constant	2.31***	1.81***	1.21***	0.88***
	(0.20)	(0.19)	(0.17)	(0.17)
adjusted R^2	0.63	0.59	0.52	0.46
Interval	100ms	1s	5s	10s
Stock FE	Yes	Yes	Yes	Yes

A Appendix: Additional Results and Panel Regression

Table A1 shows the IEX and market-wide (NBBO) quoted spread. After the D-Limit was introduced, IEX quoted spread decreased by about 34 percent. We also check 500- and 2000-millisecond price impacts, and the results are qualitatively robust. 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.

While we show IEX's market quality improved after the introduction of the D-Limit, 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,[29] 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.[30]

Our results are also consistent with the revenues generated by IEX shown in Table A2, which is an excerpt from Consolidated Tape Association (CTA) Unlisted Trading Plan (UTP) Administration's trade and quote revenue distribution. We report the IEX and total SIP revenue from 2019 to 2022. Before the launch of D-Limit (2020Q3), IEX's SIP shares were

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

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

.80% for quoting activity and 2.69% for trading activity. In 2021Q1 (post-D-Limit), the shares jump to 6.51% for quoting activity and 3.69% 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. We also find that IEX's SIP share increase are not short-lived – IEX's SIP revenue share continues to be higher in 2022 compared to 2019 or 2020.

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 does not confound the inference. We use the quarterly reports posted on the CTA plan (https://www.ctaplan.com/) and 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 $6,071,734, and that more than doubled to $16,528,989 for the first three quarters of 2021. IEX's share of the total market data revenue increased from around 2% in 2020 to over 5% 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 $1.5 million in the first three quarters from the quoting-based revenue but that increased to $10.4 million in the first three quarters of 2021. In terms of IEX's share of the total amount distributed, there is a more than sixfold increase in the share from just under 1% to above 6%. These figures are not based on our analysis but reflect the official reports from the CTA plan and UTP plan. Our calculations of IEX time and depth-adjusted contributions to the NBBO, NBB, and NBO reported in Section 3.1 are consistent with these broader trends in the market data revenue.

In Table A3, the results are for panel regressions with IEX's market share as the dependent variable. Panel A reports the results for averages across the pre- versus post-period. Panel B reports the results for daily regressions with stock fixed effects. The right-hand side variables include an indicator for the post-period, market capitalization, price, and trading volume by themselves and interacted with the post-period indicator. All right-hand side variables, excluding the post indicator, have been normalized using a z-score methodology. The left half of each panel reports the results using January and February 2021 as the post-period. The right half of each panel reports the results using October and November 2020 as the post-period. The coefficient estimates for the post-period indicator are either around 1.9 percent for the January and February 2021 post-period or around 2.6 percent for the October and November post-period. Both the estimate of 1.9 and the 2.6 are suggestive of a major change in the incentives for trading on IEX. Naturally, one interpretation is that the change we observe reflects a widespread adoption of the new discretionary limit order type after October 1st, 2020.

The results from Table A3 demonstrate some cross-sectional differences, for example, price level (p) and trading volume ($volume$). First, the price variable has a positive coefficient for the baseline specification, and there is evidence of a positive coefficient on the interaction with the post indicator. In other words, the IEX market share was positively correlated with the price level of the stock, and that relationship was strengthened in the post-period. The coefficient estimate for the interaction term of around 0.5 implies that a one standard deviation shift in the price level variable has a positive effect of a $+1.28\%$ $(+0.77\% + 0.51\%)$ for the IEX market share in the post-period. The estimated coefficients for the trading volume variable are negative, implying that holding other things equal, a one standard deviation increase in the trading volume has a negative effect of -1.56% (-1.17%+(-0.39%)) for the IEX market share in the post-period. The coefficients for the price level variable interacted with the post indicator show that the inside spread is more likely to be more than one MPV for such stocks, and it is also more likely to fluctuate over short periods of time. These characteristics will make the D-Limit order's cancel-and-reprice-resubmit functionalities more pertinent and explain the positive coefficient in the regressions.

In Table A4, the strong shift of IEX quotes at NBBO (or, NBB or NBO) is confirmed by the regression results reported in panels A and B (C and D) with the columns (1)–(4) showing results using January and February 2021 as the post period, and columns (5)–(8) showing results using October and November 2020 as the post period. The shift is stronger for the Oct–Nov post period with the coefficient on the post-indicator around 16%, compared to an estimate around 10% for the sample using Jan–Feb as the post period. The results also indicate that there are some cross-sectional differences, but given the strong effect across all stocks indicated by the coefficient estimates on the post-indicator we will stay focus on the overall impact of the introduction of D-Limit and leave exploration of the cross-sectional differences for future research. We find robust results when we use the time- and volume weighted share at NBB and/or NBO in Table A5

Figure A1: IEX's Share of Quarterly Market Data Revenue 2019–2022

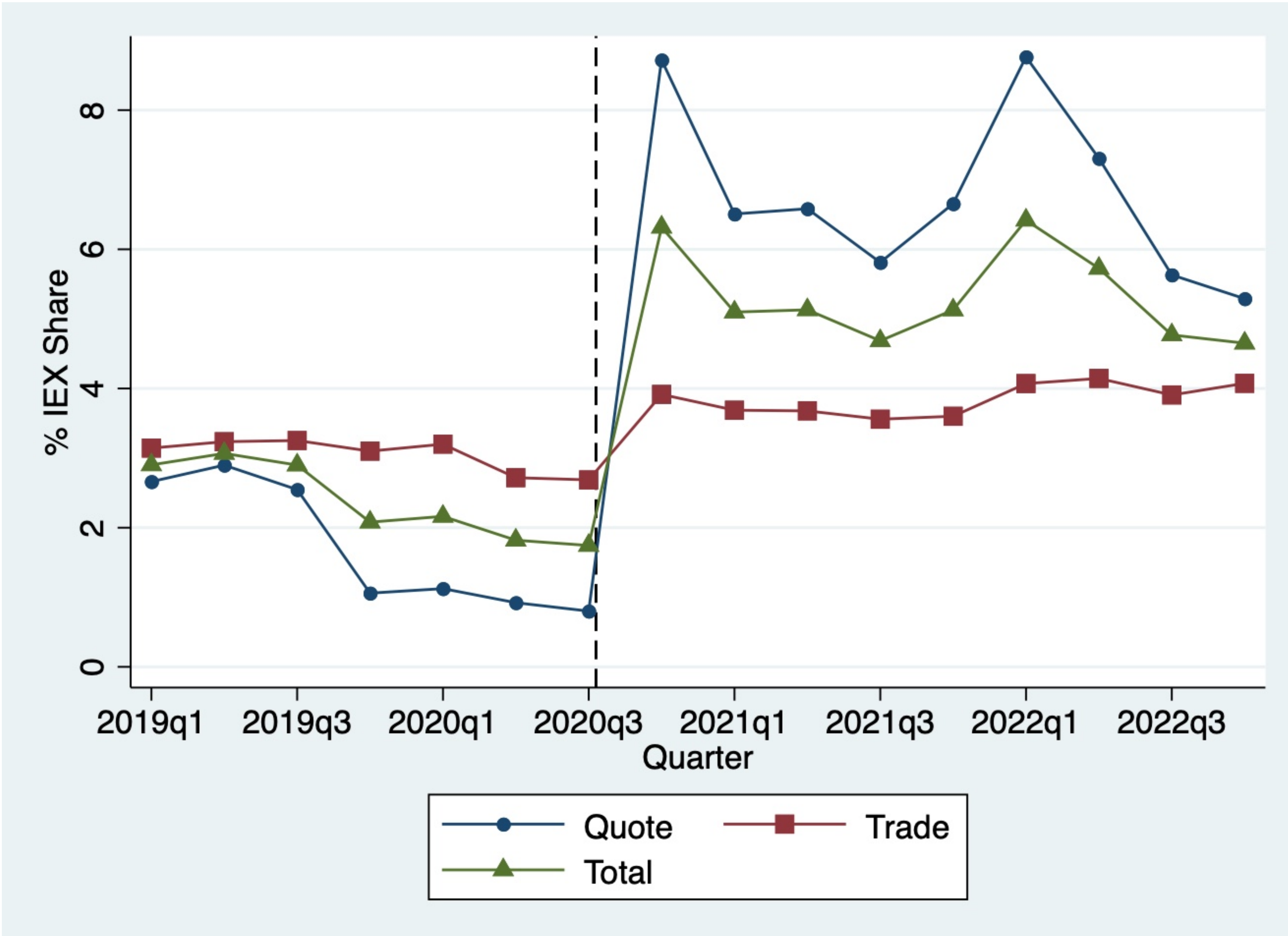

Table A1: Quoted Spread

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	463.47	394.90	260.66	312.43
se	24.43	20.34	14.48	21.23
Q1	68.86	56.24	47.20	49.95
Median	211.57	172.28	127.08	138.77
Q3	576.78	480.87	317.76	367.77

Panel B: Market-wide quoted spread (bps)				
	2020.08	2020.09	2021.01	2021.02
Mean	9.12	10.16	12.61	12.23
se	0.23	0.24	0.31	0.31
Q1	4.68	5.43	6.00	5.70
Median	7.31	8.32	10.16	9.71
Q3	11.66	13.27	17.37	17.17

Table A2: IEX SIP Revenue Share

Quarterly dollar value of market data revenue distributed to IEX is shown broken down into its two components, quoting and trading, as well as the total amount. Below that figure is the corresponding total amounts of market data revenue for the market as a whole. The third row shows IEX's percentage share for each category and quarter. Data for the period 2019 – 2022 is reported in the table. All data from the CTA plan (www.ctaplan.com) and UTP plan (www.utpplan.com) quarterly reports.

2022	Q1		Q2		Q3		Q4	
	Quote	Trade	Quote	Trade	Quote	Trade	Quote	Trade
IEX	4,734,911	2,199,248	3,958,688	2,245,778	2,965,035	2,057,006	2,823,890	2,141,395
Total	54,017,333	54,017,334	54,179,246	54,179,247	52,642,999	52,642,997	53,375,696	52,565,699
IEX %	8.77%	4.07%	7.31%	4.15%	5.63%	3.91%	5.29%	4.07%

2021	Q1		Q2		Q3		Q4	
	Quote	Trade	Quote	Trade	Quote	Trade	Quote	Trade
IEX	3,721,619	2,109,374	3,654,465	2,041,629	3,102,127	1,899,774	3,648,381	1,974,292
Total	57,184,991	57,184,991	55,509,652	55,509,654	53,375,957	53,375,957	54,815,646	54,815,647
IEX %	6.51%	3.69%	6.58%	3.68%	5.81%	3.56%	6.66%	3.60%

2020	Q1		Q2		Q3		Q4	
	Quote	Trade	Quote	Trade	Quote	Trade	Quote	Trade
IEX	558,489	1,588,912	502,859	1,481,915	445,573	1,493,986	4,513,301	2,026,364
Total	49,649,695	49,649,697	54,513,354	54,513,353	55,593,197	55,593,197	51,756,391	51,756,391
IEX %	1.12%	3.20%	0.92%	2.72%	0.80%	2.69%	8.72%	3.92%

2019	Q1		Q2		Q3		Q4	
	Quote	Trade	Quote	Trade	Quote	Trade	Quote	Trade
IEX	1,292,299	1,525,723	1,428,856	1,595,003	1,233,699	1,575,036	513,180	1,501,454
Total	48,541,038	48,541,038	49,294,575	49,294,577	48,425,949	48,425,947	48,434,168	48,434,168
IEX %	2.66%	3.14%	2.90%	3.24%	2.55%	3.25%	1.06%	3.10%

Table A3: Variations in IEX Share Change

This table presents the regression results on cross-sectional differences in the IEX's passive market share changes before and after the introduction of D-Limit order. In columns (1)–(4) of Panel A and columns (1)–(2) of Panel B, the sample period includes 2020.08–2020.09 (pre-period) and 2021.01–2021.02. (post-period) For columns (5)–(8) of Panel A and columns (3)–(4) of Panel B, the sample period includes 2020.08–2020.09 (pre-period) and 2020.10–2021.11. (post-period) In Panel A, the dependent variable is $IEXShare_{i,s}$, stock i's daily IEX passive market share average during period s where s is either pre- or post-period. Stock level control variables are all z-values of logged market cap (*mktcap*), logged price level (p), and logged daily trading volume (*volume*), which all are averages during the pre-period. In Panel B, the dependent variable is $IEXShare_{i,t}$, which is stock i's IEX passive market share on day t. Stock level control variables in Panel B includes z-values of logged daily trading volume ($volume_t$) and stock's high-low price calculated as the high price minus the low price divided by the midpoint of the two ($hilo_t$). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, ***, respectively.

Panel A: Regression with period averages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	1.92***	1.92***	1.92***	1.92***	2.62***	2.62***	2.62***	2.62***
	(0.09)	(0.09)	(0.07)	(0.06)	(0.09)	(0.09)	(0.08)	(0.06)
mktcap		−0.07				−0.07		
		(0.06)				(0.06)		
mktcap × *Post*		0.09				0.04		
		(0.10)				(0.11)		
p			0.77***				0.77***	
			(0.06)				(0.06)	
p × *Post*			0.51***				0.43***	
			(0.09)				(0.10)	
volume				−1.17***				−1.17***
				(0.04)				(0.04)
volume × *Post*				−0.39***				−0.52***
				(0.06)				(0.06)
Constant	4.38***	4.38***	4.38***	4.38***	4.38***	4.38***	4.38***	4.38***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)
Observations	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
adjusted R^2	0.23	0.23	0.50	0.70	0.33	0.33	0.52	0.74
Post Sample	2021.01–02	2021.01–02	2021.01–02	2021.01–02	2020.10-11	2020.10–11	2020.10–11	2020.10–11
Stock FE	No	No	No	No	No	No	No	No

Table A3 cont'd

Panel B: Daily regression				
	(1)	(2)	(3)	(4)
Post	1.93***	1.93***	2.62***	2.63***
	(0.02)	(0.02)	(0.02)	(0.02)
$volume_t$	0.09***		0.12***	
	(0.01)		(0.01)	
$volume_t \times Post$	−0.09***		−0.09***	
	(0.02)		(0.02)	
$hilo_t$		−0.03***		−0.03***
		(0.01)		(0.01)
$hilo_t \times Post$		0.00		0.00
		(0.02)		(0.02)
Constant	4.38***	4.38***	4.38***	4.38***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	63,995	63,995	67,194	67,194
adjusted R^2	0.47	0.47	0.50	0.50
Post Sample	2021.01–02	2021.01–02	2020.10-11	2020.10-11
Stock FE	Yes	Yes	Yes	Yes

Table A4: Variations in Time IEX is at NBB and/or NBO

This table presents the regression results on cross-sectional differences in the monthly average fraction of trading time IEX's best bid and/or offer matches 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 matches NBB or IEX's best offer matches NBO. Our sample uses trading between 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. Panels A (at NBBO), C (at NBB or NBO) and B (at NBBO), D (at NBB or NBO) are regression results that are analogous to Panels A and B in Table A3, respectively.

Panel A: Regression with period averages (at NBBO %)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	10.17***	10.17***	10.17***	10.17***	16.31***	16.31***	16.31***	16.31***
	(0.34)	(0.34)	(0.31)	(0.32)	(0.34)	(0.34)	(0.28)	(0.30)
mktcap		0.05				0.05		
		(0.18)				(0.18)		
mktcap × *Post*		−0.25				−0.61*		
		(0.39)				(0.34)		
p			−2.37***				−2.37***	
			(0.32)				(0.32)	
p × *Post*			−1.07**				−2.18***	
			(0.52)				(0.48)	
volume				2.36***				2.36***
				(0.37)				(0.37)
volume × *Post*				0.41				1.30**
				(0.62)				(0.56)
Constant	1.60***	1.60***	1.60***	1.60***	1.60***	1.60***	1.60***	1.60***
	(0.18)	(0.18)	(0.16)	(0.16)	(0.18)	(0.18)	(0.16)	(0.16)
Observations	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
adjusted R^2	0.36	0.35	0.47	0.45	0.59	0.59	0.71	0.68
Post Sample	2021.01–02	2021.01–02	2021.01–02	2021.01–02	2020.10-11	2020.10–11	2020.10–11	2020.10–11
Stock FE	No	No	No	No	No	No	No	No

Table A4 cont'd

Panel B: Daily regression (at NBBO %)				
	(1)	(2)	(3)	(4)
Post	10.17***	10.17***	16.29***	16.32***
	(0.02)	(0.02)	(0.03)	(0.03)
$volume_t$	0.12***		0.09***	
	(0.01)		(0.02)	
$volume_t \times Post$	−0.16***		−0.44***	
	(0.02)		(0.04)	
$hilo_t$		0.04***		0.03*
		(0.01)		(0.02)
$hilo_t \times Post$		−0.10***		−0.49***
		(0.02)		(0.03)
Constant	1.60***	1.60***	1.60***	1.60***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	63,995	63,995	67,194	67,194
adjusted R^2	0.89	0.89	0.85	0.85
Post Sample	2021.01–02	2021.01–02	2020.10–11	2020.10–11
Stock FE	Yes	Yes	Yes	Yes

Table A4 cont'd

Panel C: Regression with period averages (at NBB or NBO %)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	44.53***	44.53***	44.53***	44.53***	55.92***	55.92***	55.92***	55.92***
	(1.01)	(1.01)	(0.81)	(0.86)	(1.13)	(1.12)	(0.88)	(0.94)
mktcap		−1.31				−1.31		
		(0.99)				(0.99)		
mktcap × *Post*		−0.20				−0.69		
		(1.13)				(1.15)		
p			−15.78***				−15.78***	
			(1.00)				(1.00)	
p × *Post*			8.94***				3.82***	
			(1.14)				(1.20)	
volume				14.54***				14.54***
				(1.09)				(1.09)
volume × *Post*				−10.18***				−5.09***
				(1.28)				(1.37)
Constant	15.88***	15.88***	15.88***	15.88***	15.88***	15.88***	15.88***	15.88***
	(0.90)	(0.90)	(0.71)	(0.74)	(0.90)	(0.90)	(0.71)	(0.74)
Observations	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
adjusted R^2	0.55	0.55	0.71	0.67	0.61	0.61	0.76	0.72
Post Sample	2021.01–02	2021.01–02	2021.01–02	2021.01–02	2020.10-11	2020.10–11	2020.10–11	2020.10–11
Stock FE	No	No	No	No	No	No	No	No

Table A4 cont'd

Panel D: Daily regression (at NBB or NBO %)				
	(1)	(2)	(3)	(4)
Post	44.53***	44.53***	55.90***	55.95***
	(0.07)	(0.07)	(0.10)	(0.10)
$volume_t$	−0.04		−0.21***	
	(0.05)		(0.07)	
$volume_t \times Post$	0.07		−0.63***	
	(0.08)		(0.11)	
$hilo_t$		−0.01		−0.05
		(0.05)		(0.06)
$hilo_t \times Post$		−0.05		−0.72***
		(0.07)		(0.10)
Constant	15.88***	15.88***	15.88***	15.88***
	(0.05)	(0.05)	(0.06)	(0.06)
Observations	63,995	63,995	67,194	67,194
adjusted R^2	0.91	0.91	0.87	0.87
Post Sample	2021.01–02	2021.01–02	2020.10–11	2020.10–11
Stock FE	Yes	Yes	Yes	Yes

Table A5: Variations in Time and Volume Weighted Share at NBB and/or NBO

This table presents the regression results on cross-sectional differences in changes of the time and volume-weighted fraction of IEX at NBBO. That is, for each stock-day, we calculate the following:

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

Our sample uses trading between 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. Panels A and B are regression results that are analogous to Panels A and B in Table A3, respectively.

Panel 1: Regression with period averages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	19.71***	19.71***	19.71***	19.71***	24.85***	24.85***	24.85***	24.85***
	(0.19)	(0.19)	(0.18)	(0.18)	(0.35)	(0.35)	(0.35)	(0.35)
mktcap		−0.02				−0.02		
		(0.04)				(0.04)		
mktcap × *Post*		−0.44**				0.10		
		(0.21)				(0.33)		
p			−0.41***				−0.41***	
			(0.05)				(0.05)	
p × *Post*			2.12***				1.60***	
			(0.27)				(0.47)	
volume				0.30***				0.30***
				(0.05)				(0.05)
volume × *Post*				−2.60***				−1.78***
				(0.27)				(0.46)
Constant	1.72***	1.72***	1.72***	1.72***	1.72***	1.72***	1.72***	1.72***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
adjusted R^2	0.87	0.87	0.88	0.89	0.76	0.76	0.76	0.76
Post Sample	2021.01–02	2021.01–02	2021.01–02	2021.01–02	2020.10-11	2020.10–11	2020.10–11	2020.10–11
Stock FE	No	No	No	No	No	No	No	No

Table A5 cont'd

Panel B: Daily regression				
	(1)	(2)	(3)	(4)
Post	19.74***	19.71***	24.83***	24.87***
	(0.03)	(0.03)	(0.05)	(0.05)
$volume_t$	−0.08***		−0.22***	
	(0.02)		(0.03)	
$volume_t \times Post$	−0.30***		−0.50***	
	(0.03)		(0.05)	
$hilo_t$		0.04**		−0.03
		(0.02)		(0.03)
$hilo_t \times Post$		−0.08***		−0.46***
		(0.03)		(0.05)
Constant	1.72***	1.73***	1.72***	1.72***
	(0.01)	(0.02)	(0.03)	(0.03)
Observations	63,995	63,995	67,194	67,194
adjusted R^2	0.91	0.91	0.80	0.80
Post Sample	2021.01–02	2021.01–02	2020.10–11	2020.10–11
Stock FE	Yes	Yes	Yes	Yes

B Appendix: Crumbling Quote Remove Fee

Overview

On Monday, January 1, 2018, the following pricing changes are operative on the Exchange for executions that remove liquidity during periods of quote instability, as defined in IEX Rule 11.190(g), above the Crumbling Quote Remove Fee (CQRF) Threshold.

Crumbling Quote Remove Fee

The Crumbling Quote Remove Fee was a differential fee amounting to $0.0030 (30 mills) and it was added for liquidity removing orders that arrived in periods when the quote-instability indicator (CQI) was in the 'on' state. The CQRF was abolished when the D-Limit order was launched on October 1st, 2020. The text below covers a few more details and lists the SEC filings for the CQRF.

CQRF-Threshold

"CQRF Threshold" means the Crumbling Quote Remove Fee Threshold. The threshold is equal to 5% of the sum of a Member's total monthly executions on IEX if at least 1,000,000 shares during the calendar month, measured on an MPID (market participant identifier) basis.

Example Calculation of the Crumbling Quote Remove Fee

For example, assume Member XYZ executed 100,000,000 shares through its MPID 1234 during a particular month, and 6,000,000 of such shares removed liquidity while the CQI was on. The 6,000,000 shares executed when the CQI was on exceed the threshold since such shares are more than 5% of MPID 1234's monthly volume (i.e., 5,000,000) and at least 1,000,000 shares. Member XYZ would therefore be charged the fee on 1,000,000 shares which is the incremental number of shares above 5% of the 100,000,000 shares executed by MPID 1234 during the month. See SR-IEX-2017-27 for additional information.[31]

[31] SEC Release No. 34-81484.

Table B1: Mid-quote Execution (CQRF Period)

This table shows the monthly average fraction of mid-quote trades among all trades for the 768 stocks in our full sample around the Crumbling Quote Remove Fee (CQRF) period. For each stock-day (stock-time period), we calculate the percentage of trades on IEX (IEX′) executed at the mid-quote of the NBBO during a day (time period). Our sample uses trading between 9:35 a.m. to 4:00 p.m. to avoid any idiosyncrasies at the market open. We sum the number of trades at the mid-quote IEX (IEX′) divided by the sum of all number of trades at IEX (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 mean of the IEX mid-quote fraction (Panel A) and IEX′ mid-quote fraction (Panel B) in percentages.

Panel A: IEX mid-quote execution (%)				
	2017.11	2017.12	2018.01	2018.02
Overall	34.18	30.70	32.51	29.30
9:35–10:05	32.61	29.67	29.94	27.77
10:05–15:30	35.23	31.59	32.66	29.27
15:30–16:00	29.48	26.88	30.91	27.71

Panel B: Mid-quote executions at other exchanges excluding IEX (%)				
	2017.11	2017.12	2018.01	2018.02
Overall	9.51	9.14	9.26	8.41
9:35–10:05	7.85	7.61	7.65	7.26
10:05–15:30	9.31	8.75	8.96	8.24
15:30–16:00	10.76	10.72	10.73	9.29

Table B2: Time IEX is at NBB and/or NBO (CQRF Period)

This table shows the monthly average fraction of trading time IEX's best bid and/or offer matches NBB and/or NBO for the 768 stocks in our full sample around the Crumbling Quote Remove Fee (CQRF) period. 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 matches NBB or IEX's best offer matches NBO. Our sample uses trading between 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 mean of At NBBO (Panel A) and At NBB or NBO (Panel B) in percentages.

Panel A: At NBBO (%)				
	2017.11	2017.12	2018.01	2018.02
Overall	5.23	5.17	5.36	5.63
9:35–10:05	1.79	1.96	2.33	3.39
10:05–15:30	4.83	4.74	5.12	5.52
15:30–16:00	13.04	12.99	10.99	9.11

Panel B: At NBB or NBO (%)				
	2017.11	2017.12	2018.01	2018.02
Overall	26.36	28.16	34.57	43.86
9:35–10:05	15.78	19.25	25.11	32.53
10:05–15:30	25.42	27.12	34.31	44.20
15:30–16:00	47.49	48.29	46.76	51.52