Peering into the Black Box:
Trader Strategies in the Iowa Electronic Markets

Thomas S. Gruca* and Thomas A. Rietz†

Initial Draft: July 2023

Current Draft: October 2023

Abstract

We explore strategies employed by traders in the Iowa Electronic Markets' 2020 Presidential Election Winner-Takes-All Market. We replicate previous research on trader mistakes while documenting behavior consistent with two new biases: a disposition effect and an endowment effect. We explore how markets populated by mistake-prone and biased traders can result in efficient pricing. Efficiency arises from interactions between many biased and mistake prone traders, the market structure, and a smaller number of significantly more rational price-determining traders. The dynamics are not explained fully by current theories on efficient markets, market microstructure, or behavioral finance.

* Department of Marketing, Tippie College of Business, University of Iowa, Iowa City, Iowa 52242. E-mail: Thomas-Gruca@uiowa.edu.

† Department of Finance, Tippie College of Business, University of Iowa, Iowa City, Iowa 52242.E-mail: Thomas-Rietz@uiowa.edu.

I. Introduction

We study an apparently efficient market populated by traders who often seem to behave irrationally in the sense that they are obviously not value maximizing given available prices. We study trader strategies in a first attempt to understand how their, often irrational, decisions nevertheless lead to efficient market prices. Specifically, we study trader strategies in a real-money prediction market: the 2020 US Presidential election prediction market run by the Iowa Electronic Markets (IEM).

IEM contracts are designed so that prices should forecast election outcomes *if* the markets are efficient. More than 30 years of evidence shows that IEM prices are efficient. Election-eve prices do an excellent job of forecasting the ensuing vote shares for candidates. Most recently, Berg, Gruca and Rietz (2022, p. 720) report a 1.34 percentage point average absolute election-eve prediction error for U.S. Presidential Election markets, 3.35 percentage points for other U.S. election markets, and 2.12 percentage points for non-U.S. election markets over all IEM markets run since 1988. Berg, Nelson and Rietz (2008) show that IEM prices are typically closer to eventual election outcome than polls (beating polls 74% of the time in their data). Further, the relative accuracy stays roughly constant (if anything, going up) the further out the forecasts are from the election. In addition, Majumder, et al. (2009) show that IEM prices follow dynamics that mirror typical financial markets. In particular, "As with other financial markets, we find uncorrelated returns, power-law decaying volatility correlations, and, usually, power-law decaying distributions of returns" (Majumder, et al. 2009, p. 679). The simplicity of the markets, along with full information on trader actions, allows us a unique opportunity to understand how efficient pricing arises.

In addition to studying how prices forecast outcomes and behave relative to other financial markets, prediction markets can be used to understand individual trader rationality (e.g., Oliven and Rietz (2004)) and understand how traders interact with each other and the market structure to form prices. Here, we extend our understanding of trader rationality and develop evidence on theories of market price formation and trading. The IEM is an excellent testing environment because any general theory of financial markets or trader behavior should apply to IEM financial markets in addition to naturally occurring markets. Because IEM markets are finite and simple, they are easy to understand and analyze. At the end of the market, we know the value of all trades, positions, and contracts. This gives the IEM a distinct advantage over naturally occurring markets for testing financial theories.

We shed light on several theories of financial markets and trading. As simple complete contingent claims markets, IEM contracts correspond to the example contracts in Milgrom and Stokey's

(1982) "no trade theorem." If traders are risk neutral or risk averse and have concordant beliefs, there should be no trade in these markets.[1] Yet there is considerable trading among market participants. To explain the observed volume of trading in financial markets, the analytical market microstructure literature often divides traders into two distinct types: (1) "informed" or "rational" who maximize value based on information and (2) "uninformed," "noise" or "liquidity" (i.e., irrational) traders who trade for reasons other than value maximization (Madhavan 2000). We show that individual traders sometimes behave rationally (i.e., as a value maximizer), and sometimes not. In short, traders cannot be divided cleanly into two mutually exclusive groups. Our findings are more consistent with Hirshleifer and Teoh's (2003) concept of limited attention: traders do not always pay enough attention to make every trade rationally. Buy-side traders and those using market orders appear to violate rationality more often than sell-side and limit order traders. Trading experience also seems to matter. Overall, our evidence calls for a theory of trader behavior where individual traders are sometimes rational, value maximizers and sometimes not.

We also provide evidence on behavioral finance propositions. A fundamental tenet of behavioral finance is that individual biases will manifest themselves in market prices and outcomes. According to Investopedia (Hayes 2023): "Behavioral finance is an area of study focused on how psychological influences can affect market outcomes." In a review contrasting efficient markets theory and behavioral finance theory, Shleifer (2000, pp. 10-16) summarizes the behavioral finance argument as: (1) "People in general and investors in particular" are not fully rational. (2) Deviations from rationality are "highly pervasive and systematic," driving prices away from fundamental values. (3) Arbitrage is "limited" in its ability to "bring prices back to fundamental values." The IEM is a good candidate for evaluating these propositions since evidence dating back to the first IEM market in 1988 shows that traders are biased. Traders are prone to a "false consensus" effect (Forsythe, et al. (1992)) and a "wishful thinking" effect (Forsythe, Rietz and Ross (1999)). Further, they frequently deviate from value-maximizing rationality (e.g., Oliven and Rietz (2004)). Here, we add to these previously documented effects two additional biases: a disposition effect and a version of the endowment effect. While the biases and mistakes appear highly pervasive, the markets are efficient as documented above.

Behavioral finance also studies what trading strategies traders use. Using data from small retail brokerage accounts, Barber and Odean (2000) conclude that (1) investors trade a lot (more than 75% annual turnover on average) and (2) investors who trade more lose more relative to buy and hold

[1] The risk neutral/risk averse assumption make the initial contract distribution pareto optimal. If traders are risk seeking, they should trade to a budget-constrained corner position and then stop trading.

strategies. In contrast, using 401k data, Agnew, Balduzzi and Sunden (2023) conclude that investors do not trade much (more that 87% of investors do not trade at all in a given year). However, they do not conclude that active traders achieve either higher or lower returns. Both analyses suffer from a limited horizon. They can measure returns over this horizon, but do not know the results of strategies in the longer run. Here, we can analyze strategies until final asset values are determined. We analyze buy and hold verses active trading strategies. We show that some IEM traders trade very little if at all while others trade very frequently. In contrast to Barber and Odean (2000), we find that active traders profit on average and those who trade more contracts profit more.[2]

We can analyze the impact of arbitrage in our markets because they include a unique (among prediction markets) exploitable arbitrage relationship between contracts. Along with Shleifer (2000), Shleifer and Vishny (1997, p. 35) argue that arbitrage has limits in driving prices to efficient levels. Furthermore, “professional arbitrage is conducted by a relatively small number of highly specialized investors using other people's capital.” We document the strategies followed by the lone arbitrageur in our market. This trader generally kept prices within a mil of arbitrage-free levels by trading 19,889 two-contract bundles (39,798 total contracts) in 4,544 separate transactions for a total profit of $186.52. This single trader (using their own capital) could keep prices within arbitrage bounds.

We provide evidence on computerized trading in our market. At least two traders were computerized. One trader submitted tens of thousands of orders. When actively trading, less than half a second elapsed between orders submitted by this trader. This trader and one other also placed rapid fire bids and asks that thickened queues. There is considerable debate over whether computerized and “flash” traders stabilize markets (e.g., see survey by Jones (2013)) or destabilize markets (e.g., see survey by Goldstein, Kumar and Graves (2014)). Here, computerized traders took advantage of arbitrage opportunities, kept prices very close to arbitrage bounds, and increased market liquidity by thickening queues.

How does this all lead to efficient pricing? Many traders always trade at prices set by other, price-determining traders. A subset of traders submit price-determining orders: bids or asks that subsequently trade. Overall, price-determining orders are more rational and, on average, more

[2] Astute readers will note that much of the Barber and Odean (2000) observation is driven by trading costs and we have no direct trading costs in the form of commissions here. However, bid/ask spreads for individual contracts average $0.0154 (in the traded contract) at the time orders trade (where the average is weighted by traded quantity and defining the spread as 0 when bids or asks cross the opposing queue). The weighted average trade price was $0.4453, making the average round-trip costs 3.45%. This is a bit larger than the 3% total round trip cost including commissions estimated by Barber and Odean (2000) in their data. So, all else constant, we might expect the effect to be somewhat larger here, not smaller, or reversed.

profitable than other traded orders. Further, the more price-determining orders active traders submit, the more rational they appear to be. Because of the double auction market structure, price-determining bids and asks form the queues against which other traders trade. The bids and asks are kept within arbitrage bounds by the arbitrage relationships designed into the market and the trader who took advantage of them. The queues are thickened by computerized and other off-market (and also apparently more rational) traders. With the queues in place, other traders, who are more likely to be placing irrational orders, trade against these price-determining orders. Thus, they trade at more rational prices than they might have otherwise. While the price-determining traders gain on average, they also set apparently efficient prices that protect other traders significantly from their own mistakes.

II. The 2020 Winner-Takes-All Presidential Election Market

1. The Iowa Electronic Markets

The Iowa Electronic Markets (IEM) are relatively small scale, but real-money futures markets that trade futures and binary option contracts designed so that prices forecast future events. The Tippie College of Business (University of Iowa) operates these markets for teaching and research purposes. Traders invest their own money in the markets, bearing the real-money risks and reaping the real-money rewards of their activity.[3] The IEM market structure closely parallels naturally occurring financial markets as do its price dynamics (Majumder, et al. (2009)). It is an order-driven double-auction market accessed 24/7 through the Internet. Traders can place both limit and market orders. Price and time ordered queues hold outstanding bids and asks. The current best (highest) bid and best (lowest) ask are always publicly known.

One way to measure IEM accuracy is with vote-share markets, designed to forecast the relative vote shares received by candidates. Reproduced from Berg, Gruca and Rietz (2022), Figure 1 compares the election eve forecast vote shares to actual vote shares received in IEM vote-share and similar contracts. In Presidential elections (including 2020), the absolute prediction error has averaged 1.34 percentage points. Berg, Nelson and Rietz (2008) show that vote-share market forecasts are closer to eventual outcomes than polls 74% of the time overall and do not decline in relative accuracy further in advance of the election. Another type of IEM market is a Winner-Takes-All (WTA) market designed to

[3] Because IEM contracts are real futures contracts, the IEM is under the regulatory purview of the Commodity Futures Trading Commission (CFTC). The CFTC issued "no-action" letters to the IEM stating that as long as the IEM conforms to certain restrictions (related to limiting risk and conflict of interest), the CFTC will take no action against it. Under this no-action letter, IEM does not file reports that are required by regulation and therefore it is not formally regulated by, nor are its operators registered with, the CFTC.

predict probabilities of events. Berg and Rietz (2019) find prices are efficient in forecasting probabilities except possibly for transitory mispricing for tail probabilities.

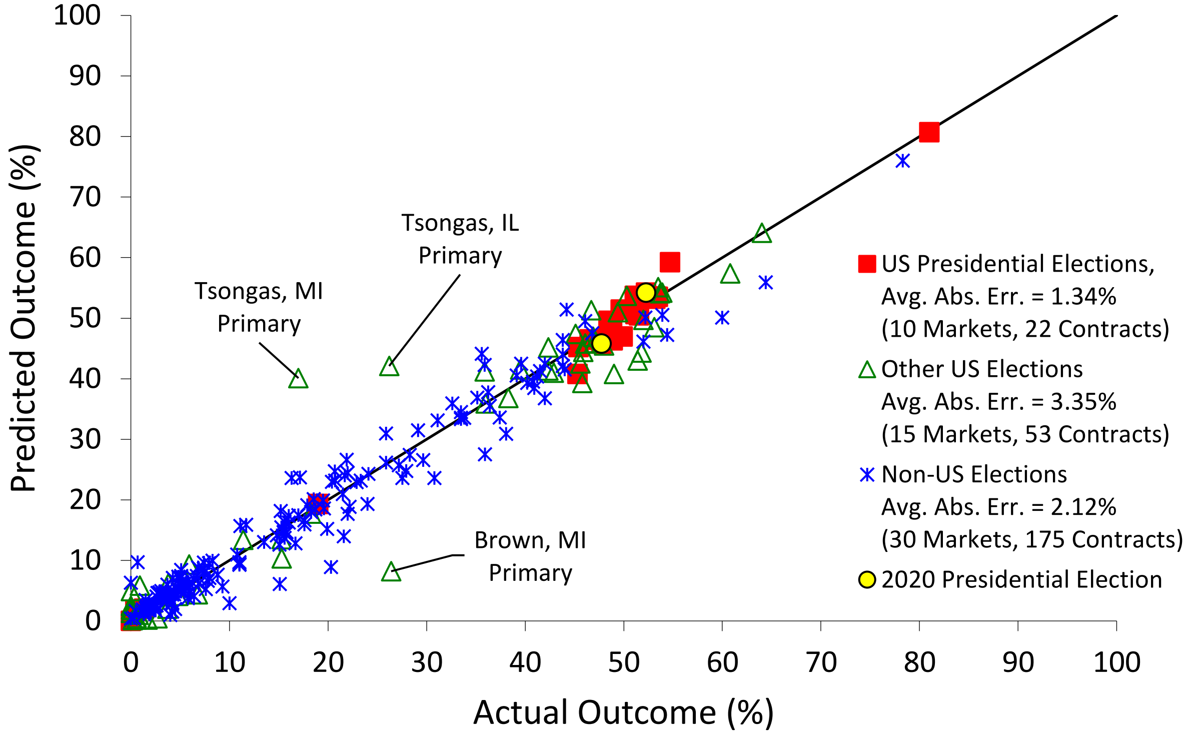

Figure 1: Accuracy of IEM markets for U.S. Presidential elections, other U.S. elections, and non-U.S. elections (reproduced from Berg, Gruca and Rietz (2022)).

We study the 2020 U.S. Presidential Election Winner-Takes-All (WTA) market. The market prospectus appears in the appendix. We describe it briefly here. There were two contracts in the market: DEM20_WTA (a.k.a., the Biden contract), and REP20_WTA (a.k.a., the Trump contract). After the election, the DEM20_WTA contract paid holders $1 if the Democratic Party nominee (Biden) received the majority of popular votes cast for the two major parties in the 2020 U.S. Presidential election and $0 otherwise. The REP20_WTA contract paid $1 if the Republican Party nominee (Trump) received the majority of the popular vote and $0 otherwise. Notice that the “bundle” portfolio of one of each contract always paid $1. This makes the contract bundle a complete set of simple state contingent claims (also known as binary options).

Traders could purchase bundles from or sell bundles to the exchange (i.e., “exchange bundles”) at any time for the fixed (and fair) price of $1. They could place bids or asks for either individual contract at any time. They could accept outstanding bids or asks for either contract at any time. Finally, they could buy or sell both contracts as “market bundles” at the sum of the asks or bids at any time.

The markets ran for 636 days from February 7, 2019 to November 4, 2020, the day after the November 3rd election. There were 355 active traders who traded 158,051 individual contracts worth $71,525.50. In addition, traders purchased 84,987 exchange bundles and sold back 23,730. They purchased 3,789 market bundles and sold 22,053. The average daily volume was 248.51 individual contracts worth $112.46. Figure 2 shows daily midnight normalized prices and daily contract volumes for this market through election eve.

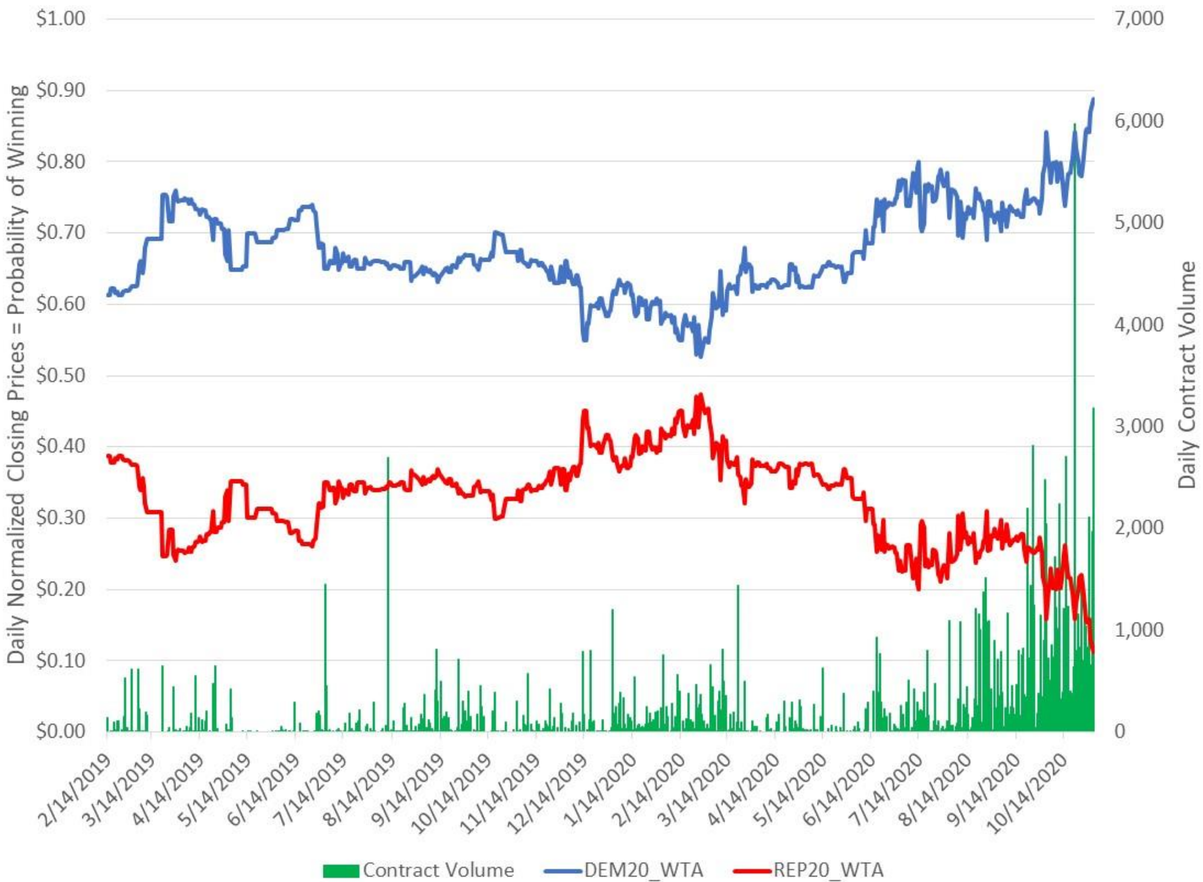

Figure 2: Daily prices for the 2020 U.S. Presidential Election Winner-Takes-All market. The upper (blue) line is the normalized closing price for DEM20_WTA. The lower (red) line is the normalized closing price for REP20_WTA. The (green) bars are the daily number of individual contracts traded.

In each IEM market, the complete bundle of contracts is a risk-free portfolio. Cash holdings are also risk-free. Both risk-free assets earn zero return. There are no transaction fees. Overall, the number of contracts of DEM20_WTA and REP20_WTA are always the same, so there is no aggregate uncertainty.

As a result, all assets should yield the risk-free return of zero.[4] Let p_t^j be the price of contract *j* on date *t* and q_t^j be the probability that contract *j* will liquidate at \$1 given information available at date *t*. Then, $p_t^j = q_t^j \cdot \$1 + \left(1 - q_t^j\right) \cdot \$0 = \$q_t^j$. Thus, the price should be the market forecast of the probability of the associated candidate taking the most popular votes. However, because of asynchronous trading and bid/ask bounce, the most recent prices may not add up to exactly 1. Therefore, we "normalize" the most recent prices by their sum when computing forecasts. Thus, normalized prices and forecast are: $\hat{p}_t^j = \frac{p_t^j}{\sum_i p_t^i}$, where *i* indexes the contracts. This ensures that the forecast probabilities sum to one.

Here, we study the trading strategies used by traders in this market. Ultimately, the strategies determine trade prices and, thus, forecasts.

III. Simple Transactions and Trading Strategies

1. Exchange Bundle Transactions

Traders can buy bundles from and sell bundles back to the exchange for \$1 any time. Traders create contracts by buying bundles from the exchange. Then, they can trade individual contracts among themselves. Exchange bundle transactions are fair trades because one of the contracts will pay \$1 at the end of the market. Table 1 summarizes exchange bundle transactions overall, while Table 2 summarizes exchange bundle trading strategies by trader.

Overall, 106 traders (out of 355 active traders, or 29.86%) submitted 2,698 exchange bundle purchase orders, creating 84,979 sets of contracts. No traders only purchased exchange bundles (i.e., they all took at least one additional action) and the average trader submitted 4 exchange bundle purchase orders. Both the number of orders per trader and the number of contracts per order are highly asymmetric with means much higher than medians. This implies some traders are much more active than others.

In contrast, only 36 traders (10.14% of active traders) sold 18,530 bundles back to the exchange. The average trader who sold back, did so 2.5 times. Like purchases, the distributions are asymmetric.

2. Market Bundle Transactions and Strategies

Traders can also buy or sell bundles at market prices any time, buying each contract at the current best bid or selling each at the current best ask. This allows traders to exploit arbitrage opportunities. If current bids sum to more than \$1, traders can buy an exchange bundle for \$1 and sell

[4] See Malinvaud (1974) for a general equilibrium proof of this proposition and Berg and Rietz (2019) for a more complete exposition in context.

at the bids for more than $1. If the sum of asks is less than $1, they can buy the bundle for less than $1 and sell to the exchange for $1. Table 1 summarizes market bundle transactions overall, while Table 2 summarizes market bundle trading strategies by trader.

Overall, 19 traders (5.35%) submitted 4,590 market bundle orders, trading 25,842 bundles of contracts. Only one trader exploited arbitrage opportunities, accounting for 4,544 (99.00%) of the market bundle transactions and 19,889 (95.60%) of the bundles traded. This resulted in a total arbitrage profit of $186.52. We discuss this trader more later.

3. Individual Contract Purchases and Sales

Traders can buy individual contracts by submitting a purchase market order. A purchase order executes at the current best ask until (1) the buyer runs out of cash, (2) the asker runs out of contracts or (3) the smaller of the quantity ordered or quantity available at the best ask is exhausted. Any remaining quantity ordered is cancelled otherwise. Traders can sell individual contracts by submitting a sale market order. A sale order executes at the current best bid until (1) the bidder runs out of cash, (2) the seller runs out of contracts, or (3) the smaller of the quantity ordered or quantity available at the best bid is exhausted. Any remaining quantity ordered is cancelled otherwise. Because trades occur at bids or asks submitted by other traders, market orders are known as “price-taking” orders.

Table 3 summarizes market order transactions, while Table 4 summarizes market order strategies by trader. More than twice as many unique traders submitted purchases than sales (218 vs 100). There was an enormous asymmetry in the total quantity ordered on the buy-side versus the sell-side (with more than 16 million contracts ordered via purchase orders and only 61,206 via sale orders). However, this is biased by a single trader who submitted 18 purchase orders for DEM20_WTA in a 20-minute span on October 15, 2020 accounting for of 16.7 million contracts ordered.[5] Table 3 also shows Quantity ordered statistics without this trader. Even without this trader, purchase order quantities exceeded sale order quantities by 2.4 to 1 (147,604 versus 61,206 contracts overall).

Table 4 shows that significantly more traders submitted purchase than sell orders (218 traders submitted purchase orders at least once while 100 traders submitted sale orders at least once). Further, in addition to exchange bundle transactions, 81 traders 22.81% ONLY submitted market purchase orders while only one trader 0.28% ONLY submitted market sale orders. Sellers were a bit more active. The

[5] Only 637 contracts in these orders actually traded for a total dollar volume of $512.232. This moved the price from $0.782 to $0.850. Within two hours the best ask on DEM20_WTA had fallen back to $0.777, below the first execution price of these orders.

average trader who submitted purchase orders did so 3 times and the average trader who submitted sale orders did so 4 times.

Overall, the data supports the following result, indicating a purchasing bias among price-taking traders who submit market orders:

Result 1: Traders who submit market orders are much more likely to submit purchase orders than sale orders.

a. Suboptimal Market Orders

Traders can effectively purchase a contract at market prices in two ways: (1) purchase at the best ask or (2) purchase an exchange bundle for $1 and sell the other contract at the best bid. Both result in holding one additional contract. The law of one price implies that these two methods should give traders the same price. However, often, they did not. Figure 3 shows election eve bids and asks as an example. It illustrates the two, potentially different, prices: a "direct" and an "indirect" price for the same net trade. A trader could have purchased a DEM20_WTA directly at the ask for $0.905 or indirectly by (1) purchasing an exchange bundle for $1 and (2) selling REP20_WTA at the bid for $0.109 leading to an indirect price of $1-0.109 = $0.891. The prices differed by $0.014. In contrast, the direct purchase price for a REP20_WTA ($0.110) equaled the indirect purchase price ($1-$0.089 = $0.110).

Contract	Bid	Ask
DEM20_WTA	$0.890	$0.905
REP20_WTA	$0.109	$0.110

Contract	Direct Price	Indirect Price	Difference
Buy DEM20_WTA	$0.905	$0.891	$0.014
Sell DEM20_WTA	$0.890	$0.890	$0.000
Buy REP20_WTA	$0.110	$0.110	$0.000
Sell REP20_WTA	$0.109	$0.095	$0.014

Figure 3: Bids and asks at midnight, November 2, 2020 and direct and indirect market prices for contracts.

Similarly, traders can effectively sell a contract at market prices in two ways: (1) sell at the best bid or (2) purchase the other contract at the best ask and sell an exchange bundle for $1. This also leads to direct and indirect prices. Again, Figure 3 shows example prices. A trader could sell a DEM20_WTA at the bid for a direct price of $0.890 which equaled the indirect price of $1-$0.110 = $0.890. A trader could sell a REP20_WTA at the bid for $0.109 or the indirect price of $1-$0.905 = $0.095, a difference of $0.109-$0.095 = $0.014.

In both cases, if a trader holds an inventory of contracts, a trader can change the order of the indirect trades. Thus, both prices are available for immediate execution if the trader makes the individual contract trade first. As a result, we define a market order as suboptimal if either (1) it was a purchase and a lower indirect price was immediately available or (2) it was a sale and a higher indirect price was immediately available.[6]

Table 3 shows the number and percentages of market orders submitted at sub-optimal prices. Not only are there significantly more market purchase orders than market sale orders, but they are much more likely to be at sub-optimal prices. Overall, 62.86% of purchase orders are not at the best price while 11.21% of sale orders are not. Sub-optimal purchase orders make up 87.29% of sub-optimal market orders. The overall rate of 39.65% is similar to the rate of 37.7% documented by Oliven and Rietz (2004).[7] However, the pattern differs, with a pronounced tendency for purchasers to submit suboptimal orders.[8]

Table 4 shows that this isn't the result of just a few traders.[9] Out of 218 traders who submit market purchase orders, 177 (81.19%) of them submit at least one sub-optimal purchase order. This amounts to almost half of all traders. Similarly, 45 out of 100 (45%) of traders who submit market sale orders submit at least one sub-optimal sale order. This leads to:

Result 2: Price-taking traders often submit market orders at sub-optimal prices. Sub-optimal orders are submitted by a large subset of traders. Purchase orders are much more likely to be sub-optimal than sale orders.

While there are many sub-optimal orders, the market structure protects traders from most of the potential costs of these orders. We define the total loss exposure as the number of contracts ordered times the difference between the submitted price and the best price available. The total loss exposure across all traders in the market was more than $1 million if all the contracts had traded at the

---

[6] Note, this also tags suboptimal indirect purchases and sales as suboptimal. For example, if a trader took the suboptimal strategy of indirectly selling REP20_WTA for $0.095, the trader would purchase a DEM20_WTA at the suboptimal direct price of $0.905 and sell a bundle. This transaction would be tagged as suboptimal because of the suboptimal direct sale of the DEM20_WTA contract.

[7] Note that, unlike here, Oliven and Rietz (2004) include bids and asks the cross the opposite queue as "price-taking" orders. Adding these to our price-taking orders increase the violation rate to 40.89%, still close to Oliven and Rietz (2004).

[8] Perhaps accounting for the difference, the market studied in Oliven and Rietz (2004) ran through TelNet (a precursor to the internet) and had a significantly different trading interface. This may have attracted different types of traders or may have resulted in them interacting with the market differently. We hope to study this in future research.

[9] We note that Oliven and Rietz (2004) only studied trades, not strategies trader by traders. They do not indicate whether their results are pervasive across traders as we document.

suboptimal prices. However, not all contracts trade because traders run out of money or contracts, or the bid or ask changes, which cancels the rest of the order. We define the upper bound of losses incurred as the quantity of contracts actually traded times the price difference.[10] This bound was $590.279 overall. Thus, the losses incurred by traders through their suboptimal actions were significantly less than they might have been. Thus:

Result 3: The market structure provides significant protection for price-taking traders who submit sub-optimal market orders.

4. Individual Contract Bids and Asks

Traders can offer to buy individual contracts by submitting a bid limit order. A bid sets a price, quantity, and expiration date and time. Unless the bidder changes the default expiration, it is "good for the day," expiring at midnight on the submission day. Bids are stored in a queue ordered first by price, then time of order. A bid for a contract executes at the bid price if (1) it is the "best bid" (the first submitted among bids at the highest price) and (2) another trader puts in a valid sell order for the contract. A bid also executes if it crosses the ask queue of the same contract. In that case, it executes at the lowest ask prices until either (1) the quantity bid is exhausted or (2) the remaining asks are at prices higher than the bid.

Traders can offer to sell individual contracts by submitting an ask limit order. An ask sets a price, quantity, and expiration date and time. Unless the asker changes the default expiration, it is "good for the day," expiring at midnight on the submission day. Asks are stored in a queue ordered first by price, then time of order. An ask for a contract executes at the ask price if (1) it is the "best ask" (the first submitted among asks at the lowest price) and (2) another trader puts in a valid purchase order for the contract. An ask also executes if it crosses the bid queue of the same contract. In that case, it executes at the highest bid prices until either (1) the quantity asked is exhausted or (2) the remaining bids are at lower prices than the ask.

Because limit orders determine trading prices, those who submit market orders are known as "price setting" orders because they set available trade prices. If a bid or ask sets a new best bid or best ask, it is known as a "market making" order because it sets the immediately available price. Finally, if a limit order trades, then that order is a "price determining" order.

Table 5 summarizes limit orders placed overall, while Table 4 summarizes limit order strategies by trader. Again, more traders are on the buy-side than the sell-side, with 235 unique traders submitting

[10] This assumes that the same quantity was available at the other contract's best bid or ask. The quantity available may have been smaller, resulting in a lower effective quantity traded, reducing losses further.

bids and 134 submitting asks. However, sell-side traders are more active, with 5,856 separate bids and 9,141 asks submitted.

There appears to be an enormous asymmetry in the total quantity ordered on the buy-side versus the sell-side (with more than 22 billion contracts ordered through bids and just over 1.5 million through asks). However, this is biased by two traders. One submitted bids of $0.00 for 1 billion contracts each for DEM20_WTA and REP20_WTA. Another submitted bids of $0 for 9,999,999,999 contracts each for DEM20_WTA and REP20_WTA. None of these bids executed any contracts. These differ from normal bids and asks because they are essentially arbitrage plays. The orders are costless to submit and trade (if one were to trade). Upon execution, a trader would have an asset that they might be able to sell for a positive amount. Table 5 also has quantity data without these four "arbitrage bids." The asymmetry disappears: the total quantity ordered in "non-arbitrage" bids and asks were 399,095 and 507,791, respectively.

Table 6 shows that significantly more traders submitted bids than asks (235 traders submitted least one bid while 134 traders submitted at least one ask). Further, in addition to exchange bundle transactions, 52 traders (14.65%) ONLY submitted bids while only 8 traders (2.25%) ONLY submitted asks. The average trader who submitted bids did so 5 times and the average trader who submitted asks did so 5 times as well.

Overall, the data supports the following result, indicating less buy-side bias among limit order traders:

Result 4: Traders who submit limit orders are somewhat more likely to be on the buy-side, but the asymmetry in orders is much smaller than for market orders. Further, the quantities ordered through limit orders are slightly higher on the sell-side.

b. Arbitrage Limit Orders

Bids of 0 and asks of $1 are essentially arbitrage trades. As discussed above, two traders submitted bids of 0 for more than 1 billion contracts each. Table 4 shows two additional traders bid 0 for smaller quantities and one trader submitted an ask for $1. Accepting such a bid or ask is weakly dominated. None of these bids or asks executed. Thus:

Result 5: Traders do not sell individual contracts for $0 or buy individual contracts for $1.

c. Off-Market Limit Orders

Off-market limit orders are bids at prices strictly less than the current best bid and asks at prices strictly higher than the current best ask. [11] Traders may submit off-market limit orders to in hopes of getting a better price or to take advantage of market swings or traders who cross the queues (discussed later). The disadvantage is that off-market limit orders may be less likely to trade. Table 4 summarizes traders who submit off-market limit orders not including those who submitted arbitrage bids of $0 and arbitrage asks of $1. Overall, 140 traders submitted at least one off-market bid and 80 submitted at least one off-market ask. This made up 59.57% of traders who submitted bids and 59.70% of traders who submitted asks. Off-market orders are quite unlikely to trade. Only 16,460 contracts traded out of 135,051 offered in off-market bids (12.19%) and 16,769 contracts traded out of 1,108,460 offered in off-market asks (1.51%). However, as we discuss below, off-market bids and asks provide depth to the queues that provide price buffers for traders who cross queues with bids and asks.

d. Market-making Limit Orders

Market-making limit orders are bids at prices strictly greater than the current best bid and asks at prices strictly less than the current best ask.[11] Traders who submit market-making orders are setting the immediately available trade prices for other traders who submit market orders. Thus, they are also price-setting trader and, if the order trades, price-determining traders. Table 4 summarizes traders who submit market-making limit orders. Overall, 211 traders submitted at least one market-making bid and 119 submitted at least one market-making ask. This made up 89.79% of traders who submitted bids and 88.81% of traders who submitted asks. Market-making orders are much more likely to trade than off-market orders. Overall, 99,976 contracts traded out of 249,318 offered in off-market bids (40.10%) and 74,406 contracts traded out of 420,642 offered in off-market asks (17.69%). This leads to:

Result 6: Market-making limit orders are much more likely to trade than off-market limit orders.

Result 7: Market-making bids are much more likely to trade than market-making asks.

As we discuss below, much of this execution asymmetry arises because market-making bids frequently create arbitrage opportunities. When they do, they trade when another trader exploits the arbitrage opportunity.

[11] Here, we exclude "at market" orders: bids at prices that equal the current best bid and asks at prices that equal the current best ask.

e. Queue-Crossing Limit Orders

Bids at prices higher than the best ask "cross" the ask queue while asks at prices less than the best bid "cross" the bid queue. Such limit orders commit the trader to buy a quantity at prices higher than currently available market prices or sell at lower prices. Queue-crossing bids execute at the lowest ask prices until (1) the trader runs out of cash, (2) the bid quantity is exhausted or (3) the remaining asks are at prices higher than the bid. Queue-crossing asks execute at highest bid prices until (1) the trader runs out of contracts, (2) the ask quantity is exhausted or (3) the remaining bids are at prices lower than the ask.

Overall, 97 unique traders submitted at least one queue-crossing bid (42.28% of all traders who submitted bids) and 75 submitted at least one queue-crossing ask (55.97% of all traders who submitted asks). Traders submitted queue-crossing bids for 58,938 contracts, of which 34,876 traded. Traders submitted queue-crossing asks for 45,060 contracts of which 22,567 traded.

Some of these orders may have been on purpose to guarantee rapid execution of at least some contracts. Others may have been mistakes. In either case, the market provides some protection to traders because (1) the full quantity may not trade and (2) contracts that do trade may trade at more favorable prices than the submitted limit order price. We define the loss exposure resulting from a queue-crossing as the quantity ordered times the difference between the bid price and the best immediately available price: the current best ask. In effect, if the trader could have traded the entire quantity at the best available price and, instead, trades the entire quantity at the bid price, this is how much more that the trader would have paid in total for the contracts. Similarly, the loss exposure for a queue-crossing ask is the quantity times the difference between the ask price and the best available bid. The upper bound on the actual loss is the actual trade quantity times the difference between the average trade price and the best available price. The total bid-side loss exposure was $2,839.86, but not all contracts traded and those that did trade were at better prices than the bid. This reduces realized losses to an upper bound of $222.32. Similarly, total ask-side loss exposure was $4,299.77, but the upper bound of realized losses was $80.20. Thus:

Result 8: The market structure provides significant protection for queue-crossing limit traders.

f. Arbitrage-Creating Limit Orders

Traders who place a bid that drives the sum of bids across contracts above $1 create an arbitrage opportunity. In addition, such limit orders are suboptimal in the sense that there is an immediately available better price. Consider the bids and asks in Figure 3. Suppose a trader placed a bid of $0.900 for DEM20_WTA. This would make the bids sum to $0.900+$0.109 = $1.009. Another trader could exploit the arbitrage opportunity by buying an exchange bundle for $1 and selling it as a market bundle for $1.009, pocketing $0.009. There is also a better price immediately available for the bidder: The bidder could have guaranteed a purchase by buying an exchange portfolio for $1 and selling the REP20_WTA for $0.110. This would give a net price of $1-$0.110 = $0.890 for a guaranteed purchase.

Similarly, traders who place an ask that drives the sum of asks across contracts below $1 create an arbitrage opportunity. Again, such limit orders are suboptimal in the sense that there is an immediately available better price. Consider the bids and asks in Figure 3. Suppose a trader placed an ask of $0.880 for DEM20_WTA, making the sum of the asks $0.880+$0.110 = $0.990. This would cross the queue and trade until the remaining best bid was less than $0.880. Suppose it fell to $0.870. Another trader could then exploit the arbitrage opportunity by buying a market bundle for $0.990 and selling it as an exchange bundle for $1, pocketing $0.010. There is also a better price immediately available for the asker: the asker could have guaranteed a net sale by buying a REP20_WTA for $0.110 and selling an exchange portfolio for $1. This would give a net price of $1-$0.110 = $0.890 for a guaranteed sale.

Table 5 shows the number and percentages of bids and asks that create arbitrage opportunities. Overall, 7.70% of bids and 1.70% of asks create arbitrage opportunities. This corresponds to 13.86% of market-making bids and 3.31% of market-making asks. Overall, 7.66% of market-making limit orders create arbitrage opportunities. This includes those that cross queues. Oliven and Rietz (2004) exclude queue-crossing bids and asks. Of the remaining market-making bids and asks, they find 5.39% create arbitrage opportunities. Dropping queue-crossing bids and asks from our data results in 4.08% of remaining market-making limit orders creating arbitrage opportunities.

Table 6 shows that this isn't the result of just a few traders.[12] Out of 211 traders who submit market-making bids, 125 (59.24%) of them submit at least one arbitrage-creating bid. This is more than a third of all traders. Similarly, 64 out of 119 (53.78%) of traders who submit market-making asks also submit at least one arbitrage-creating ask. This leads to:

Result 9: Market-making traders submit bids and asks at sub-optimal prices relatively infrequently. However, a substantial portion of market-making traders submit at least one suboptimal (arbitrage-creating) market-making order.

Again, the market structure protects traders from some of the potential costs of arbitrage-creating orders. We define the total loss exposure as the number of contracts ordered times the

[12] We note that Oliven and Rietz (2004) only studied trades, not strategies trader by traders. They do not indicate whether their results are pervasive across traders as we do.

difference between the submitted price and the best price available. The total loss exposure across all traders in the market was more than $4,216.40 if all the contracts had traded at the suboptimal prices. However, not all contracts trade because traders run out of money or contracts, or the bid or ask changes, which cancels the rest of the order. We define the upper bound of losses incurred as the quantity of contracts actually traded times the price difference.[13] This bound was $34.07 overall. Thus, again, the losses incurred by traders through their suboptimal actions were significantly less than they might have been. Once again, the market structure provides significant protection for traders who behave sub-optimally.

Result 10: The market structure provides significant protection for market-making traders who submit sub-optimal limit orders.

5. Arbitrage Exploitation

One trader exploited arbitrage opportunities. Doing so, the trader traded 22,666 exchange bundles using 1,248 separate orders and 19,889 market bundles using 4,544 separate orders. That trader was obviously computerized. The median time between market bundle transaction orders submitted by the trader was 0.514 seconds.[14]

Result 11: A single, computerized trader exploited virtually all arbitrage opportunities.

6. Summary of Simple Strategies

In addition to trading exchange bundles, a significant number of traders only use one other simple strategy: 1 only purchases market bundles; 81 only submit purchase orders (77 of them in only one contract) and 1 only submits sell orders in a single contract; 52 only submit bids (47 of them in only 1 contract) and 8 only submit asks (4 of them in only 1 contract). Thus, overall, 143 out of 355 active traders (40.28%) only follow one strategy. These traders are heavily on the buy-side of the market: 134 on the buy-side and 9 on the sell-side. Because a seller is net up one or the other contract, effectively these are all buy (or at least attempt to buy) and hold traders. Thus:

Result 12: A substantial fraction of traders establishes (or attempts to establish) a position and hold it.

In contrast, the most active traders order and trade large quantities and dollar volumes. A single trader (the arbitrage trader discussed above) submitted 11,289 individual orders while the average

[13] This assumes that the same quantity was available at the other contract's best bid or ask. The quantity available may have been smaller, resulting in a lower effective quantity traded, reducing losses further.

[14] This trader also traded 2,803 DEM20_WTA contracts using 2,377 separate orders and 2,707 REP20_WTA contracts using 2,707 separate orders.

trader submitted 7. Similarly, one trader ordered approximately 20 billion contracts (not including exchange bundles) and another ordered about 2 billion. Both bid $0 for most of these contracts and traded none as a result of the $0 bids. The average trader ordered 600 contracts outside of exchange bundles. Traded volumes were lower, but remained skewed, with a single trader trading 44,912 total individual contracts (again the arbitrage trader discussed above) and the average trader trading 266. The three most active traders in terms of dollar volumes ordered approximately $1,000,000 each, but few contracts traded other than arbitrage trades. The average trader ordered $278.63. Again, the arbitrage trader was the most active in terms of traded dollar volume at $22,607.69 for a total dollar profit of $186.52. The average trader traded individual contracts worth $128.62.

To give an idea about the distribution of activity across more typical traders, we divide traders into deciles according to the level of an activity and find the median level of activity for traders in that decile. Only the 10th decile is affected by the extreme activity levels of a few traders. The results are graphed in Figure 4. Even using medians within decile, there is still a significant skew in activity levels. Thus:

Result 13: Activity levels are highly skewed.

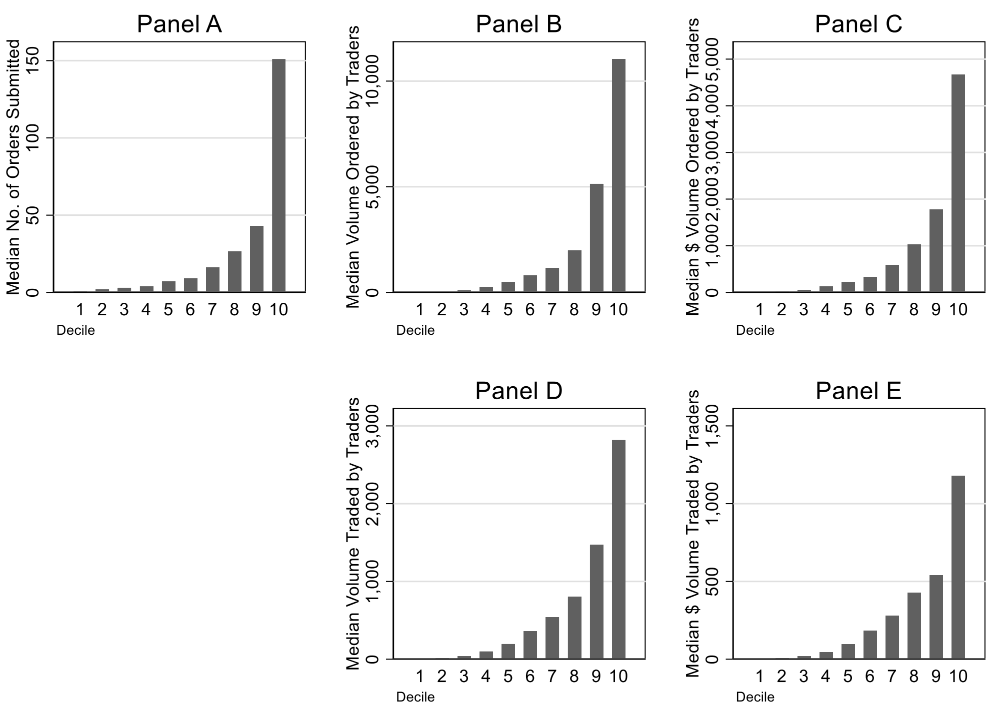

Figure 4: Trading Activity by Decile. The x-axis sorts traders by decile for the given activity and the y-axis shows the median level of activity in that decile. Panel A shows the number of orders submitted.

Panel B shows contract quantities ordered. Panel C shows dollar volumes ordered. Panel D shows quantities traded. Panel E shows dollar volumes traded.

g. Analysis of Strategies that use Sub-Optimal Prices

Schwert (2003) and Hou, Xue and Zhang (2020) show that many financial anomalies disappear or fall in magnitude after they are published in the academic literature. That is not the case here. Above, we replicate much of Oliven and Rietz's (2004) analysis that traders use sub-optimal prices. Here, we present additional evidence that the anomaly remains.

Figure 5 and Figure 6 show the main factors from Oliven and Rietz's (2004, p. 346) main regression on optimality in the current data set. Price-taking traders who submit market orders are significantly more likely to violate rationality than market-making limit order traders. Buyers are significantly more likely to violate rationality than sellers. More experienced traders are less likely to violate rationality. Larger relative spreads (defined as the spread in the traded contract divided by the spread in the other contract) result in more violations. The only apparent difference in the results comes from the order size (defined as the dollar volume submitted in the order). Here, large order sizes are associated with more violations, the opposite of Oliven and Rietz (2004).

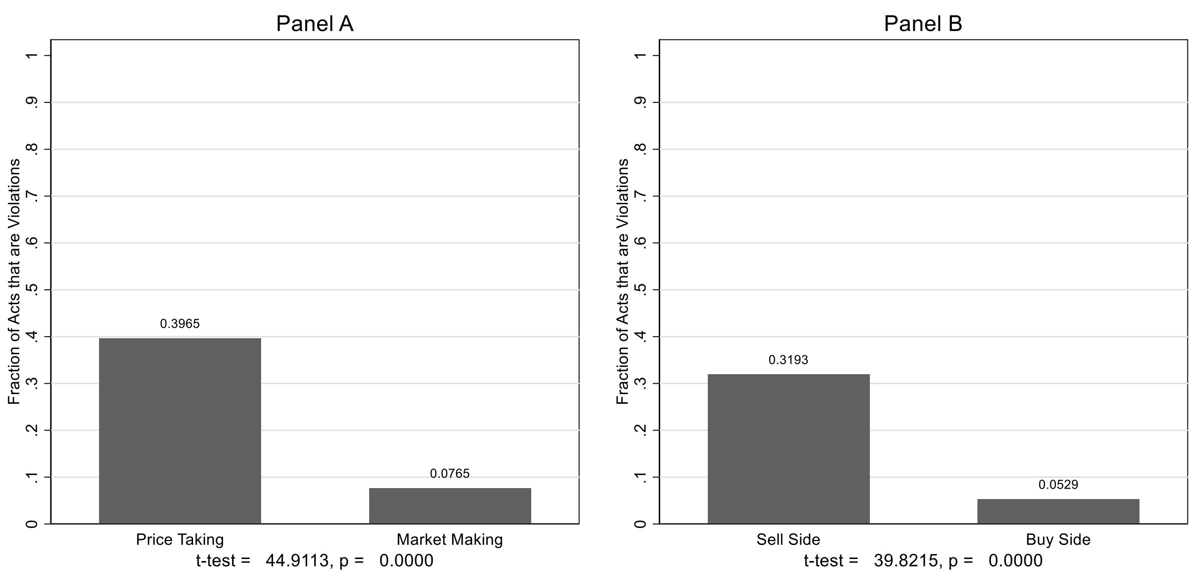

Figure 5: Impact of the trader's role and the side of the market on whether prices are suboptimal. Panel A shows the impact of whether the trader is a price-taking market order trader or a market-making limit order trader. Panel B shows the impact of whether the trader is on the sell-side or the buy-side of the market.

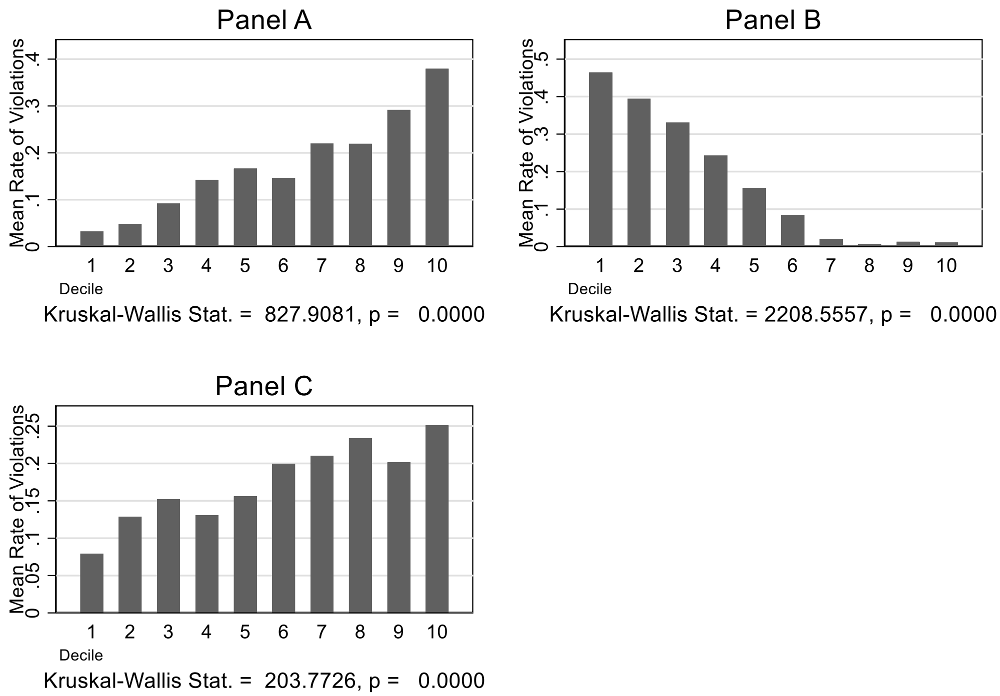

Figure 6: Impact of order size, trader experience and relative spreads on whether prices are suboptimal. Panel A shows the impact of the log of the dollar volume ordered. Panel B shows the impact of the log of the number of non-exchange-bundle orders previously submitted by the trader. Panel C shows the impact of the log of the relative spread in the market as defined in the text.

Table 7 replicates Oliven and Rietz's (2004, p. 346) regression to the extent possible given that we do not have the survey and demographic data that they used. For the most part, the results are quite similar if not somewhat stronger. Role has a similar negative coefficient. Side has a somewhat larger negative coefficient. Order Number has a larger negative coefficient. Relative Spread has a somewhat larger positive coefficient. Model specificity is similar while sensitivity is higher. The only real difference is in the sign of order size. Here, we have a positive coefficient and they have a negative coefficient.[15]

The regressions show that:

Result 14: We replicate Oliven and Rietz (2004). The anomaly they documented did not go away after publication.

Here, we go well beyond Oliven and Rietz (2004) by documenting the distribution of violations within and across traders. In contrast to market micro-structure theories that postulate two types of traders (typically either "informed" and "uninformed" or "rational" and "liquidity"), we show that (1)

[15] A robustness check Windsorizing the log of order size and log of order number at the 5th and 95th percentiles leads to similar results, so this is not just the result of a few orders.

violations occur across a range of traders and (2) for traders who submit more than a few orders, violations often occur on some, but not all, of the orders and (3) there is a correlation between the total number of orders submitted and the tendencies of traders to submit orders with violations.

Figure 7 shows histograms of the suboptimal index (fraction of violations in price-taking and market-making orders submitted by a trader) by deciles of the number of market-making and price-taking orders submitted by traders. In the first decile, traders only submitted one such order that was either a violation or not. For activity levels above that, fewer traders appear completely rational or completely irrational as measured by violations.

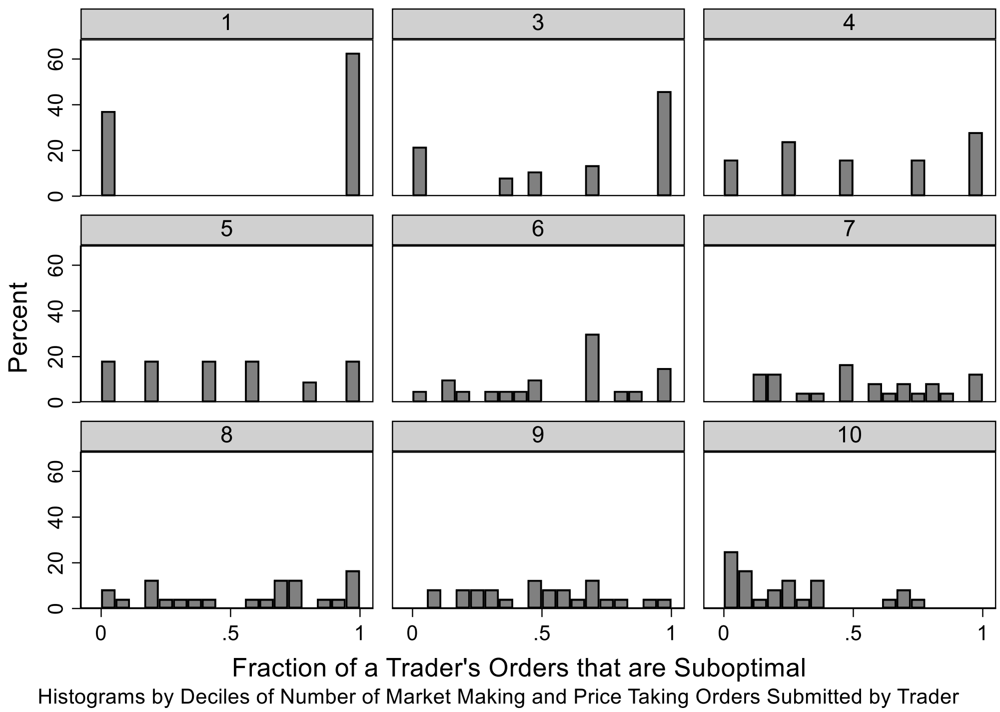

Figure 7: Histogram of the percentages of price-taking and market-making orders that are violations by deciles of the number of price-taking and market making orders submitted by the trader. (There is no 2nd decile because more than 20% of the traders only submitted one price-taking or market-making order and all are rolled into the 1st decile.)

Figure 8 shows the average violation index by trader activity decile. It appears that more active traders have fewer violations, but this is due entirely to a few extremely active traders. The raw correlation between activity level and the suboptimality index is 0.0998 with a significance level of 0.0630, but using a median regression, the significance level falls to 0.672. Thus, most traders fall prey to violations.

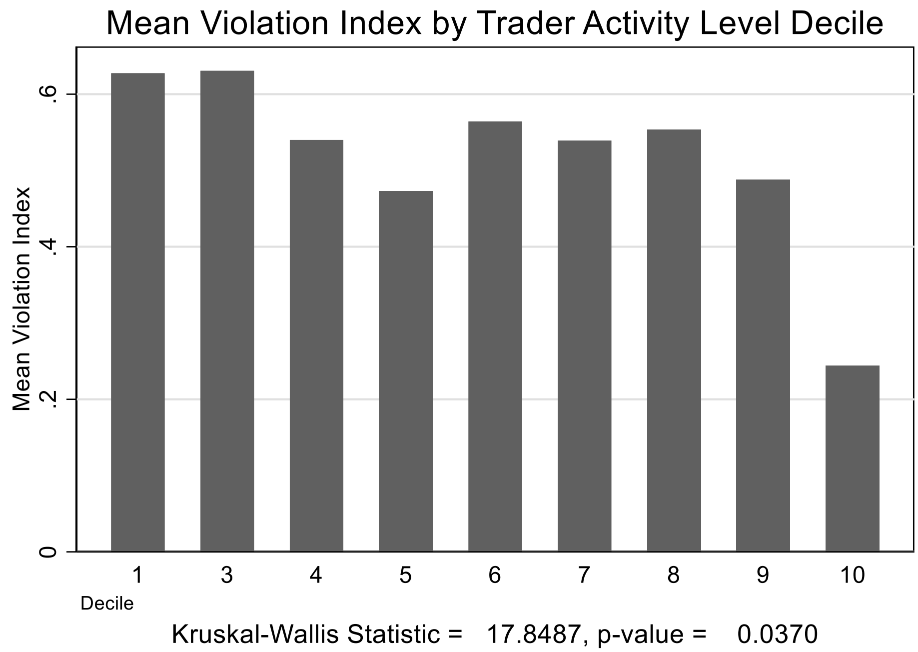

Figure 8: Impact of activity level on violations of rationality frequencies.

The evidence shows that the market is not populated by some rational and some irrational traders (as market microstructure posits). Rather, the market is populated by traders who sometimes appear to act irrationally. The field needs to develop a theory of this. However, as documented above, the market structure protects traders from their own mistakes to a significant degree. Finally, even though many traders appear to do irrational things, arbitrage trading forces prices into line and, over many years, IEM markets have proven themselves quite efficient. The field needs to develop a theory of sometimes-rational agents.

Overall, the evidence shows:

Result 15: Relatively few traders who place a significant number of price-taking or market-making orders, always violate rational pricing bounds. Similarly, relatively few always do. Thus, most active traders appear sometimes rational and sometimes irrational.

IV. More complex strategies

1. Buy and hold versus traded positions

Any individual contract trade that a trader makes establishes or unwinds a position. We define a buy and hold strategy to liquidation as any trade that (1) establishes a position that is (2) not unwound until the position is liquidated by the market. Similarly, we define a buy and hold strategy through election eve as one that is not unwound before midnight before election day. There are four ways to establish the same position:

1. Submit a purchase for a contract.
2. Submit a sale for the other contract in the portfolio.
3. Have a bid for a contract trade because it was accepted by another trader.
4. Have an ask for the other contract trade because it was accepted by another trader.

For example, buying a DEM20_WTA through either a purchase or bid would pay the holder $1 if held through the election. Similarly, buying a bundle from the market and selling the REP20_WTA would leave the trader with a DEM10_WTA that would also pay the holder $1 if held through the election. By this definition, bundle trades are not included because they do not establish a net position.

Table 8 summarizes positions established and held through liquidation (Panel A) or election eve (Panel B). Overall, traders were involved in 10,381 transactions establishing positions held through liquidation[16] for a total of 129,312 contracts, averaging nearly 12.5 contracts per transaction. Just over half of all transactions that established positions were held through liquidation.

We define "active trading" (buy and sell) strategies as any trade that establishes a position that is (1) unwound before it is liquidated by the market or (2) unwound before election day.[17] Positions are established in the same ways as buy and hold positions.

Table 9 summarizes transactions that establish active trading positions that are unwound before liquidation (Panel A) or election eve (Panel B). Overall, traders were involved in 10,216 active trading transactions[18] that were unwound before liquidation for a total of 145,852 contracts averaging 14.28 contracts per transaction. Just under half of all transactions that established positions were unwound before liquidation.

For each long Biden position, another trader holds a long Trump position. Similarly, every time a long Biden position is unwound, another trader unwinds a long Trump position. So, the number of contracts in positions held or unwound before liquidation or election eve is always equal across Biden and Trump. However, these are not evenly distributed across transactions. There were significantly more transactions establishing long Trump positions that were held to liquidation than long Biden

[1616] This includes 109 transactions that were partially held through liquidation. Panel B includes 110 positions that were partially held through midnight on election eve.

[1717] Of course, when it established, *we* cannot tell if a trader *intended* to unwind a potion before liquidation. We only observe whether the trader *actually* unwound a position before liquidation. Between election day and liquidation, traders may unwind positions with contract values known.

[1818] This includes 109 transactions that were partially unwound through liquidation. Panel B includes 110 positions that were partially unwound through midnight on election eve.

positions (t-statistic = 10.34, p-value=0.0000). On average long Trump positions lost value and long Biden positions gained. Therefore, this is consistent with a Disposition Effect on a transaction-by-transaction basis (Shefrin and Statman (1984), Odean (1998)).

Result 16: Traders appear prone to a disposition effect that makes them less likely to sell established positions after they lose value than after they gain value.

The buy-side of the market was significantly more likely to establish buy and hold positions than the sell-side. Overall, 9,089 buy-side trades established buy and hold positions involving 105,517 contracts, while 1,292 sell-side trades established buy and hold positions involving 23,795 contracts. Of those that established positions, 65% of buy-side transactions (64% of bids executed and 69% of purchases) while 19% of sell-side transactions (38% of sales and 13% of asks executed) did (t-statistic=67.44, p-value=0.0000). The opposite pattern holds for unwound positions. Again, results are similar for positions held through election-eve. Rietz (2005) documents a similar “purchasing bias” in laboratory versions of IEM markets. This is consistent with a differential willingness to pay and willingness to accept effect once an individual contract is purchased, similar to an endowment effect (Kahneman, Knetch and Thaler (1990)).

Result 17: Traders appear prone a purchasing bias or an endowment effect that makes them less likely to unwind a position established through a purchase than one established through a sale.

2. Buy and hold versus trading strategies

To assess strategies used by traders overall, we create a pseudo-dummy variable for each position established by the trader. This variable equals the fraction of the position-establishing trade that is held through liquidation. Thus, it is 1 for the 10,272 positions established that were held entirely through liquidation, 0 for the 10,107 positions established that were entirely unwound before liquidation, and the fraction of contracts held through liquidation for the 109 positions established that were partially unwound before liquidation. We define a buy and hold index variable for each trader that is the average of the trader’s buy and hold dummy variable. We define similar dummy variables and trader indices for positions held through midnight election eve.

Figure 9 show the distribution of buy and hold (versus active trading) indices for each trader. Panel A shows the indices for positions held through liquidation while Panel B shows indices for those held through election eve. In both cases, most traders either always held their positions or always unwound their positions. Of the 355 active traders, 39 (10.99%) never held an established position through liquidation, 193 (54.37%) held all established positions through liquidation, 101 (28.45%) held some, but not all, established positions through liquidation and 22 (6.20%) never established a net position.

Result 18: Most traders either always hold established positions or always unwind them.

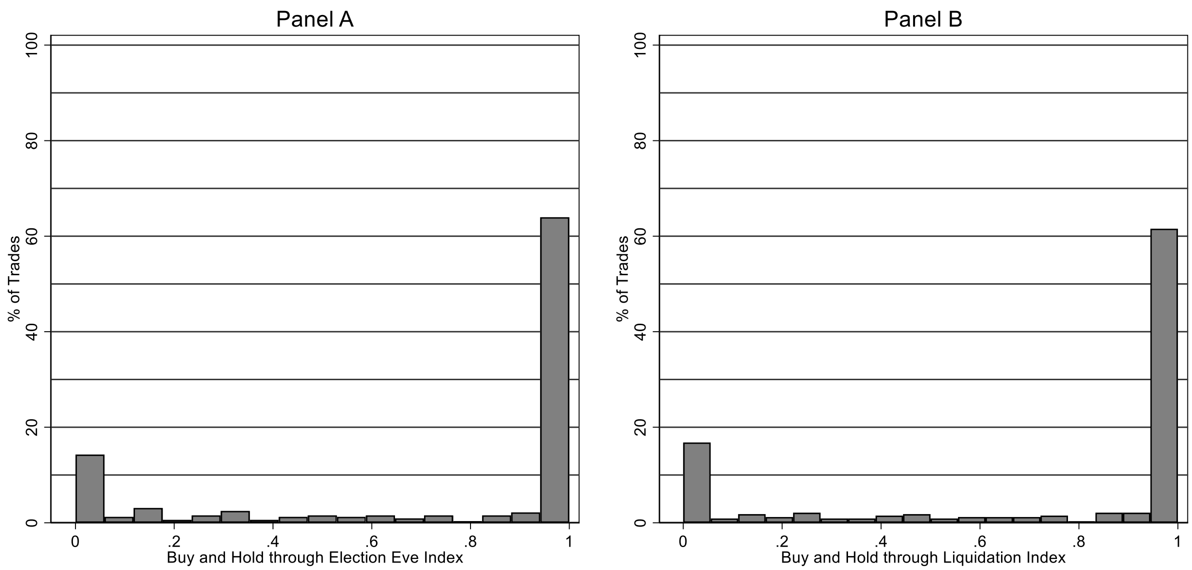

Figure 9: Distribution of buy and hold indices by trader. Panel A shows the index based on positions held through liquidation and Panel B shows the index based on those held through election eve.

The IEM is a zero-sum game. For every dollar in profits made by one trader, another trader or traders lost the same amount. For positions held through liquidation, the profit from the position is $1 minus the net price for every long Biden position and $0 minus the price for every long Trump position. For positions that are unwound, it is the difference in prices between establishing the position and unwinding it.

Figure 10 show the total profits for each trader resulting from each strategy. Panel A shows profits from buy and hold through liquidation strategies. The upper part represents traders who established long Biden position and held them through liquidation. Ex-post, these positions are profitable because they liquidated at $1. The x-axis shows the size of the position. The dashed line shows a linear fit to long Biden positions using a median (least absolute deviation) regression to dampen the effects of outliers. Larger positions lead to higher ex-post profits and deviations from the line represent traders who established positions at different initial prices. The lower part represents traders who established and held long Trump positions, which were losing positions ex-post. The dash-dot line shows a linear fit using median regression. Larger positions led to larger losses. Again, deviations from the line result from positions established at different prices.

The solid line is a linear fit to the overall data using median regression. It shows that, on average, traders who held positions lost money and the larger the position, the more they lost.

Panel B shows profits resulting from positions that were established, then unwound before liquidation (i.e., active trading strategies). The x-axis shows the number of contracts in the established positions of each trader (which were subsequently unwound). The solid line shows a linear fit using median regression while the dashed line shows a linear fit without the two outliers on the right side. Both show that, while some traders did very well and some lost a lot, active traders profited on average. The more they traded, the more they profited on average. This is the opposite of what Barber and Odean (2000) find.

Result 19: Traders who actively traded profited on average, while buy-and-hold traders lost on average. The larger the quantities in each strategy, the more the traders gained (for active trading) or lost (for buy-and-hold) on average.

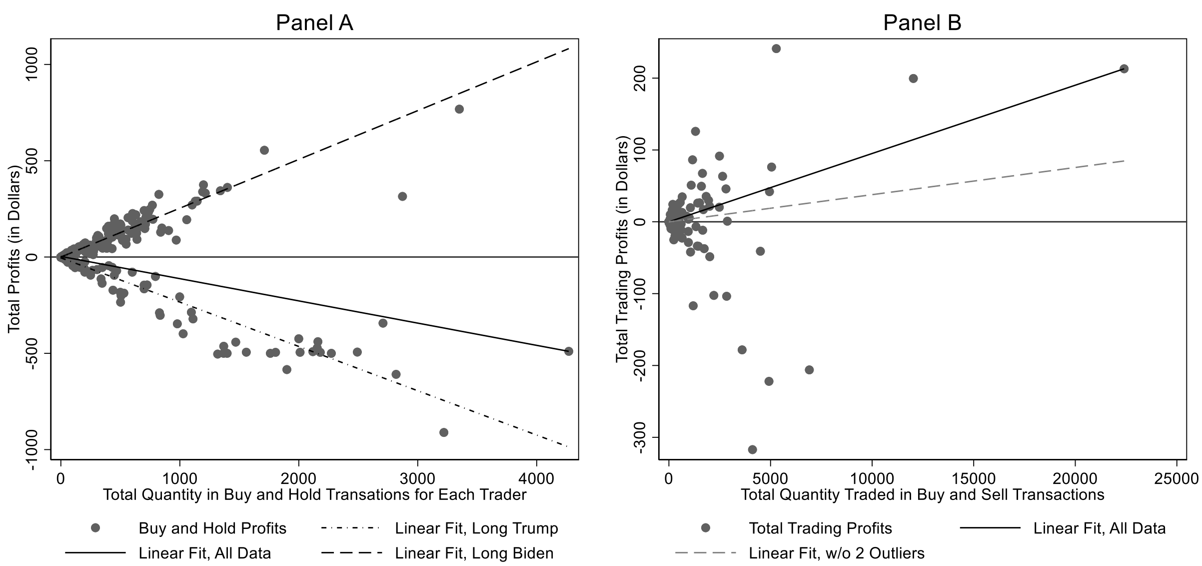

Figure 10: Total profits (in dollars) for traders resulting from buy and hold strategies (panel A) and active trading strategies (panel B). The x-axes give the total number of contracts used in the strategy by each trader.

3. Portfolio Trading and Arbitrage Strategies

Traders trade exchange bundles directly with the exchange for $1. Table 1 summarizes these transactions. The $1 price is fair because one or the other contract will pay $1 at liquidation. So, traders neither gain nor lose in such transactions. However, we can see how active traders are in exchange bundle transactions. For each trader, we find the total number of exchange bundles traded, the number purchased, and the number sold. Then, we calculate the ratio of purchased to total traded contracts. Of the 355 active traders, 249 (70.14%) never traded exchange bundles. Figure 11 Panel A shows a histogram of the total number of exchange bundles traded for traders who traded them. While the mean number traded across these 106 traders was 161 bundles, the median across all traders was 0 and some traders were much more active, trading up to 22,666 exchange bundles. Figure 11 Panel B shows the ratio of bundles purchased to the total number traded. Of the 106 traders who traded exchange bundles, 70 (66.04%) only purchased them. None only sold. More active traders bought and sold, but typically bought more than they sold.

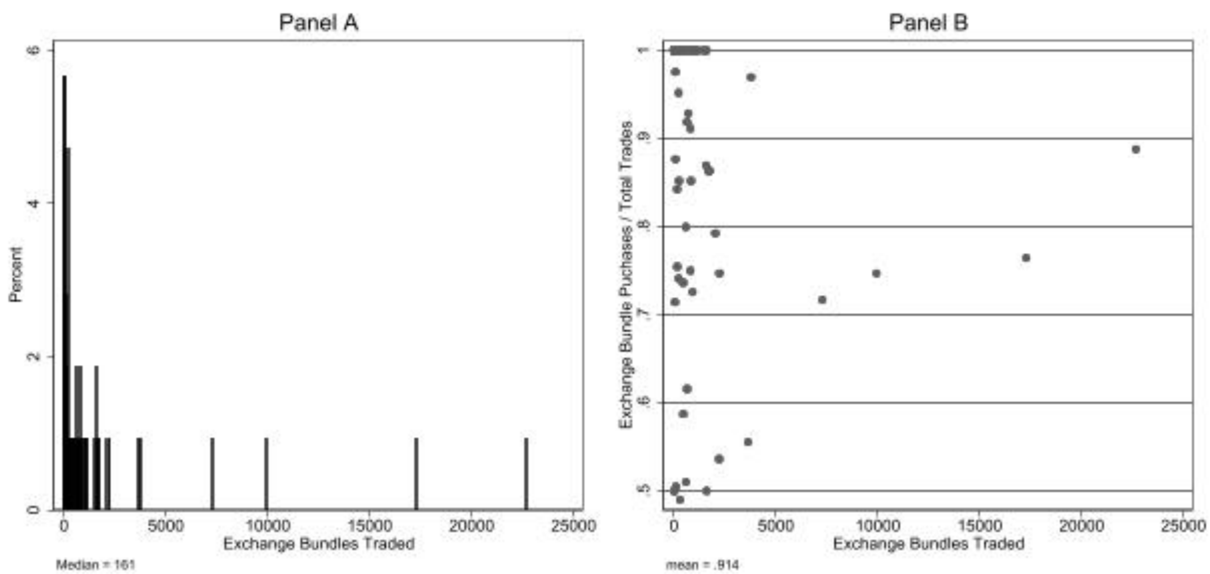

Figure 11: Exchange bundles traded for traders who traded in exchange bundles. Panel A shows a histogram of the total number of bundles traded. Panel B shows the ratio of bundles purchased to bundles traded by the total number of bundles traded.

Traders can also trade market bundles at the sum of the best bids or asks. This creates a potential arbitrage opportunity. If the bids sum to more than $1, a trader can profit by selling the market bundle and buying an exchange bundle. If the asks sum to less than $1, a trader can profit by doing the opposite.

Our first question is how long it takes to exploit arbitrage opportunities. Table 5 shows that 606 bids and asks overall created arbitrage opportunities. Of these, 379 also crossed the opposing queue and traded immediately. Two were immediately deemed infeasible. For one order, the arbitrage opportunity was eliminated because the person exploiting it 7 seconds later would have self-traded (in which case the orders are cancelled). Another bid lost queue priority because it was outbid 43 seconds later while 27 were put in the queue behind another order that had already created an arbitrage opportunity. These may have executed, but not until after the other order had cleared and only if the arbitrage opportunity still existed. Here, we focus on the 196 orders that created immediately exploitable arbitrage opportunities to see how long it took other traders to recognize and exploit the opportunities.

Figure 12 shows histograms of the time between when a feasible, non-crossing, arbitrage-creating bid or ask that had queue priority was entered and when it was traded. There are two outliers, where arbitrage opportunities existed for a few minutes. All but these two outliers traded in less than 10.5 seconds with an overall median of 5.6 seconds.

Result 20: Arbitrage opportunities are nearly always exploited withing 10 seconds of appearing, with a median of 5.6 seconds before the first arbitrage exploiting trade occurs.

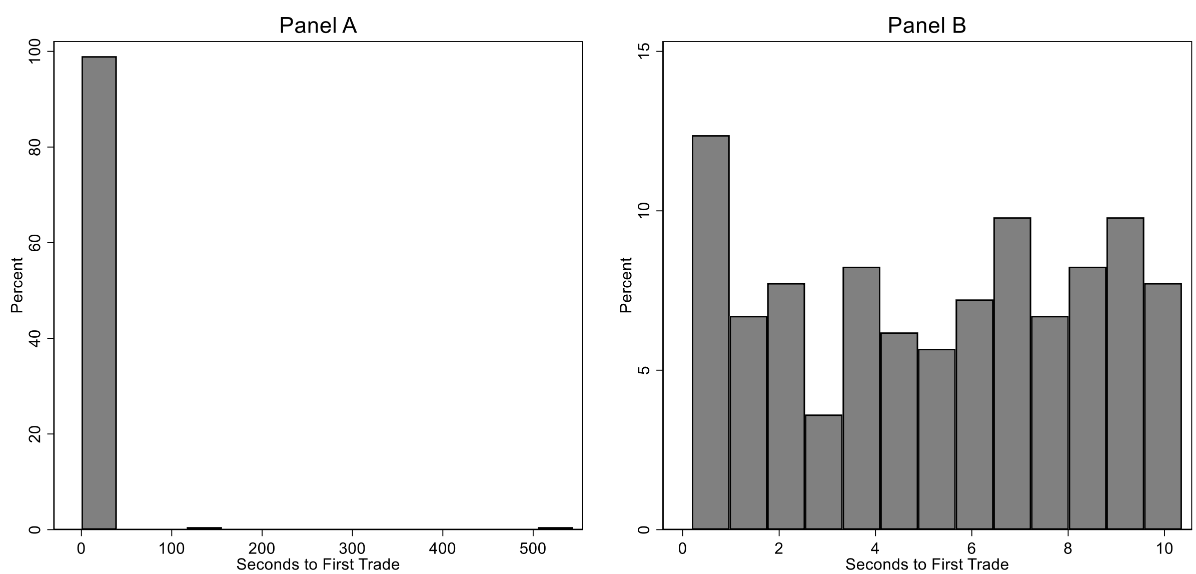

Figure 12: Time in seconds between when an arbitrage-creating, non-crossing bid or ask was entered and when it first traded

Table 2 shows that, while 19 unique traders submitted market bundle trade orders and 16 traded, only one made arbitrage profits. We report on this trader's strategy here.

Table 10 shows a typical arbitrage opportunity exploited by this trader. On March 10, 2019 at 22:31:08.0838, a trader placed a bid for 100 shares of Biden at $0.700. The best ask for Biden was

$0.680 for 14 shares followed by $0.695 for 10 shares. Thus, 24 shares traded immediately. This left the best bid for Biden at $0.700, while the best bid for Trump was $0.330, for a total of $1.03. Just 3.07 seconds later, the arbitrage trader started selling market portfolios as shown in Table 10. The trader entered 24 separate orders in a span of 11.20 seconds, selling 86 total market bundles (exhausting the Biden bid) and buying 86 exchange bundles, for a total profit of $2.58. This pattern was typical for the arbitrage trader except that the typical time to first trade was closer to 5 seconds and the quantity ordered was bumped up to 6 market bundles later in the market. This was not sufficient time to enter the orders by hand and is clear evidence of computerized trading.

Result 21: The arbitrage-exploiting trader was obviously computerized.

4. High Frequency Activity

Some traders, including the arbitrage trader discussed above, place orders at high frequency. The IEM system records order times to 1/10,000 seconds. Placing an order by hand through the web interface involves filling out a webform as follows: (1) selecting between market orders, limit orders or bundle orders by clicking on a link, (2) selecting a contract from a dropdown menu, (3) selecting an order type from a set of radio buttons, (4) filling in a quantity, (5) filling in a price if a limit order is selected, (6) accepting the default or changing the expiration time if a limit order is selected, (7) leaving a "view conformation" box checked or unchecking it, and (8) clicking a submit order button. A trader might click the "submit order" button twice before the screen refreshes. Or, a trader can reverse engineer the form and have a computer submit orders directly to the exchange using a script.

Figure 1 shows violin plots summarizing the distribution of times between actions for new orders submitted within one minute of a prior order or withdrawal[19] by the same trader. Panel A shows the distribution of the minimum time between orders submitted by a given trader if that minimum is less than one minute. There are 22 traders whose minimum time between orders is less than 5 seconds. Panel B summarizes the time differences between submitted orders across all orders submitted by the same trader with less than 1-minute differences. The left-hand side shows those for which the confirmation box was unchecked and the right-hand side shows those for which the confirmation box was checked. The bulk of orders with the confirmation box checked took more than 5 seconds while most without the confirmation box checked took less than 5 seconds.

[19] Placing an order directly through the interface takes many steps and is challenging to accomplish in 5 seconds by hand. In contrast, making a withdrawal of a prior order takes three mouse clicks and can be done quite rapidly by hand. Therefore, we look at the time between a prior action (order or withdraw) and the next order, and not between a prior action and a withdrawal.

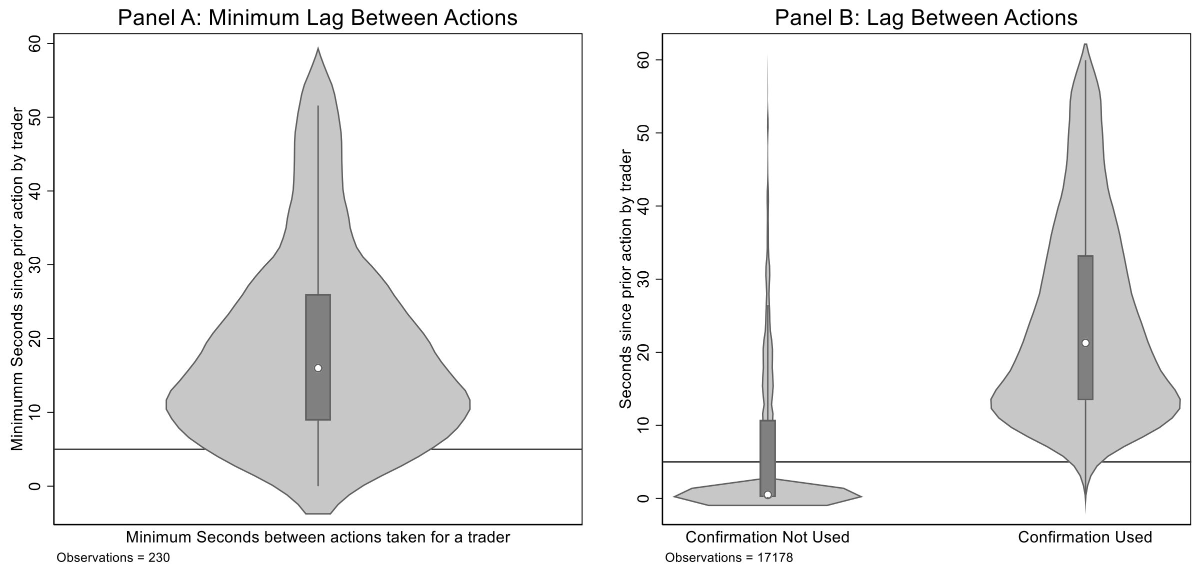

Figure 13: Violin plots of the lags between actions and orders for traders who submitted orders within one minute of another action. The width of the shaded area represents the density, the dot is the median, the box is the interquartile range, and the whiskers span the distribution except for outliers. Panel A shows the distribution of the minimum time between actions submitted by each trader who submitted orders within one minute of a prior action and Panel B shows the time between actions for trades submitted by the same trader within one minute of another action. The left had side shows orders that were submitted without confirmation and the right shows orders submitted with confirmation.

We take 5 seconds as an arbitrary cutoff and analyze the 22 traders with a lower minimum time between orders as potential computerized traders. Table 11 summarizes times between orders for traders who had at least one time between orders of less than 5 seconds. First, we filter out those who appear to have double clicked the submit button. 17 of the 22 traders had only one order placed within 5 seconds of another. The second highest time between orders for all these traders was more than 5 seconds. All these orders were the same as the previous order in terms of the order type, asset, price and quantity. These appear to be “double click” orders. In addition, Trader “O” had five sub-5 second orders, all of which appear to be double clicks.

Trader “G” is the arbitrage trader discussed above and obviously was computer trading. Out of 9,245 new orders placed withing 5 seconds of a prior action, 4,680 were associated with market and exchange bundle arbitrage trading. These orders keep prices withing arbitrage bounds and, in that sense, stabilize the market.

Other orders consisted of 3,137 asks, 1,403 bids, 1 purchase and 25 sales. These followed two relatively standard patterns based on both the arbitrage restriction and the law of one price. Consider again Figure 3 and suppose you want to buy a REP20_WTA. If you sell DEM20_WTA at the current ask ($0.905) and buy the exchange bundle for -$1.000, then you are plus 1 REP20_WTA for a net cost of $1-0.905=$0.095, less than both the current bid and ask for Trump. Trader H often placed a series of orders in apparent attempts to take advantage of such pricing asymmetries. The trader would place a new ask (or bid) at the current best ask (or bid). The trader would withdraw the ask (bid) when a new best ask (bid) improved the price, then immediately submit a new ask (or bid) at the new best ask (bid). Sometimes, this resulted in nothing more and simply stopped when the bids and asks became symmetric (i.e., they conformed to the law of one price). But, sometimes, it resulted in an arbitrage opportunity that Trader G exploited. And, sometimes, it resulted in purchases (or sales) at favorable prices. In either case, these orders provided depth to the market and, thus, stabilized market prices.

Table 12 shows an ask sequence in Biden that led to a favorable trade. The first ask in the table was for Biden at $0.725, It was withdrawn 5 seconds after another trader submitted a lower ask for $0.724. Just 0.160 seconds after the withdrawal, Trader G placed a new ask at the current best ask of $0.724. Every time the ask improved, Trader G withdrew their existing ask within 10 seconds (average 4.917 seconds) and placed a new ask at the new best ask a fraction of a second later (average 0.165 seconds). In every case, had they sold Biden and then purchased an exchange bundle, they would have effectively purchased Trump at less than the current best bid. Ultimately, Trader H sold Biden at $0.698 and purchased a bundle for $1, effectively purchasing a Trump for $0.302 (less than the best bid at the time $0.331). Trades like this are essentially an inside spread way of exploiting the failure of the law of one price due to asymmetries in the best bids and asks across contracts.

Table 13 shows a bid sequence that led to an arbitrage opportunity. Before the first bid in the table, Trader G held a bid for Biden at $0.631. That bid was withdrawn after the best bid improved to $0.632. Just 0.18 seconds after the withdrawal, Trader G placed a new bid at the current best bid of $0.632. Every time the bid improved, Trader G withdrew their existing bid within 10 seconds (average 5.866 seconds) and placed a new bid at the new best bid a fraction of a second later (average 0.156 seconds). In every case, had they purchased Biden and sold the portfolio, they would have effectively sold a Trump at more than the current best ask. Ultimately, the increasing best bid resulted in an arbitrage opportunity that Trader G began exploiting 3.05 seconds after it arose. Table 10 shows how

Trader G exploited this particular arbitrage opportunity.

In contrast to Trader G, who seemed to monitor the market constantly, Trader "H" entered orders on just a few days. But, these orders were typically placed in rapid fire sequences. For example, on May 19, 2019, Trader H placed 51 orders, many of them less than 5 seconds apart. This included 8 asks for Biden at 7 different prices, 17 bids for Biden at 16 different prices, 17 ask for Trump at 16 different prices, and 7 bids for Trump at 7 different prices. All were set to expire at midnight on election day. All were off-market (i.e., all bids were below the existing best bid and all asks above the existing best ask). Except for one Biden ask for one share (which was subsequently withdrawn), each Trump bid was a mirror image of a Biden ask (i.e., for the same quantity and at 1 minus the bid). The Trump asks exactly mirrored the Biden bids. Mostly, these were in nickel increments. These orders essentially fill the queue of off-market bids and asks. Trader H placed a similar series of orders on December 17, 2019 and October 26, 2020. On several other days, Trader H placed a small number of rapid-fire bids and asks, all off-market and apparently refilled parts of the queues. The queues prevent prices from moving quickly when someone places large bids or asks that cross the queues. Thus, these orders stabilized the markets.

On election day, Trader H placed 120 orders between 9:15 and 11:04 pm, many in less than 5 seconds, some milliseconds apart, for different contracts, at different prices. There was a series of off-market bids for Biden and asks for Trump. Then, Trader H took advantage of arbitrage opportunities with rapid bids and asks that matched opposing offers (instead of using the market bundle option). Orders were for one contract each and were usually less than a second apart, sometimes at the same recorded time. Each yielded an arbitrage profit. Finally, there was a long series of off-market bids for Biden. The next day, the trader placed a long series of off-market bids for Biden. Again, these filled queues and took advantage of arbitrage opportunities, stabilizing the market.

Result 22: At least two market traders used computerized scripts for trading. Both appear to stabilize the market by either exploiting arbitrage opportunities or filling the queue with off-market bids or asks that buffer price swings when traders cross queues.

V. Who is determining prices?

So far, we know a lot about who isn't determining prices in the market. The computerized traders are taking advantage of arbitrage opportunities through bundle trading or appear to be placing mostly off-market bids and asks. Bundle trades are at prices set by other traders and off-market bids and asks trade less frequently than market-making bids and asks. Traders who purchase and sell contracts are trading at prices set by others. Buy and hold traders have, at best, a transitory effect. Traders who place bids and asks that cross queues trade at prices set by others. Those who remain are traders who submit bids and asks that subsequently trade. We narrow our analysis to these bids, asks and traders and summarize their activities here. We further narrow our analysis to orders that were placed and traded by election eve because these trades determine market forecasts.

Of the 355 active traders, 181 placed at least one bid or ask that did not cross the queue and subsequently traded at the price set in the bid or ask, thus, determining a trade price by election-eve. Overall, these traders placed 1,415 non-crossing bids and 2,665 non-crossing asks that subsequently traded.[20]

We already know that market making bids and asks are less likely to violate rationality constraints than price taking orders. Here, we ask whether price-determining orders and price-determining traders are less likely to violate rationality constraints than other orders. The answer is yes. At the order level, we ask how often price-determining bids and asks are suboptimal relative to suboptimality rates for other individual contract orders that generated at least one trade. Figure 14 shows the difference in sub-optimality rates across price-determining orders and other orders that traded. Price-determining orders are significantly more rational in this sense.

[20] If we included queue-crossing bids and asks we add 14 traders and 884 orders, which leads to little change in the subsequent results.

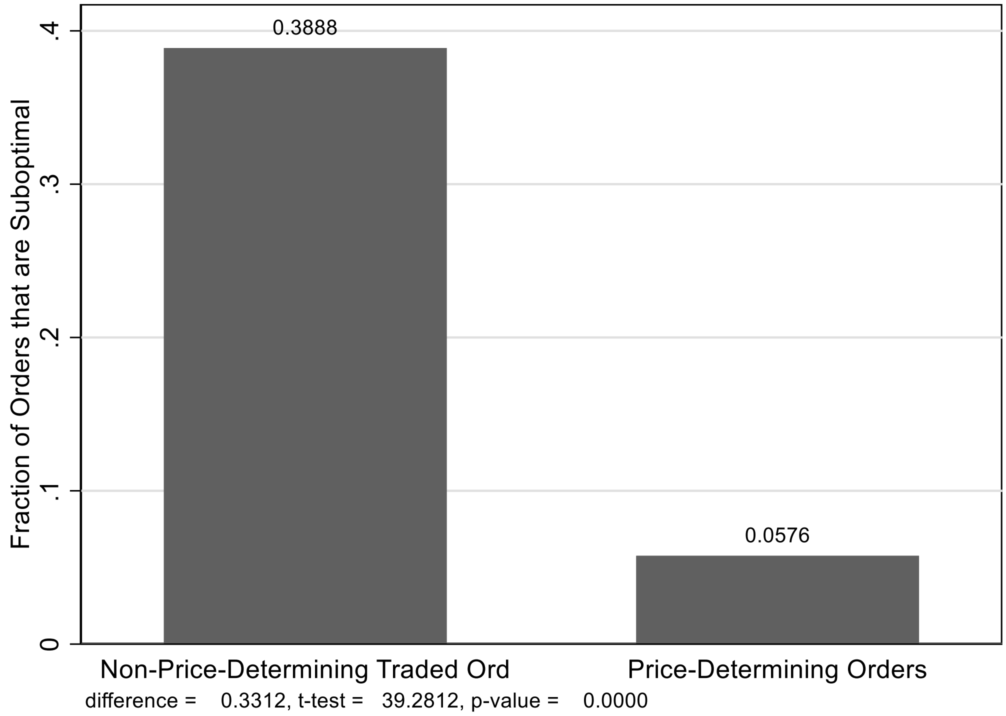

Figure 14: Fraction of orders that result in at least one trade that are suboptimal at the time the order was submitted by whether the order was a price-determining order

We can also ask whether orders that determine prices trade on average at better prices than those that trade at prices set by others. This measure is biased. First, price determining orders are bids and asks, therefore the bid/ask spread biases these orders to be more profitable on average. The average associated spread is $0.0298 across orders placed for individual contracts. We already know that many fewer price-determining orders are at suboptimal prices. Nor do they create arbitrage opportunities. Nevertheless, the average per-contract cash flows resulting from price-determining orders are higher than for non-price-determining, traded orders by significantly more than the bid/ask spread. Figure 15, Panel A shows the average cash flow per contract for non-price-determining orders across all orders in both contracts without adjusting for the ex-post value of the contracts. Panel B shows the average cash flow per contract for non-price-determining orders across all orders in both contracts adjusting for the ex-post value of the contracts (i.e., adding $1 to the cash flow for every DEM20_WTA purchased and subtracting $1 for every one sold). In either case, on average, price-determining orders traded at significantly better prices than other non-price-determining, traded orders.

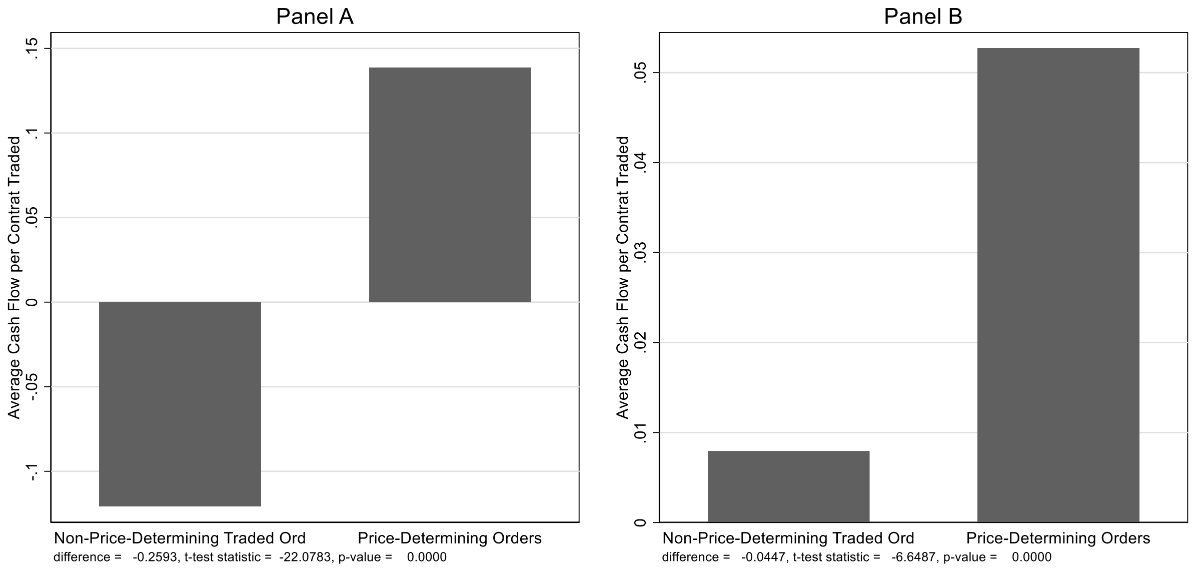

Figure 15: Average cash flow per contract for trades from price-determining orders versus non-price-determining orders. Panel A shows the unadjusted cash flows. Panel B shows cash flows adjusting for the final value of the contracts traded ($1 for DEM20_WTA and $0 for REP20_WTA)

At the trader level, we ask whether the trader's suboptimality index correlates with the number of price-determining orders they place. The number of price-determining orders submitted is highly skewed across traders, so we take the natural log of the number of price-determining orders submitted by each trader. Figure 16, Panel A shows a histogram of the log number of such orders. Then, we consider all the orders submitted by a trader that subsequently traded and ask what fraction was suboptimal at the time they were submitted. This determines a suboptimality index. Figure 16, Panel B clearly shows that the suboptimality rate declines with the number of price-determining orders submitted by a trader.

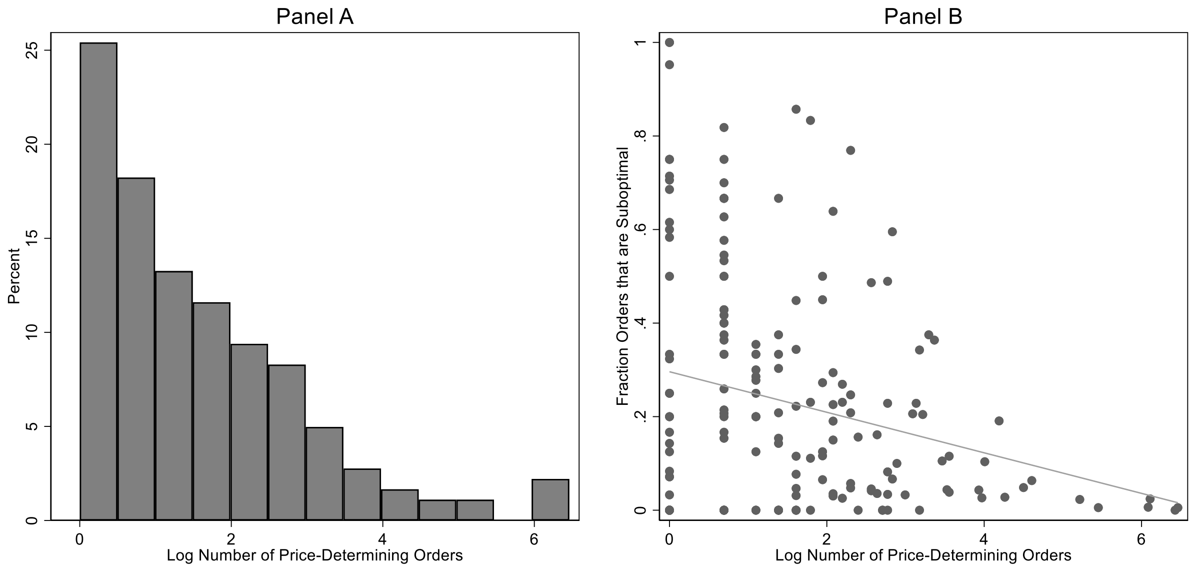

Figure 16: Panel A shows a histogram of the log of the number of price-determining orders submitted by each trader. Panel B shows the relationship between the log of the number of price-determing orders submitted by a trader and the fraction traded orders submitted by the trader that were subotpimal along with a linear fit line.

The correlation is -0.1724 across all 355 traders (p-value = 0.0012) and -0.1822 (p-value = 0.0142) across the 181 traders who submitted at least 1 price-determining order. We also generate a dummy variable that equals 1 if the trader put in at least one price-determining order. The ranksum statistic for the suboptimality index across this dummy variable is 7.721 (p-value = 0.0000). In summary:

Result 23: Price-determining orders are at more rational prices than other traded orders and they are more profitable both before the contract values are determined and after. Traders who submit more price-determining orders seem more rational than other traders. Further, the more active they are in submitting price-determining orders, the more rational these traders appear.

VI. Discussion

The IEM combines price dynamics and a market structure that mirror naturally occurring markets. It also has the simple structure and finite nature of laboratory markets. This blend makes the IEM a valuable testing ground for financial theory and can inform us about how markets populated by biased, mistake-prone traders can be, nonetheless, efficient.

Trading in this market is not perfectly rational. While the contracts mirror those in Milgrom and Stokey's (1982) "no trade theorem," there is significant trade. Traders do not divide clearly into two groups as assumed in market microstructure theory. Observed behavior is most consistent with

Hirshleifer and Teoh's (2003) concept of limited attention: traders do not always pay enough attention to make every trade rationally.

In addition to previously documented "false consensus" (Forsythe, et al. (1992)) and "wishful thinking" (Forsythe, Rietz and Ross (1999)) effects, we document two additional trader biases: a disposition effect and a version of the endowment effect. We also replicate a previously published anomaly that traders frequently to not trade at the best prices (Oliven and Rietz (2004)). This anomaly has not abated post publication. The apparent efficiency of the market combined with the biases and irrationalities runs counter to the standard behavioral finance argument. Instead, we find that more rational, price-determining traders set prices while arbitrage traders keep prices close to arbitrage bounds. Combined with the market structure, this provides significant protection to more biased and irrational traders.

We study the strategies employed by traders and their profitability. Arbitrage trading keeps prices in line, but leads to low profits. Many traders buy and hold. On average, these traders lose money. Active traders gain and, the more active they are, the more they gain and the more rational they appear. This runs counter to data from Barber and Odean (2000). We observe computerized trading that appears to stabilize prices in our market.

We show how traders and the market structure interact to form prices and discuss how these interactions may lead to efficient prices in spite of trader biases and irrationalities. In future research, we hope to provide further evidence by analyzing additional markets, studying more advanced strategies in a given market and investigating trader behavior across markets.

VII. References

Agnew, Julie, Pierluigi Balduzzi, and Annika N. Sunden. 2023. "Portfolio Choice and Trading in a Large 401(k) Plan." 93 (1): 193-215.

Barber, Brad M., and Terrance Odean. 2000. "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors." *Journal of Finance* 55 (2): 773-806.

Berg, Joyce E., and Thomas A. Rietz. 2019. "Longshots, Overconfidence and Efficiency on the Iowa Electronic Market." *International Journal of Forecasting* 35 (1): 271-287.

Berg, Joyce E., Forrest D. Nelson, and Thomas A. Rietz. 2008. "Prediction Market Accuracy in the Long Run." *International Journal of Forecasting* 24 (2): 283-298.

Berg, Joyce E., Thomas S. Gruca, and Thomas A. Rietz. 2022. "Designing Prediction Markets to Forecast Multi-Stage Elections: The 2022 French Presidential Election." *PS-Political Science & Politics* 55 (4): 719-725.

Forsythe, Robert, Forrest Nelson, George R. Neumann, and Jack Wright. 1992. "Anatomy of an Experimental Political Stock Market." *The American Economic Review* 82 (5): 1142-1161.

Forsythe, Robert, Thomas A. Rietz, and Thomas W. Ross. 1999. "Wishes, Expectations and Actions: A Survey on Price Formation in Election Stock Markets." *Journal of Economic Behavior and Organization* 39: 83-110.

Goldstein, Michael A., Pavitra Kumar, and Frank C. Graves. 2014. "Computerized and High-Frequency Trading." *The Financial Review* 49: 177–202.

Hayes, Adam. 2023. *Behavioral Finance,: Biases, Emotions and Financial Behavior.* June 27. Accessed August 16, 2023. https://www.investopedia.com/terms/b/behavioralfinance.asp.

Hirshleifer, David, and Seiw Hong Teoh. 2003. "Limited attention, information disclosure, and Financial Reporting." *Journal of Accounting and Economics*, 337–386.

Hou, Kewei, Chen Xue, and Lu Zhang. 2020. "Replicating Anomalies." *The Review of Financial Studies* 33 (5): 2019-2133.

Jones, Charles M. 2013. "What do we Know about High-frequency Trading?" *SSRN Working Paper* 1-55. Accessed August 18, 2023. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2236201.

Kahneman, Daniel, Jack L. Knetch, and Richard H. Thaler. 1990. "Experimental Tests of the Endowment Effect and the Coase Theorem." *Journal of Political Economy* 98 (6): 1325-1348.

Madhavan, Ananth. 2000. "Market microstructure: A survey." *Journal of Financial Markets*, 205-258.

Majumder, Saikat Ray, Daniel Diermeier, Thomas A. Rietz, and Amaral. Luís A. Nunes. 2009. "Price dynamics in political prediction markets." *Proceedings of the National Academy of Sciences* 106 (2): 679-684.

Milgrom, Paul, and Nancy Stokey. 1982. "Information, Trade and Common Knowledge." *Journal of Economic Theory*, 17-27.

Odean, Terrance. 1998. "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance* 53 (5): 1775-1798.

Oliven, Kenneth, and Thomas A. Rietz. 2004. "Suckers are Born, but Markets are Made: Individual Rationality, Arbitrage and Market Efficiency on an Electronic Futures Market." *Management Science* 50 (3): 336-351.

Rietz, Thomas A. 2005. "Behavioral Mis-pricing and Arbitrage in Experimental Asset Markets." *University of Iowa Finance Dapartment Working Paper.* Accessed September 8, 2023. https://www.biz.uiowa.edu/faculty/trietz/papers/market.pdf.

Schwert, G William. 2003. *Anomalies and Market Efficiency.* Vol. 1B, chap. 15 in *Handbook of the Economics of Finance*, by G.M. Constantinides, M. Harris and R.M. Stulz, 939-974. Amsterdam: Elsevier.

Shefrin, Hersh, and Meir Statman. 1984. "The Disposition to Sell Winners Too Early and Ride Loser Too Long: Theory and Evidence." *Journal of Finance* 40 (2): 777-790.

Shleifer, Andrei. 2000. *Inefficient Markets: An Introduction to Behavioral Finance.* Oxford: Oxford University Press.

Shleifer, Andrei, and Robert W. Vishny. 1997. "The Limits of Arbitrage." *The Journal of Finance*, 35-55.

VIII. Tables

Table 1:Summary of Bundle Transactions

Item	Exchange Transactions Purchases	Exchange Transactions Sales	Exchange Transactions Overall	Market Transactions Purchases	Market Transactions Sales	Market Transactions Overall
Overall Summary Statistics						
No. of Unique Traders Submitting Orders	106	36	106	10	11	19
No. of Unique Traders Trading	106	36	106	9	9	16
No. of Unique Traders making Arb. Profits	N/A	N/A	N/A	1	1	1
No. of Orders	2,698	552	3,250	449	4,141	4,590
Statistics on Quantity Ordered						
Total Quantity Ordered	84,987	23,730	108,717	3,789	22,053	25,842
Average per Order	31.50	42.99	33.45	8.44	5.33	5.63
Standard Deviation	69.89	228.71	113.77	26.53	18.34	19.31
Median	10.00	5.00	10.00	6.00	4.00	4.00
90th %'ile	90.00	85.00	89.50	6.00	6.00	6.00
Statistics on Quantity Traded						
Total Quantity Traded	84,979	18,530	103,509	2,449	18,356	20,805
Average per Order	31.50	33.57	31.85	5.45	4.43	4.53
Standard Deviation	69.89	85.43	72.75	5.38	2.59	3.00
Median	10.00	5.00	10.00	6.00	4.00	4.00
90th %'ile	90.00	85.00	89.50	6.00	6.00	6.00
Statistics on Prices						
Average Price Ordered	$1.000	$1.000	$1.000	$0.996	$ 1.010	$1.009
Standard Deviation	$0.000	$0.000	$0.000	$0.008	$ 0.012	$0.012
Average Price Traded	$1.000	$1.000	$1.000	$0.995	$ 1.010	$1.009
Standard Deviation	$0.000	$0.000	$0.000	$0.008	$ 0.012	$0.012

Table 2: Summary of Simple Bundle Trading Strategies

Item	Exchange Bundles			Market Bundles		
	Purchases	Sales	Overall	Purchases	Sales	Overall
Overall Summary						
No. of Unique Traders	355	355	355	355	355	355
No. Undertaking Action	106	36	106	10	11	19
Percent Undertaking Action at Least Once	29.86%	10.14%	29.86%	2.82%	3.10%	5.35%
No. of Traders Only Taking this Action	0	0	0	1	0	1
% of Traders Only Taking this Action	0.00%	0.00%	0.00%	0.28%	0.00%	0.28%
No. of Traders Only Taking this Action and Exchange Bundle Trades	N/A	N/A	N/A	1	0	1
% of Traders Only Taking this Action and Exchange Bundle Trades	N/A	N/A	N/A	0.28%	0.00%	0.28%
Summary of Acts per Trader						
Average No. of Acts per Trader	25.45	15.33	30.66	44.90	376.45	241.58
Std. Dev.	107.57	39.13	129.94	134.28	1236.29	1038.74
Median	4.00	2.50	4.00	1.00	3.00	1.00
90th Percentile of No. of Acts per Trader	37.00	53.00	37.00	217.50	9.00	15.00
Summary of Arbitrage Transactions						
No. of Traders Making Arbitrage Profits	N/A	N/A	N/A	1	1	1
% of Traders Making Arbitrage Profits	N/A	N/A	N/A	0.28%	0.28%	0.28%
No. of Arbitrage Profit Trades	N/A	N/A	N/A	425	4119	4544
Total Quantity of Bundles Traded	N/A	N/A	N/A	2,086	17,803	19,889
Total Arbitrage Profit	N/A	N/A	N/A	$11.55	$174.97	$186.52

Table 3:Summary of Purchase and Sale Orders

	DEM20_WTA		REP20_WTA		Overall	
Item	**Purchases**	**Sales**	**Purchases**	**Sales**	**Purchases**	**Sales**
Overall Summary Statistics						
No. of Unique Traders	164	57	90	73	218	100
No. of Unique Traders not Trading at Best Price	130	31	69	18	177	45
No. of Orders	1,108	564	793	988	1,901	1,552
No. of Orders not at Best Price	636	111	559	63	1195	174
% of Orders not at Best Price	57.40%	19.68%	70.49%	6.38%	62.86%	11.21%
Statistics on Quantity Ordered						
Total Quantity Ordered	16,774,397	25,202	77,857	36,004	16,852,254	61,206
Average per Order	15,139.35	44.68	98.18	36.44	8,864.94	39.44
Standard Deviation	159,065.40	100.32	193.69	99.45	121,641.60	99.81
Median	19.50	10.00	40.00	8.00	20.00	10.00
90th %'ile	110.00	108.00	200.00	100.00	200.00	100.00
Statistics on Quantity Ordered without One Trader who Ordered more than 11,000,000 contracts of DEM20_WTA in a 20-Minute Period						
Total Quantity Ordered	69,747	25,202	77,857	36,004	147,604	61,206
Average per Order	63.99	44.68	98.18	36.44	78.39	39.44
Standard Deviation	150.12	100.32	193.69	99.45	170.62	99.81
Median	17.00	10.00	40.00	8.00	20.00	10.00
90th %'ile	100.00	108.00	200.00	100.00	150.00	100.00
Statistics on Quantity Traded						
Total Quantity Traded	19,739	8,493	17,314	22,017	37,053	30,510
Average per Order	17.81	15.06	21.83	22.28	19.49	19.66
Standard Deviation	24.91	30.74	33.24	57.27	28.74	49.42
Median	10.00	7.00	10.00	5.00	10.00	6.00
90th %'ile	50.00	31.00	54.00	50.00	50.00	50.00
Statistics on Prices						
Average Price Ordered	$0.716	$0.697	$0.322	$0.257	$0.552	$0.417
Standard Deviation	$0.090	$0.113	$0.107	$0.079	$0.217	$0.231
Average Price Traded	$0.715	$0.696	$0.323	$0.257	$0.552	$0.416
Standard Deviation	$0.090	$0.112	$0.107	$0.079	$0.217	$0.231

Table 4: Summary of Simple Purchase/Sale Trading Strategies

	DEM20_WTA		REP20_WTA		Overall	
Item	**Purchases**	**Sales**	**Purchases**	**Sales**	**Purchases**	**Sales**
Overall Summary						
No. of Unique Traders	355	355	355	355	355	355
No. Undertaking Action	164	57	90	73	218	100
% Undertaking Action	46.20%	16.06%	25.35%	20.56%	61.41%	28.17%
No. of Traders Only Taking this Action	57	0	20	0	81	0
% of Traders Only Taking this Action	16.06%	0.00%	5.63%	0.00%	22.82%	0.00%
No. of Traders Only Taking this Action and Exchange Bundle Trades	57	0	20	1	81	1
% of Traders Only Taking this Action and Exchange Bundle Trades	16.06%	0.00%	5.63%	0.28%	22.82%	0.28%
Summary of Acts per Trader						
Average No. of Acts per Trader	6.76	9.89	8.81	13.53	8.72	15.52
Std. Dev.	13.12	16.40	14.94	26.01	15.70	29.62
Median	3.00	3.00	3.00	4.00	3.00	4.00
90th %'ile	16.00	27.00	20.50	46.00	21.00	52.00
Summary of Sub-Optimal Trading						
No. of Traders Trading at Sub-Optimal Prices	130	31	69	18	177	45
% of Traders	36.62%	8.73%	19.44%	5.07%	49.86%	12.68%
Average No. of Trades	4.89	3.58	8.10	3.50	6.75	3.87
Std. Dev.	9.14	5.16	12.81	2.75	11.76	4.65
Median	2.00	1.00	3.00	2.50	3.00	2.00
90th %'ile	11.50	8.00	19.00	9.00	17.00	9.00
Total Potential Loss Exposure	$1,026,593.00	$63.27	$973.74	$117.93	$1,027,566.00	$181.20
Upper Bound on Realized Losses	$245.48	$14.25	$274.88	$55.67	$520.36	$69.92

Table 5: Summary of Bid and Ask Orders

Item	Dem20_WTA Bids	Dem20_WTA Asks	REP20_WTA Bids	REP20_WTA Asks	Overall Bids	Overall Asks
Overall Summary Statistics						
No. of Unique Traders	176	98	132	109	235	134
No. of Orders	3,371	4,396	2,485	4,745	5,856	9,141
No. of Unique Traders with Market-making Orders	137	84	111	91	166	166
No. of Market-making Orders	1,917	2,223	1,337	2,426	3,254	4,649
Arbitrage-Creating Summary Statistics						
No. of Unique Traders Creating Arb. Opps.	74	53	59	25	125	64
No. of Orders Creating Arb. Opps.	223	99	228	56	451	155
Percentage of Orders Creating Arb. Opps.	6.62%	2.25%	9.18%	1.18%	7.70%	1.70%
No. of Market-making Orders Creating Arb. Opps.	223	99	228	55	451	154
% of Market-making Orders Creating Arb. Opps.	11.63%	4.45%	17.05%	2.27%	13.86%	3.31%
Statistics on Quantity Ordered						
Total Quantity Ordered	11,000,169,631	1,186,553	11,000,235,859	344,559	22,000,405,490	1,531,112
Average per Order	3,263,176.99	269.92	4,426,654.27	72.62	3,756,899.84	167.50
Standard Deviation	173,088,633.13	15,101.22	201,595,194.09	1,075.15	185,704,901.04	10,500.80
Median	10.00	10.00	11.00	10.00	10.00	10.00
90th %'ile	100.00	65.00	200.00	80.00	100.00	75.00
Statistics on Quantity Ordered w/o Two Traders who Bid Zero for More than 1,000,000,000 Contracts Each						
Total Quantity Ordered	166,346	184,997	232,749	322,794	399,095	507,791
Average per Order	49.61	42.20	94.50	68.58	68.62	55.86
Standard Deviation	247.88	766.96	383.23	1,068.96	313.20	935.62
Median	10.00	10.00	11.00	10.00	10.00	10.00
90th %'ile	100.00	64.00	185.00	80.00	100.00	70.00

Item	Dem20_WTA		REP20_WTA		Overall	
	Bids	Asks	Bids	Asks	Bids	Asks
Statistics on Quantity Traded						
Total Quantity Traded	42,332	37,671	74,104	53,494	116,436	91,165
Average per Order	12.56	8.57	29.82	11.27	19.88	9.97
Standard Deviation	49.12	32.77	122.12	57.08	88.25	47.00
Median	0.00	0.00	0.00	0.00	0.00	0.00
90th %'ile	25.00	23.00	70.00	24.00	50.00	23.00
Statistics on Prices						
Average Price Ordered	$0.680	$0.729	$0.270	$0.319	$0.506	$0.516
Standard Deviation	$0.122	$0.107	$0.096	$0.103	$0.231	$0.230
Average Price Traded	$0.711	$0.721	$0.274	$0.301	$0.515	$0.510
Standard Deviation	$0.098	$0.091	$0.091	$0.102	$0.238	$0.231

Table 6: Summary of Simple Bid/Ask Trading Strategies

	DEM20_WTA		REP20_WTA		Overall	
Item	**Bids**	**Asks**	**Bids**	**Asks**	**Bids**	**Asks**
Overall Summary						
No. of Unique Traders	355	355	355	355	355	355
No. Undertaking Action	176	98	132	109	235	134
%Undertaking Action	49.58%	27.61%	37.18%	30.70%	66.20%	37.75%
No. of Traders Only Taking this Action	26	0	21	0	52	0
% of Traders Only Taking this Action	7.32%	0.00%	5.92%	0.00%	14.65%	0.00%
No. of Traders Only Taking this Action and Exchange Bundle Trades	26	2	21	2	52	8
% of Traders Only Taking this Action and Exchange Bundle Trades	7.32%	0.56%	5.92%	0.56%	14.65%	2.25%
Summary of Acts per Trader						
Average No. of Acts per Trader	19.15	44.86	18.83	43.53	24.92	68.22
Std. Dev.	79.84	197.92	76.54	190.22	126.18	341.82
Median	3.00	3.00	4.00	4.00	5.00	5.00
90th %'ile	26.00	63.00	26.00	59.00	30.00	73.00
Summary of Bids at 0 and Asks at 1						
No. of Submitting Traders Submitting Such Bids/Asks	3	1	4	0	4	1
% of Submitting Traders	1.70%	1.02%	3.03%	0.00%	1.70%	0.75%
Total Quantity Submitted	11,000,009,999	2,000	11,000,010,999	0	22,000,020,998	2,000
Total Quantity Traded	0	0	0	0	0	0
Summary of Off-Market Bids and Asks not at 0 or 1						
No. of Submitting Traders Submitting Such Bids/Asks	108	49	72	63	140	80
% of Submitting Traders	61.36%	50.00%	54.55%	57.80%	59.57%	59.70%
Total Quantity Submitted	57,664	1,038,233	77,387	70,217	135,051	1,108,450
Total Quantity Traded	6,054	6,123	10,406	10,636	16,460	16,759

	DEM20_WTA		REP20_WTA		Overall	
Item	**Bids**	**Asks**	**Bids**	**Asks**	**Bids**	**Asks**
Summary of Market-Making Bids and Asks						
No. of Submitting Traders Submitting Such Bids/Asks	138	85	113	92	211	119
% of Submitting Traders	78.41%	86.73%	85.61%	84.40%	89.79%	88.81%
Total Quantity Submitted	101,945	146,310	147,373	274,332	249,318	420,642
Total Quantity Traded	36,278	31,548	63,698	42,858	99,976	74,406
Summary of Queue-Crossing Bids and Asks						
No. of Submitting Traders Submitting Such Bids/Asks	54	55	53	44	97	75
% of Submitting Traders	30.68%	56.12%	40.15%	40.37%	41.28%	55.97%
Total Quantity Submitted	16,578	18,528	42,360	26,532	58,938	45,060
Total Quantity Traded	10,491	8,067	24,385	14,500	34,876	22,567
Total Loss Exposure	$93.35	$4,116.09	$2,746.51	$183.68	$2,839.86	$4,299.77
Upper Bound for Realized Loss	$44.19	$40.87	$178.14	$39.33	$222.32	$80.20
Protection Provided by Market	$49.16	$4,075.22	$2,568.37	$144.36	$2,617.53	$4,219.58
Summary of Arbitrage-Creating Bids and Asks						
No. of Submitting Traders Submitting Such Bids/Asks	74	53	59	25	125	64
% of Submitting Traders	42.05%	54.08%	44.70%	22.94%	53.19%	47.76%
% of Market-making Traders	53.62%	62.35%	52.21%	27.17%	59.24%	53.78%
Total Quantity Ordered	26,075	10,426	46,928	9,385	73,003	19,811
Total Quantity Traded	15,496	4,641	30,115	5,950	45,611	10,591
Total Loss Exposure	$245.67	$4,139.98	$2,950.45	$76.42	$3,196.11	$4,216.40
Upper Bound for Realized Loss	$156.98	$26.64	$345.05	$7.43	$502.03	$34.07
Protection Provided by Market	$88.69	$4,113.34	$2,605.40	$68.99	$2,694.08	$4,178.12

Table 7: Logit Model Replicating Oliven and Rietz (2004)

Independ Variable	**Estimated Coefficient**	**Std. Err.**	**Z-Statistic**
Role (1=Market Maker, 0=Price Taker)	-2.0542	0.0696	-29.51*
Size (1=S	-1.6573	0.0740	-22.41*
ln(Order Size)	0.1737	0.0202	8.62*
ln(Order Number)	-0.4447	0.0199	-22.30*
ln(Relative Spread)	0.5560	0.0283	19.61*
Constant	1.4101	0.1007	14.00*

Model Classification Table

Predicted	Observed Negative (Non-violation)	Observed Positive (Violation)	Total
Negative	1,105 (73.18%)	405 (26.82%)	1,510 (100%)
Positive	869 (8.85%)	8,946 (91.15%)	9,815 (100%)
Total	1,974 (17.43%)	9,351 (82.57%)	11,325 (100%)

(Dependent Variable = 1 if Violation Occurs)

Log Likelihood =	-3,119.94	$\chi^2(5)$=	4239.06
Number of Obs. =	11,325	Prob. > χ^2 =	0.0000
Model Sensitivity =	55.98%	Psuedo-R^2 =	0.4045
Model Specificity =	95.67%	Area under ROC Curve =	0.9017

Table 8: Summary of Transactions that Establish "Buy and Hold" Positions that are Held through Liquidation or Election Eve

Panel A: Buy and Hold Potions Held through Liquidation							
	Position Taken			Original Order Type			
	Overall	Long Biden	Long Trump	Bid	Purchase	Sale	Ask
Number of Transactions	10,381	5,571	4,810	7,434	1,655	637	655
% of Total Transactions of Type that are Buy and Hold	50.43%	49.02%	54.41%	64.11%	69.33%	37.69%	13.16%
Total Quantity Bought and Held	129,312	64,656	64,656	78,759	26,758	10,258	13,537
Average Quantity in Transaction	12.46	11.61	13.44	10.59	16.17	16.10	20.67
Standard Deviation	32.85	25.01	40.04	33.71	24.94	34.54	36.45

Panel B: Buy and Hold Positions Held through Midnight Election Eve							
	Position Taken			Original Order Type			
	Overall	Long Biden	Long Trump	Bid	Purchase	Sale	Ask
Number of Transactions	9,553	5,138	4,415	6,681	1,593	647	632
% of Total Transactions of Type that are Buy and Hold	50.91%	49.50%	55.02%	64.07%	70.68%	41.34%	13.84%
Total Quantity Bought and Held	119,012	59,506	59,506	71,074	24,938	10,403	12,597
Average Quantity in Transaction	12.46	11.58	13.48	10.64	15.65	16.08	19.93
Standard Deviation	32.57	24.42	39.99	33.64	24.66	34.40	34.62

Table 9: Trades that Establish Positions that are Unwound Before Liquidation or Election Eve

Panel A: Active Trading Positions Unwound before Liquidation

	Position Taken			Original Order Type			
	Overall	**Long Biden**	**Long Trump**	**Bid**	**Purchase**	**Sale**	**Ask**
Number of Transactions	10,216	4,756	5,460	4,174	740	1,045	4,257
% of Total Transactions of Type that are Unwound	49.57%	45.97%	53.16%	35.89%	30.67%	62.31%	86.84%
Total Quantity Established and Unwound	145,852	72,926	72,926	37,677	10,295	20,252	77,628
Average Quantity in Transaction	14.28	15.33	13.36	9.03	13.91	19.38	18.24
standard Deviation	37.48	43.97	30.71	27.13	25.79	52.46	42.56

Panel B: Active Trading Positions Unwound before Midnight Election Eve

	Position Taken			Original Order Type			
	Overall	**Long Biden**	**Long Trump**	**Bid**	**Purchase**	**Sale**	**Ask**
Number of Transactions	9,219	4,273	4,946	3,755	669	912	3,883
% of Total Transactions of Type that are Unwound	49.09%	45.33%	52.85%	35.93%	29.32%	58.66%	86.16%
Total Quantity Established and Unwound	125,558	62,779	62,779	31,170	8,859	17,406	68,123
Average Quantity in Transaction	13.62	14.69	12.69	8.30	13.24	19.09	17.54
Standard Deviation	34.35	41.44	26.72	22.18	23.40	47.20	40.73

Table 10: Orders placed and traded by the arbitrage trader exploiting a single arbitrage opportunity on March 10, 2019

Order Time	Resolution Time	Bundle	Type	Quantity	Price	Elapsed Time from Prior Resolution (Sec.)
22:31:11.15311 pm	22:31:11.16911 pm	Market	Sale	4	1.03	
22:31:11.64011 pm	22:31:11.64911 pm	Market	Sale	4	1.03	0.471
22:31:12.11012 pm	22:31:12.11912 pm	Market	Sale	4	1.03	0.461
22:31:12.58912 pm	22:31:12.60012 pm	Market	Sale	4	1.03	0.470
22:31:13.09713 pm	22:31:13.12013 pm	Market	Sale	4	1.03	0.497
22:31:13.83013 pm	22:31:13.84313 pm	Market	Sale	4	1.03	0.710
22:31:14.30914 pm	22:31:14.32014 pm	Market	Sale	4	1.03	0.466
22:31:14.79014 pm	22:31:14.80714 pm	Market	Sale	4	1.03	0.470
22:31:15.28215 pm	22:31:15.30015 pm	Market	Sale	4	1.03	0.475
22:31:15.75615 pm	22:31:15.76315 pm	Market	Sale	4	1.03	0.456
22:31:16.25316 pm	22:31:16.26616 pm	Market	Sale	4	1.03	0.490
22:31:16.69716 pm	22:31:16.70716 pm	Market	Sale	4	1.03	0.431
22:31:17.15217 pm	22:31:17.16717 pm	Market	Sale	2	1.03	0.445
22:31:17.60317 pm	22:31:17.61017 pm	Exchange	Purchase	50	1	0.436
22:31:18.06618 pm	22:31:18.10918 pm	Market	Sale	4	1.03	0.456
22:31:18.58718 pm	22:31:18.59918 pm	Market	Sale	4	1.03	0.478
22:31:19.06219 pm	22:31:19.06919 pm	Market	Sale	4	1.03	0.463
22:31:19.50019 pm	22:31:19.50919 pm	Market	Sale	4	1.03	0.431
22:31:19.94219 pm	22:31:19.95219 pm	Market	Sale	4	1.03	0.433
22:31:20.43020 pm	22:31:20.43920 pm	Market	Sale	4	1.03	0.478
22:31:20.88220 pm	22:31:20.89320 pm	Market	Sale	4	1.03	0.443
22:31:21.32921 pm	22:31:21.34221 pm	Market	Sale	4	1.03	0.436
22:31:21.78221 pm	22:31:21.79221 pm	Market	Sale	4	1.03	0.440
22:31:22.35622 pm	22:31:22.36322 pm	Exchange	Purchase	36	1	0.564

Table 11: Summary of traders who had times between orders of less than 5 seconds.

		Seconds Between Orders			
Trader ID	**Count**	**Lowest**	**Second Lowest**	**Third Lowest**	**% that Were the Same Order**
A	1	1.02	12.36	12.48	100%
B	1	1.36	7.01	10.72	100%
C	1	2.71	8.87	8.91	100%
D	1	4.76	19.14	19.70	0%
E	1	0.12	12.79	12.90	100%
F	1	1.49	28.68	31.64	100%
G	1	0.39	9.49	10.26	100%
H	9,246	0.14	0.14	0.14	39%
I	134	0.00	0.00	0.00	19%
J	1	4.21	9.23	12.22	100%
K	1	3.05	10.74	12.81	100%
L	1	3.28	96.57	279.74	100%
M	1	1.19	8.64	8.86	100%
N	1	0.19	17.56	41.86	100%
O	1	4.55	5.01	5.51	100%
P	5	0.08	0.11	0.21	100%
Q	1	2.43	6.61	7.07	100%
R	11	3.89	3.94	4.02	73%
S	2	4.84	4.98	6.16	50%
T	1	4.22	6.15	7.35	0%
U	1	4.83	5.98	6.18	0%
V	1	1.47	20.90	23.65	100%
W	1	0.09	22.74	26.19	1
Total	9416	0.00	0.18	0.20	39%

Table 12: Ask sequence in DEM20_WTA by Trader "H" that ends in a trade

Action Time	Action	Elapsed Time (Sec.)	Quantity Ordered	Price	Best Bids DEM20_WTA	Best Bids REP20_WTA	Best Asks DEM20_WTA	Best Asks REP20_WTA
Mar 10, 2019, 22:31:32.98632	Ask		10.00	0.725	0.638	0.330	0.725	0.340
Mar 11, 2019, 07:31:42.79742	Withdraw	5.040	10.00	0.725	0.640	0.330	0.724	0.339
Mar 11, 2019, 07:31:42.95642	Ask	0.160	10.00	0.724	0.640	0.330	0.724	0.339
Mar 11, 2019, 14:07:17.76017	Withdraw	3.153	10.00	0.724	0.640	0.331	0.719	0.334
Mar 11, 2019, 14:07:17.92017	Ask	0.160	10.00	0.719	0.640	0.331	0.719	0.334
Mar 11, 2019, 14:13:45.43045	Withdraw	9.643	10.00	0.719	0.640	0.331	0.718	0.334
Mar 11, 2019, 14:13:45.60245	Ask	0.173	10.00	0.718	0.640	0.331	0.718	0.334
Mar 11, 2019, 14:14:47.15747	Withdraw	9.024	10.00	0.718	0.640	0.331	0.700	0.334
Mar 11, 2019, 14:14:47.31947	Ask	0.163	10.00	0.700	0.640	0.331	0.700	0.334
Mar 11, 2019, 14:15:18.33918	Withdraw	1.893	10.00	0.700	0.640	0.331	0.699	0.334
Mar 11, 2019, 14:15:18.50718	Ask	0.167	10.00	0.699	0.640	0.331	0.699	0.334
Mar 11, 2019, 17:40:17.57617	Withdraw	0.750	10.00	0.699	0.640	0.331	0.698	0.334
Mar 11, 2019, 17:40:17.74217	Ask	0.166	10.00	0.698	0.640	0.331	0.698	0.334
Mar 11, 2019, 19:58:19.29719	Sell via Accepted Ask	#N/A	10.00	0.698	0.640	0.331	0.698	0.333
Mar 11, 2019, 19:58:22.23222	Buy Exchange Bundle	2.936	5.00	1.000	0.640	0.331	0.699	0.333

Table 13: Bid sequence in DEM20_WTA by Trader "H" that ends in an arbitrage opportunity

Action Time	Action	Elapsed Time (Sec.)	Quantity Ordered	Price	Best Bids DEM20_WTA	Best Bids REP20_WTA	Best Asks DEM20_WTA	Best Asks REP20_WTA
Mar 09, 2019, 06:53:50.73350	Bid		10	0.632	0.632	0.330	0.680	0.340
Mar 09, 2019, 12:56:27.04327	Withdrawal	9.423	10	0.632	0.633	0.330	0.680	0.340
Mar 09, 2019, 12:56:27.19327	Bid	0.150	10	0.633	0.633	0.330	0.680	0.340
Mar 09, 2019, 13:27:33.31033	Withdrawal	9.163	10	0.633	0.634	0.330	0.680	0.340
Mar 09, 2019, 13:27:33.46633	Bid	0.157	10	0.634	0.634	0.330	0.680	0.340
Mar 09, 2019, 17:22:19.37619	Withdrawal	7.790	10	0.634	0.635	0.330	0.680	0.340
Mar 09, 2019, 17:22:19.53019	Bid	0.153	10	0.635	0.635	0.330	0.680	0.340
Mar 09, 2019, 18:29:57.34957	Withdrawal	2.103	10	0.635	0.636	0.330	0.680	0.340
Mar 09, 2019, 18:29:57.50357	Bid	0.153	10	0.636	0.636	0.330	0.680	0.340
Mar 10, 2019, 05:01:51.42051	Withdrawal	2.080	10	0.636	0.637	0.330	0.680	0.340
Mar 10, 2019, 05:01:51.59051	Bid	0.170	10	0.637	0.637	0.330	0.680	0.340
Mar 10, 2019, 07:38:04.6324	Withdrawal	4.636	10	0.637	0.638	0.330	0.680	0.340
Mar 10, 2019, 07:38:04.7834	Bid	0.150	9	0.638	0.638	0.330	0.680	0.340
Mar 10, 2019, 22:31:11.15311	Sell Market Bundle	3.050	4	1.03	0.7	0.330	0.725	0.340

Appendix: IEM Prospectus: 2020 US Presidential Election Winner-Takes-All Market

On Thursday, February 7, 2019, at 11:30am CST, the Iowa Electronic Market (IEM) will open trading in a winner-takes-all market based on the 2020 U.S. Presidential election.

The payoffs in this market will be based on the popular vote received by the official Democratic and Republican nominees in the 2020 U.S. Presidential election. Payoffs are NOT affected by votes received by nominees from other parties, the outcome of the electoral college or any vote taken by the House of Representatives should such a vote be necessary.

This document describes the market and should be viewed as a supplement to the Trader's Manual. Except as specified in this prospectus, trading rules for this market are the same as those specified in the Trader's Manual for the Iowa Electronic Market.

Contracts

The financial contracts initially traded in this market are:

Code	Contract Description
DEM20_WTA	$1 if the Democratic Party nominee receives the majority of popular votes cast for the two major parties in the 2020 U.S. Presidential election, $0 otherwise
REP20_WTA	$1 if the Republican Party nominee receives the majority of popular votes cast for the two major parties in the 2020 U.S. Presidential election, $0 otherwise

Determination of Liquidation Values

This is a winner-takes-all market. The payoff will be determined by which of the two nominees receives the larger share of the popular vote cast for the Democratic and Republican candidates in the 2020 U.S. Presidential election.

Contracts associated with the nominee who does not receive the larger number of popular votes in the election will pay off $0. Contracts associated with the nominee that receives the larger number of popular votes will pay off $1, provided that there have been no contract spin-offs in the market. In the event of spin-offs, payoffs are determined as described below.

The election data posted on the New York Times official website at 5pm CST on Wednesday, November 4, 2020, or as soon after as available, will be the official source used to determine payoffs. In the event that the two parties' popular votes are not reported at that website by midnight, Wednesday, November 4, 2020, the Washington Post official website will become the official source. Should neither source report popular vote by midnight Wednesday, the information reported in the print version of the New York Times on Thursday, November 5, 2020, or as soon thereafter as reported, will be used. In the event that the election is delayed or postponed, liquidation will take place in a timely fashion after the close of polling sites for the popular vote.

Liquidation formulas can be viewed while you are logged into the IEM trading system by clicking on the market name, PRES20_WTA, at the upper right hand corner of the market window.

The judgment of the IEM Governors and Directors will be final in resolving questions of typographical or clerical errors and ambiguities.

Contract Spin-Offs

The Directors of the IEM reserve the right to introduce new contracts to the market as spin-offs of existing contracts. When a contract spin-off occurs, an original contract will be replaced by two or more new contracts which subdivide the payoff space of the original contract. Contracts may be split to correspond to different vote share levels. For example, the contract DEM20_WTA could be split into two contracts, DEM20_WTA_G55 and DEM20_WTA_L55, where DEM20_WTA_G55 denotes the case in which the Democratic nominee receives the most popular votes AND that the Democratic voteshare is 55% or more of the total two-party vote, while DEM20_WTA_L55 denotes the case in which the Democratic nominee receives the most popular votes AND that the Democratic voteshare is less than 55% of the total two-party vote.

Alternatively, the contracts may be split to correspond to different potential nominees. For example, the contract UDEM20_WTA could be split into two contracts, DNAME20_WTA and a new UDEM20_WTA where DNAME20_WTA denotes the case in which the Democratic nominee receives the most popular votes AND the official nominee at the Democratic Convention was NAME, while the new UDEM20_WTA denotes the case in which the Democratic nominee receives the most popular voes AND the official nominee of the Democratic Convention is not the specifically named candidate. UDEM20_WTA may be split repeatedly as other interesting named candidates emerge. Contracts associated with named Democratic candidates will liquidate at $1 if the Democratic nominee receives the most popular votes AND the official nominee at the Democratic Convention was NAME. UDEM20_WTA will liquidate at $1 if Democratic nominee receives the most popular votes AND the official nominee of the Democratic Convention is not one of the specifically named Democratic candidates.

No holder of the pre-spinoff contracts will be adversely affected. Traders will receive the same number of each of the new contracts as they held in the original, and the sum of the liquidation values of the new contracts will equal the liquidation value of the original.

Outstanding bids and asks for the contract which is to be split will be canceled just prior to the spin-off.

Decisions to spin-off a contract will be announced at least two days in advance of the spin-off. The new contract names, the specifications regarding liquidation values and the timing of the spin-off will be included in the announcement. This announcement will appear as an Announcement on your WebEx login screen.

Contract Bundles

Fixed price contract bundles consisting of one share of each of the contracts in this market can be purchased from or sold to the IEM system at any time. The price of each fixed price contract bundle is $1.00. Because exactly one of the listed U.S. Presidential election outcomes will result from the election, the total payoff from holding a fixed price contract bundle until the market closes is $1.00.

To buy or sell fixed price contract bundles from the system, use the “Bundle Orders” option from the Trading Console. Select “Pres20_WTA” and the radio button “Buy at Fixed Price” from the Bundle Orders list to buy bundles. Select “Pres20_WTA” and the radio button “Sell at Fixed Price” to sell bundles.

Bundles consisting of one share of each of the contracts in this market may also be purchased and sold at current aggregate market prices rather than the fixed price of $1.00. To buy a market bundle at current ASK prices, use the “Bundle Orders” option as above but select “Pres20_WTA” and the radio button “Buy at Market ASK Prices.” To sell a bundle at current market BID prices, select “Pres20_WTA” and the radio button “Sell at Market BID Prices.”

Bundle purchases will be charged to your cash account and bundle sales will be credited to your cash account.

This market will remain open until contract liquidation. Liquidation values will be credited to the cash accounts of market participants.

Market Access

Current and newly enrolled IEM traders with U.S. dollar accounts will automatically be given access rights to trade in the 2020 U.S. Presidential Winner-Takes-All Market. Access to this market is achieved by logging into the IEM and choosing “PRES20_WTA” from the Navigation Bar.

Funds in a trader’s cash account are fungible across markets so new investment deposits are not required. Additional investments up to the maximum of $500 can be made at any time by using the “Adding to Your Investment” link found under “My Account” while logged into the IEM software. New traders can open accounts using the “Open An Account” button found at the IEM website, https://iem.uiowa.edu. There is a one-time account registration fee of $5.00, and investments are limited to the range of $5.00 to $500.

Requests to withdraw funds may be submitted at any time by completing the IEM’s Online Withdrawal Request form. Additional information about requesting withdrawals is available at the IEM website at https://iemweb.biz.uiowa.edu/accounts/withdrawals.html.