Speed and Latency in Treasury and e-Mini Futures Contracts – Part 1

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I. Introduction

Fast trading is a focus of regulators and many industry groups. The use of computer algorithms, co-location services, technological improvements in exchanges' matching systems, and high-speed microwave networks accelerates order entry, cancellation rates, execution speeds, and matching frequencies for equities and futures markets. Researchers from both the Commodity Futures Trading Commission (CFTC) and the U.S. Securities and Exchange Commission (SEC) have examined faster traders and automated trading strategies to better understand their effects on regulated markets.[1] Although academic research exists on the effects of speed, latency and high frequency trading, much of this research is limited by a lack of detailed, participant level, proprietary data.[2] Such data are needed to examine the response speed and latency of both algorithmic- and manual-entry participants.

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[1] See Securities and Exchange Commission, "The Speed of Equity Markets," Data Highlights 2013-05, October 9, 2013 and Richard Haynes and John Roberts, 2015, "Automated Trading in Futures Markets," White paper, Office of the Chief Economist, Commodity Futures Trading Commission.

[2] Biais, Foucault, and Moinas (2014) develop a model in which firms over-invest in speedy technologies because they ignore the negative externality of a "technological arms race." Empirically, such technologies may also have diminishing returns. Specifically, after message technology upgrades by the Nasdaq in 2010, the number of cancelled orders increased, but trading volume and bid-ask spreads were not affected (Gai, Yao, and Ye, 2012). Similarly, latency reductions at the London Stock Exchange between 2007 and 2010 resulted in increased HFT

The purpose of this research agenda is to examine regulatory data that provides trader-level information on both fast trading and latency in the Treasury futures complex and the e-Mini futures contract. This first paper focuses on the speed of trading. A companion paper examines latency and how exchange-generated data may be used to approximate trader and exchange latency statistics.

We define the speed of trading as the intensity of message traffic sourced by the trader in a specific time interval. A trader is 'fast' if the strategy and technology used by that trader results in a high level of messages over a fixed interval of time. The 'fast' in fast trading is analogous to the speed of an automobile, which is commonly measured in distance traveled over a time unit (e.g., kilometers-per-hour). The analysis in this paper measures speed over three time intervals: 500 milliseconds, 10 seconds, and 100 seconds, with the first unit being roughly the fastest expected human response speed. We report on the average, minimum, and maximum speeds of traders over these fixed intervals, with the latter providing estimates of the so-called "top speed" of various market participants.

The remainder of this paper proceeds as follows. In section II, we discuss the futures data used in this study. In sections III and IV we present results on the speed and latency characteristics in our data, respectively. Finally, section V offers a few conclusions.

II. Data

The data that we examine are for two-, five-, ten-, and thirty-year treasury futures complex and the E-Mini futures contract. We analyze order book data for all accounts from October 6, 2014 to October 17, 2014, which is nine trading days given the holiday on Monday, October 13th. This period of two weeks included a broad set of market speeds and price volatility, likely providing good upper and lower bounds for account speeds. We limit our sample analyses to those accounts with at least 6 or more messages during the sample window. This filter eliminates many of the very small accounts who may have messages on only one day in our sample. After this filter, there are 174.7 million messages, 7,865 unique automated entry, and 35,189 unique manual entry accounts in the sample.

Our analysis identifies accounts as manual or algorithmic using flags provided in the order book data.[3] The messages examined are order entry ("Function Code" 1=fc1 in the data set), order modification (fc2), order cancellation by the trader (fc3), and order execution (fc105). We focus on limit-orders as they are the vast majority of orders in futures markets. In addition, we include flags indicating the business line of each account. The business line categories we use are Bank/Dealer, Futures Commission Merchant (FCM), Hedge Fund, Non-bank Dealer, Proprietary, or Other, where the other category may include specialized finance or insurance

market share, but little change in execution quality for institutional investors (Brogaard, Hendershott, Hunt, and Ysusi, 2014).

[3] This indicator is part of the data received by the CFTC from the CME and further information can be found at CME's website (http://www.cmegroup.com/rulebook/files/cme-group-ra1210-5.pdf).

companies, treasury operations at major corporations, or other (generally smaller) entities with futures positions.[4]

Table 1 provides data on the number of unique accounts for each futures contract and whether the account is using manual or automated order entry methods. The automated order entry flag indicates whether an algorithm is involved in implementing a trading strategy. If an account is manual, this suggests that order entry involves human cognitive processes. The table also provides breakdown by the business line of the firms that hold each account. These business line descriptions were developed based on company-specific information provided to regulators. The E-mini contract has the largest number of manual- and automated-entry accounts, followed by the 10-year and thirty year U.S. Treasury contracts. These relative account tabulations parallel the relative trading volume in these contracts (not shown here).

Table 1 - Unique Accounts

(Order Book Data for October 6-17, 2014)

Type	E-mini	Two-Year Treasury	Five-Year Treasury	Ten-Year Treasury	Thirty-Year Treasury
Manual	24,464	709	1,466	4,052	3,267
Automated	4,380	797	1,887	2,705	1,857
Bank/Dealer	3,702	402	873	1,724	817
Futures Commission Merchant	8,759	208	409	1,057	1,015
Hedge Fund	221	15	168	230	133
Non-bank Dealer	557	28	84	200	112
Proprietary	4,142	432	1,105	1,792	1,687
Other Participants	5,039	303	499	1,427	1,164

Table 2 provides summary statistics for message traffic in the sample. This table shows the count of initial order submissions, the number of modifications, and the number of orders that were cancelled during the sample. These data indicate that there are often large cancellation rates for these orders, with automated accounts on average cancelling more order submissions than manual-entry accounts.

The data we examine also provides information on whether the order is for a proprietary account or entered on behalf of a customer. This field is not included in certain message types, but for the non-missing cases, Table 2 shows estimates of the fraction of orders that are proprietary or customer initiated. These estimates show that initial order submissions and modifications are 72% to 92% proprietary in origin. Note that there is no customer type

[4] This flag is the same one used in the joint interagency report on the events surrounding treasury market trades and orders on October 15th, 2014.

information for the cancellation of an order. The proprietary and customer-initiated percentages under the “All Orders” estimates do not add up to 100% as these data include the messages missing the customer type identifier. This summary implies that many more proprietary orders are cancelled compared to customer-initiated orders, so they do not map to execution messages at the same rate as found with customer-initiated orders.

III. Speed Analysis

To analyze the speed of different traders, we divided the nine-day order-book sample for every futures contract into three files, each associated with one of the three time units: one-half second (500 milliseconds), ten seconds, and 100 seconds. For each account in these files, we counted the number of messages in every time segment. The message data that we count separately are new order entries, order modifications, and order cancellations, which are all messages originating from the firm and not the exchange platform. Each of these message types is indicative of a trader’s strategy responding to one or more signals sufficient to induce this message.

Table 2 - Message Traffic by Customer Type
(Order Book Data for October 6-17, 2014)

Order Type	E-mini	Two-Year Treasury	Five-Year Treasury	Ten-Year Treasury	Thirty-Year Treasury
All Orders	78,120,370	9,243,043	24,977,272	38,610,318	23,796,613
Proprietary	59.6%	55.5%	57.1%	57.8%	58.7%
Customer-Initiated	8.1%	15.1%	7.8%	10.0%	7.0%
Order Submissions	35,144,714	3,097,998	10,447,375	15,639,004	9,961,856
Proprietary	87.4%	85.1%	92.6%	90.3%	92.4%
Customer-Initiated	12.6%	14.9%	7.4%	9.7%	7.6%
Order Modifications	17,772,029	3,426,920	5,781,201	10,538,390	5,675,809
Proprietary	89.2%	72.8%	79.5%	77.8%	84.0%
Customer-Initiated	10.8%	27.2%	20.5%	22.2%	16.0%
Order Cancellations	25,203,627	2,718,125	8,748,696	12,432,924	8,158,948

We model the intensity of message traffic within these time intervals using a log-linear model:

$$log(\mu_i) = log(n_i) + \boldsymbol{x}_i'\boldsymbol{\beta}, \quad (1)$$

where μ_i is the expected number of messages for trader i, in a pre-specified time segment. If the distribution of message counts is Poisson, this is also known as the intensity parameter. The n_i variable equals the number of time segments in which trader i generates messages, so in logarithmic form this offset variable implies that we are modelling the average *rate of message traffic* generated by trader i. The effects of covariates ($\boldsymbol{x}_i'\boldsymbol{\beta}$) are linear in this model, so with a log dependent variable a one unit change in a variate x^k implies a multiplicative effect (e^{β_k}) on the mean (μ_i). The covariates examined here are dummy variables and include whether the trader uses an algorithm for order entry, the business line of the trader, and the firm responsible for the trader's account.

Table 3 - Intensity Estimates Using Ten Second Intervals
(Order Book Data for October 6-17, 2014)

	Estimate/Wald 95% Confidence Interval/p-Value				
Parameter	**E-Mini**	**Two Yr.**	**Five Yr.**	**Ten Yr.**	**Thirty Yr.**
Intercept	0.293	0.481	0.469	0.383	0.346
	(0.276 - 0.311)	(0.386 - 0.576)	(0.415 - 0.522)	(0.351 - 0.416)	(0.318 - 0.374)
	<.0001	<.0001	<.0001	<.0001	<.0001
Automated Order Entry	0.96	0.93	0.85	0.88	0.85
	(0.913 - 1.003)	(0.796 - 1.062)	(0.771 - 0.920)	(0.825 - 0.933)	(0.798 - 0.896)
	<.0001	<.0001	<.0001	<.0001	<.0001
Dispersion	0.246	0.528	0.496	0.406	0.332
	(0.236 - 0.257)	(0.467 - 0.596)	(0.462 - 0.532)	(0.384 - 0.429)	(0.314 - 0.351)
Predicted Message Rate					
Automated	3.495	4.095	3.720	3.534	3.297
Manual	1.341	1.617	1.598	1.467	1.414
Number of Observations	34,277	1,834	4,002	8,517	6,565
Deviance	33,711	1,946	4,201	8,697	6,581
Deviance/df	0.984	1.062	1.050	1.021	1.003
Pearson Chi-Square	278,613	6,926	11,058	29,185	16,203
Pearson/df	8.129	3.781	2.765	3.428	2.469
Akaike IC	332,534	21,455	48,005	91,723	67,348
Bayesian IC	332,559	21,471	48,024	91,744	67,369

Estimates of this model are found using the maximum likelihood routine within the GENMOD procedure in SAS. Initially, we assumed a Poisson distribution for message counts (Y), but the deviance and Pearson chi-squared statistics indicated that there was over-dispersion in the count data. In other words, the Poisson assumption that the mean and variance are equal was not supported in these data. To address this issue, we estimated message counts under the assumption that they followed a negative binomial distribution, which allows more flexibility in the variance relative to the mean. Specifically, the variance of message counts in the negative binomial distribution is as follows:

$$Var(Y) = \mu_i + \kappa\,\mu_i^2, \qquad (2)$$

where the kappa (κ) parameter acts as a measure of the over-dispersion of the data relative to the Poisson model. As $\kappa \to 0$, the negative binomial approaches the Poisson distribution with mean (or intensity) parameter μ_i.

Table 3 shows estimated results for the negative binomial model in which only the automated order entry dummy variable is included as a covariate. This variable is highly significant across all futures contracts and indicates that automated entry accounts are more active, and thus faster on average, than manual entry accounts. For comparison, we show the predicted number of messages for a ten second interval below these coefficients. The differences between the predicted message rates for manual and automated accounts in Table 3 would indicate that automated accounts are expected to enter between 2.3 and 2.6 times more messages than manual entry accounts in this sample. Interestingly, the two-year Treasury shows the fastest average speed for both manual and automated entry accounts across these contracts, though it is not the most active by volume.

In addition, the goodness-of-fit measures in Table 3 suggest that the negative binomial model provides a good fit to the ten-second count data. The deviance/degrees-of-freedom is close to one, indicating minimal over-dispersion after estimating the negative binomial dispersion parameter. The confidence intervals shown for the estimated dispersion parameter also indicate that it is not approaching zero, so the Poisson distribution would not be a good fit for these data.

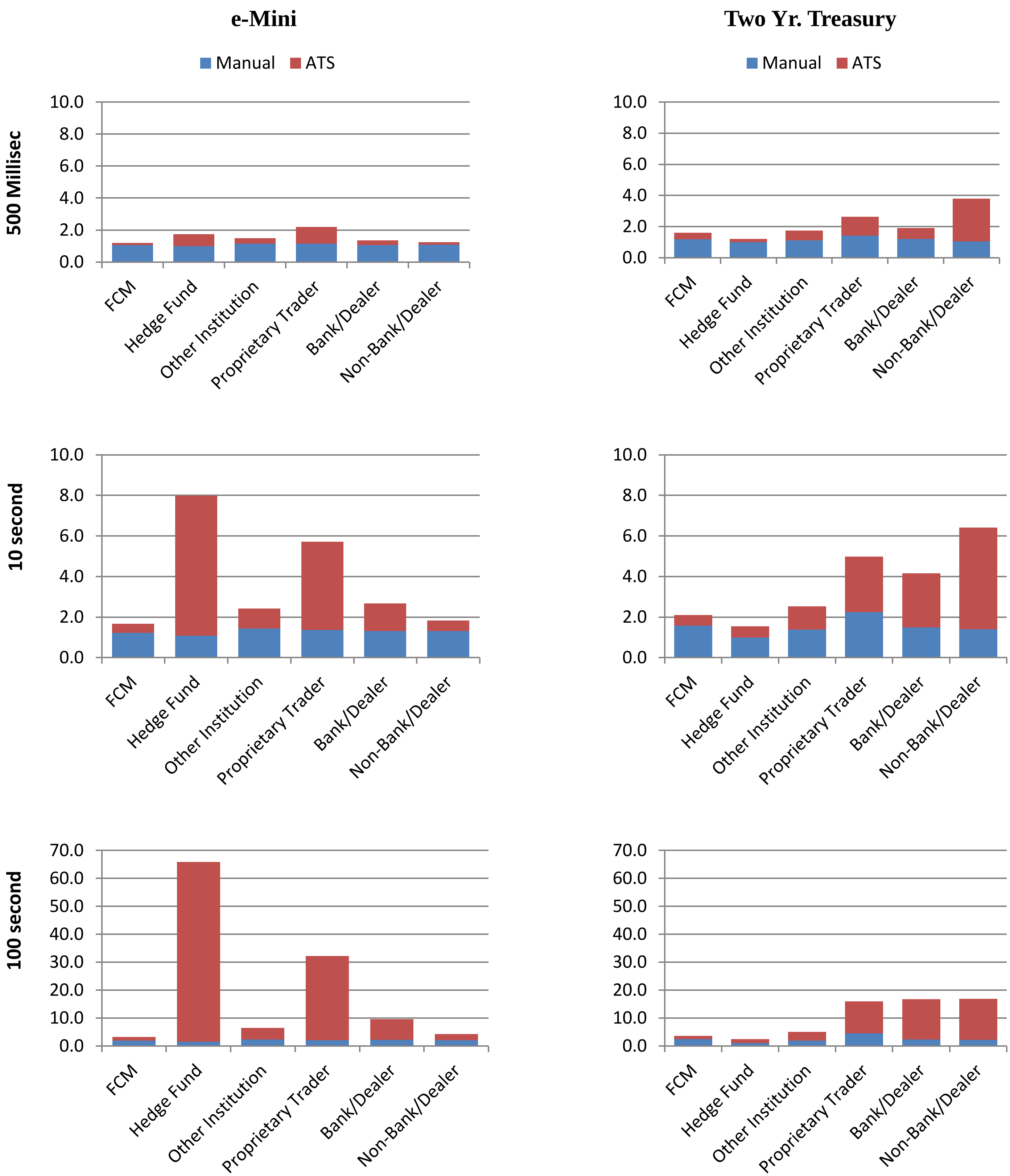
We also estimated two more general model specifications of speed for these futures contracts. The first specification computes speed by business type using an additional control for when the account is either automated or manual entry. The second model estimates speed, controlling for firm effects. In the second model, we estimate an "all account" average effect for automated or manual entry as firms tend to specialize in the method of entry. The results for these two models are shown in Figures 1 and 2, respectively.

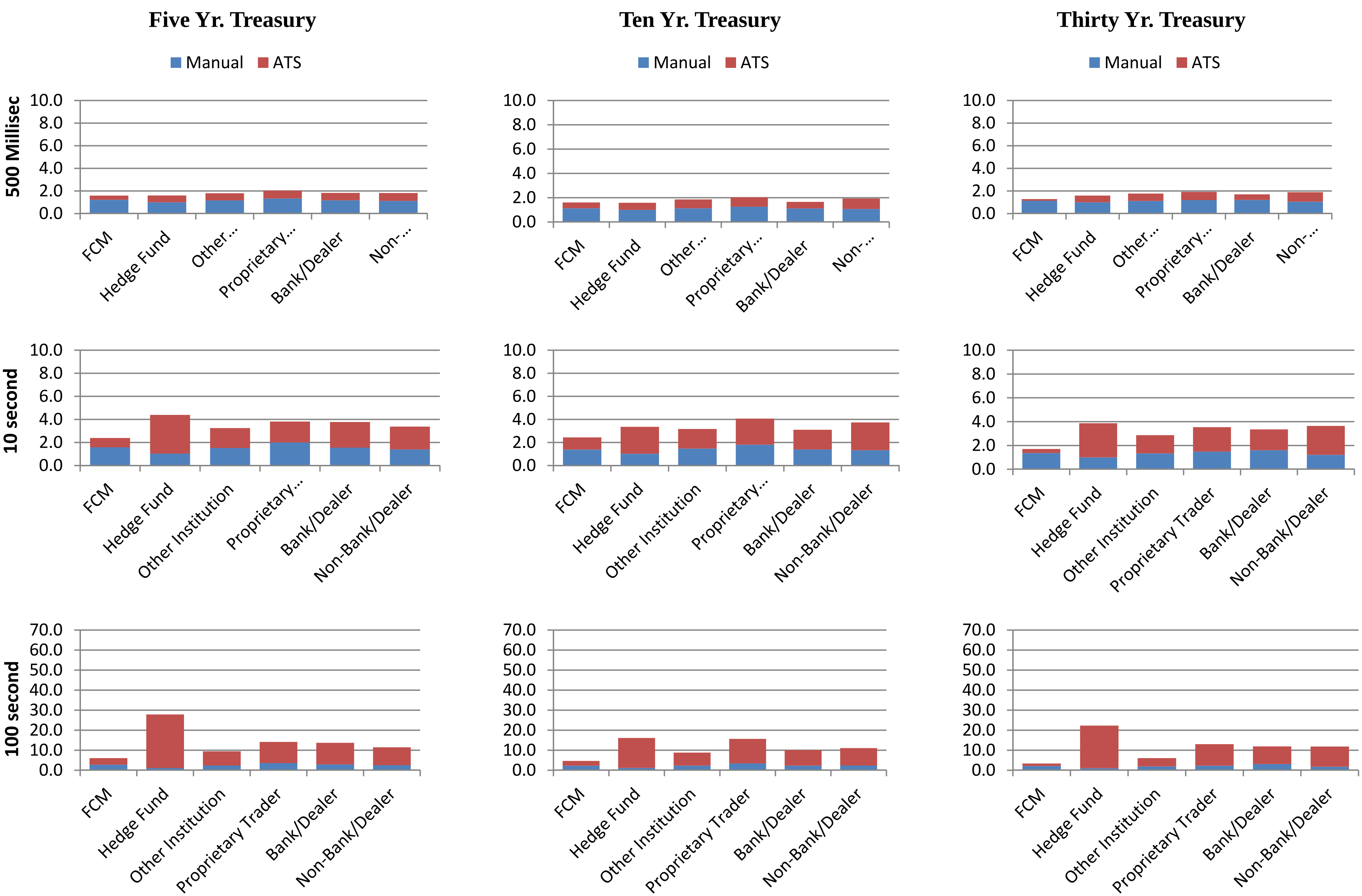
Figure 1 contains six panels of speed information by business type on the first page and nine similar panels on the second page. On the first page, the first column is for the e-mini futures contract and the second column is for the two-year treasury futures contract. The time unit measured is shown on the left side of each row. The data shown in each figure is the estimated average speed for each business type. The average speed of an automated entry account is shown by the total height of the column and the speed of the manual entry account is shown as the height of the first section of a column – all estimated automated speeds exceed manual speeds. Also note that the vertical axis is scaled with the same length for the 500 millisecond and 10 second figures for easier comparison, but that the scale changes for the 100-second time unit in the last row.

Figure 1 reveals several features of the sample data: Proprietary traders using automated entry are the fastest group for the e-Mini contract when measured at 500 millisecond intervals. For the two-year treasury it is automated non-bank dealers who are fastest, and they are significantly faster than other business types. We also observe that the average speed of manual entry traders varies only by a small amount for the 500 millisecond estimates.

At ten second time units, hedge funds using automated entry are on average fastest in the e-Mini contract with automated proprietary traders on average two messages-per-10-seconds behind hedge funds. In two-year treasuries, automated non-bank dealers are still fastest on average, but the relative speed difference has decreased. At 100 second units, the relative speed difference between non-bank dealers, proprietary traders, and bank dealers effectively disappears in two-year treasuries. In contrast, the relative speed gap between these categories increases when the time unit shifts from ten to 100 seconds for the e-Mini contract. Thus, for these two futures contracts, defining who is fast depends significantly on the time interval used to measure speed, indicating that different participant types are likely incorporating distinct trading strategies.

Figure 1 – Speed of e-Mini, 2-, 5-, 10-, and 30-year Treasury Futures Accounts by Business Type




Five Yr. Treasury
Ten Yr. Treasury
Thirty Yr. Treasury
Manual
ATS
500 Millisec
10 second
100 second
0.0
2.0
4.0
6.0
8.0
10.0
20.0
30.0
40.0
50.0
60.0
70.0
FCM
Hedge Fund
Other...
Proprietary...
Bank/Dealer
Non-...
Other Institution
Non-Bank/Dealer
Proprietary Trader

The average speed for manual entry traders is just over one message per 500 milliseconds for the 500 millisecond panels on the first page of Figure 1. This is because it is rare for any manual entry trader to enter two or more messages within 500 milliseconds of each other. In the ten second time unit we observe more variation for these accounts, with proprietary traders in two-year treasuries having the most rapid message entry speeds. Although difficult to perceive, the average manual entry speeds at 100 second intervals show only slightly more messages than the counts for ten second intervals. In effect, the "typical" entry strategy of manual traders does not appear to vary between ten and 100 second windows. That is, if the average manual strategy calls for two messages implemented within a given ten seconds interval then that strategy is unlikely to call for many additional messages over the next 90 seconds.

The second page of Figure 1 shows the same type of information for five-year, ten-year, and thirty-year treasury futures contracts. There is much similarity in the speed results by business line for a given time interval across the three products. While a visual analysis of the panels on this page seems to indicate that the hedge fund group might have relatively faster speeds compared to other business types at 10 and 100 second time intervals, their differential speed is nowhere near speed differences observed on the first page of this figure. In effect, these traders may be adopting similar strategies across the medium- to long-term Treasury complex, which then give rise to similar average speeds by business line.

We also estimated the negative binomial model controlling for firm effects. These estimates compute average speeds across all of the accounts belonging to a specific firm. The number of firms varies by futures contract from 224 in the two-year treasury to 490 in the e-Mini. To summarize the large number of speeds across the different firms, we report the minimum, cutoffs for the 10th and 90th percentiles, and maximum speeds observed by each futures contract. In all cases, both the average and median speeds across these firms will be found between the 10th and 90th percentile cutoff speeds.

Figure 2 presents these speed summaries across firms in three time units: 500 millisecond, 10 seconds, and 100 seconds. Each graph contains the range of firm speeds for all five futures contracts. For example, the first graph in the first row shows the speeds for automated entry traders within the 500 millisecond interval. This graph shows that in the two-year contract the maximum speed is approximately 12 messages per 500 milliseconds and the minimum speed is approximately 1 message per 500 milliseconds. The 10th and 90th percentile cutoff speeds are indicated on the graphs by the top and bottom of the gray shaded box respectively and height of the box corresponds to the distribution of the speeds between the 10th and 90th percentiles. For the 500 millisecond time interval, the 10th and 90th percentile cutoff speeds correspond to 1.25 messages and 2.88 messages per 500 milliseconds, respectively. The nearest of the 10th and 90th percentile cutoffs indicates that the vast majority of automated entry firms (>80%) operate with strategies that place between one and three messages per 500 milliseconds. Only 10 percent of firms implement strategies that operate at average speeds faster than this entry range.

We also see in Figure 2 that manual entry speed statistics show lower maximum speeds for all contracts—particularly at the 10 and 100 second units—but show somewhat similar message speeds for the 10^{th} to 90^{th} percentiles ranges[5]. The main difference in these percentiles is that the automated entry accounts exhibit a greater 90^{th} percentile cutoff than the manual entry accounts. As suggested by the example above, the vast majority of firms operate strategies that generate fairly low message rates. However, there are at least 10 percent of firms that operate strategies which produce message rates several times faster than the typical firm. Specifically, in the 10 second time unit, the upper decile of speeds range from 6 to 37 messages per 10 seconds for the ten year Treasury contract.

IV. Conclusion

The purpose of this paper was to examine regulatory data from futures markets to provide trader-level information on both fast trading in the Treasury futures complex and the e-Mini futures contract. The sample data show that there is a variety of trading speeds in these contracts. There are some very fast trading strategies—10 to 12 messages per 500 milliseconds—but the majority of trading firms operate at lower speeds—between 1 and 3 messages per 500 milliseconds for automated entry traders and from 1 to 1.8 messages per 500 milliseconds for manual entry traders. We also found that hedge funds, proprietary funds, and non-bank dealers operated the fastest trading strategies compared to other business types, while also discovering that speed comparisons are very sensitive to the time interval chosen.

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[5] We realize that our analysis shows *very fast* maximum speeds for manual entry traders such as nearly ten messages in a 500 millisecond interval. Because the automated order entry flag we utilize is part of the data set and not a computed statistic, we recognize that this flag may be mislabeled for some observations in the data set, so our maximum speed statistics for manual traders might be erroneous.

Figure 2 – Maximum, Minimum, 10th and 90th Percentile Speeds across Sample Firms