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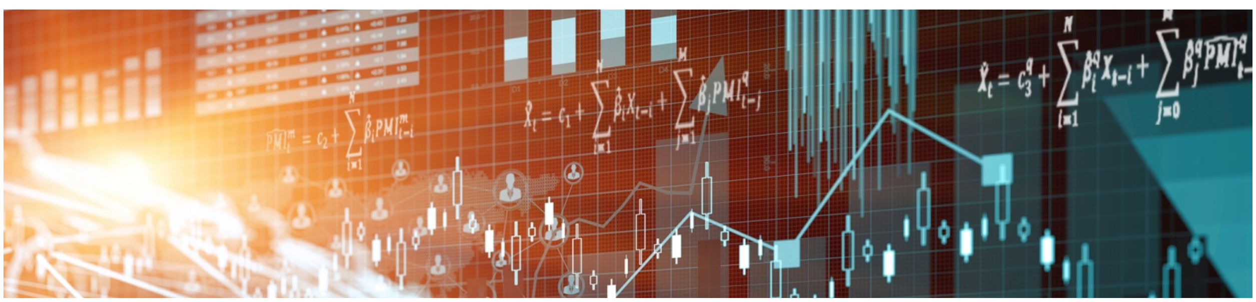
Retail Order Flow Segmentation



by Corey Garriott and Adrian Walton

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Abstract

In August 2012, the New York Stock Exchange launched the Retail Liquidity Program (RLP), a trading facility that enables participating organizations to quote dark limit orders executable only by retail traders. A Hasbrouck (1991) structural vector autoregression shows that the facility increased the information content of the order flow by distinguishing retail trades from relatively more informed trades. A differences-in-differences event study finds that the RLP launch impacted market quality. Stocks with substantial RLP activity experienced mildly improved relative bid-ask spreads, effective spreads, price impacts and return autocorrelations in both the RLP and non-RLP segments.

JEL classification: G20, G14, L10
Bank classification: Financial markets; Market structure and pricing; Financial system regulation and policies

Résumé

En août 2012, la Bourse de New York a lancé le Retail Liquidity Program (RLP), une plateforme de négociation qui permet aux organisations participantes de se porter contrepartie des ordres à cours limité invisibles, exécutables uniquement par des intermédiaires agissant pour le compte de clients de détail. Nos modèles VAR structurels inspirés de Hasbrouck (1991) montrent que la séparation des opérations de détail de celles réalisées par des investisseurs plus avertis effectuée par ce dispositif accroît le contenu informatif des flux d'ordres. Par ailleurs, une étude événementielle fondée sur la méthode des doubles différences fait apparaître que le lancement du RLP a influé sur la qualité du marché en général. Pour les actions les plus activement négociées sur cette plateforme, on observe une légère amélioration des écarts relatifs entre les cours acheteur et vendeur, des écarts effectifs, de l'incidence sur les cours, et des coefficients d'autocorrélation des rendements, non seulement dans le segment RLP, mais aussi dans les autres segments de la Bourse de New York.

Classification JEL : G20, G14, L10
Classification de la Banque : Marchés financiers; Structure de marché et fixation des prix; Réglementation et politiques relatives au système financier

Non-Technical Summary

Retail traders are a profitable class of counterparty for financial intermediaries because they are typically less sophisticated and have less information about future prices than institutional traders. We study a facility on the New York Stock Exchange (NYSE) that allows intermediaries to trade specifically with retail traders. The facility, the Retail Liquidity Program (RLP), was launched in 2012. Similar facilities have since launched on other exchanges. Academics and regulators have pointed out that trading facilities restricted to certain types of counterparty may benefit the targeted counterparties to the detriment of others.

We test whether the segmentation of retail trading on the NYSE affected the quality of trading opportunities for retail and non-retail traders by measuring transaction costs before and after the RLP was launched. Our first finding is that the segmentation facility was slightly beneficial for both retail and non-retail traders, lowering their transaction costs.

An important outcome of the trading of financial assets is price discovery. A competitive trading environment provides a mechanism for finding the fair price of an asset. It is important for regulators to understand how changes to the way financial assets are traded might affect the price-discovery process and to ensure it remains effective. Our second finding is that segmentation of retail traders improves the price-discovery process by allowing market participants to distinguish between retail trades, which contribute little to price discovery, and non-retail trades, which contribute more so.

1. Introduction

A major driver of market-structure innovation is the value of knowing whether a potential counterparty is a desirable trading partner. Market participants are more likely to lose money when trading with sophisticated counterparties such as arbitrageurs, hedge funds and large institutional asset managers. Sophisticated counterparties tend to transact in large quantities and tend to buy before prices rise and sell before prices fall. In contrast, retail traders are a safer class of counterparty. Retail trades are small and less correlated with future prices. The desire to trade with retail counterparties has motivated the design of market structure that provides access specifically to retail orders. This is a type of order-flow segmentation. Segmentation creates a tension. While retail counterparties receive improved trading opportunities, counterparties in the wider market may be left with worse trading opportunities and hence worse market quality. Regulators have expressed concerns that segmentation may be detrimental to market quality.

In this paper, we study the launch of a new trading facility that enables retail order-flow segmentation. In August 2012, the New York Stock Exchange (NYSE) launched the Retail Liquidity Program (RLP). The RLP segments retail order flow by enabling participants to transact with retail traders by quoting dark (non-displayed) limit orders at prices that improve on the prevailing displayed limit orders. We study the RLP using event-study methodology and show the RLP had a mild and positive impact on market-quality measures. Moreover, the RLP improved the price-discovery process. A Hasbrouck (1991) vector autoregression (VAR) on the order flow shows that RLP improved market participants' ability to forecast prices by distinguishing retail trades from more-informed trades.

Order-flow segmentation is no longer novel and has been studied in Easley, Kiefer and O'Hara (1996), Battalio (1997) and Parlour and Rajan (2001). Our paper contributes by studying order-flow segmentation in a novel market structure. Historically, most segmentation has occurred off-exchange in a broker crossing network, a market structure that is opaque and order-driven. The RLP segments order flow within a quote-driven and competitive stock exchange. Segmentation may have different costs and benefits on exchanges than it does among private broker networks. Battalio (1997) finds that bid-ask spreads tighten when a broker purchases order flow for execution off-exchange. Our findings are similar for exchange-based segmentation. A second contribution of the paper is the study of a dataset in which it is possible to identify the trades of the segmented parties. We can verify that segmentation increases the informational value of the order flow, as is often supposed. A third contribution is that one of our results is theoretically unexpected. Theory on segmented venues often predicts that the outcome of segmentation should be to worsen market liquidity for a particular segment of the market, and we find the opposite effect. We give suggestions for how theory might be expanded to include this case in the conclusions.

The work can also contribute to the formation of securities regulation. Securities-regulatory authorities have expressed the concern about dark pools that segmentation may deprive certain market participants of trading opportunities (IOSCO 2010, OSC 2010). This could reduce the liquidity externality, the reduction of trading costs that comes from pooling traders (Battalio and Holden 2001). This paper provides results that can contribute to the regulatory discussion.

Retail segmentation on exchanges is becoming more common. The first exchange-based segmentation program was the Canadian Alpha IntraSpread in 2011. The NYSE Euronext and BATS followed in 2012, Nasdaq in 2014, and recently again in Canada, Aequitas in 2015. The programs can be seen as an attempt by exchanges to compete for retail business that is threatened by broker internalization, the practice of brokers matching buyers and sellers off-exchange. Many retail brokers execute orders privately, usually by matching them with their other retail client orders or by routing them to various off-exchange broker networks, both of which allow brokers to avoid paying fees to execute orders on an exchange. The RLP can substitute for broker internalization because its liquidity is pre-trade opaque and segmented, just as in internalization networks. In addition, it adds the advantage of the competitive exchange-based trading environment.

The RLP tries to serve three client bases. For liquidity providers, the RLP guarantees interaction with retail traders; for retail traders, the RLP guarantees price improvement, albeit slight; for retail brokers, the RLP requires no fee to execute. Retail order flow is profitable for liquidity suppliers to fill, since trade sizes are usually small and have balanced direction (buy or sell), and trades are relatively uncorrelated with future price movements and future order flow (Easley, Kiefer and O'Hara 1996).

Zhu (2014) is the most applicable theory that gives a set of expectations for the likely outcomes of the RLP. The paper models a dark pool that incentivizes segmentation. It predicts that segmentation is good for price discovery but bad for liquidity on the exchange. The first prediction holds because segmentation concentrates informed traders on the exchange, while the second holds because market makers become less willing to provide liquidity on the exchange due to the higher concentration of informed traders.

We test four hypotheses derived from Zhu (2014) that are discussed in detail in section 2. The first two hypotheses concern the informational characteristics of trade on the NYSE and the RLP and are tested to ensure the model is a good fit for the RLP. The hypotheses are that RLP trades contribute relatively less to price discovery and that distinguishing between RLP trades and non-RLP (hereafter referred to as "lit") trades aids the price-discovery process. We find the model is indeed a good fit for the RLP. The last two hypotheses are formed using two consequences the model derives in such an environment. Price efficiency should improve, while liquidity for lit trades should deteriorate. We find price efficiency improves but liquidity for lit trades also slightly improves. The result is theoretically unexpected, so we discuss potential extensions to theory in the conclusions.

The study employs Trade and Quote (TAQ) data from the NYSE in a window around the RLP launch date. The dataset contains information on all trades and best bid and ask quotes and sizes on all stocks traded on the NYSE and NYSE Arca from 1 April 2012 to 1 August 2013. RLP trades are identified by having subpenny prices, that is, prices that take values off the usual tick grid of one cent for displayed limit orders. At the time, subpenny trades were not otherwise possible on the NYSE's main venue.

The methodology used to test the first two hypotheses, those on the informational characteristics of order flow, is structural VAR. We fit structural VAR models on returns and order flows and analyze how the RLP and lit components of the order flow contribute to price discovery. We compute impulse-response functions and information shares for RLP, lit, and undifferentiated order flow using the techniques of Hasbrouck (1991). In the data, an impulse of lit trades causes a visibly larger response in the log return than does an impulse of RLP trades. We also find the information share of the RLP and lit order flows is greater than that of the undifferentiated flows. Put differently, the segmented order flow is a better predictor of the price than the undifferentiated order flow. For both RLP and lit flow, the impact on return decays quickly on average after 10 minutes. Our interpretation is that the RLP is aiding price discovery at the 10-minute horizon.

The methodology used to test the second two hypotheses, those on the effect of segmentation on market quality, is the differences-in-differences event study. During the sample period of our dataset, the RLP was launched on the NYSE's main exchange (simply referred to as the NYSE) but not NYSE Arca (simply referred to as Arca), another exchange owned and operated by the NYSE. We use stocks that traded only on Arca (and not on the NYSE) as a control group. Stocks that traded on Arca were eventually eligible for an RLP that launched on Arca in 2014. Overall, we find the RLP leads to a slight improvement in four standard market-quality measures: relative bid-ask spreads improve by around one basis point from an unconditional average of 12 basis points; effective spreads improve by around half a basis point from an unconditional average of 10 basis points; price impact decreases by half a basis point from an unconditional average of 3.5 basis points; and the return autocorrelation decreases by around 0.01 from an unconditional average of 0.06.

The results are economically small in size, likely because treatment stocks have an average of only 3.5% of trading volume in the RLP. To demonstrate the results are nevertheless robust, we use several event-study specifications. We examine the results using both the simple, "single-difference" event study and also the difference-in-differences event study. We estimate each differences-in-differences regression using six specifications that successively include more control variates. We fit the differences-in-differences model once over the entire sample and again over four within-period subsamples. Last, to ensure our selection of control stocks is robust, we construct a weighted panel of control stocks for each treatment stock in our sample and fit the event studies again. For each of the model specifications above, the general result of the paper persists: the RLP results in a slight improvement in market quality. The robustness exercises show that, in order to believe the impact is not present, one would have to believe another factor affected four market-quality measures on sets of stocks on the NYSE but not Arca around the launch of the RLP, a factor that is not explained by fixed effects, lags or common liquidity determinants, and a factor that persisted both throughout the sample and equally in each of the within-period subsamples.

In our conclusions, we emphasize the economics of segmentation. RLP orders are dark mostly because darkness permits price improvement in a market with a regulatory tick-size constraint on visible limit orders. Dark orders do not have to obey tick-size regulation, so darkness enables price improvement on the regulatory tick. Darkness may have less relation with market-quality outcomes than might be suspected, even in a wider setting such as Zhu (2014). The model uses darkness solely as a way to incentivize segmentation, and since the model is static, the darkness plays no additional role. In the RLP, segmentation is guaranteed and exogenous, so in our setting darkness does not even provide the incentive to segment.

The results are relevant to theory. Theory on dark segmentation generally predicts an improvement in price efficiency and contains ambiguous results about liquidity. We employ Zhu (2014) to generate empirical hypotheses and treat his model in some detail in section 2. Boulatov and George (2013) make similar predictions to Zhu (2014) in that dark liquidity may improve price efficiency. They model informed traders' choices between providing or demanding liquidity and find that they will be more willing to provide liquidity in a totally dark market than in a totally lit market. Competition in a dark market is more intense, leading to greater liquidity and more informative prices.

Theory on segmentation has focused on brokers' routing decisions and competition among venues. Parlour and Rajan (2003) model payment for order flow with competing market makers who quote bid-ask spreads, competing brokers who choose a commission to be paid by an investor, and investors who choose a broker to minimize total transaction costs. Payment for order flow increases spreads and increases the ratio of limit to market orders. It can lead to lower brokerage commissions but wider bid-ask spreads and higher transaction costs for market makers. Battalio and Holden (2001) also model payment for order flow and distinguish between traders' externally and internally verifiable characteristics. The model predicts that the potential benefits of payment for order flow or internalization depend on the competitiveness of brokers.

Empirical papers on dark liquidity come to varying conclusions about its effect on market quality. Foley and Putniņš (2014) is a related study that investigates restrictions on dark trading in Canada. They find that dark trading benefits market quality by reducing quoted, effective and realized spreads and increasing informational efficiency. Further, they find dark midpoint-crossing systems do not benefit market quality. Using a regulatory dataset, Comerton-Forde, Malinova and Park (2016) find the Canadian restrictions on dark trading resulted in greater quoted depth in the lit market. They also find the rule change resulted in higher fees for retail brokers and higher rebates for high-frequency market makers. One of the dark pools affected by the rule change, Alpha IntraSpread, has the same features as the NYSE's RLP. Our study is distinguished from the above by studying the launch of a single trading facility rather than a rule change that indiscriminately affected multiple types of trading venue in different ways. We also study a facility in the larger and more liquid US market.

Fleming and Nguyen (2013) also study dark liquidity in the US Treasuries market. They find greater use of dark liquidity at volatile times and that its informational role becomes relatively less important during those volatile times. Higher usage of dark liquidity is correlated with higher market depth, lower bid-ask spreads and higher trading intensity. Boni, Brown and Leach (2013) study dark pools with participation constraints and find that stronger constraints lead to less serial correlation in returns, volume and volatility tend to lead other markets to a smaller degree, and more trade clustering occurs across days. Hatheway, Kwan and Zheng (2013) analyze segmentation and dark orders in US equity markets. They find trading in dark markets reduces price efficiency and increases transaction costs, with the exception of large dark transactions and dark trading in small stocks.

The remainder of the paper is organized as follows: section 2 describes our hypotheses in detail; section 3 describes the data; section 4 gives details on the methodology; section 5 discusses the results; and section 6 offers some conclusions.

2. Hypotheses

There are four hypotheses tested in the paper. The first two hypotheses are about how the RLP alters the informational character of the order flow. The second two hypotheses are about how the RLP impacts market quality.

The motivation for the hypotheses derives from Zhu (2014), which models traders' choices to use either a dark midquote crossing facility or a traditional exchange. As is common in microstructure, there are three types of agent: informed traders, uninformed traders and exchange-based market makers. The dark crossing facility matches buy and sell market orders at the exchange's midquote. Traders strategically choose venues in equilibrium. In the crossing facility, execution is not certain, since there can be more buy orders than sell orders or vice versa. The uncertainty of execution in the crossing facility discourages the participation of informed agents more than it does the uninformed, because the informed agents' information is short-lived. Thus the dark crossing facility endogenously segments the market, concentrating informed activity in the public exchange. Due to the concentration of informed activity, price efficiency is better, and liquidity on the exchange is worse.

We motivate hypotheses using Zhu (2014) because the NYSE RLP is much like the dark crossing network in the model. It guarantees price improvement versus the main exchange, and it presents execution risk since limit orders are not displayed. Unlike the model crossing network, the NYSE RLP segments the market exogenously—liquidity is only accessible by brokers executing retail market orders. Nevertheless, we believe the theory is a good match because the active mechanism in Zhu (2014) is segmentation. The role of darkness in the model is to create the execution risk that incentivizes the segmentation. In a sense, the data are ideal, since it is already true by assumption that segmentation occurs, so it is possible to test the predicted impact of the segmentation directly. This leads us to the following two hypotheses:

Hypothesis 1: The RLP order flow is less informed than the non-RLP order flow.

Hypothesis 2: Segmentation improves the informativeness of the total order flow.

To ensure the RLP segmentation is between the more- and less-informed components of the order flow, we first test the hypothesis that RLP flow is indeed less informative than lit. Then we test whether the facility increases the informativeness of the order flow overall. If so, the segmentation does offer a superior way to discover prices from the order flow, as in the model. We follow with the hypotheses on the impact:

Hypothesis 3: Participation in the RLP affects a stock's liquidity.

Hypothesis 4: Participation in the RLP affects a stock's price efficiency.

The removal of the retail order flow to the RLP concentrates the more informed order flow on the main exchange, which should improve price efficiency. However, more informed order flow is more costly to fill. Market makers could compensate by widening bid-ask spreads on the main exchange. The third and fourth hypotheses ask whether these two impacts result from the first and second hypotheses.

It is not clear that the outcome will be as in Zhu (2014). One limitation of the model is that it is static. The model shows the option to trade in the dark concentrates informed agents on the exchange, which otherwise resembles the classic limit-order market modelled in Glosten and Milgrom (1985). The impact of concentrating informed agents on an exchange is given in Glosten and Milgrom's (1985) Proposition 5, which also points to dynamic effects. Although an increase in informed activity has the *immediate impact* of increasing the bid-ask spread, *future spreads* are tighter as informational differences between the informed agents and the market maker decrease more quickly.[1] This intuition is formalized in Roșu (2016), who predicts that an increase in informed traders'

[1] In Proposition 3 the expected spread squared times volume is bounded above, so if spreads are increased early in the lifetime of the game then they must be decreased later.

information results in an immediate increase in bid-ask spreads followed by a decrease in bid-ask spreads, which occurs at a speed proportional to the degree of informed trading, as in Glosten and Milgrom (1985). It is possible the same economic mechanism could be active on the RLP, resulting in superior price efficiency as well as superior liquidity.

3. Data

Our dataset contains information on trades and best bid and ask quotes on all stocks traded on the NYSE and Arca for 333 trading days from 1 April 2012 to 1 August 2013.[2] The data consist of time-stamped reports of all trade prices and quantities and time-stamped reports of all best bid and best ask prices and quantities, for each stock and exchange. The trades are not marked by the sign of trade (buyer- or seller-initiated), so we impute the sign of trade using the Lee and Ready (1991) algorithm.

We mark trades on the NYSE that have subpenny prices after 1 August 2012 as RLP and all other trades are marked lit. The NYSE reports that no trades can take a subpenny price on the NYSE's main venue except via the RLP. Indeed, there were no trades on the NYSE before 1 August 2012 in our sample that had subpenny prices. This approach may slightly underestimate the total activity in the RLP. For example, for stocks with bid-ask spreads greater than one cent, RLP trades could occur at prices on the regular tick grid of one cent.

Treatment stocks

Treatment stocks are defined as stocks that had at least 1% RLP volume share. We choose 35 treatment stocks using the following criteria. Before choosing treatment stocks, we sample the data. We drop all small-cap stocks (stocks with a market capitalization

[2] We augment the dataset with metadata from Compustat.

under US$2 billion), all exchange-traded funds and all share classes other than common equity. Stocks that were cross-listed in Canada were removed from the sample, since they were eligible for a similar program to the RLP, Alpha IntraSpread. We drop stocks that had a minimum price below $2.00 at any time during the sample period, since they may have been eligible for subpenny pricing on the NYSE due to their low price. We drop stocks that are eligible for a separate RLP on another NYSE-operated exchange, the NYSE MKT. Before sampling, the data included trades and quotes for 3,993 stocks that trade on the NYSE. After removing small-cap stocks, exchange-traded funds, cross-listed stocks, non-common equity share classes and stocks with a low price, 2,265 stocks remain.

Of the 2,265 sample stocks, 49 had an average of over 1% of total volume on the NYSE that traded in the RLP. Of these 49 stocks with relatively heavy usage of the RLP, 14 had sparsely populated data, that is, fewer than 10 days of complete data before and after the launch of the RLP. We designate the remaining 35 stocks the sample of treatment stocks.

Control stocks

We create a pool of control stocks from the set of all stocks that were traded on Arca and *not* on the NYSE and therefore were ineligible for the RLP. From the set of stocks that traded on Arca and not on the NYSE, we sample using the same criteria used to define treatment stocks (except for the threshold for RLP activity). There are 184 candidate control stocks that fit the criteria. We create a matched sample by pairing treatment stocks one-to-one with control stocks. For each treatment stock, we select the nearest neighbour by average sample market capitalization without replacement. Measures of liquidity for certain control stocks on 26 December 2012 were extreme, so we drop the day from the sample.

Data for computing information shares: returns and order flow

For the purposes of computing information shares, we compute a return variable and three order-flow variables: five-minute log midquote returns, five-minute net RLP order flow, five-minute net lit order flow, and the five-minute net undifferentiated order flow (RLP and lit together), for days after the launch of the RLP on 1 August 2012. Five-minute log midquote returns are computed for every five-minute time increment by taking the log of the ratio of the midquote to the five-minute-lagged midquote. Order flow variables are computed for each five-minute time increment by summing trading volumes within the period, where buyer-initiated trades and seller-initiated trades are signed positive and negative, respectively. All order flow variables are signed positive for net buying and negative for net selling. The choice of five minutes results in a granular set of observations while ensuring the RLP net order flow is non-zero for most time intervals.

Data for conducting differences-in-differences: market-quality measures

For the purposes of running the event studies, we compute daily averages of four standard market-quality measures: the relative bid-ask spread, the effective spread, the five-second price impact and the five-second return autocorrelation. The first three measure liquidity, while the return autocorrelation is used to measure price efficiency. The choice of five seconds is standard for price impacts and autocorrelations. For these measures we use the standard formulae:

Relative bid-ask spread	$\frac{ask - bid}{midquote}$
Effective spread	$2 * sign\ of\ trade * \frac{price - midquote}{midquote}$

Five-second price impact	$sign\ of\ trade * \frac{midquote_{t+5\ seconds} - midquote_t}{midquote_t}$
Five-second return autocorrelation	$corr(return_{t+5\ seconds}, return_t)$,

where the subscripts t and t+5 *seconds* denote observations at a particular time t and five seconds later; *bid, ask* and *midquote* denote the best bid and ask prices, and their mean, the midquote; *sign of trade* denotes whether a trade was buy- or sell-initiated as computed using the Lee and Ready (1991) algorithm; *return* denotes the five-second log midquote return; and *corr* denotes the correlation operator.

We eliminate trades from the sample that are flagged as occurring during the opening or closing auctions. We take daily averages of the above measures over standard trading hours, from 9:30 a.m. to 4:00 p.m.

Summary statistics

Table 1 provides summary statistics on market quality and market capitalization for the 35 stocks identified as treatment stocks and the 35 matched control stocks. Panel A shows summary statistics for treatment stocks before the launch of the RLP, from April 2012 until July 2012, and Panel B shows summary statistics for treatment stocks after the launch of the RLP, from August 2012 until August 2013. Panel C shows summary statistics for control stocks before the launch of the RLP, and Panel D shows summary statistics for control stocks after the launch of the RLP. The columns of the table give the average, standard deviation, minimum, 25th percentile, 50th percentile, 75th percentile and maximum for each market-quality measure and for market capitalization.

TABLE 1 ABOUT HERE

Volume is the average number of shares traded per day in thousands of shares. *RLP Volume* is the average number of shares traded in the RLP per day in thousands of shares. *Relative Spread* is the average daily relative spread. *Effective Spread* is the average daily effective spread. *Price Impact* is the average daily five-second price impact. *Autocorrelation* is the average daily absolute five-second autocorrelation of the midquote.

For treatment stocks, average volume decreased from 2,541K shares per day to 2,492K after the launch of the RLP. RLP volume after launch was 89K shares per day or roughly 3.5% of total volume. Since overall volume decreased, it is unlikely that the RLP attracted new order flow that was previously traded off the NYSE. Each of the liquidity measures improved for treatment stocks after the launch of the RLP. The average relative bid-ask spread decreased from 12.1 to 10.5 basis points. Similarly, the average effective spread decreased from 9.9 basis points to 8.7 basis points, while the average price impact decreased from 3.6 basis points to 3.2 basis points. Average absolute autocorrelation remained at 0.06. Average market capitalization increased after the launch of the RLP from $188.24 to $237.71 billion.

For control stocks, average volume decreased from 311K to 243K shares per day after the launch of the RLP. Control stocks had less volume than treatment stocks across the sample period. This is a weakness of the control group and one reason we also perform the regression using a weighted panel of control stocks (Table 7). The weighted panel ensures the result is not spuriously driven by a particular selection of the 35 control stocks from the 184 candidates.

Liquidity measures for control stocks were relatively unchanged when compared to the liquidity measures of the treatment stocks. The relative average bid-ask spread increased from 12.8 to 12.9 basis points. The average effective spread decreased from 7.2 to 6.8 basis points. Average price impact increased from 2.5 to 2.8 basis points. Average absolute autocorrelation increased from 0.09 to 0.10. Market capitalization for control stocks increased after the launch of the RLP from $182.44 to $215.06 billion.

Panel E shows the difference in the means of market-quality measures and market-quality factors before and after the launch of the RLP for treatment and control stocks. Volume decreased for both treatment and control stocks over the sample, while market capitalization increased. Each of the liquidity measures for treatment stocks decreased after the launch of the RLP: the relative spread by 1.5 basis points, effective spread by 1.2 basis points and price impact by 0.5 basis points. For control stocks, these liquidity measures had no consistent pattern: the effective spread decreased slightly, by 0.37 basis points, while the relative spread and price impact increased slightly, by 0.11 and 0.24 basis points, respectively. There was no average change in autocorrelation for treatment stocks, while the autocorrelation for control stocks increased by 0.01 after the launch of the RLP.

Figure 1 shows the liquidity history for treatment stocks over the sample period. Panel A shows the relative bid-ask spread, while Panel B shows the total and RLP volume in thousands of shares per day.

FIGURE 1 ABOUT HERE

The relative bid-ask spread is roughly 11 basis points on average in the beginning of the sample and falls to roughly 10 basis points from September 2012 until January 2013. Total volume is roughly constant over the sample period. Volume in the RLP increased steadily from after the RLPs launch in August 2012 until September 2012. RLP volume remains roughly constant at 3.5% of total volume thereafter.

4. Methodology

We use two statistical methodologies: structural VAR for our first two hypotheses on the informational characteristics of the order flow, and the differences-in-differences event study to test our second two hypotheses on the effects of the RLP on market quality.

VAR and information shares

We fit the structural VAR model using the five-minute order-flow and return data described above for each month and stock in our sample, starting with August 2012 (the first treatment month) and every subsequent month. We fit two specifications. First, we fit a structural VAR on return and the total order flow:

$$r_t = \alpha_1 + \sum_{\tau=1}^{6} \beta_{r,r}^{\tau} r_{t-\tau(5\,min)} + \sum_{\tau=0}^{6} \beta_{r,flow}^{\tau}\, flow_{t-\tau(5\,min)} + \varepsilon_{1,t}$$

$$flow_t = \alpha_2 + \sum_{\tau=1}^{6} \beta_{flow,r}^{\tau} r_{t-\tau(5\,min)} + \sum_{\tau=1}^{6} \beta_{flow,flow}^{\tau}\, flow_{t-\tau(5\,min)} + \varepsilon_{2,t},$$

where r_t is the five-minute log-return; $flow_t$ is the signed total five-minute net order flow; β are coefficients indexed by variables with subscripts and by time with superscripts; α are constants; and ε are error terms. The variable τ indexes the lag terms, for example, and $t - \tau(5\ min)$ means a lag of τ times five minutes for τ = 0, 1, 2, etc. We fit the model using six lag terms, hence the upper limit on the summands is 6. Following Hasbrouk (1991), the limit of summation for $flow_t$ in the return process starts from 0 to allow order flow to have a contemporaneous effect on return. The assumption is that prices are driven by order flow and not the reverse. The model imposes that there are no contemporaneous effects between return and itself, flow and itself, and no contemporaneous effect of return on flow.

We also fit a second structural VAR, now on return and the segregated lit flow and RLP flow:

$$r_t = \alpha_1 + \sum_{\tau=1}^{6} \beta_{r,r}^{\tau} r_{t-\tau(5\,min)} + \sum_{\tau=0}^{6} \beta_{r,RLP}^{\tau}\, RLP_{t-\tau(5\,min)} + \sum_{\tau=0}^{6} \beta_{r,lit}^{\tau}\, lit_{t-\tau(5\,min)} + \varepsilon_{1,t}$$

$$RLP_t = \alpha_2 + \sum_{\tau=1}^{6} \beta_{RLP,r}^{\tau} r_{t-\tau(5\,min)} + \sum_{\tau=1}^{6} \beta_{RLP,RLP}^{\tau}\, RLP_{t-\tau(5\,min)} + \sum_{\tau=1}^{6} \beta_{RLP,lit}^{\tau}\, lit_{t-\tau(5\,min)} + \varepsilon_{1,t}$$

$$lit_t = \alpha_3 + \sum_{\tau=1}^{6} \beta_{lit,r}^{\tau}\, r_{t-\tau(5\,min)} + \sum_{\tau=1}^{6} \beta_{lit,RLP}^{\tau}\, RLP_{t-\tau(5\,min)} + \sum_{\tau=1}^{6} \beta_{lit,lit}^{\tau}\, lit_{t-\tau(5\,min)} + \varepsilon_{1,t},$$

where r_t is the five-minute log-return; RLP_t is the net five-minute order flow specifically in the RLP, and lit_t is the net five-minute order flow *not* in the RLP; and β, α and ε are as above. As in the VAR described above, the limits of summation for RLP_t and lit_t in the return process start from 0 to allow the flows to have a contemporaneous effect on return.

From the VAR models we compute two sets of results: the orthogonalized impulse-response functions and the corresponding information shares. The information shares are those used by Hasbrouck (1991) and have been used to assess the contribution of the order flow to price in a variety of settings. Both the impulse-response functions and the information shares derive from the moving-average representations of the VAR models:

$$\begin{pmatrix} r_t \\ flow_t \end{pmatrix} = \sum_{\tau=0}^{\infty} \begin{pmatrix} a_\tau & b_\tau \\ c_\tau & d_\tau \end{pmatrix} \begin{pmatrix} \varepsilon_{r,t-\tau} \\ \varepsilon_{flow,t-\tau} \end{pmatrix}$$

$$\begin{pmatrix} r_t \\ RLP_t \\ lit_t \end{pmatrix} = \sum_{\tau=0}^{\infty} \begin{pmatrix} e_\tau & f_\tau & g_\tau \\ h_\tau & i_\tau & j_\tau \\ k_\tau & l_\tau & m_\tau \end{pmatrix} \begin{pmatrix} \varepsilon_{r,t-\tau} \\ \varepsilon_{RLP,t-\tau} \\ \varepsilon_{lit,t-\tau} \end{pmatrix},$$

where the terms a_τ through m_τ are the coefficients of the orthogonalized impulse-response functions for step τ, and the ε are serially uncorrelated innovations. The information content of a time series as an explainer of the return process is the cumulation of its associated impulse-response coefficients in the moving-average representation (Hasbrouck 1991). For each component of the order flow we compute information shares, the proportion of variance of return attributable to the component. For the above models the information shares of the total undifferentiated order flow, RLP order flow, lit order flow and the aggregate segmented (the sum of shares of RLP and lit) order flows are

$$share_{flow} = \frac{\hat{\sigma}_{flow}^2 \left(\sum_{\tau=0}^{\infty} b_\tau\right)^2}{\hat{\sigma}_r^2 \left(\sum_{\tau=0}^{\infty} a_\tau\right)^2 + \hat{\sigma}_{flow}^2 \left(\sum_{\tau=0}^{\infty} b_\tau\right)^2}$$

$$share_{RLP} = \frac{\hat{\sigma}_{RLP}^2 (\sum_{\tau=0}^{\infty} f_\tau)^2}{\hat{\sigma}_r^2 (\sum_{\tau=0}^{\infty} e_\tau)^2 + \hat{\sigma}_{RLP}^2 (\sum_{\tau=0}^{\infty} f_\tau)^2 + \hat{\sigma}_{lit}^2 (\sum_{\tau=0}^{\infty} g_\tau)^2}$$

$$share_{lit} = \frac{\hat{\sigma}_{lit}^2 (\sum_{\tau=0}^{\infty} g_\tau)^2}{\hat{\sigma}_r^2 (\sum_{\tau=0}^{\infty} e_\tau)^2 + \hat{\sigma}_{RLP}^2 (\sum_{\tau=0}^{\infty} f_\tau)^2 + \hat{\sigma}_{lit}^2 (\sum_{\tau=0}^{\infty} g_\tau)^2}$$

$$share_{segmented} = \frac{\hat{\sigma}_{RLP}^2 (\sum_{\tau=0}^{\infty} f_\tau)^2 + \hat{\sigma}_{lit}^2 (\sum_{\tau=0}^{\infty} g_\tau)^2}{\hat{\sigma}_r^2 (\sum_{\tau=0}^{\infty} e_\tau)^2 + \hat{\sigma}_{RLP}^2 (\sum_{\tau=0}^{\infty} f_\tau)^2 + \hat{\sigma}_{lit}^2 (\sum_{\tau=0}^{\infty} g_\tau)^2},$$

where $\hat{\sigma}_{flow}^2$, $\hat{\sigma}_{RLP}^2$ and $\hat{\sigma}_{lit}^2$ are the estimated variances of the VAR innovations for the respective error terms (using root mean-squared error) for the respective model.

Differences-in-differences

We use the differences-in differences event study to assess the impact of the RLP launch on market quality. The methodology compares the change in market quality for treatment stocks to the change in market quality for control stocks. We used daily averages of the four market-quality measures described above. Specifically, we regress each market-quality measure on a treatment dummy equalling one during the period in which a stock was eligible for the RLP, on an after-period dummy equalling one during the period following the launch of the RLP for all stocks, on stock and control fixed effects, and on control variates. For all measures, the differences-in-differences model specification is

$$measure_{i,t} = \beta treatment_{i,t} + \gamma after_t + \delta X_i + FE_i + \varepsilon_{i,t},$$

where i is the index for the stock (including both treatments and controls), t is the day index, *measure* is the metric of interest (e.g., relative bid-ask spread), *treatment* is a treatment dummy equalling one if stock i is a treatment stock and the date is after 1 August 2012, *after* is an after-period dummy equalling one if the date is after 1 August 2012, *FE* is a fixed effect for each treatment stock and control stock, X is a vector of control variates for the stock, and ε is the error term. The fixed effects span the sample, so there is no constant of regression. The differences-in-differences impact coefficient is β.

The model is fit over six specifications. Specification 1 excludes the control-stock observations and all control variates. The regression coefficient β is then the treatment effect from a simple or "single-difference" event study that compares market quality only for treatment stocks before and after the launch of the RLP. Specification 2 includes the control-stock observations and continues to exclude control variates. Specifications 3 through 6 introduce a steadily greater number of control variates. Specification 3 includes the common equity-market liquidity determinants, the stock's log market capitalization and log daily volume. Specification 4 includes a market-wide liquidity factor, the stock-specific factor score from principal component analysis. The factor score equals the first principal component of the daily observations of the treatment and control market-quality measure multiplied by the stock-specific eigenvalue. Specification 5 includes the rolling 10-day volatility. Last, specification 6 includes the previous day's value of the market-quality metric for the stock. For each specification, standard errors are clustered by stock and date.

The model is fit both over the entire post-period of data and also over four subsamples of data spanning four different time periods. All model fits use observations from the three-month pre-period sample, April–July 2012. They differ by the post-period data. The post-period in the first fit, reported in each table's Panel A, is the entire sample after 1 August 2012. The second through fifth fits compare the pre-period to four three-month post-periods: Q4 2012, Q1 2013, Q2 2013, and Q3 2013. The second through fifth fits are reported in each table's Panels B–E.

5. Results

Figure 2 shows the impulse-response function for the monthly VARs fit on the log return and the two order flows (RLP and lit) averaged over all months and all 35 treatment stocks.

FIGURE 2 ABOUT HERE

The contemporaneous impact on the return of a one standard-deviation shock to the lit order flow is around 5 basis points. The lit flow still impacts the return after five minutes by around 2 basis points. For the RLP flow, the contemporaneous and first-lag return impacts of a one standard-deviation shock are both less than one basis point. Both flows appear to have no appreciable impact on the return after 10 minutes (two lags).

TABLE 2 ABOUT HERE

Table 2 Panel A shows summary statistics for the information shares of segments of the order flow. The share for *Total order flow* is the information share of the order flow for the VAR model fit by stock by month on the log return and total order flow. The share for *Lit* is the information share of the lit order flow for the VAR model fit by stock by month on log return, lit order flow and RLP order flow. The share for *RLP* is the information share of the RLP order flow for the VAR model fit by stock by month on log return, lit order flow and RLP order flow.

The total order flow had an information share of 26.3% on average. For lit order flow, the information share was 25.4% on average. For RLP order flow the information share was 10 times lower, 2.4% on average.

Hypotheses 1 and 2 in this paper ask whether the RLP order flow is demonstrably less informed and whether segmentation adds information to the order flow. Table 2 Panel B reports the differences of means between order flows and t-statistics on the differences. *Difference of lit and RLP* is the difference between the lit and RLP information shares. *Difference of total and lit plus RLP* is the difference between the information share of the total order flow with the information shares of the sum of the segmented lit and RLP order flows. The difference between lit and RLP was on average 23.0% with statistical significance. This result is to be expected and demonstrates the desirability of RLP order flow for intermediaries. The sum of lit and RLP information shares was on average 1.5% more than the information share of the total order flow with statistical significance. The increase in the information earned by differentiating RLP and lit order flow shows that using the RLP marker to distinguish RLP trades from lit trades can increase the explanatory power of the order flow. Segmentation does appear to remove noise from the signal, as hypothesized. We next measure the impact on market quality.

Hypotheses 3 and 4 in this paper concern whether participation in the RLP affects stocks' liquidity and price efficiency. Figure 1, Panel A shows the relative bid-ask spread of treatment stocks and control stocks over the sample period. Before the launch of the RLP, the average bid-ask spreads for treatment and control stocks were close on average and co-moved. In September 2012 the level of the control series shifts upward and the level of the treatment series shifts downward. The spike in the relative bid-ask spread of treatment stocks on 26 December 2012 is an outlier and was dropped from the sample. The results were stronger with the outlier.

Tables 3 to 7 give the results of differences-in-differences event studies on four market-quality measures. The rows of the tables give the regression coefficients and their associated t-statistics for specific variables across six different specifications of the event study on relative bid-ask spreads, effective spreads, price impacts and absolute return autocorrelations. A blank entry indicates a variate is not included in the regression.

The columns of Tables 3–7 correspond to the different specifications of the event study. Specification 1 excludes the control-stock observations and gives the treatment effect of a classic, single-difference event study. Specifications 2–6 estimate the differenced differences. Specifications 3–6 include a progressively larger set of control variates, starting with log market capitalization and log daily volume, then adding the market-wide liquidity factor, then the 10-day moving average of the closing price, and last the lagged value of the dependent variable. *Treatment* is a dummy variable that indicates the period after the launch of the RLP for treatment stocks. *After* is a dummy variable that indicates the period after the launch of the RLP for all stocks. *Market cap* is the daily market capitalization in billions. *Volume* is the number of shares traded per day. *Market-wide liquidity* is the stock-specific factor score from principal component analysis. *10-day volatility* is the 10-day rolling volatility of the close price. The variables *Lagged relative spread, Lagged eff. spread, Lagged price impact* and *Lagged acorr.* correspond to each of the four market-quality measures lagged by one day. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Each Panel A for Tables 3 through 6 shows results for the entire sample period, from April 2012 to August 2013. We then test subsamples to ensure our result holds throughout the sample period. Panels B through E show results for a sample period limited to three months prior to the launch of the RLP and three months after. Panel B shows results when the sample period is limited to Q3 2012 and Q4 2012; Panel C shows results when the sample period is limited to Q3 2012 and Q1 2013; Panel D shows results when the sample period is limited to Q3 2012 and Q2 2013; and Panel E shows results when the sample period is limited to Q3 2012 and Q3 2013. Each regression specification 1 to 6 in Panels B through E corresponds to those in Panel A. For Panels B through E we exclude reporting of variables other than *Treatment* and *After* for brevity.

TABLE 3 ABOUT HERE

Table 3 Panel A shows that the relative spread decreased for treatment over the sample period. The result is consistently statistically significant for each of the regression specifications. For treatment stocks (specification 1), the average relative spread decreased by 1.4 basis points over the sample period. When control stocks are included in the regression (specification 2), the difference is more pronounced; relative spreads decrease by 2.0 basis points. This is because control stocks experience a widening of relative spreads over the sample period, resulting in a negative estimate of the treatment variable that was larger in magnitude. The R^2 drops from 0.839 to 0.608 because control stocks are added to the regression as dependent variables going from specification 1 to specification 2. In the remaining specifications, 3 to 6, the magnitude of the regression coefficient for relative spread on the treatment dummy attenuates as more and more covariates are added to the regression. The sign remains negative and statistically significant, dropping to 0.7 basis points for specification 6.

In Table 3, Panels B through E show that participation in the RLP leads to lower relative spreads in four subsample time periods. The treatment effect in specification 2 is negative and statistically significant in all panels. For specification 6, it misses significance in Panel C, which studies the post-period Q1 2013.

TABLE 4 ABOUT HERE

Table 4 shows a milder result for effective spreads. Panel A shows the results for the regression over the entire sample. The regression coefficient for the treatment dummy is negative but is statistically significant only for specifications 1 and 2. In specification 2, the treatment effect is 0.9 basis points, but in specification 6 the effect is 0.2 basis points and has a t-statistic of only 1.38.

In Table 4, Panels B through E show how the results for effective spread vary over time. The results are hit and miss. The weakest period is Panel B, comparing Q2 2012 to Q4 2012. While each coefficient of the treatment dummy is negative, the only one with statistical significance is the simple differences-in-differences, specification 2. Panels C through E do show evidence of a decrease in effective spreads when comparing Q2 2012 to the remaining periods. The regression coefficients in specification 6 for panels C through E range from 0.3 basis points to 0.6 basis points and are nearly significant, with t-statistics all greater than 1.63.

TABLE 5 ABOUT HERE

Table 5 gives the effect of the RLP on price impact. Panel A shows that price impact decreased for treatment stocks over the sample period. The decrease resulting from the RLP ranges between 0.4 and 0.6 basis points depending on the specification. In specification 6, the RLP leads to a decrease in price impact of 0.5 basis points with a t-statistic of 4.38.

In Table 5, Panels B through E show how the effect of the RLP on price impact varies over time. All regression specifications except for Panel A specification 1 show negative and statistically significant coefficients for the treatment effect. In specification 6 for Panels B through E, the treatment effect ranges from 0.6 basis points to 0.9 basis points.

TABLE 6 ABOUT HERE

Table 6 gives the effect of the RLP on price efficiency as measured by the absolute autocorrelation of the return of the midquote. Panel A shows the RLP increased price efficiency over the sample period. The simple treatment effect (specification 1) is positive, small (0.003) and statistically insignificant, indicating that absolute autocorrelation was generally unchanged for treatment stocks over the sample period. When control stocks are added to the regression (specification 2), the regression coefficient for the treatment dummy becomes negative and statistically significant, -0.01. Control stocks experienced an increase in absolute autocorrelation over the sample, while treatment stocks did not. Specifications 3 through 6 continue to show the RLP decreased the absolute autocorrelation of the midquote. The impact in these specifications ranges from -0.008 to -0.009.

Table 6 Panels B through E show how the result on autocorrelation varies by the time period. The impact misses significance in Panel B for specifications 3–6, meaning we fail to find good evidence the RLP had an impact on price efficiency in Q4 2012. In fact, the simple treatment effect (Panel B specification 1) is positive and significant, and the treatment effect becomes negative and significant when control stocks are included in the regression (specification 2). For Panels C through E, the treatment effect ranges from -0.01 to -0.04 and is significant in specifications 3 through 6. For these panels, the simple treatment effect (specification 1) is small and insignificant, and the addition of control stocks and control variates makes the treatment coefficients negative and significant.

The general takeaway from the differences-in-differences regression results in Tables 3 through 6 is that the RLP led to slightly higher liquidity as well as slightly greater price efficiency. Except for the effective spread, the result is robust across regression specifications and over time in our sample period. For the effective spread and price impact, the result was weak in Q4 2012. This may be due to a gradual adoption of the RLP by liquidity providers and retail brokers.

To demonstrate that our results are robust to the selection of control stocks, we repeat the regressions with an alternative methodology for the choice of control observations. Rather than matching treatments and controls one-to-one, we use a weighted average of all stocks in our pools of candidate control stocks. Once for each of the 35 treatment stocks, for each of the 184 candidate control stocks, weights were generated equal to the squared difference between a treatment stock and the candidate control stock's market capitalization divided by the sum of such differences over the candidate control stocks. Hence for each treatment stock, the weights on the candidate control stocks add to one. The weights were then used to generate a weighted set of 184 control stock observations for each daily observation of a treatment stock.

TABLE 7 ABOUT HERE

Table 7 Panel A shows the results for relative bid-ask spread using the weighted panel of controls. Each regression coefficient for the treatment dummy is negative with statistical significance except for specification 3. The treatment effect in specification 6 is 0.7 basis points.

Table 7 Panel B shows the results for effective spread using the weighted panel of controls. The results are not statistically significant, and we fail to conclude from the differences-in-differences event study that the RLP had an effect on the effective spread. The treatment effect ranges from 1.1 to 0.3 basis points.

Table 7 Panel C shows the results for price impact using the weighted panel of controls. Each regression coefficient for the treatment dummy is negative with significance. The treatment effect ranges from 0.4 to 0.6 basis points.

Table 7 Panel D shows the results for absolute autocorrelation of returns using the weighted panel of controls. The simple treatment effect (specification 1) is small, positive and insignificant, and the addition of control stocks and control variates to the regression produces negative and significant regression coefficients for the treatment dummy in specifications 4 through 6.

In general, the results of the differences-in-differences regressions using a weighted panel of control stocks are similar to those produced by the one-to-one matched sample presented in Tables 3 through 6. All market-quality measures tend to improve slightly following the launch of the RLP. However, results for effective spread were statistically insignificant when a weighted panel of controls was used.

6. Conclusions

We find the launch of the NYSE's Retail Liquidity Program resulted in a small positive impact on market quality. While it is not surprising that retail traders might benefit from RLP due to its mandated price improvement, the overall effects of segmentation are more challenging to predict. Our results indicate that other classes of traders are not worse off when retail traders are segmented.

We analyze the mechanism by which segmentation affects market quality by computing the information share of each component of the order flow using the techniques of Hasbrouck (1991). The analysis shows that RLP order flow impounds significantly less information into prices than does lit order flow. The result demonstrates the economics of the program: intermediaries are exposed to lower adverse selection risk when offering liquidity to retail traders. We find the sum of the information shares of RLP trades and lit trades is larger than the information share of the total order flow, indicating there is more information available from the order flow when it is segmented.

We measure the effect of the RLP by testing measures of market quality before and after the launch of the NYSE's RLP using a differences-in-differences regression. Bid-ask spread, effective spread, price impact and autocorrelation decrease for stocks that saw relatively heavy use of the RLP. Our result is robust to the time period and the choice of control stocks. First, we match controls to treatments one-to-one from a pool of control stocks that were ineligible for the RLP. Second, we run the regression using a weighted panel of all candidate control stocks. Our weakest results are those for effective spreads. The weighted panel of control stocks eliminated statistical significance for effective spreads. Both model specifications return the same overall conclusion: market quality mildly increased for stocks that had relatively high volumes in the RLP for the sample as a whole and throughout four subperiods.

Our analysis is consistent with other empirical evidence that segmentation of retail traders, either through broker internalization, payment for order flow, or other programs similar to the NYSE's RLP, have beneficial or innocuous effects on market quality. Although many retail segmentation programs operate as dark pools, we demonstrate a mechanism that is consistent with explicit segmentation and unrelated to pre-trade transparency. We argue the effect on market quality is due more to segmentation than to pre-trade opacity. In the NYSE's case, pre-trade opacity was introduced mostly to enable market makers to offer better pricing to retail traders than is allowed by regulation for stocks constrained by the regulatory minimum tick size.

We frame our results as tests of hypotheses generated by the static theory model of Zhu (2014). Segmentation may worsen liquidity for lit trades, all else equal, but since the order flow contributes more to price discovery, all else is not equal. Illiquidity due to informational differences between market order submitters and limit order submitters may diminish more quickly, resulting in greater average liquidity. Our results show the worsening in liquidity is either economically insignificant or dominated by the effects of greater price efficiency. A possible extension of Zhu (2014) or of other papers on dark markets and segmentation might explore the dynamics to show whether concentrating informed agents on the exchange may improve liquidity in a multi-period setting. The dynamic effect of concentrating informed agents is noted briefly in Glosten and Milgrom (1985) and more thoroughly studied in Roșu (2016). An extension to these models could include the interaction of segmentation with dark liquidity, and investigate how the effect varies if information is long-lived or short-lived.

References

Battalio, R. H. (1997). Third Market Broker-Dealers: Cost Competitors or Cream Skimmers? *The Journal of Finance*, 52(1), 341-352.

Battalio, R. & Holden, C. W. (2001). A simple model of payment for order flow, internalization, and total trading cost. *Journal of Financial Markets*, 4(1), 33-71.

Boni, L., Brown, D. C. & Leach, J. C. (2013). Dark pool exclusivity matters. *Available at SSRN 2055808*.

Boulatov, A. & George, T. J. (2013). Hidden and displayed liquidity in securities markets with informed liquidity providers. *Review of Financial Studies*, 26(8), 2096-2137.

Comerton-Forde, C., Malinova, K. & Park, A. (2016). Regulating Dark Trading: Order Flow Segmentation and Market Quality. *Available at SSRN 2755392*

Easley, D., Kiefer, N. M. & O'Hara, M. (1996). Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow. *The Journal of Finance*, 51(3), 811-833.

Fleming, M. J. & Nguyen, G. (2013). Order flow segmentation and the role of dark trading in the price discovery of US treasury securities. *FRB of New York Staff Report*, (624).

Foley, S. & Putniņš, T. J. (2014). Should we be afraid of the dark? Dark trading and market quality. Dark Trading and Market Quality (August 18, 2014).

Glosten, L. R. & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1), 71-100.

Hasbrouck, J. (1991). Measuring the information content of stock trades. *Journal of Finance*, 179-207.

Hatheway, F., Kwan, A. & Zheng, H. (2013). An empirical analysis of market segmentation on US equities markets. *Available at SSRN 2275101*.

IOSCO. (2010). Issues Raised by Dark Liquidity. *Available at https://www.iosco.org/library/pubdocs/pdf/IOSCOPD336.pdf.*

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315-1335.

Lee, C. & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, 46(2), 733-746.

OSC. (2010). Position Paper 23-405—Dark Liquidity in the Canadian Market. *Available at http://www.osc.gov.on.ca/documents/en/Securities-Category2/csa_20101119_23-405_dark-liquidity.pdf*

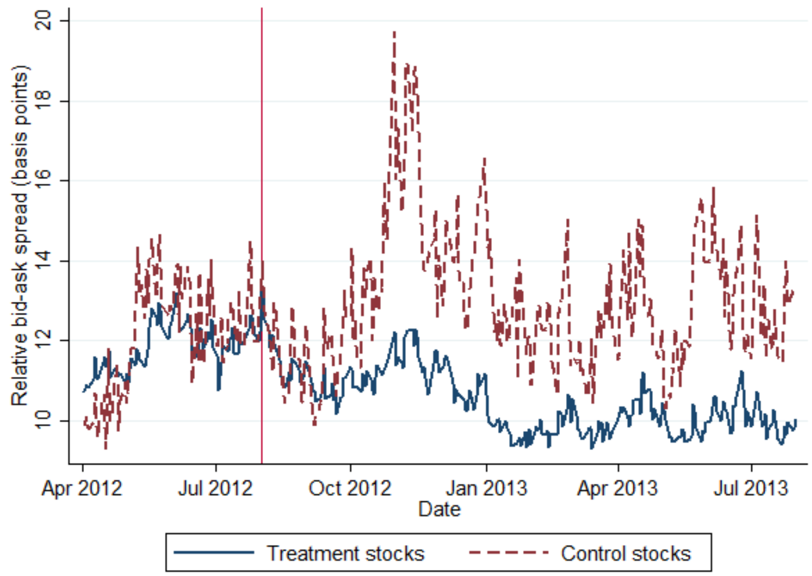
Parlour, C. A. & Rajan, U. (2003). Payment for order flow. *Journal of Financial Economics*, 68(3), 379-411.

Roşu, I. (2016). Liquidity and information in order driven markets. *Available at SSRN 1286193*.

Zhu, H. (2014). Do dark pools harm price discovery? *Review of Financial Studies*, 27(3), 747-789.

Figure 1: Liquidity history. This figure shows the liquidity over the sample period. Panel A shows the relative bid-ask spread over the sample period for treatment and control stocks. The blue line represents the relative bid-ask spread for control stocks; the red line represents the relative bid-ask spread for treatment stocks. The vertical line indicates the launch of the RLP on 1 August 2012. Panel B shows the total volume and RLP volume.

Panel A: Relative bid-ask spread for treatment and control stocks over the sample period.



Panel B: Volume for treatment stocks over the sample period.

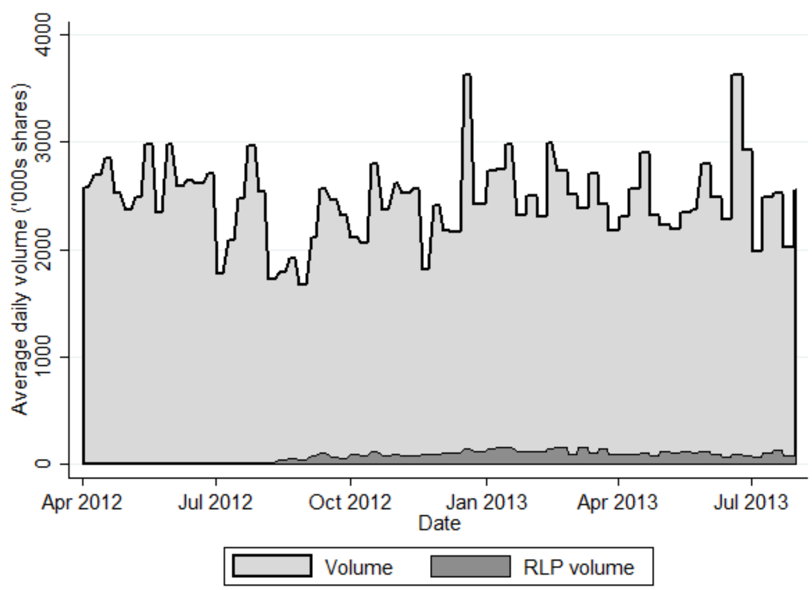


Figure 2: Impulse-response functions for RLP and lit order flow. This figure plots orthogonalized impulse-response coefficients for each component of the order flow against their corresponding lags. The blue line represents the response of return to a one-standard deviation shock to the lit order flow; the red dashed line represents the response of return to a one-standard deviation shock to the RLP order flow.

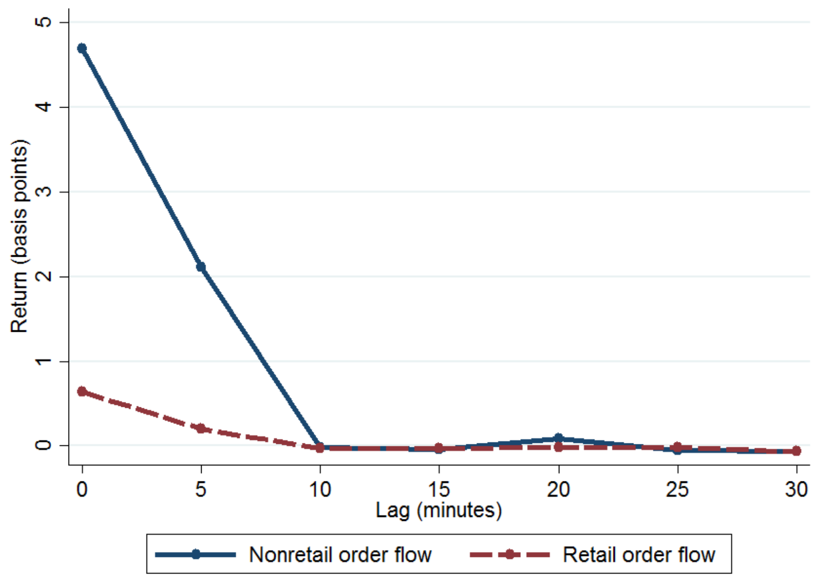


Table 1: Summary statistics for treatment and control stocks. This table gives summary statistics on market quality and market cap for the 35 stocks identified as treatment stocks and the 35 matched control stocks. The columns of the table give the average, standard deviation, minimum, 25th percentile, 50th percentile, 75th percentile, and maximum for each measure. Panel A shows summary statistics for treatment stocks before the launch of the RLP, from April 2012 until July 2012, and Panel B shows summary statistics for treatment stocks after the launch of the RLP, August 2012 until August 2013. Panel C shows summary statistics for control stocks before the launch of the RLP, and Panel D shows summary statistics for control stocks after the launch of the RLP. Panel E shows the difference in means for each variable for both treatment and control stocks. *Volume* is the average number of shares traded per day in thousands of shares. *RLP Volume* is the average number of shares traded in the RLP per day in thousands of shares. *Relative Spread* is the average relative spread. *Effective Spread* is the average five-second effective spread. *Price Impact* is the average five-second price impact. *Autocorrelation* is the average daily absolute five-second autocorrelation of the midquote. *Market Cap* is average market capitalization over the period in billions.

Panel A: Summary statistics for treatment stocks before the launch of the RLP.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Volume	2540.88	4039.83	29.75	507.82	1320.61	2537.54	38129.25
Relative Spread	12.05	7.20	2.59	8.35	10.40	13.47	48.63
Effective Spread	9.91	6.59	2.18	6.61	8.49	11.41	53.90
Price Impact	3.64	1.65	-0.21	2.43	3.48	4.54	26.57
Autocorrelation	0.06	0.04	0.00	0.03	0.05	0.08	0.30
Market Cap	188.24	376.56	16.33	28.46	64.45	157.35	2216.54

Panel B: Summary statistics for treatment stocks after the launch of the RLP.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Volume	2491.85	4896.33	22.69	398.95	1156.48	2351.92	207285.34
RLP volume	89.38	402.89	0.00	1.80	11.15	38.35	9202.98
Relative spread	10.54	5.97	2.05	7.13	9.14	12.15	48.36
Effective spread	8.73	5.48	1.84	5.68	7.46	10.31	41.91
Price impact	3.19	1.43	-3.14	2.20	3.02	3.90	26.08
Autocorrelation	0.06	0.05	0.00	0.03	0.05	0.09	0.50
Market cap	237.71	459.43	12.11	36.30	81.11	167.06	2570.55

Panel C: Summary statistics for control stocks before the launch of the RLP.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Volume	310.83	446.25	10.73	88.03	169.45	349.81	5431.86
Relative spread	12.83	8.55	2.31	6.80	10.54	16.49	60.56
Effective spread	7.15	4.52	1.81	3.88	5.88	9.07	41.25
Price impact	2.52	1.65	-0.08	1.37	2.07	3.16	13.92
Autocorrelation	0.09	0.06	0.00	0.04	0.08	0.12	0.59
Market cap	182.44	326.78	10.92	28.99	63.32	152.18	1663.42

Panel D: Summary statistics for control stocks after the launch of the RLP.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Volume	243.09	383.16	6.00	68.91	127.13	262.45	7072.84
Relative spread	12.94	11.99	1.69	6.22	10.09	16.47	457.72
Effective spread	6.78	5.33	1.08	3.52	5.32	8.42	108.73
Price impact	2.76	2.09	-0.70	1.48	2.25	3.40	42.24
Autocorrelation	0.10	0.09	0.00	0.04	0.09	0.14	0.79
Market cap	215.06	408.38	13.94	32.99	72.52	159.60	2533.08

Panel E: Difference in means before and after the launch of the RLP for treatment and control stocks.

	Treatment stocks	Control stocks
Volume	-49.03	-67.74
Relative spread	-1.51	0.11
Effective spread	-1.18	-0.37
Price impact	-0.45	0.24
Autocorrelation	0	0.01
Market cap	49.47	32.62

Table 2: Information shares. This table gives summary statistics and results for a T-test on difference in means for information shares computed using a vector autoregression model. Information shares are computed monthly for each of the 35 treatment stocks.

Panel A reports summary statistics. The columns of the table give the average, standard deviation, 25th percentile, 50th percentile and 75th percentile for each segment of the order flow. *Lit* is the information share of lit orders; *RLP* is the information share of RLP orders; *Total order flow* is the information share of all undifferentiated orders; *RLP and lit* is the sum of information shares for RLP and lit orders.

Panel B reports the average difference between information shares for various segments of the order flow. *Difference of lit, RLP* is the difference between lit and RLP information shares; *Difference of total and lit plus RLP* is the difference between the sum of RLP and lit minus the aggregate information shares. *N* is the number of observations. The *t*-statistic is in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Panel A: Summary statistics for information shares

	Mean	Std. Dev.	P25	P50	P75
Total order flow	26.27	19.56	12.12	21.98	36.52
Lit	25.40	19.42	10.85	20.56	37.05
RLP	2.37	8.25	0.17	0.66	1.94

Panel B: T-test for difference in means

Difference of lit and RLP	23.03***
	(16.25)
Difference of total and lit plus RLP	1.493***
	(4.21)
N	419

Table 3: Differences-in-differences event study of the impact of the launch of the RLP on relative bid-ask spreads. The rows of the table give the regression coefficients and their associated t-statistics for specific variables across six different specifications of the event study on relative bid-ask spreads. A blank entry indicates exclusion from the regression. The columns of the table correspond to different specifications of the event study. In specification (1), only treatment stocks are included in the regression; in specification (2), treatment stocks and control stocks are included; in specification (3), *Market cap* and *Volume* are included; and so on.

Treatment is a dummy variable that equals one during the period after the launch of the RLP for treatment stocks. *After* is a dummy variable that equals one during the period after the launch of the RLP for all stocks. *Market cap* is the daily market capitalization in billions. *Volume* is the number of shares traded per day in thousands of shares. *Market-wide liquidity* is the stock-specific factor score from principal component analysis. *10-day volatility* is the 10-day rolling volatility of the midquote. *Lagged relative spread* is the relative bid-ask spread lagged by one day. *Constant* is the constant of regression. *N* is the number of observations. R^2 is the coefficient of determination. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Panel A shows results for the entire sample period, from April 2012 to August 2013. Panels B through E show results for a sample period limited to three months prior to the launch of the RLP and three months after. Panel B shows results when the sample period is limited to Q3 2012 and Q4 2012; Panel C shows to Q3 2012 and Q1 2013; Panel D shows Q3 2012 and Q2 2013; and Panel E shows Q3 2012 and Q3 2013. Each regression specification (1) to (6) in Panels B through E corresponds to those in Panel A, but we exclude reporting of variables other than *Treatment* and *After* for brevity.

Panel A: Impact on relative spread, entire sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.389**	-1.987***	-1.262**	-0.931**	-0.932**	-0.653*
	(-2.43)	(-3.11)	(-2.20)	(-2.03)	(-2.08)	(-1.87)
After		0.661	0.832*	0.991**	1.066***	0.785**
		(1.62)	(1.93)	(2.54)	(2.74)	(2.38)
Market cap			-5.302***	-3.189**	-3.126**	-2.488**
			(-3.79)	(-2.42)	(-2.38)	(-2.22)
Volume			-1.797***	-1.690***	-1.808***	-1.512***
			(-5.18)	(-5.39)	(-5.73)	(-5.11)
Market-wide liquidity				0.904***	0.891***	0.716***
				(15.03)	(15.08)	(7.16)
10-day volatility					4.602***	3.820***
					(2.98)	(3.12)
Lagged relative spread						0.225**
						(2.13)
Constant	11.81***	12.09***	119.7***	84.20***	84.24***	67.73***
	(29.21)	(42.83)	(5.12)	(3.66)	(3.67)	(3.28)
N	11640	23090	23090	20650	20650	20580
R^2	0.839	0.608	0.626	0.827	0.828	0.854

Panel B: Impact on relative spread, Q2 2012 and Q4 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.857	-2.779***	-2.301***	-1.980**	-1.990**	-1.263**
	(-1.58)	(-2.87)	(-2.63)	(-2.35)	(-2.36)	(-2.25)
After		1.953**	2.089**	1.936**	1.977**	1.277**
		(2.32)	(2.54)	(2.43)	(2.46)	(2.35)
N	4366	8639	8639	8190	8190	8120
R^2	0.880	0.749	0.763	0.856	0.856	0.887

Panel C: Impact on relative spread, Q2 2012 and Q1 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-2.222***	-1.787**	-0.724	-0.947**	-0.949**	-0.315
	(-3.92)	(-2.42)	(-1.13)	(-2.07)	(-2.07)	(-1.40)
After		-0.437	-0.201	0.899*	0.917*	0.368
		(-0.85)	(-0.34)	(1.89)	(1.88)	(1.52)
N	4339	8639	8639	8190	8190	8190
R^2	0.879	0.815	0.832	0.850	0.850	0.900

Panel D: Impact on relative spread, Q2 2012 and Q2 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.927**	-2.033**	-1.058	-1.350***	-1.342***	-0.489**
	(-2.54)	(-2.01)	(-1.18)	(-2.64)	(-2.64)	(-1.97)
After		0.108	0.535	1.737***	1.752***	0.703***
		(0.15)	(0.76)	(3.65)	(3.69)	(3.13)
N	4474	8918	8918	8330	8330	8330
R^2	0.826	0.807	0.830	0.880	0.881	0.921

Panel E: Impact on relative spread, Q2 2012 and Q3 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-2.171***	-3.365**	-2.515*	-1.270**	-1.300**	-1.137*
	(-2.94)	(-2.15)	(-1.69)	(-2.06)	(-2.13)	(-1.95)
After		1.203	2.167	1.771***	1.808***	1.629***
		(0.84)	(1.41)	(3.07)	(3.11)	(2.93)
N	3008	5921	5921	5460	5460	5460
R^2	0.867	0.456	0.467	0.900	0.900	0.904

Table 4: Differences-in-differences event study of the impact of the launch of the RLP on effective spreads. The rows of the table give the regression coefficients and their associated t-statistics for specific variables across six different specifications of the event study on effective spreads. A blank entry indicates exclusion from the regression. The columns of the table correspond to different specifications of the event study. In specification (1), only treatment stocks are included in the regression; in specification (2), treatment stocks and control stocks are included; in specification (3), *Market cap* and *Volume* are included; and so on.

Treatment is a dummy variable that equals one during the period after the launch of the RLP for treatment stocks. *After* is a dummy variable that equals one during the period after the launch of the RLP for all stocks. *Market cap* is the daily market capitalization in billions. *Volume* is the number of shares traded per day in thousands of shares. *Market-wide liquidity* is the stock-specific factor score from principal component analysis. *10-day volatility* is the 10-day rolling volatility of the midquote. *Lagged effective spread* is the five-second effective spread lagged by one day. *Constant* is the constant of regression. *N* is the number of observations. R^2 is the coefficient of determination. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Panel A shows results for the entire sample period, from April 2012 to August 2013. Panels B through E show results for a sample period limited to three months prior to the launch of the RLP and three months after. Panel B shows results when the sample period is limited to Q3 2012 and Q4 2012; Panel C shows Q3 2012 and Q1 2013; Panel D shows Q3 2012 and Q2 2013; and Panel E shows Q3 2012 and Q3 2013. Each regression specification (1) to (6) in Panels B through E corresponds to those in Panel A, but we exclude reporting of variables other than *Treatment* and *After* for brevity.

Panel A: Impact on effective spread, entire sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.114**	-0.938**	-0.430	-0.440	-0.441	-0.244
	(-2.41)	(-2.01)	(-1.08)	(-1.42)	(-1.46)	(-1.38)
After		-0.194	0.264	0.518**	0.577**	0.327**
		(-0.86)	(0.99)	(2.29)	(2.57)	(2.29)
Market cap			-4.909***	-3.344***	-3.295***	-1.878***
			(-4.30)	(-3.37)	(-3.32)	(-3.98)
Volume			-0.493**	-0.405**	-0.497***	-0.294**
			(-2.43)	(-2.50)	(-3.04)	(-2.50)
Market-wide liquidity				0.563***	0.553***	0.340***
				(8.73)	(8.79)	(4.65)
10-day volatility					3.607***	1.989***
					(3.88)	(2.95)
Lagged eff. spread						0.420***
						(5.45)
Constant	9.751***	8.392***	92.73***	66.39***	66.42***	38.06***
	(29.78)	(41.02)	(4.87)	(3.97)	(3.98)	(4.74)
N	11640	23090	23090	20650	20650	20580
R^2	0.867	0.761	0.783	0.804	0.804	0.841

Panel B: Impact on effective spread, Q2 2012 and Q4 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.515	-0.959*	-0.648	-0.661	-0.672	-0.354
	(-1.18)	(-1.69)	(-1.39)	(-1.41)	(-1.44)	(-1.47)
After		0.452	0.808*	0.827**	0.872**	0.477**
		(1.14)	(1.92)	(2.00)	(2.10)	(2.11)
N	4401	8709	8709	8260	8260	8260
R^2	0.906	0.750	0.762	0.757	0.757	0.780

Panel C: Impact on effective spread, Q2 2012 and Q1 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.686***	-1.109**	-0.456	-0.608*	-0.611*	-0.311*
	(-3.61)	(-2.13)	(-1.08)	(-1.89)	(-1.91)	(-1.95)
After		-0.580**	-0.0778	0.606*	0.639**	0.338**
		(-2.16)	(-0.21)	(1.92)	(2.01)	(2.13)
N	4339	8639	8639	8190	8190	8190
R^2	0.896	0.819	0.831	0.843	0.843	0.882

Panel D: Impact on effective spread, Q2 2012 and Q2 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.759***	-1.216	-0.633	-0.838**	-0.829**	-0.579
	(-2.87)	(-1.61)	(-0.96)	(-2.03)	(-2.02)	(-1.63)
After		-0.550	0.121	0.992**	1.010**	0.711*
		(-1.16)	(0.23)	(2.28)	(2.34)	(1.83)
N	4474	8918	8918	8330	8330	8330
R^2	0.857	0.756	0.771	0.811	0.812	0.828

Panel E: Impact on effective spread, Q2 2012 and Q3 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.831***	-1.055	-0.523	-0.689*	-0.727*	-0.481
	(-3.02)	(-1.49)	(-0.83)	(-1.76)	(-1.87)	(-1.63)
After		-0.782*	0.452	1.259***	1.305***	0.885***
		(-1.88)	(0.84)	(3.19)	(3.33)	(2.96)
N	3008	5921	5921	5460	5460	5460
R^2	0.892	0.837	0.855	0.881	0.882	0.894

Table 5: Differences-in-differences event study of the impact of the launch of the RLP on relative five-second price impacts. The rows of the table give the regression coefficients and their associated t-statistics for specific variables across six different specifications of the event study on five-second price impacts. A blank entry indicates exclusion from the regression. The columns of the table correspond to different specifications of the event study. In specification (1), only treatment stocks are included in the regression; in specification (2), treatment stocks and control stocks are included; in specification (3), *Market cap* and *Volume* are included; and so on.

Treatment is a dummy variable that equals one during the period after the launch of the RLP for treatment stocks. *After* is a dummy variable that equals one during the period after the launch of the RLP for all stocks. *Market cap* is the daily market capitalization in billions. *Volume* is the number of shares traded per day in thousands of shares. *Market-wide liquidity* is the stock-specific factor score from principal component analysis. *10-day volatility* is the 10-day rolling volatility of the midquote. *Lagged price impact* is the five-second relative price impact lagged by one day. *Constant* is the constant of regression. *N* is the number of observations. R^2 is the coefficient of determination. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Panel A shows results for the entire sample period, from April 2012 to August 2013. Panels B through E show results for a sample period limited to three months prior to the launch of the RLP and three months after. Panel B shows results when the sample period is limited to Q3 2012 and Q4 2012; Panel C shows Q3 2012 and Q1 2013; Panel D shows Q3 2012 and Q2 2013; and Panel E shows Q3 2012 and Q3 2013. Each regression specification (1) to (6) in Panels B through E corresponds to those in Panel A, but we exclude reporting of variables other than *Treatment* and *After* for brevity.

Panel A: Impact on five-second price impact, entire sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.356***	-0.627***	-0.486***	-0.510***	-0.510***	-0.456***
	(-2.62)	(-4.25)	(-3.51)	(-4.14)	(-4.27)	(-4.38)
After		0.299***	0.469***	0.540***	0.574***	0.503***
		(3.53)	(4.81)	(5.82)	(6.29)	(6.77)
Market cap			-1.516***	-0.976***	-0.946***	-0.553***
			(-4.97)	(-3.46)	(-3.41)	(-3.27)
Volume			-0.0414	-0.0183	-0.0730	-0.0145
			(-0.43)	(-0.21)	(-0.84)	(-0.20)
Market-wide liquidity				0.190***	0.184***	0.125***
				(9.36)	(9.38)	(5.08)
10-day volatility					2.129***	1.700***
					(3.96)	(3.62)
Lagged price impact						0.116***
						(4.32)
Constant	3.529***	3.001***	27.61***	18.62***	18.64***	10.74***
	(36.30)	(46.58)	(5.21)	(3.76)	(3.80)	(3.58)
N	11640	23090	23090	20650	20650	20580
R^2	0.411	0.494	0.513	0.537	0.540	0.567

Panel B: Impact on five-second price impact, Q2 2012 and Q4 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.144	-0.832***	-0.745***	-0.769***	-0.776***	-0.671***
	(-1.11)	(-3.97)	(-3.86)	(-3.93)	(-4.03)	(-4.77)
After		0.699***	0.823***	0.831***	0.861***	0.733***
		(4.01)	(4.70)	(4.85)	(5.03)	(6.35)
N	4366	8639	8639	8190	8190	8120
R^2	0.434	0.585	0.596	0.597	0.599	0.633

Panel C: Impact on five-second price impact, Q2 2012 and Q1 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.738***	-1.066***	-0.909***	-0.954***	-0.957***	-0.892***
	(-5.10)	(-6.28)	(-5.70)	(-6.97)	(-7.11)	(-7.15)
After		0.330***	0.516***	0.699***	0.723***	0.658***
		(3.22)	(3.99)	(6.44)	(6.74)	(6.98)
N	4339	8639	8639	8190	8190	8190
R^2	0.482	0.559	0.570	0.579	0.582	0.600

Panel D: Impact on five-second price impact, Q2 2012 and Q2 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.501***	-0.725***	-0.583***	-0.654***	-0.649***	-0.602***
	(-2.79)	(-3.13)	(-2.64)	(-3.85)	(-3.91)	(-3.60)
After		0.227	0.458***	0.687***	0.697***	0.641***
		(1.43)	(2.68)	(5.06)	(5.21)	(4.64)
N	4474	8918	8918	8330	8330	8330
R^2	0.408	0.509	0.520	0.556	0.559	0.564

Panel E: Impact on five-second price impact, Q2 2012 and Q3 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.722***	-0.814***	-0.684***	-0.737***	-0.767***	-0.720***
	(-3.77)	(-3.40)	(-2.85)	(-4.05)	(-4.41)	(-4.21)
After		0.0929	0.496***	0.749***	0.785***	0.706***
		(0.58)	(2.92)	(5.74)	(6.18)	(5.39)
N	3008	5921	5921	5460	5460	5460
R^2	0.452	0.573	0.590	0.625	0.629	0.634

Table 6: Differences-in-differences event study of the impact of the launch of the RLP on the absolute value of five-second return autocorrelations. The rows of the table give the regression coefficients and their associated t-statistics for specific variables across six different specifications of the event study on five-second return autocorrelations. A blank entry indicates exclusion from the regression. The columns of the table correspond to different specifications of the event study. In specification (1), only treatment stocks are included in the regression; in specification (2), treatment stocks and control stocks are included; in specification (3), *Market cap* and *Volume* are included; and so on.

Treatment is a dummy variable that equals one during the period after the launch of the RLP for treatment stocks. *After* is a dummy variable that equals one during the period after the launch of the RLP for all stocks. *Market cap* is the daily market capitalization in billions. *Volume* is the number of shares traded per day in thousands of shares. *Market-wide liquidity* is the stock-specific factor score from principal component analysis. *10-day volatility* is the 10-day rolling volatility of the midquote. *Lagged autocorrelation* is the absolute five-second autocorrelation lagged by one day. *Constant* is the constant of regression. *N* is the number of observations. R^2 is the coefficient of determination. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Panel A shows results for the entire sample period, from April 2012 to August 2013. Panels B through E show results for a sample period limited to three months prior to the launch of the RLP and three months after. Panel B shows results when the sample period is limited to Q3 2012 and Q4 2012; Panel C shows Q3 2012 and Q1 2013; Panel D shows Q3 2012 and Q2 2013; and Panel E shows Q3 2012 and Q3 2013. Each regression specification (1) to (6) in Panels B through E corresponds to those in Panel A, but we exclude reporting of variables other than *Treatment* and *After* for brevity.

Panel A: Impact on return autocorrelation, entire sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.00338	-0.0115**	-0.00975**	-0.00938**	-0.00937**	-0.00805**
	(1.20)	(-2.53)	(-2.15)	(-2.13)	(-2.13)	(-2.04)
After		0.0164***	0.0144***	0.0144***	0.0143***	0.0124***
		(4.49)	(4.07)	(4.20)	(4.11)	(3.95)
Market cap			-0.00434	0.00277	0.00269	0.00255
			(-0.77)	(0.44)	(0.42)	(0.45)
Volume			-0.00978***	-0.00973***	-0.00958***	-0.00872***
			(-6.86)	(-6.54)	(-6.35)	(-6.10)
Mkwd. liquidity				0.00165***	0.00167***	0.00147***
				(2.76)	(2.78)	(2.75)
10-day volatility					-0.00584	-0.00473
					(-0.46)	(-0.42)
Lagged acorr.						0.123***
						(9.08)
Constant	0.0583***	0.0724***	0.269***	0.154	0.154	0.136
	(29.32)	(39.31)	(2.80)	(1.44)	(1.44)	(1.44)
N	11640	23090	23090	20650	20650	20580
R^2	0.163	0.210	0.215	0.218	0.218	0.229

Panel B: Impact on return autocorrelation, Q2 2012 and Q4 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.00629**	-0.00921*	-0.00763	-0.00705	-0.00702	-0.00582
	(2.21)	(-1.83)	(-1.61)	(-1.51)	(-1.51)	(-1.41)
After		0.0158***	0.0143***	0.0132***	0.0131***	0.0111***
		(3.65)	(3.20)	(2.99)	(2.95)	(2.84)
N	4366	8639	8639	8190	8190	8120
R^2	0.163	0.254	0.262	0.268	0.268	0.279

Panel C: Impact on return autocorrelation, Q2 2012 and Q1 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.00283	-0.0148**	-0.0113*	-0.0115**	-0.0115**	-0.00995**
	(1.06)	(-2.49)	(-1.92)	(-2.10)	(-2.10)	(-2.06)
After		0.0177***	0.0166***	0.0206***	0.0205***	0.0178***
		(3.30)	(3.02)	(3.90)	(3.86)	(3.78)
N	4339	8639	8639	8190	8190	8190
R^2	0.178	0.242	0.247	0.250	0.250	0.261

Panel D: Impact on return autocorrelation, Q2 2012 and Q2 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.00379	-0.0177***	-0.0145**	-0.0161***	-0.0162***	-0.0145**
	(0.93)	(-2.63)	(-2.23)	(-2.59)	(-2.61)	(-2.52)
After		0.0217***	0.0206***	0.0250***	0.0250***	0.0225***
		(3.98)	(3.92)	(5.12)	(5.06)	(4.98)
N	4474	8918	8918	8330	8330	8330
R^2	0.194	0.238	0.244	0.248	0.248	0.255

Panel E: Impact on return autocorrelation, Q2 2012 and Q3 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.00443	-0.0416***	-0.0390***	-0.0425***	-0.0424***	-0.0376***
	(-1.03)	(-5.19)	(-5.04)	(-5.38)	(-5.32)	(-5.10)
After		0.0375***	0.0368***	0.0403***	0.0401***	0.0353***
		(5.62)	(5.54)	(5.54)	(5.42)	(5.09)
N	3008	5921	5921	5460	5460	5460
R^2	0.172	0.270	0.275	0.281	0.281	0.292

Table 7: Differences-in-differences event study of the RLP's impact on market quality with a weighted panel of controls. The rows of the table give the regression coefficients and their associated t-statistics for specific variables across six different specifications of the event study for four market-quality measures. A blank entry indicates exclusion from the regression. The columns of the table correspond to different specifications of the event study. In specification (1), only treatment stocks are included in the regression; in specification (2), treatment stocks and control stocks are included; in specification (3), *Market cap* and *Volume* are included; and so on. Rather than using control stocks matched on-to-one with treatments (reported in Tables 3 through 6) a weighted panel of controls is used for each treatment stock.

Treatment is a dummy variable that equals one during the period after the launch of the RLP for treatment stocks. *After* is a dummy variable that equals one during the period after the launch of the RLP for all stocks. *Market cap* is the daily market capitalization in billions. *Volume* is the number of shares traded per day in thousands of shares. *Market-wide liquidity* is the stock-specific factor score from principal component analysis. *10-day volatility* is the 10-day rolling volatility of the midquote. *Lagged autocorrelation* is the absolute five-second autocorrelation lagged by one day. *Constant* is the constant of regression. *N* is the number of observations. R^2 is the coefficient of determination. *, **, *** represent statistical significance at the 10%, 5%, and 1% level. Panels A through D show results for relative spread, effective spread, price impact and autocorrelation over the entire sample period, from April 2012 to August 2013.

Panel A: Impact on relative spread, entire sample, weighted panel of controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.389**	-1.201*	-0.932	-0.978**	-1.040**	-0.738**
	(-2.43)	(-1.86)	(-1.47)	(-2.22)	(-2.51)	(-2.24)
After		-0.208	-0.348	0.337	0.497**	0.355*
		(-0.54)	(-0.98)	(1.14)	(2.09)	(1.72)
Market cap			-1.859*	0.288	0.303	0.126
			(-1.91)	(0.48)	(0.51)	(0.27)
Volume			-2.437***	-2.068***	-2.130***	-1.774***
			(-8.68)	(-10.18)	(-11.65)	(-9.20)
Market-wide liquidity				1.000***	1.004***	0.779***
				(31.63)	(38.57)	(7.12)
10-day volatility					3.871***	3.165***
					(2.59)	(2.59)
Lagged relative spread						0.244**
						(2.17)
Constant	11.81***	12.63***	70.98***	32.24***	32.26***	27.92***
	(29.21)	(45.24)	(4.41)	(3.12)	(3.17)	(3.16)
N	11640	1718905	1718905	1548750	1548400	1543150
R^2	0.839	0.568	0.592	0.786	0.801	0.831

Panel B: Impact on effective spread, entire sample, weighted panel of controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.114**	-0.520	-0.346	-0.512	-0.547	-0.334
	(-2.41)	(-1.08)	(-0.76)	(-1.44)	(-1.60)	(-1.59)
After		-0.656***	-0.498***	-0.0769	0.0206	0.0158
		(-3.32)	(-2.62)	(-0.46)	(0.16)	(0.18)
Market cap			-1.822***	-0.502	-0.494	-0.281
			(-3.58)	(-1.45)	(-1.45)	(-1.39)
Volume			-0.462***	-0.328***	-0.381***	-0.238***
			(-3.24)	(-2.89)	(-3.74)	(-3.36)
Market-wide liquidity				0.524***	0.525***	0.337***
				(20.92)	(23.83)	(11.25)
10-day volatility					2.604***	1.515**
					(2.74)	(2.53)
Lagged relative spread						0.388***
						(10.54)
Constant	9.751***	7.146***	41.21***	18.55***	18.74***	11.19***
	(29.78)	(48.33)	(4.65)	(3.13)	(3.20)	(3.27)
N	11640	1718905	1718905	1548750	1548400	1543150
R^2	0.867	0.618	0.627	0.676	0.690	0.738

Panel C: Impact on five-second price impact, entire sample, weighted panel of controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.356***	-0.577***	-0.513***	-0.588***	-0.597***	-0.523***
	(-2.62)	(-3.96)	(-3.70)	(-4.89)	(-5.19)	(-5.28)
After		0.244***	0.319***	0.445***	0.483***	0.479***
		(3.44)	(4.48)	(6.62)	(7.94)	(9.39)
Market cap			-0.718***	-0.271*	-0.267*	-0.189*
			(-3.63)	(-1.79)	(-1.80)	(-1.68)
Volume			-0.0983*	-0.0541	-0.0914**	-0.0407
			(-1.84)	(-1.18)	(-2.14)	(-1.25)
Market-wide liquidity				0.173***	0.171***	0.106***
				(18.68)	(19.94)	(9.16)
10-day volatility					1.412***	1.042***
					(2.82)	(2.70)
Lagged price impact						1336.4***
						(8.96)
Constant	3.529***	2.532***	14.95***	7.293***	7.512***	4.823***
	(36.30)	(50.01)	(4.42)	(2.88)	(3.01)	(2.62)
N	11640	1718905	1718905	1548750	1548400	1543150
R^2	0.411	0.476	0.481	0.510	0.517	0.553

Panel D: Impact on five-second return autocorrelation, entire sample, weighted panel of controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.00338	-0.00562	-0.00587	-0.00678*	-0.00679*	-0.00611*
	(1.20)	(-1.57)	(-1.57)	(-1.89)	(-1.89)	(-1.87)
After		0.00993***	0.00688***	0.00924***	0.00940***	0.00848***
		(4.16)	(2.93)	(3.95)	(4.01)	(3.91)
Market cap			0.00969*	0.0164***	0.0165***	0.0150***
			(1.79)	(2.90)	(2.90)	(2.91)
Volume			-0.0119***	-0.0112***	-0.0114***	-0.0106***
			(-11.82)	(-11.23)	(-11.23)	(-11.25)
Mktwd. liquidity				0.00245***	0.00243***	0.00222***
				(3.62)	(3.62)	(3.63)
10-day volatility					0.00821	0.00762
					(1.16)	(1.21)
Lagged acorr.						0.0979***
						(10.85)
Constant	0.0583***	0.0942***	0.0859	-0.0314	-0.0297	-0.0246
	(29.32)	(51.85)	(0.99)	(-0.35)	(-0.33)	(-0.30)
N	11640	1718905	1718905	1548750	1548400	1543150
R^2	0.163	0.104	0.111	0.116	0.116	0.124