Ultra-Fast Activity and Intraday Market Quality

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ABSTRACT

This paper studies the intraday relationship between ultra-fast machine-driven activity (UFA) and market quality in automated equity markets. We find that higher UFA is associated with lower intraday market quality (greater quoted and effective spreads and lower depth). This effect is economically significant, and robust to different specifications, endogeneity tests, and alternative measures of UFA. Our results hold after controlling for volatility, periods of unusually high UFA (a proxy for quote stuffing), and periods where UFA is primarily driven by fleeting orders inside the spread (a proxy for spoofing and competition between liquidity providers).

Keywords: High-Frequency Trading; HFT; Algorithmic Trading; Market Quality; Low Latency; Intraday trading; spoofing; fleeting orders; quote stuffing

I. Introduction

In many modern financial markets, the vast majority of trading decisions are made and executed by computers.[1] A large fraction of these trades comes from proprietary trading strategies. Another large proportion comes from investment banks and brokerage firms that operate algorithms for their own benefit or to execute the trading instructions of clients, including large financial institutions. For at least some, if not most of these algorithms, speed (also referred to as time-to-market or latency) is a vital ingredient. The increased importance of speed has led to an unprecedented growth in innovations in

[1]For example, in 2012, TABB Group estimated that high-frequency trading algorithms participated in over 50% of all US equity market trades.

hardware, software, and algorithm design oriented towards improving message processing and execution speed which, although optimal for individual firms, raises concerns for regulators and other market observers.[2] In parallel, academic research on this area has proliferated with sometimes seemingly contradictory results: some find that these technologies have improved overall market quality through more efficient and cheaper market making and order execution, while others find increased volatility and the proliferation of market distorting strategies such as 'spoofing', 'quote stuffing', etc. Much of the empirical research has focused on significant changes in the trading environment to identify the overall effect of these technological developments.

In this paper we consider how the amount of fast computer-based trading interacts with other market factors in determining intraday variations in market quality variables. We provide a thorough empirical study of equity market quality and its relationship with a measure that only captures machine-based trading, which we refer to as ultra-fast activity (UFA). This measure of computer-driven activity is the frequency of occurrence of fleeting orders (i.e. orders that are posted and canceled too quickly to be due to any human).[3] Our main contribution is to document the negative intraday relationship between computer-driven activity and market quality on NASDAQ. We find that at times when the activity of machines is high, quoted and effective spreads increase, and the depth of the limit-order-book (LOB) decreases. This result is obtained using variables constructed minute-by-minute and is robust to the use of a variety of estimation techniques and econometric specifications.

The measure of machine-driven activity we use is defined to capture only activity generated by machines and in such a way that it is not mechanically linked to market quality. To build our measures of UFA we employ publicly available data for NASDAQ (TotalView-ITCH), which contain millisecond-stamped messages, and we construct it by counting, in every minute, the number of limit orders that are posted and, within 100 milliseconds (ms), are subsequently canceled. We label this post-and-cancel activity measure as $PC100$, and use the order and trade messages sent to NASDAQ to build it. $PC100$ is

[2] For example see Biais, Foucault, and Moinas (2015), Aquilina and Ysusi (2016), Bouveret, Guillaumie, Roqueiro, Winkler, and Nauhaus (2014) or U.S. Securities Exchange Commission (2014).

[3] Hasbrouck and Saar (2009) define fleeting orders using a 2-second window. We use a much narrower window of 100ms, though our results are robust to using a narrower window of 50ms. Our measure coincides with NFLT100 defined independently in Scholtus, van Dijk, and Frijns (2014).

explicitly designed to capture activity arising from machines, as human reaction times exceed 100ms.[4] Thus, our measure does not reflect the activity of manual traders nor that of algorithms operating at relatively low frequencies. Note that this measure should not have a mechanical relationship with spreads or depth as we are time-weighting these measures and the frequency of $PC100$ is not large for most of the assets in our sample.[5]

The extant literature uses messages sent to the exchange to build measures of algorithmic trading. Our measure relates to those because $PC100$ employs a subset of the messages sent to NASDAQ. In particular, the work of Hendershott, Jones, and Menkveld (2011), and Boehmer, Fong, and Wu (2014) employ message-to-trades ratio (measured daily) to determine the presence of algorithmic traders or high-frequency trading (HFT). Although the use of messages as a proxy for the presence of machines could be contaminated by human activity not related to UFA (see Scholtus, van Dijk, and Frijns (2014)), our results are robust to using the message-based measure of algorithmic trading (AT) proposed by Hendershott, Jones, and Menkveld (2011).

In addition, because $PC100$ is built with a subset of all canceled orders, it also relates to the measures used in papers that focus on fleeting orders or cancellation activity as introduced in Hasbrouck and Saar (2009), and to those that relate market quality with cancellation rates, e.g. Egginton, Van Ness, and Van Ness (2016), and Gao, Mizrach, and Ozturk (2015). In general, these papers also find that a large number of cancellations is associated with lower market quality. However, because we focus on rapid post-and-cancel activity, our $PC100$ measure contains a low proportion of all canceled orders, thus it is not mechanically related to the general cancellation rate. For example, for March 2013 less than 20 percent of all cancellations are contained in $PC100$ for that month.

With $PC100$ as a measure of UFA, we look at intraday variation in the market quality variables: spreads and depth. For comparability with previous work, our study focuses on the same 120 stocks as in Brogaard, Hendershott, and Riordan (2014) and covers the month of March in every year from 2007 to 2015. Our measures of market quality are: quoted spread, effective spread, and depth (with the latter

[4] The 100ms threshold is used to determine false starts in athletics competition. Brosnan, Hayes, and Harrison (2017) find that this threshold may even be too narrow and a slightly higher one of 115 to 119ms for men should be used to avoid not detecting some false starts which currently may not be detected.

[5] If there is a mechanical effect on spreads, it would go against our results, as a fleeting order can only change the spread if it reduces it. As for depth, again, a fleeting order can only increase depth while our results go in the opposite direction. Furthermore, to verify the lack of a mechanical relationship, we run the analysis on quoted spreads using only $PC100$ events that did not change the spread and find no significant differences in the results.

measured at two points in the order book). We aggregate our data to a one-minute frequency by time-weighting quoted spreads and depth within a minute, while the effective spread is volume-weighted within each minute. As controls we use time-of-day dummies, volatility, and the absolute value of order imbalance.[6] To study intraday variation we standardize all variables and run double-clustered panel data analysis across assets. Each panel includes data for the month of March in one of the years in the sample.[7] In contrast, the extant literature mostly focuses on the effect of variation across assets (e.g. Boehmer, Fong, and Wu (2014), Brogaard, Hendershott, and Riordan (2014), Conrad, Wahal, and Xiang (2015), Hagströmer and Norden (2013)), variation from a single asset (Scholtus, van Dijk, and Frijns (2014)), or exploit variations from a specific event (Hendershott, Jones, and Menkveld (2011), van Kervel (2015))). By using intraday variation across assets our analysis focuses on interactions across the variables of interest at a time scale (one minute) that is immediately relevant to algorithms concerned with fast trading. Moreover, by standardizing the variables, our analysis provides an estimate of the magnitude of the effect in a common scale for all assets. We find that the estimated coefficients are robust across time and different subsets of assets grouped by traded volume.[8] Also, these results complement existing results that study cross-sectional variation across assets. We also estimated the model in cross-section using aggregated variables in levels (not standardized) and we obtain results that are consistent with the extant literature.[9] The analysis in Hasbrouck and Saar (2013) however, is very close to ours though using a different measure and obtains different results which we discuss in detail below.

Our result could arise because greater UFA is a consequence of worsened market quality, or because greater UFA has a detrimental effect on market quality, or both. Our first step is to address possible endogeneity concerns using instrumental variables. We find that our results hold using two plausible instruments: (i) Lagged $PC100$, and (ii) the instrument obtained by averaging UFA across other stocks

[6]The absolute value of order imbalance is highly correlated with raw volume which is another variable commonly used as a key determinant of market quality.

[7]We take the variables for March of each year and each asset (separately) and standardize by subtracting the (insample) mean and the (insample) standard deviation of that variable. Thus, our analysis is done in terms of the effect of intraday changes measured in standard deviations from the mean.

[8]The results are also robust to changing the sample. We ran the same analysis with a new sample of 300 assets. Assets were selected from using the Fama-French size deciles, 30 assets from each decile (15 from NYSE and 15 from NASDAQ). The data was obtained for March 2013 and the results are very similar. The results are available from the authors and in an Internet Appendix.

[9]We ran a cross-sectional OLS version of our baseline model using levels of median values of minute-by-minute observations for 2013 and we obtain positive coefficients on $PC100$ when regressing on depth and negative ones when regressing on spreads.

as suggested by Hasbrouck and Saar (2013). As a second step, we consider the possibility of an omitted variable. Thus, we incorporate market-wide effects using the methodology of Chordia, Roll, and Subrahmanyam (2000). We find that the omitted variables are significant, however the effect of UFA still holds. We then repeat the instrumental variable (IV) analysis and find evidence that the inclusion of market-wide effects reduces the initial endogeneity problems of UFA. In particular, we find that for a large proportion of the IV regressions, after including market-wide effects, we cannot reject the exogeneity of our control (UFA). Also, the IV analysis rejects a positive relationship between UFA and market quality variables –the estimations imply a negative or insignificant relationship.

To test the robustness of our results we also consider the AT measure proposed in Hendershott, Jones, and Menkveld (2011) as an alternative UFA metric. This measure also has a consistent negative effect on market liquidity across time and stocks. Moreover, we consider a number of other variations such as segmenting the sample by volume quintiles, drawing a completely new sample, and using alternative time horizons for measuring UFA. In all cases the effects remain. We also verify the robustness of the endogeneity analysis by using a simultaneous equation estimation approach for the cross-effects of market quality and $PC100$, following Hasbrouck and Saar (2013).[10] our benchmark results are robust to various changes in data definitions and model specification. Overall, the negative effect we find of UFA on market quality is very robust and possibly causal (at least in a substantial number of cases).

Our findings are consistent with the analysis of van Kervel (2015), who studies trading between competing venues. The difference between our results and those in extant work may arise because UFA pools together the activity of all fast traders, not just high-frequency traders (as in Kirilenko, Kyle, Samadi, and Tuzun (2010)). Our data do not allow us to identify the trading strategies that lead to algorithms posting and canceling quotes quickly, but there is no immediate reason to assume that such behavior is confined to high-frequency traders (for example it might also come from execution algorithms from traders who want to take a directional position or liquidate an existing position).

Thus, our results contrast with much (though not all) of the empirical literature that studies alternative measures of high frequency (HF) trading or algorithmic trading that find such trading to be associated with better market quality and price efficiency.[11]

[10] We thank the referee for suggesting this.

[11] See Hendershott, Jones, and Menkveld (2011), Brogaard, Hendershott, and Riordan (2014), or Hagströmer and Norden (2013), among others.

The work of Hendershott, Jones, and Menkveld (2011) compares stock liquidity levels before and after the introduction of a speed increasing technology (automated quote dissemination). Similarly, Boehmer, Fong, and Wu (2014) employs data from 39 exchanges (excluding US exchanges) for the period 2001 to 2009 to assess the effect of AT, proxied by co-location facilities, on market quality. We, however, focus on intraday variations in market quality after controlling for levels and volatility of the variables across assets.

There is also a literature that studies fast trading activity by looking at the behavior of a specific subset of traders labeled HFTs. Theoretically, faster traders could have both positive and negative effects on market quality (Biais, Foucault, and Moinas (2015), Brogaard, Hagströmer, Nordén, and Riordan (2015), Foucault, Kozhan, and Tham (2017)). Empirically, the NASDAQ stock exchange has released data that identifies a subset of traders as HFTs, which is used in, amongst others, Brogaard, Hendershott, and Riordan (2014). They find that liquidity provision by these traders is profitable despite suffering from trading against better informed traders, while their liquidity taking activity in anticipation of price changes is suggestive of improved price efficiency; though it could also be interpreted as toxic trading—see Foucault, Kozhan, and Tham (2017). They conclude that HFTs impose adverse selection costs on other investors, which could explain why UFA, if taken as a signal of this adverse selection, is associated with lower market quality. The work of Hagströmer and Norden (2013) does a similar exercise using data from NASDAQ-OMX Stockholm and finds that HFT market making firms mitigate intraday price volatility. There is also evidence that HFT activity may not be always positive. Scholtus, van Dijk, and Frijns (2014) find that around macroeconomic news announcements, market quality and algorithmic activity measures react. Moreover, depth measures decline, while quoted spreads, adverse selection costs and volatility measures increase around news releases. Hendershott and Riordan (2013) document lower cancellation rates by high-frequency traders at times of wider spreads in the Deutsche Borse in 2008. This is consistent with our benchmark analysis. Hendershott and Riordan (2013) propose that this is due to machine-trading being motivated by the optimization of their strategies to market conditions. Our analysis goes to great length to control for market conditions and still we find that UFA and related variables continue to have a negative association with market quality which lead us to consider that the relationship may be causal. Tong (2015) and Korajczyk and Murphy (2017) also find evidence that HFTs worsen some aspects of market quality

The closest paper in this literature is Hasbrouck and Saar (2013) who use a methodology very close to ours. Like us, they use NASDAQ data while focusing on the months of October 2007 and June 2008, and look at intraday variations using standardized variables. However, their measure (RunsInProgress) is tied to HFT activity. Their results are diametrically opposed to ours.[12] Thus, our measure is not capturing overall HFT activity but a subset of their behavior that is associated with negative market quality.

An early theoretical contribution that identifies such behaviors is in Cartea and Penalva (2012). The authors propose that greater speed could allow fast traders to profitably intermediate between liquidity demanders and liquidity suppliers. This additional intermediation layer would increase execution costs and microstructure volatility. This idea is employed in Clark-Joseph (2014) and Hirschey (2017) who develop models that describe how speed can serve to anticipate (some would say, front-run) the movements of other traders.

Fast trading is associated with asymmetric information and toxic flow (Biais, Foucault, and Moinas (2015), Hoffmann (2014), Foucault, Hombert, and Roşu (2015), Foucault, Kozhan, and Tham (2017)), and UFA could be both a measure an indicator of the presence of asymmetric information in the market.

More closely related to our work is the literature that directly addresses the flickering/fleeting orders which UFA measures directly. UFA could be a byproduct of liquidity provision strategies (Baruch and Glosten (2013), Hasbrouck (2013)). Conversely, Hasbrouck (2013) argues that high-frequency activity in the LOB induces volatility in a market's bid and offer quotes, which subsequently degrades the informational content of the quotes, exacerbates execution price risk for marketable orders, and impairs the reliability of the quotes as reference marks for the pricing of dark trades. In addition, some authors theorize that UFA could be an indicator of disruptive trading activity. One such behavior is quote stuffing, studied in Gao, Mizrach, and Ozturk (2015) who find that quote stuffing in NASDAQ, NYSE, Archipelago and Amex widens spreads and raises volatility.

Similarly, Egginton, Van Ness, and Van Ness (2016) and Gao, Mizrach, and Ozturk (2015), who look at cancellation activity rates and find that a large number of cancellations is associated with lower

[12] We reconstructed the Hasbrouck and Saar (2013) measure for the month of march 2013 with one minute sampling rate. It displays a very low correlation with UFA. We also used it in our analysis instead of UFA and the results are the opposite of the ones we find and consistent with those in Hasbrouck and Saar (2013).

market quality. Van Ness, Van Ness, and Watson (2015) find a negative relationship between cancellations and market quality though using a very different analysis, namely two-stage least squares cross-sectional regression applied on daily averages.

The remainder of this paper proceeds as follows. In Section II we discuss the data we employ and in Section III we show how we build the $PC100$ measure and our market quality measures. In Section IV we present the methodology used in our main empirical work and in Section V we present the results including the robustness checks. Section VI looks at several possible economic explanations for the effect of UFA and its economic significance. We conclude in Section VII and collect tables in the Appendix.

II. Data

We use Total-View-ITCH which is publicly available data from NASDAQ. The data are time-stamped to the millisecond and contain every message to post, or cancel a limit order, and messages that indicate the execution (partial or total) of a displayed or non-displayed order. Although non-displayed orders are not visible in the data when they are submitted to the LOB, one can see them (ex-post) if they execute against a marketable order.

It is worth noting that our study focuses only on NASDAQ data. This is one of many venues that are open for trade in US cash equities. Although NASDAQ has gradually lost market share it remains as one of the dominant venues for trade and, in 2014, had an estimated market share of 20%. Thus, while our data are far from a comprehensive view of order flow, NASDAQ handles a significant share of all trading and, what is more important, our sample covers 9 months, each from a different year (from 2007 to 2015).

Our study focuses on 120 stocks, exactly the same stocks as those studied in Brogaard, Hendershott, and Riordan (2014). We use the message data to build the full LOB in these stocks, for the month of March in each of the years between 2007 and 2015 to construct our measures of market quality. Because the list of 120 stocks was created in 2008, there are firms that were not in existence prior to 2008 and others that left the sample. The number of firms available in March each year is given in the last column of Table I.

III. Measuring UFA and Market Quality

Our measure of UFA is defined as the number of limit orders within a given minute that are posted and subsequently canceled within 100ms. We call this measure $PC100$. The contribution of a post-cancel pair to $PC100$ is recorded for the minute in which the cancel message is recorded. To avoid the special circumstances at the times surrounding the market open and close, we omit the first and last half hours of each day of trading from our analysis. Market quality measures are constructed for the same one-minute windows.

Our market quality measures are:

- $QS_{i,t}$. Quoted spread for asset i is the time-weighted (by millisecond) average, over minute t, of $(a_{t'} - b_{t'})/m_{t'}$ where $a_{t'}$ is the best ask, $b_{t'}$ the best bid, $m_{t'}$ the midprice, and t' indexes observations within a minute.
- $ES_{i,t}$. Effective (half) spread for asset i is an intra-minute average of $D_{t'}(p_{t'} - m_{t'})/m_{t'}$. Here, $D_{t'}$ is a direction indicator for the trade at t' ($+1$ for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'}$ the prevailing midquote (prior to an execution). Trade directions are available from the data and do not need to be estimated. The within-minute average spread is computed by weighting each observation by trade size.
- $DX_{i,t}$. Depth for asset i is calculated as the sum of the total US dollar value resting on the LOB within $X \in \{1, 10\}$ basis points of the best bid and ask, again time-weighted over minute t.[13]

Other variables used in the analysis are:

[13] In contrast to the usual depth measures which are limited by the availability of data on the LOB, our measure of depth is constructed to account for the relative tick size by measuring depth at given distances relative to the current best bid/ask, in percentage terms, rather than a given number of levels away. A number of recent studies, e.g. van Kervel (2015), also use this same measure of depth. Depth at 1bp coincides with the usual measure of depth at the touch for assets with a price lower than \$100 (more than 90 percent of the sample for all years, except 2014 (87%) and 2015 (82%)).

- $PCX_{i,t}$. Our measure of UFA. Number of limit orders that are posted and subsequently canceled within X ms, where $X \in \{1, 10, 50, 100, 600\}$ and within minute t for asset i.
- $MOIMB_{i,t}$. Market order imbalance for asset i is calculated as the absolute US dollar value of the difference between market buy volume and market sell volume in a one-minute interval.
- $VOLATM_{i,t}$. Average realized volatility in the last half hour for asset i is measured as $\frac{1}{n}|\sum_{s=1}^{n} \ln(m_{t-s}/m_{t-s-1})|$ where m_s is the midquote at end of minute s, and $n = 30$.
- $AT_{i,t}$. We also construct the measure of algorithmic activity employed in Hendershott, Jones, and Menkveld (2011). This measure is defined as the ratio of dollar traded volume to the aggregate number of order messages (i.e. posts, cancels, executions, expiries) for each stock i over a one-minute interval. We build this ratio, measuring volume in hundreds of dollars, for each stock and each minute in our data. A large number for the ratio suggests low algorithmic activity, as volume is being generated with few messages, while a low number suggests intense algorithmic activity (as there are many messages for each dollar traded).
- $NMess_{i,t}$. Number of messages for asset i within minute t. These include posting, canceling, and execution of visible limit orders, as well as execution of hidden orders.

Table I shows means and standard deviations, by year, for the variables used in the analysis. The data used to construct this table are winsorized and used as input in all subsequent analyses.[14] The winsorization is applied to the 0.5th (left tail) and 99.5th (right tail) percentile for data on each stock, variable and year (i.e. for each stock/year combination, we take every variable and set the value of the realizations below (above) the 0.5th (99.5th) percentile to the value at the 0.5th (99.5th) percentile).[15]

The first four columns show the market quality measures, the following four columns show the post-and-cancel measure using four windows: $PC1$, $PC50$, $PC100$, and $PC600$. The next two columns are explanatory variables we use in the main regressions and the last three columns are the AT variable, the number of messages per minute, and the number of assets in the sample for that month of march.

Starting with the penultimate column, we see that overall, NASDAQ message activity levels rise through the early part of the sample and the financial crisis, peaking in 2009, before dropping sharply

[14]The winsorization makes use of Stata command winsor2, as documented in Yu-jun (2014).

[15]Minutes without observations are dropped. This is particularly relevant for effective spreads, as our sample contains infrequently traded assets that may have a substantial proportion of minutes without trading (and hence without effective spreads). However, as our results are consistent across subgroups of assets, they are not affected by this.

in 2013. As this is NASDAQ only activity, changes over time may be driven by overall market activity fluctuations and also by fragmentation, changing the proportion of order flow that goes to NASDAQ.[16] $PC100$ also shows evidence of rising towards 2009, and then dipping to peak again in 2013. As one would expect, the measure AT shows roughly the opposite pattern. In 2009 \$1 of volume is associated with fewer messages, meaning low AT. At the beginning of the sample period (2007, 2008), there were, on average, many more messages per \$1 of volume meaning that AT was high. Spreads, both quoted and effective, are relatively stable for the whole sample with the notable exception of 2009 and 2007 when they were more than 100% greater than the greatest value in all the other years (2008). Depth deep in the book, as measured by $D10$, is relatively stable except for the sharp decline in 2008, peaking in 2009. Closer to the best prices, as measured by $D1$, we observe the same decline up to 2009, however after depth recovered in 2010, we observe a continued decline up to 2015 which, although higher than in 2009, is lower than in 2008.

Figure 1 shows mean $PC100$ for quintiles of our 120 firms, from largest to smallest using traded dollar volume (for each year), for the years 2007 to 2015. The figure shows that firms in Q5, with higher traded dollar volume, have higher mean $PC100$. The lower the dollar traded volume, the lower is the mean $PC100$. It is clear that there is more UFA in large firms but there is no clear pattern of UFA rising or declining in our sample. Consistent with Table I, UFA peaked in 2014, with mean $PC100$ close to 200 per minute for the most active quintile of firms. Figure 2 shows the means of the market quality measures by quintiles, which reflects the known relationship between size and market quality.

Table II shows the (average) correlation matrix for the variables shown in Table I. These figures are averages across stocks and across years. As one would expect, quoted and effective spreads are positively correlated, and both are negatively correlated with our depth measures. Interestingly, $PC100$ is positively correlated with spreads and negatively correlated with depth (i.e. in raw terms, UFA is negatively related to market quality). Our UFA measure is also positively correlated with volatility, order imbalance and message frequency and, again as expected, (weakly) negatively correlated with the Hendershott, Jones, and Menkveld (2011) AT measure.[17]

[16] Over the period under study, NASDAQ has seen a gradual decline in market share from around 26 percent in 2007 to around 18 per cent by the of 2015 (in terms of notional value–using data obtained from batstrading.com).

[17] It is worth noting that scaling our $PC100$ measure by the number of messages in a minute does not greatly alter the patterns of correlations in this table.

In the panel regression analysis that follow we standardize all (winsorized) variables, that is, for each (winsorized) variable, asset, and year, we subtract the (in-sample) mean and divide by the (in-sample) standard deviation of each variable, where means and standard deviations are computed for each variable, asset, and year, separately.

IV. Methodology

Our goal is to understand the effect that UFA has on market quality. For each year, we define $L_{i,t}$ to be the market quality measure of interest, and run a panel regression, as shown below, where data are pooled across our 120 sample stocks. For each year $(2007-2015)$ we estimate separate regressions using our data for March.

$$L_{i,t} = \alpha_{0,i} + \alpha_{0,t30} + \alpha_1\, PC100_{i,t} + \alpha_2\, MOIMB_{i,t} + \alpha_3\, VOLATM_{i,t} + \varepsilon_{i,t}\,, \tag{1}$$

where $\varepsilon_{i,t}$ is an error term. In these specifications we control for stock-level fixed effects ($\alpha_{0,i}$) and half-hour time-of-day fixed effects ($\alpha_{0,t30}$, for a total of 10 dummies). By using standardized variables, our analysis differs from most of the previous literature, in that our coefficients are determined after eliminating asset specific variable characteristics such as their mean and variance.[18] In particular, consider two different assets: APL and AMZ. Suppose APL has the following characteristics: the mean and standard deviation of $PC100$ are 100 and 10 respectively, and 30 and 10 bps for quoted spread, whereas the mean and standard deviation of $PC100$ of AMZ are 300 and 60, and 90 and 60 for quoted spread, respectively. Suppose we estimate that $\alpha_1 = 0.12$. This implies that after observing $PC100$ at 1 standard deviation above its mean for APL, say $PC100 = 110$, the expected level of quoted spread conditional on this is above its unconditional mean, namely $30 + 0.12 \times 10 = 31.2$ bps. However, when looking at the AMZ asset, the expected level of the quoted spread conditional on an equivalently high level of $PC100$ (which for this asset would be $PC100$ at 360) is $90 + 0.12 \times 60 = 97.2$ bps. Using standardized variables we obtain coefficient estimates that are stable across samples (time and volume

[18]Two notable exceptions are Hasbrouck and Saar (2013) and Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2016).

groups), and robust to pooling assets with substantial heterogeneity in the scale of both the explanatory and estimated variables.

As we are interested on the relationship between UFA and measures of market quality, we take into account factors that determine market quality. We employ two classic factors: market activity and price fluctuations. With regards to market activity, Hasbrouck and Saar (2013) use trading intensity, which is measured as the average volume over the past 10 minutes to capture stock-specific informational events or liquidity shocks that could be driving changes in market quality measures. In the literature we find a number of other measures that are highly correlated amongst themselves and to total volume. Our $MOIMB$ variable tries to capture this effect while taking into account the possible additional information in the sign of trades, more precisely, in the relative (im)balance between buys and sells. $MOIMB$ has an average correlation of 0.79 with traded volume, and our results do not differ substantially if we use volume instead of $MOIMB$. Our second control variable, $VOLATM$, also tries to capture stock-specific informational or liquidity events, in this case via the magnitude of price fluctuations.

In addition to estimating the model for the full set of 120 stocks for each year, we also estimate separate models for the 5 volume-based quintiles defined and used earlier. This allows us to evaluate the effects of UFA in the cross-section of stocks and its robustness across liquidity groups (as measured by traded volume).

The results from the baseline panel regression above are summarized and discussed in the next section, after which we discuss estimates from various specifications that demonstrate the robustness of our baseline results.

V. Results: UFA and Market Quality

A. Main Results

Table III shows estimation results of the panel regression model, model (1), for all assets and for the years 2013 and 2009 (results for all years, 2007 to 2015, are displayed graphically in Figure 3, and the accompanying numbers are in Table IV). The estimation clusters the errors by asset and time (day-minute). We highlight year 2013 because it is representative of the majority of years in our sample. We also include 2009 because March of that year was very unusual and the results tend to be weakest relative to other month-years in the sample. It was the first March after the Lehman crisis and the S&P500 hit a 13-year low on March 9, 2009.[19]

For each year include the estimated coefficient on the variable of interest ($PC100$) as well as those for the two control variables ($MOIMB$, which measures US dollar market order imbalance for the asset of interest, and $VOLATM$, the realized volatility of the one-minute return of the asset of interest for the previous half hour). We run regressions for 4 different dependent variables (quoted spreads, effective spreads, and the two depth measures) and the results from these are in different columns of the table. Finally, each cell of the table contains two numbers. The first is the coefficient on the variable of interest ($\hat{\alpha}_i$, $i \in \{1,2,3\}$), and the second is the standard error. Also, for the tables for selected years (2009 and 2013) we also include the corresponding adjusted R-squared and number of observations.[20]

The key result from this table is that our measure of UFA tends to be associated with significantly worse market quality. It leads to greater quoted and effective spreads and lower depth posted in the LOB. These effects tend to be quantitatively larger and somewhat more stable in 2013 (and most years), relative to the crisis year of 2009. To interpret the coefficient magnitudes, recall that all variables have been standardized prior to running the regression. Thus, for example, the coefficient of 0.124 on the quoted spread in 2013 means that a one standard deviation increase in $PC100$ is associated with a 0.124 standard deviations increase in the spread. From the figures one can see that the effects of $PC100$ are consistently significant for quoted spreads, and their magnitude is around twice that of the coefficient in effective half-spread regressions. We also observe that the effect on depth at 1bp is negative and significant, and of similar or greater magnitude than the effect on depth deeper into the limit order book. In a later section we discuss the economic significance of our results.

For comparison, Figure 3 also includes the coefficients from regressions where instead of $PC100$, we use the AT measure of Hendershott, Jones, and Menkveld (2011) as a dependent variable. The

[19] This effect is also visible in the descriptive statistics on Table I.

[20] Table IV includes the estimated coefficient for the $PC100$ variable for all the years, as well as the coefficients estimated for each of five quintile groups where each quintile group contains all assets that have aggregate traded volume in that corresponding quintile. The complete regression results for all the years and groups is available upon request. The number of observations varies by year and by quintile. For example, for 2013, the regressions with all the assets has 732600 observations. Note that minutes without trading do not have observations for effective spreads, so these regressions have fewer observations, for example for 2013 there are 396456 observations.

figures demonstrate that the relationship between $PC100$ and AT with market quality is similar. If anything, the magnitude of the AT measure is greater and more consistent for all market quality measures, except for some years and variable $D10$. Note that the analysis in Hendershott, Jones, and Menkveld (2011) establishes that the increased level of machine activity following a technological change that facilitated machine-driven trading was accompanied by an increase in the level of market quality variables. Such an effect would not be captured by our analysis, as our variables are normalized by their in-sample means and standard deviations. However, our analysis would identify if the technological change altered the intraday relationship between machine-activity and market quality variables.

Figures 4 to 7 present plots of the year-to-year variation in the coefficients on $PC100$, for the entire panel of stocks, separately for the five activity based quintiles of stocks, and for all of the dependent variables.[21] There is no clear monotonic variation of the coefficients on spreads across stock activity quintiles (within individual years). However, there is evidence that the effects of UFA on all market quality measures is consistently negative, when significant.

As reported in the introduction, these results contrast with those from other parts of the literature. However, this is not so surprising as our analysis differs from those in the literature in terms of variables and methodology. Our UFA measure is not a measure of HFT or the activity of traders that may be classified as high-frequency traders, but rather the activity of algorithms that are operating at ultra-fast speeds. After controlling for volume imbalance and volatility, the $PC100$ measure may be indicative of the activities of a particular subset of fast traders, also driving the AT measure (capturing the activities of fast traders in general). Also, as can be seen from the Table, the estimated coefficients on the controls are consistent with those in the literature (Madhavan (2000), Stoll (2000)).

B. Endogeneity

Endogeneity is a concern in attempting to understand how UFA drives market quality. Intraday variables are subject to common shocks and it is possible that market quality affects UFA and/or UFA may be driving market quality (e.g. ultra-fast traders might be more active at times of greater market qual-

[21]The regression output upon which these figures are in Table III.

ity). However, the question is whether these interactions are distorting our inference in a qualitatively significant way. To address this concern we identify IVs for $PC100$.

The first approach is to use the lagged value of the suspect variable as an instrument. We employ the standard two-stage IV analysis[22] using lagged $PC100$ as instrument under the standard assumptions that $PC100$ is autocorrelated (which it is) and that $PC100$ at $t-1$ is uncorrelated with the innovations at t. Table V shows results for 2009 and 2013 (all years are reported in Table VI). In Table VI we include the results for all years for the full sample and the five subgroups by traded volume. The results are qualitatively the same as those in our baseline results: higher UFA is associated with worsening market quality.

As a second alternative, we construct another IV following the approach of Hasbrouck and Saar (2013) (HS) who argue that UFA may be correlated across stocks but that the effect of UFA on market quality of one particular stock should be unaffected by the incidence of UFA in an unrelated stock. Thus, one can instrument UFA in a particular stock using UFA in unrelated stocks. We instrument UFA for stock i with the average contemporaneous UFA for all other stocks in the sample (excluding related stocks such as those in the same industry or index).[23] Table VII contains the results obtained using the IV for 2013 and 2009 (the results for all years are in Table VIII). We find that the IV results are stronger than the benchmark results (in Table III: 193 coefficients in the IV as compared with 190 in the benchmark analysis are significant and support the hypothesis of an intraday negative relationship between UFA and market quality). The IV coefficients are of the same sign, but larger in magnitude than those in the benchmark analysis.

We also run exogeneity tests for UFA using the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous.[24] We find evidence for the need to instrument UFA in the benchmark analysis. In particular, at this stage of the analysis we reject the null hypothesis that UFA can be treated as ex-

[22]We use the "ivreg2" command in Stata.

[23]For each asset we determine whether it belongs to either the NASDAQ100, or the S&P500, and we obtain its industry SIC code. For each asset i, asset j is unrelated with i if it has a different SIC code and if j is not in any index that asset i belongs to.

[24]This test corresponds to the endog option for the ivreg2 command in Stata. For further documentation see Baum, Schaffer, Stillman, et al. (2007)

ogenous when using lagged $PC100$ as instrument for all four of the 2013 IV estimations (one for each market quality variable). However, as shown in the following section, this may be due to an omitted variable. We include the results of the exogeneity tests in Table VI: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold. With the HS instruments, the exogeneity tests display similar results. When using the lagged value as instrument, we find that around 45% of estimated coefficients fail to reject exogeneity, and for the HS instrument only in 20% of cases do we fail to reject the exogeneity hypothesis. As shown below, this changes significantly when we include an omitted variable.

C. Controlling for commonality in market quality across stocks

An alternative approach is to address the cause of endogeneity directly and try to find a variable that is or proxies for the omitted source of endogeneity. Previous research has demonstrated the existence of market-wide factors in market quality determination (Chordia, Roll, and Subrahmanyam (2000) for example). Thus it is possible that the endogeneity of our variables is due to an omitted variable problem due to the exclusion of these market-level effects. To check this we modified our regression specification in the following way:

$$\begin{aligned} L_{i,t} &= \alpha_{0,i} + \alpha_{0,t30} + \alpha_1 PC100_{i,t} + \alpha_2 MOIMB_{i,t} + \alpha_3 VOLATM_{i,t} \\ &\quad + \alpha_4 \hat{L}_{i,t} + \alpha_5 \hat{L}_{i,t+1} + \alpha_6 \hat{L}_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $\hat{L}_{i,t}$ is the average value of market quality across all other stocks in the sample for day-minute t. Thus, the new specification allows market-wide market quality to affect stock level market quality. To allow for dynamics in this relationship we include the first lead and the first lag of the market quality variable also. Table IX contains the results from these estimations for 2009 and 2013 (results for all years are in Table X). As with the estimations of model (1), the results for 2013 are much stronger and more consistent than for 2009 and the sign and magnitude of the coefficients are similar to those in the baseline estimation presented in Table III. Overall, although there is a small reduction in the number of significant coefficients supporting the hypothesis (178 significant coefficients as compared with 190 in the benchmark analysis), we continue to find evidence for the negative relationship between market quality and UFA.

Again, we consider the possibility that our estimation suffers from endogeneity of UFA, so we repeat the analysis including market-wide liquidity effects in the IV estimations and the exogeneity tests (both using lagged endogenous variable and the Hasbrouck and Saar (2013) approach). The results are described in Tables XI-XIV. We find two key results. First, we repeat the exogeneity tests and find that the number of regressions for which we fail to reject the exogeneity hypothesis increases: from 45% to 55% of coefficients for the lagged value of $PC100$ as instrument, and from 20% to 71% for the Hasbrouck-Saar instrument. This supports the hypothesis that the endogeneity problems in the benchmark regressions are at least in part due to the omission of market-wide effects (both contemporaneous and in expectation–proxied by the lead values of the market-wide variable). However, the use of the IVs reduces the number of coefficients that are significant: only 80 (37%) are significant and in support of the negative relationship with market quality and 21 (10%) are significant and contradict the negative relationship with market quality. The combination of the tests of significance of the coefficients and exogeneity of the estimates suggests that the IV analysis is noisy and lends some support to the hypothesis of a negative relation between UFA and market quality.

D. Simultaneous estimation of market quality and UFA

Another way to address the endogeneity issue is to jointly estimate the effects of market quality and UFA on each other. We follow the methodological approach behind Table 7 in Hasbrouck and Saar (2013): We create an additional instrumental variable for market quality using the quoted spread built with the best bid and ask prices across all markets, except NASDAQ (*NBBOnoNQ_QSbps*), and we use 2SLS to estimate the following system:[25]

$$
\begin{aligned}
MQ_{i,t} &= a_0 + a_1\, PC100_{i,t} + a_2\, NBBOnoNQ\_QSbps_{i,t} + a_3\, MOIMB_{i,t} + a_4\, VOLATM_{i,t} + e_{1,i,t} \\
PC100_{i,t} &= b_0 + b_1\, MQ_{i,t} + b_2\, PC100HS_{i,t} + b_3\, MOIMB_{i,t} + b_4\, VOLATM_{i,t} + e_{2,i,t}\,,
\end{aligned}
$$

[25] The estimation is done with Stata's "reg3" command and includes 2013 data but not 2009. The omission of the analysis for 2009 is due to the lack of access to the 2009 TAQ dataset by the authors.

where MQ is a place holder for each of our four measures of market quality (QS, ES, $D01$, and $D10$) and *PC100HS* is the IV for UFA we constructed in our analysis described in Section V.B.

Table XV contains the results of the estimation using data for 2013. Again we find that the estimated effect of UFA on market quality is negative and consistent in magnitude with the estimates on Table VII.

E. Robustness checks

In addition to the estimations described so far, we run the basic regression, equation (1), with many small changes in specification and with many variations in the construction of the data, but with little noticeable change in the results.

We run the analysis with a new sample: 300 assets randomly sampled by size using the Fama-French size deciles, 30 assets from each decile (15 from NYSE and 15 from NASDAQ), using data for March 2013.[26] We run the analysis by separating the original sample of 120 assets into quintiles using traded dollar volume (for every year from 2009 to 2016) and have included the results in tables accompanying the results for the whole sample. Neither of these changes has qualitative effects on the results.

We ran regressions stock-by-stock and examined average coefficients. We used alternative PC measures ($PC50$ and $PC600$) without any significant changes in the results. As indicated above, we also used the well-known Hendershott, Jones, and Menkveld (2011) AT proxy instead of $PC100$ as a measure of UFA. This allows us to check whether our results are robust to our particular choice of UFA metric without any substantive changes in the results. In none of these cases do the basic results change in any economically significant way.[27]

[26] The results are available from the authors and in an Internet Appendix.

[27] We also ran a regression that looks at the complement of UFA, that is at slow post-cancels, using the total post-cancels minus $PC600$, and the results have the opposite sign as those for $PC100$ (and $PC600$).

VI. The Economics of UFA

Our analysis is primarily an empirical one. However, in this section we consider what economic effects drive UFA and why they lead to the negative relationship with liquidity that we observe.

A plausible explanation of the economics behind our results is that UFA is a public signal of worsening market making conditions (e.g. greater asymmetric information), which would naturally lead to worsening market quality.[28] However, there are other models that provide alternative economic rationales for UFA, which have specific empirical predictions. To explore these, we build several variables to identify the implied effects of these theories and their relationship with market quality variables and we analyze them empirically to see if they find support in the data. In the subsequent sections we consider three possible explanations (quote stuffing, liquidity provision, and adjustments to changes in volatility).

A. Quote Stuffing

Quote stuffing defines a strategy in which orders are used with a signal jamming purpose. A trader may want to post a large number of orders as part of a strategy to overload the information processing capacity of his competitors, as analysed for example in Egginton, Van Ness, and Van Ness (2016).[29]

Thus, our benchmark results would be due to quote stuffing if greater UFA would create a sufficiently significant load on traders and/or their trading systems to interfere with or drive out other traders and adversely affect market quality. However, as traders and trading systems are designed to deal with a substantial amount of information, this effect could only appear if UFA is of an unusually large order of magnitude, and would be unlikely to be present outside of such extreme episodes.

To test the effect of unusually large UFA on market quality, we use the classical methodology proposed by John Tukey (see McGill, Tukey, and Larsen (1978)) to identify outliers in $PC100$. We

[28] Cartea and Penalva (2012), Hoffmann (2014), Foucault, Hombert, and Roşu (2015) and Biais, Foucault, and Moinas (2015).

[29] NASDAQ defines quote stuffing as: "A practice of placing an unusual number of buy or sell orders on a particular security and then immediately canceling them. This can create confusion in the market and trading opportunities for algorithmic traders." (http://www.nasdaq.com/investing/glossary/q/quote-stuffing)

define an episode with an unusually large amount of $PC100$ for asset i as a minute in which the measure of $PC100$ is greater than η_i, where

$$\eta_i = PC100_{i,Q3} + 1.5\,(PC100_{i,Q3} - PC100_{i,Q1}),$$

$PC100_{i,Q3}$ is the third quartile of the sample of observations of $PC100$ for asset i, and $PC100_{i,Q3} - PC100_{i,Q1}$ is the interquartile range. Using η_i we define the dummy $d_{i,QS} = 1$ if $PC100_{i,Q3} > \eta_i$ and zero otherwise. These episodes with unusually large levels of UFA (outliers) are, somewhat surprisingly, not unusual –for 2013 they represent 23.8 percent of our sample, which implies that $PC100$ has very fat tails.

We introduce the dummy variable into our benchmark model, and we interact it with $PC100$. We find that during quote stuffing episodes market quality is worse: d_{QS} has a positive and significant coefficient on both quoted and effective spreads, and a negative one for depth close to the spread ($D1$). Results for 2013 and 2009 are summarized in Table XVI, and all results are in Table XVII. As with previous results, the year 2013 is representative of all but the year 2009, with its highly unusual circumstances.

The coefficients of the dummy variables for depth far from the spread (at $D10$) are not significant for half of the years in the sample. However, all other dummy coefficients are significant and with the same sign as those of the coefficients of $PC100$ in the benchmark regressions. The interaction term is significant and in the opposite direction as the $PC100$ coefficient. However, the magnitude of this coefficient is not sufficiently large to compensate that of the estimated unconditional effect of $PC100$, let alone, that of the dummy. So the presence of additional variables that separate high $PC100$ episodes does not invalidate our earlier analysis: the effect we found earlier is still occurring. Furthermore, the negative effect of $PC100$ on market quality is greater outside large $PC100$ episodes. For example, the coefficient of $PC100$ on quoted spreads in March 2013 increases from 0.116 to 0.155, that on the effective spread increases from 0.06 to 0.11, for $D1$ decreases from -0.06 to -0.13, and for $D10$ decreases from -0.033 to -0.062.

Therefore, episodes with a large amount of fleeting orders are associated with worsened market quality, but our results on UFA persist.

B. Liquidity Provision and Spoofing

Further explanations of the relationship between UFA and market quality can be obtained from three empirically related theories described in Hasbrouck (2013)'s study, two of which are associated with the provision of liquidity, and the last, spoofing, which is related to market manipulation or strategic "misinformation".

The first theory proposes that traders (trading algorithms) are often sending large numbers of quotes in a short span of time to garner information on market conditions. For example, we may be observing "Edgeworth cycles" in prices as one side of the market displays very gradual price improvements which quickly disappear. These gradual improvements can be considered as the equivalent of an impromptu clock auction as traders on one side of the market improve prices to test the market's demand elasticity (as proposed by Leach and Madhavan (1993) for a monopolistic dealer, or in Noel (2012) for energy prices). The theory states that greater competition will lead to an increase in this type of behavior and improved market quality.

Alternatively, frequent quoting activity could be part of a mixed strategy equilibrium in liquidity provision, as proposed in Varian (1980), and Baruch and Glosten (2013). These papers consider a situation in which traders post offers to trade at different prices but a posted offer becomes quickly suboptimal, so that in equilibrium, the optimal strategy is to randomize the posting of offers over a range of prices which results in a rapid posting-and-canceling of orders. In contrast with the previous theory, greater competition will lead to a decrease in this type of behavior, and better market quality.

Finally, the quoting activity could be part of a strategy that gains a trading advantage by generating noise in the learning process of other traders as proposed in Egginton, Van Ness, and Van Ness (2016). This could result in a strategy commonly known as spoofing, whereby traders will post aggressive offers that improve the price without any intention to trade on them, but rather, to try to provoke a reaction from other traders. This would lead to worsening market quality if the rest of the market withdraws liquidity in reaction to this behavior. Alternatively, we would observe the same effect if spoofing is more likely to occur during times with lower market quality.

A common feature of these explanations is that we should observe a significant number of price improvements. In the case of spoofing and mixed strategy liquidity provision, these price improving quotes are quickly canceled, whereas the gradual price improvements in Edgeworth cycles could be canceled quickly (if quotes are eliminated as new, better ones are introduced) or more gradually (if quotes are left in the order book until the end of the price improvement phase of the cycle, and this price improvement phase is sufficiently long).

Our UFA measure includes all fast-canceled orders, not just the ones that generate price improvements. Therefore, we separate post-cancel pairs into two: aggressive and non-aggressive. An aggressive post-cancel is one where the quote changes the best bid/ask when it is posted, and hence, represents an order that improves quoted prices. We find that aggressive post-and-cancel pairs represent 18.5 percent of $PC100$ in our sample. We compute the number of aggressive $PC100$ as a proportion of the total number of $PC100$ in each minute (for each asset). A high value of this ratio indicates an episode where the type of behavior described by the above theories is most prominent. In particular, it would be associated with greater spoofing and with less competitive liquidity provision in the mixed strategy equilibrium models (Baruch and Glosten (2013)) but greater competition in the Edgeworth cycle models (Hasbrouck (2013)).[30]

To analyze how UFA affects market quality controlling for aggressive and non-aggressive post-and-cancel pairs we proceed as follows. We create a dummy variable, denoted by d_{aggX}, which is one when the ratio of aggressive $PC100$ to total $PC100$ is above a certain cutoff level denoted by X (we use $X = 50$ percent and $X = 75$ percent as cutoffs) and zero otherwise. We find that 9.4 (resp. 4.3) percent of our sample represents episodes with a high proportion of aggressive d_{agg50} (resp. d_{agg75}) $PC100$s in 2013.

We introduce the dummy variable in our benchmark model and interact it with $PC100$, as we did above in subsection A. We find that the effect of $PC100$ remains approximately the same as those of the benchmark regressions whether we use d_{agg50} or d_{agg75}. Table XVIII shows the results for 2013 and 2009, and Table XIX shows results for all years. Again, we find that the interaction term is not significantly different from zero except for $D1$ (depth close to the best price), whereas the coefficients on the dummy are significant and point to an exacerbation of the effect of UFA, i.e. lower market quality.

[30]In the mixed strategy model, the use of mixed strategies by individual traders generates more frequent episodes of aggressive fleeting orders when there is less competition, as the population aggregates of the mixed strategies tends to display fewer price changes when the number of liquidity traders increases.

Thus, differentiating episodes where UFA is mostly determined by aggressive orders inside the spread does not alter our main results, although average market quality at those times is worse than expected. The fact that the relationship between $PC100$ and liquidity doesn't change when $PC100$ orders are mostly aggressive suggests that our results are not driven by fleeting orders caused by competitive market making or by spoofing.

C. Volatility driven UFA

Another possibility is that UFA is a byproduct of algorithm design, and responds to changes in volatility. Our analysis has already considered this possibility by incorporating volatility as an explanatory variable, namely $VOLATM$. However, because algorithms may be reacting differently under different volatility environments, we allow for a more flexible effect of volatility on our market quality variables, and test if UFA continues to have the same effect (sign) and to be significant.

We allow for different volatility environments and a direct effect of volatility on market quality by separating the data into different samples and running the same analysis as in equation (1). We separate all the data (for each year) into different groups sorted by volatility. Each group contains observations that have similar volatility conditions as determined by the (standardized) value of the $VOLATM$ variable. Thus, the least volatile observations are gathered in the group $VOLATM < -1.5$, that is $VOLATM$ is less than 1.5 standard deviations below its mean. Similarly, the most volatile observations are gathered in the group $VOLATM \geq 3$, that is $VOLATM$ is greater than 3 standard deviations above its mean. This asymmetry between the tails is imposed by the fact that our variable of interest, $VOLATM$, has a natural floor (zero). In between the two extreme volatility environments, we create intervals of realizations of volatility half a standard deviation wide. This gives us a total of 11 different samples, ordered by volatility. Then, within each sample, we run the benchmark panel regression as described by equation (1).

The results are summarized in Table XX for the years 2013 and 2009.[31] The basic pattern we observe is that the effect of UFA has the same sign as in the benchmark model. For spreads, the effect of UFA is strongest for lower volatility levels and can be insignificant (though with the same

[31]The complete set of tables for all the years is available upon request. The pattern is the same as in the other tables, namely 2013 is representative of all the years except 2009.

sign) for extremely high volatility levels. Again, the effect is qualitatively the same, but weaker for effective spreads. For depth, the effect of UFA is negative and is significant in most cases.[32] The effect is stronger for depth close to the bid-ask. Again, the extreme circumstances of March 2009 weaken our results to the point where we find essentially no significant effect of UFA on depth that month. However, the signs continue to be (mostly) negative and the lack of significance only occurs during this period.

Thus, we find that the effect of UFA is present even within periods with very similar volatility conditions, and our results cannot be explained solely as a byproduct of trading behavior associated with changes in volatility. The weakening significance in these regressions for larger levels of volatility can be interpreted as being due to the fact that in volatile periods there's so much going on that $PC100$ is less visible, while $PC100$ orders might be very noticeable in quiet times.

D. Economic significance

Here we show the effect of UFA on market quality by looking at the effects of a one standard deviation in $PC100$ on our measures of quoted and effective spread, and on the depth of the posted liquidity on the order book. Table XXI shows the results measured in percentage terms. These numbers reflect the estimated difference between the unconditional mean of the market quality variables (QS, ES, $D10$, and $D1$) and the mean conditional on one standard deviation increase in $PC100$, as a percentage of the unconditional mean of the variable, computed for each asset/year separately. For 2013 we find that a one standard deviation increase in $PC100$ leads to an increase of 4.8% in assets' quoted spreads on average. This increase has a standard deviation of 2.6 percent, and its interquartile range is [3.1% – 6.0%].

Interestingly, looking at the median effects, we observe that the strongest effects on market quality occur in the most recent years: the highest effects for spreads occur in 2015, while for $D1$ the strongest effect is in 2014. For 2010 the strongest effect appears in 2011 and the second strongest effect is found for 2014 as well. On the other hand, the weakest economic effects on market quality are found around the time of the financial crisis: on spreads it occurs in 2010, and on depth in 2009.

[32] The strongest results (most significance) are found for 2010 and 2011 (unreported, available upon request).

VII. Conclusions

We use millisecond-stamped data for NASDAQ to build a measure of ultra-fast activity (UFA) for the month of March in each of the years 2007 to 2015. Our results indicate that, using minutely data, ultra-fast activity is associated with lower market quality in stock markets. When UFA increases, quoted spreads increase, effective spreads increase, and the depth of the limit order book decreases. The sign of these effects is stable across the years in our data sample although there are some differences in the magnitude of these effects when comparing across years or different traded volume quintiles.

The results are also economically significant. For example, in March 2013 the effect of a one standard deviation in UFA generated on average an increase of between 3 and 6 percent in the quoted spread and effective spreads, as well as a drop of between 3 and 4 percent for depth measured close to the best bid and ask prices.

Our results are robust to controlling for market-wide market quality effects, to using various econometric methods to account for endogeneity of our UFA measure, and to various changes in data definitions and model specification. Moreover, we find that another measure of computer-based activity proposed in the literature, the AT metric of Hendershott, Jones, and Menkveld (2011) also has a consistent negative effect on market quality across time and stocks at the minutely sampling frequency. This effect is in most cases larger in magnitude than the effect of our measure of UFA.

One explanation is that $PC100$ is used as an indicator of the presence of better informed traders, as suggested by Foucault, Hombert, and Roşu (2015). Alternative possible explanations for the negative relationship between UFA and liquidity are that there are traders with a manipulative intent (spoofing, quote stuffing) or that UFA is a byproduct of competition for liquidity provision (Hasbrouck (2013)). We build variables to identify these effects and though we find them to indicate an additional worsening of market quality, our results continue to hold: greater UFA goes hand-in-hand with lower liquidity.

Our results are in line with some of the most recent empirical evidence that finds a negative relationship between high-speed machine-driven trading and market quality. This indicates that the known positive effects of market making HFT traders on liquidity may, under certain conditions, be outweighed by effects of other high-speed machine-driven trading strategies. Looking at aggregate intraday machine-driven activity leads to different conclusions than looking at isolated groups of traders.

Finally, our results have important regulatory implications. Our work suggests that particular types of order submission and cancellation strategies might need to be looked at rather carefully, but it should not be construed as justifying wholesale regulation of groups of market participants (e.g. high-frequency traders) defined by the quality of their technology or the half life of their inventory holdings.

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Table I
Summary statistics

The table shows the mean and standard deviation for the main variables in our analysis by year: quoted spread (*QS*), effective spread (*ES*), Depths at different levels (*D*1, *D*10 – depth at 1, and 10bps respectively), our measure of UFA using 1 ms (PC1), 50 ms (PC50), 100ms (PC100), and 600 ms (PC600), volatility measured as the realized volatility over the previous half hour ($VOLATM \times 10^6$), market-order imbalance (*MOIMB*), the measure of AT in Hendershott, Jones, and Menkveld (2011) (*AT*), and the number of messages (*N.Mess*). All variables exclude the first and last half hour of trading, and winsorization is applied at the 0.5th (left tail) and 99.5th (right tail) percentile for data on each stock.

	QS	*ES*	*D*1	*D*10	*PC*1	*PC*50	*PC*100	*PC*600	*VOLATM*	*MOIMB*	*AT*	*N.Mess.*	*N.Firms*
							2015						
Mean	17.84	5.54	68494	470011	15.3	46.9	51.4	67.4	481.6	39717.0	1.4	355.9	99
S.D.	22.29	6.96	99225	732170	31.6	102.4	114.1	152.1	217.3	78362.2	1.8	582.5	
							2014						
Mean	15.19	4.78	72972	466562	22.6	54.9	60.6	81.5	472.4	45298.2	1.6	392.5	107
S.D.	14.51	4.43	127633	748413	45.9	94.8	104.2	136.0	210.7	100489.9	3.3	514.0	
							2013						
Mean	19.40	5.17	79475	430129	13.8	30.6	33.4	42.0	409.0	37594.6	1.5	228.4	111
S.D.	27.06	6.25	147927	725516	22.7	43.1	46.3	57.3	190.2	116281.8	3.0	268.6	
							2012						
Mean	14.11	4.53	101055	597030	19.1	39.6	44.5	59.7	418.7	43535.8	1.2	333.5	113
S.D.	12.85	3.89	213907	987252	29.5	54.6	60.5	81.1	154.6	143129.2	3.4	372.0	
							2011						
Mean	14.52	4.47	95313	548301	9.3	32.3	38.4	56.9	530.1	44455.2	1.3	333.5	116
S.D.	12.53	3.39	244096	1129857	18.7	69.5	77.8	107.1	183.8	132210.9	2.7	434.8	
							2010						
Mean	15.10	4.63	121326	589989	3.3	23.0	27.6	44.8	459.9	44433.6	1.4	329.8	118
S.D.	20.21	4.58	265400	1051279	7.2	46.9	55.8	87.3	223.3	100656.4	2.9	436.8	
							2009						
Mean	44.84	13.09	51277	146212	1.4	39.6	53.1	86.1	1335.2	39633.2	1.0	535.5	120
S.D.	77.42	20.87	107126	277805	3.0	62.5	81.8	129.3	560.6	83108.3	1.9	748.2	
							2008						
Mean	21.29	6.38	74668	320749	0.5	30.0	36.5	62.7	885.8	67376.3	2.4	435.1	120
S.D.	19.82	5.86	166403	718554	1.5	66.0	80.3	129.2	251.4	160489.9	3.3	651.4	
							2007						
Mean	50.17	18.35	116561	483037	0.1	19.9	23.1	35.0	818.6	63363.9	2.4	281.9	118
S.D.	241.25	105.97	279409	969919	0.5	59.7	64.8	81.1	1018.4	153224.6	2.3	436.6	

Table II

Correlation matrix: average of the correlation matrices of March for years 2007 to 2015.

The table shows the average across years of the average pairwise correlation between variables for each asset-year. All variables exclude the first and last hour of trading, and winsorization is applied at the 0.5th (left tail) and 99.5th (right tail) percentile for data on each stock.

	QS	*ES*	*D1*	*D10*	*PC1*	*PC50*	*PC100*	*PC600*	*VOLATM*	*MOIMB*	*AT*	*N.Mess*
QS	1											
ES	0.47	1										
D1	-0.10	-0.08	1									
D10	-0.17	-0.12	0.67	1								
PC1	0.08	0.04	-0.03	-0.05	1							
PC50	0.13	0.09	-0.05	-0.07	0.66	1						
PC100	0.14	0.10	-0.06	-0.08	0.65	0.98	1					
PC600	0.15	0.11	-0.06	-0.08	0.61	0.93	0.96	1				
VOLATM	0.37	0.22	-0.19	-0.31	0.13	0.19	0.20	0.23	1			
MOIMB	-0.04	-0.03	0.10	0.05	0.24	0.29	0.30	0.32	0.08	1		
AT	-0.13	-0.13	0.14	0.06	0.11	0.09	0.09	0.10	0.02	0.67	1	
N.Mess	0.16	0.13	-0.06	-0.06	0.53	0.79	0.82	0.89	0.27	0.39	0.12	1

Table III
The effect of UFA on market quality: baseline results.

Regression coefficients for the panel regression described by Equation (1):

$$L_{i,t} = \alpha_{0,i} + \alpha_{0,t30} + \alpha_1\ PC100_{i,t} + \alpha_2\ MOIMB_{i,t} + \alpha_3\ VOLATM_{i,t} + \varepsilon_{i,t}.$$

on Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB. *MOIMB* represents US dollar market order imbalance for asset i, *VOLATM* represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, *PC*100 is the number of limit orders that are posted and, within 100 milliseconds (ms), subsequently canceled. We also include (but do not display) dummies for time effects using 30-minute intervals $t30$ (there is one dummy for 10:00-10:30, another for 10:30-11:00, etc for a total of 10 dummy variables plus the constant). All theses variables are standardized, and the panel estimation clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

VARIABLES	QS	ES	D01	D10
		2013		
$PC100$ (α_1)	0.124$^{\mathbf{a}}$	0.0793$^{\mathbf{a}}$	−0.0676$^{\mathbf{a}}$	−0.0328$^{\mathbf{a}}$
	(0.0105)	(0.00854)	(0.00684)	(0.00670)
MOIMB (α_2)	−0.122$^{\mathbf{a}}$	−0.0182$^{\mathbf{b}}$	0.126$^{\mathbf{a}}$	0.0604$^{\mathbf{a}}$
	(0.00578)	(0.00741)	(0.00716)	(0.00586)
VOLATM (α_3)	0.240$^{\mathbf{a}}$	0.123$^{\mathbf{a}}$	−0.134$^{\mathbf{a}}$	−0.220$^{\mathbf{a}}$
	(0.0121)	(0.00826)	(0.0112)	(0.0115)
Observations	732,600	396,456	732,600	732,600
R-squared	0.148	0.054	0.065	0.154
		2009		
$PC100$ (α_1)	0.0543$^{\mathbf{a}}$	0.0379$^{\mathbf{a}}$	-0.00227	0.00420
	(0.0100)	(0.00741)	(0.00687)	(0.00627)
MOIMB (α_2)	−0.0851$^{\mathbf{a}}$	−0.0864$^{\mathbf{a}}$	0.115$^{\mathbf{a}}$	0.0700$^{\mathbf{a}}$
	(0.00633)	(0.00740)	(0.00557)	(0.00478)
VOLATM (α_3)	0.298$^{\mathbf{a}}$	0.175$^{\mathbf{a}}$	−0.150$^{\mathbf{a}}$	−0.206$^{\mathbf{a}}$
	(0.0105)	(0.00966)	(0.0144)	(0.0161)
Observations	870,210	599,805	870,210	870,210
R-squared	0.136	0.044	0.054	0.096

Table IV
The effect of UFA on market quality: Benchmark

Coefficient of $PC100$, model (1), on Quoted Spread, Effective Spread, and Depths at different levels in the LOB. Below each coefficient we show the standard errors of the regression. Significance levels are denoted by $\mathbf{a} < 0.1$ percent, $\mathbf{b} < 1$ percent, $\mathbf{c} < 5$ percent.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.142^{a}	0.114^{a}	0.140^{a}	0.175^{a}	0.161^{a}	0.124^{a}	0.119^{a}	0.111^{a}	0.0842^{a}	0.143^{a}	0.163^{a}	0.104^{a}	0.124^{a}	0.158^{a}	0.105^{a}	0.171^{a}	0.146^{a}	0.0607^{a}
	(0.00858)	(0.0297)	(0.0255)	(0.0138)	(0.0131)	(0.0125)	(0.0108)	(0.0330)	(0.0226)	(0.0191)	(0.0302)	(0.0108)	(0.0105)	(0.0275)	(0.0267)	(0.0221)	(0.0165)	(0.0182)
ES	0.105^{a}	0.0979^{a}	0.113^{a}	0.123^{a}	0.113^{a}	0.0706^{a}	0.0639^{a}	0.0650^{a}	0.0472^{a}	0.0757^{a}	0.0652^{a}	0.0626^{a}	0.0793^{a}	0.0922^{a}	0.0650^{a}	0.0792^{a}	0.0858^{a}	0.0661^{a}
	(0.00854)	(0.0260)	(0.0195)	(0.00999)	(0.0165)	(0.0105)	(0.00730)	(0.0189)	(0.0157)	(0.0120)	(0.0156)	(0.0107)	(0.00854)	(0.0195)	(0.0209)	(0.0178)	(0.0122)	(0.0103)
D01	-0.0774^{a}	-0.156^{a}	-0.117^{a}	-0.0642^{a}	-0.0366^{a}	-0.0260^{a}	-0.0799^{a}	-0.115^{a}	-0.108^{a}	-0.0631^{a}	-0.0552^{a}	-0.0462^{a}	-0.0676^{a}	-0.103^{a}	-0.0840^{a}	-0.0380^{a}	-0.0508^{a}	-0.0505^{a}
	(0.00829)	(0.0192)	(0.0181)	(0.0109)	(0.00998)	(0.00806)	(0.00686)	(0.0193)	(0.0155)	(0.00752)	(0.0108)	(0.00880)	(0.00684)	(0.0207)	(0.0127)	(0.0141)	(0.0122)	(0.00827)
D10	-0.0481^{a}	-0.101^{a}	-0.0670^{a}	-0.0367^{a}	-0.0211^{b}	-0.00736	-0.0480^{a}	-0.0541^{b}	-0.0469^{a}	-0.0258^{a}	-0.0421^{a}	-0.0346^{a}	-0.0328^{a}	-0.0422^{c}	-0.0184	-0.00104	-0.0311^{a}	-0.0364^{a}
	(0.00728)	(0.0183)	(0.0173)	(0.0120)	(0.00943)	(0.00934)	(0.00719)	(0.0214)	(0.0175)	(0.00972)	(0.0128)	(0.00929)	(0.00670)	(0.0229)	(0.0126)	(0.0149)	(0.00867)	(0.0101)
	2012						2011						2010					
QS	0.0932^{a}	0.0916^{b}	0.108^{a}	0.124^{a}	0.0960^{a}	0.0881^{a}	0.105^{a}	0.119^{a}	0.131^{a}	0.0888^{a}	0.110^{a}	0.0915^{a}	0.124^{a}	0.0934^{a}	0.113^{a}	0.132^{a}	0.141^{a}	0.147^{a}
	(0.0106)	(0.0367)	(0.0297)	(0.0215)	(0.0142)	(0.0125)	(0.00885)	(0.0265)	(0.0211)	(0.0164)	(0.0175)	(0.0179)	(0.00761)	(0.0212)	(0.0180)	(0.0120)	(0.0179)	(0.0145)
ES	0.0640^{a}	0.0732^{a}	0.0573^{b}	0.0741^{a}	0.0598^{a}	0.0641^{a}	0.0670^{a}	0.0846^{a}	0.0601^{a}	0.0382^{a}	0.0719^{a}	0.0716^{a}	0.0209^{b}	-0.0493^{b}	0.0175	0.0357^{b}	0.0683^{a}	0.0910^{a}
	(0.00911)	(0.0220)	(0.0234)	(0.0138)	(0.0101)	(0.0122)	(0.00624)	(0.0147)	(0.0138)	(0.0144)	(0.00857)	(0.0116)	(0.00871)	(0.0208)	(0.0126)	(0.0172)	(0.0127)	(0.00929)
D01	-0.0718^{a}	-0.0743^{a}	-0.0927^{a}	-0.0449^{a}	-0.0515^{a}	-0.0590^{a}	-0.0680^{a}	-0.118^{a}	-0.0985^{a}	-0.0468^{a}	-0.0382^{a}	-0.0234^{b}	-0.0605^{a}	-0.0747^{a}	-0.0940^{a}	-0.0541^{a}	-0.0421^{a}	-0.0433^{a}
	(0.00553)	(0.0148)	(0.0116)	(0.00876)	(0.00963)	(0.00929)	(0.00577)	(0.0111)	(0.0107)	(0.0107)	(0.00719)	(0.00930)	(0.00411)	(0.0115)	(0.0109)	(0.00647)	(0.00598)	(0.00434)
D10	-0.0313^{a}	-0.00824	-0.0111	-0.00130	-0.0298^{a}	-0.0432^{a}	-0.0612^{a}	-0.0982^{a}	-0.0784^{a}	-0.0442^{a}	-0.0254^{a}	-0.0157	-0.0444^{a}	-0.0481^{a}	-0.0409^{a}	-0.0348^{a}	-0.0308^{a}	-0.0352^{a}
	(0.00771)	(0.0178)	(0.0238)	(0.0137)	(0.00856)	(0.00861)	(0.00575)	(0.0107)	(0.00934)	(0.00843)	(0.00906)	(0.0101)	(0.00389)	(0.00968)	(0.00885)	(0.00801)	(0.00762)	(0.00468)
	2009						2008						2007					
QS	0.0543^{a}	0.00205	0.0301	0.0754^{a}	0.0991^{a}	0.0600^{a}	0.104^{a}	0.102^{a}	0.104^{a}	0.0950^{a}	0.126^{a}	0.0954^{a}	0.0413^{a}	0.0763^{a}	0.0621^{a}	0.0717^{a}	0.0308^{c}	-0.0287^{a}
	(0.0100)	(0.0230)	(0.0265)	(0.0234)	(0.0153)	(0.0169)	(0.00800)	(0.0154)	(0.0167)	(0.0208)	(0.0185)	(0.0178)	(0.00710)	(0.0129)	(0.0133)	(0.0154)	(0.0164)	(0.00739)
ES	0.0379^{a}	0.0146	0.0276^{c}	0.0435^{a}	0.0650^{a}	0.0579^{a}	0.0730^{a}	0.0615^{a}	0.0911^{a}	0.0482^{a}	0.0818^{a}	0.0871^{a}	0.0239^{b}	0.0127	0.0402^{b}	0.0695^{a}	0.0449^{a}	-0.0103^{b}
	(0.00741)	(0.0172)	(0.0167)	(0.0147)	(0.00987)	(0.0155)	(0.00785)	(0.0222)	(0.0116)	(0.0181)	(0.0119)	(0.0135)	(0.0104)	(0.0262)	(0.0177)	(0.00991)	(0.0118)	(0.00507)
D01	-0.00227	0.00447	-0.00211	0.00664	-0.0158^{b}	-0.00328	-0.0430^{a}	-0.0856^{a}	-0.0435^{a}	-0.0379^{a}	-0.0184^{b}	-0.0160^{a}	-0.0657^{a}	-0.119^{a}	-0.0638^{a}	-0.0443^{a}	-0.0174^{b}	-0.0286^{a}
	(0.00687)	(0.0218)	(0.0183)	(0.0125)	(0.00720)	(0.0110)	(0.00494)	(0.0153)	(0.00890)	(0.00937)	(0.00762)	(0.00407)	(0.00592)	(0.00853)	(0.00873)	(0.00757)	(0.00683)	(0.00606)
D10	0.00420	0.0181	0.0196	0.00836	-0.0163^{b}	0.000312	-0.0257^{a}	-0.0463^{a}	-0.00731	-0.0270^{b}	-0.00876	-0.0165^{a}	-0.0618^{a}	-0.0898^{a}	-0.0614^{a}	-0.0379^{a}	-0.0141^{c}	-0.0188^{a}
	(0.00627)	(0.0168)	(0.0151)	(0.0118)	(0.00758)	(0.0115)	(0.00535)	(0.0167)	(0.00960)	(0.0135)	(0.00715)	(0.00428)	(0.00602)	(0.00543)	(0.0120)	(0.00885)	(0.00725)	(0.00697)

Table V
The effect of UFA on market quality: lagged PC as instrument

This table shows the coefficient of the IV of *PC*100 on Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB. The IV used is the lagged value of *PC*100. All these variables are standardized. The estimation includes 30minute dummies and clustered errors by asset id and time (day-minute). Below each coefficient we show the standard errors, the number of observations, and the adjusted R^2 of the regression, and we include the p-value of the exogeneity test. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	QS	ES	D1	D10
	2013			
*PC*100	0.290[a]	0.158[a]	-0.140[a]	-0.0605[a]
	(0.0269)	(0.0179)	(0.0201)	(0.0199)
Observations	723,800	394,566	723,800	723,800
R-squared	0.124	0.045	0.061	0.153
EndogP	-	0.000	0.000	0.043
	2009			
*PC*100	**0.0442**[c]	0.00867	**0.00139**	**0.00103**
	(0.0256)	(0.0184)	(0.0173)	(0.0158)
Observations	867,573	597,793	867,573	867,573
R-squared	0.134	0.043	0.054	0.095
EndogP	0.553	0.0228	0.764	0.723

Table VI
The effect of UFA on market quality: lagged PC as instrument

Coefficient of the lagged value of $PC100$ on Quoted Spread, Effective Spread and Depths at different levels in the LOB. Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.282^{a}	**0.182^{a}**	0.232^{a}	0.384^{a}	0.359^{a}	0.283^{a}	0.242^{a}	0.110^{b}	0.101^{c}	0.351^{a}	0.415^{a}	0.316^{a}	0.290^{a}	0.278^{a}	0.220^{a}	0.466^{a}	0.397^{a}	0.146^{a}
	(0.0217)	(0.0565)	(0.0493)	(0.0388)	(0.0410)	(0.0520)	(0.0271)	(0.0457)	(0.0544)	(0.0419)	(0.0566)	(0.0304)	(0.0269)	(0.0507)	(0.0608)	(0.0527)	(0.0597)	(0.0525)
ES	0.144^{a}	**0.0840^{b}**	0.162^{a}	0.202^{a}	**0.154^{a}**	0.182^{a}	0.0982^{a}	0.0598^{b}	0.0468	0.165^{a}	0.181^{a}	**0.113^{a}**	0.158^{a}	0.141^{a}	**0.0782^{a}**	0.240^{a}	0.239^{a}	0.167^{a}
	(0.0170)	(0.0388)	(0.0337)	(0.0276)	(0.0392)	(0.0214)	(0.0169)	(0.0279)	(0.0311)	(0.0255)	(0.0409)	(0.0310)	(0.0179)	(0.0297)	(0.0292)	(0.0484)	(0.0402)	(0.0320)
D01	-0.143^{a}	-0.258^{a}	-0.212^{a}	**-0.103^{a}**	**-0.0740^{a}**	**-0.0460^{c}**	-0.148^{a}	-0.174^{a}	-0.220^{a}	-0.0898^{a}	-0.112^{a}	**-0.0752^{b}**	-0.140^{a}	**-0.170^{a}**	-0.167^{a}	**-0.0534**	-0.118^{a}	-0.131^{a}
	(0.0210)	(0.0555)	(0.0529)	(0.0326)	(0.0271)	(0.0252)	(0.0193)	(0.0451)	(0.0379)	(0.0290)	(0.0347)	(0.0382)	(0.0201)	(0.0574)	(0.0460)	(0.0377)	(0.0334)	(0.0270)
D10	-0.0762^{a}	**-0.169^{a}**	**-0.0921^{c}**	**-0.0549**	**-0.0156**	**0.0147**	-0.0719^{a}	-0.0643	-0.0619	-0.00345	-0.0680	**-0.0261**	-0.0605^{a}	**-0.0683**	**-0.00582**	**0.0338**	**-0.0551^{c}**	-0.0849^{a}
	(0.0190)	(0.0505)	(0.0482)	(0.0356)	(0.0235)	(0.0259)	(0.0229)	(0.0511)	(0.0552)	(0.0410)	(0.0444)	(0.0381)	(0.0199)	(0.0619)	(0.0390)	(0.0462)	(0.0287)	(0.0296)
	2012						2011						2010					
QS	0.137^{a}	-0.0145	**0.0936**	0.280^{a}	0.275^{a}	0.266^{a}	0.153^{a}	**0.135^{a}**	0.175^{a}	**0.113^{a}**	0.203^{a}	**0.173^{a}**	0.229^{a}	**0.0743^{c}**	**0.160^{a}**	0.328^{a}	0.312^{a}	0.346^{a}
	(0.0306)	(0.0615)	(0.0721)	(0.0593)	(0.0422)	(0.0490)	(0.0209)	(0.0522)	(0.0356)	(0.0387)	(0.0445)	(0.0602)	(0.0219)	(0.0441)	(0.0451)	(0.0360)	(0.0480)	(0.0446)
ES	**0.0590^{b}**	**0.0186**	**0.0332**	**0.126^{a}**	0.153^{a}	0.158^{a}	**0.0763^{a}**	**0.0954^{a}**	**0.0625^{a}**	**0.0264**	0.110^{a}	**0.0950^{b}**	0.0524^{a}	**-0.0311**	**0.0429**	**0.0896^{c}**	0.169^{a}	0.215^{a}
	(0.0250)	(0.0418)	(0.0551)	(0.0422)	(0.0355)	(0.0416)	(0.0133)	(0.0291)	(0.0239)	(0.0293)	(0.0213)	(0.0470)	(0.0189)	(0.0403)	(0.0282)	(0.0543)	(0.0351)	(0.0328)
D01	-0.142^{a}	-0.132^{a}	-0.190^{a}	**-0.0609^{c}**	**-0.0819^{a}**	**-0.118^{a}**	-0.121^{a}	-0.214^{a}	-0.155^{a}	**-0.0754^{a}**	**-0.0580^{b}**	**-0.0163**	-0.129^{a}	**-0.115^{a}**	-0.207^{a}	-0.115^{a}	-0.0828^{a}	-0.0964^{a}
	(0.0188)	(0.0409)	(0.0399)	(0.0362)	(0.0315)	(0.0381)	(0.0144)	(0.0263)	(0.0240)	(0.0248)	(0.0238)	(0.0300)	(0.0110)	(0.0306)	(0.0278)	(0.0212)	(0.0187)	(0.0123)
D10	**-0.0501^{b}**	**-0.00264**	**-0.0209**	**0.0659**	**-0.0265**	**-0.0638^{c}**	-0.121^{a}	-0.188^{a}	-0.140^{a}	-0.0778^{a}	**-0.0328**	**-0.00465**	-0.101^{a}	-0.0870^{a}	-0.112^{a}	**-0.0637^{b}**	**-0.0500^{b}**	-0.0741^{a}
	(0.0235)	(0.0405)	(0.0612)	(0.0547)	(0.0335)	(0.0353)	(0.0153)	(0.0295)	(0.0205)	(0.0227)	(0.0290)	(0.0327)	(0.0115)	(0.0244)	(0.0251)	(0.0291)	(0.0223)	(0.0139)
	2009						2008						2007					
QS	**0.0442^{c}**	-0.133^{a}	-0.0484	**0.114^{b}**	0.230^{a}	0.154^{a}	0.147^{a}	**0.0923^{a}**	**0.139^{a}**	**0.128^{a}**	0.215^{a}	0.191^{a}	**0.0554^{a}**	**0.0752^{b}**	**0.0872^{a}**	0.178^{a}	**0.0654**	-0.101^{a}
	(0.0256)	(0.0457)	(0.0516)	(0.0539)	(0.0453)	(0.0561)	(0.0188)	(0.0266)	(0.0389)	(0.0438)	(0.0508)	(0.0530)	(0.0179)	(0.0317)	(0.0320)	(0.0458)	(0.0448)	(0.0250)
ES	0.00867	-0.0820^{b}	-0.0194	**0.0550**	0.147^{a}	**0.110^{a}**	0.0974^{a}	**0.0625^{b}**	0.125^{a}	**0.0715^{a}**	0.126^{a}	0.151^{a}	**0.0413^{b}**	**0.0143**	**0.0745^{a}**	0.136^{a}	**0.0868^{a}**	**-0.0157**
	(0.0184)	(0.0341)	(0.0346)	(0.0367)	(0.0259)	(0.0427)	(0.0141)	(0.0295)	(0.0263)	(0.0253)	(0.0315)	(0.0421)	(0.0176)	(0.0360)	(0.0250)	(0.0275)	(0.0311)	(0.0119)
D01	**0.00139**	**0.0260**	**-0.0109**	**0.0192**	-0.0481^{a}	**0.0234**	-0.0695^{a}	**-0.116^{a}**	-0.0714^{a}	**-0.0602^{a}**	**-0.0207**	**-0.0247^{c}**	-0.145^{a}	-0.219^{a}	-0.128^{a}	-0.102^{a}	**-0.0285**	-0.0641^{a}
	(0.0173)	(0.0421)	(0.0395)	(0.0318)	(0.0165)	(0.0310)	(0.0108)	(0.0282)	(0.0193)	(0.0229)	(0.0196)	(0.0139)	(0.0146)	(0.0248)	(0.0242)	(0.0203)	(0.0205)	(0.0173)
D10	**0.00103**	**0.0398**	**-0.000194**	**0.0105**	-0.0542^{a}	**0.0314**	-0.0439^{a}	**-0.0645^{b}**	**-0.0187**	**-0.0341**	**-0.00237**	**-0.0285^{b}**	-0.156^{a}	-0.199^{a}	-0.155^{a}	-0.0970^{a}	**-0.0239**	**-0.0428^{b}**
	(0.0158)	(0.0341)	(0.0333)	(0.0293)	(0.0201)	(0.0315)	(0.0128)	(0.0299)	(0.0243)	(0.0350)	(0.0198)	(0.0141)	(0.0153)	(0.0138)	(0.0324)	(0.0254)	(0.0211)	(0.0208)

Table VII
The effect of UFA on market quality: Hasbrouck-Saar Instrument

This table shows the coefficient of the IV of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB. The I.V. used is the $PC100$ constructed using the procedure in Hasbrouck and Saar (2013). All these variables are standardized. The estimation includes 30minute dummies and clustered errors by asset id and time (day-minute). Below each coefficient we show the standard errors, the number of observations, and the adjusted R^2 of the regression, and we include the p-value of the exogeneity test. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	QS	ES	D1	D10
		2013		
$PC100$	0.522[a]	0.354[a]	-0.223[a]	-0.134[a]
	(0.0351)	(0.0285)	(0.0291)	(0.0303)
Observations	726,000	396,098	726,000	726,000
R-squared	0.022	-0.027	0.046	0.148
EndogP	-	-	0.000	0.001
		2009		
$PC100$	0.525[a]	0.195[a]	**-0.0427**	-0.108[a]
	(0.0368)	(0.0227)	(0.0281)	(0.0286)
Observations	870,210	599,805	870,210	870,210
R-squared	-0.069	0.018	0.053	0.084
EndogP	-	0.000	0.156	0.000

Table VIII
The effect of UFA on market quality: Hasbrouck-Saar instrument

This table shows the coefficient of the IV of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB. The IV used is the $PC100$ constructed using the procedure in Hasbrouck and Saar (2013). All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we how the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.745^{a}	0.576^{a}	0.650^{a}	0.934^{a}	0.895^{a}	**0.391**^{b}	0.683^{a}	0.501^{a}	0.623^{a}	0.745^{a}	0.895^{a}	0.607^{a}	0.522^{a}	0.531^{a}	0.633^{a}	0.590^{a}	0.432^{a}	0.288^{a}
	(0.0497)	(0.0713)	(0.0580)	(0.137)	(0.157)	(0.173)	(0.0391)	(0.0431)	(0.0609)	(0.0839)	(0.148)	(0.121)	(0.0351)	(0.0676)	(0.0760)	(0.0669)	(0.0614)	(0.0888)
ES	0.567^{a}	0.441^{a}	0.525^{a}	0.719^{a}	0.732^{a}	0.620^{a}	0.457^{a}	0.376^{a}	0.446^{a}	0.514^{a}	0.550^{a}	0.451^{a}	0.354^{a}	0.368^{a}	0.435^{a}	0.321^{a}	0.223^{a}	**0.0398**
	(0.0432)	(0.0586)	(0.0553)	(0.151)	(0.168)	(0.204)	(0.0279)	(0.0383)	(0.0503)	(0.0680)	(0.112)	(0.102)	(0.0285)	(0.0564)	(0.0499)	(0.0625)	(0.0578)	(0.0684)
D01	-0.354^{a}	-0.365^{a}	-0.360^{a}	-0.504^{a}	**-0.210**^{c}	-0.386^{b}	-0.358^{a}	-0.386^{a}	-0.381^{a}	-0.558^{a}	-0.285^{a}	**-0.155**	-0.223^{a}	-0.381^{a}	-0.375^{a}	-0.217^{a}	**-0.164**^{b}	**0.0334**
	(0.0352)	(0.0322)	(0.0520)	(0.0867)	(0.108)	(0.166)	(0.0338)	(0.0355)	(0.0505)	(0.0959)	(0.0621)	(0.148)	(0.0291)	(0.0386)	(0.0518)	(0.0443)	(0.0656)	(0.106)
D10	-0.386^{a}	-0.289^{a}	-0.368^{a}	-0.742^{a}	-0.264^{a}	**-0.384**^{c}	-0.253^{a}	-0.289^{a}	-0.351^{a}	-0.398^{a}	-0.281^{a}	**-0.0911**	-0.134^{a}	-0.293^{a}	-0.329^{a}	**-0.0503**	**-0.152**^{c}	**-0.0416**
	(0.0460)	(0.0413)	(0.0721)	(0.134)	(0.101)	(0.203)	(0.0374)	(0.0440)	(0.0573)	(0.107)	(0.0619)	(0.144)	(0.0303)	(0.0352)	(0.0573)	(0.0624)	(0.0811)	(0.0993)
	2012						2011						2010					
QS	0.392^{a}	**0.163**^{a}	0.331^{a}	0.550^{a}	0.440^{a}	0.350^{a}	0.590^{a}	0.386^{a}	0.559^{a}	0.726^{a}	0.677^{a}	0.583^{a}	0.366^{a}	**0.162**^{c}	0.422^{a}	0.437^{a}	0.461^{a}	**0.257**^{b}
	(0.0272)	(0.0499)	(0.0572)	(0.0414)	(0.0583)	(0.0492)	(0.0454)	(0.0869)	(0.0791)	(0.121)	(0.0978)	(0.106)	(0.0384)	(0.0920)	(0.0723)	(0.0495)	(0.0818)	(0.101)
ES	0.263^{a}	0.236^{a}	0.233^{a}	0.357^{a}	0.242^{a}	**0.0894**^{c}	0.292^{a}	0.347^{a}	0.327^{a}	0.265^{a}	0.192^{a}	**0.114**^{c}	0.0792^{a}	**-0.0162**	0.136^{b}	0.138^{a}	**0.0327**	-0.122^{c}
	(0.0245)	(0.0526)	(0.0478)	(0.0431)	(0.0426)	(0.0498)	(0.0282)	(0.0532)	(0.0505)	(0.0752)	(0.0586)	(0.0619)	(0.0291)	(0.0761)	(0.0541)	(0.0337)	(0.0688)	(0.0676)
D01	-0.187^{a}	-0.259^{a}	-0.241^{a}	-0.161^{a}	-0.134^{a}	-0.220^{a}	-0.198^{a}	-0.314^{a}	-0.270^{a}	**-0.121**^{b}	**-0.150**^{b}	**-0.145**^{b}	-0.122^{a}	-0.199^{a}	-0.194^{a}	**-0.0599**	**0.0292**	-0.236^{a}
	(0.0170)	(0.0270)	(0.0310)	(0.0376)	(0.0315)	(0.0505)	(0.0230)	(0.0341)	(0.0312)	(0.0490)	(0.0659)	(0.0676)	(0.0238)	(0.0541)	(0.0266)	(0.0438)	(0.0787)	(0.0833)
D10	-0.120^{a}	-0.233^{a}	-0.193^{a}	**-0.0658**^{c}	**-0.0996**^{b}	-0.181^{a}	-0.233^{a}	-0.321^{a}	-0.368^{a}	-0.270^{a}	**-0.116**	**-0.148**^{c}	**-0.0879**^{a}	-0.246^{a}	**-0.104**^{b}	**-0.132**^{b}	**0.0489**	-0.294^{a}
	(0.0208)	(0.0275)	(0.0476)	(0.0400)	(0.0471)	(0.0555)	(0.0283)	(0.0517)	(0.0452)	(0.0619)	(0.0759)	(0.0884)	(0.0319)	(0.0505)	(0.0463)	(0.0613)	(0.0981)	(0.0859)
	2009						2008						2007					
QS	0.525^{a}	0.383^{a}	0.406^{a}	0.501^{a}	0.729^{a}	1.237^{a}	2.060^{a}	1.026^{a}	1.830^{a}	2.306^{a}	2.615^{a}	2.991^{a}	1.695^{a}	0.698^{a}	2.120^{a}	2.525^{a}	2.619^{a}	0.539^{c}
	(0.0368)	(0.0569)	(0.0541)	(0.0663)	(0.105)	(0.283)	(0.180)	(0.121)	(0.259)	(0.392)	(0.615)	(0.754)	(0.245)	(0.161)	(0.403)	(0.622)	(0.858)	(0.326)
ES	0.195^{a}	0.214^{a}	0.166^{a}	0.181^{a}	0.234^{a}	**0.365**^{c}	0.891^{a}	0.571^{a}	0.929^{a}	0.847^{a}	1.177^{a}	2.258^{c}	0.938^{a}	0.281^{a}	0.883^{a}	1.552^{a}	3.267	0.265^{b}
	(0.0227)	(0.0432)	(0.0420)	(0.0396)	(0.0712)	(0.217)	(0.0910)	(0.0926)	(0.131)	(0.203)	(0.392)	(1.355)	(0.131)	(0.0837)	(0.211)	(0.478)	(2.240)	(0.127)
D01	**-0.0427**	-0.0916^{a}	**-0.0802**^{b}	**0.0242**	**0.0306**	**0.0259**	-0.452^{a}	-0.341^{a}	-0.658^{a}	-0.535^{a}	**-0.271**^{b}	**-0.162**	-0.470^{a}	-0.478^{a}	-0.980^{a}	-0.802^{a}	-1.106^{b}	**0.261**
	(0.0281)	(0.0351)	(0.0364)	(0.0465)	(0.0636)	(0.237)	(0.0663)	(0.0818)	(0.123)	(0.156)	(0.137)	(0.236)	(0.107)	(0.0648)	(0.229)	(0.181)	(0.459)	(0.263)
D10	-0.108^{a}	-0.195^{a}	-0.0825^{b}	**-0.0525**	**-0.0745**	**-0.0547**	-0.550^{a}	-0.345^{a}	-0.683^{a}	-0.825^{a}	-0.463^{b}	**-0.415**^{c}	-1.004^{a}	-0.685^{a}	-1.945^{a}	-1.911^{a}	-1.580^{b}	**0.129**
	(0.0286)	(0.0409)	(0.0404)	(0.0491)	(0.0632)	(0.225)	(0.0785)	(0.0817)	(0.157)	(0.204)	(0.187)	(0.252)	(0.167)	(0.0957)	(0.387)	(0.396)	(0.659)	(0.238)

Table IX
The effect of UFA on market quality: controlling for market-wide liquidity.

Coefficient of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB in the estimation of the following equation

$$L_{i,t} = \alpha_{0,i} + \alpha_{0,30t} + \alpha_1\, PC100_{i,t} + \alpha_2\, MOIMB_{i,t} + \alpha_3\, VOLATM_{i,t} + \alpha_4 \hat{L}_{i,t} + \alpha_5 \hat{L}_{i,t+1} + \alpha_6 \hat{L}_{i,t-1} + \varepsilon_{i,t},$$

where $MOIMB$ represents US dollar market order imbalance for asset i and minute t (each minute is different for each day), $VOLATM$ represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, $PC100$ is the number of limit orders that are posted and, within 100 ms, subsequently canceled, and $\hat{L}_{i,t}$ is the market-wide liquidity measure at date (minute) t. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

VARIABLES	QS	ES	D01	D10
		2013		
$PC100(\alpha_1)$	0.116[a]	0.0554[a]	−0.0620[a]	−0.0259[a]
	(0.0105)	(0.0109)	(0.00674)	(0.00675)
MOIMB (α_2)	−0.121[a]	−0.0140	0.125[a]	0.0582[a]
	(0.00573)	(0.00909)	(0.00712)	(0.00595)
VOLATM (α_3)	0.200[a]	0.0790[a]	−0.119[a]	−0.200[a]
	(0.0136)	(0.0102)	(0.0104)	(0.0109)
$\hat{L}_t$ (α_4)	0.379[a]	0.571[a]	0.275[a]	0.300[a]
	(0.0313)	(0.0256)	(0.0224)	(0.0345)
$\hat{L}_{t+1}$ (α_5)	0.102[a]	0.0655[a]	0.143[a]	0.150[a]
	(0.0171)	(0.0229)	(0.0178)	(0.0343)
$\hat{L}_{t-1}$ (α_6)	0.0573[a]	0.0759[a]	0.0975[a]	0.0864[a]
	(0.0177)	(0.0174)	(0.0199)	(0.0332)
Observations	721,600	244,214	721,600	721,600
R-squared	0.156	0.065	0.070	0.161
		2009		
$PC100(\alpha_1)$	0.0453[a]	0.0279[a]	−0.000764	0.00728
	(0.0100)	(0.00839)	(0.00683)	(0.00617)
MOIMB (α_2)	−0.0879[a]	−0.103[a]	0.113[a]	0.0686[a]
	(0.00620)	(0.00931)	(0.00551)	(0.00456)
VOLATM (α_3)	0.229[a]	0.104[a]	−0.133[a]	−0.160[a]
	(0.0140)	(0.0136)	(0.0146)	(0.0151)
$\hat{L}_t$ (α_4)	0.532[a]	0.547[a]	0.271[a]	0.336[a]
	(0.0383)	(0.0298)	-0.0206	(0.0290)
$\hat{L}_{t+1}$ (α_5)	0.132[a]	0.186[a]	0.123[a]	0.165[a]
	(0.0397)	(0.0399)	(0.0217)	(0.0298)
$\hat{L}_{t-1}$ (α_6)	−0.00887	0.147[a]	0.0866[a]	0.121[a]
	(0.0359)	(0.0412)	(0.0223)	(0.0233)
Observations	864,936	445,194	864,936	864,936
R-squared	0.160	0.077	0.058	0.109

Table X

The effect of UFA on market quality: Benchmark plus Market-wide Liquidity

Coefficient of $PC100$, model (2) controlling for commonality in market quality, on Quoted Spread, Effective Spread and Depths at different levels in the LOB. Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** <0.1 percent, **b** <1 percent, **c** <5 percent.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.127^a	0.0648^b	0.101^a	0.166^a	0.153^a	0.127^a	0.108^a	0.0709^b	0.0605^b	0.133^a	0.156^a	0.112^a	0.116^a	0.133^a	0.0862^a	0.163^a	0.139^a	0.0637^a
	(0.00901)	(0.0284)	(0.0252)	(0.0144)	(0.0139)	(0.0136)	(0.0115)	(0.0352)	(0.0273)	(0.0197)	(0.0308)	(0.00849)	(0.0105)	(0.0312)	(0.0287)	(0.0220)	(0.0160)	(0.0175)
ES	0.0780^a	0.0592^b	0.0747^a	0.109^a	0.103^a	0.0885^a	0.0379^a	0.0276	0.0228	0.0665^a	0.0554^a	0.0870^a	0.0554^a	0.0622^a	0.0305^c	0.0648^a	0.0935^a	0.110^a
	(0.0120)	(0.0274)	(0.0195)	(0.0115)	(0.0225)	(0.0172)	(0.00986)	(0.0188)	(0.0193)	(0.0111)	(0.0201)	(0.0183)	(0.0109)	(0.0199)	(0.0185)	(0.0168)	(0.0140)	(0.0175)
D1	-0.0732^a	-0.144^a	-0.0995^a	-0.0600^a	-0.0334^a	-0.0294^a	-0.0699^a	-0.0871^a	-0.0914^a	-0.0571^a	-0.0502^a	-0.0420^a	-0.0620^a	-0.0886^a	-0.0755^a	-0.0346^b	-0.0468^a	-0.0492^a
	(0.00765)	(0.0179)	(0.0169)	(0.0103)	(0.00941)	(0.00887)	(0.00635)	(0.0181)	(0.0155)	(0.00783)	(0.0105)	(0.00917)	(0.00674)	(0.0213)	(0.0124)	(0.0137)	(0.0120)	(0.00915)
D10	-0.0395^a	-0.0798^a	-0.0421^b	-0.0300^a	-0.0172^c	-0.0121	-0.0366^a	-0.0261	-0.0314^c	-0.0178^c	-0.0366^a	-0.0305^a	-0.0259^a	-0.0326	-0.0120	0.00622	-0.0244^a	-0.0345^a
	(0.00661)	(0.0164)	(0.0175)	(0.0116)	(0.00939)	(0.0105)	(0.00697)	(0.0206)	(0.0185)	(0.00958)	(0.0124)	(0.00983)	(0.00675)	(0.0232)	(0.0123)	(0.0148)	(0.00892)	(0.0109)
	2012						2011						2010					
QS	0.0892^a	0.0896^b	0.0935^a	0.118^a	0.0935^a	0.0902^a	0.0805^a	0.0553^b	0.0907^a	0.0676^a	0.0977^a	0.0833^a	0.119^a	0.0732^a	0.101^a	0.128^a	0.138^a	0.149^a
	(0.0106)	(0.0352)	(0.0275)	(0.0223)	(0.0144)	(0.0116)	(0.00893)	(0.0246)	(0.0227)	(0.0170)	(0.0188)	(0.0181)	(0.00785)	(0.0208)	(0.0185)	(0.0125)	(0.0179)	(0.0145)
ES	0.0464^a	0.0546^a	0.0311	0.0616^a	0.0731^a	0.0573^a	0.0418^a	0.0447^a	0.0321^b	0.0294	0.0639^a	0.0591^a	0.00137	-0.0514^b	0.0197	0.0189	0.0637^a	0.122^a
	(0.0124)	(0.0210)	(0.0247)	(0.0168)	(0.0136)	(0.0215)	(0.00808)	(0.0149)	(0.0137)	(0.0191)	(0.00988)	(0.0172)	(0.0107)	(0.0221)	(0.0133)	(0.0227)	(0.0137)	(0.0164)
D1	-0.0642^a	-0.0546^a	-0.0775^a	-0.0408^a	-0.0471^a	-0.0580^a	-0.0585^a	-0.0898^a	-0.0828^a	-0.0420^a	-0.0350^a	-0.0206^b	-0.0586^a	-0.0676^a	-0.0895^a	-0.0535^a	-0.0423^a	-0.0434^a
	(0.00536)	(0.0141)	(0.0116)	(0.00865)	(0.00971)	(0.00952)	(0.00509)	(0.0107)	(0.00981)	(0.0101)	(0.00711)	(0.00933)	(0.00384)	(0.0111)	(0.00918)	(0.00633)	(0.00593)	(0.00443)
D10	-0.0270^a	0.00245	0.00149	0.00162	-0.0276^a	-0.0447^a	-0.0477^a	-0.0637^a	-0.0493^a	-0.0341^a	-0.0209^b	-0.0130	-0.0414^a	-0.0366^a	-0.0338^a	-0.0318^a	-0.0306^a	-0.0361^a
	(0.00783)	(0.0168)	(0.0228)	(0.0139)	(0.00895)	(0.00909)	(0.00478)	(0.00847)	(0.00662)	(0.00721)	(0.00933)	(0.0103)	(0.00378)	(0.00889)	(0.00877)	(0.00831)	(0.00771)	(0.00465)
	2009						2008						2007					
QS	0.0453^a	-0.0166	0.0210	0.0664^a	0.0882^a	0.0592^a	0.0859^a	0.0398^a	0.0816^a	0.0816^a	0.120^a	0.0911^a	0.0304^a	0.0369^a	0.0469^a	0.0677^a	0.0291^c	-0.0318^a
	(0.0100)	(0.0236)	(0.0267)	(0.0232)	(0.0155)	(0.0167)	(0.00842)	(0.0152)	(0.0180)	(0.0206)	(0.0197)	(0.0185)	(0.00691)	(0.0117)	(0.0126)	(0.0157)	(0.0166)	(0.00762)
ES	0.0279^a	0.0141	0.0259	0.0357^b	0.0566^a	0.0966^a	0.0613^a	0.0277	0.0792^a	0.0455^b	0.0930^a	0.112^a	0.0202	-0.00485	0.0389^b	0.0761^a	0.0534^a	-0.00587
	(0.00839)	(0.0166)	(0.0158)	(0.0164)	(0.0111)	(0.0243)	(0.00936)	(0.0211)	(0.0122)	(0.0198)	(0.0147)	(0.0157)	(0.0132)	(0.0250)	(0.0172)	(0.0105)	(0.0150)	(0.00718)
D1	-0.000764	0.00615	-0.00119	0.00821	-0.0140^b	-0.00296	-0.0390^a	-0.0690^a	-0.0392^a	-0.0346^a	-0.0186^b	-0.0158^a	-0.0598^a	-0.102^a	-0.0564^a	-0.0425^a	-0.0158^b	-0.0286^a
	(0.00683)	(0.0220)	(0.0182)	(0.0126)	(0.00709)	(0.0111)	(0.00461)	(0.0156)	(0.00828)	(0.00919)	(0.00745)	(0.00421)	(0.00535)	(0.00792)	(0.00807)	(0.00747)	(0.00670)	(0.00617)
D10	0.00728	0.0211	0.0206	0.0121	-0.0118	0.000679	-0.0198^a	-0.0175	-0.000271	-0.0227^c	-0.00904	-0.0164^a	-0.0504^a	-0.0612^a	-0.0443^a	-0.0325^a	-0.0116^c	-0.0186^a
	(0.00617)	(0.0171)	(0.0147)	(0.0121)	(0.00741)	(0.0114)	(0.00506)	(0.0163)	(0.00937)	(0.0133)	(0.00699)	(0.00439)	(0.00508)	(0.00590)	(0.0102)	(0.00881)	(0.00696)	(0.00666)

Table XI
The effect of UFA on market quality: Lag-PC100 instrument plus market-wide liquidity.

This table shows the coefficient of the I.V. of *PC*100 on Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB, controlling by market-wide liquidity, as in Table IX. The I.V. used is the *PC*100 constructed using the procedure in Hasbrouck and Saar (2013). All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	QS	ES	D1	D10
		2013		
*PC*100	0.260[a]	0.0814[a]	-0.123[a]	**-0.0440**[b]
	(0.0276)	(0.0189)	(0.0200)	(0.0202)
Observations	721,600	244,214	721,600	721,600
R-squared	0.139	0.064	0.067	0.161
EndogP	0.00	0.02	0.00	0.20
		2009		
*PC*100	**0.0263**	-0.0147	**0.00602**	**0.00907**
	(0.0256)	(0.0190)	(0.0173)	(0.0156)
Observations	864,936	445,194	864,936	864,936
R-squared	0.160	0.076	0.058	0.109
EndogP	0.27	0.00	0.54	0.86

Table XII
The effect of UFA on market quality: Lag-PC100 instrument with market-wide liquidity

Coefficient of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB in the estimation of model (2), where $MOIMB$ represents US dollar market order imbalance for asset i and minute t (each minute is different for each day), $VOLATM$ represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, $PC100$ is the number of limit orders that are posted and, within 100 ms, subsequently canceled, and $\hat{L}_{i,t}$ is the market-wide liquidity measure at date (minute) t. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.241^{a}	**0.0638**	**0.132**^{a}	0.354^{a}	0.363^{a}	0.278^{a}	0.201^{a}	**0.00746**	**0.0279**	0.317^{a}	0.390^{a}	0.308^{a}	0.260^{a}	0.212^{a}	**0.160**^{b}	0.447^{a}	0.380^{a}	**0.134**^{a}
	(0.0231)	(0.0520)	(0.0511)	(0.0379)	(0.0457)	(0.0446)	(0.0299)	(0.0489)	(0.0712)	(0.0452)	(0.0584)	(0.0300)	(0.0276)	(0.0600)	(0.0680)	(0.0523)	(0.0589)	(0.0516)
ES	**0.0763**^{a}	0.00428	**0.0804**^{b}	0.211^{a}	**0.145**^{a}	0.238^{a}	**0.0247**	-0.0270	**0.00380**	0.163^{a}	**0.107**^{b}	0.202^{a}	0.0814^{a}	**0.0741**^{b}	**0.0180**	0.187^{a}	0.249^{a}	0.250^{a}
	(0.0211)	(0.0400)	(0.0345)	(0.0273)	(0.0553)	(0.0342)	(0.0213)	(0.0285)	(0.0454)	(0.0320)	(0.0469)	(0.0449)	(0.0189)	(0.0327)	(0.0288)	(0.0486)	(0.0495)	(0.0425)
D01	-0.123^{a}	-0.225^{a}	**-0.168**^{a}	**-0.0937**^{a}	**-0.0654**^{b}	**-0.0436**^{b}	-0.118^{a}	**-0.105**^{a}	-0.171^{a}	**-0.0702**^{b}	**-0.0968**^{a}	**-0.0660**^{c}	-0.123^{a}	**-0.134**^{b}	**-0.136**^{a}	**-0.0435**	-0.106^{a}	-0.127^{a}
	(0.0196)	(0.0533)	(0.0517)	(0.0311)	(0.0296)	(0.0213)	(0.0184)	(0.0401)	(0.0382)	(0.0303)	(0.0346)	(0.0365)	(0.0200)	(0.0598)	(0.0443)	(0.0368)	(0.0326)	(0.0282)
D10	**-0.0502**^{a}	**-0.117**^{b}	**-0.0333**	**-0.0452**	**-0.00687**	**0.0184**	**-0.0418**^{c}	**0.00434**	**-0.0150**	**0.0197**	**-0.0511**	**-0.0200**	**-0.0440**^{b}	**-0.0453**	**0.0132**	**0.0517**	**-0.0364**	-0.0809^{a}
	(0.0177)	(0.0460)	(0.0507)	(0.0339)	(0.0270)	(0.0217)	(0.0226)	(0.0494)	(0.0579)	(0.0399)	(0.0439)	(0.0370)	(0.0202)	(0.0629)	(0.0381)	(0.0463)	(0.0292)	(0.0306)
	2012						2011						2010					
QS	**0.118**^{a}	-0.0234	**0.0436**	0.255^{a}	0.265^{a}	0.256^{a}	**0.0978**^{a}	-0.0154	**0.0904**^{b}	**0.0676**	0.175^{a}	**0.152**^{b}	0.211^{a}	**0.0209**	**0.121**^{a}	0.312^{a}	0.306^{a}	0.343^{a}
	(0.0289)	(0.0537)	(0.0604)	(0.0608)	(0.0418)	(0.0460)	(0.0223)	(0.0531)	(0.0438)	(0.0421)	(0.0474)	(0.0597)	(0.0230)	(0.0463)	(0.0464)	(0.0371)	(0.0476)	(0.0449)
ES	0.00397	-0.0109	**-0.0195**	**0.102**^{b}	0.184^{a}	0.179^{b}	0.0141	-0.00141	**0.00464**	**0.0209**	**0.0857**^{a}	**0.0618**	**0.0132**	**-0.0563**	**0.0296**	**0.0463**	0.145^{a}	0.216^{a}
	(0.0260)	(0.0366)	(0.0545)	(0.0461)	(0.0555)	(0.0832)	(0.0158)	(0.0304)	(0.0262)	(0.0371)	(0.0229)	(0.0425)	(0.0222)	(0.0447)	(0.0312)	(0.0670)	(0.0408)	(0.0415)
D01	-0.118^{a}	**-0.0845**^{b}	-0.148^{a}	**-0.0441**	**-0.0669**^{b}	**-0.107**^{a}	-0.0994^{a}	-0.149^{a}	-0.119^{a}	**-0.0629**^{a}	**-0.0505**^{b}	**-0.00939**	-0.119^{a}	**-0.0925**^{a}	-0.186^{a}	-0.108^{a}	-0.0825^{a}	-0.0933^{a}
	(0.0182)	(0.0381)	(0.0392)	(0.0351)	(0.0318)	(0.0377)	(0.0128)	(0.0254)	(0.0230)	(0.0230)	(0.0229)	(0.0294)	(0.0104)	(0.0287)	(0.0244)	(0.0213)	(0.0182)	(0.0126)
D10	**-0.0383**	**0.0191**	**0.0119**	**0.0789**	**-0.0187**	**-0.0661**^{c}	-0.0914^{a}	-0.109^{a}	-0.0761^{a}	**-0.0543**^{a}	**-0.0243**	**0.00142**	-0.0905^{a}	**-0.0566**^{a}	-0.0902^{a}	**-0.0507**^{c}	**-0.0499**^{b}	-0.0718^{a}
	(0.0234)	(0.0370)	(0.0563)	(0.0551)	(0.0346)	(0.0357)	(0.0134)	(0.0237)	(0.0177)	(0.0189)	(0.0292)	(0.0327)	(0.0112)	(0.0218)	(0.0252)	(0.0297)	(0.0224)	(0.0141)
	2009						2008						2007					
QS	**0.0263**	-0.165^{a}	-0.0621	**0.0986**^{c}	0.202^{a}	0.153^{a}	0.113^{a}	-0.00837	**0.0951**^{b}	**0.102**^{b}	0.209^{a}	0.187^{a}	**0.0266**	-0.0258	**0.0479**	0.169^{a}	**0.0604**	-0.111^{a}
	(0.0256)	(0.0486)	(0.0510)	(0.0537)	(0.0466)	(0.0552)	(0.0197)	(0.0295)	(0.0413)	(0.0419)	(0.0533)	(0.0542)	(0.0182)	(0.0306)	(0.0307)	(0.0472)	(0.0455)	(0.0263)
ES	-0.0147	-0.0847^{b}	-0.0237	**0.0445**	0.137^{a}	0.196^{a}	**0.0691**^{a}	-0.00701	**0.0984**^{a}	**0.0700**^{b}	0.149^{a}	**0.187**^{a}	**0.0289**	**-0.0359**	**0.0603**^{b}	0.154^{a}	0.137^{a}	**0.0252**
	(0.0190)	(0.0347)	(0.0320)	(0.0376)	(0.0324)	(0.0487)	(0.0158)	(0.0292)	(0.0268)	(0.0274)	(0.0358)	(0.0449)	(0.0205)	(0.0344)	(0.0256)	(0.0298)	(0.0465)	(0.0255)
D01	**0.00602**	**0.0314**	**-0.00688**	**0.0268**	-0.0411^{b}	**0.0228**	-0.0612^{a}	**-0.0845**^{a}	-0.0611^{a}	**-0.0538**^{b}	**-0.0219**	**-0.0258**^{c}	-0.130^{a}	-0.176^{a}	-0.111^{a}	-0.0973^{a}	**-0.0232**	-0.0629^{a}
	(0.0173)	(0.0422)	(0.0396)	(0.0322)	(0.0164)	(0.0312)	(0.0102)	(0.0295)	(0.0175)	(0.0223)	(0.0189)	(0.0143)	(0.0133)	(0.0224)	(0.0218)	(0.0199)	(0.0201)	(0.0175)
D10	**0.00907**	**0.0473**	**0.00388**	**0.0231**	**-0.0402**^{b}	**0.0310**	**-0.0315**^{b}	**-0.00505**	**-0.00165**	**-0.0262**	**-0.00345**	**-0.0301**^{b}	-0.126^{a}	-0.128^{a}	-0.112^{a}	-0.0826^{a}	**-0.0157**	**-0.0418**^{b}
	(0.0156)	(0.0349)	(0.0321)	(0.0300)	(0.0196)	(0.0313)	(0.0123)	(0.0313)	(0.0235)	(0.0341)	(0.0191)	(0.0146)	(0.0130)	(0.0149)	(0.0260)	(0.0249)	(0.0200)	(0.0197)

Table XIII

The effect of UFA on market quality: Hasbrouck-Saar instrument plus market-wide liquidity.

This table shows the coefficient of the I.V. of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB, controlling by market-wide liquidity, as in Table IX. The I.V. used is the $PC100$ constructed using the procedure in Hasbrouck and Saar (2013). All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	QS	ES	D1	D10
		2013		
$PC100$	**0.144**[a]	**0.103**[a]	**-0.0476**	0.0807[b]
	(0.0384)	(0.0242)	(0.0304)	(0.0336)
Observations	721,600	244,214	721,600	721,600
R-squared	0.156	0.063	0.070	0.152
EndogP	0.463	0.101	0.621	0.00138
		2009		
$PC100$	**0.0571**	**0.00142**	**0.0189**	0.0754[b]
	(0.0593)	(0.0366)	(0.0290)	(0.0323)
Observations	864,936	445,194	864,936	864,936
R-squared	0.160	0.077	0.058	0.104
EndogP	0.842	0.455	0.503	0.0392

Table XIV

The effect of UFA on market quality: Hasbrouck-Saar instrument with market-wide liquidity

Coefficient of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB in the estimation of model (2), where $MOIMB$ represents US dollar market order imbalance for asset i and minute t (each minute is different for each day), $VOLATM$ represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, $PC100$ is the number of limit orders that are posted and, within 100 ms, subsequently canceled, and $\hat{L}_{i,t}$ is the market-wide liquidity measure at date (minute) t. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. We use the typeface to describe the results of exogeneity tests: when the tests fail to reject the exogeneity hypothesis we display the estimated coefficients in bold.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.00766	**0.0473**	**0.143**^{a}	**0.259**^{a}	**0.215**^{c}	**-0.323**	0.288^a	0.245^a	0.314^a	0.336^a	**0.325**^{a}	**0.0993**	**0.144**^{a}	0.297^a	0.341^a	**0.230**^{a}	-0.0348	-0.425^a
	(0.0527)	(0.0612)	(0.0399)	(0.0820)	(0.120)	(0.226)	(0.0453)	(0.0466)	(0.0676)	(0.0717)	(0.105)	(0.0881)	(0.0384)	(0.0434)	(0.0673)	(0.0569)	(0.0798)	(0.140)
ES	**0.0416**	**0.0782**^{a}	**0.134**^{a}	**0.00380**	**0.0802**	**-0.0196**	0.124^a	0.140^a	0.219^a	**0.0632**	**0.0133**	**0.0721**	**0.103**^{a}	**0.149**^{a}	0.161^a	**-0.0483**	**-0.0150**	**-0.158**
	(0.0326)	(0.0259)	(0.0343)	(0.0903)	(0.148)	(0.579)	(0.0311)	(0.0370)	(0.0439)	(0.0558)	(0.0805)	(0.188)	(0.0242)	(0.0405)	(0.0374)	(0.0611)	(0.0497)	(0.216)
D01	**-0.0775**^{b}	-0.244^a	-0.195^a	-0.235^a	**0.0964**	**0.211**	**-0.0593**	-0.228^a	**-0.146**^{b}	-0.352^a	**0.0281**	0.370^a	**-0.0476**	-0.274^a	-0.232^a	**-0.0516**	**0.0231**	**0.223**
	(0.0376)	(0.0284)	(0.0412)	(0.0644)	(0.0960)	(0.147)	(0.0396)	(0.0363)	(0.0593)	(0.0648)	(0.0925)	(0.116)	(0.0304)	(0.0363)	(0.0438)	(0.0519)	(0.0530)	(0.140)
D10	0.0709^c	**-0.0619**^{b}	**-0.0802**	**-0.125**	**0.107**	**0.140**	0.111^a	**-0.0878**^{b}	**-0.101**	**-0.0369**	**0.124**	0.338^a	0.0807^b	-0.177^a	-0.149^a	0.260^a	**0.104**	**0.146**
	(0.0401)	(0.0312)	(0.0507)	(0.0824)	(0.1000)	(0.129)	(0.0398)	(0.0365)	(0.0746)	(0.0624)	(0.0983)	(0.112)	(0.0336)	(0.0410)	(0.0491)	(0.0626)	(0.0855)	(0.131)
	2012						2011						2010					
QS	**0.175**^{a}	-0.167^a	**0.0559**	0.439^a	0.348^a	**0.117**	**0.148**^{a}	**-0.0756**	**0.258**^{a}	**0.223**^{b}	**0.160**^{c}	**0.168**^{c}	**0.0618**	-0.338^c	**0.227**^{b}	**0.244**^{a}	**0.171**	**-0.0948**
	(0.0448)	(0.0641)	(0.0856)	(0.0880)	(0.0823)	(0.0822)	(0.0509)	(0.123)	(0.0905)	(0.101)	(0.0874)	(0.0860)	(0.0722)	(0.180)	(0.105)	(0.0893)	(0.152)	(0.188)
ES	**0.0267**	**-0.00712**	**0.00208**	0.205^a	**0.120**^{c}	**-0.187**	**0.0613**^{b}	**0.132**^{a}	**0.109**^{b}	**0.0234**	**0.00856**	**0.0904**	**0.00315**	**-0.133**	**0.101**^{c}	**0.0938**	**-0.0628**	**-0.135**
	(0.0267)	(0.0414)	(0.0337)	(0.0632)	(0.0690)	(0.165)	(0.0264)	(0.0430)	(0.0441)	(0.0730)	(0.0505)	(0.0916)	(0.0450)	(0.0968)	(0.0583)	(0.0593)	(0.114)	(0.164)
D01	**-0.0527**^{a}	-0.135^a	**-0.0980**^{a}	**-0.0696**^{b}	**-0.0419**^{b}	**-0.0861**	0.00816	**-0.128**^{a}	**-0.104**^{a}	**0.0368**	**0.0204**	**0.0236**	0.00968	**-0.0398**	**-0.0965**^{a}	**0.0217**	**0.0163**	**-0.0120**
	(0.0164)	(0.0253)	(0.0292)	(0.0339)	(0.0201)	(0.0568)	(0.0204)	(0.0278)	(0.0321)	(0.0442)	(0.0444)	(0.0550)	(0.0229)	(0.0439)	(0.0239)	(0.0543)	(0.0706)	(0.0809)
D10	0.0238	**-0.0205**	**0.0112**	**0.0760**	**-0.0287**	-0.220^a	0.0971^a	**-0.0788**^{a}	**-0.0420**	0.0806^c	0.110^b	**0.0293**	0.0811^b	**-0.0714**	**0.0334**	**0.0162**	**0.111**	**-0.188**^{c}
	(0.0266)	(0.0398)	(0.0548)	(0.0652)	(0.0637)	(0.0788)	(0.0213)	(0.0305)	(0.0334)	(0.0465)	(0.0521)	(0.0567)	(0.0333)	(0.0548)	(0.0378)	(0.0607)	(0.104)	(0.101)
	2009						2008						2007					
QS	**0.0571**	**-0.0411**	**0.0818**	**0.181**^{b}	**0.209**^{c}	**0.186**	**-0.0513**	**0.279**^{c}	0.927^a	0.895^a	-0.237^c	-0.979^a	**0.712**^{c}	**0.177**	**0.543**^{c}	0.805^a	0.844^b	**0.143**
	(0.0593)	(0.117)	(0.0914)	(0.0734)	(0.126)	(0.320)	(0.211)	(0.149)	(0.317)	(0.316)	(0.140)	(0.335)	(0.426)	(0.158)	(0.305)	(0.235)	(0.341)	(0.182)
ES	**0.00142**	**0.0264**	**0.0129**	**0.0509**	**0.0218**	**2.471**	**-0.0227**	**0.130**^{c}	**0.222**	**0.141**	**-0.288**	**0.0580**	0.387^a	**0.0724**	**0.315**	0.417^b	**0.466**	**-0.0123**
	(0.0366)	(0.0625)	(0.0601)	(0.0465)	(0.114)	(7.268)	(0.0859)	(0.0672)	(0.136)	(0.146)	(0.225)	(0.338)	(0.136)	(0.0784)	(0.232)	(0.166)	(0.320)	(0.0832)
D01	**0.0189**	**-0.0700**^{c}	**-0.0430**	**0.0752**	0.128^b	**0.233**	**0.0231**	**-0.161**^{c}	-0.324^a	**-0.265**^{c}	0.270^c	**0.446**^{c}	0.605^a	**-0.163**^{a}	**-0.281**	**-0.294**	**-0.0720**	0.515^b
	(0.0290)	(0.0380)	(0.0406)	(0.0501)	(0.0550)	(0.195)	(0.0744)	(0.0854)	(0.0987)	(0.146)	(0.152)	(0.239)	(0.190)	(0.0533)	(0.252)	(0.194)	(0.407)	(0.235)
D10	0.0754^b	-0.102^c	**0.0503**	**0.105**^{b}	0.155^a	**0.253**	0.201^b	**-0.00926**	**0.0427**	-0.440^a	**0.147**	**0.324**^{c}	1.309^a	**-0.0392**	**0.110**	-0.479^b	**0.00253**	**0.346**
	(0.0323)	(0.0522)	(0.0495)	(0.0474)	(0.0586)	(0.180)	(0.0836)	(0.0856)	(0.137)	(0.163)	(0.140)	(0.196)	(0.296)	(0.0468)	(0.287)	(0.214)	(0.520)	(0.212)

Table XV
The effect of UFA on market quality: Simultaneous equation estimation

This table presents pooled 2SLS regression analyses that relate UFA to market quality. The UFA measure is PC100. As an instrument of$PC100$we use *PC100HS* which is the average for all other stocks, excluding stock *i* itself and stocks in the same industry and index as *i*. MQ is a placeholder denoting Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB ($D01$ and $D10$). As an instrument for MQ we use *NBBOnoNQ_QSbps*, the average quoted spread (in bps) where the spread is computed as the NBBO of all other (non-NASDAQ) trading venues using TAQ data. All these variables are standardized. The estimation includes 30minute dummies. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent. The estimated system is the following:

$$\begin{aligned} MQ_{i,t} &= \alpha_0 + \alpha_1 PC100_{i,t} + \alpha_2 NBBOnoNQ\_QSbps_{i,t} + \alpha_3 MOIMB_{i,t} + \alpha_4 VOLATM_{i,t} + e_{1,i,t} \\ PC100_{i,t} &= \beta_0 + \beta_1 MQ_{i,t} + \beta_2 PC100HS_{i,t} + \beta_3 MOIMB_{i,t} + \beta_4 VOLATM_{i,t} + e_{2,i,t}. \end{aligned}$$

MQ	α_1	α_2	α_3	α_4	β_1	β_2	β_3	β_4
QS	0.668**a**	0.0390**a**	−0.319**a**	−0.0021	0.131**a**	0.444**a**	0.287**a**	0.244**a**
ES	0.339**a**	0.0229**a**	−0.121**a**	0.0623**a**	0.293**a**	0.559**a**	0.250**a**	0.208**a**
D01	−0.293**a**	−0.0100**a**	0.220**a**	−0.0294**a**	−0.483**a**	0.418**a**	0.337**a**	0.215**a**
D10	−0.283**a**	−0.0106**a**	0.158**a**	−0.0372**a**	−0.461**a**	0.424**a**	0.306**a**	0.215**a**

Table XVI
The Effect of Quote Stuffing: 2013 and 2009

Coefficient of $PC100$, the quote-stuffing dummy (d_{QS}), and their interaction, ($d_{QS} \times PC100$) on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB in the estimation of the following equation

$$L_{i,t} = \alpha_{0,i} + \alpha_{0,30t} + \alpha_1\, PC100_{i,t} + \alpha_2\, MOIMB_{i,t} + \alpha_3\, VOLATM_{i,t} + \alpha_4\, d_{i,t,QS} + \alpha_5\, d_{i,t,QS} \times PC100_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where $MOIMB$ represents US dollar market order imbalance for asset i and minute t (each minute is different for each day), $VOLATM$ represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, $PC100$ is the number of limit orders that are posted and, within 100 ms, subsequently canceled, and $\hat{L}_{i,t}$ is the market-wide liquidity measure at date (minute) t. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

	QS	ES	D1	D10
		2013		
d_{QS}	0.162**a**	0.177**a**	-0.127**a**	-0.0548**a**
	(0.0267)	(0.0415)	(0.0144)	(0.0172)
$PC100$	0.169**a**	0.145**a**	-0.140**a**	-0.0561**a**
	(0.0191)	(0.0249)	(0.0165)	(0.0157)
$PC100 \times d_{QS}$	-0.100**a**	-0.134**a**	0.130**a**	0.0460**a**
	(0.0175)	(0.0269)	(0.0143)	(0.0134)
Observations	726,000	396,098	726,000	726,000
R-squared	0.151	0.057	0.068	0.157
		2009		
d_{QS}	0.143**a**	0.107**a**	-0.0398**b**	-0.0166
	(0.0250)	(0.0176)	(0.0155)	(0.0165)
$PC100$	0.0393	0.0113	-0.0431**b**	-0.00551
	(0.0239)	(0.0196)	(0.0194)	(0.0174)
$PC100 \times d_{QS}$	-0.0158	0.00831	0.0605**a**	0.0161
	(0.0232)	(0.0186)	(0.0178)	(0.0161)
Observations	870,210	599,805	870,210	870,210
R-squared	0.137	0.045	0.055	0.096

Table XVII
The Effect of Quote Stuffing

Coefficient of $PC100$, the quote-stuffing dummy (d_{QS}), and their interaction, ($d_{QS} \times PC100$), in model (3). Significance levels are denoted by **a** $<$ 0.1 percent, **b** $<$ 1 percent, **c** $<$ 5 percent.

	d_{QS}	$PC100$	$PC100 \times d_{QS}$	d_{QS}	$PC100$	$PC100 \times d_{QS}$	d_{QS}	$PC100$	$PC100 \times d_{QS}$
		2015			2014			2013	
QS	$0.241^{\mathbf{a}}$	$0.178^{\mathbf{a}}$	$-0.109^{\mathbf{a}}$	$0.111^{\mathbf{a}}$	$0.122^{\mathbf{a}}$	-0.0303	$0.162^{\mathbf{a}}$	$0.169^{\mathbf{a}}$	$-0.100^{\mathbf{a}}$
ES	$0.117^{\mathbf{a}}$	$0.175^{\mathbf{a}}$	$-0.128^{\mathbf{a}}$	$0.102^{\mathbf{a}}$	$0.110^{\mathbf{a}}$	$-0.0881^{\mathbf{a}}$	$0.177^{\mathbf{a}}$	$0.145^{\mathbf{a}}$	$-0.134^{\mathbf{a}}$
D1	$-0.104^{\mathbf{a}}$	$-0.184^{\mathbf{a}}$	$0.168^{\mathbf{a}}$	$-0.167^{\mathbf{a}}$	$-0.178^{\mathbf{a}}$	$0.174^{\mathbf{a}}$	$-0.127^{\mathbf{a}}$	$-0.140^{\mathbf{a}}$	$0.130^{\mathbf{a}}$
D10	-0.0192	$-0.102^{\mathbf{a}}$	$0.0744^{\mathbf{a}}$	$-0.0877^{\mathbf{a}}$	$-0.0909^{\mathbf{a}}$	$0.0810^{\mathbf{a}}$	$-0.0548^{\mathbf{a}}$	$-0.0561^{\mathbf{a}}$	$0.0460^{\mathbf{a}}$
		2012			2011			2010	
QS	$0.111^{\mathbf{a}}$	$0.125^{\mathbf{a}}$	$-0.0695^{\mathbf{a}}$	$0.186^{\mathbf{a}}$	$0.197^{\mathbf{a}}$	$-0.164^{\mathbf{a}}$	$0.302^{\mathbf{a}}$	$0.208^{\mathbf{a}}$	$-0.176^{\mathbf{a}}$
ES	$0.0968^{\mathbf{a}}$	$0.173^{\mathbf{a}}$	$-0.162^{\mathbf{a}}$	$0.103^{\mathbf{a}}$	$0.163^{\mathbf{a}}$	$-0.145^{\mathbf{a}}$	$0.112^{\mathbf{a}}$	$-0.0411^{\mathbf{b}}$	$0.0500^{\mathbf{a}}$
D1	$-0.111^{\mathbf{a}}$	$-0.164^{\mathbf{a}}$	$0.148^{\mathbf{a}}$	$-0.0949^{\mathbf{a}}$	$-0.237^{\mathbf{a}}$	$0.234^{\mathbf{a}}$	$-0.100^{\mathbf{a}}$	$-0.202^{\mathbf{a}}$	$0.197^{\mathbf{a}}$
D10	-0.0190	$-0.0673^{\mathbf{a}}$	$0.0518^{\mathbf{a}}$	$-0.0397^{\mathbf{a}}$	$-0.215^{\mathbf{a}}$	$0.201^{\mathbf{a}}$	$-0.0526^{\mathbf{a}}$	$-0.135^{\mathbf{a}}$	$0.124^{\mathbf{a}}$
		2009			2008			2007	
QS	$0.143^{\mathbf{a}}$	0.0393	-0.0158	$0.201^{\mathbf{a}}$	$0.234^{\mathbf{a}}$	$-0.198^{\mathbf{a}}$	$0.0605^{\mathbf{a}}$	$0.106^{\mathbf{a}}$	$-0.0850^{\mathbf{a}}$
ES	$0.107^{\mathbf{a}}$	0.0113	0.00831	$0.144^{\mathbf{a}}$	$0.116^{\mathbf{a}}$	$-0.0846^{\mathbf{a}}$	$0.134^{\mathbf{a}}$	$-0.124^{\mathbf{a}}$	$0.140^{\mathbf{a}}$
D1	$-0.0398^{\mathbf{b}}$	$-0.0431^{\mathbf{b}}$	$0.0605^{\mathbf{a}}$	$-0.0364^{\mathbf{a}}$	$-0.219^{\mathbf{a}}$	$0.213^{\mathbf{a}}$	$-0.0690^{\mathbf{a}}$	$-0.370^{\mathbf{a}}$	$0.354^{\mathbf{a}}$
D10	-0.0166	-0.00551	0.0161	0.00189	$-0.160^{\mathbf{a}}$	$0.155^{\mathbf{a}}$	$-0.0616^{\mathbf{a}}$	$-0.331^{\mathbf{a}}$	$0.313^{\mathbf{a}}$

Table XVIII
Liquidity Provision: 2013 and 2009

Coefficient of $PC100$, the dummy for high aggressive $PC100$s (d_{agg50}: percentage of aggressive $PC100$ above the median, d_{agg75}: percentage of aggressive $PC100$ above the third quartile), and their interaction, ($d_{aggX} \times PC100$, with $X \in \{50, 75\}$) on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB in the estimation of the following equation

$$L_{i,t} = \alpha_{0,i} + \alpha_{0,30t} + \alpha_1\, PC100_{i,t} + \alpha_2\, MOIMB_{i,t} + \alpha_3\, VOLATM_{i,t} + \alpha_4\, d_{i,t,aggX} + \alpha_5\, d_{i,t,aggX} \times PC100_{i,t} + \varepsilon_{i,t}, \quad (4)$$

where $MOIMB$ represents US dollar market order imbalance for asset i and minute t (each minute is different for each day), $VOLATM$ represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, $PC100$ is the number of limit orders that are posted and, within 100 ms, subsequently canceled, and $\hat{L}_{i,t}$ is the market-wide liquidity measure at date (minute) t. All theses variables are standardized. The estimation includes 30 minute dummies and clusters errors by asset id and time (day-minute). Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

	d_{agg50}	$PC100$	$d_{agg50} \times PC100$	d_{agg75}	$PC100$	$d_{agg75} \times PC100$
	2013			2013		
QS	0.243**a**	0.129**a**	-0.0410**b**	0.223**a**	0.130**a**	-0.0658**a**
ES	0.174**a**	0.0823**a**	-0.00888	0.126**a**	0.0811**a**	-0.0147
D1	-0.0583**a**	-0.0773**a**	0.0687**a**	-0.0567**a**	-0.0721**a**	0.0671**a**
D10	-0.0320**a**	-0.0367**a**	0.0308**a**	-0.0335**b**	-0.0340**a**	0.0238**b**
	2009			2009		
QS	0.267**a**	0.0513**a**	-0.0175	0.258**a**	0.0535**a**	-0.0209**c**
ES	0.114**a**	0.0360**a**	0.00546	0.0823**a**	0.0377**a**	-0.00185
D1	-0.0447**a**	-0.00292	0.0114	-0.0371**b**	-0.00232	0.00532
D10	-0.00232	0.00385	0.00292	0.0144	0.00417	-0.00135

Table XIX
Liquidity Provision.

Coefficient of $PC100$, the dummy for high fraction of aggressive $PC100$ (d_{agg50}), and their interaction, ($d_{agg50} \times PC100$), in model (4). Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

	d_{agg50}	$PC100$	$d_{agg50} \times PC100$	d_{agg50}	$PC100$	$d_{agg50} \times PC100$	d_{agg50}	$PC100$	$d_{agg50} \times PC100$
	2015			2014			2013		
QS	0.182^{a}	0.149^{a}	-0.0488^{a}	0.165^{a}	0.123^{a}	-0.0202	0.243^{a}	0.129^{a}	-0.0410^{b}
ES	0.163^{a}	0.113^{a}	-0.0641^{a}	0.118^{a}	0.0657^{a}	-0.00824	0.174^{a}	0.0823^{a}	-0.00888
D1	-0.0879^{a}	-0.0912^{a}	0.0730^{a}	-0.0760^{a}	-0.0866^{a}	0.0610^{a}	-0.0583^{a}	-0.0773^{a}	0.0687^{a}
D10	-0.0240^{c}	-0.0592^{a}	0.0573^{a}	-0.0210	-0.0525^{a}	0.0470^{a}	-0.0320^{a}	-0.0367^{a}	0.0308^{a}
	2012			2011			2010		
QS	0.388^{a}	0.0924^{a}	-0.0191	0.274^{a}	0.102^{a}	-0.0422^{a}	0.447^{a}	0.114^{a}	-0.0198^{c}
ES	0.222^{a}	0.0661^{a}	-0.0429^{a}	0.116^{a}	0.0676^{a}	-0.0195^{b}	0.237^{a}	0.0100	0.0573^{a}
D1	-0.0130	-0.0774^{a}	0.0739^{a}	-0.0536^{a}	-0.0831^{a}	0.0800^{a}	-0.0768^{a}	-0.0738^{a}	0.0727^{a}
D10	-0.00669	-0.0347^{a}	0.0525^{a}	-0.0308^{a}	-0.0772^{a}	0.0803^{a}	-0.0422^{a}	-0.0554^{a}	0.0569^{a}
	2009			2008			2007		
QS	0.267^{a}	0.0513^{a}	-0.0175	0.305^{a}	0.0969^{a}	-0.0166^{c}	0.211^{a}	0.0509^{a}	-0.0683^{a}
ES	0.114^{a}	0.0360^{a}	0.00546	0.147^{a}	0.0706^{a}	-0.00525	0.205^{a}	0.0187	0.00151
D1	-0.0447^{a}	-0.00292	0.0114	-0.0648^{a}	-0.0501^{a}	0.0454^{a}	-0.0891^{a}	-0.0776^{a}	0.0584^{a}
D10	-0.00232	0.00385	0.00292	-0.0489^{a}	-0.0318^{a}	0.0381^{a}	-0.0647^{a}	-0.0782^{a}	0.0721^{a}

Table XX
The effect of UFA by volatility levels

Coefficient of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB in the estimation of model (2), where $MOIMB$ represents US dollar market order imbalance for asset i and minute t (each minute is different for each day), $VOLATM$ represents volatility for asset i and minute t measured as the realized volatility over the previous half hour, $PC100$ is the number of limit orders that are posted and, within 100 ms, subsequently canceled, and $\hat{L}_{i,t}$ is the market-wide liquidity measure at date (minute) t. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors and the number of observations of the regression. Each columns represents the results from the regression over the sample of observations with a similar level of (standardised) volatility. Thus, the column labelled $-0.5 \leq x < 0$ only includes observations for which (standardised) $VOLATM$ had a value between -0.5 and 0. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

		$x < -1.5$	$-1.5 \leq x < -1$	$-1 \leq x < -0.5$	$-0.5 \leq x < 0$	$0 \leq x < 0.5$	$0.5 \leq x < 1$	$1 \leq x < 1.5$	$1.5 \leq x < 2$	$2 \leq x < 2.5$	$2.5 \leq x < 3$	$x \geq 3$
							2013					
QS	coeff	0.127**a**	0.0911**a**	0.0974**a**	0.103**a**	0.117**a**	0.119**a**	0.127**a**	0.126**a**	0.140**a**	0.153**a**	0.167**a**
	s.e.	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)	(0.0241)
ES	coeff	0.0684**a**	0.0767**a**	0.0507**a**	0.0574**a**	0.0666**a**	0.0675**a**	0.0743**a**	0.0821**a**	0.0937**a**	0.115**a**	0.152**a**
	s.e.	(0.0148)	(0.0174)	(0.0149)	(0.0127)	(0.0112)	(0.00921)	(0.00925)	(0.00888)	(0.0111)	(0.0148)	(0.0322)
D1	coeff	-0.0699**a**	-0.0574**a**	-0.0775**a**	-0.0474**a**	-0.0503**a**	-0.0513**a**	-0.0525**a**	-0.0615**a**	-0.0800**a**	-0.124**a**	-0.290**a**
	s.e.	(0.0126)	(0.0128)	(0.0105)	(0.0103)	(0.00850)	(0.00715)	(0.00721)	(0.00836)	(0.00964)	(0.0154)	(0.0501)
D10	coeff	-0.0820**a**	-0.0444**a**	-0.0479**a**	-0.0232**b**	-0.0205**b**	-0.0216**a**	-0.0200**a**	-0.0204**b**	-0.0361**a**	-0.0504**a**	-0.0926**b**
	s.e.	(0.0169)	(0.0146)	(0.0119)	(0.0117)	(0.00847)	(0.00773)	(0.00749)	(0.00812)	(0.00861)	(0.0132)	(0.0407)
							2009					
QS	coeff	0.0182	0.0448**b**	0.0439**b**	0.0510**a**	0.0503**a**	0.0486**a**	0.0519**a**	0.0609**a**	0.0620**a**	0.0635**a**	0.0848**a**
	s.e.	(0.0272)	(0.0189)	(0.0198)	(0.0156)	(0.0140)	(0.0119)	(0.0105)	(0.0102)	(0.0111)	(0.0161)	(0.0272)
ES	coeff	0.0376**b**	0.0567**a**	0.0389**b**	0.0339**a**	0.0417**a**	0.0376**a**	0.0322**a**	0.0392**a**	0.0413**a**	0.0417**a**	0.0330**b**
	s.e.	(0.0184)	(0.0144)	(0.0152)	(0.0121)	(0.0105)	(0.00857)	(0.00867)	(0.00724)	(0.00840)	(0.0112)	(0.0167)
D1	coeff	-0.0353**b**	-0.0178	-0.0109	-0.00912	-0.00498	-0.00485	-0.00488	0.00934	0.00549	0.00138	-0.0351
	s.e.	(0.0150)	(0.0122)	(0.0123)	(0.0103)	(0.00845)	(0.00734)	(0.00651)	(0.00742)	(0.0102)	(0.0137)	(0.0316)
D10	coeff	-0.0390**a**	-0.00301	-0.0103	-0.0127	-0.00242	-0.000199	0.00548	0.0197**a**	0.0142	0.00330	-0.0353
	s.e.	(0.0146)	(0.0131)	(0.0107)	(0.00896)	(0.00802)	(0.00593)	(0.00630)	(0.00693)	(0.00970)	(0.0133)	(0.0269)

Table XXI
Economic Significance. The effect of UFA on market quality measured in percentage terms (relative to mean market quality for the asset/year).

		2015	2014	2013	2012	2011	2010	2009	2008	2007
QS	Mean	6.0%	4.1%	4.8%	2.9%	3.6%	5.2%	2.1%	4.2%	2.5%
	St.Dev.	3.0%	1.9%	2.6%	1.5%	1.7%	12.5%	1.1%	1.9%	1.9%
	Q1	7.4%	5.4%	6.0%	4.0%	5.0%	5.1%	2.6%	5.2%	3.1%
	Median	6.3%	4.6%	5.1%	3.4%	4.0%	4.5%	2.1%	4.2%	1.9%
	Q3	4.4%	3.2%	3.1%	1.3%	2.4%	2.5%	1.4%	3.0%	1.2%
ES	Mean	5.6%	3.5%	5.1%	3.3%	3.6%	1.0%	2.4%	4.7%	1.9%
	St.Dev.	2.2%	1.2%	2.5%	1.3%	1.7%	0.6%	1.3%	2.3%	1.5%
	Q1	7.0%	4.4%	6.2%	4.2%	4.8%	1.4%	3.1%	6.4%	2.4%
	Median	5.9%	3.7%	5.1%	3.6%	3.9%	1.1%	2.5%	4.6%	1.4%
	Q3	4.0%	2.6%	3.6%	2.3%	1.9%	0.5%	1.2%	2.8%	0.8%
D1	Mean	-3.9%	-4.4%	-3.9%	-3.6%	-4.8%	-4.1%	-0.1%	-2.7%	-4.3%
	St.Dev.	1.2%	1.5%	2.1%	1.2%	5.2%	1.7%	0.1%	1.2%	1.9%
	Q1	-3.1%	-3.5%	-2.7%	-2.9%	-3.1%	-3.0%	-0.1%	-1.9%	-3.2%
	Median	-3.5%	-4.1%	-3.2%	-3.4%	-3.7%	-3.6%	-0.1%	-2.4%	-3.8%
	Q3	-4.2%	-4.7%	-4.2%	-4.1%	-4.4%	-4.6%	-0.2%	-3.0%	-4.7%
D10	Mean	-2.3%	-2.3%	-1.7%	-1.4%	-4.0%	-2.5%	0.3%	-1.7%	-3.8%
	St.Dev.	1.1%	1.1%	1.1%	0.7%	3.8%	1.2%	0.2%	0.9%	1.8%
	Q1	-1.6%	-1.7%	-1.1%	-0.9%	-2.4%	-1.6%	0.3%	-1.2%	-2.6%
	Median	-1.9%	-2.1%	-1.4%	-1.2%	-2.9%	-2.1%	0.2%	-1.5%	-3.2%
	Q3	-2.7%	-2.6%	-1.9%	-1.7%	-3.8%	-3.0%	0.2%	-1.9%	-4.7%

Table XXII
The effect of UFA on market quality: AT

Coefficient of AT on Quoted Spread, Effective Spread and Depths at different levels in the LOB. Below each coefficient we show the standard errors and the adjusted R^2 of the regression. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1	All	Q5	Q4	Q3	Q2	Q1
	2015						2014						2013					
QS	0.186^{a}	0.173^{a}	0.242^{a}	0.248^{a}	0.148^{a}	0.107^{a}	0.203^{a}	0.206^{a}	0.259^{a}	0.247^{a}	0.172^{a}	0.116^{a}	0.175^{a}	0.223^{a}	0.239^{a}	0.202^{a}	0.137^{a}	0.0743^{a}
	(0.0111)	(0.0283)	(0.0255)	(0.0187)	(0.0128)	(0.0106)	(0.0103)	(0.0253)	(0.0244)	(0.0187)	(0.0123)	(0.0111)	(0.0111)	(0.0255)	(0.0255)	(0.0203)	(0.0142)	(0.0132)
ES	0.117^{a}	0.0794^{b}	0.136^{a}	0.221^{a}	0.105^{a}	0.0733^{a}	0.128^{a}	0.0993^{b}	0.158^{a}	0.191^{a}	0.138^{a}	0.0927^{a}	0.118^{a}	0.122^{a}	0.141^{a}	0.157^{a}	0.125^{a}	0.0838^{a}
	(0.0123)	(0.0365)	(0.0307)	(0.0165)	(0.0127)	(0.0111)	(0.0143)	(0.0447)	(0.0396)	(0.0238)	(0.0121)	(0.00895)	(0.0133)	(0.0451)	(0.0326)	(0.0168)	(0.0111)	(0.0124)
D1	-0.113^{a}	-0.212^{a}	-0.186^{a}	-0.0931^{a}	-0.0386^{a}	-0.0210^{b}	-0.141^{a}	-0.215^{a}	-0.214^{a}	-0.135^{a}	-0.0769^{a}	-0.0565^{a}	-0.0955^{a}	-0.170^{a}	-0.129^{a}	-0.0454^{a}	-0.0507^{a}	-0.0627^{a}
	(0.0112)	(0.0205)	(0.0265)	(0.0147)	(0.00985)	(0.0105)	(0.0101)	(0.0205)	(0.0212)	(0.0206)	(0.0122)	(0.00731)	(0.00904)	(0.0203)	(0.0219)	(0.0137)	(0.0160)	(0.0102)
D10	-0.0262^{a}	-0.0598^{a}	-0.018	-0.0196	-0.0127	-0.0135	-0.0501^{a}	-0.0690^{a}	-0.0826^{a}	-0.0308^{b}	-0.0351^{b}	-0.0371^{a}	-0.00643	-0.0217	-0.00635	0.0361^{b}	0.0084	-0.0481^{a}
	(0.00755)	(0.0179)	(0.0200)	(0.0160)	(0.0133)	(0.00952)	(0.00794)	(0.0205)	(0.0189)	(0.0143)	(0.0140)	(0.00809)	(0.00722)	(0.0189)	(0.0137)	(0.0151)	(0.0156)	(0.0118)
	2012						2011						2010					
QS	0.150^{a}	0.0808^{a}	0.163^{a}	0.248^{a}	0.165^{a}	0.113^{a}	0.170^{a}	0.153^{a}	0.220^{a}	0.208^{a}	0.162^{a}	0.117^{a}	0.162^{a}	0.127^{a}	0.205^{a}	0.185^{a}	0.163^{a}	0.115^{a}
	(0.0121)	(0.0294)	(0.0319)	(0.0235)	(0.0157)	(0.0134)	(0.0106)	(0.0301)	(0.0281)	(0.0181)	(0.0143)	(0.0132)	(0.0112)	(0.0321)	(0.0298)	(0.0289)	(0.0175)	(0.0116)
ES	0.0664^{a}	-0.0299	0.0614	0.173^{a}	0.112^{a}	0.0810^{a}	0.102^{a}	0.0522	0.166^{a}	0.141^{a}	0.124^{a}	0.0738^{a}	0.137^{a}	0.165^{a}	0.159^{a}	0.149^{a}	0.121^{a}	0.0817^{a}
	(0.0157)	(0.0473)	(0.0408)	(0.0290)	(0.0130)	(0.0125)	(0.0131)	(0.0476)	(0.0266)	(0.0146)	(0.0120)	(0.00874)	(0.00770)	(0.0220)	(0.0180)	(0.0187)	(0.0141)	(0.0109)
D1	-0.104^{a}	-0.155^{a}	-0.164^{a}	-0.0692^{a}	-0.0600^{a}	-0.0541^{a}	-0.122^{a}	-0.223^{a}	-0.216^{a}	-0.0355^{c}	-0.0603^{a}	-0.0615^{a}	-0.110^{a}	-0.131^{a}	-0.189^{a}	-0.107^{a}	-0.0818^{a}	-0.0652^{a}
	(0.00895)	(0.0232)	(0.0195)	(0.0103)	(0.0132)	(0.0105)	(0.0125)	(0.0282)	(0.0238)	(0.0192)	(0.0124)	(0.0133)	(0.00943)	(0.0246)	(0.0252)	(0.0190)	(0.0110)	(0.00780)
D10	-0.00986	-0.0101	-0.00897	0.0201	-0.00626	-0.0324^{a}	-0.0418^{a}	-0.0871^{a}	-0.0752^{a}	0.00634	-0.0116	-0.0392^{a}	-0.0133^{c}	-0.00533	0.0385^{b}	-0.0522^{a}	-0.0394^{a}	-0.0469^{a}
	(0.00772)	(0.0178)	(0.0250)	(0.0151)	(0.0144)	(0.00794)	(0.00684)	(0.0105)	(0.0134)	(0.0118)	(0.0133)	(0.0134)	(0.00749)	(0.0171)	(0.0173)	(0.0178)	(0.0108)	(0.00869)
	2009						2008						2007					
QS	0.155^{a}	0.152^{a}	0.188^{a}	0.227^{a}	0.149^{a}	0.0568^{a}	0.169^{a}	0.0909^{a}	0.244^{a}	0.223^{a}	0.191^{a}	0.0947^{a}	0.0945^{a}	0.0543^{b}	0.129^{a}	0.168^{a}	0.100^{a}	0.000548
	(0.0122)	(0.0279)	(0.0318)	(0.0241)	(0.0233)	(0.0161)	(0.0124)	(0.0326)	(0.0245)	(0.0277)	(0.0158)	(0.0171)	(0.0120)	(0.0253)	(0.0210)	(0.0278)	(0.0276)	(0.0120)
ES	0.151^{a}	0.213^{a}	0.207^{a}	0.172^{a}	0.107^{a}	0.0469^{a}	0.144^{a}	0.164^{a}	0.188^{a}	0.159^{a}	0.135^{a}	0.0723^{a}	0.0975^{a}	0.149^{a}	0.0980^{a}	0.131^{a}	0.0725^{a}	-0.0197^{c}
	(0.00999)	(0.0218)	(0.0209)	(0.0147)	(0.0162)	(0.0166)	(0.00901)	(0.0201)	(0.0230)	(0.0174)	(0.0155)	(0.0137)	(0.00968)	(0.0174)	(0.0192)	(0.0230)	(0.0201)	(0.0113)
D1	-0.0812^{a}	-0.126^{a}	-0.107^{a}	-0.0652^{a}	-0.0767^{a}	-0.0471^{a}	-0.129^{a}	-0.182^{a}	-0.198^{a}	-0.142^{a}	-0.0820^{a}	-0.0382^{a}	-0.128^{a}	-0.219^{a}	-0.152^{a}	-0.115^{a}	-0.0565^{a}	-0.0583^{a}
	(0.00857)	(0.0208)	(0.0166)	(0.0207)	(0.0137)	(0.0152)	(0.00932)	(0.0238)	(0.0164)	(0.0169)	(0.0121)	(0.0104)	(0.0102)	(0.0233)	(0.0199)	(0.0190)	(0.0135)	(0.0146)
D10	-0.0216^{b}	-0.0411^{c}	0.0112	-0.00885	-0.0634^{a}	-0.0470^{a}	-0.0375^{a}	-0.0405^{b}	-0.026	-0.0833^{a}	-0.0343^{b}	-0.0315^{a}	-0.0698^{a}	-0.127^{a}	-0.0867^{a}	-0.0531^{a}	-0.0222^{c}	-0.0220^{c}
	(0.00918)	(0.0219)	(0.0201)	(0.0208)	(0.0169)	(0.0155)	(0.00904)	(0.0194)	(0.0218)	(0.0263)	(0.0147)	(0.0109)	(0.00805)	(0.0126)	(0.0177)	(0.0185)	(0.0130)	(0.0130)

Table XXIII

The effect of UFA on market quality: Minutes with no movements in the bid-ask.

This table shows the coefficient of *PC*100 on Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB, in the baseline analysis. The regressions only use data from the subsample of asset-minutes in which the bid or ask price does not change at all (it is the same at each sampling point, i.e. at the end of each millisecond, within the minute). Data is aggregated for all available assets. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors of the regression. Significance levels are denoted by **a** $<$ 0.1 percent, **b** $<$ 1 percent, **c** $<$ 5 percent.

	2015	2014	2013	2012	2011	2010	2009	2008	2007
QS	0.177[a]	0.375[a]	0.359[a]	0.118[a]	0.104[b]	-0.000866	0.0121	0.0209	0.00399
	(0.0311)	(0.0927)	(0.0770)	(0.0287)	(0.0531)	(0.0187)	(0.0203)	(0.0150)	(0.0110)
ES	1.040[a]	0.840[a]	0.512[a]	0.154[a]	0.00879	-0.0603[b]	-0.0178	-0.0976[a]	-0.0804[a]
	(0.113)	(0.0900)	(0.118)	(0.0440)	(0.0563)	(0.0254)	(0.0216)	(0.0371)	(0.0106)
D01	-0.310[a]	-0.173[a]	-0.272[a]	-0.106[a]	-0.121[a]	-0.0377[c]	-0.0348[b]	-0.0443[b]	-0.0617[a]
	(0.0549)	(0.0431)	(0.0429)	(0.0256)	(0.0228)	(0.0220)	(0.0141)	(0.0209)	(0.0122)
D10	-0.154[a]	-0.0916[a]	-0.139[a]	-0.0695[a]	-0.0850[a]	-0.0273[c]	-0.00643	-0.0144	-0.0371[a]
	(0.0256)	(0.0314)	(0.0276)	(0.0197)	(0.0191)	(0.0152)	(0.0138)	(0.0186)	(0.0106)

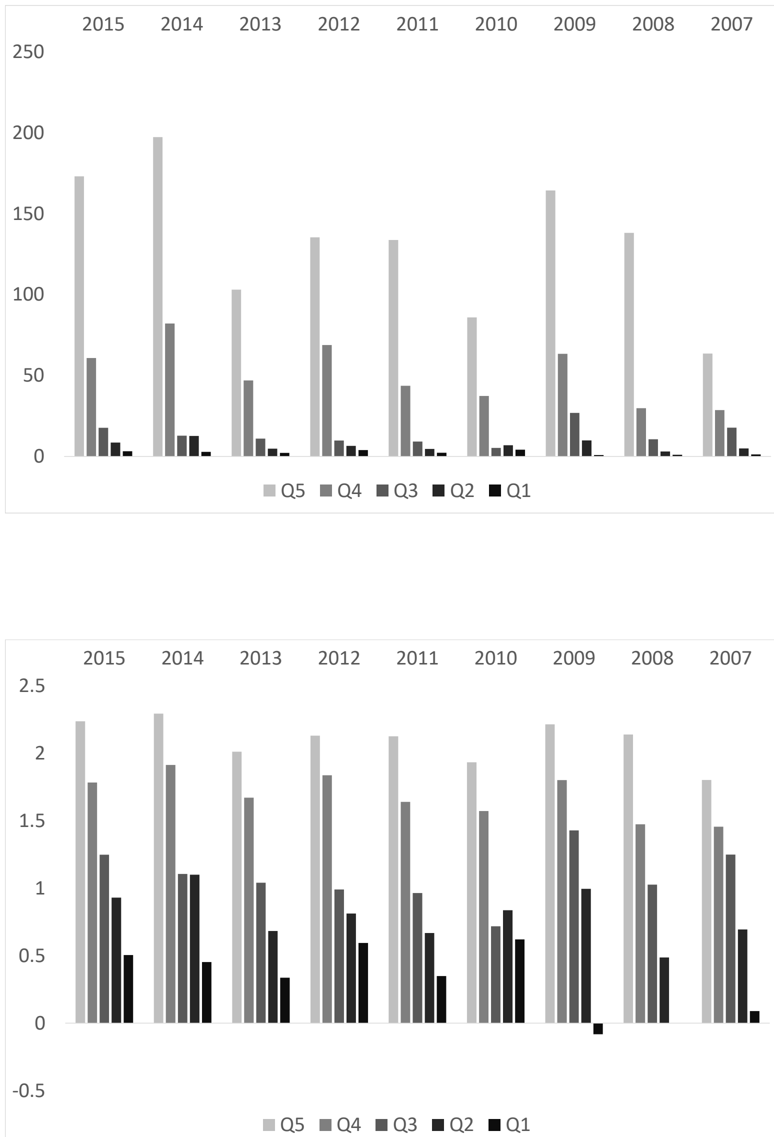
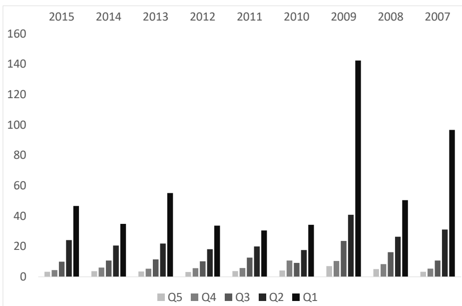
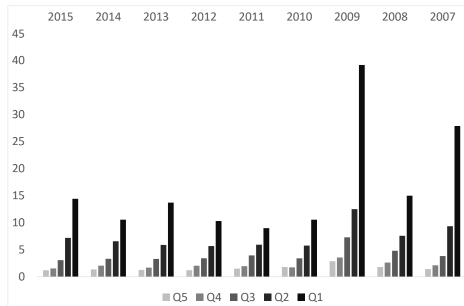


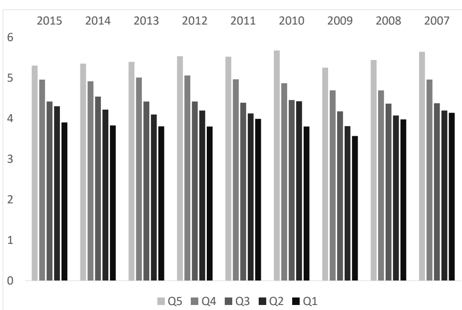
Figure 1. Mean of *PC*100 (top) and log *PC*100 (bottom) for quintiles ranked using traded dollar volume. Q5 is the quintile with firms that registered the highest dollar traded volume (first bar for each year), and Q1 those with the lowest (last bar in each year).



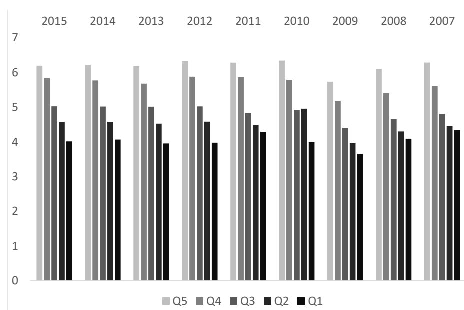
(a) Quoted Spread



(b) Effective Spread

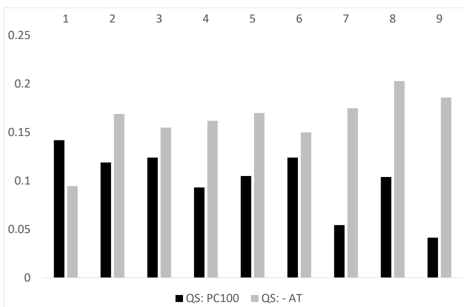


(c) log Depth 1

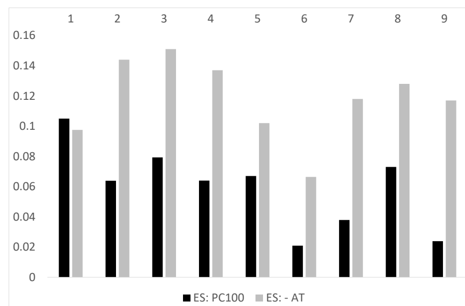


(d) log Depth 10

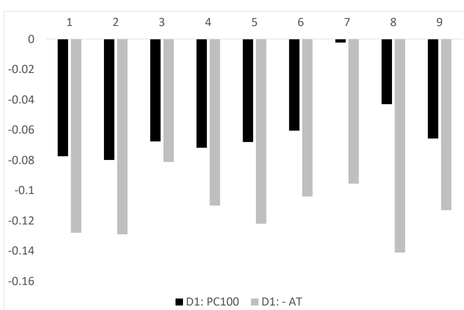
Figure 2. Mean of market quality variables for quintiles ranked using traded dollar volume. Q5 is the quintile with firms that registered the highest dollar traded volume (first bar for each year), and Q1 those with the lowest (last bar in each year). Depth measured in thousands of dollars.



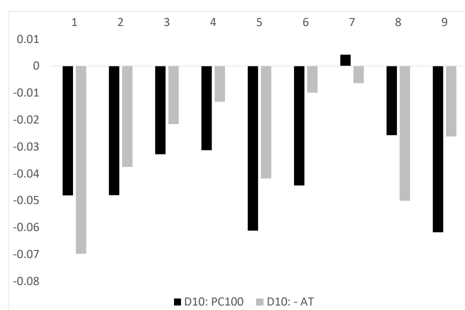
(a) Quoted Spread



(b) Effective Spread



(c) Depth 1



(d) Depth 10

Figure 3. Panel regression coefficients for $PC100$ (black bars) and AT (gray bars). See Table III.

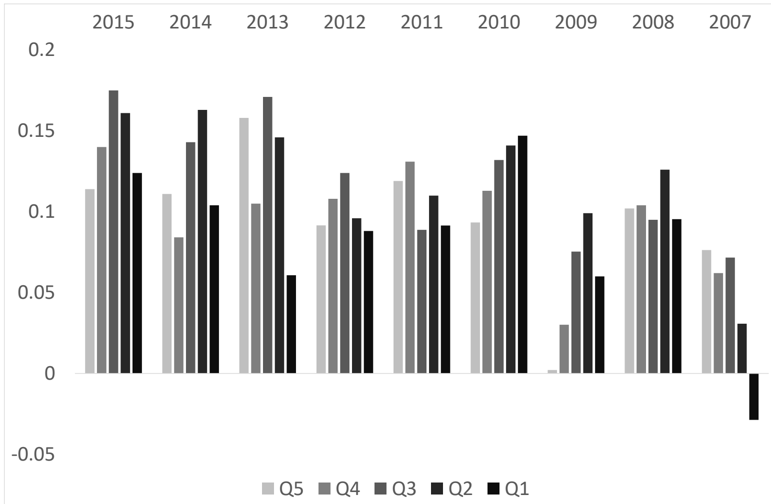


Figure 4. Quoted spread coefficient for quintiles ranked using traded dollar volume. Q5 is the quintile with firms that registered the highest dollar traded volume (first bar for each year), and Q1 those with the lowest (last bar).

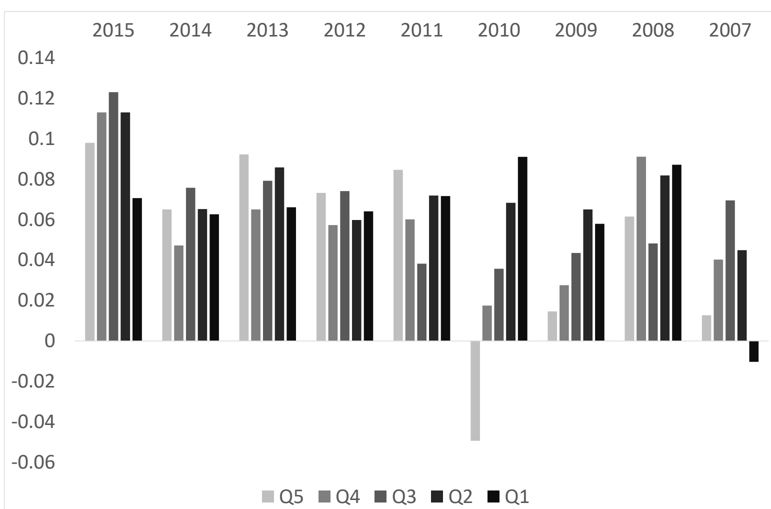


Figure 5. Effective spread coefficient for quintiles ranked using traded dollar volume. Q5 is the quintile with firms that registered the highest dollar traded volume (first bar for each year), and Q1 those with the lowest (last bar).

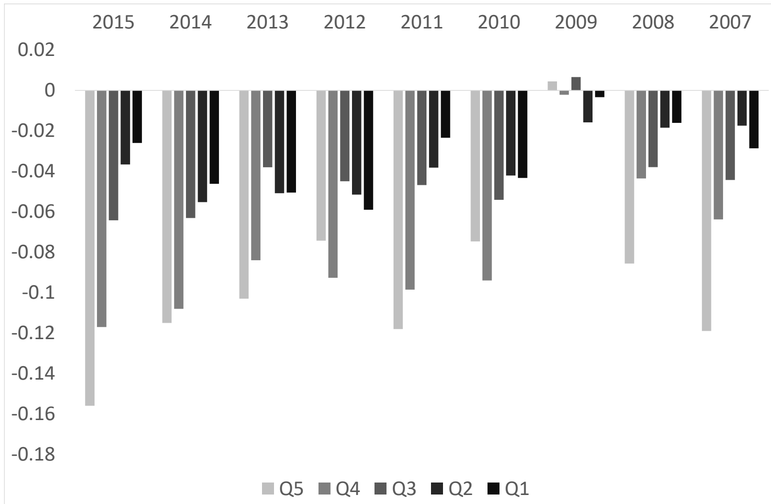


Figure 6. Depth at 1 bp coefficient for quintiles ranked using traded dollar volume. Q5 is the quintile with firms that registered the highest dollar traded volume (first bar for each year), and Q1 those with the lowest (last bar).

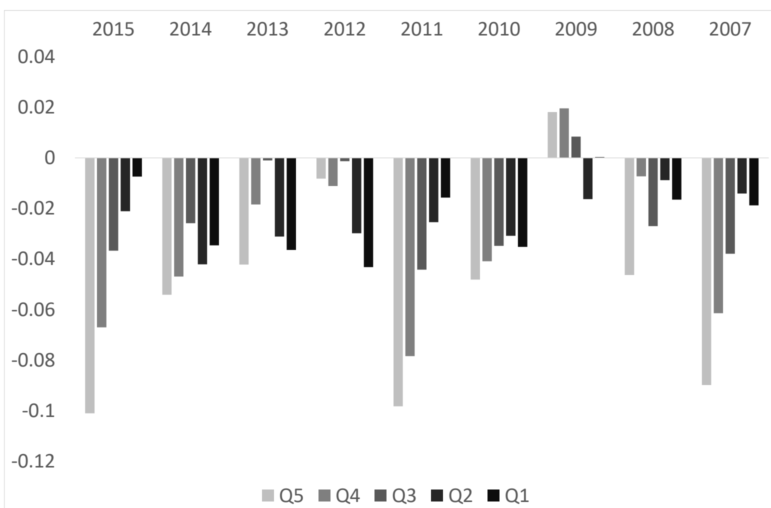


Figure 7. Depth at 10 bps coefficient for quintiles ranked using traded dollar volume. Q5 is the quintile with firms that registered the highest dollar traded volume (first bar for each year), and Q1 those with the lowest (last bar).

VIII. Internet Appendix

Table XXIV
The effect of UFA on market quality: baseline results with alternative random sample.

This table shows the coefficient of $PC100$ on Quoted Spread (QS), Effective Spread (ES) and Depths at different levels in the LOB, in the baseline analysis for the month of march 2013. The table replicates the analysis in Table III for march 2013 using an newly drawn random sample. The new sample randomly draws assets by size deciles (taken from K.R.French's website for February 2013). We randomly select 30 assets from each size decile, 15 from NYSE and 15 from NASDAQ, for a total of 300 assets. Of the 300, 11 are dropped from the sample due to insufficient data (8 from NASDAQ and 3 from NYSE). We also include separate regressions for NYSE and NASDAQ assets.

Data is aggregated for all available assets. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors of the regression and the adjusted R-squared. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

2013	All	NASDAQ	NYSE
QS	0.121[a]	0.159[a]	0.087[a]
	(0.0069)	(0.0099)	(0.0084)
	0.145	0.147	0.146
ES	0.080[a]	0.089[a]	0.070[a]
	(0.0048)	(0.0069)	(0.0066)
	0.056	0.061	0.052
D1	−0.066[a]	−0.074[a]	−0.058[a]
	(0.0040)	(0.0054)	(0.0055)
	0.061	0.067	0.056
D10	−0.031[a]	−0.037[a]	−0.026[a]
	(0.0039)	(0.0054)	(0.0053)
	0.146	0.153	0.139
Firms	289	142	147
Obs (QS, D1, D10)	1,907,070	936,870	970,200
Obs (ES)	921,850	501,486	420,364

Table XXV
The effect of UFA on market quality: baseline results using Runs.

This table shows the coefficient of *Runs* on Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB, in the baseline analysis for the month of march 2013. *Runs* is the RunsInProgress variable constructed as in Hasbrouck and Saar (2013). The table replicates the analysis in Table III for march 2013 using the RunsInProgress measure instead of the PC100, and the same controls for absolute signed volume and volatility. We also include the correlation table between the variables Runs, PC100, QS, and the two depth measures, D1 and D10. ES has been excluded to avoid issues relating to the presence/absence of trades in the minutes under observation.

Data is aggregated for all available assets. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors of the regression and the adjusted R-squared. Significance levels are denoted by **a** < 0.1 percent, **b** < 1 percent, **c** < 5 percent.

	QS	ES	D1	D10
Runs	$-0.056^{\mathbf{a}}$	$-0.024^{\mathbf{a}}$	$0.076^{\mathbf{a}}$	$0.14^{\mathbf{a}}$
	(0.0105)	(0.0068)	(0.0095)	(0.0145)
Observations	726,000	396,098	726,000	726,000
R-squared	0.140	0.048	0.067	0.175

Correlations

	Runs	PC100	QS	D1	D10
Runs	1.00				
PC100	0.07	1.00			
QS	- 0.05	0.14	1.00		
D1	0.07	- 0.05	- 0.11	1.00	
D10	0.13	- 0.07	- 0.17	0.63	1.00

Table XXVI

The effect of UFA on market quality: baseline results by NASDAQ NBBO.

This table shows the coefficient of *PC*100 on Quoted Spread (*QS*), Effective Spread (*ES*) and Depths at different levels in the LOB, in the baseline analysis for the month of march 2013, separated by deciles of time spent at the NBBO. The table replicates the analysis in Table III for march 2013 separating the sample into groups according to the percentage of time (per minute) in which both the NASDAQ bid and ask coincide with the NBBO. The column labeled *High* uses only minutes in the top three deciles for which the NASDAQ bid and ask coincided with the NBBO, that labeled *Mid* the middle four deciles, and that labeled *Low* the bottom three deciles. The cutoff between Low and Mid is 0.036 (3.6%), while that between Mid and High is 0.9782 (97.82%).

Data is aggregated for all available assets. All theses variables are standardized. The estimation includes 30minute dummies and clusters errors by asset id and time (day-minute). Below each coefficient we show the standard errors of the regression and the adjusted R-squared. Significance levels are denoted by **a** <0.1 percent, **b** <1 percent, **c** <5 percent.

	High	Mid	Low
QS	$0.090^{\mathbf{a}}$	$0.123^{\mathbf{a}}$	$0.096^{\mathbf{a}}$
	(0.0106)	(0.0141)	(0.0153)
	0.075	0.173	0.167
ES	$0.181^{\mathbf{a}}$	$0.048^{\mathbf{a}}$	$0.061^{\mathbf{a}}$
	(0.0105)	(0.00777)	(0.0120)
	0.060	0.062	0.065
D1	$-0.191^{\mathbf{a}}$	$-0.029^{\mathbf{a}}$	$-0.031^{\mathbf{a}}$
	(0.0117)	(0.00651)	(0.00926)
	0.125	0.071	0.018
D10	$-0.087^{\mathbf{a}}$	-0.005	$-0.024^{\mathbf{a}}$
	(0.0105)	(0.00793)	(0.00783)
	0.184	0.218	0.064
Obs (QS, D1, D10)	221,508	280,204	224,288
Obs (ES)	117,585	220,788	57,725