Low-Latency Trading

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Abstract

This paper studies market activity in the “millisecond environment,” where computer algorithms respond to each other almost instantaneously. Using order-level NASDAQ data, we find that the millisecond environment consists of activity by some traders who respond to market events (like changes in the limit order book) within roughly 2-3 ms, and others who seem to cycle in wall-clock time (e.g. access the market every second). We define low-latency activity as strategies that respond to market events in the millisecond environment, the hallmark of proprietary trading by a variety of players including electronic market makers and statistical arbitrage desks. We construct a measure of low-latency activity by identifying “strategic runs,” which are linked submissions, cancellations, and executions that are likely to be parts of a dynamic strategy. We use this measure to study the impact that low-latency activity has on market quality both during normal market conditions and during a period of declining prices and heightened economic uncertainty. Our conclusion is that increased low-latency activity improves traditional market quality measures such as short-term volatility, spreads, and displayed depth in the limit order book.

I. Introduction

Our financial environment is characterized by the ever increasing pace of both information gathering and the actions prompted by this information. Speed is important to traders in financial markets for two main reasons. First, the inherent fundamental volatility of financial securities means that rebalancing positions faster could result in higher utility. Second, irrespective of the absolute speed, being faster than other traders can create profit opportunities by enabling a prompt response to news or market-generated events. This latter consideration appears to drive an "arms race" where traders employ cutting-edge technology and locate computers in close proximity to the trading venue in order to cut down on the latency of their orders and gain an advantage. As a result, today's markets experience intense activity in the "millisecond environment," where computer algorithms respond to each other at a pace 100 times faster than it would take for a human trader to blink.

While there are many definitions for the term "latency," we view it in the context of the time it takes to observe a market event (e.g., a new bid price in the limit order book), through the time it takes to analyze this event and send an order to the exchange that responds to the event.[1] Exchanges have been investing heavily in upgrading their systems to reduce the time it takes to send information to customers as well as to accept and handle customers' orders. They also began offering traders the ability to co-locate their computer systems in close proxy to the exchange's system, reducing the time it takes for messages to reach customers to less than a millisecond (a thousand of a second). As traders have also invested in the technology to process information faster, the entire information-processing-action cycle has been reduced by some traders to a few milliseconds.

[1] More specifically, we define latency as the sum of three components: the time it takes for information to reach the trader, the time it takes for the trader's algorithms to analyze the information, and the time it takes for the generated action to reach the exchange and get implemented. The latencies claimed by many trading venues, however, are usually defined much more narrowly, typically as the processing delay measured from the entry of the order (at the vendor's computer) to the transmission of an acknowledgement (from the vendor's computer).

An important question is who benefits from such massive investment in technology. After all, most trading is a zero sum game, and the reduction in fundamental risk mentioned above would seem incomprehensibly small for time intervals in the order of several milliseconds. There is a new set of traders in the market who implement low-latency strategies, which we define as strategies that respond to market events in the millisecond environment. These traders now generate most message activity in financial markets and according to some accounts also take part in the majority of the trades.[2] While it appears that intermediated trading is on the rise (with these low-latency traders providing liquidity to other market participants), it is unclear whether low-latency activity harms or helps market quality.

Our goal in this paper is to examine the influence of these low-latency traders on the market environment. We begin by studying the millisecond environment to ascertain how low-latency strategies affect the time-series properties of market activity. We then ask the following question: how does the interaction of these traders in the millisecond environment impact the quality of markets that human investors can observe? In other words, we would like to know how their activity aggregates to affect attributes such as the short-term volatility of stocks, the total price impact of trades, and the depth of the market. To investigate these questions, we utilize NASDAQ order-level data (TotalView-ITCH) that are identical to those supplied to subscribers, providing real-time information about orders and executions on the NASDAQ system. Each entry (submission, cancellation, or execution of an order) is time-stamped to the millisecond, and hence these data provide a very detailed view of activity on the NASDAQ system.

We find that the millisecond environment shows evidence of two types of activities: one by traders who respond to market events and the other by traders who seem to operate according to a schedule (e.g., access the market every second). The activity of the latter creates periodicities in the time-series properties of market activity based on wall-clock time. We believe that low-latency activity (i.e., strategies that

[2] See, for example, the discussion of high-frequency traders in the SEC's Concept Release on Equity Market Structure.

respond to market events) is the hallmark of proprietary trading by electronic market making firms as well as statistical arbitrage operations in hedge funds and other financial firms. On the other hand, the periodicity is more likely generated by the activity of agency algorithms employed to minimize trading costs of buy-side money managers. The interaction among different types of algorithms gives rise to intense episodes of submissions and cancellations of limit orders that start and stop abruptly, but these need not lead to intensified trading in the stocks. In other words, observing these episodes reveals that intense high-frequency activity in the millisecond environment need not translate into a surge in high-frequency trading.

We use the data to construct "strategic runs" of linked messages that describe dynamic order placement strategies. By tracking submissions, cancellations, and executions that can be associated with each other, we create a measure of low-latency activity. We use a simultaneous equation framework to examine how the intensity of low-latency activity affects market quality measures. We find that an increase in low-latency activity lowers short-term volatility, reduces quoted spreads and the total price impact of trades, and increases depth in the limit order book. If our econometric framework successfully corrects for the simultaneity between low-latency activity and market attributes, then the activity of low-latency traders is beneficial by traditional standards about which investors care.

Furthermore, we employ two distinct sample periods to investigate whether the impact of low-latency trading on market quality (and the millisecond environment in general) differs between "normal times" and periods of declining prices and heightened uncertainty in the market. Our first sample period, October 2007, is characterized by a relatively flat (or slightly increasing) market. Our second sample period, June 2008, is characterized by declining prices (the NASDAQ was down 8% in that month) and high uncertainty following the fire sale of Bear Sterns. We find that the millisecond environment with its various attributes is rather similar across the two sample periods. More importantly, low-latency activity enhances market quality is both environments though during stressful times it appears to help reduce volatility in smaller stocks more than it does in larger stocks.[3]

Our paper relates to the small but growing strands in the literature on speed in financial markets as well as on algorithmic trading. In particular, Riordan and Storkenmaier (2008), Easley, Hendershott, and Ramadorai (2009), and Hendershott and Moulton (2009) examine market-wide changes in technology that affect the latency of information transmission and execution, but reach conflicting conclusions as to the impact of such changes on market quality. There are several papers on algorithmic trading that characterize the trading environment on the Deutsche Boerse (Gsell (2008), Gsell and Gomber (2008), Groth (2009), Prix, Loistl, and Huetl (2007), Hendershott and Riordan (2009)), and two papers that study U.S. markets: Hendershott, Jones, and Menkveld (2009) and Brogaard (2010). None of these papers study the characteristics of the millisecond environment, but the latter two papers attempt to evaluate the impact of algorithmic trading on market quality in the U.S., a goal we share as well.[4]

The rest of this paper proceeds as follows. The next section describes the sample and the dataset we use. Section III characterizes the new trading environment. We provide evidence on the intensity, periodicity, and episodic nature of activity in the "millisecond environment," and construct a measure of low-latency activity by linking orders to strategic runs that represent dynamic strategies. Section IV studies how the activity of low-latency traders in the millisecond environment influences attributes of market quality such as liquidity and short-term volatility. In Section V we discuss related papers and how our findings fit within the context of the literature. Section VI concludes the paper with a discussion of low-latency trading from the perspectives of market microstructure and the regulatory environment.

[3] We note that this does not imply that the activity of low-latency traders would help curb volatility during extremely brief episodes such as the "flash crash" of May 2010, in which the market declined by about 7% over a 15-minute interval before partially rebounding.

[4] The joint CFTC/SEC report on the "flash crash" of May 6, 2010, looks at the role of high-frequency trading in this extreme episode (U. S. Commodity Futures Trading Commission and the U.S. Securities and Exchange Commission, 2010). Although much can be learned from extreme events, our study, in contrast, uses sample periods that are longer and arguably more representative.

II. Data and Sample

II.A. NASDAQ Order-Level Data

The NASDAQ Stock Market is a pure agency market. It operates an electronic limit order book that utilizes the INET architecture (which was purchased by NASDAQ in 2005).[5] All submitted orders must be price-contingent (i.e., limit orders), and traders who seek immediate execution need to price the limit orders to be marketable (e.g., a buy order priced at or above the prevailing ask price). Traders can designate their orders to display in the NASDAQ book or mark them as "non-displayed," in which case they reside in the book but are invisible to all traders. Execution priority follows price, visibility, and time. All displayed quantities at a price are executed before non-displayed quantities at that price can trade.

The NASDAQ data we use, TotalView-ITCH, are identical to those supplied to subscribers, providing real-time information about orders and executions on the NASDAQ system. These data are comprised of time-sequenced messages that describe the history of trade and book activity. Each message is time-stamped to the millisecond (i.e., one-thousand of a second), and hence these data provide a detailed picture of the trading process and the state of the NASDAQ book. We are able to observe four different types of messages in the TotalView-ITCH dataset: (i) the addition of a displayed order to the book, (ii) the cancellation of a displayed order, (iii) the execution of a displayed order, and (iv) the execution of a non-displayed order.

With respect to executions, we believe that the meaningful economic event is the arrival of the marketable order. In the data, when an incoming order executes against multiple standing orders in the book, separate messages are generated for each standing order. We view these as single marketable order arrival, so we group as one event multiple execution messages that have the same millisecond time stamp, are in the same direction, and occur in a sequence unbroken by any non-execution message. The component executions need not occur at the same price, and some (or all) of the executions may occur against non-displayed quantities.

[5] See Hasbrouck and Saar (2009) for a more detailed description of the INET market structure.

II.B. Sample

Our sample is constructed to capture variation across firms and across market conditions. We begin by identifying all common, domestic stocks in CRSP that are NASDAQ-listed in the last quarter of 2007.[6] We then take the top 500 stocks, ranked by market capitalization as of September 30, 2007. Our first sample period is October of 2007 (23 trading days). The market was relatively flat during that time, with the S&P 500 Index starting the month at 1,547.04 and ending it at 1549.38. The NASDAQ Composite Index was relatively flat but ended the month up 4.34%. Our 2007 sample is intended to reflect a "normal" market environment.

Our second sample period is June 2008 (21 trading days), which represents a time of heightened uncertainty in the market between the fire sale of Bear Sterns in March of 2008 and the Chapter 11 filing of Lehman Brothers in September of that year. During the month of June, the S&P 500 Index lost 7.58%, and the NASDAQ Composite Index was down 7.99%. In the second period, we continue to follow the firms in the 2007 sample, less 29 stocks that were acquired or switched primary listing. For brevity, we refer to the October 2007 and June 2008 samples as "2007" and "2008," respectively.

In our dynamic analysis we use summary statistics constructed over 10-minute intervals. To ensure the accuracy of these statistics, we impose a minimum message count cutoff. A firm is excluded from a sample if more than ten percent of the 10-minute intervals had fewer than 250 messages. Google and Apple are excluded due to computational limitations. Net of these exclusions, the 2007 sample contains 345 stocks, and the 2008 sample contains 394 stocks.

Table 1 provides summary statistics for the stocks in both sample periods using information from CRSP and the NASDAQ dataset. Panel A summarizes the measures obtained from CRSP. In the 2007 sample, market capitalization ranges from $789 Million to $276 Billion, with a median of slightly over $2 Billion. The sample also spans a range of trading activity and price levels. The most active stock exhibits an average daily

[6] NASDASQ introduced the three-tier initiative for listed stocks in July of 2006. We use CRSP's NMSIND=5 and NMSIND=6 codes to identify eligible NASDAQ stocks for the sample (which is roughly equivalent to the former designation of "NASDAQ National Market" stocks).

volume of 77 million shares; the median is about one million shares. Average closing prices range from $2 to $272 with a median of $29. Panel B summarizes data collected from NASDAQ. In 2007 the median firm had 27,130 order submissions (daily average), 24,374 cancellations and 2,489 executions. Statistics for the 2008 sample are similar.

III. Characterizing the New Trading Environment

III.A. Intensity, periodicity, and High-Frequency Episodes

III.A.a Intensity

Current market observers often comment on the rapid pace of activity. In fact, the typical average message rate is unremarkable. The sum of the median number of submissions and cancellations for 2007 is 66,587. With 23,400 seconds in a 6.5 hour trading session, a representative average message arrival rate appears to be roughly three messages per second.

The average, however, belies the intensely episodic nature of the activity. To illustrate this, we estimate the hazard rate for the inter-message durations. The hazard rate is the message arrival intensity (for a given stock), conditional on the time elapsed since the last message (for that stock). Figure 1 depicts graphs of the hazard functions for two types of messages: (i) those that do not involve the execution of trades (arrivals and cancellations of nonmarketable limit orders), and (ii) executions of trades (against both displayed and non-displayed limit orders). Panel A presents the hazard rates up to 100 ms, while Panel B shows the hazard rates up to 1000 ms (i.e., one second). The hazard rates we observe in the market exhibit three striking characteristics: a very high initial level, a rapid decline, and (in the case of non-execution events) a small number of apparent peaks.

In the first millisecond (after the preceding message) the hazard rate for submissions/cancellations is 334 messages per second in 2007, and 283 messages per second in 2008, i.e., roughly one hundred times the average arrival intensity. These high values, however, rapidly dissipate. In 2008, the initial hazard rate drops by about 90 percent in the first ten milliseconds, and by about 98% in the first hundred milliseconds.

A declining hazard rate is consistent with event clustering. This is a common feature of financial data, and is often modeled statistically by dependent duration models (e.g., Engle and Russell (1998), and Hautsch (2004)). From an economic perspective, variation in trading intensity has long been believed to reflect variation in information intensity. While the information can be diverse in type and origin, it is often viewed as relating to the fundamental value of the stock and originating from outside the market (e.g., a news conference with the CEO or a change in an analyst's earnings forecast). At horizons of extreme brevity, however, there is simply not sufficient time for an agent to be reacting to anything *except* very local market information. The information is about whether someone is interested in buying or selling, and it may lead to a transient price movement rather than a permanent shift.

While the hazard rate graphs are dominated by the rapid decay, they also exhibit local peaks. Over the very short run (Panel A), submissions/cancellations have distinct peaks in both the 2007 and 2008 samples at 60 ms. There are also discernible peaks at 11-12 ms. These are somewhat less visible because they occur in a region dominated by the rapid decay. They are nevertheless about 25% higher than the average surrounding values. These peaks do not appear as distinctly in the execution hazard rates. The latter, however, also peak around 2-3 ms, a feature discussed in more detail below. Over a longer interval (Panel B), submissions/cancellations exhibit peaks around 100 and (partially visible) 1,000 ms.

What do these peaks represent? The peaks at 60, 100 and 1,000 ms correspond to "natural" rates (1,000 times per minute, ten times per second, and once per second), and so may reflect algorithms that access the market periodically. The peaks at shorter durations, however, may represent strategic responses to market events, and so serve as useful indications of effective latency. Both possibilities warrant further investigation. We turn next to the periodicities, deferring the analysis of strategic responses to Section III.C.

III.A.b Periodicity

To further characterize the periodicities, we examine the level of activity in wall-clock time (the hazard rate analyses are effectively set in event time). The timestamps in the data are milliseconds past midnight. Therefore for a given timestamp *t*, the quantity $\text{mod}(t,1000)$ is the millisecond remainder, i.e., a millisecond time stamp within the second. Assuming that message arrival rates are constant or (if stochastic) well-mixed within a sample we would expect the millisecond remainders to be uniformly distributed over the integers $\{0,1,\ldots,999\}$.

The data, however, tell a different story. Panel A of Figure 2 depicts the sample distribution of the millisecond remainders. The null hypothesis is indicated by the horizontal line at 0.001. The distributions in both sample periods exhibit marked departures from uniformity. Both feature strong peaks occurring shortly after the one-second boundary (at roughly 10-30 ms.), and also around 150 ms. Broad elevations occur around 600 ms. We believe that these peaks are indicative of automated trading systems that periodically access the market, near the second and the half-second. These intervals are substantially longer than the sub-100 ms horizon that characterizes the elevated hazard rates.

In other words, unlike low-latency traders who respond to market-created events, these algorithms submit a message and revisit it at fixed intervals. For example, if an algorithm were to revisit the possibility of modifying an order every five calendar seconds, we would observe that the algorithm revises the message at 5 ms or 15 ms or 55 ms depending on how fast it sends a message (e.g., cancellation, submission) to the market. In other words, we observe several peaks rather than one probably due to differences in the location of traders (e.g., the round-trip New York to Chicago transmission time is about twelve milliseconds) and the computing technology they utilize. Algorithms that cycle every half a second could be generating the peak at the 550 reminder.

To investigate whether there might exist longer periodicities, we construct the sample distribution of timestamps mod 10,000 (Figure 2, Panel B). These graphs are dominated by the strong one-second cycles, but also appear to contain two- and ten-second variations.

One could suggest that even if a significant fraction of market participants were to have their algorithms cycle in a one-second frequency, the occurrence times would be more smoothly distributed due to randomness in clock synchronizations. We believe, however, that the periodicity can be initiated even by a few, relatively large, market participants. Furthermore, as long as someone is sending messages in a periodic manner, their actions will provoke strategic responses by others who monitor the market continuously (the low-latency traders) and these responses will tend to amplify the periodicity.

III.A.c High-Frequency Episodes

Both the short-term intensity dependence and clock-time periodicity could in principle be modeled statistically with standard time series decomposition techniques. Our attempts to accomplish this (with spectral and wavelet analysis), however, were not very fruitful. Despite this, certain idiosyncrasies of the decompositions did reveal to us another characteristic of the millisecond environment. Much high-frequency activity is not only episodic, but is also strikingly abrupt in commencement and completion.

Panel A of Figure 3 shows both submissions and cancellations (the bars) and cumulative executions (the dashed line) for ticker symbol INWK (InnerWorkings Inc.) on June 2, 2008 at about 2:08pm.[7] The first noteworthy feature of this figure is that the burst of high-frequency submissions and cancellations (around 100 messages per second) starts suddenly and stops abruptly after about one minute and forty seconds. The level of activity during this time is over 100 times the level of activity in terms of submissions and cancellations before and after the episode. The second noteworthy feature of the

[7] One could identify these episodes simply by looking at (many) plots of submission and cancellation counts. Our attention was drawn to them, however, by wavelet decompositions that flagged particularly strong components in message activity at various frequencies. Measures we constructed from the wavelet analysis were unable to consistently characterize the intensity of low-latency responses to market events, but they quickly located the instances of high-frequency activity discussed here.

figure is that the number and pattern of executions (in the dashed line) does not change much during this high-frequency episode.

Panel B of Figure 3 shows another such episode in ticker symbol SANM (Sanmina-SCI Corp.) on June 17, 2008 at around 12:07pm, while Panel C of the figure presents an episode in GNTX (Gentex Corp.) on June 12, 2008 at around 12:18pm. They all share the same features: (i) a sudden onset of intense activity of submissions and cancellations of limit orders that stops abruptly after a short period of time, and (ii) lack of change in the pattern of executions before, during, or after these high-frequency episodes. These figures suggest to us that the term "high-frequency trading" that is used to describe some low-latency activity is generally a misnomer: there is indeed high-frequency activity, but it does not lead necessarily to intense trading. It simply manifests in intense submissions and cancellations of orders. And while the episodes in Figure 2 last from one minute and twenty seconds to three minutes, other episodes we have observed could last only a couple of seconds but contain thousands of messages.[8]

The millisecond environment therefore consists of activity by some traders who respond to market events and others who seem to cycle in wall-clock time. This activity could give rise to intense episodes of submissions and cancellations of limit orders that start and stop abruptly, but these episodes need not be accompanied by intensified trading in the stocks. Before we proceed to measure low latency trading and investigate its impact on market quality, it would be useful to have a short discussion of the type of market participants whose activity shapes the millisecond environment.

III.B. The Players: Proprietary Algorithms and Agency Algorithms

Much trading and message activity in U.S. equity markets is commonly attributed to trading algorithms.[9] However, not all algorithms serve the same purpose and therefore the

[8] A recent newspaper article notes that such episodes are called "quote stuffing" by practitioners (Lauricella and Strasburg (2010)). Some suspect that these are used by proprietary traders to manipulate prices and create profit opportunities for executing trades. While this is certainly possible, our observation that there is no change in the pattern of executions during or immediately after many of these episodes suggests that the story behind this phenomenon may be more complex.

[9] The SEC's Concept Release on Equity Market Structure cites media reports that attribute 50% or more of equity market volume to proprietary algorithms (the "high-frequency traders"). A report by the Tabb Group

patterns they induce in market data and the impact they have on market quality could depend on their specific objectives. Broadly speaking, however, we can categorize algorithmic activity into two separate branches with very different properties: Agency Algorithms (AA) and Proprietary Algorithms (PA). The first category is comprised of algorithms used by buy-side institutions to minimize the cost of executing trades in the process of implementing changes in their investment portfolios. The second category is comprised of algorithms used by electronic market makers, hedge funds, proprietary trading desks of large financial firms, and independent statistical arbitrage firms that are meant to profit from the trading environment itself (as opposed to investing in stocks).[10]

Agency Algorithms (AA): These are used by buy-side institutions as well as the brokers who serve them to buy and sell shares. They have been in existence for about two decades, but the last ten years have witnessed a dramatic increase in their appeal due to the change to trading in penny increments (in 2001) and increased fragmentation in U.S. equity markets (following Reg ATS in 1998 and Reg NMS in 2005). These algorithms break up large orders into pieces that are then sent over time to multiple trading venues.[11] The algorithms determine the size, timing, and venue for each piece depending on input parameters for each order (e.g., the desired horizon for the execution), algorithm-specific parameters that are estimated from historical data, possibly real-time data received from the market, and feedback about the execution of the different pieces.

The key characteristic of AA is that the choice of which stock to trade and how much to buy or sell is made by a portfolio manager who has an investing (rather than trading) horizon in mind. The algorithms are meant to minimize execution costs relative to a specific benchmark (e.g., volume-weighted average price or market price at the time the order arrives at the trading desk), and they are most often developed by sell-side brokers or independent software vendors to serve buy-side clients. Their ultimate goal is to execute a desired position change and hence can be viewed as demanding liquidity

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(July 14, 2010) suggests that buy-side institutions use "low-touch" agency algorithms for about a third of their trading needs.

[10] Sellberg (2010) refers to these two categories as "alpha-preserving" (agency) and "alpha-creating" (proprietary) algorithms.

[11] See, for example, Bergan and Devine (2005).

even if they are implemented using a dynamic limit order strategy that utilizes nonmarketable limit orders.

Proprietary Algorithms (PA): This is a collective name for many strategies and hence, unlike AA, it is more difficult to have a concise characterization of their nature. Nonetheless, these algorithms often belong to the following two broad categories: (i) electronic market making, or (ii) statistical arbitrage trading.

Electronic (or automated) market makers are dealers who buy and sell for their own account in a list of securities. These firms use algorithms to generate buy and sell limit orders and dynamically update these orders by applying pre-determined logic to real-time data. Like traditional dealers, they often profit from the small differences between the bid and ask prices and aim at carrying only a small inventory. Another source of profit for such firms is the liquidity rebates offered by many trading venues. These rebates (typically a quarter of a penny per share) are offered to attract liquidity providers and are funded by fees that liquidity demanders pay for execution.

Statistical Arbitrage trading is carried out by the proprietary trading desks of larger financial firms, hedge funds, and independent specialty firms. They analyze historical data for individual stocks and groups of assets in a search for trading patterns (within assets or across assets) that can be exploited for profit. These profit opportunities represent temporary deviations from historical patterns (e.g., pairs trading) or stem from identification of a certain trading need in the market (e.g., a large trader that attempts to execute an order and temporarily changes the time-series behavior of prices). Broadly speaking, most of these strategies rely on convergence of prices and the expectation that the market price will revert back after temporary imbalances. Some of these traders attempt to profit from identifying the footprints of buy-side algorithms and trade ahead of or against them. Their goal is to profit at the expense of buy-side institutions by employing algorithms that are more sophisticated than typical AA (Donefer (2010)).[12]

[12] The SEC's Concept Release on Equity Market Structure provides more information about these strategies and categorizes them into three groups: arbitrage (usually between related securities or markets), structural (exploiting market structure features or inference about trading interest), and directional (momentum and reversal trading based on anticipation of an intraday price movement).

The goals of AA and PA differ from each other, and therefore the specifications of the algorithms and the technology that they require are also dissimilar. AA are based on historical estimates of price impact and execution probabilities across multiple trading venues and over time, and often require much less real-time input except for tracking the pieces of the orders they execute. For example, volume-weighted average price algorithms attempt to distribute executions over time in proportion to the aggregate trading and achieve the average price for the stock. While some AA offer functionality such as pegging (e.g., tracking the bid or ask side of the market) or discretion (e.g., converting a nonmarketable limit buy order into a marketable order when the ask price decreases), typical AA do not require millisecond responses to changing market conditions.

We believe that the clock-time periodicity we have identified in Section III.A.b is driven by these AA. Some algorithms simply check market conditions and execution status every second (or several seconds) and respond to the changes they encounter. Their orders reach the market with a lag that depends on the configurations and locations of their computers, generating the sample distributions of remainders. The similarities between the 2007 and 2008 samples suggest phenomena that are pervasive and do not disappear over time or in different market conditions.

One might conjecture that these patterns cannot be sustainable because sophisticated algorithms will take advantage of them and eliminate them. While there is no doubt that PA respond to such regularities, these responses only serve to accentuate the clock-time periodicities rather than eliminate them. It is also the case that PA supply liquidity to AA and therefore it is conceivable that clustering at certain times help AA execute their orders by increasing available liquidity. As such, AA that operate in calendar time would have little incentive to change, making these patterns we identify in the data persist over time.

In contrast to AA, the hallmark of PA is speed: low-latency capabilities. In other words, what distinguishes them from AA is their need to respond to market events. Therefore, these algorithms utilize co-location, which is the ability to place computers in close proximity to the stock exchange's servers, and special computing technology to create an edge in the strategic interaction of the millisecond environment. While AA are used in the service of buy-side investing and hence seem justified by the social benefit often attributed to delegated portfolio management (e.g., diversification), the societal benefits of PA are more elusive. If we take electronic market making to be an extension of traditional market making, it provides the service of bridging the intertemporal disaggregation of order flow in continuous markets. Unlike traditional dealers, however, these electronic market making firms have no explicit obligations with respect to market presence or market quality, an issue we will further discuss in Section VI.

The societal benefit from the statistical arbitrage and other types of low-latency trading is more difficult to ascertain. One could view them as aiding price discovery by eliminating transient price disturbances, but such an argument at the millisecond environment is a bit tenuous. After all, at such speeds and for such short intervals it is difficult to determine what constitutes a real innovation to the true value of the security as opposed to a transitory influence on the price. The social utility in identifying buy-side interest and trading ahead of it is even more difficult to ascertain.

Furthermore, the race to interact with the market environment faster and faster requires investing vast resources in technology. PA are at the forefront of such investment, but they are not alone: AA providers respond by creating algorithms that enable clients to implement somewhat more sophisticated strategies that respond to market conditions along pre-defined parameters. Even exchanges such as NASDAQ get into the game by offering clients simple algorithms like pegging or discretionary orders through a platform that is operated by the exchange and connects directly to the execution engine.[13] Together, these algorithms constitute "low-latency trading" that shapes the millisecond environment and therefore begs the question whether it harms or improves market quality along dimensions about which we care outside of the millisecond

[13] NASDAQ's RASH (Routing and Special Handling) protocol enables clients to use advanced functionality such as discretion (predetermined criteria for converting standing limit orders to marketable orders), random reserve (of partially non-displayed limit orders), pegging (to the relevant side of the market or the midquote), and routing to other trading venues.

environment. Answering this question is the goal of Section IV, but as a pre-requisite it necessitates developing a measure of low-latency activity.

III.C. Responding to the Market Environment

Our definition of low-latency trading is "strategies that respond to market events in the millisecond environment." Although any event might be expected to affect all subsequent events, our interest here is the speed of response. It is therefore reasonable to focus on conditioning events that seem especially likely to trigger rapid reactions. One such event is the improvement of a quote. An increase in the bid may lead to an immediate trade (against the bid) as potential sellers race to hit it. Alternatively, competing buyers may race to cancel and resubmit their own bids to remain competitive and achieve or maintain time priority. We call the former response a same-side execution, and the latter response a same-side submission/cancellation. Sell side events, subsequent to a decrease in the ask price, are defined similarly.

Our analysis requires only a slight change to the estimation of the hazard rates depicted in Figure 1. These earlier results are unconditional in the sense that they reflect durations subsequent to events of all types. The present characterization focuses on hazard rates subsequent to order submissions that improve the quote. Figure 4 (Panel A) depicts the conditional hazard rates for same-side events (pooled over bid increases and ask decreases).

In the discussion of Figure 1, we noted small local peaks at approximately 2-3 ms. These peaks are much more sharply defined in the conditional analysis, particularly for executions. This suggests that the fastest responders are subject to 2-3 ms latency. For comparison purposes, we note that human reaction times are generally thought to be on the order of 200 milliseconds (Kosinski (2010)). Therefore, it is a reasonable to assume that these responses represent actions by automated agents (various types of trading algorithms). The figure suggests that the time it takes for some low-latency traders to observe the market event, process the information, and act on it is indeed very short.

The hazard rates depicted in Panel B of Figure 4 are conditional on an order cancellation that resulted in the deterioration of the quote (a drop in the bid or increase in the ask). Peaks at 2-3 ms. are visible for same-side submissions and cancellations, presumably reflecting the repricing of orders pegged to the same-side quote. For executions, the peak is very small in 2007 and non-existent in 2008. Perhaps unsurprising, withdrawal of a bid (for example) does not induce sellers to chase it.

III.D. Strategic Runs

The evidence to this point has emphasized message timing. One would ideally like to track low-latency activity in order to decipher its impact on the market. Before turning to the methodology we use to track the algorithms, it is instructive to present two particular message sets that we believe are typical. It appears that at least some of the activity consists of algorithms that either "play" with one another or submit and cancel repeatedly in an apparent attempt to trigger an action on the part of another algorithm.

Panel A of Table 2 is an excerpt from the message file for ticker symbol ADCT on October 2, 2007 beginning at 09:51:57.849 and ending at 09:53:04.012 (roughly 66 seconds). Over this period, there were 35 submissions (and 35 cancels) of orders to buy 100 shares, and 32 submissions (and 32 cancels) of orders to buy 300 shares. The pricing of the orders caused the bid quote to rapidly oscillate between \$20.04 and \$20.05. The difference in order sizes and the brief intervals between cancelations and submissions suggest that the traffic is being generated by algorithms that seem to respond to each other.[14]

Panel B of Table 2 describes messages (for the same stock on the same day) between 09:57:18.839 and 09:58:36.268 (about 78 seconds). Over this period, orders to sell 100 shares were submitted (and quickly cancelled) 142 times. During much of this period there was no activity except for these messages. As a result of these orders, the ask quote rapidly oscillated between \$20.13 and \$20.14.

[14] When a similar sequence of events was discussed with a group of practitioners, one person pointed out that the sequence could have been generated by a single player intending to give the appearance of multiple competing buyers. Fictitious trades ("wash sales") are clearly considered illegal in the US, but this scenario would not involve trades, only quotes.

The underlying logic behind each algorithm that generates such strategic runs of messages is difficult to reverse engineer. It could be that some algorithms attempt to trigger an action on the part of other algorithms (e.g., canceling and resubmitting at a more aggressive price) and then interact with them. Whatever the reasoning, it is clear that an algorithm that repeatedly submits orders and cancels them within 10 ms does not intend to interact with human traders (whose response time would probably take more than 200 ms even if their attention is focused on this particular security). These algorithms operate in their own space: they are intended to trigger a response from (or respond to) other algorithms. Activity in the limit order book is dominated nowadays by this kind of interaction between automated algorithms, in contrast to a decade ago when human traders still ruled. How, then, are these algorithms affect the environment that the human traders observe? How is such activity related to market quality measures computed over minutes rather than milliseconds? In order to answer these questions, we need to create a measure of the activity of these low-latency traders.

We construct such a measure by identifying "strategic runs," which are linked submissions, cancellations, and executions that are likely to be parts of a dynamic strategy. Since our data do not identify individual traders, our methodology no doubt introduces some noise into the identification of low-latency activity. We nevertheless believe that other attributes of the messages can used to infer linked sequences. In particular, our "strategic runs" (or simply, in this context, "runs") are constructed as follows. Reference numbers supplied with the data unambiguously link an individual limit order with its subsequent cancellation or execution. The point of inference comes in deciding whether a cancellation can be linked to either a subsequent submission of a nonmarketable limit order or a subsequent execution that occurs when the same order is resent to the market priced to be marketable. We impute such a link when the cancellation is followed within one second by a limit order submission or by an execution in the same direction and for the same quantity. To be eligible for further analysis, we require that a run have at least one such resubmission.

We build the runs forward throughout the day. A limit order or a cancellation can be associated with only one run. An execution, however, might involve two runs. A canonical limit order strategy involves an initial submission priced away from the market, subsequent repricing to make the order more aggressive, and finally (if the order isn't executed) cancellation and resubmission of a marketable order. Thus, the passive side of an execution might be associated with one run, while the active side might be associated with another run (in the opposite direction) that became marketable.[15]

Our procedure linked roughly 60 percent of the cancellations in the 2007 sample, and 55 percent in the 2008 sample. Although we allow up to a one second delay from cancellation to resubmission, most resubmissions occur much more promptly. The median resubmission delay in our runs is one millisecond. The length of a run can be measured by the number of linked messages. The simplest run would have three messages, a submission of a nonmarketable limit order, its cancellation, and its resubmission as a marketable limit order that executes immediately (i.e., an "active execution"). The shortest run that does not involve an execution is a limit order that was submitted, cancelled, resubmitted, and cancelled or expired at the end of the day. Our sample periods, however, feature many runs of 10 or more linked messages and the longest run we identify has 93,243 messages. We identify about 57 million runs in the 2007 sample period and 78 million runs in the 2008 sample period.

Panel A of Table 3 looks at summary statistics for the runs. We observe that around 80% of the runs have 3 to 9 messages, but the longer runs (10 or more messages) constitute approximately half of the messages that are associated with strategic runs. The proportion of runs that were (at least partially) executed is 33.57% in 2007 and 27.34% in 2008. Interestingly, 22.74% of the 2007 runs (17.77% in 2008) achieved passive executions, that is, when a limit order was hit by an incoming marketable order. This is

[15] Of course, we cannot assert that the *intent* of the active side was to submit a marketable order. A limit order might be priced slightly short of the best visible opposing quote, and yet achieve execution against a hidden limit order. In this case, we observe an execution at the price of the hidden order, but we don't know the limit price specified in the order that executed against the hidden order.

notable because it can be interpreted as an average fill rate for runs, and stands in contrast to the fill rate for individual limit orders, which is much lower.[16]

About 10.95% (9.64%) of the runs in the 2007 (2008) sample period end with a switch to active execution. That is, a limit order is cancelled and replaced with a marketable order. These numbers attest to the importance of strategies that pursue execution in a gradual fashion. In the combined 2007 and 2008 samples there are a total of 57,848,674 executions. There were (combined) 13,799,814 runs that realized active executions. Since all runs by definition start with a nonmarketable limit order, we can determine that 23.9% (13,799,814/57,848,674) of all executions were preceded by an attempt to obtain a passive execution. This highlights the fluidity with which liquidity suppliers and demanders, often modeled as distinct populations, can in fact switch roles.

Our methodology to impute links between orders no doubt results in misclassifications that introduce an error into the analysis. However, we believe that the longer the run we impute, the more likely it is that it represents the activity of a real low-latency strategy that responds to market events. In other words, to capture the algorithms that interact with each other in real time (like those in Table 2) it is best to restrict our attention to strategic runs beyond a certain number of messages. We therefore use runs of 10 or more messages to construct a measure of low-latency traders that we use in the rest of the analysis. While the 10-message cutoff somewhat arbitrary, these runs represent about a half of the total number of messages that are linked to runs in each sample period, and we also believe that such longer runs characterize the episodes associated with intense high-frequency activity as in Figure 3.

Panel B of Table 3 shows the elapsed time from the beginning to the end of runs of 10 or more messages. It is interesting to note that many of the runs between 10 and 99 messages start and end within a tenth of a second (there are 497,317 such runs in 2007 and 180,675 in 2008). Nonetheless, most of these runs evolve over one to ten minutes, and time to completion of a run in general increases in the number of messages. Still, the

[16] The low fill rate of limit orders seems to characterize the modern electronic limit order book environment. Hasbrouck and Saar (2009) report a fill rate of 7.99% for a 2004 sample of Inet data.

intensity of the high-frequency episodes we describe in Figure 3 is reflected in the fact that many of the very long runs (1000 messages and above) start and end within a single minute.

IV. Low-Latency Trading and Market Quality

Agents who engage in low-latency trading and interact with the market over millisecond horizons are at one extreme in the continuum of market participants. Most investors either cannot or choose not to engage the market at this speed.[17] These investors' experience with the market is still best described with the traditional market quality measures in the market microstructure arsenal. Hence, a natural question to ask is how does low-latency activity with its algorithms that interact in milliseconds relate to depth in the market or the range of prices that can be observed over minutes or hours? This question does not have an obvious answer. It seems to resemble the challenge faced by physicists when attempting to relate quantum mechanics' subatomic interactions to our daily life that appears to be governed by Newtonian mechanics. However, if we believe that healthy markets need to attract longer-term investors whose beliefs and preferences are essential for the determination of market prices, then market quality should be measured using time intervals that are easily observed by these investors.

We therefore seek to characterize the influence of low-latency trading on measures of liquidity and short-term volatility observed over 10-minute intervals throughout the day. Measures such as the range between high and low prices in these intervals, the effective and quoted spreads, and the depth of the exchange's limit order book should give us a sense of market quality. And while we would likely not capture every instance of PA in each interval of time, the strategic runs we have identified in the previous section could be used to construct a measure of low-latency activity.

[17] The recent SEC Concept Release on Equity Market Structure refers in this context to "long-term investors … who provide capital investment and are willing to accept the risk of ownership in listed companies for an extended period of time" (p. 33).

IV.A. Measures and Methodology

To measure the intensity of low-latency activity in a stock in each ten-minute interval we use the time-weighted average of the number of strategic runs of 10 messages or more the stock experiences in the interval (*RunsInProcess*).[18] Higher values of *RunsInProcess* indicate greater low-latency activity.

We use our NASDAQ order-level data to compute several measures that represent different aspects of market quality: a measure of short-term volatility and three measures of liquidity. The first measure, *HighLow*, is defined as the highest midquote in an interval minus the lowest midquote in the same interval. The second measure, *EffSprd*, is the average effective spread (or total price impact) of all trades on NASDAQ during the ten-minute interval (where the effective spread of a trade is computed as the absolute value of the difference between the transaction price and the prevailing midquote). The third measure, *Spread*, is the time-weighted average quoted spread (ask price minus the bid price) on the NASDAQ system in an interval. The fourth measure, *NearDepth*, is the time-weighted average number of shares in the book up to 10 cents from the best posted prices.[19]

Although a ten-minute window is a reasonable interval over which to average the market quality measures, it is sufficiently long (particularly for the low-latency traders) that the analysis must confront the issue of simultaneity. For example, while we aim to test whether low-latency trading affects short-term volatility, it is quite possible that short-term volatility attracts or deters low-latency activity and hence affects the number of runs that we can observe in the interval.

To address this problem we propose a two-equation simultaneous equation model in which one of the endogenous variables is *RunsInProcess* (our low-latency activity measure) and the other endogenous variable is the market quality measure (i.e., we

[18] The time-weighting of this measure works as follows. Say we construct this variable for the interval 9:50:00am-10:00:00am. If a strategic run started at 9:45:00am and ended at 10:01:00am, it was active for the entire interval and hence it adds 1 to the RunsInProcess measure. A run that started at 9:45:00am and ended at 9:51:00am was active for one minute (out of ten) in this interval, and hence adds 0.1 to the measure. Similarly, a runs that was active for 6 seconds within this interval adds 0.01.

[19] We have also conducted all the tests with a depth measure defined as the time-weighted average number of shares in the book up to 50 cents from the best prices, and the results were similar.

estimate the model separately for *HighLow, EffSprd, Spread, and NearDepth*). This variable is indicated in the specifications by the placeholder *MktQuality*. The key to estimating such a model is to identify an instrument for market quality that does not directly affect *RunsInProcess* and an instrument for *RunsInProcess* that does not directly affect market quality in the stock.

As an instrument for $RunsInProcess_{i,t}$ (the number of runs of 10 messages or more in stock *i* in interval *t*) we use the average number of runs of 10 messages or more in the same interval for the other stocks in our sample (excluding stock *i*), denoted $RunsNotI_t$. Low-latency activity is determined by the number of players in the low-latency field (e.g., how many electronic market makers and statistical arbitrage firms are using low-latency strategies), by the state of the limit order book and stock-specific trading activity in the interval, and by market conditions that affect how aggressive low-latency firms are during that time.[20] The instrument $RunsNotI_t$ is determined by the number of low-latency firms and how active they are in the market during that interval, but at the same time it does not utilize information about stock *i* and hence is not a direct determinant of the liquidity or volatility of stock *i* in interval *t*, rendering it an appropriate instrument.

As an instrument for market quality we use a measure that is closely related to the liquidity of the stock in the interval, but does not directly determine the number of strategic runs in that stock. Our chief measure is the dollar effective spread (absolute value of the distance between the transaction price and the midquote) computed for the same stock and during the same time interval only from trades executed on other (non-NASDAQ) trading venues. This variable is denoted $EffSprdNotNAS_{i,t}$, and is computed using the TAQ database. This instrument reflects the general liquidity of the stock in the interval, but it does not reflect the activity on NASDAQ and hence would not be directly determined by the number of strategic runs that are taking place on the NASDAQ system. To examine the robustness of our result to this specific instrument, we repeat the analysis

[20] The "flash crash" on May 6, 2010, could be viewed as an example of how overall market conditions can affect the aggressiveness of low-latency traders in individual stocks. According to a Wall Street Journal article by Scott Patterson and Tom Lauricella, several electronic market making firms pulled back from the market because the market as a whole seemed too volatile.

using another instrument with a similar flavor, the time-weighted average quoted spread from TAQ, excluding NASDAQ quotes (denoted $SpreadNotNas_{i,t}$).

With these instruments, we use Two-Stage-Least-Squares (2SLS) to estimate the following two-equation simultaneous equation model for each market quality measure:

$$\begin{aligned} MktQuality_{i,t} &= a_1 RunsInProcess_{i,t} + a_2 EffSprdNotNAS_{i,t} + e_{1,t} \\ RunsInProccess_{i,t} &= b_1 MktQuality_{i,t} + b_2 RunsNotI_{i,t} + e_{2,t} \end{aligned}$$

where $i = 1,...,N$ indexes firms, $t = 1,...,T$ indexes 10-minute time intervals, and *MktQuality* represents one of the market quality measures: *HighLow*, *EffSpread*, *Spread*, and *NearDepth*. All variables are standardized to have zero-mean and unit variance, obviating the need for intercepts in the specification.

The 2SLS methodology effectively replaces $RunsInProcess_{i,t}$ in the first equation with the fitted values from the regression of $RunsInProcess_{i,t}$ on the instruments. Similarly $MktQuality_{i,t}$ in the second equation is replaced with the fitted values of the regression of $MktQuality_{i,t}$ on the instruments. This gives us a consistent estimate of the a_1 coefficient that tells us how low-latency activity affects market quality. We estimate the system by pooling observations across all stocks and all time intervals. The standardization of the variables essentially implements a fixed-effects specification. A potential disadvantage of pooling is that the errors of different stocks may not be identically distributed. For robustness, we also report summary measures of the coefficients from stock-by-stock estimations of the system. While stock-by-stock analysis does not assume identically distributed errors across stocks, it leaves us with a much smaller number of observations for each estimation (897 in the 2007 sample period and 819 in the 2008 sample period) and hence has reduced power relative to the pooled time-series/cross-sectional specification.

IV.B. Results

Panel A of Table 4 presents the estimated coefficients of the pooled system side-by-side for the 2007 and 2008 sample periods. First we note that the two instruments have the expected signs and are highly significant. Specifically, the coefficient a_2 indicates that when liquidity off NASDAQ is higher, our NASDAQ market quality measures show higher liquidity and lower volatility. Similarly, the coefficient b_2 is positive in all specifications, indicating that higher low-latency activity in a specific stock in an interval is associated with higher low-latency activity in other stocks on the NASDAQ system. Second, the estimated b_1 coefficients tell us that low-latency activity is attracted to more liquid and less volatile stocks.

The most interesting coefficient is a_1, which measures the impact of low-latency activity on the market quality measures. We observe that higher low-latency activity implies lower posted and effective spreads, greater depth, and lower short-term volatility. Moreover, the impact of low-latency activity on market quality is similar in the 2007 and 2008 sample periods. The fact that low-latency trading decreases short-term volatility and contributes to depth in the 2008 sample period where the market is relentlessly going down and there is heightened uncertainty in the economic environment is particularly noteworthy. It seems to suggest that PA activity creates a positive externality in the market at the time that the market needs it the most. Panel B of Table 4 presents roughly similar results from the estimation of the system with $SpreadNotNas_{i,t}$ as the instrument for market liquidity.[21]

It is possible, however, that the impact of low-latency trading on market quality would differ for stocks that are somehow fundamentally dissimilar, like small versus large market capitalization stocks. Table 5 presents system estimates in subsamples consisting of four quartiles ranked by the average market capitalization over the sample period.[22] There is not much pattern across the quartiles in the manner low-latency activity affects short-term volatility in the 2007 sample period. The picture in the 2008 sample is different: It appears that during more stressful times, low-latency activity helps reduce volatility in smaller stocks more than it does in larger stocks.

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[21] The only difference in the results with $\mathrm{SpreadNotNas}_{i,t}$ as the instrument is that the coefficient a_1 is not statistically significant for the EffSprd measure in the 2008 sample period.

[22] The results in the table are presented with $\mathrm{EffSprdNotNAS}_{i,t}$ as the instrument for the market quality measures. We obtain similar results (with similar patterns across the quartiles) using $\mathrm{SpreadNotNas}_{i,t}$ as the instrument.

Another interesting pattern can be observed in the coefficient b_1, which tells us how market quality affects low-latency trading. While low-latency activity increases in market quality for larger stocks in the 2007 sample period, no such relationship is found for smaller stocks, where the coefficient has the opposite sign but is not statistically significant. During the stressful period of June 2008, however, the b_1 coefficients suggest a different behavior: Higher liquidity encourages low-latency trading in smaller stocks but not in the top quartile of stocks by market capitalization where we observe the opposite pattern (though the absolute magnitude of the coefficient in large cap stocks is rather small and hence the effect is probably not very strong).

Lastly, Table 6 shows summary statistics for the stock-by-stock estimations. The results suggest similar conclusions concerning the effect of low-latency trading on market quality. In particular, an increase in low-latency activity decreases short-term volatility, decreases quoted spreads, and increases displayed depth in the limit order book. This is true both in the 2007 and 2008 sample periods. The median coefficient is insignificant when the liquidity measure is *EffSprd* in both sample periods. The only consistent difference between the pooled estimation and the stock-by-stock analysis is that none of the median coefficients of b_1 is statistically significant. In other words, while the impact of low-latency trading on market quality seems robust, our finding that low-latency activity is attracted to more liquid and less volatile stocks should be somewhat qualified due to the insignificant results in the stock-by-stock analysis.

V. Related Literature

Our paper can be viewed from two, somewhat related, angles: speed of interaction and information dissemination in financial markets, and the characteristics of algorithmic trading and its impact on the market environment. The academic literature in finance on both areas is at its infancy, but there are nonetheless several papers that are related to our study and are discussed below.

On the notion of speed, Hendershott and Moulton (2009) look at the introduction of the NYSE's Hybrid Market in 2006 that enabled automatic execution and reduced the execution time for NYSE market orders from ten seconds to less than a second. They find that this reduction in the latency of trading resulted in worsened liquidity (e.g., spreads increased) but improved the informational efficiency of prices. An opposite conclusion with respect to liquidity is reached by Riordan and Storkenmaier (2008), who examine a change in latency on the Deutsche Boerse' Xetra system. It could be that the impact of a change in latency on market quality depends on how exactly it affects competition among liquidity suppliers (e.g., the entrance of electronic market makers who can add liquidity but also crowed out traditional liquidity providers) and the level of sophistication of liquidity demanders (e.g., their adoption of algorithms to implement dynamic limit order strategies that can both supply and demand liquidity). Easley, Hendershott, and Ramadorai (2009) examine a change in trading technology on the NYSE in 1980 that increased both the speed and the transparency of the market and find improved liquidity that they attribute to the increased competition from off-exchange traders who were better able to compete with the specialists and floor brokers.[23]

A few papers on algorithmic trading come from Germany due to the availability of data from the Deutsche Boerse that flags orders sent by an algorithm as opposed to a human trader.[24] Gsell (2008) shows that the majority of orders generated by algorithms demand rather than supply liquidity and are smaller than those sent by human traders, while Groth (2009) finds that algorithmic orders have a higher execution rate than non-algorithmic orders. Gsell and Gomber (2008) show evidence consistent with pegging strategies, and Prix, Loistl, and Huetl (2007), like us, attempt to impute algorithmic strategies. They note that there are certain regularities in the activity of these algorithms, some of which tend to cycle every 60 seconds. Hendershott and Riordan (2009) look at

[23]Cespa and Foucault (2008) provide a theoretical model in which some traders observe market information ("the tape") with a delay. In other words, they investigate latency in market information, which is a component of our latency concept that is comprised of the time it takes to observe market information, to process market information, and implement an action in response to the market information. In their framework, price efficiency is impaired and the risk premium increases when some traders have faster and others have slower access to information. Boulatov and Dierker (2007) investigate the issue of latency in market information from the perspective of how much money the exchange can charge for price data. Their theoretical model suggests that selling real-time data can be detrimental to liquidity but at the same time enhances the informational efficiency of prices.

[24] The flag is based on self reporting, but firms have a fee incentive to identify themselves as algorithmic traders and hence these papers assume that most algorithmic trading is captured by this flag.

the 30 DAX stocks and find that algorithmic trades have a larger price impact than non-algorithmic trades and seem to contribute more to price discovery.

Three papers that focus on U.S. markets are the most related to our study. Hendershott, Jones, and Menkveld (2009) use a measure of NYSE message traffic as a catch all proxy for both AA and PA. Using an event study approach around the introduction of autoquoting by the NYSE in 2003, the authors document that an increase in their measure for algorithmic trading (number of messages) affected only the largest stocks. For these stocks, liquidity improved in the sense that quoted and effective spreads declined, but quoted depth decreased which is less consistent with an improvement in market quality. Large-cap stocks also experienced better price discovery. We, on the other hand, find an improvement in market quality using all measures, including depth and short-term volatility, and for all stocks rather than just the largest stocks.[25] This could be driven by our measure of low-latency trading that attempts to capture more PA activity than AA activity. Furthermore, it is conceivable that the primary impact of autoquoting in 2003 was on AA as there was much less competition to NYSE specialists from electronic market making firms before the NYSE implemented the Hybrid market in 2006.

In a contemporaneous paper, Brogaard (2010) investigates the impact of high-frequency trading on market quality using a dataset that contains the activity of 26 high-frequency traders in 120 stocks. He reports that high-frequency traders contribute to liquidity provision in the market, that their trades help price discovery more than trades of other market participants, and that their activity appears to lower volatility. His results, therefore, complement our findings on market quality measures in Section IV, which is especially important given the differences in the design of the experiments in the two papers.

There is no doubt that Brogaard's data on the 26 traders is of high quality: he observes their actual trading activity. On the other hand, his data covers only a subset of

[25] The average market capitalization (in billion dollars) of sample quintiles reported in Table 1 of Hendershott, Jones, and Menkveld (2009) is 28.99, 4.09, 1.71, 0.90, and 0.41. This corresponds rather well to our sample where the average market capitalization of quintiles is 21.4, 3.8, 2.1, 1.4, and 1.0, though we may have fewer very large and very small stocks compared to their sample.

PA that is more likely to be dominated by electronic market makers (that provide liquidity) relative to their real weight in the PA space.[26] Since our measure of low-latency trading relies on imputed strategic runs, we are more likely capture a broader picture of PA and perhaps even some AA that adopt the same tools to respond to market conditions.[27] Another important difference between the two papers is that the analysis in Brogaard's paper is done using data on one week in February 2010 where the NASDAQ Composite Index was basically flat, while our 2008 sample provides insights on what happens at times of declining prices and heightened uncertainty. The ability to study low-latency activity during a stressful period for the market is especially important when the conclusion from the analysis of "normal times" is that these traders improve, rather than harm, market quality.

We note, though, that traders engaged in low-latency activity could impact the market in a negative fashion at times of extreme market stress. The joint CFTC/SEC report regarding the "flash crash" of May 6, 2010, presents a detailed picture of such an event. The report notes that many high-frequency traders scaled down, stopped, or significantly curtailed their trading at some point during this episode. Furthermore, some of the high-frequency traders escalated their aggressive selling during the rapid price decline, removing significant liquidity from the market and hence contributing to the decline. Our study suggests that such behavior is not representative of the manner in which low-latency activity impacts market conditions outside of such extreme episodes.

Lastly, our paper relates to the analysis of Hasbrouck and Saar (2009) who present evidence consistent with the implementation of dynamic trading strategies by market participants using order-level data from the INET ECN. Hasbrouck and Saar emphasize how technology changed the nature of the market environment. Our paper

[26] Brogaard's data do not include several important types of PA traders. First, they lack the proprietary trading desks of larger, integrated firms like Goldman Sachs or JP Morgan. Second, they ignore many of the statistical arbitrage firms that use the services of direct access brokers (such as Lime Brokerage or Swift Trade) that specialize in providing services to high-frequency traders.

[27] This is the reason behind our labeling of these traders "low-latency traders" rather than "high-frequency traders." Unlike one or the other terms that are prevalent in the media, our definition is based on an economic idea: Traders who respond to market events.

provides striking evidence on attributes of the millisecond environment that demonstrate how computer algorithms born out of the technological “arms race” are completely taking over market interactions.

VI. Conclusions

Our paper makes two contributions. First, it describes the millisecond environment in which trading takes place in equity markets. The clock-time periodicities, the episodic nature of high-frequency activity, and the manner in which trading responds to market events over millisecond horizons characterize a fundamental change from the manner in which stock markets operated even a few years ago. Second, we study the impact that low-latency activity has on market quality both during normal market conditions and during a period of declining prices and heightened economic uncertainty. Our conclusion is that increased low-latency activity improves traditional yardsticks for market quality such as liquidity and short-term volatility. The picture that emerges from our analysis is that of a new market reality comprised mostly of algorithms that interact with other algorithms. Our results do not support the view, however, that the conventional measures of liquidity familiar to long-term investors have worsened in consequence.

The economic issues associated with latency in financial markets are not new, and the private advantage of low-latency capabilities was noted well before the advent of our current millisecond environment:

> For some years prior to [the introduction of the telegraph in 1846], William C. Bridges, a stock broker, together with several others, had maintained a unique private ‘telegraph’ system between Philadelphia and New York. By the ingenious device of establishing stations on high points across New Jersey, on which signals were given by semaphore in the daytime and by light flashes at night, discerned with the aid of telescopes, information on lottery numbers, stock prices, etc., was conveyed in as short a time as ten minutes between the two cities.
> (Barnes, 1911, p. 9)

Nor are low-latency’s effects on price dynamics new concerns:

> Some of the mysterious movements in the stock markets of Philadelphia and New York were popularly ascribed to this pioneer financial news bureau.
> (Barnes, ibid)

What is the real economic cost of a delay? It depends on both risk and the potential for strategic interaction. At current latency levels it is difficult to attach much importance to the risk borne over the period of delay. Suppose a daily log volatility of 0.03 (roughly corresponding, over 250 trading days, to a 47% annual volatility). If the daily volatility is unconditionally distributed evenly over the 6.5 hour trading day, then the volatility over 10 ms is a negligible 0.2 basis points.

The importance of delay for strategic interactions, however, might be much greater. Suppose that the daily volatility is generated by a single randomly-timed announcement that causes the value to change (equiprobably) by ±3%. This 3% can be captured by a first-mover who observes the announcement and takes a long or short position against others yet unaware, irrespective of whether his absolute time advantage is one minute or one microsecond.

Furthermore, the market itself creates events in the form of imbalances of supply and demand that could be of value to traders who are fast enough to respond to them. There is no doubt that being faster than others entails private advantage, but is it socially beneficial? The first mover in the case of fundamental news imposes costs on other traders, and high adverse selection costs could cause market failure. The fast traders that take advantage of market events could provide valuable liquidity to those seeking immediacy and hence enhance market quality, but could also step ahead of large orders in the book imposing costs on other liquidity providers (as described in the specialist context by Seppi (1997)).

It is striking how much the economic essence of the current environment, with its millisecond interactions and high tech flavor, resembles the old floor-based exchanges. The old floor-based exchanges (like the NYSE) were physically compact spaces where one could pay a fixed cost to get access to the space (by buying a membership). Being on the floor gave traders a timing advantage as off-floor traders encountered delays. In the new environment, the exchange is simply a computer server. The new "floor" is the physically compact rack on which the server sits. By paying a cost, traders can rent a slot for their computers next to the exchange's server (the so-called "co-location" practice). This gives the traders a timing advantage because co-location cuts down on the time it takes to get the information from the exchange (via direct data feeds) and send the orders back to the exchange. Other traders off the co-located environment encounter delays.

In fact, it appears that the current environment result in even more intermediation than the old exchange floor. NYSE specialists (the designated market makers on the exchange floor) had a participation rate of 25.3% of the volume just a decade before our sample period.[28] News reports assert that high-frequency traders, some of which operate as electronic market makers, participate in as much as 60% of the volume in today's markets. This could be a cause for concern, as one of the goals of the National Market System envisioned by the Exchange Act of 1934 was to create a situation whereby investors' orders could be executed without the participation of a dealer. In other words, excessive dealing with its associated rents was viewed as unhealthy for our financial markets in the Exchange Act, and the SEC was given the mandate to facilitate markets that would emphasize direct investor-to-investor interaction.

It appears as if regulatory changes over the past decade (e.g., Reg ATS, decimalization, and Reg NMS) coupled with improvements in technology created the opposite environment: A fertile ground for the old market makers to return with a vengeance under a different disguise. A potential undesirable outcome of these changes is that investors could lose faith in the fairness of trading in financial markets due to the presence of these professionals who are perceived to always have the upper hand in trading. Current practice indeed allows sophisticated traders to get market information via direct data feeds before others can observe it on the tape and act on it. Is this fair? In Regulation Fair Disclosure, the SEC took the stand that firms cannot release fundamental information to a subset of investors before others. On the other hand, Rule 603(a)

[28] See New York Stock Exchange Fact Book 1998 Data.

established a different approach to market data, whereby market centers could sell data directly to subscribers, in effect creating a tiered system of investors with respect to access to information about market events.[29]

While there is some theoretical work on the issue of differential access to market data (see Boulatov and Dierker (2007) and Cespa and Foucault (2008)), there is less guidance on how co-location, with its preferential access to both data and execution services, affects the welfare of investors. It is possible that the resulting increase in intermediation is actually desirable in today's fast paced financial markets. If investors do not tolerate delay when trading, it is difficult to assure instantaneous execution without intermediation. And if competition in electronic market making ensures that the cost investors have to pay for dealer services is low, the argument goes, what is the harm in increased intermediation? One problem with this argument is that the new electronic market making firms are not exactly like the old NYSE specialists; the missing element is the lack of affirmative and negative obligations.

In the face of transient supply and demand, NYSE specialists were obligated to stabilize prices and maintain continuous presence in the market. They were subject to restrictions on reaching across the market to take liquidity (destabilizing trades). They were prohibited from "interpositioning" (trading separately against buyers and sellers who otherwise would have traded directly). The electronic market making firms and other low-latency traders have no such obligations. Their efficiency and lack of obligations could therefore drive traditional suppliers of liquidity out of business by gaining at their expense in normal times. As a result, at times of severe market stress, low-latency traders can simply step away from the market, causing fragility that did not exist in the old model.

One of the contributions of our study is the finding that at times of declining prices and heightened economic uncertainty, the nature of the millisecond environment

[29] Rule 603(a) prohibits an SRO or a broker-dealer from supplying the data via direct feeds faster than it supplies it to the Securities Industry Automation Corporation (SIAC) that processes the data and distributes the "tape." However, the operation of processing and retransmitting data via SIAC appears to add 5 to 10 millisecond and hence subscribers to direct exchange data feeds "see" the information before others who observe the tape.

and the positive influence of low-latency activity on market quality remains. However, we cannot rule out that there is another potential state of sudden, severe, market stress in which the lack of obligations would result in a market failure. The experience of the "flash crash" in May of 2010 demonstrates that such fragility is certainly possible when a few big players step aside and nobody is left to post limit orders.

One solution to this problem could be to couple co-location with an obligation to maintain continuous quoting presence in the market. While some firms might choose to abandon co-location, those left would have the speed advantage and hence would be willing to accept the added risk associated with continuous quoting presence. Market marking profits at normal times would then be used to subsidize losses during market stress, an arrangement that worked well in the past (e.g., on the NYSE), and it is worthwhile reexamining its merit. Some market making firms have already suggested that a solution in this spirit is feasible.[30]

Lastly, we believe that it is important to recognize that guaranteeing equal access to market data when the market is both continuous and fragmented, as it currently is in the United States, may be physically impossible. First, Gode and Sunder (2000) claim that when traders are dispersed geographically, transmission delays are sufficiently large to prevent equitable access to a continuous market. Our evidence on the speed of execution against improved quotes suggests that some players are responding within 2-3 ms, while the New York and Chicago roundtrip (1159 km) is about 8 ms even at the speed of light.

Second, even if one views co-location as the ultimate equalizer of dispersed traders, it leads to the impossibility of achieving equal access in fragmented markets. Since the same stock is traded on multiple trading venues, a co-located computer near the servers of exchange A would be at a disadvantage in responding to market events in the same securities on exchange B compared to computers co-located with exchange B. Hence, unless markets change from continuous auctions to a sequence of call auctions,

[30] Representatives of GETCO, Virtu Financial, and Knight Capital Group sent a letter to the SEC on July 9, 2010, titled "Market Maker Obligations" that discusses their proposal to impose such obligations. See also an article by Scott Patterson in the Wall Street Journal on July 13, 2010.

some traders will always have lower latency than others. Our findings in this paper suggest that this situation is not all bad, even if investors have to get used to a new state of affairs whereby market activity is governed to a large extent by computer algorithms that play with one another in the millisecond environment.

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Table 1

Summary Statistics

This table presents summary statistics for the stocks in our sample. The universe of stocks used in the study is comprised of the 500 largest stocks by market capitalization on September 28, 2007. We investigate trading in these stocks in two sample periods: (i) October 2007 (23 trading days), and (ii) June 2008 (21 trading days). Since the main econometric analysis in the paper requires sufficient level of activity in the stocks, we apply the following screen to the stocks in each sample period: A firm is rejected if the proportion of 10-minute intervals with fewer than 250 messages is above 10%. A "message" for the purpose of this screen could be a submission, a cancellation, or an execution of a limit order. After applying the screen (and dropping Google and Apple due to computational limitations), our sample consists of 345 stocks in the October 2007 sample period and 394 stocks in the June 2008 sample period. In Panel A we report summary statistics from the CRSP database. *MktCap* is the market capitalization of the firms computed using closing prices on the last trading day prior to the start of the sample period. *ClsPrice* is the average closing price, *AvgVol* is the average daily share volume, and *AvgRet* is the average daily return. These variables are averaged across time for each firm, and the table entries refer to the sample distribution of these firm-averages. Panel B presents summary statistics from the NASDAQ market computed using TotalView-ITCH data. We report the average daily number of orders submitted, cancelled, and executed in each sample period, along with the average daily number of shares executed. The summary measures for the limit order book include the time-weighted average depth in the book, the time-weighted average depth near current market prices (i.e., within 10 cents of the best bid or ask prices), and the time-weighted average dollar quoted spread (the distance between the bid and ask prices). We also report the effective (half) spread, defined as the absolute value of the difference between the transaction price and the quote midpoint, averaged across all transactions.

Panel A: CRSP Summary Statistics

	2007				2008			
	MktCap (*$Million*)	*ClsPrice* (*$*)	*AvgVol* (*1,000s*)	*AvgRet* (*%*)	*MktCap* (*$Million*)	*ClsPrice* (*$*)	*AvgVol* (*1,000s*)	*AvgRet* (*%*)
Mean	5,936	34.98	3,092	0.110	4,908	30.09	2,871	-0.565
Median	2,069	29.07	1,074	0.123	1,648	24.67	1,116	-0.512
Std	18,402	25.55	7,950	0.557	16,337	27.84	6,263	0.618
Min	789	2.22	202	-2.675	286	2.32	112	-3.449
Max	275,598	272.07	77,151	1.933	263,752	278.66	74,514	0.817

Panel B. NASDAQ (TotalView-ITCH) Summary Statistics

		Number of Submissions	Number of Cancellations	Number of Executions	Shares Executed (1,000s)	Depth (1,000s)	Near Depth (1,000s)	Quoted Spread ($)	Eff. Half Spread ($)
2007	Mean	41,477	37,126	3,593	1,363	243	29	0.033	0.007
	Median	27,130	24,374	2,489	548	74	6	0.025	0.005
	Std	44,334	40,039	3,290	3,154	813	129	0.031	0.007
	Min	9,658	8,013	695	130	13	1	0.010	0.003
	Max	305,688	308,178	22,644	32,305	7,979	1,555	0.313	0.078
2008	Mean	52,756	48,671	3,546	1,177	254	22	0.034	0.006
	Median	34,875	31,712	2,329	486	78	5	0.023	0.004
	Std	54,978	50,882	3,666	2,556	886	77	0.039	0.007
	Min	8,889	7,983	291	42	10	0	0.010	0.002
	Max	401,140	409,803	28,105	32,406	12,502	1,241	0.462	0.087

Table 2

Examples of Strategic Runs for Ticker Symbol ADCT on October 2, 2007

This table presents examples of "strategic runs," which are linked submissions, cancellations, and executions that are likely to be parts of a dynamic strategy of a trading algorithm. The examples are taken from activity in one stock (ATC Telecommunications, ticker symbol ADCT) on October 2, 2007. We identify the existence of these strategic runs by imputing links between different submissions, cancellations, and executions based on direction, size, and timing. In the two cases presented below, the activity in the table constitutes all messages in this stock (i.e., there are no intervening messages that are unrelated to these strategic runs). In Panel A, we present order activity starting around 9:51:57am where two algorithms "play" with each other (i.e., they submit and cancel messages in response to one another). The messages sent by the second algorithm are highlighted in the table. The algorithms are active for one minute and 12 seconds, sending 137 messages (submissions and cancellations) to the market. In Panel B we present order activity starting around 9:57:18am where one algorithm submits and cancels orders. The algorithm is active for one minute and eighteen seconds, sending 142 messages (submissions and cancellations) to the market.

Panel A: ADCT Order Activity Starting 09:51:57.849

Time	Message	B/S	Shares	Price	Bid	Offer
09:51:57.849	Submission	Buy	100	20.00	20.03	20.05
09:52:13.860	Submission	Buy	300	20.03	20.03	20.04
09:52:16.580	Cancellation	Buy	300	20.03	20.03	20.04
09:52:16.581	Submission	Buy	300	20.03	20.03	20.04
09:52:23.245	Cancellation	Buy	100	20.00	20.04	20.05
09:52:23.245	Submission	Buy	100	20.04	20.04	20.05
09:52:23.356	Cancellation	Buy	300	20.03	20.04	20.05
09:52:23.357	Submission	Buy	300	20.04	20.04	20.05
09:52:26.307	Cancellation	Buy	300	20.04	20.05	20.07
09:52:26.308	Submission	Buy	300	20.05	20.05	20.07
09:52:29.401	Cancellation	Buy	300	20.05	20.04	20.07
09:52:29.402	Submission	Buy	300	20.04	20.04	20.07
09:52:29.402	Cancellation	Buy	100	20.04	20.04	20.07
09:52:29.403	Submission	Buy	100	20.00	20.04	20.07
09:52:32.665	Cancellation	Buy	100	20.00	20.04	20.07
09:52:32.665	Submission	Buy	100	20.05	20.05	20.07
09:52:32.672	Cancellation	Buy	100	20.05	20.04	20.07
09:52:32.678	Submission	Buy	100	20.05	20.05	20.07
09:52:32.707	Cancellation	Buy	100	20.05	20.04	20.07
09:52:32.708	Submission	Buy	100	20.05	20.05	20.07
09:52:32.717	Cancellation	Buy	100	20.05	20.04	20.07
09:52:32.745	Cancellation	Buy	300	20.04	20.04	20.07
09:52:32.745	Submission	Buy	100	20.05	20.05	20.07
09:52:32.746	Submission	Buy	300	20.05	20.05	20.07
09:52:32.747	Cancellation	Buy	100	20.05	20.05	20.07
09:52:32.772	Submission	Buy	100	20.02	20.05	20.07
09:52:32.776	Cancellation	Buy	300	20.05	20.04	20.07
09:52:32.777	Cancellation	Buy	100	20.02	20.04	20.07
09:52:32.777	Submission	Buy	300	20.04	20.04	20.07
09:52:32.778	Submission	Buy	100	20.05	20.05	20.07
09:52:32.778	Cancellation	Buy	300	20.04	20.05	20.07
09:52:32.779	Submission	Buy	300	20.05	20.05	20.07
09:52:32.779	Cancellation	Buy	100	20.05	20.05	20.07
09:52:32.807	Cancellation	Buy	300	20.05	20.04	20.07
09:52:32.808	Submission	Buy	100	20.02	20.04	20.07
09:52:32.808	Submission	Buy	300	20.04	20.04	20.07
09:52:32.809	Cancellation	Buy	100	20.02	20.04	20.07

… the interaction between the two strategic runs continues for 95 additional messages until a limit order of the 300-share run is executed by an incoming marketable order at 09:53:09.365.

Panel B: ADCT Order Activity Starting 09:57:18.839

Time	Message	B/S	Shares	Price	Bid	Ask
09:57:18.839	Submission	Sell	100	20.18	20.11	20.14
09:57:18.869	Cancellation	Sell	100	20.18	20.11	20.14
09:57:18.871	Submission	Sell	100	20.13	20.11	20.13
09:57:18.881	Cancellation	Sell	100	20.13	20.11	20.14
09:57:18.892	Submission	Sell	100	20.16	20.11	20.14
09:57:18.899	Cancellation	Sell	100	20.16	20.11	20.14
09:57:18.902	Submission	Sell	100	20.13	20.11	20.13
09:57:18.911	Cancellation	Sell	100	20.13	20.11	20.14
09:57:18.922	Submission	Sell	100	20.16	20.11	20.14
09:57:18.925	Cancellation	Sell	100	20.16	20.11	20.14
09:57:18.942	Submission	Sell	100	20.13	20.11	20.13
09:57:18.954	Cancellation	Sell	100	20.13	20.11	20.14
09:57:18.958	Submission	Sell	100	20.13	20.11	20.13
09:57:18.961	Cancellation	Sell	100	20.13	20.11	20.14
09:57:18.973	Submission	Sell	100	20.13	20.11	20.13
09:57:18.984	Cancellation	Sell	100	20.13	20.11	20.14
09:57:18.985	Submission	Sell	100	20.16	20.11	20.14
09:57:18.995	Cancellation	Sell	100	20.16	20.11	20.14
09:57:18.996	Submission	Sell	100	20.13	20.11	20.13
09:57:19.002	Cancellation	Sell	100	20.13	20.11	20.14
09:57:19.004	Submission	Sell	100	20.16	20.11	20.14
09:57:19.807	Cancellation	Sell	100	20.16	20.11	20.13
09:57:19.807	Submission	Sell	100	20.13	20.11	20.13
09:57:20.451	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.461	Submission	Sell	100	20.13	20.11	20.13
09:57:20.471	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.480	Submission	Sell	100	20.13	20.11	20.13
09:57:20.481	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.484	Submission	Sell	100	20.13	20.11	20.13
09:57:20.499	Cancellation	Sell	100	20.13	20.11	20.14

Time	Message	B/S	Shares	Price	Bid	Ask
09:57:20.513	Submission	Sell	100	20.13	20.11	20.13
09:57:20.521	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.532	Submission	Sell	100	20.13	20.11	20.13
09:57:20.533	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.542	Submission	Sell	100	20.13	20.11	20.13
09:57:20.554	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.562	Submission	Sell	100	20.13	20.11	20.13
09:57:20.571	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.581	Submission	Sell	100	20.13	20.11	20.13
09:57:20.592	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.601	Submission	Sell	100	20.13	20.11	20.13
09:57:20.611	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.622	Submission	Sell	100	20.13	20.11	20.13
09:57:20.667	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.671	Submission	Sell	100	20.13	20.11	20.13
09:57:20.681	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.742	Submission	Sell	100	20.13	20.11	20.13
09:57:20.756	Cancellation	Sell	100	20.13	20.11	20.14
09:57:20.761	Submission	Sell	100	20.13	20.11	20.13

… the strategic run continues for 89 additional messages until it stops at 09:58:36.268.

Table 3

Strategic Runs

This table presents summary statistics for “strategic runs,” which are linked submissions, cancellations, and executions that are likely to be parts of a dynamic strategy. The imputed links between different submissions, cancellations, and executions are based on direction, size, and timing. Specifically, when a cancellation is followed within one second by a submission of a limit order in the same direction and for the same quantity, or by an execution in the same direction and for the same quantity, we impute a link between the messages. Because prompt transmission of a new limit order in a dynamic strategy may be more important than the cancellation of the standing order, we also link events where the new order or execution precedes the cancellation by up to 100 milliseconds. The methodology that tracks the strategic runs also takes note of partial executions and partial cancellations of orders. In Panel A we sort runs into categories by length (i.e., the number of linked messages), and report information about the number of runs, messages, and executions (separately active and passive) within each category. An active execution is when the run ends with a marketable limit order that executes immediately. A passive execution is when a standing limit order that is part of a run is executed by an incoming marketable order. One run could potentially result in both a passive execution and an active execution if the passive execution did not exhaust the order, and the reminder was cancelled and resubmitted to generate an immediate active execution. Panel B shows the elapsed time from the beginning to the end of runs of 10 or more messages, which are the runs that we use to construct our measure of low-latency activity.

Panel A: Summary Statistics of Strategic Runs

	Length Of Runs	Runs (#)	Runs (%)	Messages (#)	Messages (%)	Active Exec. (#)	Active Exec. Rate	Passive Exec. (#)	Passive Exec. Rate	Total Exec. (#)	Total Exec. Rate
	3-4	27,344,930	47.99%	105,690,858	22.53%	3,720,292	13.61%	5,476,480	20.03%	9,172,711	33.54%
	5-9	17,998,854	31.59%	118,037,347	25.17%	1,882,712	10.46%	4,941,592	27.46%	6,798,313	37.77%
	10-14	6,560,499	11.51%	75,353,085	16.07%	284,960	4.34%	1,468,072	22.38%	1,744,893	26.60%
2007	15-19	1,842,320	3.23%	30,948,629	6.60%	173,262	9.40%	418,977	22.74%	589,789	32.01%
	20-99	3,073,546	5.39%	100,494,251	21.43%	172,094	5.60%	619,304	20.15%	787,245	25.61%
	100+	160,903	0.28%	38,503,154	8.21%	6,529	4.06%	31,316	19.46%	37,508	23.31%
	All	56,981,052	100.00%	469,027,324	100.00%	6,239,849	10.95%	12,955,71	22.74%	19,130,459	33.57%
	3-4	40,284,620	51.35%	156,714,747	26.25%	4,459,563	11.07%	5,916,127	14.69%	10,355,650	25.71%
	5-9	23,744,638	30.27%	155,608,785	26.06%	2,297,553	9.68%	5,324,835	22.43%	7,599,729	32.01%
	10-14	8,262,256	10.53%	94,723,010	15.87%	354,704	4.29%	1,600,453	19.37%	1,948,080	23.58%
2008	15-19	2,295,030	2.93%	38,561,692	6.46%	221,307	9.64%	451,793	19.69%	671,084	29.24%
	20-99	3,696,434	4.71%	118,816,877	19.90%	219,686	5.94%	627,419	16.97%	844,207	22.84%
	100+	160,661	0.20%	32,615,369	5.46%	7,152	4.45%	22,687	14.12%	29,695	18.48%
	All	78,443,639	100.00%	597,040,480	100.00%	7,559,965	9.64%	13,943,314	17.77%	21,448,445	27.34%

Panel B: Distribution of Elapsed Time for Runs of 10 or more Messages

			Elapsed Time					
	Length of Run	Number of Runs	< 0.1 sec.	[0.1,1) sec.	[1,60) sec.	[1,10) min.	[10,60) min.	> 60 min.
2007	10-14	6,560,499	276,703	353,093	3,015,701	2,386,218	462,458	66,326
	15-19	1,842,320	73,978	93,759	763,002	716,794	172,526	22,261
	20-99	3,073,546	124,008	218,861	1,075,282	1,109,339	458,586	87,470
	100-999	158,032	218	16,827	43,277	32,977	24,090	40,643
	1,000-4,999	2,523	0	0	1,392	609	263	259
	5,000+	348	0	0	126	134	30	58
	All	11,637,268	474,907	682,540	4,898,780	4,246,071	1,117,953	217,017
2008	10-14	8,262,256	109,077	164,355	3,785,673	3,572,232	560,216	70,703
	15-19	2,295,030	25,984	34,601	842,787	1,148,372	218,637	24,649
	20-99	3,696,434	38,955	74,953	987,683	1,791,617	694,245	108,981
	100-999	159,401	45	5,613	32,396	35,553	32,696	53,098
	1,000-4,999	1,211	0	0	600	442	83	86
	5,000+	49	0	0	16	21	5	7
	All	14,414,381	174,061	279,522	5,649,155	6,548,237	1,505,882	257,524

Table 4

Simultaneous Equation Model: Low-Latency Trading and Market Quality

This table presents analysis of the manner in which low-latency trading affects market quality. To measure the intensity of low-latency activity in a stock in each ten-minute interval, we use the time-weighted average of the number of strategic runs of 10 messages or more the stock experiences in the interval (*RunsInProcess*). We use NASDAQ order-level data to compute several measures that represent different aspects of market quality on the NASDAQ system in each time interval: (i) *HighLow* is the highest midquote minus the lowest midquote in the same interval, (ii) *EffSprd* is the average effective spread (or total price impact) of a trade, computed as the absolute value of the difference between the transaction price and the prevailing midquote, (iii) *Spread* is the time-weighted average quoted spread (ask price minus the bid price), and (iv) *NearDepth* is the time-weighted average number of shares in the book up to 10 cents from the best posted prices. Due to the potential simultaneity between market quality and low-latency trading, we estimate the following two-equation simultaneous equation model for *RunsInProcess* and each of the market quality measures (*HighLow, EffSprd, Spread, and NearDepth*):

$$MktQuality_{i,t} = a_1 RunsInProcess_{i,t} + a_2 EffSprdNotNAS_{i,t} + e_{1,t}$$

$$RunsInProccess_{i,t} = b_1 MktQuality_{i,t} + b_2 RunsNotI_{i,t} + e_{2,t}$$

As an instrument for *RunsInProcess* we use *RunsNotI*, which is the average number of runs of 10 messages or more in the same interval for the other stocks in our sample (excluding stock *i*). In Panel A, we present the results with our main instrument for the market quality measures: *EffSprdNotNas*, which is the average dollar effective spread computed from trades executed in the same stock and during the same time interval on other trading venues (from the TAQ database). For robustness, we present in Panel B the analysis with an alternative instrument, *SpreadNotNas*, which is the time-weighted average quoted spread (from TAQ) that excludes NASDAQ quotes. We estimate the simultaneous equation model by pooling observations across all stocks and all time intervals. To enable a meaningful pooling of data, we standardize each variable by subtracting from each observation the stock-specific time-series average and dividing by the stock-specific time-series standard deviation. Hence, this formulation essentially implements a fixed-effects specification. We report the coefficients and the p-values (against a two-sided alternative) side-by-side for the 2007 and 2008 sample periods.

Panel A: Estimates of the Simultaneous Equation Model with Instruments *EffSprdNotNAS* and *RunsNotI*

		2007				2008			
		a_1	**a_2**	**b_1**	**b_2**	**a_1**	**a_2**	**b_1**	**b_2**
HighLow	Coef.	-0.339	0.474	-0.054	0.534	-0.451	0.463	-0.121	0.485
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Spread	Coef.	-0.501	0.572	-0.044	0.532	-0.531	0.551	-0.101	0.485
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
EffSprd	Coef.	-0.114	0.293	-0.088	0.538	-0.039	0.158	-0.367	0.505
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
NearDepth	Coef.	0.444	-0.217	0.114	0.516	0.644	-0.138	0.334	0.402
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)

Panel B: Estimates of the Simultaneous Equation Model with Instruments *SpreadNotNAS* and *RunsNotI*

		2007				2008			
		a_1	**a_2**	**b_1**	**b_2**	**a_1**	**a_2**	**b_1**	**b_2**
HighLow	Coef.	-0.362	0.366	-0.157	0.494	-0.416	0.404	-0.169	0.463
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Spread	Coef.	-0.254	0.744	-0.080	0.513	-0.177	0.797	-0.090	0.490
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
EffSprd	Coef.	-0.115	0.242	-0.245	0.509	0.002	0.168	-0.436	0.499
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(0.671)	(<.001)	(<.001)	(<.001)
NearDepth	Coef.	0.344	-0.289	0.197	0.488	0.565	-0.190	0.317	0.409
	p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)

Table 5

Low-Latency Trading and Market Quality by Size Quartiles

This table presents the results of a simultaneous equation model of low-latency trading and market quality separately for stocks in each firm-size quartile. To measure the intensity of low-latency activity in a stock in each ten-minute interval, we use the time-weighted average of the number of strategic runs of 10 messages or more the stock experiences in the interval (*RunsInProcess*). We use NASDAQ order-level data to compute several measures that represent different aspects of market quality on the NASDAQ system in each time interval: (i) *HighLow* is the highest midquote minus the lowest midquote in the same interval, (ii) *EffSprd* is the average effective spread (or total price impact) of a trade, computed as the absolute value of the difference between the transaction price and the prevailing midquote, (iii) *Spread* is the time-weighted average quoted spread (ask price minus the bid price), and (iv) *NearDepth* is the time-weighted average number of shares in the book up to 10 cents from the best posted prices. Due to the potential simultaneity between market quality and low-latency trading, we estimate the following two-equation simultaneous equation model for *RunsInProcess* and each of the market quality measures (*HighLow*, *EffSprd, Spread, and NearDepth*):

$$MktQuality_{i,t} = a_1 RunsInProcess_{i,t} + a_2 EffSprdNotNAS_{i,t} + e_{1,t}$$
$$RunsInProccess_{i,t} = b_1 MktQuality_{i,t} + b_2 RunsNotI_{i,t} + e_{2,t}$$

As an instrument for *RunsInProcess* we use *RunsNotI*, which is the average number of runs of 10 messages or more in the same interval for the other stocks in our sample (excluding stock *i*). In Panel A, we present the results with our main instrument for the market quality measures: *EffSprdNotNas*, which is the average dollar effective spread computed from trades executed in the same stock and during the same time interval on other trading venues (from the TAQ database). We estimate the simultaneous equation model by pooling observations across all stocks and all time intervals. To enable a meaningful pooling of data, we standardize each variable by subtracting from each observation the stock-specific time-series average and dividing by the stock-specific time-series standard deviation. Hence, this formulation essentially implements a fixed-effects specification. We report the coefficients and the p-values (against a two-sided alternative) side-by-side for the 2007 and 2008 sample periods.

Dep. Var.			2007 a$_1$	a$_2$	b$_1$	b$_2$	2008 a$_1$	a$_2$	b$_1$	b$_2$
HighLow	Q1 (small)	Coef.	-0.348	0.451	0.016	0.531	-0.654	0.415	-0.197	0.338
		p-value	(<.001)	(<.001)	(0.090)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q2	Coef.	-0.377	0.455	0.003	0.534	-0.646	0.407	-0.191	0.336
		p-value	(<.001)	(<.001)	(0.712)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q3	Coef.	-0.334	0.475	-0.033	0.533	-0.455	0.464	-0.127	0.484
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q4 (large)	Coef.	-0.312	0.500	-0.133	0.539	-0.279	0.521	0.017	0.713
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Spread	Q1 (small)	Coef.	-0.562	0.569	0.013	0.532	-0.742	0.486	-0.169	0.339
		p-value	(<.001)	(<.001)	(0.090)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q2	Coef.	-0.530	0.577	0.002	0.534	-0.758	0.494	-0.158	0.337
		p-value	(<.001)	(<.001)	(0.712)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q3	Coef.	-0.523	0.586	-0.027	0.532	-0.542	0.547	-0.108	0.484
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q4 (large)	Coef.	-0.437	0.562	-0.117	0.534	-0.334	0.625	0.014	0.713
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
EffSprd	Q1 (small)	Coef.	-0.098	0.263	0.028	0.530	-0.033	0.102	-0.888	0.377
		p-value	(<.001)	(<.001)	(0.091)	(<.001)	(0.003)	(<.001)	(<.001)	(<.001)
	Q2	Coef.	-0.079	0.304	0.004	0.533	-0.031	0.120	-0.720	0.374
		p-value	(<.001)	(<.001)	(0.743)	(<.001)	(0.002)	(<.001)	(<.001)	(<.001)
	Q3	Coef.	-0.104	0.319	-0.049	0.536	-0.030	0.170	-0.363	0.508
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q4 (large)	Coef.	-0.152	0.276	-0.243	0.542	-0.043	0.219	0.041	0.711
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
NearDepth	Q1 (small)	Coef.	0.423	-0.188	-0.039	0.537	0.769	-0.088	0.584	0.214
		p-value	(<.001)	(<.001)	(0.093)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q2	Coef.	0.527	-0.192	-0.007	0.535	0.764	-0.094	0.549	0.222
		p-value	(<.001)	(<.001)	(0.712)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q3	Coef.	0.432	-0.209	0.073	0.522	0.646	-0.122	0.385	0.386
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
	Q4 (large)	Coef.	0.406	-0.259	0.242	0.507	0.534	-0.215	-0.042	0.726
		p-value	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)

Table 6

Stock-by-Stock Estimation of Simultaneous Equation Model

This table presents the median coefficient estimate (and its p-value) from a stock-by-stock estimation of a simultaneous equation model that we use to examine the manner in which low-latency trading affects market quality To measure the intensity of low-latency activity in a stock in each ten-minute interval, we use the time-weighted average of the number of strategic runs of 10 messages or more the stock experiences in the interval (*RunsInProcess*). We use NASDAQ order-level data to compute several measures that represent different aspects of market quality on the NASDAQ system in each time interval: (i) *HighLow* is the highest midquote minus the lowest midquote in the same interval, (ii) *EffSprd* is the average effective spread (or total price impact) of a trade, computed as the absolute value of the difference between the transaction price and the prevailing midquote, (iii) *Spread* is the time-weighted average quoted spread (ask price minus the bid price), and (iv) *NearDepth* is the time-weighted average number of shares in the book up to 10 cents from the best posted prices. Due to the potential simultaneity between market quality and low-latency trading, we estimate the following two-equation simultaneous equation model for *RunsInProcess* and each of the market quality measures (*HighLow, EffSprd, Spread, and NearDepth*):

$$MktQuality_{i,t} = a_1 RunsInProcess_{i,t} + a_2 EffSprdNotNAS_{i,t} + e_{1,t}$$

$$RunsInProcess_{i,t} = b_1 MktQuality_{i,t} + b_2 RunsNotI_{i,t} + e_{2,t}$$

As an instrument for *RunsInProcess* we use *RunsNotI*, which is the average number of runs of 10 messages or more in the same interval for the other stocks in our sample (excluding stock *i*). In Panel A, we present the results with our main instrument for the market quality measures: *EffSprdNotNas*, which is the average dollar effective spread computed from trades executed in the same stock and during the same time interval on other trading venues (from the TAQ database). For robustness, we present in Panel B the analysis with an alternative instrument, *SpreadNotNas*, which is the time-weighted average quoted spread (from TAQ) that excludes NASDAQ quotes. We standardize each variable by subtracting from each observation the stock-specific time-series average and dividing by the stock-specific time-series standard deviation. Hence, this formulation essentially implements a fixed-effects specification. We estimate the simultaneous equation model for each stock separately, and report the median coefficient (across the stocks) and its p-value.

Panel A: Cross-Sectional Median Coefficient Estimate when Instruments are *EffSprdNotNAS* and *RunsNotI*

		2007				2008			
		a_1	**a_2**	**b_1**	**b_2**	**a_1**	**a_2**	**b_1**	**b_2**
HighLow	Coef.	-0.317	0.480	-0.036	0.549	-0.459	0.457	-0.124	0.479
	p-value	(<.001)	(<.001)	(0.519)	(<.001)	(<.001)	(<.001)	(0.046)	(<.001)
Spread	Coef.	-0.471	0.619	-0.026	0.551	-0.519	0.554	-0.112	0.475
	p-value	(<.001)	(<.001)	(0.647)	(<.001)	(<.001)	(<.001)	(0.116)	(<.001)
EffSprd	Coef.	-0.112	0.305	-0.035	0.550	-0.030	0.165	-0.126	0.504
	p-value	(0.040)	(<.001)	(0.808)	(<.001)	(0.511)	(0.036)	(0.780)	(<.001)
NearDepth	Coef.	0.443	-0.215	0.081	0.543	0.652	-0.142	0.350	0.376
	p-value	(<.001)	(<.001)	(0.407)	(<.001)	(<.001)	(<.001)	(0.014)	(<.001)

Panel B: Cross-Sectional Median Coefficient Estimate when Instruments are *SpreadNotNAS* and *RunsNotI*

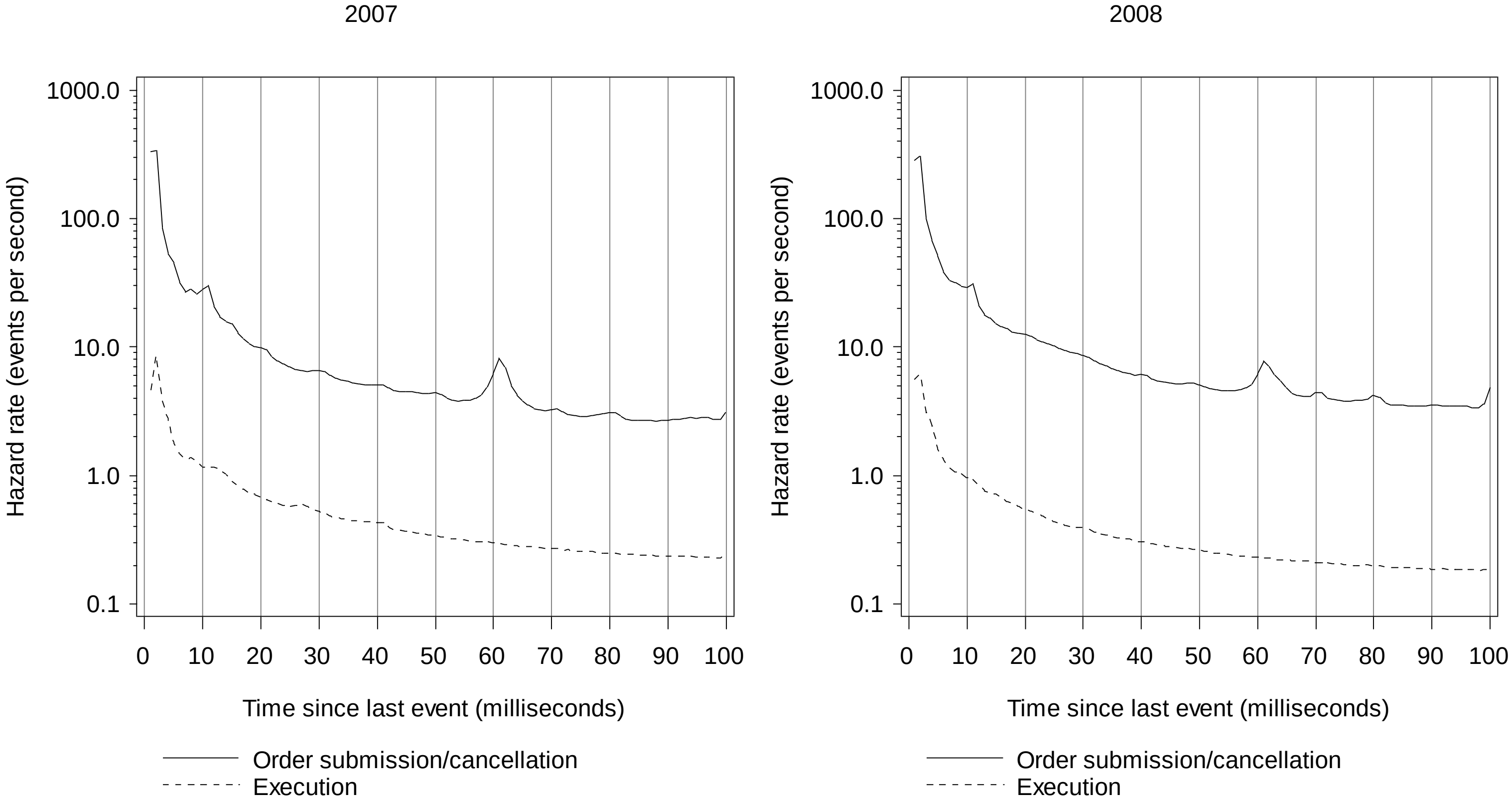
		2007				2008			
		a_1	**a_2**	**b_1**	**b_2**	**a_1**	**a_2**	**b_1**	**b_2**
HighLow	Coef.	-0.331	0.390	-0.119	0.511	-0.398	0.414	-0.157	0.461
	p-value	(<.001)	(<.001)	(0.112)	(<.001)	(<.001)	(<.001)	(0.030)	(<.001)
Spread	Coef.	-0.214	0.790	-0.065	0.534	-0.132	0.842	-0.077	0.485
	p-value	(<.001)	(<.001)	(0.114)	(<.001)	(<.001)	(<.001)	(0.091)	(<.001)
EffSprd	Coef.	-0.089	0.244	-0.159	0.532	0.012	0.168	-0.102	0.518
	p-value	(0.092)	(<.001)	(0.421)	(<.001)	(0.827)	(0.411)	(0.062)	(<.001)
NearDepth	Coef.	0.325	-0.299	0.175	0.503	0.568	-0.204	0.309	0.392
	p-value	(<.001)	(<.001)	(0.532)	(<.001)	(<.001)	(<.001)	(<.001)	(0.016)

Figure 1

Hazard Rates of Orders and Trades

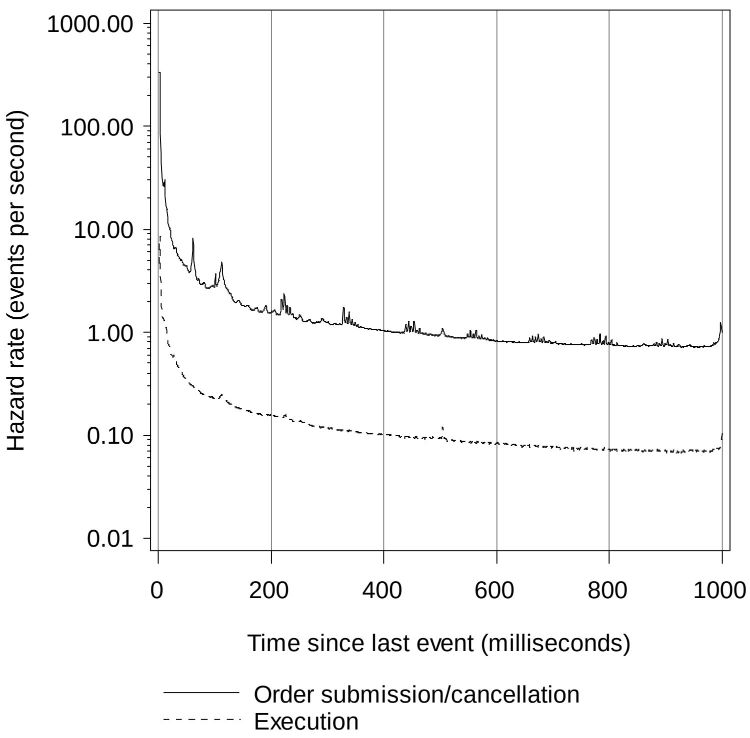
This figure presents estimated hazard rates for (i) order submissions and cancellations (i.e., all messages that do not involve trade execution), and (ii) trade executions. In the estimation of the submission/cancellation hazard rate, execution is assumed to be an exogenous censoring process, while in the estimation of the execution hazard rate, submissions and cancellations are assumed to be the exogenous censoring process. The estimated hazard rate plotted at time *t* is the estimated average over the interval [*t*–1 ms, *t*). The hazard rate for submissions/cancellations can be interpreted as the intensity of submissions and cancellations of limit orders conditional on the elapsed time since any market event (which can be a submission, a cancellation, or an execution). Similarly, the hazard rate for execution of trades can be interpreted as the intensity of executions conditional on the elapsed time subsequent to any market event. The hazard rates are estimated using the life-table method. In Panel A, we plot the hazard rates up to 100 milliseconds side-by-side for the 2007 and 2008 sample periods. This plot enables us to observe in greater detail very short-term patterns. In Panel B we plot the hazard rates up to one second.

Panel A: Hazard Rates of Submissions/Cancellations and Executions up to 100ms



Panel B: Hazard Rates of Submissions/Cancellations and Executions up to 1000ms

2007



2008

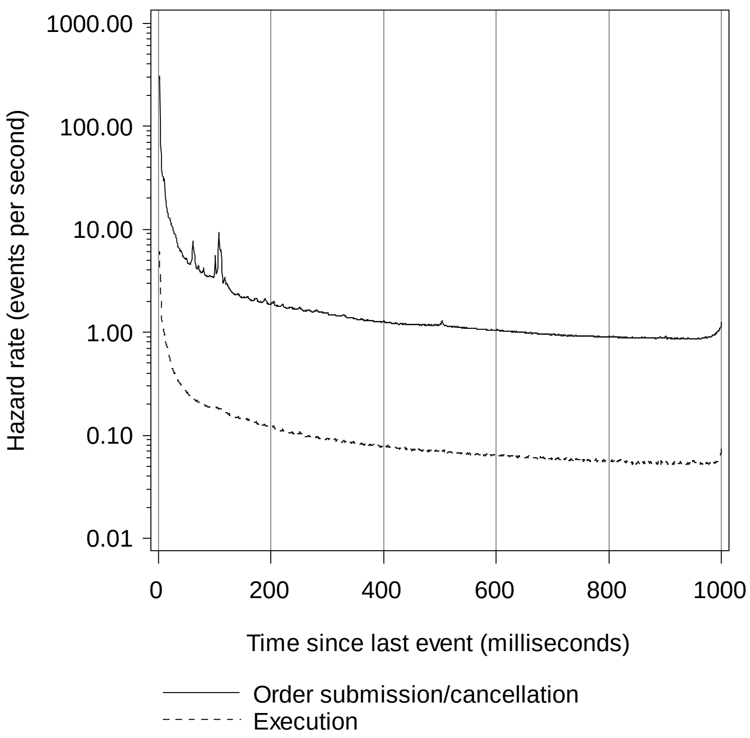
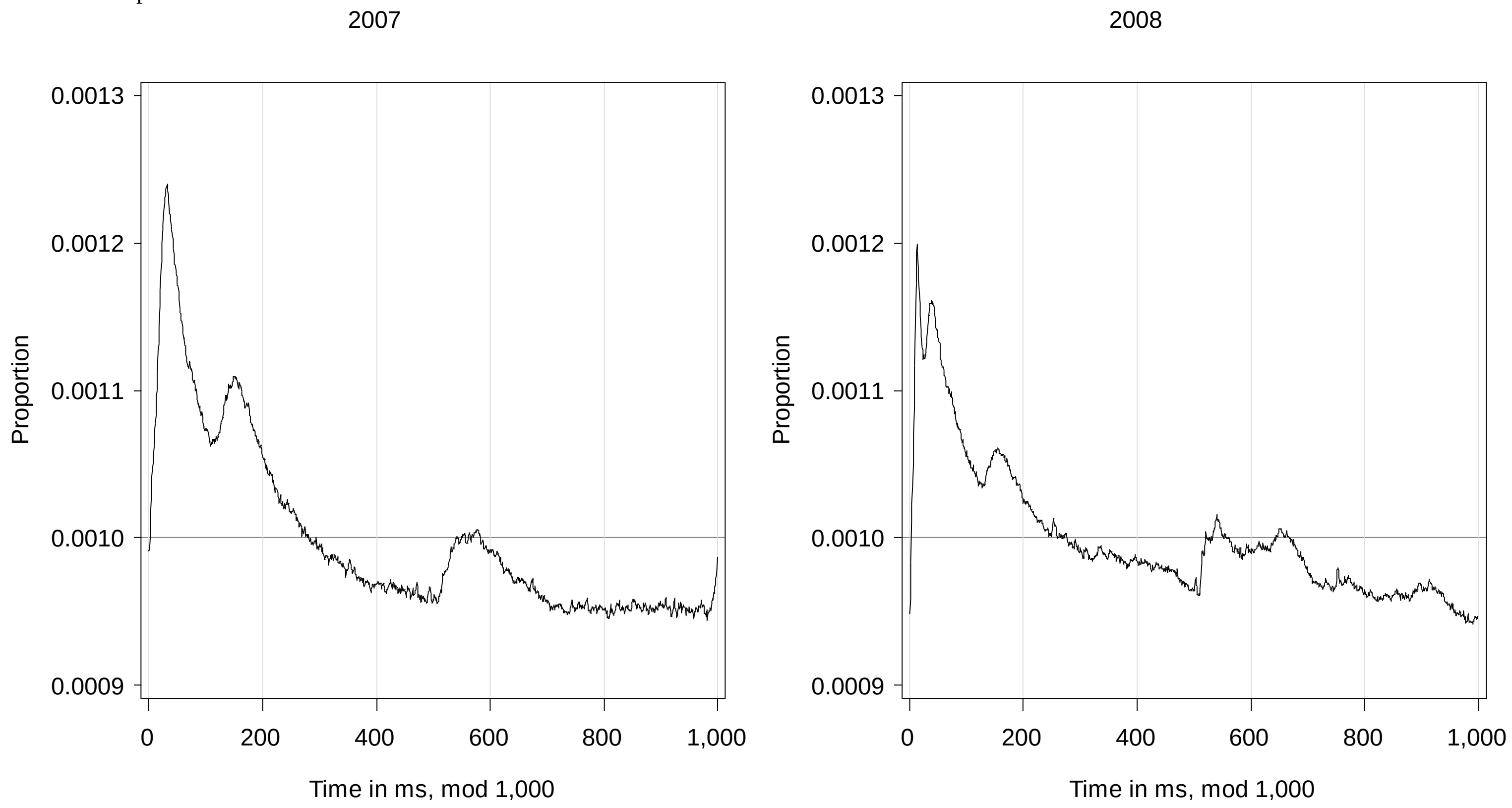


Figure 2

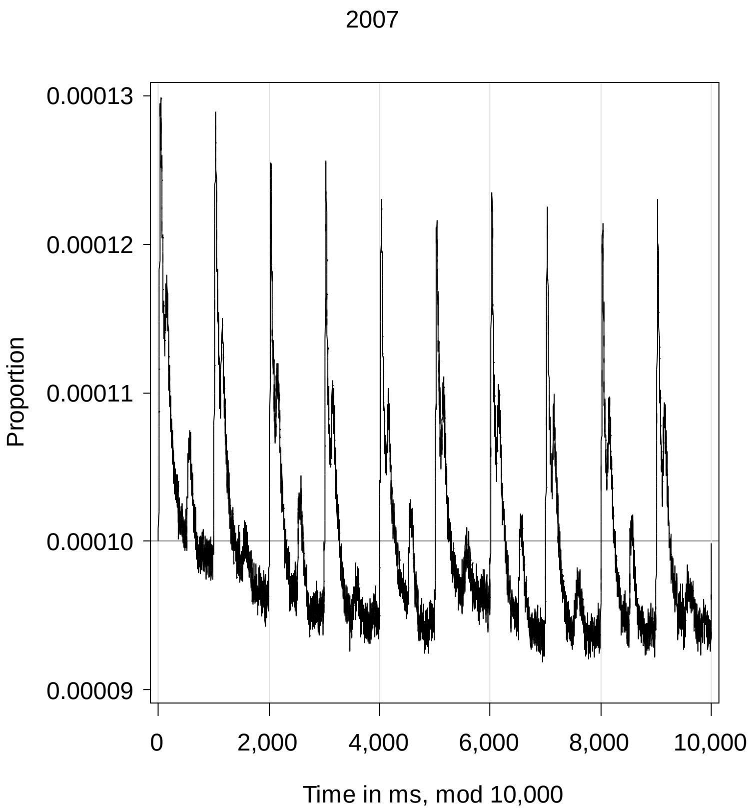
Clock-time Periodicities of Market Activity

This figure presents clock-time periodicities in message arrival to the market. The original time stamps are milliseconds past midnight. The one-second remainder is the time stamp mod 1,000, i.e., the number of milliseconds past the one-second mark. The ten-second remainder is the time stamp mod 10,000, the number of milliseconds past the ten-second mark. In Panel A, we plot the sample distribution of one-second remainders side-by-side for the 2007 and 2008 sample periods. Panel B plots the sample distribution of ten-second remainders. The horizontal lines in the graphs indicate the position of the uniform distribution (the null hypothesis).

Panel A: Sample Distributions of One-Second Millisecond Remainders



Panel B: Sample Distributions of Ten-Second Millisecond Remainders



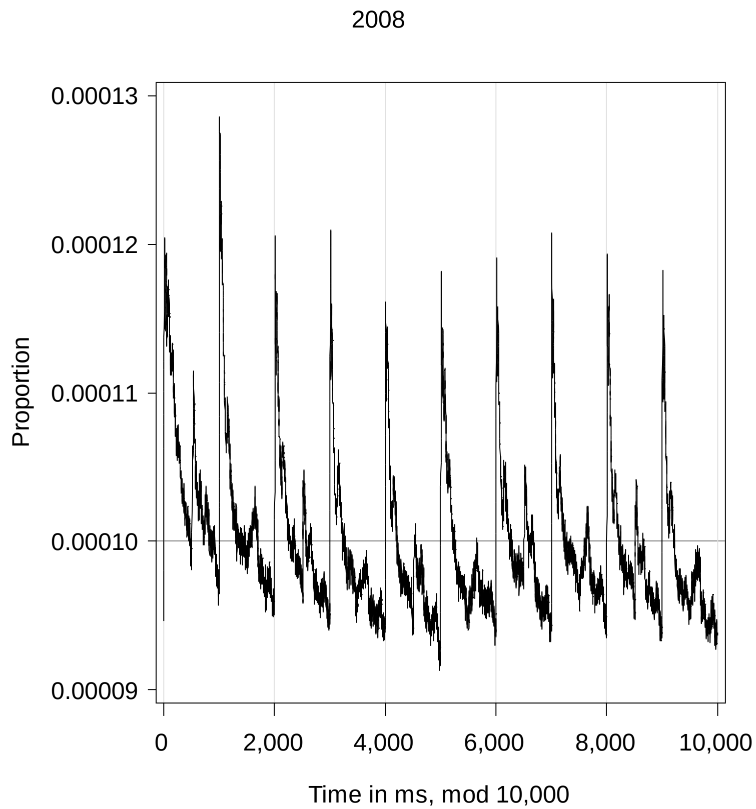
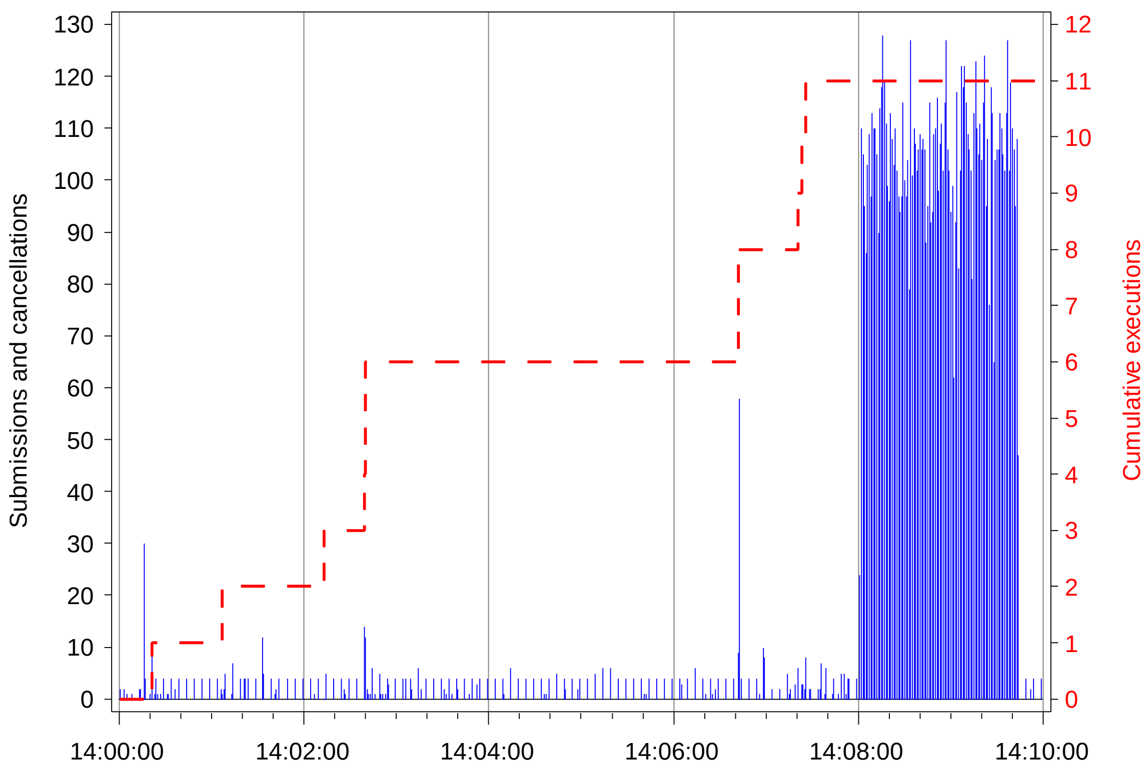


Figure 3

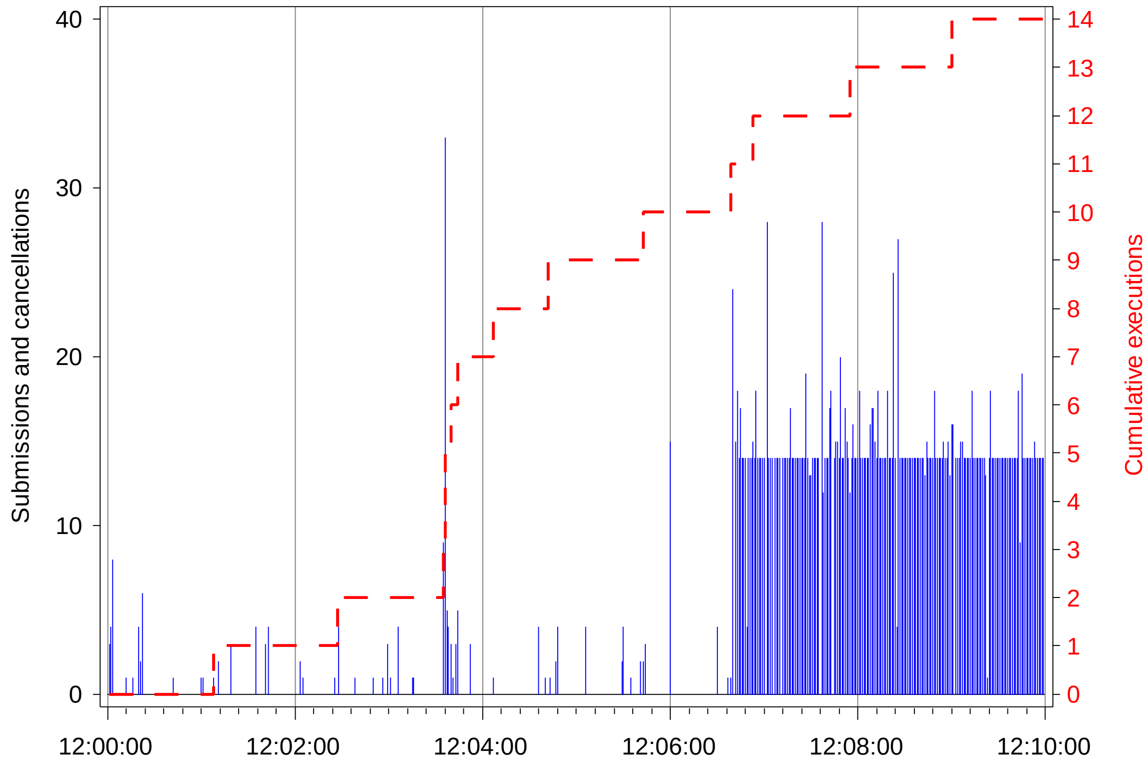
Episodic Nature of High-Frequency Activity

This figure presents examples of episodes with intense high-frequency activity. These specific episodes were identified using wavelet analysis, but many such episodes are clearly visible when looking at the time-series of submissions and cancellations. In each of the panels, the bars represent the intensity of submissions and cancellations (measured on the left y-axis) and the dashed line provides cumulative executions (measured on the right y-axis). In Panel A, we show an episode on June 2, 2008, in the ticker symbol INWK (InnerWorkings Inc.) where 11,505 messages were sent to the market in approximately one minute and forty seconds. In Panel B, we show an episode on June 17, 2008, in ticker symbol SANM (Sanmina-SCI Corp.) where 3,013 messages were sent to the market in approximately three minutes and fifteen seconds. In Panel C, we show an episode on June 12, 2008, in ticker symbol GNTX (Gentex Corp.) where 14,925 messages were sent to the market in approximately one minute and twenty seconds. In all these episodes, activity by means of submission and cancellations is several orders of magnitude larger than the normal level for the stock. Still, the number and pattern of executions do not change during these high-frequency episodes.

Panel A: INWK on June 2, 2008, 2:00pm to 2:10pm (11,505 Messages)



Panel B: SANM on June 17, 2008, 12:00pm to 12:10pm (3,013 Messages)



Panel C: GNTX on June 12, 2008, 12:00pm to 12:20pm (14,925 Messages)

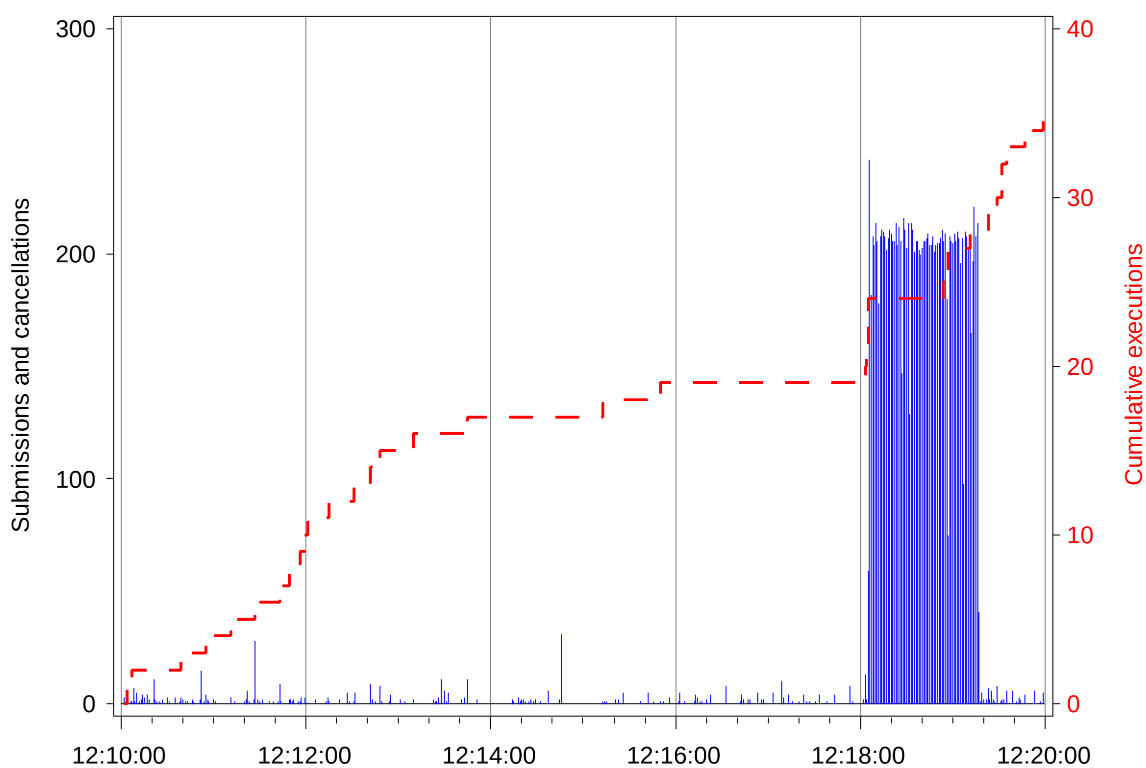
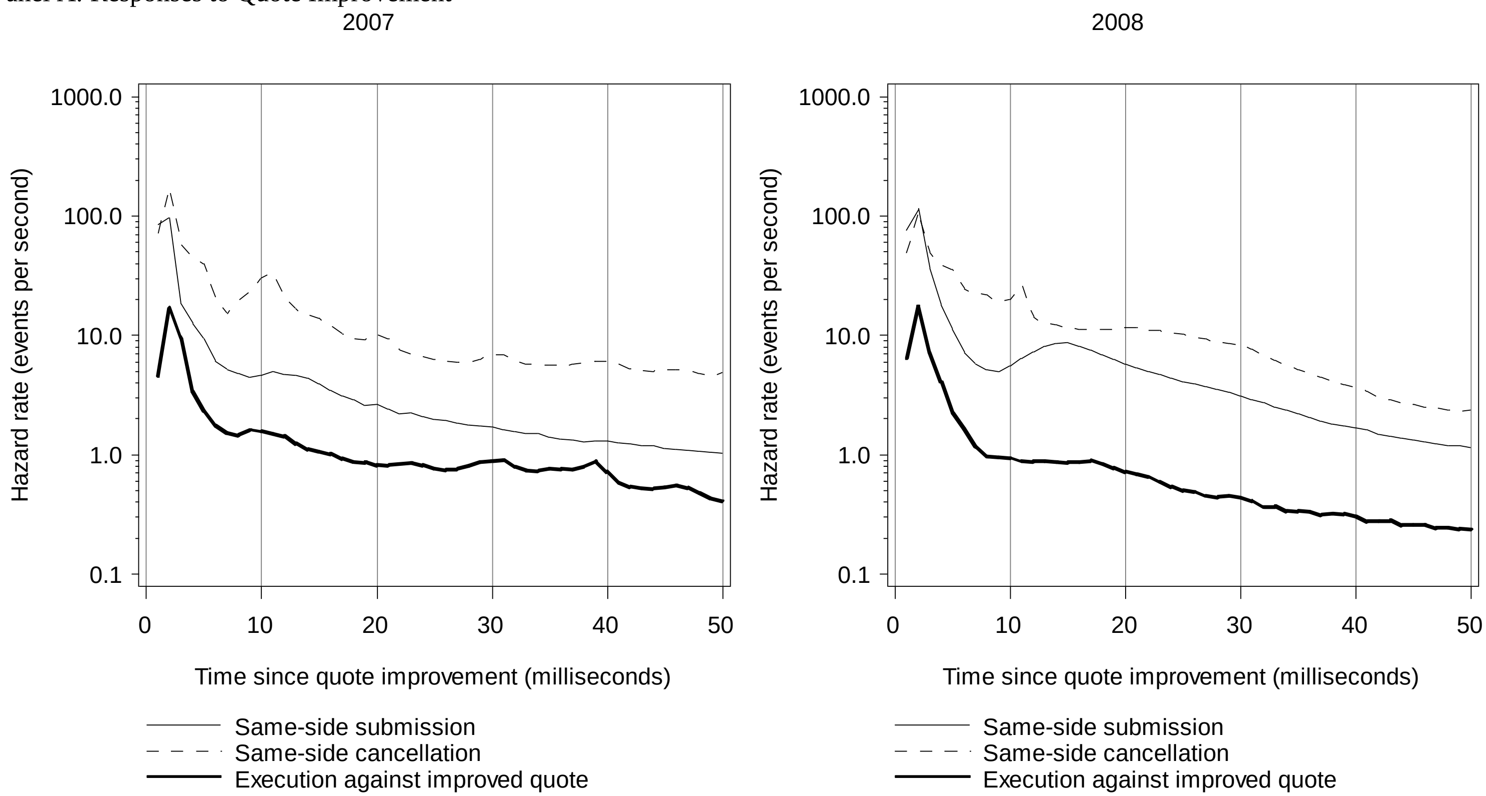


Figure 4
Speed of Response to Market Events

This figure looks at the speed of responses to certain market events that have well-defined economic meaning. In Panel A, the market event is an improved quote via the submission of a new limit order—either an increase in the best bid price or a decrease in the best ask price. Subsequent to this market event, we estimate (separately) the hazard rates for three types of responses: (i) a limit order submission on the same side as the improvement (e.g., buy order submitted following an improvement in the bid price), (ii) a cancellation of a standing limit order on the same side, and (iii) an execution against the improved quote (e.g., the best bid price is executed by an incoming sell order). In Panel B, the market event is deterioration in the quote as a result of a cancellation of a standing limit order (e.g., a limit buy order alone at the best bid price is cancelled and the best bid price therefore decreases). Subsequent to this market event, we estimate (separately) the hazard rates for three types of responses: (i) a limit order submission on the same side as the quote deterioration, (ii) a cancellation of a standing limit order on the same side, and (iii) an execution against the worsened quote. In all estimations, any event other than the one whose hazard rate is being estimated is taken as an exogenous censoring event. The estimated hazard rate plotted at time t is the estimated average over the interval [t–1 ms, t). The hazard rate for a response can be interpreted as the intensity of the response conditional on the elapsed time since the conditioning market event (e.g., the improved quote in Panel A).

Panel A: Responses to Quote Improvement



Panel B: Responses to Quote Deterioration Due to a Limit Order Cancellation