Anticipatory Traders and Trading Speed

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ABSTRACT

We examine whether speed is an important characteristic of traders who anticipate local price trends. These anticipatory participants correctly trade prior to the overall market and systematically act before other participants. They use manual and algorithmic order entry methods, but most are not fast enough to be high frequency traders (HFTs). Those anticipating price reversals appear informed while those trading early appear skilled. The case for them affecting the volume of other traders is weak. A follow-up sample three years later shows significant attrition in accounts and a meaningful difficulty maintaining the anticipatory strategy. To identify these traders, we devise novel methods to isolate local price trends using order book data from the WTI crude oil futures market.

Keywords: High frequency traders (HFT), Algorithmic traders, Manual traders, Anticipatory traders, WTI crude oil futures

JEL classification: G10, G13

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I. INTRODUCTION

The growth of high frequency trading (HFT) in financial markets has led to concerns that such traders may use processing speed to disadvantage other participants. Theoretical models suggest that HFT traders may gain by entering new markets to compete with slower participants (Hoffmann 2014; Biais, Foucault, and Moinas 2015).[1] Consistent with theory, fast traders have an advantage if they process news or intraday order information quickly in order to anticipate future order flows and prices. Liquidity costs may increase if these anticipatory traders discover an underlying parent order from the child order flow (O'Hara 2015). In this light, anticipatory trading may reduce market efficiency by temporarily raising (or lowering) price from what would occur without such participants (Brunnermeier and Pedersen 2005). However, if parent orders are informed then anticipatory trading may increase efficiency by faster price discovery, which is made even more efficient when HFTs are anticipatory traders.

Brogaard, Hendershott, and Riordan (2014), Hirschey (2016), and Jiang, Lo, and Valente (2013) provide support for anticipatory trading by some HFTs. These analyses show that HFTs appear to identify and trade before short-horizon price movements in equity and fixed income markets. However, the correlation between non-HFT activity and subsequent price changes is often positive in these results, so the relationship between the presumed comparative advantage of HFTs and the ability to anticipate price changes is unclear.

[1] Some researchers also suggest that anticipatory trading generates negative externalities, such as reducing liquidity provision, vitiating behavior as with quote stuffing, or inducing slower traders to depart (e.g., Ye, Yao, and Gai, 2013; Biais, Foucault, and Moinas, 2014; Foucault, Kozhan and Tham, 2014; Han, Khapko, and Kyle, 2014; Menkveld, and Zoican, 2014).

This study seeks to determine whether the ability to trade at high speeds is necessary for anticipatory trading. Our approach is different from the previous HFT literature because we identify all sample traders—not just HFTs—who can repeatedly execute trades that anticipate subsequent intraday price changes ("anticipatory traders"). We do not pre-condition the analysis on an already specified group of HFTs or use filters designed to isolate such traders from other participants.[2] Once we have identified the group of anticipatory traders, we examine whether speed is a determining characteristic to confirm whether anticipatory strategies are a HFT phenomenon.

To find anticipatory traders we develop a novel method to identify temporary, directional changes in intraday prices, which we call price paths. Conditional on these short-term price movements, we identify who is successful at trading in the beginning (or end) of such paths. We identify two types of anticipatory traders: those that act early during a directional price change ("*Type E*"), and those that forecast an up-coming price reversal ("*Type R*"). Early refers to trades in the first 10% of path volume and to act before a price reversal means to trade correctly in the last 10% of the previous path's volume.

Our sample provides evidence that a relatively small fraction of traders—4.1% (11.1%) out of 7,554 tested with 2.5% (5%) control rates—anticipate short-term directional price changes and/or price reversals. We find more Type R than Type E participants, with both groups containing algorithmic- and manual-entry traders. An investigation of Sharpe ratios for these traders confirms the relative success of these anticipatory strategies. However, most of

[2] Biais and Foucault (2014) and U.S. Securities and Exchange Commission (2014) offer a detailed discussion of the conditioning methods used in recent HFT research. Such methods may vitiate inferences about the overall population behavior.

these traders do not appear to be HFTs and accordingly our tests support the view that speed is not a significant determinant of anticipatory trading.[3]

The data examined are a subset of the regulatory information collected from exchanges by the Commodity Futures Trading Commission (CFTC). Our primary analysis uses anonymous account-level information from both order book and trade files for the WTI crude oil futures contract traded on the CME/Nymex exchange. We use two different samples for analysis. The initial sample is for the December 2011 expiration and contains 48 trading days beginning on September 12, 2011. The follow-up sample is for the October 2014 expiration and covers 35 days beginning on August 1, 2014. The WTI contract is one of the most active futures contracts with high volumes and daily participation by 1,000s of accounts.

Although most HFT research uses equity market data, futures markets involve many HFTs and exhibit many features found in equity markets.[4] Both equity and futures exchanges offer subscribers real-time, low-latency access to order book information, trading volumes are correlated through time and market quality patterns are similar. Specifically, crude oil and equity price volatility are highly correlated, bid-ask spreads decreased as volumes increased, and execution speeds have increased with the growth of HFT participants.[5] One important difference is that equity markets offer multiple execution venues for the same security. Thus,

[3] Note that our results do not imply that speed is unimportant in a general sense as increases in participant speeds are connected to market quality improvements. For example, HFTs are associated with spread-decreasing limit orders (Carrion 2013; Hagströmer, Nordén, and Zhang 2014), providing liquidity against temporary shocks (Brogaard, Hendershott, and Riodan 2014), and spread decreases in general (Hendershott, Jones, and Menkveld 2011) and when they are the new entrants (Brogaard and Garriott 2015). See Menkveld (2016) for a recent review of this literature.

[4] See Fishe and Smith (2017) for a discussion of HFT research in commodity markets and the findings in Kirilenko, Kyle, Samadi and Tuzun (2015) regarding HFT activity during the Flash crash.

[5] Recent equity statistics are summarized in Angel, Harris, and Spratt (2015) and related references. The market quality and volatility characteristics of WTI crude oil futures are found in Brunetti, Büyükşahin, and Harris (2016), Raman, Robe and Yadav (2016), Easley, Prado, and O'Hara (2016), and Haynes and Roberts (2015, 2017), the latter discusses speed characteristics for several commodities.

a caveat to our findings is that while speed may be less important for anticipatory strategies in consolidated futures markets, the gains from quoting on multiple platforms may generate a comparative advantage for HFTs to use such strategies in equity markets.

To make inferences about the speed of Type E and Type R traders, we measure order book latencies; specifically, the time between order entry and either cancellation or execution messages. We make speed inferences from all account orders as well as from a bootstrap simulation that gives equal weight to each participant account, thereby reducing the impact of skewness from high volume accounts (Fishe and Smith 2017). In these results, both Type E and Type R participants appear slower, on average, than other participants in both cancellation and execution speeds. Algorithmic traders are faster, but being algorithmic and either Type E or Type R does not further increase speed. Also, the average proprietary trader is faster than when trades are done on behalf of customers, and those who modify orders are, on average, much slower to both cancel and execute trades. Finally, Type E and Type R groups do not act faster when they are trading in the first or last 10% of path volume, respectively, indicating that they do not seem to be strategically using speed for their anticipatory strategy.

To find anticipatory traders, our methods examine thousands of trader histories and test statistics. We limit the possibility of false positives by controlling for the *false discovery rate* (FDR) as defined by Benjamini and Hochberg (1995) and implemented by Storey (2002) and Fishe and Smith (2012). Our results use both 2.5% and 5% control rates for the FDR.

We identify local price paths by considering how a trader with near perfect foresight might act. This trader would try to initiate trades in the correct direction at or around price reversals, and seek confirmation that price changes were directional and not merely random noise.[6] The sequential probability ratio test (SPRT) by Wald (1945) identifies such directional price paths. This approach provides a test for non-random, trending behavior and allows us to pinpoint turning points between up and down price trends.[7] The price path method uses information that traders do not have at the time of their trades, so it is a conservative approach and biased against finding such systematically successful participants.

Given that some participants are anticipatory traders the question arises as to whether they are advantaged because they bring new information to the market or because they make better predictions relative to information derived from market activity. Theoretical models suggest that HFTs may benefit from faster access to information or news trading, which may also be the case for anticipatory traders.[8] Thus, we investigate price behavior in paths both with and without Type E and Type R participants. We use clock time deciles in these paths to control for the endogeneity generated from selecting Type E and Type R groups based on volume deciles. We find no significant differences in price changes when Type E traders are in the first (or second) time decile of a price path. However, Type R traders appear informed as the first time decile in a path shows significant additional price movement when they trade in the last time decile of the previous path. This deviation occurs in the correct direction for both increasing and decreasing price paths.

We also examine whether Type E and Type R traders affect the trading volume of other participants. For example, they may incite other participants to trade—a so-called

[6] Our approach makes results conditional on local price paths in the same way that research on the "Flash Crash" or other market events is conditional on trade paths around those events (e.g., Kirilenko, Kyle, Samadi, and Tuzun, 2015; Menkveld and Yueshen, 2013).

[7] An alternative is to use a preset condition to define whether prices have changed sufficiently to identify turning points (cf., Hautsch, 2012, p.36).

[8] Better predictions may involve statistical representations of dynamic limit-order book models (e.g., Cont, Stoikov and Talreja, 2010; Huang and Kercheval, 2012) and/or access and ability to act on information that affects prices before others act (Foucault, Hombert and Rosu, 2016).

"momentum-ignition" effect—and thereby are not exactly anticipatory because they have caused others to trade.[9] Our results show no effects for Type R traders, but possibly some weak effects for Type E traders, although not aligned with their first decile trades.

Finally, we examine whether these traders retain their skills using the 2014 sample. We find substantial attrition among accounts, so that only 35% of the 2011 accounts are found trading three years later.[10] Of those that remain we find that 9% of the Type E group continues with an anticipatory strategy, while 20% of the Type R group continues with the reversal strategy. In total, the 2014 sample shows a 24% (11%) reduction in the total size of these Type E and Type R groups at the 2.5% (5%) FDR control rate. Analogous to the difficulty of fund managers maintaining a "Hot Hand", these findings suggest that anticipatory trading became more difficult to implement after 2011 and that the Type E or early trading strategy was the relatively more ephemeral strategy (Barras, Scaillet, and Wermers 2010).

This paper proceeds as follows. Section II discusses the related literature. Section III describes the methods used to identify anticipatory traders, along with a general discussion of the price path approach. Section IV discusses the data and how we measure speed. Section V provides our analyses and results. Finally, Section VI offers several conclusions.

II. RELATED LITERATURE

Several researchers offer evidence on anticipatory trading. Jiang, Lo and Valente (2013) analyze how often transactions are in the right direction compared to subsequent price

[9] Momentum ignition and other follower-inducing strategies require that other participants believe there is a positive probability of very recent informed trades (Allen and Gale, 1992). These strategies are among those thought to be used by HFT firms (U. S. Securities and Exchange Commission, 2014).
[10] Boyd and Kurov (2012) also find significant attrition by participants in energy futures after side-by-side electronic trading began in 2006. Their estimates imply a 50% loss of traders after 2.5 years.

changes around macroeconomic announcements. Frino, Ibikunle, Mollica, and Steffen (2016) follow a similar approach for trading in Brent oil futures around the London fixing period. Bae, Dixon, and Lee (2017) study the front-running of large orders for the KOSPI 200 futures contract. All of these studies report evidence of anticipatory trading, but do not resolve the question of whether speed is necessary. Importantly, Jiang, Lo and Valente (2013) find that non-HFT limit orders are more informative for future prices than HFT limit orders. These latter results suggest that anticipatory traders are not singly defined by an HFT label.[11]

Other more general studies by Brogaard, Hendershott, and Riordan (2014) and Hirschey (2016) use a Nasdaq sample with HFT participation noted in the trade data. Brogaard et al. find that the correlation between net order flow for all sample HFTs and subsequent returns is positive, but it is short lived and quite low—less than 4% at one second and near zero at two seconds. Interestingly, they find that non-HFTs demanding liquidity show higher, longer lived correlations with subsequent returns than HFTs demanding liquidity, implying that sub-groups excluding HFTs also appear informed. Hirschey (2016) also finds that liquidity-demanding trades by HFTs precede liquidity-demanding trades by non-HFTs. These studies leave unanswered the question of why some non-HFTs are predictive of returns if HFTs have anticipated their net orders. A possible explanation arising from our results is that successful anticipatory strategies are found among both HFT and non-HFT groups, so the Nasdaq HFT filter does not sufficiently separate anticipatory from non-anticipatory behavior.

Anticipatory trading may be similar to momentum trading strategies. Bikhchandani, Hirshleifer, and Welch (1992) and Allen and Gale (1992) are momentum studies that may

[11] Clark-Joseph (2012) suggests that aggressive HFTs execute multiple, generally unprofitable smaller size orders for the purpose of obtaining order book information. When this information indicates a high propensity for a directional price movement, the firm then profits from well-timed larger orders.

include anticipatory behavior.[12] Bikhchandani et al. develop a model in which informational cascades cause momentum reactions. Those who react first are like anticipatory traders. Allen and Gale show that traders are affected by big traders because of the likelihood that they may be informed. Thus, smaller traders have an incentive to trade in the same direction as a big trader, making the big trader appear anticipatory. These environments may create "following trades" by investors, which imply that some traders may be misclassified as anticipatory. To sort out the degree to which such traders vitiate our results, we examine the overall volume behavior following trades by those identified as anticipatory.

Lastly our study addresses the use of filters to identify HFTs for analysis. Others have observed that sample filters—inventory turnover, trading volume, cancellations, etc.—pose a problem for population inference. Biais and Foucault (2014) and the U.S. Securities and Exchange Commission (2014) discuss several of the filter methods used to classify data as algorithmic- or HFT-related. Biais and Foucault warn that "One problem with this approach is that it may select HFTs with a specific trading style…while excluding others (p. 10)." Thus, rather than pre-condition the analysis on a subset of trader characteristics, we seek to infer those population characteristics by identifying all traders associated with a specific strategy.

III. METHODS

Our analysis involves statistical methods to identify intraday price trends. The discussion below explains how such paths are identified and how the FDR method is used to find participants who can systematically execute trades during selected segments on these paths.

[12] De Long, Shleifer, Summers, and Waldman (1990), Hirshleifer, Subrahmanyam, and Titman (1994), Chan, Jegadeesh, and Lakonishok (1996), and Dong, Polk and Skouras (2014) offer examples of general momentum behavior.

a. Local Price Paths

Our approach to identify price paths uses statistical methods to locate sequences where price changes exhibit some degree of short-term predictability. We use the SPRT to define the local neighborhood size and to test for non-randomness. In the resulting sequences, we then search for local price extrema.

The process starts with the transaction price series from which we remove P_t if $P_t = P_{t-1}$, keeping the first price of each such sequence to preserve unique price levels. Then, we remove all sequences of contiguous bid-ask bounce. Specifically, all cases in which $\Delta P_t = -\Delta P_{t-1}$ are excluded. We retain the prices into and out of such sequences, but remove the intermediate implied bid-ask trades. For example, consider the price sequence, $P_t \equiv \{3,4,5,5,4,4,5,4,5,6\}$. After the first filter, the sequence is $P_t^* \equiv \{3,4,5,4,5,4,5,6\}$, from which we retain $P_1^*, P_2^*, P_7^*, and\ P_8^*$ after the second filter. The purpose behind removing bid-ask bounce sequences is to exclude periods in which liquidity replenishment is sufficient to satisfy liquidity demand. These sequences may provide information, but arguably provide little help identifying a price trend. Note that after we have identified the price trends, we restore *all* observations to the dataset for identification of Type E and R participants.

The above procedure produces a sequence in which $\Delta P_t \neq 0\ \ \forall_t$. We then define a set of candidate prices based on the SPRT test results. Within a group of *K* prices, the price P_{t^*} is a candidate for a local *minimum* at trade t^* if

(i) the count of *previous* price changes, $n^- \geq \delta K$, where $n^- = 1(\Delta P_t < 0)$ for $t \in \{t^*, t^* - 1, t^* - 2, \ldots, t^* - K\}$, and

(ii) the count of *subsequent* price changes, $n^{+} \geq \delta K$, where $n^{+} = 1(\Delta P_t > 0)$ for $t \in \{t^* + 1, t^* + 2, \dots, t^* + K\}$.

The parameter $\delta \in [0,1]$ creates a consistency condition and is used to assign confidence to our selection mechanism based on the power of the SPRT. The parameter K defines the local neighborhood of trades. For example, if K is large and $\delta = 1$, then every price change before the candidate local minimum will decrement the previous price towards the minimum and every price change after the local minimum will increment the previous price away from the minimum. We use the same approach, but reverse the inequalities to define a candidate local *maximum* price.[13]

The basic statistical properties of error rates guide the selection of the consistency parameter and the size of the local neighborhood. Consider the null hypothesis that the binary variable tracking the sign of any price change is binomial with null parameter, $H_o: q = 0.5$, which normalizes the null distribution of sign changes to a random sequence. A participant attempting to detect a price change is most concerned about rejecting this null in the neighborhood of a candidate price extrema. Thus, it is useful to establish confidence that the null is rejected. The SPRT provides a means of identifying the appropriate size of the local neighborhood necessary to reject the null as this test is uniformly most powerful against any other test in its expected stopping time (Wald, 1948).

The SPRT computes the likelihood ratio for each successive observation in the trade sequence given a null and alternative hypothesis. It uses type I (α) and type II (β) errors rates for these hypotheses to establish bounds for rejecting one hypothesis versus another. In our

[13] This method may produce cases in which multiple minimums or maximums are contiguous on a price path. We remove such cases by selecting a global maximum or minimum in such sequences. The final price paths alternate in the sign of ΔP_t, where this price change is from the beginning to the end of a path.

calculations we set both of these error rates equal to 10 percent, which then feeds back to the neighborhood size and consistency parameter.

To determine the neighborhood size, we simulate the number of trades necessary to reject the null ($H_o: q = 0.5$) against the alternative ($H_a: q = 0.8$). We use a strongly convincing alternative versus one closer to the null as participants would not rely on a testing method for local trends if it required a large number of trades, perhaps more than might be observed in a local trend. Using small differences between the null and alternative hypotheses creates longer required sampling sequences. With 1,500 simulations, we found that if participants selected 17 observations, then in only 10 percent of the cases would they require more observations before rejecting the null. As this choice equals the required Type II error rate ($\beta = 10\%$), we use 17 observations on both sides of a candidate price to define the local neighborhood.

To define the consistency parameter, we use a choice that follows from the Type I error rate (α = 10%). Under the null hypothesis, this error rate is $\Pr[\sum x \geq x' \mid K = K^*] \leq 0.10$, where $x \in \{0,1\}$ to indicate either a negative or positive price change. As the neighborhood size is set by the SPRT such that $K^* = 17$, using the binomial distribution, the cutoff for 10 percent arises when $10 < x' < 11$. We experimented on randomly chosen days with both choices and found that $x' = 10$ gave somewhat more paths, but the overlap was near 100% with $x' = 11$. As more paths are expected to make it more difficult to consistently trade in the correct direction, we used $x' = 10$ in our analysis. Thus if at least 10 out of 17 price changes are observed with the appropriate sign—positive (negative) before a candidate price maximum (minimum) and negative (positive) after the candidate price—then we define that price as a valid “candidate” for a local extrema. This approach produces a consistency parameter δ approximately equal to 60%.[14] To choose among the set of valid candidate prices within the same neighborhood, we select based on the conditions:

(iii) $P_{t^*}^{min} = min\{P_{t^*}, P_t\} \ \forall_{t \neq t^*}$, where $t \in \{t^* - K, t^* - K - 1, \dots, t^* + K\}$ for a minimum, and

(iv) $P_{t^*}^{max} = max\{P_{t^*}, P_t\} \ \forall_{t \neq t^*}$, where $t \in \{t^* - K, t^* - K - 1, \dots, t^* + K\}$ for a maximum.

Figure 1 illustrates how to conceptualize the working of the price path algorithm and the relative location of anticipatory traders. The figure shows a sequence of trades (the "x*'s*") for a portion of the day's trading. There are periods with market-making activity in which non-price moving liquidity-based trading creates a bid-ask bounce sequence (shaded areas). When new information about the value of the asset arrives or liquidity demand changes, the market price reacts until the information is impounded in the price or new liquidity arrives to resolve the imbalance. Local price reversals occur at the specified price extrema (the circled trades).

In the figure, Type E traders possess skills to process order flow and information to systematically forecast the short-term direction of prices. These participants react quickly *after* a price reversal occurs. Type R traders may use strategies that analyze order book liquidity or new information to place limit order prices near upcoming price reversals. The trades of these participants occur *before* but close to the local price extrema.

[14] We also simulated our results with Type I and Type II error rates equal to 5%. These simulations gave a neighborhood size of 24 observations to maintain the type II error rate and a consistency parameter of approximately 63%.

b. Finding Anticipatory Traders

To identify which participants may be making use of an anticipatory strategy, we use the *False Discovery Rate* (FDR) method of Benjamini and Hochberg (1995) as applied by Storey (2002) and Fishe and Smith (2012), which adjusts for multiple testing problems.[15] The FDR controls for the expected proportion of false discoveries in our sample. By effectively adjusting test statistic critical values, the FDR method limits these expected mistakes to a pre-specified proportion of successful statistics. We use both a 2.5 and 5 percent control rates, so we often report two sets of results. The FDR method gives greater confidence that the participants we identify as anticipatory traders are truly either Type E or Type R traders.

We use a volume metric to determine whether a trader may be classified as participating early or late in a price path. Let $x_{i,t}^{j} \in \boldsymbol{X}_j$ be the quantity traded by participant *i* at time *t* in the vector of all trades ($\boldsymbol{X}_j$) on price path *j*. If participant *i* is a buyer (seller) at time *t* in path *j* then $x_{i,t}^{j} > 0$ $\left(x_{i,t}^{j} < 0\right)$. If participant *i* does not trade at time *t* in path *j* then $x_{i,t}^{j} = 0$. The heaviside function, $s_{i,t}^{j} = h\left(x_{i,t}^{j} \in \boldsymbol{X}_j; d\right)$, defines whether trade $x_{i,t}^{j}$ arises in the first d^{th} percentile of path *j*'s volume. The heaviside function equals 1 if the trade is in the first d^{th} percentile and equals zero otherwise. The price direction along path *j* is defined to be increasing (decreasing) if $\Delta P_j > 0$ ($\Delta P_j < 0$), where the first and last trade prices on the path are used to compute this difference.

Participants are identified as successful *Type E* traders on a given path if their trades occur in the first d^{th} percentile of path volume and their trades are on the correct side for the path's

[15] Recent applications of FDR include Barras, Scaillet, and Wermers (2010) who sought to identify fund managers with positive alpha performance, Bajgrowicz and Scaillet (2012) who examine the success of technical trading rules, Fishe and Smith (2012) who identified the number of informed traders in several futures contracts, and Harvey, Liu, and Zhu (2014) who examine threshold critical values necessary to claim a new risk factor after hundreds of asset pricing tests by previous researchers.

price change. For a given value of d, we compute the sample frequency of successes for each participant:

$$F_i^{Type\ E} = \frac{\sum_{j=1}^{J}\sum_{t=1}^{T_j}\mathbf{1}\left(x_{i,t}^{j}>0,\ \ \Delta P_j>0 \mid s_{i,t}^{j}=1\right)+\mathbf{1}\left(x_{i,t}^{j}<0,\ \ \Delta P_j<0 \mid s_{i,t}^{j}=1\right)}{\sum_{j=1}^{J}\sum_{t}^{T_j}\mathbf{1}\left(x_{i,t}^{j}\neq 0\right)}, \qquad (1)$$

where **1**( ) is the binary indicator function based on the given expression, T_j is the number of trades on path j, and J is the number of price paths in the sample.

To determine the null hypothesis, consider what may arise for traders who are not attempting to compute turning points for intraday prices. If a trader is randomly placing both buys and sells during the day in small sizes, then across all paths we might expect to find about 10% of these trades in the first 10% of path volume with $d = 10$. But how many of these are expected to be successful, meaning that they are aligned with the price path direction? The answer depends on how volume is distributed across up and down paths as well as how a trader mixes order size and side (e.g., buy or sell sides). If volume is approximately equally distributed between up and down paths, order sizes are small, and order sides are about equal in number, then a null of 5% may be appropriate for these tests. However, volume is on average higher in down paths, traders often vary order sizes, and many traders end up with an unequal number of buys and sells. Such differences will alter the relevant null hypothesis.

Rather than seek a general solution for such nuances, we back up a step and impose a more restrictive condition in our tests. The measure in equation (1) is a statistic indicating the proportion of participant *i's* trades that were executed in the first d^{th} percentile of volume *and* were in the correct price direction. This proportion is conditional on our perfect foresight calculation of local price trends. If $d = 10$, then it is clear from how the price paths are created that a trader has a 10% chance of executing (a buy or sell) within the first 10% of path volume assuming trades are randomly placed during the day. Appropriate adjustments for order size or order side will lower this fraction. Thus, *to make it more difficult* to find successful anticipatory traders we use 10% as the null hypothesis. For each trader we test the null hypothesis, $H_0\colon F_i^{type\ E} = \frac{d}{100}$. This is a binomial test and will have statistical power if a participant trades a sufficient number of times.

For our empirical work, we set *d* = 10 to identify Type E traders. To identify Type R traders, we consider the *last* 10th percentile of trading volume to be indicative of whether a trader uses information or foresight to anticipate the coming reversal of the price path. To measure success for Type R traders, we compute the proportion analogous to equation (1) using *d* = 90 to define the heaviside function:

$$F_i^{type\ R} = \frac{\sum_{j=1}^{J} \sum_{t=1}^{T_j} \mathbf{1}\left(x_{i,t}^j > 0,\ \Delta P_j < 0 \mid s_{i,t}^j = 0\right) + \mathbf{1}\left(x_{i,t}^j < 0,\ \Delta P_j > 0 \mid s_{i,t}^j = 0\right)}{\sum_{j=1}^{J} \sum_{t}^{T_j} \mathbf{1}\left(x_{i,t}^j \neq 0\right)}. \qquad (2)$$

The null hypothesis that we test to identify Type R traders is $H_0\colon F_i^{type\ R} = \frac{100-d}{100}$. Note that to ensure statistical power, we confine our investigation to participants with more than 30 trades in our sample.

IV. DATA

The data are derived from audit trail files for the CME/Nymex WTI light sweet crude oil futures contract. The WTI contract is traded worldwide on the Globex electronic platform. For the WTI contract each one cent move in price represents a $10 change in contract value, which provides leveraged returns even for relatively small changes in price when weighed against the relatively low margin requirements.

Our initial sample covers the period from September 12, 2011 to contract expiration (48 days). This period is selected based on the trading and open interest activity in the December 2011 contract, which is the first or second most active month in the year. A follow-up sample was available from August 1, 2014 to September 19, 2014 (35 days) for the October 2014 expiration, which was the nearby contract for most of this period. These data are used to examine whether anticipatory strategies survive through time. Both samples contain all trades and orders posted, modified, and/or cancelled on the CME/Nymex exchange. We test for anticipatory trading in both samples, using participant accounts which have 30 or more trades. This cutoff is imposed to provide power to the FDR method.

In order to determine price paths using the SPRT described above, we remove non-price forming trades from the sample, which are mainly transfers and offsets. We filter out spread trades where both sides are holding the spread as these trades provide only relative price information. However, if the initial side of a spread trade is an outright, we keep that side's price if it is for the correct expiration.

Table 1 provides statistics on the trading volume, number of participants based on manual- and algorithmic entry, and order book data calculated across days in both samples.[16] The WTI contract is quite active in the two samples with an average of 178,447 (225,723) contracts traded each day in 2011 (2014). There is a daily average of 2,285 (4,173) accounts active in 2011 (2014). The majority of these accounts use manual entry methods to place orders. Algorithmic accounts increased from a daily average of 421 to 704 between samples. Participants act to modify on average 62-67% of new orders and eventually cancel an average

[16] A trader is manual or algorithmic based on a specific variable (Tag 1028) found in the exchange-created dataset. See the CME Globex reference guide for additional details on this tag and reporting requirements (http://www.cmegroup.com/globex/files/GlobexRefGd.pdf).

between 82-86% of those orders. Both samples show that the WTI crude oil contract is traded in a quote-driven market, with market orders on average less than 2.5% of daily orders. In this analysis, we do not examine stop orders, offsets, transfer messages, or special order types, such as TAS (Trade at settlement) trades.

V. ANALYSIS

The first task is to estimate local price paths in the 2011 data. Then we use the FDR method to assess whether any participants systematically trade in the correct direction on a path. After identifying such traders, we examine whether anticipatory traders are rewarded by computing Sharpe ratios by accounts. We then examine their characteristics relative to other traders, specifically cancelation and execution speeds. Next, the question of whether such traders are informed is addressed as well as whether the volume of other traders is affected by anticipatory traders. Finally, we compare the 2011 and 2014 samples to investigate whether the Type E and Type R groups retain their skills three years later.

a. Local Price Paths

We apply the SPRT method to find local price paths for each day in the sample. Table 2 reports summary statistics derived from all price paths as well as paths that contain anticipatory traders (see below). Path information is summarized by price direction. The data show the average and median path returns in percent, average path duration in seconds, average path volume, average number of trades, and average number of participants in a price path. Average and median returns are nearly equal between up and down paths, with up paths about 12.5% longer in duration. Up paths also average greater volume and trades, so the near equal returns imply that prices trend up slower than they trend down. There are somewhat more than 80 participants on average on these paths, suggesting for a competitive environment for price discovery.[17]

b. Identifying Anticipatory Participants

The FDR method uses the binomial statistics in equations (1) and (2) to identify Type E and Type R participants. This method produces a two-tailed test in which our focus is on the upper tail results. We examine results for 2.5% and 5% FDR control rates. Note that the 5% control rate includes all of the 2.5% control rate accounts as it is less restrictive. The 2.5% (5%) tests found 112 (301) Type E and 196 (542) Type R participant accounts. We also identified 4 (25) overlaps between Type E and Type R groups for the 2.5% (5%) control rate. These accounts appear to have exceptional timing skills. Within these two groups, we find a total of 150 are algorithmic traders; 52 in the Type E group and 98 in the Type R group in the 5% control rate tests. The remaining traders use manual order entry methods.

Table 2 also provides path characteristics when Type E and Type R accounts are active anywhere on a price path. For these entries, the average number of unique participants refers to anticipatory traders, not to all traders. Thus, there are on average one to two Type E and seven Type R traders active on these paths. Notably, when Type E accounts are active, average and median path returns are greater in absolute value, volume and trades increase, and path duration is greater. When Type R accounts are active, average and median path returns are about same as the all path statistics. Thus, Type E accounts may be somewhat more successful than Type R accounts in identifying paths with larger price changes. We explore whether this suggests informed trading by either anticipatory type below.

[17] Additional summary data on the sample and price paths are available from the internet Appendix for this paper. See https://sites.google.com/view/anticipatorytrading/.

c. Aggregate Sharpe Ratios

Sharpe ratios examine if the traders identified as anticipatory use a strategy that offers benefits relative to the risk. Otherwise, such strategies will become ephemeral as other, more dominant strategies are recognized, or such traders lose their skills. Both Menkveld (2013) and Conrad and Wahal (2016) compute Sharpe ratios using high frequency trading data. Our approach closely follows Menkveld as his method incorporates trading fees and margins. The primary difference here is that we do not know a participant's inventory at the start of the sample, because our sample begins months after trading starts in the December 2011 expiration. Thus, we focus on the gross cash flows from trades to compute Sharpe ratios.

Following Menkveld (2013), a participant's average gross cash flow from trading on a given day is given by:

$$\bar{\pi}_i = \frac{1}{T}\sum_{t=1}^{T} -\Delta\left(n_t^i P_t\right) - \left|\Delta n_t^i\right| \tau \qquad (3)$$

where T is the total number of trades for participant i during the day, n_t^i measures the cumulative net position after the t^{th} trade, P_t is the price of the futures contract, and τ captures the exchange and clearing fees paid by the participant.[18] The capital employed (m_i) is estimated from the Nymex daily margin requirements for the highest absolute position held during the day.[19] Daily returns are estimated by: $r_i = \bar{\pi}_i - r_f m_i$, where the risk-free rate (r_f) is proxied using daily one-year constant maturity treasury bill rates. These returns are averaged across trading days to compute the mean return (μ_i) and standard deviation (σ_i) for

[18] The cumulative net position is set to zero at the start of the sample. As the position accumulates, the first trade on a new day is netted against the last cumulative position of that participant, generally the previous day's last net position. The end-of-day mark-to-market approach is not appropriate here because the initial inventory position of each participant is unknown.

[19] Exchange and clearing fees may vary across participants because of exchange incentive programs. We could classify many participants into specific programs, but not all. Thus, we applied the worst-case fees (and margins) to all participants, thereby reducing the estimated Sharpe ratios.

the Sharpe ratio, which is given by, $S_i = \frac{a(r_i)\mu_i}{\sigma_i}$, where $a(r_i)$ is an annualization factor that may be used to adjust for autocorrelation in returns (Lo 2002; Table 2).

Table 3 shows the estimated Sharpe ratios for Type E and Type R anticipatory traders identified using the 2.5% and 5% FDR control rates. Sharpe ratios for the "All Other" group and the sub-group of participants who are both Type_E and Type R are also included. Sharpe ratio results for an unadjusted annualization factor ($\sqrt{254}$) and one adjusted for first-order autocorrelation—coefficient is 'rho'—are shown in the table.

Sharpe ratios reveal that the Type_E group performs better than Type_R group with both groups exceeding the average performance of the All Other group. Notably, the overlapping participants within the Type_E and Type_R groups show exceptional performance. This latter group is both trading early and late on a price path, which would be an optimal reversal strategy. For comparison, Nagel (2012) finds annualized Sharpe ratios between 4.91 and 9.58 using a daily reversal strategy on individual equities between 1998 and 2010. This range is similar to the 4.78 to 5.48 range reported for the overlapping Type_E and Type_R participants. The daily return ratios reported by Menkveld (2013, Table 3) for a single HFT are also close to these values; as are the very short horizon annualized Sharpe ratios found by Conrad and Wahal (2016) using realized spreads.

Conrad and Wahal (2016) find that as the calculation horizon for spreads increases, the Sharpe ratio decreases to values similar to those for the All Other participants group. While some in the All Other group trade frequently, the majority do not which makes them more comparable to a longer horizon result. Nagel also reports a realized Sharpe ratio of 0.26 for the CRSP value-weighted index, also similar to that found for the All Other group. As these participants are close to representative of the overall futures market, they may perform similar to an overall market index. In addition, because the contract here is a derivative, there is a zero-sum effect that suggests the average gross cash flows aggregated over all trades during the life of a contract approach zero (without fees). Although the sample is only over the ending months of the contract, this effect may also help explain the relatively low Sharpe ratios found for the All Other group.

d. Speed Characteristics

A central question is whether anticipatory traders are high frequency traders in the usual sense of the term. The Securities and Exchange Commission (2014) offers five criteria to identify high frequency traders: (1) high speed in routing and executing orders, (2) use of co-location services, (3) short time between establishing and liquidating positions, (4) using a submit and cancel approach to orders, and (5) ending trading sessions with near zero inventories. We have information on items (1), (3), and (4) from the order book data, which is the source for participant speeds.

A participant's speed is found by comparing the initial order submission time to the exit time of each order.[20] Specifically, we calculate the time between order entry and either cancellation or execution.[21] For cancels, order duration is the difference between the time the CME/Nymex received the cancel message and the initial order confirmation time. If an order executes, duration is the difference between the CME/Nymex confirmation time and the initial order confirm time. This execution duration depends on a host of factors that affect the order book, such as liquidity flows and new information about price, as well as the initial and

[20] We do not use modification messages to measure speed because they do not remove an order from the book, so they are not part of the exit accounting.
[21] Orders may also exit by administrative action, but we exclude these from the sample.

subsequent decisions of the participant placing the order. A comparison of these speeds across all orders for Type E and Type R participants is shown in Table 4.

In Table 4, Panels A and B report average (minutes) and median (seconds) speeds, respectively, and Panel C reports the distribution of messages by Type E, Type R, and all other participants. There are clear differences between average and median speeds across participant types. Average speeds are slow, measured in minutes suggesting that account level behavior is very different than market level speeds.[22] These median and average speed differences show that skewness (and possibly outliers) affects the statistics for all groups including the all other category. Thus, for inferences we focus on the median data.

Considering the SEC criteria, we see that Type E and Type R accounts are slower to cancel than the median cancel speed of all other participants, with or without modification messages. Type R algorithmic accounts are more than ten times slower than the All Other algorithmic accounts. All groups use cancellations, but Type E—particularly algorithmic entry—is below the frequencies shown in Panel C for All Other accounts, while Type R is above for manual and below for algorithmic entry. For algorithmic comparisons, both Type E and Type R fall short of using a "submit and cancel" approach compared to other participants.

Execution speeds for Type R accounts are also slower than the All Other group. However, execution speeds for Type E accounts are faster, which may be due to the greater use of market orders and marketable limit orders by Type E participants. This is consistent with the high execution percentage reported in Panel C, suggesting that Type E accounts place orders with the intention of execution, with few cancellations. In contrast, Type R participants have

[22] Market level speed computes the difference between two successive cancelations or executions without regard to who is the participant. For example, Hasbrouck and Saar (2013) find 2-3 millisecond peaks in hazard rates that measure market responses after a quote improvement, although there are long tails in these rates.

much higher modification rates compared to All Others and lower execution rates. This suggests that they modify their orders often and relatively few of those orders are executed. It appears that Type R accounts may be modifying to search for the end of a price path. In general, these statistics do not suggest that HFT-like speeds are necessary to implement an anticipatory strategy.

To validate our interpretation of the summary statistics in Table 4, we specify a regression model with characteristics partitioned by a set of dummy variables, some of which identify these anticipatory groups. In the regression model, the effects of the anticipatory participants are measured relative to other omitted groups. Table 5 shows regression results using order cancellation speed as the dependent variable. The transformation, natural logarithm of one plus the cancellation speed (in seconds with fractional milliseconds), is used in these regressions.[23] The variables, "First 10% of Path Volume", "Last 10% of Path Volume", and "Between 10% to 50% of Path Volume", indicate whether the cancellation message occurs during the first 10% of path volume, last 10%, or during the first half of volume that excludes the first 10%, respectively. The "Type E Trader" and "Type R Trader" variables indicate whether the message is by a Type E or Type R participant, respectively. Type E and Type R participants are those identified using the 5% control rate for the FDR. Interaction terms are included in selected models: (1) Type E trader in the first 10% volume bin; (2) Type R trader in the last 10% volume bin; (3) Type E trader that is also algorithmic (ATS); and (4) Type R trader that is also algorithmic. Additional binary variables are "Modified Order" if there are any modification messages to the original order, "Proprietary trader" if the trade is made from a proprietary account, "Buy-Sell Indicator" which is one if this is a buy order, and the

[23] The dependent variables in Tables 5 and 6 are log(1+duration) because the order confirmation time of a market order equals its execution time, so duration will be zero for these orders.

"Algorithmic Trader" variable which is one if this side of the trade was submitted by a computer algorithm. As all variables are binary, the intercept captures the omitted categories.

The parentheses below each coefficient in Table 5 shows p-values, computed using heteroscedasticity-consistent standard errors. The adjusted R-squared for each model is shown at the bottom of the table. The sample size is 30,870,518 observations.

The intercept term captures the average decision speed of the omitted group, which in the most general case (Model VI) is a non-anticipatory, non-proprietary, manual participant, canceling during the 50-90% of path volume with no order modifications. The average cancellation speed of the omitted group is 27.361 seconds, which decreases to an average of 3.094 seconds if these are algorithmic participants. The estimates in Models II-IV show that Type E and Type R participants are slower than the omitted group until we control for other order characteristics. Specifically, Model VI shows that the average cancellation speed of manual Type E (Type R) traders is 38.375 (68.622) seconds. Type E (Type R) traders who are algorithmic are slower that the omitted algorithmic group with an average cancellation speed of 9.169 (10.252) seconds. From these estimates, the algorithmic and modified order coefficients have the largest impact on average cancellation speeds.

Table 5 also shows that cancels during the first and last 10% of path volume are marginally faster for all traders. However, the interaction terms for Type E and Type R participants show no significant effect for Type E participants and a slowdown in speed for Type R participants during the last 10% of path volume. Combined with the results above, these findings suggest that fast cancellation speeds are not a significant characteristic of anticipatory trading.

Table 5 includes regression estimates under the "Bootstrap" column heading. These estimates are averages of coefficient results from 1,500 random samples (with replacement) in which each trader account is chosen *once* per sample. The purpose is to equal weight each account in the regression so that the numerous orders from HFT participants do not skew the resulting coefficients (Fishe and Smith 2017). The 95% confidence intervals (“C.I.”) from these simulations are shown below the average coefficient value.

The confidence interval results show that there are fewer significant variables. Of those that are significant, the Type E and Type R dummies continue to indicate slower cancel speeds relative to the omitted group. The effects of HFT trading volumes are clear in the new algorithmic trader coefficient, which decreases by 71% in absolute value from Model VI. Interestingly, the proprietary trader coefficient nearly quadruples, suggesting that those participants are much faster than the omitted group. While inferences about the duration of orders ending in a cancel message are correctly derived from Models I-VI, inferences about participants from such message durations are better reflected in the bootstrap results. These results continue to show that being fast as measured by cancellation speeds is not a meaningful determinant of who is an anticipatory trader.

Table 6 presents speed results using the data on trade executions. In addition to the binary variables in Table 5, we include a dummy variable for whether a participant was on the aggressive side of the trade. Model VI coefficient estimates evaluated at the mean show a sample execution speed of 0.818 seconds. This is somewhat faster than equity execution speeds for Nasdaq- and NYSE-listed securities in 2011 and 2012 (Angel, Harris, and Spratt 2015). Part of the reason for this low average is the effect of aggressive orders, which lower the base speed of the omitted group from 6.034 seconds to 2.233 seconds. In isolation, a manual Type E (Type R) participant is 0.655 (2.337) seconds slower with executions than the base speed of the omitted group. However, being an algorithmic trader increases these speeds with the base group executing in an average of 3.38 seconds and the Type E (Type R) group slower with an average speed of 5.832 (6.878) seconds. Even so, these anticipatory traders are not faster than non-anticipatory traders as measured by execution speeds.

In addition, some of these observations no longer hold in the bootstrap results for the execution sample. These coefficients were created in the same manner as described for the cancelation sample. The interaction between Type E and Type R groups with the first and last 10% of volume is not significant, so there is no acceleration of speed in those periods based on participant inferences. Also, the interaction terms between Type E or Type R groups and the algorithmic variable are not significant. Thus, in an equal-weighted sample, Type E and Type R participants are no faster than other algorithmic participants.

e. Measuring Information and Volume Effects

Two important issues in this analysis are whether anticipatory traders have an information advantage and/or a skill at short-term price prediction, and whether the volume of other traders is affected by these participants. We first examine whether new information is provided by anticipatory traders. Because anticipatory traders are selected using a volume decile rule, investigating price changes using volume deciles presents an endogeneity issue. To avoid that problem, we divide each price path into time deciles. We examine the first and second time decile bins for Type E traders and the last bin in the previous path as well as the first bin in the current path for Type R traders. We compute the price change in each bin *relative* to the absolute price change in the path. Table 7 reports these average relative price changes for bins with and without anticipatory traders and for “up” and “down” price paths separately. These results are reported for groups selected using both the 2.5% and 5% FDR control rates. The averages using all bins are also shown for comparison.

For Type E comparisons, we examine the bin averages conditional on whether Type E traders are transacting in Bin#1. Similarly, for Type R comparisons, we condition on whether Type R traders are transacting in Bin#10 on the previous path. If these traders bring new information to the market, then in the current or next bin we expect a difference in relative prices when they are in the current (Type E) or previous (Type R) path. We find no significant differences in relative price changes for bins with and without Type E traders using 2.5% or 5% control rates. When the average is across all bins, the up paths show a difference when the highly skilled Type E group (2.5% control rate) is in time bin#1 of a path, consistent with our findings in Table 2. However, this result is not due to a nearby bin so it is not closely connected to the early presence of a Type E trader.

In contrast, the Type R results suggest an information effect if a Type R participant trades in the last time bin on the previous path. The effect is not in the last bin, but appears in Bin#1 on the next path where relative prices change by 3.1% to 3.7% in absolute value. This result holds for both the 2.5% and 5% control rate results for the Type R group. It is also focused on the nearby bin as the "all bins" results show no significant relative price change. These results suggest that Type R participants appear to have valuable short-term price information while the Type E participants appear to have superior forecasting skills.

Our second set of results address whether anticipatory traders affect the volume of trading by other market participants. If such traders increase volume by other participants, then price moves may be "caused" by their anticipatory trading, a "momentum-ignition" effect. In this event, they are not "anticipatory" because, instead of indirectly anticipating other's actions, they directly caused them. We use a VAR model of price and volume to examine this question. This model is estimated using bin data across the 15,765 price paths. Table 8 shows reduced form results for the VAR model.

In Table 8, first differences of price and volume are used to improve series stationarity.[24] Results are shown in Panel A for the anticipatory participants identified using the 2.5% FDR control rate. Panel B shows estimates for the 5% FDR control rate. As the data are bin specific, the differences for price and volume are relative to the previous bin.[25] End-of-bin prices are used to calculate price deltas. Both price and the volume of all other participants (i.e., not Type E or Type R) are endogenous, while the trading volume of Type E or Type R participants is exogenous, which implies that these variables enter these models contemporaneously. We also include a dummy exogenous variable for whether Type E (Type R) participants trade in Bin#1 (Bin#10 of the last path). This variable is the focus here because we want to know whether the volume of trading by other participants is affected by anticipatory traders, especially in those bins where they are likely implementing their anticipatory strategy. We consider effects for participants in the full sample and for the Type E group in Bin#2, and for the Type R group in Bin#1.[26]

The results in Table 8 suggest that contemporaneous, same bin trading by Type E participants is associated with reduced volume deltas by other traders, but the reverse holds for Type R participants (Model 1). Important for momentum claims, we observe that trading by Type E participants in Bin#1 is correlated with higher volume deltas for all other

[24] Adjusted Dickey-Fuller tests indicate that bin prices are stationary in first differences. Volume by trader type is generally stationary in levels and always stationary in first differences.
[25] These price changes differ from those in Table 7, which are relative to the absolute value of the path's price change. Thus, the dependent variable ΔP_t is the price change observed for a specific bin.
[26] We also estimated the VAR model without overlaps between Type E and Type R traders on a given path. This filter did not change our conclusions.

participants (Model 2). This effect appears to be driven by actions later in the price path because the Bin#2 results show no significant effects when Type E participants are in Bin#1. In contrast, Type R participants in Bin#10 on the previous path have a significant negative effect on volume deltas in the next path, both on average across bins and in Bin#1 on the next path. In short, Type R participants are not associated with a "momentum ignition" effect, but Type E participants may incite some volume effect, but this effect is not contiguous to activity in Bin#1.[27]

f. Skill Retention

Lastly, we examine whether these traders retain their skills in a subsequent sample. Unfortunately, the WTI crude oil futures data from 2014 shows substantial attrition among the 2011 accounts with only 35% of the 2011 accounts included. This attrition is similar to that found by Boyd and Kurov (2012) in energy futures after side-by-side electronic trading began on the Globex platform in 2006. Several factors contribute to this result, including oil price volatility, rule changes under Dodd-Frank raising capital requirements, and flows into and out of energy markets after the 2008-09 financial crises.[28] Notably, the bankruptcy of MF Global on October 31, 2011 forced thousands of customers to find alternative clearing arrangements, which generally led to new account designations.[29] Thus, a caveat to the out-of-sample results

[27] The specific bin results on Type E participants were also estimated for Bin#3. There is a significant negative effect from contemporaneous volume and an insignificant effect for the Bin#1 dummy variable.
[28] These factors also contributed to a decline in Futures Commission Merchants (FCM) and rotation of customers to new executing brokers. See http://www.thetradenews.com/Asset-Classes/Derivatives/FCM-client-clearing-numbers-in-steep-decline/.
[29] At the time, MF Global was the eighth largest bankruptcy in U.S. history. It managed over 36,000 customer accounts, many of which were involved with futures and options trading (Gibbons 2012). Approximately 800 of our sample participants used MF Global as the executing broker, and we expect that many of these may still be trading but active with another commodities broker.

is that they may under-state the success of our two groups as some participants may appear successful under a new executing broker.

Table 9 summarizes our findings for the 2014 sample. Panel A shows the size of the Type E and Type R groups in both 2011 and 2014, Panel B shows the counts for those who are found in both samples, and Panel C identifies the number of overlaps who retain the anticipatory strategy. The percent of sample figures in Panel A indicate that the anticipatory strategy was relatively more difficult to execute in 2014: There are 24% (11%) fewer anticipatory participants at the 2.5% (5%) FDR control rate. These decreases are not as large for the 2011 participants that overlap the 2014 data as shown in Panel B. Those successful at the 2.5% control rate show a decrease of 12%, but there is an increase of 3% for the 5% control rate results. In effect those who do continue to trade three years later are more experienced and perhaps better able to maintain a strategy compared to newer participants.

Only a small number of the Type E overlaps—7 participants or 9%—continue to implement that strategy in 2014. Skill retention for Type R participants is higher—27 participants or 20%—indicating that this group may have adopted a more durable strategy. These counts are likely lower bounds because of the need for many participants to find new executing brokers during the gap. Thus, some continuing but unidentified accounts may be among those identified as successful in the 2014 sample. Even so, the results indicate that anticipatory trading became more difficult between 2011 and 2014 and that the Type E or early trading strategy was the relatively more difficult strategy to maintain.

Finally, we examined the speed of the 2,669 participants who overlapped between the 2011 and 2014 samples using data for both samples. Table 10 reports these results following the regression methods in Tables 5 and 6, and modeling both cancellation and execution speeds. The Type E and Type R participants are those who were significant at the 5% control rate in the 2011 sample. We include binary variables for algorithmic traders, a dummy for the 2014 observations, and control variables for participants who are Type E or Type R in both samples. The latter variables show incremental effects for these participants compared to those same types in 2011 who did not maintain these strategies. We want to determine whether those who successfully continued as anticipatory traders in 2014 were aided by operating at faster speeds, thereby making speed important to strategy survival.

The base models for cancel and execution speeds in Table 10 show that manual entry cancel and execution speeds decreased between samples, indirectly supporting Hoffmann's (2014) theory that slower traders will place orders with lower execution probabilities when competing with faster traders. Algorithmic entry speeds increased for executions in 2014, but cancel speeds decreased, suggesting that electronic traders adjusted the role of cancelations in their strategies, possibly affected by new anti-spoofing laws.[30] Cancel speeds for Type E participants did not change, but execution speeds increased. For Type R, execution speeds decreased, while cancel speeds increased. These are mixed findings on the role of speed between the 2011 and 2014 samples.

Importantly, these results are for anticipatory traders identified in 2011, who also are identified as trading in 2014. As Table 9 shows, only a small number of these participants continued to successfully implement the anticipatory strategy. Table 10 identifies these special participants as "Participant 'X' in both samples." We want to determine if speed increased or decreased for these continuing participants.

[30] Section 747 of the Dodd-Frank legislation of 2010 specifically prohibited any trading, practice, or conduct that "…is commonly known to the trade as, 'spoofing' (bidding or offering with the intent to cancel the bid or offer before execution)."

Table 10 shows that the continuing Type E participants are no faster at cancelations or executions than non-continuing Type E participants. If they are algorithmic, however, they are faster with both actions. The 2014 dummy is not significant alone for either cancelations or executions, but combined with the algorithmic indicator it shows a significant *positive* effect on execution speeds. Thus, the only clear effect for continuing Type E participants is that they are *slower* to execute in 2014 if they are algorithmic.

Estimates for the continuing Type R participants show that they are faster (slower) at cancellations (executions) than non-continuing Type R, while they are slower for both actions if they are algorithmic. Curiously, they are slower (faster) with cancelations (executions) in 2014, but if they are algorithmic these findings reverse themselves. In 2014, manual entry, continuing Type R participants appear to be enabled by faster (slower) execution (cancelation) speeds, but algorithmic entry participants operate with slower (faster) execution (cancelation) speeds. It appears that continuing the Type R strategy required adjusting the use of cancel messages as manual-entry participants slowed and algorithmic entry increased cancel speeds, making the importance of speed ambiguous to continuing the anticipatory strategy.

VI. CONCLUSION

We identify and examine a select group of participants who can anticipate short term, intraday price movements. The purpose is to understand whether such strategies require high-speed actions or rather, are populated with HFTs. We identify two groups of anticipatory traders who are prescient early in a price path (Type E) or who trade immediately before a reversal in the price path (Type R). Sharpe ratios show that their risk-adjusted performance exceeds that of other participants. Importantly, there is a mixture of both algorithmic- and manual-entry traders within these groups, so that speed per sé is not necessary or sufficient to conduct an anticipatory strategy.

Regression results show that a number of factors affect message speed. Algorithmic and proprietary traders are faster than manual-entry, customer-directed participants. Those who use modifications are much slower than other participants are, and aggressive traders have demonstratively faster execution speeds, likely because they are entering market orders. Type E and Type R groups are found to be slower than other traders, confirming the result that speed is not an essential characteristic of anticipatory trading.

We also investigated whether anticipatory traders bought new information to the market and whether they caused momentum trading by others. There is some evidence that Type R traders are informed in nearby bins, but no evidence of information in Type E trades. Volume effects are present, but weak for Type E traders and are of the wrong sign for Type R traders.

Lastly, we examined whether anticipatory traders retained their skills three years later in a similar sample. Attrition from the original sample qualifies these claims. Even so, the evidence suggests that the skills held by Type E participants are relatively ephemeral, but that Type R participants show more durability with their strategies, with the role of speed in strategy survival being ambiguous between manual- and algorithmic-entry participants.

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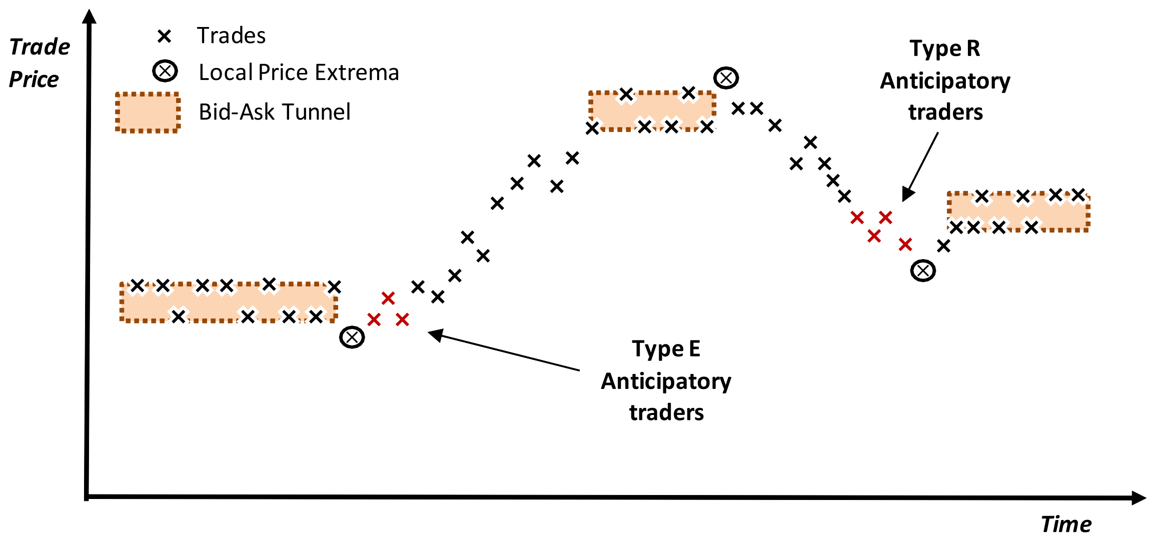

Figure 1. Price paths and anticipatory traders

This figure illustrates a sequence of trades (the "*x's*") from participant order flow. When new information about the value of the asset arrives or liquidity demand changes, the market price reacts until the information is impounded in the price structure or new liquidity arrives to resolve the imbalance. Non-price moving liquidity based trading is shown as trades along a bid-ask bounce sequence (shaded areas). Price reversals occur at the specified local price extrema (the circled trades). A participant that processes the skills to process order flow and trade information to systematically forecast the short-term direction of trade prices is known as a Type E anticipatory traders. A participant who processes new information or market flow signals to systematic forecast the subsequent reversal in local trade price trend is known as a Type R anticipatory trader.

Table 1
Daily Characteristics of Sample Data

Summary statistics are shown for messages and orders in the WTI crude oil contract expiring in December 2011 in Panel A and expiring on October 2014 in Panel B. These data are for outright or outright-to-spread orders as these orders are price informing for each expiration. The 2011 sample covers all trading days from September 12 to November 18, 2011 and the 2014 sample covers August 1 to September 19, 2014. The table provides average, median, standard deviation, minimum and maximum statistics across sample days for volume, number of unique traders (algorithmic or manual order entry methods), message types (entry, modification, or cancellation), and order types (market or limit). Note that message and order counts may not add up exactly as some order types arise from different message origins, such as a market order being generated from a modified message that was originally a limit order.

Characteristics	Average	Median	Standard Deviation	Minimum	Maximum
Panel A: 2011 Sample - December 2011 Expiration					
Trading Volume	178,447	53,456	181,564	8,243	565,140
Count of:					
- Algorithmic Traders	421	280	318	47	890
- Manual Traders	1,864	1,088	1,474	242	4,388
- Order Entry Messages	819,799	506,624	562,948	7,649	2,095,500
- Modification Messages	552,411	390,795	400,678	5,475	1,579,307
- Cancellation Messages	705,919	480,767	451,195	3,837	1,764,984
- Market Orders	11,075	3,711	11,429	431	34,926
- Limit Orders	816,439	505,980	559,644	7,408	2,087,561
Panel B: 2014 Sample - October 2014 Expiration					
Trading Volume	225,723	270,396	156,284	8,401	486,328
Count of:					
- Algorithmic Traders	704	934	397	29	1,262
- Manual Traders	3,469	4,692	2,287	243	6,533
- Order Entry Messages	781,966	762,280	301,255	216,777	1,415,200
- Modification Messages	484,818	500,726	137,082	220,791	829,322
- Cancellation Messages	640,131	663,227	226,690	192,038	1,134,177
- Market Orders	17,673	20,012	12,099	1,068	41,268
- Limit Orders	776,262	760,971	297,646	215,233	1,402,853

Table 2
Local Price Path Characteristics

Summary statistics are shown for all local price paths in the December 2011 WTI crude oil contract. The paths are computed from intraday prices on outright trades or spread trades with one side being outright. The sample covers all trading days from September 12 to November 18, 2011. The table summarizes information by month and path direction for all price paths, price paths with Type E participants, and price paths with Type R participants. The table shows average and median path returns, average path duration in seconds, average path volume in contracts, and the average number of trades. The average number of unique participants is shown for all paths. Type E and Type R participants are selected using the 5% FDR control rate.

					Average			
Description	Path Direction	Path Count	Average Path Ret. (%)	Median Path Ret. (%)	Path Duration (sec)	Path Volume	Number of Trades	Number of Unique Participants
All Price Paths	down	7,903	-0.148	-0.119	115.6	569.5	447.6	88.8
	up	7,916	0.149	0.118	102.8	513.7	402.3	82.0
Price Paths with Type E Participants	down	2,455	-0.193	-0.156	190.7	892.8	692.8	121.6
	up	2,290	0.204	0.166	175.6	876.2	678.1	120.5
Price Paths with Type R Participants	down	7,140	-0.148	-0.120	114.4	612.8	482.3	95.2
	up	6,996	0.152	0.122	102.5	562.5	441.1	89.1

Table 3

Sharpe Ratios for Anticipatory Traders

The table shows annualized Sharpe ratios for selected groups of participants. The Sharpe ratios are estimated for each participant using the method described by Menkveld (2013). Trade-to-trade cash flows are averaged daily to compute mean returns, which net out capital employed based on daily margin requirements and an estimate of the risk-free rate obtained from daily one-year Treasury bill yields. Daily returns are averaged across trading days to compute the mean and standard deviation of daily returns used in the Sharpe ratio. Both annualized and adjusted ratios are computed. The adjusted ratios follow the methods in Lo (2002) for a first-order autocorrelation model of returns. The reported ratios are averaged over each participant within a group. Groups are those participants identified as Type_E or Type_R using 2.5% and 5% control rates (C.R.) for the FDR tests, and the collection of "All Other" participants who are those found not significant in these FDR tests. The overlap group includes participants who are in both Type_E and Type_R groups. Heteroscedastic-consistent p-values are shown for the estimated first-order autocorrelation coefficient ('rho'). The "na" indicates that the number of observations is too small for meaningful inferences.

	Type E Participants		Type R Participants		Overlaps for Type_E and Type_R		All Other Participants	
Variable	2.5% C.R.	5% C.R.	2.5% C.R.	5% C.R.	2.5% C.R.	5% C.R.	2.5% C.R.	5% C.R.
Sharpe Ratio	1.046	0.830	0.523	0.531	na	4.784	0.371	0.376
Adj. Sharpe Ratio	1.126	1.046	0.531	0.535	na	5.858	0.353	0.362
rho	-0.082	-0.139	-0.023	-0.015	na	-0.109	0.043	0.034
p-value(rho)	0.304	0.179	0.569	0.651	na	0.434	0.151	0.292
Count of Participants	112	301	196	542	na	25	7,250	6,736

Table 4
Speed Characteristics from Order Book Messages

The table shows the average (minutes) and median (seconds) durations between four message types: order entry to either order cancellation or execution, and order entry to cancellation or execution with no intermediate modification messages (No Mods). These calculations are grouped by Type_E, Type_R, and "All Other" participants, and partitioned into manual-entry and algorithmic-entry methods. The Type_E and Type_R participants are those found using the 5% control rate in FDR tests. Averages and medians shown are across messages for each group and entry type. Panel A shows summary statistics for averages across messages, Panel B shows median statistics, and Panel C shows the distribution and total number of messages by message type. A "**" ("*") indicates that tests of whether Type E or Type R are different from the corresponding average for All Other participants are significant at the 1% (5%) level of significance. Wilcoxon and Median tests are used to test whether the medians are also different between Type E or Type R and the All Other group durations. The least significant result is reported for the latter tests.

	Type E Participants		Type R Participants		All Other Participants	
Ending Message	Man-Entry	Algo-Entry	Man-Entry	Algo-Entry	Man-Entry	Algo-Entry
Panel A: Average Duration between Messages (minutes)						
Cancellation	25.04**	7.59**	5.82**	0.68**	9.44	1.29
Cancellation (No Mods)	24.76**	3.98**	5.11**	0.51**	8.67	1.11
Execution	16.19**	7.03	8.07**	2.76	11.55	3.03
Execution (No Mods)	4.73**	2.03*	3.33**	0.58	2.24	0.59
Panel B: Median Duration between Messages (seconds)						
Cancellation	54.56**	0.83*	60.07**	7.93**	23.18	0.73
Cancellation (No Mods)	35.49**	0.27	59.92**	7.42**	20.11	0.40
Execution	4.32**	0.01**	17.43**	1.83**	8.18	0.10
Execution (No Mods)	0.07**	0.00**	9.21**	0.18**	0.87	0.04
Panel C: Message Distribution						
Cancellation	8.5%	2.8%	32.7%	13.4%	15.8%	57.8%
Modification	4.3%	59.5%	22.7%	84.0%	12.8%	33.1%
Execution	87.3%	37.7%	44.6%	2.6%	71.4%	9.1%
Total Messages	68,128	51,454	294,194	5,409,423	3,995,440	54,335,721

Table 5

Participant Cancellation Speeds

This table shows regression results for the speed of cancellation controlling for characteristics of the participants, position within a price path, and other features of the trade. The speed of cancellations equals the difference between the time the Nymex receives a cancellation message and the confirmation time of the original order (in seconds with fractional milliseconds). The dependent variable is the natural logarithm of one plus the cancellation speed. The variables, "First 10% of Path Volume", "Last 10% of Path Volume", and "Between 10% to 50% of Path Volume", are binary variables indicating whether the cancellation message occurs during the first 10% of path volume, last 10%, or during the first half of volume that excludes the first 10%, respectively. The "Type E Trader" and "Type R Trader" are binary variables indicating whether the cancel message is made by a Type E or Type R trader, respectively. There are interaction terms in selected models: (1) Type E trader in the first 10% volume bin, (2) Type R trader in the last 10% volume bin, (3) Type E trader that is also algorithmic, and (4) Type R trader that is also algorithmic. Additional variables are "Modified Order" if there are any modification messages to the original order, "Proprietary trader" if the order is made from a proprietary account, "Buy-Sell Indicator" which is one if this is a buyside order, and the "Algorithmic Trader" variable which is one if this cancel message was submitted by a computer algorithm. The intercept captures the omitted categories. The p-values are computed using heteroscedastic-consistent standard errors and are shown in parentheses below each coefficient. The "Bootstrap" column shows coefficient results from 1,500 random samples in which each account is chosen only once per sample. For these regressions, Type E and Type R traders are defined using the 5% FDR control rate. The 95% confidence intervals ("C.I.") are shown below the average coefficient value for these simulations. The full sample size is 30,870,518 observations.

	Dependent Variable: Ln(1+Cancellation Speed)						Bootstrap
Independent Variable	I	II	III	IV	V	VI	Average/95% C.I.
First 10% of Path Volume	-0.037 (<0.001)		-0.035 (<0.001)	-0.036 (<0.001)		-0.027 (<0.001)	0.038 (-0.09; 0.16)
Last 10% of Path Volume	-0.046 (<0.001)		-0.046 (<0.001)	-0.047 (<0.001)		-0.036 (<0.001)	-0.002 (-0.12; 0.11)
Between 10% to 50% of Path Volume	-0.015 (<0.001)		-0.014 (<0.001)	-0.014 (<0.001)		-0.013 (<0.001)	0.029 (-0.05; 0.11)
Type E Trader		1.929 (<0.001)	1.930 (<0.001)	1.933 (<0.001)		0.328 (<0.001)	0.455 (0.18; 0.74)
Type R Trader		1.430 (<0.001)	1.430 (<0.001)	1.422 (<0.001)		0.898 (<0.001)	0.423 (0.23; 0.60)
Interaction Term: Type E and First 10% of Path Volume				-0.271 (0.766)		-0.024 (0.772)	-0.176 (-1.03; 0.72)
Interaction Term: Type R and Last 10% of Path Volume				0.063 (<0.001)		0.074 (<0.001)	-0.285 (-0.81; 0.26)
Modified Order					1.091 (<0.001)	1.094 (<0.001)	1.080 (0.96; 1.19)
Proprietary Trader					-0.778 (<0.001)	-0.516 (<0.001)	-1.975 (-2.05; -1.91)
Buy-Sell Indicator					-0.001 (0.002)	-0.002 (<0.001)	0.097 (0.03; 0.17)
Algorithmic Trader					-1.834 (<0.001)	-1.935 (<0.001)	-0.553 (-0.63; -0.48)
Interaction Term: Type E and Algorithmic Trader						0.582 (0.029)	-0.098 (-0.72; 0.57)
Interaction Term: Type R and Algorithmic Trader						0.113 (<0.001)	-0.043 (-0.40; 0.30)
Intercept	1.111 (<0.001)	1.057 (<0.001)	1.072 (<0.001)	1.072 (<0.001)	3.505 (<0.001)	3.345 (<0.001)	4.301 (4.24; 4.36)
Adjusted R squared Regression (p-value)	0.0% (<0.001)	2.8% (<0.001)	2.8% (<0.001)	2.8% (<0.001)	13.3% (<0.001)	14.5% (<0.001)	12.1% (11.4% - 12.8%)

Table 6

Participant Execution Speeds

This table shows regression results for the speed of execution controlling for characteristics of the participants, position within a price path, and other features of the trade. The speed of an individual execution equals the difference between the time the Nymex confirms a trade execution and the time it receives the initial order from the participant (in seconds with fractional milliseconds). The dependent variable is the natural logarithm of one plus the execution speed. The variables, "First 10% of Path Volume", "Last 10% of Path Volume", and "Between 10% to 50% of Path Volume", are binary variables indicating whether the cancellation message occurs during the first 10% of path volume, last 10%, or during the first half of volume that excludes the first 10%, respectively. The "Type E Trader" and "Type R Trader" are binary variables indicating whether the trade is made a Type E or Type R trader, respectively. There are interaction terms in selected models: (1) Type E trader in the first 10% volume bin, (2) Type R trader in the last 10% volume bin, (3) Type E trader that is also algorithimic, and (4) Type R trader that is also algorithimic. Additional binary variables are "Modified Order" if there are any modification messages to the original order, "Proprietary trader" if the trade is made from a proprietary account, "Buy-Sell Indicator" which is one if this is the buyside of a trade, and the "Algorithmic Trader" variable which is one if this side of the trade was submitted by a computer. The intercept captures the omitted categories. The p-values are computed using heteroscedastic-consistent standard errors and are shown in parentheses below each coefficient. For these regressions, Type E and Type R traders are defined using the 5% FDR control rate. The "Bootstrap" column shows coefficient results from 1,500 random samples in which each trader account is chosen only once per sample. The 95% confidence interval ("C.I.") is shown below the average coefficient value for these simulations. The full sample size is 6,738,138 observations.

	Dependent Variable: Ln(1+Execution Speed)						Bootstrap
Independent Variable	I	II	III	IV	V	VI	Average/95% C.I.
First 10% of Path Volume	-0.024		-0.022	-0.018		-0.041	-0.092
	(<0.001)		(<0.001)	(<0.001)		(<0.001)	(-0.16; -0.03)
Last 10% of Path Volume	-0.038		-0.058	-0.066		-0.031	0.079
	(<0.001)		(<0.001)	(<0.001)		(<0.001)	(0.01; 0.15)
Between 10% to 50% of Path Volume	-0.060		-0.052	-0.052		-0.048	-0.110
	(<0.001)		(<0.001)	(<0.001)		(<0.001)	(-0.15; -0.07)
Type E Trader		0.571	0.570	0.630		0.504	0.126
		(<0.001)	(<0.001)	(<0.001)		(<0.001)	(-0.07; 0.32)
Type R Trader		1.388	1.388	1.363		1.205	0.409
		(<0.001)	(<0.001)	(<0.001)		(<0.001)	(0.25; 0.56)
Interaction Term: Type E and First 10% of Path Volume				-0.292		-0.171	-0.109
				(<0.001)		(<0.001)	(-0.46; 0.26)
Interaction Term: Type R and Last 10% of Path Volume				0.166		0.107	0.080
				(<0.001)		(0.004)	(-0.29; 0.46)
Aggressive Side of Trade					-1.596	-1.562	-2.696
					(<0.001)	(<0.001)	(-2.73; -2.66)
Modified Order					0.887	0.875	1.582
					(<0.001)	(<0.001)	(1.48; 1.67)
Proprietary Trader					-0.079	-0.049	-0.432
					(<0.001)	(<0.001)	(-0.50; -0.35)
Buy-Sell Indicator					0.003	0.004	-0.007
					(0.002)	(0.832)	(-0.04; 0.03)
Algorithmic Trader					-0.508	-0.474	-0.063
					(<0.001)	(<0.001)	(-0.10; -0.02)
Interaction Term: Type E and Algorithmic Trader						-0.060	-0.312
						(0.01)	(-0.65; 0.06)
Interaction Term: Type R and Algorithmic Trader						-0.618	0.269
						(<0.001)	(-0.07; 0.59)
Intercept	0.940	0.855	0.884	0.885	2.011	1.951	2.876
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(2.82; 2.93)
Adjusted R squared	0.1%	2.7%	2.7%	2.7%	28.6%	28.8%	39.7%
Regression (p-value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(38.9% -40.5%)

Table 7

Do Anticipatory Traders Bring New Information to the Market?

To test whether Type E or Type R anticipatory traders bring new price information to the market, the price change in each bin relative to the absolute price change in the path is computed for specific bins, and across all bins. For these calculations, price paths are divided by ten equal time periods across each path. Using time deciles avoids the endogeneity of volume deciles because volume is used in the selection process for Type E and Type R participants. Averages of these data are reported for different cases based on whether Type E or Type R participants are trading in a given time bin in a price path. Results for both the 2.5% and 5% FDR control rates are shown. The first two columns report averages across all bins separating the averages for relative price changes into "up" and "down" trending paths, respectively. The remaining columns also average the relative price changes by upward and downward paths, but only use specific time bins in the calculation. The figures shown in parentheses beneath these averages are p-values for the t-test of comparing two means (unequal variances).

	Means of Sample Data - Relative Price Changes by Bin							
	Up	Down	Up Price Paths			Down Price Paths		
	All Bins		Bin#10	Bin#1	Bin#2	Bin#10	Bin#1	Bin#2
Path Characteristics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Type E (2.5%) in Current Path Time Bin#1	0.088	-0.089		0.271	0.070		-0.267	-0.075
Type E (2.5%) in Current Path Time Bin#1	0.092	-0.077		0.264	0.094		-0.373	-0.046
p-value for t-Test of Diff.	(0.000)	(0.627)		(0.813)	(0.281)		(0.419)	(0.315)
No Type E (5%) in Current Path Time Bin#1	0.088	-0.088		0.273	0.070		-0.267	-0.075
Type E (5%) in Current Path Time Bin#1	0.089	-0.089		0.245	0.077		-0.299	-0.064
p-value for t-Test of Diff.	(0.755)	(0.921)		(0.055)	(0.526)		(0.448)	(0.436)
No Type R (2.5%) in Previous Path Time Bin#10	0.088	-0.088	0.202	0.256		-0.181	-0.256	
Type R (2.5%) in Previous Path Time Bin#10	0.089	-0.089	0.194	0.292		-0.171	-0.289	
p-value for t-Test of Diff.	(0.752)	(0.954)	(0.174)	(0.000)		(0.330)	(0.005)	
No Type R (5%) in Previous Path Time Bin#10	0.088	-0.088	0.202	0.252		-(0.182)	-(0.254)	
Type R (5%) in Previous Path Time Bin#10	0.089	-0.089	0.195	0.289		-(0.172)	-(0.285)	
p-value for t-Test of Diff.	(0.759)	(0.875)	(0.256)	(0.000)		(0.216)	(0.002)	

Table 8
Volume Effects of Anticipatory Traders

This table estimates VAR models of volume and price using bin data derived from sample price paths. Prices and volume are differenced for stationarity, although volume is generally stationary without differencing. Delta price uses end-of-bin trade prices and delta volume is the change in bin volume for all traders excluding Type E and Type R traders. These VAR models are estimated with one lag, but ten lags produced similar results. The exogenous variables are delta volume for either Type E or Type R traders and dummies variables for whether Type E participants traded in Bin#1 of the current path or Type R participants traded in Bin#10 of the previous path. Results are shown for the 2.5% FDR control rate in Panel A and for the 5% FDR control rate in Panel B. VAR estimates are calculated using all sample bins, and for Bin#2 only for Type E tests and Bin#1 only for Type R tests. Two models are estimated in each panel to show the effects with and without anticipatory trades in either Bin#1 (Type E) of the current path or Bin#10 (Type R) in the last path. The cumulative impulse responses are the coefficients on the associated variable in each model. The significance of these estimated coefficients is indicated by a sign for the 5% level and a double sign for the 1% level. An 'ns' indicates that the coefficient was not significant. The Akaike information criterion (AIC) is shown for model comparison.

	'X' = Type E Participant and 'Z' = #1				'X' = Type R Participant and 'Z' = #10 Last Path			
	All Bins		Bin#2 Only		All Bins		Bin#1 Only	
Exogenous Variables	ΔP_t	ΔV_t	ΔP_t	ΔV_t	ΔP_t	ΔV_t	ΔP_t	ΔV_t
Panel A: Type E and Type R Participants found using 2.5% FDR Control Rate								
<u>Model 1</u>								
Delta(Type 'X' Volume in Bin)	-	- -	- -	- -	ns	+ +	ns	+ +
- Cumulative Impulse Response	-0.00	-0.29	-0.00	-1.03	ns	0.33	ns	3.64
- Akaike Info. Criterion	265.357		-18.679		265.130		64.582	
<u>Model 2</u>								
Delta(Type 'X' Volume in Bin)	-	- -	- -	- -	ns	+ +	ns	+ +
- Cumulative Impulse Response	-0.00	-0.29	-0.00	-1.03	ns	0.30	ns	3.36
Dummy for Type 'X' in Bin 'Z'	ns	+ +	- -	ns	ns	- -	ns	- -
- Cumulative Impulse Response	ns	4.98	-0.01	ns	ns	-4.57	ns	-10.96
- Akaike Info. Criterion	265.208		-18.712		264.004		64.497	
Panel B: Type E and Type R Participants found using 5% FDR Control Rate								
<u>Model 1</u>								
Delta(Type 'X' Volume in Bin)	ns	- -	- -	- -	ns	+ +	ns	+ +
- Cumulative Impulse Response	ns	-0.29	-0.00	-0.96	ns	0.35	ns	3.70
- Akaike Info. Criterion	262.455		-17.453		262.192		63.574	
<u>Model 2</u>								
Delta(Type 'X' Volume in Bin)	ns	- -	- -	- -	ns	+ +	ns	+ +
- Cumulative Impulse Response	ns	-0.29	-0.00	-0.97	ns	0.32	ns	3.52
Dummy for Type 'X' in Bin 'Z'	ns	+ +	- -	ns	ns	- -	ns	- -
- Cumulative Impulse Response	ns	4.38	-0.00	ns	ns	-4.22	ns	-8.67
- Akaike Info. Criterion	262.078		-17.469		261.160		63.514	

Table 9

Type E and Type R Participants in 2011 and 2014

Counts of Type E and Type R participants are reported from FDR tests using crude oil futures data in 2011 and 2014. The 2011 sample is for the December expiration and includes all trading days between September 12th to November 18th. The 2014 sample is for the October expiration and includes trading days from August 1st to September 18th. Significant accounts are those identified as Type_E or Type_R using 2.5% and 5% control rates (C.R.) in the FDR tests. Panel A identifies Type E and Type R participants found in the two samples and the sample size. Panel B identifies the number of Type E and Type R participants who traded in both samples. There were 2,669 accounts identified as trading in both samples. Panel C identifies whether the Type E and Type R participants found in 2011 retained those characteristics in the 2014 sample. The first two columns in Panel C report the retention counts by control rate and the percentage of that count relative to the "type" totals observed in 2011 for the overlapping acounts. The last two columns report the retention counts and percentages measured relative the 2014 total for overlapping accounts.

	2011 Sample		2014 Sample	
Descriptor	2.5% C.R.	5% C.R.	2.5% C.R.	5% C.R.
Panel A: Type E and Type R participants in 2011 and 2014 samples				
Type E Participants	112	301	101	322
Percent of Sample	1.5%	4.0%	1.2%	4.0%
Type R Participants	196	542	133	425
Percent of Sample	2.6%	7.2%	1.6%	5.3%
Sample Size	7,554		8,087	
Panel B: Only accounts included in both 2011 and 2014 samples				
Type E Participants	35	81	38	95
Percent of Sample	1.3%	3.0%	1.4%	3.6%
Type R Participants	65	138	50	131
Percent of Sample	2.4%	5.2%	1.9%	4.9%
Sample Size	2,669		2,669	
Panel C: Skill retention in 2014 for accounts in both samples				
Type E in 2011	1 (2.8%)	7 (8.6%)	0 (2.6%)	7 (7.4%)
Type R in 2011	5 (7.7%)	27 (19.6%)	5 (10.0%)	27 (20.6%)

Table 10

Speed Characteristics of Participants in both 2011 and 2014 Samples

In the sub-sample of 2,669 accounts that traded in both 2011 and 2014, this table shows regression estimates of cancel and execution speeds using the logarithmic transform for the dependent variable defined in Tables 5 and 6. The independent variables are all binary. The base case model includes a dummy for observations in the 2014 sample, dummy for algorithmic traders (ATS), and an interaction term between ATS and the dummy for the 2014 sample. Type E and Type R models include the base case variables, a dummy if the participant is Type 'X' as identified in the 2011 sample, where 'X' is either Type E or Type R in the regression, and interaction terms for observations in the 2014 sample and/or algorithmic participants. The final set of variables are defined for those Type E or Type R particpants who are also identified as that same type in the 2014 sample; that is, the overlapping anticipatory traders. These variables include interaction terms for the 2014 sample and whether the participant is algorithmic. The intercept captures the omitted categories, which in a manual-entry participant. For these regressions, Type E and Type R traders are defined using the 5% FDR control rate in the 2011 sample. The p-values are computed using heteroscedastic-consistent standard errors and are shown in parentheses below each coefficient. An 'na' indicates that there were not enough independent observations to include that variable. The sample size of the cancel (execution) speed regression is 17,729,475 (4,789,309).

	Dependent Variable					
	Ln(1+Cancel Speed)			Ln(1+Execution Speed)		
Independent Variable	Base Model	X = 'Type E'	X = 'Type R'	Base Model	X = 'Type E'	X = 'Type R'
Intercept	3.704	3.700	3.242	1.928	1.920	1.833
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Sample 2014 Dummy	-0.260	-0.257	0.128	0.588	0.596	0.609
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Algorithmic Trader (ATS)	-2.838	-2.833	-2.384	-0.682	-0.672	-0.586
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Dummy 2014 and ATS	0.961	0.956	0.563	-0.731	-0.743	-0.763
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Participant 'X'		1.302	1.291		0.533	1.318
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
Participant 'X' and Dummy 2014		-0.193	-1.019		-0.477	0.642
		(0.323)	(<0.001)		(<0.001)	(<0.001)
Participant 'X' and ATS		-0.270	-0.416		-0.825	-1.717
		(0.124)	(<0.001)		(<0.001)	(<0.001)
Participant 'X' and ATS and Dummy 2014		0.742	1.197		1.019	0.203
		(0.002)	(<0.001)		(<0.001)	(<0.001)
Participant 'X' in both samples		-0.061	-0.064		-0.108	0.711
		(0.865)	(0.009)		(0.199)	(<0.001)
Participant 'X' in both samples and ATS		-2.165	1.346		-0.686	0.228
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
Participant 'X' in both samples and Dummy 2014		-0.430	1.192		-1.088	-1.468
		(0.445)	(<0.001)		(0.445)	(<0.001)
Participant 'X' in both samples and Dummy 2014 and ATS		na	-2.443		0.619	1.728
		na	(<0.001)		(0.046)	(<0.001)
Adjusted R squared	8.5%	8.6%	9.2%	4.4%	4.5%	5.3%
Regression (p-value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)