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Every Cloud Has a Silver Lining: Fast Trading, Microwave Connectivity, and Trading Costs

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ABSTRACT

Modern markets are characterized by speed differentials, with some traders being fractions of a second faster than others. Theoretical models suggest that such differentials may have both positive and negative effects on liquidity and gains from trade. We examine these effects by studying a series of exogenous weather episodes that temporarily remove the speed advantages of the fastest traders by disrupting their microwave networks. The disruptions are associated with lower adverse selection and lower trading costs. In additional analysis, we show that the long-term removal of speed differentials results in similar effects and also increases gains from trade.

COMPETITION ON RELATIVE SPEED IS A DEFINING characteristic of modern markets where trading firms invest heavily to gain a speed advantage over their rivals. The race to acquire the fastest technology often leads to subsecond speed differentials among traders. A rich theoretical literature suggests that such differentials may have opposing effects on liquidity and gains from

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trade.[1] On the one hand, speed may allow liquidity providers to reduce their adverse selection exposure and manage inventories more efficiently. Alternatively, speed may allow traders to pick off limit orders before liquidity providers adjust to new information. The former effect has a positive impact on liquidity and may increase gains from trade, whereas the latter may have the opposite impact. To shed light on the net effect, we examine a two-year time series of exogenous weather-related intraday shocks to speed differentials. The results indicate that when the differentials exist, liquidity is impaired. In an additional analysis, we show that the long-term removal of speed differentials is associated with liquidity improvements and greater gains from trade.

In the main analysis, we examine liquidity when heavy precipitation disrupts microwave transmissions between Chicago and New York. During our 2011 through 2012 sample period, traders send information between the two cities via either a fiber optic cable or a microwave network. The microwave networks, which are about 30% faster than the cable, have two important characteristics. First, only a small group of trading firms has access to them, and these firms engage in constant competition for the top speed by retrofitting continuously. Second, precipitation (i.e., rain and snow) disrupts them. The first characteristic creates a speed advantage for select traders, whereas the second characteristic occasionally removes this advantage. We show that when the microwave speed advantage is removed, adverse selection and trading costs decline by up to 6.7% and 5.2%, respectively.

The effect of precipitation on microwave communications is well known in physics, but has not previously been examined in the financial markets context. To confirm that precipitation does indeed serve as a shock to information transmission speeds, we show that equities in New York react to futures signals from Chicago two milliseconds slower when it rains or snows. During our sample period, two milliseconds is precisely the difference between the microwave and fiber optic transmission speeds. Furthermore, the data show that when microwave signals arrive from the futures market, equity arbitrage algorithms pick off the stale quotes, while liquidity-providing algorithms reprice their quotes. As such, consistent with the theoretical literature, market participants rely on speed to both supply and demand liquidity.

Given that speed is used for both liquidity supply and demand, how do the abovementioned adverse selection costs emerge? To clarify the mechanism, it is useful to think of two groups of market participants: Group 1—those with access to microwave networks, and Group 2—those without such access. Participants from both groups often act as liquidity providers. As such, the National Best Bid and Offer (NBBO) is a combination of quotes from many competitors. When futures reveal information that is not yet reflected in equity prices, and

[1] See Hoffmann (2014), Biais, Foucault, and Moinas (2015), Budish, Cramton, and Shim (2015), Foucault, Hombert, and Roşu (2016), Jovanovic and Menkveld (2016), Aït-Sahalia and Sağlam (2017), Foucault, Kozhan, and Tham (2017), Menkveld and Zoican (2017), and Baldauf and Mollner (2020), among others. We review this literature and relate our findings to its predictions later in the Introduction.

the microwave networks are functional, Group 1 adversely selects Group 2. However, when the networks are disrupted, the speed advantage of Group 1 disappears, picking-off activity declines, and adverse selection subsides. This reduction in adverse selection for the average liquidity provider is captured by our tests.

While our precipitation-based analysis sheds light on the relations among speed differentials, adverse selection, and liquidity, it is less conclusive when it comes to gains from trade proxied by nonarbitrage volume. Overall, trading volume decreases during the precipitation episodes due to a decrease in arbitrage volume. In the meantime, nonarbitrage volume remains unchanged. This result seems to suggest that the negative liquidity effects of speed differentials do not result in reduced gains from trade. It is possible, however, that heavy precipitation episodes, which last only 30 minutes, are not sufficiently long for substantial nonarbitrage volume to emerge.

To shed light on this possibility, we use an event that removes the microwave-driven speed differentials for a substantially longer period. In late 2012, one of the microwave technology providers began to sell information transmitted through its network, the fastest at the time, to anyone who was willing to subscribe. This new offering was eagerly embraced by market participants and disrupted the status quo characterized by speed differentials. The network maintained speed leadership for an extended period, allowing us to observe the effects of a long-term removal of speed differentials. Using difference-in-differences analysis, we show that, similar to the precipitation episodes, the long-term removal of speed differentials is associated with lower adverse selection and trading costs. Notably, in this case we find that trading volume increases, consistent with the notion of greater gains from trade.

The liquidity and gains-from-trade effects of trading speed and speed differentials are examined by a rich theoretical literature that focuses on adverse selection and inventory management. The models of adverse selection go back to Copeland and Galai (1983) and Foucault, Röell, and Sandås (2003), who detail liquidity effects of picking-off risk. Foucault and Moinas (2019) note that recent market structure changes (e.g., automation of the trading process and increases in trading and information transmission speeds) likely make picking-off risk more acute and complex. Examining this complexity, recent theory proposes several channels that may affect adverse selection, with an emphasis on speed differentials. Some of the models focus on liquidity taking by fast traders (Biais, Foucault, and Moinas (2015), Foucault, Hombert, and Roşu (2016), Foucault, Kozhan, and Tham (2017)), while others examine liquidity provision and suggest that fast market participants endogenously become suppliers of liquidity (Hoffman (2014), Jovanovic and Menkveld (2016)).[2]

[2] Additional adverse selection channels include continuous order processing, which may reduce market makers' ability to reprice stale quotes even in the absence of speed differentials (Budish, Cramton, and Shim (2015)), and exchange speed, which may affect the frequency with which market makers encounter uninformed traders (Menkveld and Zoican (2017)).

While the channels vary, the literature generally agrees that speed advantages may aid both liquidity demand and supply. Our results are consistent with this view.

Several models suggest that speed differentials may affect gains from trade. Hoffmann (2014) describes a market in which fast traders can revise their quotes quickly upon the arrival of news, increasing adverse selection for the slow traders. The latter are forced to submit limit orders with low execution probabilities, and gains from trade are reduced. Biais, Foucault, and Moinas (2015) show that while speed differentials may improve the ability of privately informed market participants to act on profitable trading opportunities, thereby increasing gains from trade, the differentials may also reduce gains from trade as fast traders generate adverse selection and do not fully internalize its cost. As such, investments in speed may be socially excessive. Budish, Cramton, and Shim (2015) model a market in which the only benefit of speed is faster access to information. In this setting, investment in speed is always excessive. Our results support the possibility of reduced gains from trade associated with speed differentials.

Aït-Sahalia and Sağlam (2017) propose that speed advantages may allow market makers to revise quotes more efficiently and thereby reduce inventory costs. Brogaard et al. (2015) show that inventory costs, proxied by realized spreads, decline when liquidity providers are better able to predict order flow due to an increase in the speed of exchange access. In a similar vein, we suggest that when arbitrage activity declines in the absence of speed differentials, inventories of the average market maker may be subject to fewer shocks, leading to a decline in inventory costs. In line with this view, realized spreads decline both during the precipitation episodes and following the long-term removal of speed differentials.

Our results contribute to a growing empirical literature that examines fast algorithm-driven trading. Hendershott, Jones, and Menkveld (2011) show that such trading tends to improve liquidity when it is used to aid market making, while Brogaard, Hendershott, and Riordan (2014) and Chaboud et al. (2014) find that it improves price efficiency and price discovery. Recent research revisits these issues, going into greater detail and often using account-level regulatory data. The findings suggest that (i) capital constraints may inhibit the stability of liquidity supply by fast traders (Kirilenko et al. (2017), Brogaard et al. (2018)), (ii) liquidity provided by fast traders may not benefit all categories of market participants (Korajczyk and Murphy (2018), Kervel and Menkveld (2019)), and (iii) algorithms may reduce price informativeness in the long run by discouraging information acquisition by slower market participants (Weller (2017), Baldauf and Mollner (2020)). Our contribution to this literature is in examining the liquidity and gains-from-trade effects of speed differentials that result from the speed race.

Closest to our study is Brogaard et al. (2015), who examine a colocation upgrade that allows subscribers to access the exchange engine faster. Brogaard et al. (2015) show that those who choose to upgrade are predominantly market makers and that the upgrade reduces their inventory costs. Importantly, the upgrade improves the speed of all subscribers by the same increment, while the speed race examined in our study produces speed differentials. As such, our institutional setting lends itself to examining a different set of predictions, namely, predictions related to adverse selection. Our analysis is therefore complementary to Brogaard et al. (2015).

Finally, this study is related to, but distinct from, research streams that (i) use weather phenomena as exogenous shocks to the incorporation of information into prices and (ii) seek to understand how weather affects the behavior of market participants. The first stream uses weather-driven variation in information flow to test theories of informed agent behavior and shed light on price volatility. Specifically, using weather variation in the 18$^{\text{th}}$ century, Koudijs (2015) shows that informed agents behave strategically, spreading trades over time when their private information is long lived. Koudijs (2016) examines the components of price volatility, distinguishing between those related to public news, private news, and liquidity shocks. Our study differs in that we use weather to examine the effects of speed differentials on liquidity and gains from trade, thereby testing a different set of theoretical predictions. The second stream finds that poor weather is associated with pessimism, which affects stock returns and price discovery (Hirshleifer and Shumway (2003), Goetzmann et al. (2014), deHaan, Madsen, and Piotroski (2017)). In the Internet Appendix, we show that this effect does not drive our results.[3]

To summarize, our contribution to the literature is as follows. First, we shed new light on the predictions of theoretical models that examine the effects of speed differentials on adverse selection, liquidity, and gains from trade. Second, we provide empirical evidence on the mechanics of the arbitrage process between futures and equities. Third, we offer evidence complementary to existing empirical research on the relation between market quality and trading speed. Some market participants claim that faster markets are unconditionally better; our results suggest that the benefits are conditional on how speed advancements are used, and whether they allow for the emergence of speed differentials. Finally, we describe a new approach to measuring exogenous variation in relative information transmission speed.

The remainder of the paper is organized as follows. Section I discusses the history and physics of information transmission between Chicago and New York. Section II describes the data and sample. Section III discusses our main empirical tests. Section IV concludes.

I. Institutional Background

In the world of fast trading, the physics of signal transmission plays an important role. Currently, fiber optic cable is the most common way to transmit information over long distances. Such cables have connected Chicago and New York since the mid-1980s, when they replaced legacy copper cables. However, their paths are not optimal for ultra-fast communications—the cables

[3] The Internet Appendix may be found in the online version of this article.

were placed along existing railway lines, going from Chicago south to Pittsburgh and then around the Appalachian Mountains in eastern Pennsylvania, therefore substantially exceeding the straight-line distance between Chicago and New York. Recognizing the potential for latency reduction from a more streamlined setup, in 2010 technology company Spread Networks laid a cable with significantly fewer detours that went through the mountains rather than around them and shaved 1.5 milliseconds off the signal transmission speed, from 8.0 milliseconds to 6.5 milliseconds.[4] Many latency-sensitive trading firms promptly switched to the new cable, although the subscription price was significantly greater than that of the legacy cables.

While fiber is a fast transmission medium, it is not the fastest. Microwaves travel through air faster than photons travel through fiber, and therefore a network of microwave transmitters placed along a fiber optic cable line can shave additional milliseconds off the signal transmission time. At the time of this study, microwave networks offer information transmission speeds that are about 30% faster than the Spread Networks cable, 4.5 milliseconds versus 6.5 milliseconds.[5] However, although faster than cable, microwaves have a notable disadvantage—they are relatively easily disrupted. Among the disruptors are rain droplets and snowflakes, especially when the rain or snowfall are substantial.[6] During such disruptions, microwave users lose their speed advantage and must either stop trading or switch to fiber. Market participants suggest that their systems detect disruptions in real time and adjust automatically.

Laughlin, Aguirre, and Grundfest (2014) note that the first microwave network that linked Chicago and New York was operational in early 2011, with several additional networks built later in 2011 and 2012. Access to microwave transmissions during this period was restricted to a small group of firms for two reasons. First, the Federal Communications Commission (FCC) limited the number of network licenses, citing airwave congestion. As a result, only about 15 networks were built. Second, low microwave bandwidth meant that each network was normally used by only one trading firm. The bandwidth was so limiting that firms sharing a network was virtually unheard of; even single-user firms had to ration which information to transmit via microwave and which to relegate to fiber. Microwave transmissions were generally used for the most profitable arbitrage strategies, namely, those arising from index

[4] The speed statistics come from Zayo Group, the current owner of Spread Networks (https://bit.ly/2DT2udm). For more information on the Spread Networks cable, see "Wall Street's speed war," by C. Steiner, Forbes Magazine, September 27, 2010 (https://bit.ly/2t6QlwG), and "Raging bulls: How Wall Street got addicted to light-speed trading," by J. Adler, Wired Business, August 3, 2012 (https://bit.ly/2TvuLk8).

[5] In Section III.A, we confirm these figures using equity and futures data. In technical terms, the refractive index of air is about 1.0003, while it is 1.458 for fused silica used to make fiber optic cables (https://bit.ly/21L6VNk). Since the speed of signal transmission declines with the refractive index, microwaves transmit information faster than fiber.

[6] For more information on this phenomenon, often referred to as "rain fade," see https://bit.ly/2uSX5gp.

futures to exchange-traded funds (ETFs) arbitrage, with the focus on the most active futures.[7]

II. Data and Sample

We use four data sources. First, to identify periods of microwave disruptions, we obtain precipitation data from the National Oceanic and Atmospheric Administration (NOAA, http://www.noaa.gov). Second, to examine equity liquidity and volume, we use the millisecond Daily Trade and Quote (DTAQ) data. Third, to study information transmission between futures and equities, we use order and trade data provided by the Chicago Mercantile Exchange (CME). Finally, to shed light on equity order submissions, we use NASDAQ ITCH data. Our main DTAQ and ITCH analyses span the two-year period from January 2011 through December 2012. Additional DTAQ analyses cover (i) the period prior to the introduction of microwave networks (2010), (ii) the period immediately following the removal of speed differentials (the first few months of 2013), and (iii) the two-year period following the removal of speed differentials (2013 through 2014). We examine one year of the CME data, 2012.

To achieve the fastest speeds, microwave networks follow paths that are as straight as possible and therefore are rather close to each other. For illustration, Figure 1 shows the microwave transmitter locations of three networks connecting the Chicago and New York data centers.[8] Location data are obtained from the FCC. Going east from the CME data center, the networks pass through Illinois, Indiana, Ohio, and western Pennsylvania before splitting in eastern Pennsylvania. The southern branches then go to NASDAQ's data center in Carteret, and the northern branches go to the NYSE in Mahwah. To avoid clutter, Figure 1 shows only three networks; the FCC data indicate that all networks follow similar paths.

A. Precipitation Data

NOAA data contain precipitation statistics collected by weather stations across the United States in 15-minute intervals. The data also contain precise station locations. The stations report in local time, so for stations in Illinois and northwestern Indiana located in the Central time zone we add one hour to reported times to match the DTAQ time stamps. A standard piece of equipment at each station is a precipitation tank that measures accumulated

[7] For more information on limited microwave bandwidth, see Singla et al. (2015). Also, one of the microwave network operators stated in a press release: "…we choose the relevant bits of data… like E-Mini S&P index futures contracts, treasury futures – things that are real market movers and have a lot of volume. We only transfer those because if you transfer everything you clog up pipes and incur buffering delays, which we want to avoid at all costs" (cited from "Quincy prescribes LD4 co-lo for CME data," by F. Kilburn, Quincy Data, May 2, 2013 (https://bit.ly/2NhpJ5c)).

[8] We acknowledge that during our sample period, the data centers of all equity exchanges were located in the state of New Jersey rather than in New York. We use the term *New York* to conform to earlier literature on futures-to-equities information transmission.

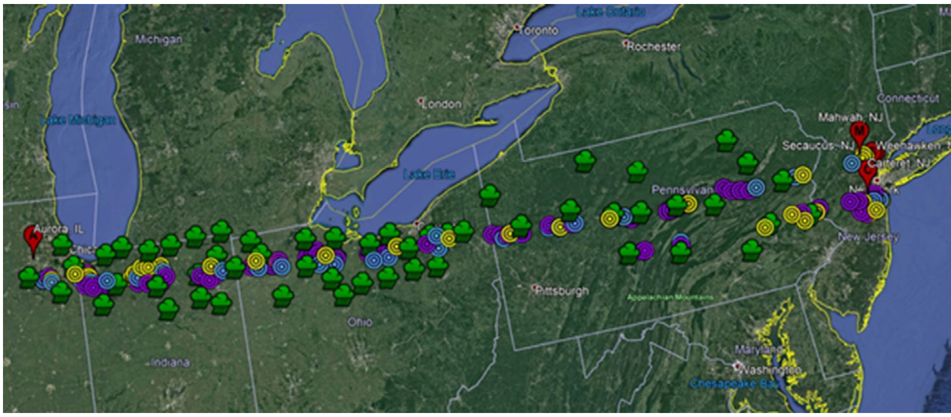

Figure 1. Locations of microwave transmitters and weather stations. The figure shows microwave transmitter locations of three microwave networks (radial markers) obtained from the Federal Communications Commission. While there are more than three microwave networks between Chicago and New York during the sample period, we plot only three to avoid clutter; the remaining networks follow similar paths. The figure also shows the weather stations (rain cloud icons) located near the microwave network paths. Station data come from the National Oceanic and Atmospheric Administration. The pin markers indicate locations of the CME data center in Aurora, IL, the NYSE data center in Mahwah, NJ, the NASDAQ data center in Carteret, NJ, the BATS data center in Weehawken, NJ, and the Direct Edge data center in Secaucus, NJ. (Color figure can be viewed at wileyonlinelibrary.com)

precipitation every 15 minutes and reports it to the central database. We focus on the data collected by 54 stations located along the Chicago-New York corridor (Figure 1).[9]

To create the precipitation variable, *PRECIP*, for each 15-minute interval t we compute total precipitation reported by the sample stations and divide it by the number of reporting stations. Panel A of Table I indicates that an average station reports 0.002 inches of precipitation per interval. The distribution is rather skewed, with a median of 0.001 suggesting that periods of low precipitation are occasionally interrupted by significant rain or snow. We note that the microwave networks are most likely to be disrupted when precipitation is substantial. We therefore focus on high levels of precipitation and create two additional metrics, *PRECIP*1 and *PRECIP*2, which capture intervals when precipitation is more than one-half and more than one standard deviation greater than the quarterly mean. These metrics represent 11.48% and 7.61% of all intervals and last on average 2.4 and 2.2 intervals (36 and

[9] The NOAA data set contains reports from 58 stations. Several stations are located in close proximity to each other, raising the concern that precipitation may be double-counted. To alleviate this concern, we drop the easternmost station if any two stations are located within 10 miles of each other. This leaves us with a final sample of 54 stations. In the Internet Appendix, we show that the results are robust to using station samples of different sizes, including the 58-station sample, and to using an alternative precipitation data set.

Table I

Descriptive Statistics

The table reports descriptive statistics for precipitation over the 2011 through 2012 period (Panel A) and for the sample of ETFs (Panel B). Precipitation statistics are collected during regular trading hours (9:30 a.m. to 4:00 p.m. Eastern time) from 54 NOAA weather stations located along the Chicago-New York microwave paths. The stations report precipitation updates every 15 minutes. In Panel A, *PRECIP* captures total precipitation in inches per 15-minute interval divided by the number of reporting stations. In addition, we report the percentage of intervals with significant precipitation: *PRECIP*1, precipitation is more than half a standard deviation above the quarterly average, and *PRECIP*2, precipitation is more than one standard deviation above the quarterly average. Finally, we report the length (in 15-minute intervals) of an average period with consecutive *PRECIP*1 or *PRECIP*2. A length of 2.4 is equivalent to 36 minutes. Panel B classifies the sample ETFs into categories according to the underlying asset basket.

Panel A: Precipitation	
PRECIP, inches per interval	
Mean	0.002
Median	0.001
Std. dev.	0.005
% intervals with *PRECIP*1	11.48
% intervals with *PRECIP*2	7.61
Length of *PRECIP*1, intervals	
Mean	2.4
Median	1.0
Std. dev.	3.5
Length of *PRECIP*2, intervals	
Mean	2.2
Median	1.0
Std. dev.	3.4
Panel B: ETF Sample	
Equities	
U.S. equity index	50
International index	22
Interest rate products	20
Metals	4
Real estate	1
Other	3

33 minutes), respectively. As such, significant precipitation is observed sufficiently frequently and varies intraday.

B. Sample Assets

The importance of information flows between the futures markets in Chicago and the equity markets in New York is well recognized in the literature. Kawaller, Koch, and Koch (1987) and Chan (1992) find that futures markets lead price discovery, while Baron et al. (2019) show that modern trading firms use futures prices as a source of information. Hasbrouck (2003) reports that the direction of information flow between futures and equities depends on futures trading activity—active futures tend to lead price discovery. Given that the most active futures contracts are the index futures, our focus in the equity market is on the corresponding ETFs. As long as price discovery via futures is nontrivial, the speed of information transmission between Chicago and New York may matter for ETF liquidity. In the Internet Appendix, we confirm that in our setting futures do indeed lead price discovery.

We focus on the 100 most actively traded ETFs. Of these, 50 ETFs track U.S. equity indexes, 22 international indexes, 20 corporate or treasury interest rate indexes, 4 metals (i.e., gold and silver), 1 a real estate portfolio, and 3 other assets (Panel B of Table I). Many sample ETFs track the same baskets of securities as the CME futures contracts (e.g., the QQQ ETF tracks the same index as the E-mini NASDAQ-100 futures). Others track baskets similar to those of major CME contracts. For example, the iShares Russell 1000 ETF does not have a corresponding CME futures contract during our sample period, but a portion of price discovery in this ETF comes from futures on other indexes such as the S&P 500.[10]

C. DTAQ Data and Summary Statistics

Following Holden and Jacobsen (2014), we combine the DTAQ NBBO and Quote files to obtain the complete NBBO record and merge the resulting data with the Trade file. We sign trades using the Lee and Ready (1991) algorithm and drop the first and last five minutes of the trading day to reduce the effects of opening and closing procedures.[11] Panel A of Table II reports market activity statistics. Precipitation data are in 15-minute intervals, and we aggregate the statistics accordingly. An average ETF has 6,239 NBBO updates every 15 minutes, which is equivalent to about seven updates per second, and trades 552 times every 15 minutes, for a total volume of 213,954 shares.

To examine the extent of picking-off risk, we rely on the price impact metric *PRIMP*, computed as twice the signed difference between the midquote at a time after the trade and the midquote at the time of the trade, that is, $PRIMP_t = 2q_t\ (mid_{t+\gamma} - mid_t)$, where q_t is the trade direction indicator, mid_t is the midquote as given by $(NBBO\ Ask_t + NBBO\ Bid_t)/2$, and γ indicates the time elapsed since the trade. Recent research uses γs of just a few seconds. For instance, O'Hara (2015) suggests that 5- to 15-second intervals may be appropriate, while Conrad, Wahal, and Xiang (2015) use price impacts up to 20 seconds. To conform to these studies, we focus on 15-second price impacts. In the Internet Appendix, we show that the results are robust to using 1-, 5-, 30-, and 60-second price impacts.

Panel B of Table II reports summary statistics for the price impacts, and the NBBO, effective, and realized spreads. The NBBO spread is the difference between the lowest offer and the highest bid across all markets. The

[10] The CME delisted E-mini Russell 1000 futures contract in 2007 and relisted it in 2015.

[11] Chakrabarty, Pascual, and Shkilko (2015) show that the Lee-Ready algorithm performs well in a 2011 equity sample.

Table II

Market Activity and Trading Costs (DTAQ Sample)

The table presents summary statistics for the sample of 100 ETFs over the 2011 through 2012 period. Statistics are derived from the millisecond DTAQ data and aggregated into 15-minute intervals to match precipitation data. Panel A reports market activity statistics, and Panel B reports statistics on spreads and their components. Volatility is defined as the difference between the high and low midquotes in a 15-minute interval divided by the average of the two midquotes. For display purposes we scale volatility by × 10,000. Price impact, *PRIMP*, is twice the signed difference between the NBBO midquote 15 seconds after the trade and the midquote at the time of the trade. The NBBO spread, *NBBO*, is the difference between the lowest offer quote and the highest bid quote across all markets. The effective spread, *ESP*, is twice the signed difference between the trade price and the corresponding midquote. The realized spread, *RSP*, is the difference between the effective spread and the corresponding price impact. Price impacts, effective spreads, and realized spreads are volume-weighted. We first estimate the means for each ETF and then compute the means, standard deviations, and quartile values across ETFs.

	Mean (1)	Std. Dev. (2)	25% (3)	Median (4)	75% (5)
Panel A: Activity Statistics					
# NBBO updates	6,239	8,853	649	3,380	8,940
# trades	552	1,442	28	89	410
Volume, sh.	213,954	589,416	10,466	30,694	135,101
Price, $	65.55	33.08	39.46	60.62	84.35
Volatility	2.37	4.47	0.80	1.22	2.24
Panel B: Trading Cost Statistics, ¢					
PRIMP	0.59	0.35	0.31	0.51	0.85
NBBO	2.50	3.97	1.04	1.37	2.41
ESP	2.47	3.55	1.15	1.40	2.51
RSP	1.88	3.50	0.49	0.86	2.13

effective spread, *ESP*, is our main trading cost metric and is twice the signed difference between the prevailing midquote and the trade price p_t, that is, $ESP_t = 2q_t\ (p_t - mid_t)$. The realized spread, *RSP*, represents the difference between liquidity providers' revenue and their adverse selection cost and is the difference between the effective spread and the price impact. We volume-weight price impacts, the effective spread, and the realized spread. The average NBBO spread is 2.50 cents, the effective spread is 2.47 cents, the price impact is 0.59 cents, and the realized spread is 1.88 cents.

III. Empirical Findings

A. Precipitation and Information Transmission Speed

Our empirical analyses rely on the premise that precipitation disrupts microwave networks and slows down the fastest traders. To offer empirical support for this premise, in Figure 2 we describe abnormal trading and quoting in SPY, the ETF that tracks the S&P 500 index, after a signal from the S&P

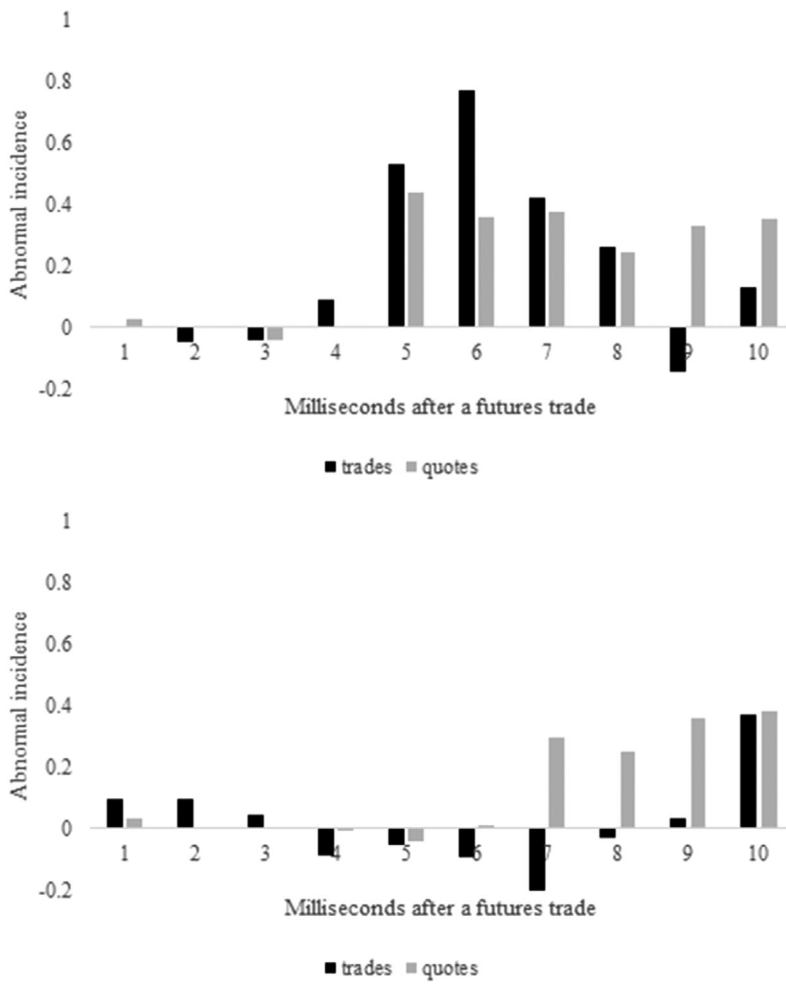

Figure 2. ETF trades and quotes following futures signals (CME sample). The figure reports a millisecond-by-millisecond timeline of ETF trades and quotes that follow a futures signal at $t = 0$. We treat all futures price changes as possible signals and examine ETF activity in the direction of the signal (e.g., ETF purchases and ETF offer quote increases if the signal is positive). The upper figure captures periods of low precipitation (*PRECIP* below the mean), and the lower figure captures heavy precipitation (*PRECIP* is at least one standard deviation above the mean). The black (grey) bars represent trades (quotes). Abnormal activity is measured as the number of trades or quotes scaled by its no-arbitrage mean. The no-arbitrage mean is the sample average number of trades or quotes in milliseconds 1 through n after a standalone futures signal, with $n = 4$ when precipitation is low and $n = 6$ when it is high. We drop quote changes that are likely caused by trade executions. To reduce serial correlation effects, we focus on the standalone futures signals, those not preceded by another signal. The figure focuses on the reactions of the S&P 500 ETF to the signals from the S&P 500 e-mini. Note: light covers the distance from Chicago to New York in about 4 milliseconds, a microwave signal covers this distance in about 4.5 milliseconds, and the same signal takes 6.5 milliseconds to pass through fiber.

500 e-mini is received in New York. We treat all futures price changes as possible signals and examine ETF activity in the direction of the signal (e.g., if the signal is positive, that is, the e-mini price increases, we focus on the ETF purchases and offer quote increases). To avoid counting the picking off instances as quote updates, we drop quote changes that are likely caused by trade executions. To reduce serial correlation effects, we use the standalone signals, those not preceded by another signal in the previous 10 milliseconds. We distinguish between two weather states: when precipitation is low (*PRECIP* is below the mean) and when it is heavy (*PRECIP* is at least one standard deviation above the mean). Abnormal activity is measured as the number of trades or quotes in ETF i in millisecond t scaled by its no-arbitrage mean.[12]

The upper panel of Figure 2 shows that when precipitation is low, ETF trades and quotes intensify five milliseconds after a futures trade. Meanwhile, when precipitation is heavy (the lower panel), the reaction occurs seven milliseconds after a futures trade. During our sample period, two milliseconds is precisely the difference in speed between the microwaves and the fiber cable. As such, the data corroborate the notion that precipitation slows the fastest traders by the two-millisecond difference between the microwave and cable speeds.[13]

B. Liquidity Supply and Demand

Figure 2 suggests that when the microwave networks are functional, trading firms use them for two purposes: (i) to reprice their own quotes and (ii) to pick off the quotes of others. When precipitation is low, both trades and quote changes are abnormally high in the fifth and sixth milliseconds. Trade executions increase by an average of 64.83%, while quote changes increase by 39.91%. In turn, when precipitation is heavy, the incidence of quote changes increases by 29.32% in the seventh millisecond, while trading activity declines. The latter result is consistent with arbitrage algorithms switching off when the microwave networks are disrupted, although it may not be immediately clear why the number of trades is below normal. After all, even though the arbitrage algorithms switch off, routine marketable orders should remain unaffected. Quote repricing is the most likely reason for this result. As quotes are repriced upon receipt of the futures signal, routine marketable orders

[12] We define the no-arbitrage mean as the average number of trades (quotes) in milliseconds 1 through n after a standalone futures signal, with $n = 4$ when precipitation is low and $n = 6$ when it is high. During the no-arbitrage period, the futures signal has not yet reached the equity market, while the previous signals have had sufficient time to be incorporated into prices.

[13] Until mid-2015, U.S. exchanges were not required to synchronize their clocks (Bartlett and McCrary (2019)). During our sample period, the CME data are misaligned with DTAQ trades by about one millisecond, and we adjust for this misalignment. Without the adjustment, it appears that ETF trading during periods of low precipitation picks up four milliseconds after a futures signal, which would require microwave speeds to be faster than the speed of light. Importantly, the adjustment does not affect the inference of the two-millisecond speed advantage of the fastest traders. This is because the adjustment shifts the low and heavy precipitation series equally, and the difference between them remains the same.

Table III

Precipitation and Trade Price Impacts (DTAQ Sample)

Panel A compares price impacts during episodes of heavy precipitation, when $PRECIP2 = 1$, and during episodes with less precipitation, when $PRECIP2 = 0$. Panel B reports coefficient estimates from the panel regression $PRIMP_{it} = \alpha_0 + \beta_1 PRECIP_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}$, where $PRIMP_{it}$ is the price impact in ETF i during 15-minute interval t, *PRECIP* is precipitation in the Chicago-New York corridor, *VOL* is the natural log of share volume, and *VOLAT* is the volatility proxy as defined in Table II. In addition to the continuous *PRECIP* variable, we use *PRECIP*1 and *PRECIP*2 to identify the most significant precipitation events. All models control for security and intraday fixed effects, and all standard errors (in parentheses) are heteroskedasticity-robust. We winsorize 0.01% of nondummy variables. Controlling for the fixed effects suppresses the intercept. *** and ** indicate statistical significance at the 1% and 5% levels based on the corresponding t-statistics. The sample covers the 2011 through 2012 period. The number of observations is 1,139,700.

	(1)	(2)	(3)
Panel A: Univariate Differences			
$PRECIP2 = 0$	0.60		
$PRECIP2 = 1$	0.56		
Panel B: Regression			
PRECIP	−0.002**		
	(0.001)		
*PRECIP*1		−0.016***	
		(0.002)	
*PRECIP*2			−0.023***
			(0.003)
VOL	0.137***	0.136***	0.136***
	(0.001)	(0.001)	(0.001)
VOLAT	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)

submitted at stale prices do not execute, leading to a momentary dip in trading activity.

C. Adverse Selection

Since microwave technology allows some traders to pick off the quotes of others (using the taxonomy from the Introduction, Group 1 picks off Group 2), we may observe a reduction in price impacts when precipitation disrupts microwave connectivity. We examine this possibility in Panel A of Table III by comparing price impacts for an average liquidity provider during the heavy precipitation episodes ($PRECIP2 = 1$) and the remaining episodes ($PRECIP2 = 0$). The results show that when precipitation is heavy, price impacts decline from 0.60 cents to 0.56 cents, or by 6.7%.

To test the picking-off hypothesis in a more formal setting, in Panel B we turn to the following regression setup:

$$PRIMP_{it} = \alpha_0 + \beta_1 PRECIP_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}, \tag{1}$$

where $PRIMP_{it}$ is the average price impact in ETF i during 15-minute interval t, *PRECIP* is total precipitation, *VOL* is the natural log of share volume, and *VOLAT* is the volatility proxy defined earlier.[14] In specifications (2) and (3), we substitute *PRECIP* with *PRECIP*1 and *PRECIP*2 to capture the most significant precipitation events. All models control for security and intraday fixed effects, and all standard errors (in parentheses) are heteroskedasticity robust. In the Internet Appendix, we show that the results are robust to clustering standard errors across securities and over time, equal-weighting price impacts, and scaling price impacts by the price of the underlying asset.

The results confirm that price impacts decline with precipitation, specifically, by 0.002¢ per one-unit increase in *PRECIP*. Perhaps more importantly, instances of intense precipitation as captured by *PRECIP*1 and *PRECIP*2 are associated with price impact declines of 0.016¢ and 0.023¢ (or 2.7% and 3.8%). These results confirm that microwave connectivity is disrupted mainly when precipitation is the heaviest. Accordingly, in the remainder of the study we focus on the heavy precipitation episodes captured by *PRECIP*2.

D. Displayed Liquidity and Trading Costs

Adverse selection is a cost of market making. Given that this cost declines when precipitation is heavy, and assuming that liquidity provision is competitive, spreads should also decline. The univariate results in Panel A of Table IV show that this is indeed the case. When precipitation is heavy, NBBO spreads and effective spreads decline by 0.12¢ and 0.13¢ (or 4.8% and 5.2%). The regression results in Panel B further suggest that during the *PRECIP*2 episodes, the NBBO spreads decline by 0.040¢ and effective spreads decline by 0.065¢.

The argument above relies on the notion of competitive liquidity provision documented by many recent studies (e.g., Hendershott, Jones, and Menkveld (2011), Brogaard, Hendershott, and Riordan (2014), Brogaard et al. (2015)). In our setting, the competitiveness notion is somewhat nuanced and requires further clarification. Recall that when precipitation is low, adverse selection costs accrue to Group 2, which represents traders without microwave access. Expectedly, these traders widen their spreads to compensate for the cost increase. In the meantime, it seems logical that competition within Group 1, whose members do not incur these costs, should prevent spreads from widening. If this mechanism is indeed at work, the spreads should not narrow when the microwave users lose their speed advantage.

[14] Volume and volatility are often used as determinants of adverse selection and trading costs (see, for instance, Brogaard et al. (2015)). Also, as we show in Section III.E, these two variables change with precipitation and therefore we include them as controls.

Table IV

Displayed Liquidity and Trading Costs (DTAQ Sample)

Panel A compares the NBBO spread, effective spread, and realized spread during episodes of heavy precipitation, when $PRECIP2 = 1$, and during episodes with less precipitation, when $PRECIP2 = 0$. Panel B reports coefficient estimates from the panel regression $DEPVAR_{it} = \alpha_0 + \beta_1 PRECIP2_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}$, where $DEPVAR_{it}$ is the quoted NBBO spread, the effective spread (*ESP*), or the realized spread (*RSP*) in asset i during 15-minute interval t, and all other variables are as previously defined. All models control for security and intraday fixed effects, and all standard errors (in parentheses) are heteroskedasticity-robust. We winsorize 0.01% of nondummy variables. Controlling for the fixed effects suppresses the intercept. *** and ** indicate statistical significance at the 1% and 5% levels based on the corresponding t-statistics. The sample covers the 2011 through 2012 period. The number of observations is 1,139,700.

	NBBO (1)	*ESP* (2)	*RSP* (3)
	Panel A: Univariate Differences		
$PRECIP2 = 0$	2.51	2.48	1.88
$PRECIP2 = 1$	2.39	2.35	1.78
	Panel B: Regressions		
PRECIP2	−0.040***	−0.065***	−0.041**
	(0.005)	(0.018)	(0.018)
VOL	−0.163***	0.317***	0.180***
	(0.002)	(0.008)	(0.008)
VOLAT	0.124***	0.162***	0.141***
	(0.011)	(0.022)	(0.022)

To clarify why the spreads do narrow, we highlight two important institutional characteristics. First, recall that firms in Group 1 compete with one another to be the fastest. This competition results in a speed hierarchy, whereby the speed leader among N microwave users adversely selects the remaining $N-1$, the next-fastest trader adversely selects the remaining $N-2$, and so on. Second, microwave bandwidth is limited, restricting the number of futures contracts that a network can be dedicated to. As such, the fastest trader usually arbitrages the most profitable contracts, the second-fastest trader focuses on the next few available contracts, and so forth.

Taken together, these two institutional characteristics imply that for a futures contract X, there is a speed leader that picks off the quotes of all other market participants in related equities, while for a futures contract Y, a different speed leader does the same. Importantly, since only the speed leader avoids adverse selection in each asset (all other firms in Groups 1 and 2 are adversely selected by the respective leaders), the leader faces no competitive pressure to narrow spreads. In addition, the leader has high technology costs and naturally tends to quote wider spreads to recoup them.

Brogaard et al. (2015) show that speeding up exchange access decreases realized spreads. They attribute this finding to market makers' improved ability to predict incoming marketable orders, which leads to a reduction in inventory costs. Along the same lines, we propose that the reduction in arbitrage activity driven by the microwave disruptions may improve market makers' ability to predict liquidity-demanding order flow and thereby reduce inventory costs. The data support this conjecture; in Panel B of Table IV, realized spreads decline by 0.10¢ (5.3%).

The economic significance of the precipitation effect on effective spreads varies between 2.6% in the regression setting and 5.2% in the univariate setting. In the next section, we show that volume and volatility (two known trading cost determinants) also vary in precipitation and therefore likely absorb some of the economic effect when used as regressors. As such, it is sensible to view the regression results as the lower bound of the precipitation effect.[15]

To further put these results into perspective, total trading cost savings from eliminating speed differentials are between \$0.45 and \$0.90 million per ETF-year.[16] We note that the magnitude of liquidity effects associated with speed differentials is likely to be setting-dependent. For instance, microwave networks are widely used to transmit information between major U.S. equity exchanges located in New Jersey, leading to an arms race similar to that in the Chicago-New York corridor. Chakrabarty et al. (2020) examine common equities traded on these exchanges in the 2011 through 2012 period and report price impacts that are three times larger than those we report for ETFs. As such, eliminating speed differentials in equities may result in trading cost savings that are greater than those reported here. In line with this possibility, Aquilina, Budish, and O'Neil (2020) quantify the global cost of latency arbitrage in equities to be \$5 billion annually.

The reduction in trading costs during the microwave disruptions may come through two channels: (i) an increase in limit order aggressiveness due to the reduction in the costs of providing liquidity and (ii) an increase in the liquidity demanders' ability to obtain better prices due to reduced competition for liquidity from arbitragers. In this section, we use ITCH data to examine whether, consistent with the first channel, liquidity provision shows signs of strengthening. Results in the next section reveal a decline in arbitrage volume and therefore support the second channel.

Using ITCH data for the 2011 through 2012 period, we compute two new dependent variables: the percentage of nonmarketable limit orders that (i) match the prevailing DTAQ NBBO and (ii) improve the NBBO. Both variables are scaled by the total number of limit order submissions. If liquidity supply does indeed strengthen when the microwave networks are disrupted, we should see an increase in the percentage of order submissions that match or improve the NBBO. Panel A of Table V reports that when precipitation is low, 28.88 of

[15] For comparison, Brogaard et al. (2015) report that an across-the-board speed increase in the Swedish market results in a 2.0% reduction in effective spreads.

[16] The calculation accounts for the fact that an average ETF trades 213,954 shares every 15 minutes, and the cost of trading one share is half of the effective spread. The calculation also assumes 250 trading days to a year: $\$903{,}956 = 0.13 \times 0.5 \times 0.01 \times 213{,}954 \times 4 \times 6.5 \times 250$.

Table V
Limit Order Aggressiveness (ITCH Sample)

Panel A reports summary statistics for two limit order aggressiveness proxies derived from the ITCH limit order book data, namely, the number of limit orders that match or improve the NBBO, scaled by the number of total limit order submissions. Panel B reports the coefficient estimates from the regression $DEPVAR_{it} = \alpha_0 + \beta_1 PRECIP2_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}$, where $DEPVAR_{it}$ is one of the two limit order aggressiveness proxies, and the remaining variables are as previously defined, with volume derived from the ITCH data. All models control for security and intraday fixed effects, and all standard errors (in parentheses) are heteroskedasticity-robust. We winsorize 0.01% of nondummy variables. Controlling for the fixed effects suppresses the intercept. *** indicates statistical significance at the 1% level based on the corresponding t-statistics. The sample covers the 2011 through 2012 period. The number of observations is 1,165,493.

	Match	Improve
Panel A: Univariate Differences		
$PRECIP2 = 0$	28.88	1.29
$PRECIP2 = 1$	29.37	1.27
Panel B: Regressions		
$PRECIP2$	0.431***	−0.008
	(0.046)	(0.011)
VOL	1.770***	0.318***
	(0.014)	(0.003)
$VOLAT$	−0.243***	−0.060***
	(0.031)	(0.009)

every 100 limit orders match the prevailing NBBO and 1.29 improve it. Consistent with the strengthening of liquidity supply, the incidence of matching orders increases by 0.49, or 1.7%, when precipitation is heavy. The incidence of NBBO-improving orders, however, does not change. Panel B corroborates these results in a regression setting.

E. Volatility and Trading Activity

The effect of fast trading on volatility has been examined by several studies, some of which report the effect to be negative (Hasbrouck and Saar (2013), Brogaard, Hendershott, and Riordan (2014)), while others show it to be positive (Zhang (2010), Boehmer, Fong, and Wu (2018)). In a theoretical model, Du and Zhu (2015) predict that volatility may increase when some traders are faster than others.[17] Roşu (2019) further shows that as volume increases in fast trading, volatility may also increase. Our results are consistent with these predictions. In particular, Table VI shows that when precipitation is heavy, volatility decreases.

[17] We refer to the prepublication version of Du and Zhu (2015), available at https://bit.ly/2DUkggo.

Table VI

Volatility and Trading Activity (DTAQ Sample)

The table presents coefficient estimates from the panel regression $DEPVAR_{it} = \alpha_0 + \beta_1 PRECIP2_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}$, where $DEPVAR_{it}$ is volatility or trading volume in asset i during 15-minute interval t, and all other variables are as previously defined. When volume (volatility) is the dependent variable, we do not use it as a control. To conform with Table II, in Panel A volume is reported as the number of shares scaled by 100,000. In Panel B, we use the natural log of volume. All models control for security and intraday fixed effects, and all standard errors (in parentheses) are heteroskedasticity-robust. We winsorize 0.01% of nondummy variables. Controlling for the fixed effects suppresses the intercept. *** indicates statistical significance at the 1% level based on the corresponding t-statistics. The sample covers the 2011 through 2012 period. The number of observations is 1,139,709.

	VOLAT	*VOL*
Panel A: Univariate Differences		
*PRECIP*2 = 0	2.40	2.15
*PRECIP*2 = 1	2.00	2.01
Panel B: Regressions		
*PRECIP*2	−0.038***	−0.034***
	(0.006)	(0.003)
VOL	−0.041***	
	(0.005)	
VOLAT		−0.007***
		(0.001)

Our finding that precipitation episodes are associated with greater price impacts and lower trading costs implies that speed differentials may lead to a redistribution of gains from trade from slow to fast traders. Perhaps more importantly, the differentials may also affect social efficiency, as higher trading costs force some participants to forgo trading. To shed some light on this issue, we turn to the relation between precipitation and trading volume. Recall from Figure 2 that arbitrage activity declines during microwave disruptions, potentially reducing volume. However, lower trading costs associated with the disruptions may attract additional trading interest from nonarbitragers (the end users) and hence increase total trading volume. In Table VI, we examine the net effect. The data show that trading volume is lower when precipitation is heavy, consistent with the arbitrage effect dominating. Specifically, Panel B suggests that trading volume declines by 0.3%.

To provide further evidence on the behavior of end users, we return to the CME futures data to separate ETF trading volume into two components: (i) that plausibly due to the Chicago-New York arbitrage (*arbitrage volume*) and (ii) the remaining volume (*end-user volume*). Recall that microwave technology transmits information between Chicago and New York in 4.5 milliseconds. Figure 2 shows that equity arbitrage trades follow futures signals as quickly as technology allows. We use this timeline to identify ETF volume that is plausibly related to arbitrage.

Specifically, we assume that a nontrivial share of ETF trades in the fifth millisecond after a futures signal is due to arbitrage. We also recognize that arbitrage positions must be closed once prices adjust to new information. Finally, we anticipate that arbitrage trades are usually followed by a round of liquidity provider rebalancing, whereby liquidity providers trade out of inventory accrued through their interaction with the arbitrageur. The timing of position closures and rebalancing trades is unknown to us, but market participants suggest that they occur rather quickly, usually in a matter of milliseconds.

For our purposes, position opening, closing, and subsequent rebalancing generate arbitrage-related volume. We use several window lengths to capture such volume, starting with the shortest window that contains milliseconds 5 and 6 and gradually expanding it to a window containing milliseconds 5 through 20. Trading volume occurring outside the [+5; +20]-millisecond window is labeled *end-user volume*. We use all futures-ETF combinations available from the CME data: (i) the S&P 500 e-mini and its three corresponding ETFs: SPY, IVV, and VO; (ii) the NASDAQ 100 e-mini and its correspondent, QQQ; (iii) the S&P MidCap 400 e-mini and MDY, IJH, and VOO; and finally (iv) the Financial Sector Select and its correspondent, XLF.

Panel A of Table VII uses the [+5; +6]-millisecond window and examines the relation between precipitation and the two volume components in the equation (1) regression framework. The results suggest that the decline in total volume documented above is driven entirely by arbitrage volume, while end-user volume is unaffected by precipitation. Panel B shows that this result is robust to changing the arbitrage window length.

It is possible that end-user volume is insensitive to microwave downtimes because precipitation episodes are too brief for the end users to react. A portfolio manager who accounts for trading costs may not change her decisions at a frequency high enough to be affected by the fleeting precipitation episodes, yet she may respond to a longer lasting period of lower trading costs. To shed light on this possibility, we examine an event that removes speed differentials for a period of at least several months. Consistent with the view that speed differentials make some users leave the market untraded, trading cost reductions associated with this event are accompanied by an increase in trading volume.

At the end of December 2012, Quincy Data, a division of the trading technology firm McKay Brothers, disrupted the prevailing microwave business model. Instead of selling bandwidth on its network for private use, Quincy began selling information transmitted by the network to anyone willing to subscribe.[18] Subscribers obtained access to an information transmission channel that was faster than the rest of the existing networks. As such, Quincy effectively expanded the group of market participants who had access to the top speeds.[19]

[18] “Quincy Data Announces Launch of Extreme-Low Latency Wireless Market Data,” December 21, 2012 (https://bit.ly/2I5wiJ4).

[19] Industry sources suggest that the number of Quincy launch customers was sufficiently large to disrupt the existing speed hierarchy: “Quincy Data and McKay Brothers Plan Additional Microwave Links and Super Fast Market Data Services,” July 31, 2013 (https://bit.ly/2RpdN5l). In

Table VII

Arbitrage and End-User Volume (CME Sample)

The table presents evidence on changes in arbitrage and end-user volume during the heavy precipitation episodes. Arbitrage volume is defined as ETF volume in millisecond 5 up to millisecond 20 after a futures signal. End-user volume is defined as ETF volume that occurs outside the [+5; +20]-millisecond (ms) window. We vary the arbitrage window length from short (i.e., [+5; +6] ms) to long (i.e., [+5; +20] ms) to account for uncertainly in the timing of arbitrage position closures and liquidity provider rebalancing that follows arbitrage events. Panel A reports results for the [+5; +6]-ms window and reports coefficient estimates from the regression model $DEPVAR_{it} = \alpha_0 + \beta_1 PRECIP2_t + \beta_2 VOLAT_{it} + \varepsilon_{it}$, where $DEPVAR_{it}$ is the natural log of arbitrage or end-user volume in ETF i during interval t, $PRECIP2$ is an indicator variable that denotes heavy precipitation, and $VOLAT$ is volatility as previously defined. Panel B reports $PRECIP2$ coefficients for alternative arbitrage window lengths: [+5; +7], [+5; +10], [+5; +15], and [+5; +20] ms. All models control for security and intraday fixed effects, and all standard errors (in parentheses) are heteroskedasticity-robust. We winsorize 0.01% of nondummy variables. Controlling for the fixed effects suppresses the intercept. The data come from the 2012 sample of CME futures and the corresponding ETF contracts (i.e., SPY, IVV, VO, MDY, IJH, VOO, QQQ, and XLF). *** indicates statistical significance at the 1% level based on the corresponding t-statistics.

Panel A: 5–6 ms Arbitrage Window		
	Arbitrage Volume (1)	End-User Volume (2)
PRECIP2	−0.106***	−0.013
	(0.025)	(0.026)
VOLAT	−0.004	0.012
	(0.021)	(0.006)
Panel B: Alternative Arbitrage Windows, *PRECIP2* Coefficient Estimates		
5–7 ms	−0.116***	−0.013
	(0.025)	(0.026)
5–10 ms	−0.119***	−0.018
	(0.024)	(0.026)
5–15 ms	−0.131***	−0.019
	(0.023)	(0.026)
5–20 ms	−0.121***	−0.017
	(0.022)	(0.026)

In essence, the precipitation episodes in the 2011 through 2012 period may be viewed as short-term disruptions of the speed hierarchy, while the Quincy event is a long-term disruption. We expect that the Quincy event may lead to a trading cost reduction similar to that observed during the precipitation episodes. More importantly, the long-term nature of the Quincy event may

addition, the firm appears to have retained its speed leadership for a long period of time: "Fintech Focus," July 29, 2016 (https://bit.ly/2uEsOHx), "Trading Infrastructure - The Trend Towards Outsourcing," November 21, 2017 (https://bit.ly/2SiFOe0).

result in a trading volume increase.[20] To examine these conjectures, we carry out an event study of trading costs and volume in the wake of the Quincy launch.

The Quincy network became operational at the end of December 2012. We use September, October, and November 2012 as the pre-event period and February, March, and April 2013 as the postevent period. To establish a baseline, we begin with the simple event study regression

$$DEPVAR_{it} = \alpha_0 + \beta_1 POST_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}, \tag{2}$$

where $DEPVAR_{it}$ is the price impact, effective spread, realized spread, or trading volume in ETF i on day t, $POST_t$ is an indicator variable equal to one in the postevent window, and the remaining control variables are as previously defined. When volume is the dependent variable, we drop it as a control.

The results in Panel A of Table VIII suggest that the Quincy event is associated with a decline in price impacts. Trading costs also decline, driven by reductions in both price impacts and realized spreads. Perhaps most importantly, trading volume increases by 0.226, or 2.3%, consistent with the relatively high trading costs associated with speed differentials previously hindering end-user participation.

It is important to note that the volume increase above nets out the Quincy-driven decline in arbitrage volume and the increase in end-user volume. The CME data that allow us to separate the two volume types in Table VII do not extend to 2013, so we do not carry out a similar separation. This said, we back out a sensible, though cautious, end-user volume estimate by combining the insights from Tables VI and VII. From Table VI we know that heavy precipitation is associated with a 0.3% decline in total volume, and Table VII suggests that this decline is due entirely to arbitrage volume. As such, the net post-Quincy volume increase of 2.3% obtains if end-user volume increases by 2.6% (= 0.3 + 2.3).

We recognize that the setup in equation (2) may be susceptible to confounding effects. For instance, it may capture a market-wide decline in price impacts and trading costs, and a market-wide increase in volume unrelated to the Quincy event. To examine this possibility, we turn to a matched sample of common stocks. Stocks and ETFs share many market structure characteristics—they trade on the same platforms during the same hours, and fast market participants normally trade both. However, stocks are less affected by the microwave-assisted arbitrage. As we mention previously, trading firms use microwave networks for the most profitable signals, those produced by the most frequently traded instruments. Such instruments are predominantly index futures (single stock futures are rare and not frequently traded), and thus microwave technology is deployed mainly for the index futures-ETF arbitrage. We discuss empirical results that corroborate this view shortly.

[20] Due to limited bandwidth, Quincy transmitted only the most valuable signals, such as those from the S&P 500 e-mini and other active futures. Given the importance of indexes tracked by such futures, we expect that many sample ETFs were affected by the Quincy launch.

Table VIII

The Quincy Launch: An Event Study (DTAQ Sample)

The table presents evidence on changes in adverse selection, liquidity costs, and trading volume in the wake of the Quincy launch, which removed speed differentials in the Chicago-New York corridor. The event occurred in late December 2012. We define the pre-event period as September through November 2012 and the postevent period as February through April 2013. In Panel A, we estimate the following model for the ETF sample: $DEPVAR_{it} = \alpha_0 + \beta_1 POST_t + \beta_2 VOL_{it} + \beta_3 VOLAT_{it} + \varepsilon_{it}$, where $DEPVAR_{it}$ is the price impact, effective spread, realized spread, or natural log of trading volume in ETF i on day t, $POST_t$ is an indicator variable equal to one in the postevent window, and the remaining control variables are as previously defined. When volume is the dependent variable, we drop it as a control. We winsorize 0.01% of nondummy variables. The model is estimated with stock fixed effects. In Panel B, we expand the model to include a matched sample of common stocks: $DEPVAR_{it} = \alpha_0 + \beta_1 POST_t + \beta_2 POST \times ETF_{it} + \beta_3 ETF_i + \beta_4 VOL_{it} + \beta_5 VOLAT_{it} + \varepsilon_{it}$, where $DEPVAR_{it}$ are as previously defined, ETF is a dummy variable for the ETF sample, and all remaining control variables are as previously defined. When volume is the dependent variable, we drop it as a control. Standard errors (in parentheses) are heteroskedasticity-robust. *** and ** indicate statistical significance at the 1% and 5% levels based on the corresponding t-statistics.

	PRIMP (1)	*ESP* (2)	*RSP* (3)	*VOL* (4)
	Panel A: ETF Sample			
POST	−0.092***	−0.295***	−0.201***	0.226***
	(0.006)	(0.039)	(0.039)	(0.009)
VOL	0.127***	0.120	−0.008	
	(0.014)	(0.063)	(0.066)	
VOLAT	0.032	0.310***	0.281**	0.001
	(0.021)	(0.117)	(0.121)	(0.005)
	Panel B: Matched Sample			
POST	0.001	0.382***	0.380***	−0.005
	(0.024)	(0.073)	(0.063)	(0.031)
POST × *ETF*	−0.075***	−0.476***	−0.397***	0.185***
	(0.025)	(0.089)	(0.080)	(0.046)
ETF	−1.036***	−1.288***	−0.255***	0.256***
	(0.017)	(0.067)	(0.064)	(0.033)
VOL	0.025***	−0.686***	−0.712***	
	(0.003)	(0.021)	(0.020)	
VOLAT	−0.006	0.470***	0.477***	−0.013
	(0.008)	(0.069)	(0.072)	(0.010)
INTERCEPT	1.318***	9.538***	8.223***	9.791***
	(0.038)	(0.211)	(0.203)	(0.026)

To create the matched sample, we employ three metrics commonly used for this purpose: market capitalization, price, and trading volume. We collect these metrics for the sample ETFs and the universe of stocks in August 2012, the month preceding the pre-event period, and compute the matching error for each ETF-stock pair $i - j$ as

$$matcherror_{ij} = \sum_{k=1}^{3} \left(\frac{C_k^i - C_k^j}{C_k^i + C_k^j} \right)^2, \tag{3}$$

where C_k is one of the three characteristics above, with market capitalization and volume expressed as natural logs. We then select pairs with the smallest matching errors (without replacement) until all ETFs are allocated a pair. The procedure is rather successful—market capitalizations and prices do not differ economically or statistically, while volumes differ marginally.

Before we discuss the matched-sample results, we briefly return to the idea that microwave-assisted arbitrage mostly affects ETFs rather than individual stocks. Recall that heavy precipitation is associated with a decline in ETF price impacts. When we perform the same analysis for the matched stocks, we obtain an insignificant coefficient on *PRECIP*2. As such, we are reasonably confident that the matched-sample analysis allows us to isolate the effects of the Quincy event. To carry out this analysis, we expand equation (2) as follows:

$$\begin{aligned} DEPVAR_{it} = \alpha_0 &+ \beta_1 POST_t + \beta_2 POST \times ETF_{it} \\ &+ \beta_3 ETF_i + \beta_4 VOL_{it} + \beta_5 VOLAT_{it} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where ETF_i is a dummy variable for the main sample ETFs, and all other variables are as previously defined.

The matched-sample results are reported in Panel B of Table VIII. In this panel, the variable *POST* captures the post-Quincy changes in the matched stocks, while the interacted $POST \times ETF$ variable indicates whether these changes are different for the sample ETFs. All $POST \times ETF$ coefficients are consistent with the baseline result. For instance, specification (1) suggests that while the price impacts for the matched stocks do not change, the main sample ETFs see a significant decline. The ETF effective and realized spreads also decline compared to the matches, while ETF volume increases. The *POST* coefficients are either insignificant or have signs opposite those of the ETFs, mitigating concerns related to confounding effects.[21]

F. Additional Costs of the Speed Race

In addition to the lost gains from trade, two features of the speed race are worth discussing: the technology cost effect and the asset pricing/corporate investment effect. The microwave networks emerged less than a year after the unveiling of the Spread Networks cable, which itself had a price tag of

[21] We note that the effective spreads of the matched stocks increase in the postevent window. This phenomenon does not have a primary bearing on our results and has been documented previously. In a multiyear sample of common equities, DeGennaro, Kamstra, and Kramer (2018) show that effective spreads are greater in the first few months of the year compared to the last few months. Our data contain a similar pattern, with a similar economic magnitude.

$300 million.[22] Cost estimates of building a microwave network range from $8 million (Laughlin, Aguirre, and Grundfest (2014, p. 287)) to $13.5 million.[23] Using the lowest estimate and assuming that the number of networks is about 15, microwave connectivity adds at least $120 million to the cost of the race. Market participants further suggest that leases, staffing, power, maintenance, and incessant retrofitting add several million per network-year in operating costs.

If the price impacts discussed above are sufficiently representative of arbitrage revenues, two issues are worth further discussion. First, the revenues per ETF-year are relatively modest compared to the cost of building and operating a network, at about $0.3 million.[24] Second, the revenues are markedly skewed toward the futures contracts that produce the most profitable signals, leading to large disparities in network profitability—the networks that boast the top speeds get to transmit the most lucrative signals and are considerably more profitable than the rest. During our sample period, as network operators realize that their speed has become subpar due to competitors' retrofitting, they too have to retrofit to regain profitability.

It is not immediately obvious if such investments are socially beneficial. Absent liquidity improvements, it is possible that investors benefit from the increase in the speed of price discovery. Such benefits are difficult to quantify, and we leave this issue for future research. However, we note that while adding new networks increases the range of instruments for which price discovery speeds up by two milliseconds, retrofitting existing networks improves the speed of price discovery considerably less.

The speed race continues to this day and is becoming increasingly costly. Market participants expect that the undersea cables that currently connect remote markets such as New York and London may soon be supplemented by Low Earth Orbit (LEO) satellites. According to reports, an LEO satellite constellation may require investments north of $3 billion and may have limited bandwidth, leading to speed advantages for a select group of trading firms that are able to afford the service. In addition, satellite technology may be faster than the current undersea cable only part of the time.[25] To remain competitive, fast traders will likely have to gain access to both transmission channels,

[22] "Wall Street's speed war," by C. Steiner, Forbes Magazine, September 27, 2010 (https://bit.ly/2t6QlwG).

[23] "The secret world of microwave networks," by S. Anthony, Ars Technica, November 3, 2016 (https://bit.ly/2FkDtLo). The author quotes an estimate between GBP 2.5 and 5 million to build a network between London and Frankfurt. Given that the straight-line distance between Chicago and New York is 1.8 times greater, the estimate converts to GBP 4.5 to 9 million or USD 6.75 to 13.5 million using 2011 exchange rates.

[24] Similar to footnote 15, $\$278{,}140 = 0.04 \times 0.5 \times 0.01 \times 213{,}954 \times 4 \times 6.5 \times 250$. Note that although limited microwave bandwidth restricts the number of futures signals a network can transmit, it does not restrict the number of ETFs that may be arbitraged based on these signals. If a particular e-mini affects prices of n ETFs, the network that dominates the arbitrage in this e-mini will profit from each of these ETFs.

[25] See "SpaceX is opening up the next frontier for HFT," by S. Rosov, June 25, 2019 (https://cfa.is/2OqNb1S), "Satellite startup LeoSat secures customer for high-speed trading," by R. Wall, *Wall*

incurring the associated costs. To justify such costs as welfare enhancing, the benefits of relatively small improvements in the speed of price discovery must be sizeable, and traders must value the time it takes to realize gains from trade exceptionally highly (Foucault and Moinas (2019)).

One additional point worth mentioning relates to the asset pricing and corporate investment implications of speed differentials. A rich literature (e.g., Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005)) finds that investors require a return premium to compensate for asset illiquidity and illiquidity risk. More recently, Brugler, Comerton-Forde, and Hendershott (2018) show that illiquidity affects the cost of raising capital, potentially impairing firms' ability to pursue investment opportunities. Since the technological arms race occurs not only in the Chicago-New York corridor but also in equity markets around the world, the effects of speed differentials on asset prices and corporate investment may be far reaching.

IV. Conclusions

We examine the effects of speed differentials, one of the defining characteristics of modern markets, on liquidity and gains from trade. During our sample period, microwave networks offer speeds that are 30% greater than the nearest competitor, the fiber optic cable. These networks are accessible by a relatively small group of trading firms, which continuously retrofit them to compete with each other for top speed. A rich theoretical literature suggests that the resulting speed differentials may have both positive and negative effects on liquidity. We use the sensitivity of microwave transmissions to precipitation to examine liquidity when speed differentials are removed. The data show that when this happens, adverse selection and trading costs decline.

We reexamine this result in an alternative setting. In particular, we use a new product offering by one of the microwave technology providers that allows multiple trading firms to subscribe to the fastest network, effectively removing speed differentials for an extended time period. The liquidity effects of this event are similar to those observed during precipitation episodes—adverse selection and trading costs decline. More importantly, the long-term nature of the trading cost reduction positively affects gains from trade, as trading volume increases.

The speed race continues to this day and has spread to markets outside the United States. Trading firms compete using technology that ranges from laser transmitters to LEO satellites. Given the sizeable investments required to acquire such technology and the effects on liquidity and gains from trade documented here, the social efficiency of the race is a question that may require further attention from academics and regulators.

Street Journal, September 6, 2016 (https://on.wsj.com/2WGJHdY), and Stéphane Tyč of McKay Brothers at the 2017 Chicago Trading Show (https://bit.ly/2GvmaqO).

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.