Intraday Serial Correlation and the Predictability of Returns in the U.S. Treasury Note Futures Market

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This study examines the intraday price patterns in the U.S. Treasury note futures market. Significantly negative serial correlations of price changes have been found throughout the trading day. The serial correlations are consistently negative throughout the trading day and have declined considerably over time. In addition, it is seen that the level of recent daily serial correlations is predictive of correlations throughout the trading day. A trading strategy has been tested based on these results and shows that excess profits can be earned. Importantly, the trading results are seen to improve when the level of serial correlation is used to refine the trading strategy.
JEL classification: G11; G14
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1. Introduction

In this study, electronic tick-by-tick data has been used on Treasury note futures to examine intraday price patterns. The Chicago Board of Trade (CBOT) maintains a record of all electronic trading, which represents every price change throughout the day. Using these data, the serial correlations and volatility of intraday price changes for each trading day and for sub-periods within each day have been measured. It has been found that serial correlation is consistently negative throughout the day, while price changes are more volatile at the beginning of the trading day. Daily and intraday serial correlations decline considerably over a time period.[1]

Neftci (1991) classifies three types of trading strategies, including trend crossing strategies. Trend crossing strategies issue signals of market turning points when the time series of prices cross some level defined by various minima or maxima of prices. It is the choice of level that differentiates one trading rule from another. In this study, a type of trend crossing trading rule known as a "channel rule" is tested; this methodology is not new. Taylor (1994) tested a channel rule on currency futures. The results indicate that the channel rule is effective at predicting the sign of price changes, which is sufficient to generate positive trading profits.

Several authors have documented the explanatory power of past information. For example, Chang and Hu (2009) have presented two trading models that earn excess returns in the Taiwan stock market. They have also shown that returns can be improved by added a leading indicator to the strategy. Lukac and Brorsen (1990) simulated 23 technical trading systems on 30 futures contracts for the period 1976-1986. They showed that all of the systems tested generated significant, positive returns. Brock, Lakonishok and LeBaron (1992) tested moving average oscillators and trading range breakout rules on the Dow Jones Industrial Average (DJIA) for the period 1897-1986. Their results reveal that technical analysis helps to predict stock price changes, a finding inconsistent with popular null models such as the random walk model.

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[1] When the sample is limited to auction data, it is found that serial correlation is highest at the beginning and end of each trading day. This is consistent with the findings of Locke and Onayev (2005). However, electronic trading data has a more constant intraday serial correlation.

A number of authors have studied the use of technical analysis using intraday data. Puri and Philippatos (2008) have found an asymmetric volume-return relationship for LIFFE currency and interest rate futures. Thompson and Waller (1986) found that trading profits associated with a filter rule are larger for contracts nearing maturity. Brorsen (1989) tested a scalping strategy on corn futures and found that scalping returns are highest during periods of high market volume. Martell and Trevino (1990) found that by breaking a contract price history into days, the behavior of intraday price changes for a given contract is not homogeneous over time. A filter rule based on the autocorrelation of the previous trading day is shown to generate positive trading profits. Neftci and Policano (1990) used intraday tick-by-tick data on Treasury bill futures to test the predictive power of past prices and trading times. They found that while lagged values of returns have predictive power, trading times do not.

The above studies using intraday price data indicate significant negative serial correlation in price changes, implying reversals in returns measured over short time periods. These reversals are thought to be the result of movements from the bid to the ask price. It was also found that this serial correlation may not be stable over time. Kidd and Brorsen (2004) found some evidence of reduced autocorrelation in daily futures prices, which may partially explain the reduced returns to technical analysis during the period 1991-2001. It was found that variations in the level of serial correlation will affect the profitability of technical trading strategies; trend-following strategies will become more profitable as serial correlation becomes more positive and contrarian strategies will become more profitable as serial correlation becomes more negative.

This study contributes to the literature in several ways. First, the existence of significant negative serial correlation in the U.S Treasury note futures market based on electronic trading data is documented. Second, it is established that the level of serial correlation is predictable based on the recent level of serial correlation. Finally, it is shown that this information improves trading strategies designed to exploit negative serial correlation. This information can be useful for traders, scalpers, and speculators.

This article is organized as follows: the data is described in Section II and in Section III daily and intraday serial correlation are tested. In Section IV the trading strategy is defined and in Section V the results of the trading strategy are summarized. In Section VI the trading strategy is improved upon using ex-ante information. Finally, the results are summarized in Section VII.

2. Data

Electronic tick-by-tick data is employed on 10-year U.S. Treasury note futures contracts traded on the Chicago Board of Trade (CBOT). U.S. Treasury-note futures contracts are traded for delivery in March, June, September, and December and have a face value of $100,000. U.S. Treasury-note futures contracts are the most actively traded long-term financial futures contract in the time period examined. The CBOT maintains a time-stamped series of tick-data, which represents every price change throughout the day. Tick-data is used because the timing of each tick is accurately recorded by the exchange. Transaction data representing all trades are available, but the timing associated with each trade is not reliable. The sample includes all transaction price changes on 17 quarterly U.S. Treasury-note futures contracts beginning with the September 2000 contract and ending with the September 2005 contract.

The sample is restricted to tick-by-tick data on the most liquid futures contracts. U.S. Treasury-note futures contracts typically become illiquid during the delivery month. Trading on each contract ends at noon on the seventh business day preceding the delivery date, which is the last business day of the delivery month. In the month preceding delivery, traders roll from the expiring contract to the next contract on the "roll day." For each contract, prices beginning on the roll day and ending on the trading day prior to the next roll day are used.

While electronic trading data are used, the sample data set is restricted to the open auction period, which is the most liquid trading time. Open auction in U.S. Treasury Note futures occurs from 7:20 AM CST to 2:00 PM CST. By convention of the CBOT, the trading day is divided into time periods. This convention is followed to identify intraday time periods. The first trading period is ten-minutes and the rest of the day is divided into 15-minute trading increments, each designated by a letter code—the first trading period is *B*, the second trading period is C, the third trading period is D, etc. A break down of the trading day by trading time period is shown in Table 1.

The final sample comprises 17,726,552 observations for the 1,077 trading day period from September 1, 2000 to December 31, 2004. The data include transaction price, date and time (hour, minute and second). U.S. Treasury note futures generally tick every 1 to 2 seconds. Daily trading volume over the time period examined averages 79,868 contracts and daily open interest averages 651,688 contracts.

Table 1
Treasury Futures Trading Day in Time Periods

Period	Start Time CST	End Time CST	Period	Start Time CST	End Time CST
B	7:20:00 AM	7:30:00 AM	P	10:45:01 AM	11:00:00 AM
C	7:30:01 AM	7:45:00 AM	Q	11:00:01 AM	11:15:00 AM
D	7:45:01 AM	8:00:00 AM	R	11:15:01 AM	11:30:00 AM
E	8:00:01 AM	8:15:00 AM	S	11:30:01 AM	11:45:00 AM
F	8:15:01 AM	8:30:00 AM	T	11:45:01 AM	12:00:00 PM
G	8:30:01 AM	8:45:00 AM	U	12:00:01 PM	12:15:00 PM
H	8:45:01 AM	9:00:00 AM	V	12:15:01 PM	12:30:00 PM
I	9:00:01 AM	9:15:00 AM	W	12:30:01 PM	12:45:00 PM
J	9:15:01 AM	9:30:00 AM	X	12:45:01 PM	1:00:00 PM
K	9:30:01 AM	9:45:00 AM	Y	1:00:01 PM	1:15:00 PM
L	9:45:01 AM	10:00:00 AM	Z	1:15:01 PM	1:30:00 PM
M	10:00:01 AM	10:15:00 AM	1	1:30:01 PM	1:45:00 PM
N	10:15:01 AM	10:30:00 AM	2	1:45:01 PM	2:00:00 PM
O	10:30:01 AM	10:45:00 AM			

Notes: This table outlines the CBOT convention of designating time periods in the trading day with code letters and numbers. The initial trading period (B-period) is 10-minutes and the remainder of the day consists of 15-minute time periods. This convention is followed to identify intraday time periods. All times are in Central Standard Time (CST).

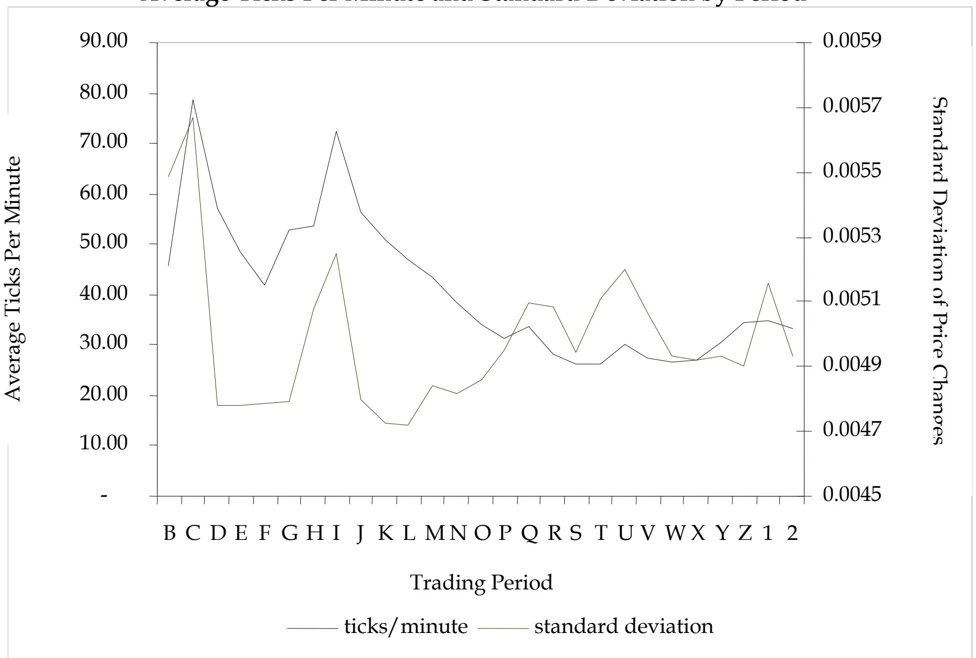
Trading activity, as measured by ticks per minute, is most active at the market open. Standard deviations of price changes closely match the pattern of ticks per minute and follow the frequently documented reverse-J pattern (See, for example Admati and Pfleiderer (1988), Hong and Wang (2000), and Cyree and Winters (2001)). For the sample, the C-period is found to be the most active, with an average of 78.81 ticks per minute. It is found that trading activity reaches a minimum of 26.03 ticks per minute in the S-period. The increase in trading activity in the C-period and I-period is attributed to the release of economic information (7:30 AM CST and 9:00 AM CST) and in the G-period to the opening of the New York Stock Exchange (8:30 AM CST). These results are consistent with those of Bollerslev, Cai and Song (2000), who found spikes in returns in these periods. The average number of ticks per minute and the standard deviation by period are presented in Figure I.

3. Tests of Serial Correlation

The test for the persistence of price patterns is done by examining the serial correlation of price changes. For each trading day, the first-order serial correlation statistics of price changes is calculated for all trades occurring in that trading day.[2] These calculations produce one *daily serial*

[2] The second-order and third-order serial correlations for each period are also calculated. The calculated statistics are considerably smaller and statistically insignificant.

Figure I
Average Ticks Per Minute and Standard Deviation by Period



Notes: The average tick per minute is equal to the total number of ticks in the time period divided by the number of minutes in the period. Standard deviations are calculated for price changes in each time period. The average ticks per minute and the standard deviation are measured for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

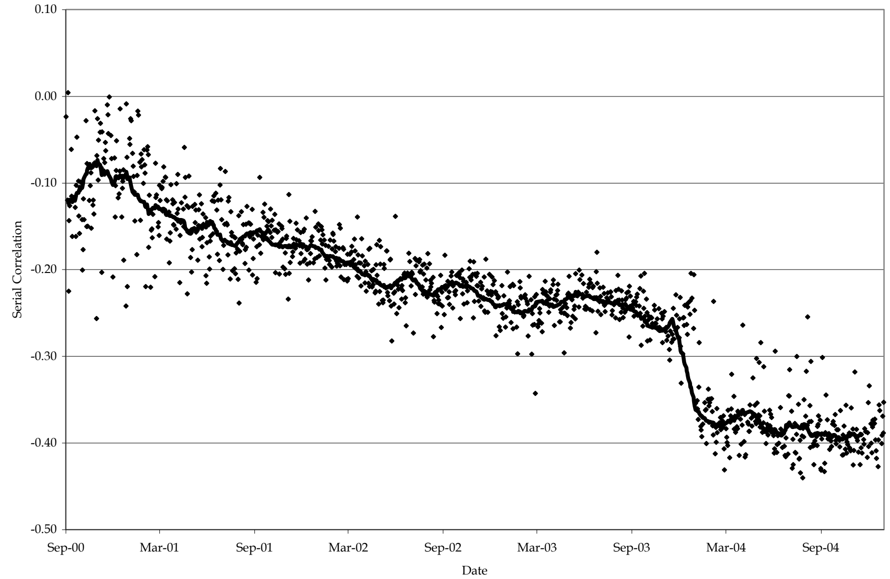
correlation statistic for each trading day in the sample. The daily serial correlations of price changes for each of the 1,077 trading days are examined and shown in Figure II. It is found that the daily serial correlations are consistently negative and have declined steadily over time and are particularly low from the end of 2003 through the end of 2004. This time period corresponds with a significant decrease in trading volume in the futures market. A 30-day lagged moving average of daily serial correlations is employed to measure the *level of serial correlation*, which is also presented in Figure II. The 30-day moving average shows variations in the level of serial correlation during the sample period.

In addition, the serial correlation for individual trading time periods is measured. For each time period in a trading day, the first-order serial correlation statistic of price changes for all trades occurring in that time period is calculated. For each trading day, these calculations produce 27 serial correlation statistics, one per period. The intraday median first-order serial correlations by time period are shown in Figure III.[3] The results for the entire sample period and for 2004 are presented. Negative serial correlations are expected when market prices trade within a close range over a particular time period, whereas positive serial correlations are expected when market prices trend over the time period. It is found that median serial correlations are negative for all periods examined and have decreased over time. [4] Median serial correlation for the entire 2004 trading year is nearly double that of the entire sample. Serial correlations are relatively steady over the trading day[5].

[3] The mean serial correlation by time period is also calculated. The means and medians are very similar for every time period.

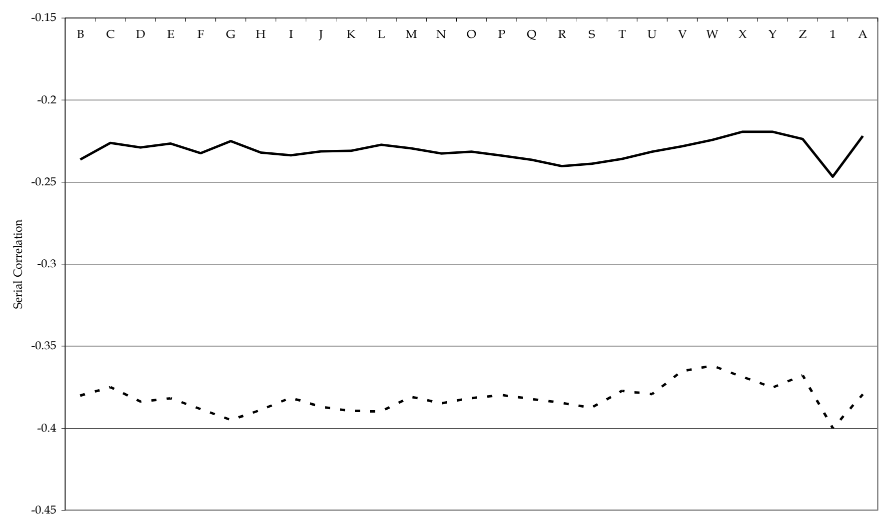
[4] Bollerslev, Cai and Song (2000) found zero autocorrelations of raw returns and positive autocorrelations of absolute returns over 5-minute intervals in the U.S. Treasury Bond futures market. Similar positive serial correlations of absolute price changes have been found in this study.

Figure II
Daily Serial Correlations of Intraday Price Changes



Notes: For each trading day, the first-order serial correlation of price changes occurring on that day is calculated. The moving average is calculated as a 30-day lagged moving average of daily serial correlations. The results are based on U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

Figure III
Median Intraday Serial Correlations by Trading Period



Notes: Serial correlations are measured for each time period and the median by time period is presented. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004. The results are shown for the entire time period and all of 2004. The tests indicate that the means in every time period are significantly different from zero at a 0.01 level.

[5] Unlike the electronic data presented here, open auction data over the same time period has significantly higher median serial correlation in the beginning and end of the trading day. Median serial correlation is relatively flat for the other time periods.

Since tick-by-tick data represent the actual trading path of price changes in the futures market, negative serial correlation indicates that prices do not trend in short time intervals. The results of this study provide evidence that price changes are affected by the intraday pattern of serial correlation and by variations in the overall level of serial correlation. These results are particularly important for traders using a contrarian trading strategy, which would be expected to produce higher profits when serial correlation is strongly negative. The results suggest that a contrarian strategy would be more profitable at the beginning and end of the trading day. Moreover, a contrarian strategy would be more profitable if the overall level of serial correlation was sufficiently persistent that traders could identify days on which serial correlation was likely to be negative.

To test for the persistence of the level of serial correlation, serial correlations are regressed in each period of a trading day on the level of serial correlation as measured by the 30-day lagged moving average of serial correlation. The regression takes the form:

$$\rho_{p,t} = \alpha + \beta(MA_{t-1}) + \varepsilon \tag{1}$$

where, $\rho_{p,t}$ is the serial correlation of price changes in period p of day t, and MA_{t-1} is the 30-day lagged moving average of daily serial correlations, ρ_t, calculated as:

$$MA_{t-1} = \frac{1}{30}\sum_{t-30}^{t-1}\rho_t \ . \tag{2}$$

The results of these regressions are summarized in Table 2. The results indicate that the level of recent serial correlation is strongly related to serial correlations in each time period. Specifically, the 30-day moving average of past serial correlations is predictive of serial correlation in each time period of a trading day.

These results are significant for scalpers and speculators in U.S. Treasury futures. They indicate that traders can use the information about recent price behavior to improve the profitability of trading strategies. In the next section a simple trading strategy designed to exploit negative serial correlation is defined. Subsequently, ex-ante moving averages are used to adjust the strategy and test the profitability of the refined strategy.

4. Trading Strategy

A trading strategy known as the "channel rule" is tested, which is designed to exploit negative serial correlation by time period. The trading strategy is executed when the market price reaches a high or low for the day. For lows, the contract is purchased and simultaneously a sell order k ticks above and a stop-loss sell order k ticks below the low price are placed. For highs, the contract is sold and simultaneously a buy order k ticks below and a stop-loss buy order k ticks above the high price are placed. If not executed, the position is closed at the end of the time period. Each tick is equal to $1/64^{th}$ of a point and the strategy is tested for $k = 1$ and 2.

In the B-period, for example, the first trade is identified as the open price, OP. Each subsequent trade is then identified as a high or a low for the day. For the t^{th} trade, the high price, hp_t, is identified as:

$$hp_t = \max\{OP, P_1, P_2, \ldots, P_t\}, \tag{3}$$

where, P_i is the price of the i^{th} trade, $i = 1,2,\ldots,t$. The low price, lp_t, is identified as:

$$lp_t = \min\{OP, P_1, P_2, \ldots, P_t\}. \tag{4}$$

In subsequent periods, new highs or lows in the market are established based on previous extremes in the trading day. For this reason, in the absence of large changes in volatility, extreme prices are more likely to be found in early periods. In the sample, 0.22% of all trades are classified as highs or lows. The percentage of all trades in each period classified as extremes is presented in Figure IV. As more trades are made throughout the day, there is a smaller likelihood that a given trade will fall outside the already-established range of prices. By design, the highest incidence of extreme prices occurs during the B-period, with 1.3% of all trades classified as extremes. On average, 0.21% of all trades are extreme prices.

Table 2
Regression Results of Serial Correlation

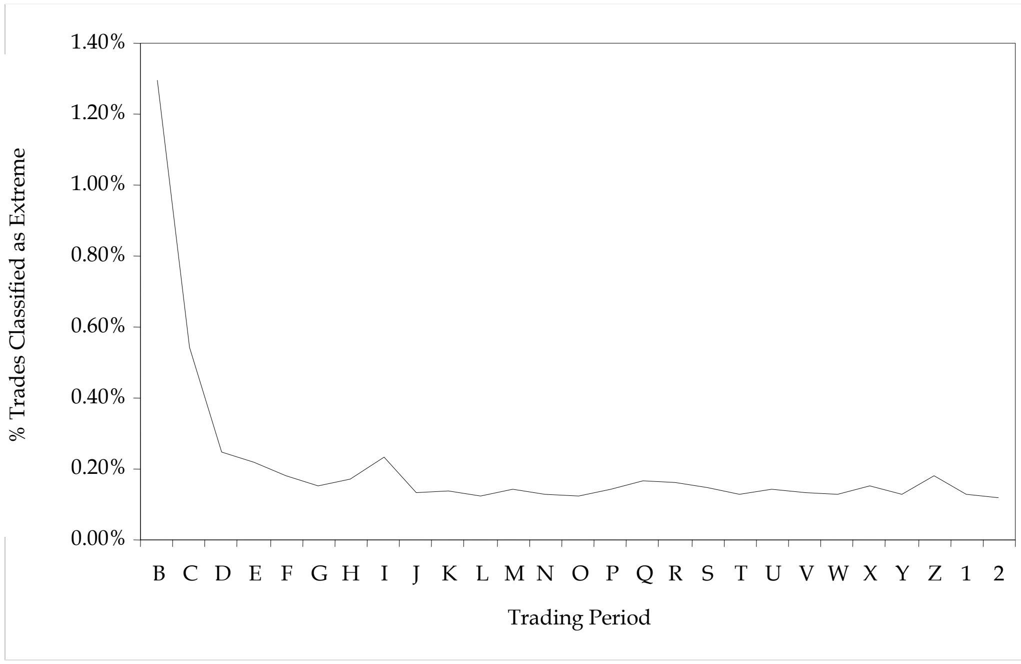
Trading Time Period	Adjusted R^2	Coefficient Estimate	Standard Error	t-statistic*
B	48.03%	0.9306	0.03119	29.83
C	61.62%	1.0243	0.02606	39.31
D	61.28%	1.0181	0.02608	39.03
E	56.62%	1.0142	0.02861	35.45
F	56.99%	1.0297	0.02883	35.71
G	69.43%	1.1321	0.02421	46.76
H	61.54%	1.0382	0.02645	39.25
I	61.67%	0.9987	0.02537	39.36
J	65.91%	1.0720	0.02485	43.41
K	61.05%	1.0330	0.02659	38.85
L	60.69%	1.0823	0.02808	38.55
M	58.96%	1.0658	0.02866	37.19
N	56.57%	1.0318	0.02914	35.41
O	49.60%	1.0019	0.03255	30.78
P	52.45%	1.0570	0.03244	32.59
Q	49.41%	1.0085	0.03289	30.67
R	41.11%	0.9542	0.03680	25.93
S	45.32%	0.9865	0.03492	28.25
T	44.29%	0.9848	0.03559	27.76
U	42.76%	0.9590	0.03575	26.82
V	41.39%	0.9087	0.03484	26.08
W	42.53%	0.9655	0.03617	26.70
X	44.89%	1.0055	0.03590	28.01
Y	51.62%	1.0463	0.03264	32.05
Z	48.89%	0.9927	0.03271	30.35
1	56.36%	1.1063	0.03137	35.26
2	53.81%	1.1068	0.03305	33.49

Notes: * All t-statistics are significant at a 1% level, n = 963 for all regressions. Each model measures the relationship between serial correlation in a trading period (dependent variable) and the moving average of daily serial correlations (independent variable). The moving average is calculated as the 30-day lagged moving average of intraday serial correlations ending one-trading day prior to the current trading day. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004. The t-statistic measures the significance of the regression coefficient.

Consider an extreme price that occurs during period p. If a high price, hp_j, is reached during this period, the contract is sold and simultaneous buy and stop-loss buy orders are placed. Let $\{P_{j+1}, P_{j+2}, \ldots, P_l\}_p$ be the set of subsequent prices for trades that occur during period p where P_l is the last trade in the time period. A trade is classified as a *win* if the price falls k ticks below the high price:

$$hp_j - \min\{P_{j+1}, P_{j+2}, \ldots, P_{l-1}\}_p \geq k(1/64)\,. \tag{5}$$

Figure IV
Percentage of Trades Classified as Extreme Prices by Trading Period



Notes: The number extreme prices, high or low, identified in each time period based on the trading strategy are presented in this figure. Since an extreme price is a daily maximum or minimum, most extremes occur early in the trading day. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

A trade is classified as a loss if the price rises k ticks above the high price:

$$\max\{P_{j+1}, P_{j+2}, \ldots, P_{l-1}\}_p - hp_j \geq k(1/64)\ . \tag{6}$$

If the contract prices stay k-1 ticks above or below the high price, hp_j, then the position is closed at the end of the trading period at the final trading price, P_l, and the trade is classified as a *draw*.
If a low price, lp_j, is reached during the period, the contract is bought and simultaneous sell and stop-loss sell orders are placed. In this situation, a trade is classified as a *win* if the price rises k ticks above the low price:

$$\max\{P_{j+1}, P_{j+2}, \ldots, P_{l-1}\}_p - lp_j \geq k(1/64)\ . \tag{7}$$

A trade is classified as a loss if the price falls k ticks below the low price:

$$lp_j - \min\{P_{j+1}, P_{j+2}, \ldots, P_{l-1}\}_p \geq k(1/64)\ . \tag{8}$$

If the contract prices stay within k-1 ticks above or below the low price, lp_j, then the position is closed at the end of the trading period at the final trading price, P_l, and the trade is classified as a draw. The decision rules are summarized in Table 3 and the profits associated with each outcome are shown.

The trading strategy described above could result in multiple trades in a given period. The tests are restricted to the first high and the first low in each period for tick sizes up to 1/16th (k=1,2). This restriction limits the trading strategy to only one possible high trade and one possible low trade per time period. High and low trading trades may overlap in time and be executed in the same period.

Table 3
Decision Rule for Extreme Trades in Period *p*

Extreme	Classification	Price Range	Profit
Highs	Win	$\min\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p \le hp_j - k(1/64)$	*k(1/64)*
	Loss	$\max\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p \ge hp_j + k(1/64)$	*-k(1/64)*
	Draw	$\max\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p < hp_j + k(1/64)$ and $\min\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p) > hp_j - k(1/64)$	$hp_j - P_l$
Lows	Win	$\max\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p \ge lp_j + k(1/64)$	*k(1/64)*
	Loss	$\min\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p \le lp_j - k(1/64)$	*-k(1/64)*
	Draw	$\max\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p < lp_j + k(1/64)$ and $\min\{P_{j+1}, P_{j+2},\ldots,P_{l-1}\}_p) > lp_j - k(1/64)$	$P_l - lp_j$

Notes: The decision rules and profit for a k-tick trading strategy are summarized in this table. If the trade reaches the target gain of *k* ticks, it is classified as a win. If the trade hits the stop loss limit of –k *ticks*, it is classified as a loss. Otherwise, the trade is a draw. A draw results in a payoff between zero and *k* ticks.

5. Trading Strategy Results

The extreme price trading strategy in each period for the 1,077 trading days in the sample are tested. The results indicate that the strategy would have been executed 9,575 times, which is approximately 16.5% of the time periods.[6] Approximately one-half of all trades **(**46.5%) are trades at low prices. Extreme price trades in the *B*-period account for 18.8% of all trades.

The percentage of extreme price trades resulting in a win, loss, or draw for each period by tick size is shown in Table 4. The overall win rate is 60.5% for low trades and 62.9% for high trades using a one-tick spread and 52.4% for low trades and 52.9% for high trades using a two-tick spread. It is found that for one and two-tick spreads, win percentages are relatively stable across time periods.[7]

If the percentage of trades classified as wins is lower for higher tick sizes, the strategy may still be profitable because the per-trade profit and loss will be higher. To measure this, the average profit per trade by period is calculated. For a *k*-tick spread, the profit per trade in period *p*, measured in ticks, is calculated as:

$$\pi_{\mathrm{p}} = \frac{k(W_p) - k(L_p) + d_p(D_p)}{N_p}, \tag{9}$$

where,

π_p = gross profit per trade in period p, measured in ticks[8];

W_p = the number of wins in period p; L_p = the number of losses in period p;

D_p = the number of draws in period p; d_p = the average profit per draw in period p, in ticks;

N_p = $W_p + L_p + D_p$, the total number of trades.

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[6] Using this methodology, the strategy is executed 9,575 times. There are 29,079 periods in the sample (1,077 trading days times 27 periods per day). Hence, one high and one low trade executed per period would result in 58,158 trades.

[7] Three and four-tick trading strategies are also tested. It is found that the win percentage is considerably lower and the draw percentage considerably higher for three-tick and four-tick spreads.

[8] For one-tick strategies, gross profit can be thought of as the percentage of profitable trades by time period.

Table 4:
Percentage of Trades Resulting in a Win, Loss, or Draw by Tick Spread for Extreme Price Trading Strategy

Panel A: Target Gain = One Tick (k=1)

	Low Trades				High Trades			
Trading Period	Number Trades	Wins	Losses	Draws	Number Trades	Wins	Losses	Draws
B	899	65.2%	34.5%	0.3%	898	64.8%	34.4%	0.8%
C	584	60.6%	38.9%	0.5%	595	56.3%	42.5%	1.2%
D	299	60.2%	38.5%	1.3%	306	58.8%	40.5%	0.7%
E	240	61.7%	37.5%	0.8%	229	63.3%	35.4%	1.3%
F	165	57.6%	42.4%	0.0%	184	64.1%	34.2%	1.6%
G	176	62.5%	37.5%	0.0%	211	60.2%	37.9%	1.9%
H	164	60.4%	39.0%	0.6%	193	64.8%	34.7%	0.5%
I	227	55.5%	43.2%	1.3%	241	60.6%	39.0%	0.4%
J	140	52.1%	47.9%	0.0%	164	58.5%	39.6%	1.8%
K	126	59.5%	38.9%	1.6%	157	63.7%	34.4%	1.9%
L	106	55.7%	43.4%	0.9%	144	71.5%	27.8%	0.7%
M	100	46.0%	54.0%	0.0%	138	64.5%	33.3%	2.2%
N	87	66.7%	32.2%	1.1%	129	62.8%	36.4%	0.8%
O	86	65.1%	33.7%	1.2%	108	57.4%	40.7%	1.9%
P	91	62.6%	36.3%	1.1%	124	64.5%	35.5%	0.0%
Q	89	53.9%	44.9%	1.1%	143	61.5%	38.5%	0.0%
R	83	65.1%	34.9%	0.0%	110	64.5%	33.6%	1.8%
S	90	55.6%	44.4%	0.0%	94	61.7%	37.2%	1.1%
T	78	64.1%	35.9%	0.0%	88	65.9%	34.1%	0.0%
U	84	51.2%	47.6%	1.2%	103	68.9%	31.1%	0.0%
V	78	56.4%	41.0%	2.6%	93	71.0%	29.0%	0.0%
W	81	63.0%	34.6%	2.5%	86	61.6%	33.7%	4.7%
X	78	53.8%	44.9%	1.3%	99	58.6%	41.4%	0.0%
Y	69	65.2%	34.8%	0.0%	102	70.6%	28.4%	1.0%
Z	86	69.8%	27.9%	2.3%	132	62.1%	37.9%	0.0%
1	75	57.3%	41.3%	1.3%	118	64.4%	35.6%	0.0%
2	73	57.5%	42.5%	0.0%	132	75.8%	24.2%	0.0%
Overall	4,454	60.5%	38.8%	0.7%	5,121	62.9%	36.1%	1.0%

Notes: If the trade reaches the target gain of *k* ticks, it is classified as a win. If the trade hits the stop loss limit of –k *ticks*, it is classified as a loss. Otherwise, the trade is a draw. Panel A and Panel B present the results for low and high trades when k=1 and k=2, respectively. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

Panel B: Target Gain = Two Ticks (k=2)

	Low Trades				High Trades			
Trading Period	Number Trades	Wins	Losses	Draws	Number Trades	Wins	Losses	Draws
B	899	60.4%	35.4%	4.2%	898	57.0%	36.3%	6.7%
C	584	52.4%	43.8%	3.8%	595	48.1%	46.1%	5.9%
D	299	49.8%	43.1%	7.0%	306	52.6%	39.2%	8.2%
E	240	52.1%	37.5%	10.4%	229	52.4%	36.7%	10.9%
F	165	53.3%	37.0%	9.7%	184	50.0%	37.0%	13.0%
G	176	54.0%	37.5%	8.5%	211	62.1%	29.4%	8.5%
H	164	51.8%	39.6%	8.5%	193	58.5%	32.6%	8.8%
I	227	44.9%	49.3%	5.7%	241	53.1%	41.5%	5.4%
J	140	47.9%	45.7%	6.4%	164	51.8%	40.9%	7.3%
K	126	50.8%	42.1%	7.1%	157	53.5%	33.1%	13.4%
L	106	50.9%	43.4%	5.7%	144	52.8%	38.2%	9.0%
M	100	44.0%	54.0%	2.0%	138	55.1%	33.3%	11.6%
N	87	54.0%	32.2%	13.8%	129	53.5%	41.9%	4.7%
O	86	48.8%	39.5%	11.6%	108	52.8%	38.0%	9.3%
P	91	51.6%	34.1%	14.3%	124	54.0%	37.1%	8.9%
Q	89	49.4%	43.8%	6.7%	143	48.3%	43.4%	8.4%
R	83	45.8%	34.9%	19.3%	110	49.1%	44.5%	6.4%
S	90	48.9%	38.9%	12.2%	94	53.2%	35.1%	11.7%
T	78	43.6%	42.3%	14.1%	88	54.5%	33.0%	12.5%
U	84	47.6%	44.0%	8.3%	103	51.5%	37.9%	10.7%
V	78	50.0%	39.7%	10.3%	93	49.5%	38.7%	11.8%
W	81	51.9%	42.0%	6.2%	86	50.0%	36.0%	14.0%
X	78	43.6%	47.4%	9.0%	99	43.4%	48.5%	8.1%
Y	69	59.4%	36.2%	4.3%	102	47.1%	36.3%	16.7%
Z	86	55.8%	32.6%	11.6%	132	51.5%	37.9%	10.6%
1	75	45.3%	46.7%	8.0%	118	50.8%	36.4%	12.7%
2	73	54.8%	38.4%	6.8%	132	54.5%	31.8%	13.6%
Overall	**4,454**	**52.4%**	**40.4%**	**7.2%**	**5,121**	**52.9%**	**38.2%**	**8.8%**

Notes: If the trade reaches the target gain of *k* ticks, it is classified as a win. If the trade hits the stop loss limit of –k *ticks*, it is classified as a loss. Otherwise, the trade is a draw. Panel A and Panel B present the results for low and high trades when k=1 and k=2, respectively. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

The profit per trade by period for each strategy is shown in Table 5. It can be seen that both trading strategies provide excess return. The overall profit per trade is highest for the two-tick spread. For a two-tick spread, the profit per trade is 0.2584 ticks for low trades and 0.3046 ticks for high. Transaction costs in the futures market vary with trade size and activity. Based on information from the CBOT, it is estimated that round-trip costs to execute the trading strategy would be approximately 0.20 ticks per trade. Thus, this trading strategy provides excess trading profits under both strategies.

Table 5
Gross Profit Per Round-Trip Trade by Time Period

Trading Period	k=1		k=2	
	Low Trades	High Trades	Low Trades	High Trades
B	0.3070	0.3040	0.5095	0.4076
C	0.2175	0.1378	0.1781	0.0403
D	0.2174	0.1830	0.1572	0.2941
E	0.2417	0.2795	0.2917	0.3406
F	0.1515	0.2989	0.3515	0.2989
G	0.2500	0.2227	0.3636	0.6351
H	0.2134	0.3005	0.2866	0.5181
I	0.1233	0.2158	-0.0837	0.2407
J	0.0429	0.1890	0.0357	0.2195
K	0.2063	0.2930	0.1825	0.4395
L	0.1226	0.4375	0.1698	0.3194
M	-0.0800	0.3116	-0.1900	0.4493
N	0.3448	0.2636	0.4943	0.2326
O	0.3140	0.1667	0.2326	0.2870
P	0.2637	0.2903	0.4725	0.3065
Q	0.0899	0.2308	0.1124	0.0909
R	0.3012	0.3091	0.2651	0.1182
S	0.1111	0.2447	0.2556	0.3830
T	0.2821	0.3182	0.0897	0.4318
U	0.0357	0.3786	0.0476	0.3204
V	0.1538	0.4194	0.1795	0.2473
W	0.2840	0.2791	0.2099	0.3256
X	0.0897	0.1717	-0.0769	-0.0606
Y	0.3043	0.4216	0.4783	0.2549
Z	0.4186	0.2424	0.4651	0.3030
1	0.1600	0.2881	0.0000	0.2797
2	0.1507	0.5152	0.3425	0.5000
Overall	**0.2227**	**0.2679**	**0.2584**	**0.3046**

Notes: The profit per round-trip trade based on extreme price trading strategy for 1 and 2 ticks is presented in this table. Trades are identified as low trades and high trades for each strategy. Gross profit is measured in ticks per trade which can be easily compared to transaction costs. Based on information from the CBOT, it is estimated that round-trip costs to execute the trading strategy would be approximately 0.20 ticks per trade. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

As expected, the strategy used in this study is more profitable if prices remain in a tight range during the period. Short-term changes in prices that trigger trading are quickly reversed, thereby yielding trading profits. Alternatively, if price changes trend during the period, then the trading position is more likely to be closed with a stop-loss order. One possible explanation for the observed trading profits by period is that price changes exhibit less trend in periods with high profits. Periods with high negative serial correlations are more likely to trade within a range of prices, and periods with positive serial correlation are more likely to trend.

6. Improving Trading Results with Ex-ante Information

Given the results, an ability to predict negative serial correlation in a time period is expected to improve the profitability of the trading strategy. As seen earlier, there is a significant relationship between serial correlation in any time period and the recent level of serial correlation, as measured by the 30-day lagged moving average of serial correlations. In this section, it is shown that the recent level of serial correlation affects trading profits for the day and in each time period. If lower levels of serial correlation predict higher profitability, this information can be used to improve the profitability of the trading strategy.

For each day, the level of serial correlation is measured by calculating a moving average of serial correlation for the prior 30 days. Subsequently, the sample is divided into trading days where the level of serial correlation falls below a pre-specified limit. The limits are defined in increments of 0.05 or 0.10. Trade takes place only if the moving average of serial correlation for the prior 30-days is less than or equal to the limit. For example, by setting a limit of -0.10, all trading days with a moving average of serial correlations greater than -0.10 are eliminated. This information would be known by traders and could be used to determine whether to execute the strategy on that trading day. The serial correlation limits of 0.00, -0.10, -0.20, -0.30, and -0.35 are set.[9] The trading profits per trade for the day and by time period for each limit are measured.

The overall results are summarized in Figure V. The use of the ex-ante moving average of serial correlations improves the trading profits for all the strategies. Since serial correlation is consistently negative throughout the trading day, it is expected that lower limits will improve the trading strategy trading profits the most. These results are strongest for limits set below -0.30. It is found that trading profits per trade for the two-tick strategy improve the most. For these trades, trading profit per tick more than doubles to 0.6080 and 0.6384 for low and high trades, respectively, based on serial correlation trading limits of -0.30.

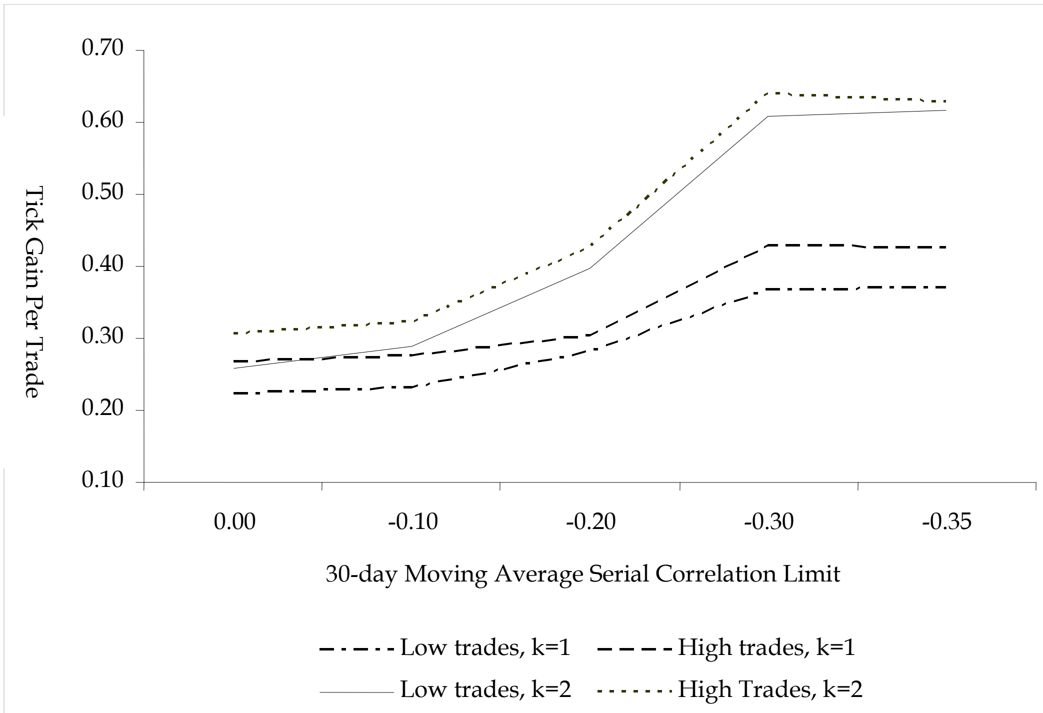
The percentage of winning trades based on the refined serial correlation strategy is also reported. The number of winning trades increases consistently as ex-ante autocorrelation decreases. The percentage of winning trades based on the 30-day moving average serial correlation limits is reported in Table 6. As described above, lower limits are set on the moving average of serial correlations and a trade takes place only if the limits are reached. It is found that the trading strategy wins in over 60% of trades when the autocorrelation limit is set below -0.30. For high trades (k=1), the winning percentages exceed 70%. Overall, these results indicate that ex-ante information based on 30-day moving averages of serial correlation can significantly improve trading profitability in the U.S. Treasury note futures market.

7. Conclusion

In this study, intraday trading in the U.S. Treasury note futures market has been examined. Specifically, the serial correlation of intraday price changes is examined. The results show negative serial correlation throughout the trading day. It is found that serial correlation is consistently low and has declined steadily over the past few years. A 30-day lagged moving average of daily serial correlations is used to measure the overall level of intraday serial correlation. Moreover, it is shown

[9] Since none of the 30-day moving average serial correlations are below -0.40, -0.35 is established as the lower limit.

Figure V
Overall Profit Per Trade by 30-day Moving Average Serial Correlation Limit



Notes: The overall profit per trade based on the level of ex-ante moving average serial correlation is presented in this graph. Trades take place only if the 30-day moving average is less than or equal to the limit. Profit is measured in ticks per trade which can be easily compared to transaction costs. Based on information from the CBOT, it is estimated that round-trip costs to execute the trading strategy would be approximately 0.20 ticks per trade. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

Table 6
Percentage of Winning Trades based on 30-day Moving Average Serial Correlation

Trade Category	30-day Moving Average Serial Correlation Limit					
	All Trades	0.00	-0.10	-0.20	-0.30	-0.35
Low Trades, k=1	60.5%	60.5%	61.2%	63.8%	68.1%	68.3%
High Trades, k=1	62.9%	62.9%	63.3%	65.0%	71.0%	70.8%
Low Trades, k=2	52.4%	52.4%	53.5%	57.0%	61.0%	61.1%
High Trades, k=2	52.9%	52.9%	53.7%	57.2%	60.8%	60.6%

Notes: The percentage of winning trades based on the level of ex-ante moving average serial correlation is presented in this table. Trades take place only if the 30-day moving average is ≤ the limit. The results are based on tick-by-tick data for U.S. Treasury Note futures contracts for 1,077 trading days from September 1, 2000 to December 31, 2004.

that recent levels of serial correlation are predictive of future serial correlation for every time period in a trading day.

An ex-ante technical trading strategy constructed to exploit negative serial correlation in the U.S. Treasury note futures market has been tested. The trading strategy consists of identifying daily extremes in the market. If a daily low is reached, the contract is bought and a stop loss is established. If a daily high is reached, the contract is sold and a stop loss is established. In each case, k ticks of gain are targeted within the trading period. This strategy is tested for k = 1 and 2 ticks from the extreme. It is seen that this trading strategy is profitable for both strategies, but is more profitable for k=2 strategies.

The results provide evidence that it is possible to obtain excess profits in the futures market for U.S. Treasury notes. Further evidence is provided that the profitability of this strategy is related to variations in the serial correlation of intraday price changes. The strategy is shown to be more profitable (1) during periods within a trading day when serial correlation is low and (2) on days when the recent level of serial correlation has been low. Importantly, it is shown that recent levels of serial correlation are predictive of future serial correlation for all time periods in a trading day.

Since recent levels of serial correlation are predictive of intraday serial correlation, our trading strategies are refined using this information. Traders observing past price behavior can restrict trading to days where the recent level of serial correlation has been low. The results indicate that this refinement significantly improves trading profits and winning trades can exceed 70% of all trades. These results are important for scalpers and speculators in U.S. Treasury note futures. The trading strategy results are especially relevant because they are based on electronic trading data. Trading platforms exist in the electronic market that can be easily adapted to trading algorithms. Therefore, it is likely that the trading strategy that has been tested can be employed in the U.S. Treasury note futures market.

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