TRADING TREASURY FUTURES: A VECTOR AUTOREGRESSIVE (VAR) ANALYSIS ON THE VOLUME-VOLATILITY RELATION

WENCHAO LIAO*

February 10, 2008

Preliminary Draft. Comments Welcome.

ABSTRACT

Does trading by hedgers or speculators destabilize the Treasury futures market? And if it is the case, how do they destabilize the market? I examine in this paper** the empirical relation of volume and volatility—which is central to the market microstructure literature—in the context of Treasury futures trading. Vector autoregressive (VAR) analysis is conducted on the 2-, 5-, 10-, and 30-year Treasury futures contracts traded at the Chicago Board of Trade. With some mixed results, it can be roughly concluded that speculators destabilize the Treasury futures market, causing a more turbulent trading pattern as evident in the increased price volatility. The same can not be said of the hedgers; available evidence at best suggests a weak relation between hedging and a decreased price volatility (indicating a market being stabilized). To my knowledge, this study is the first in applying the VAR technique to the context of Treasury futures trading. It is also the first in examining the volume and open interest by constructing two different trading activity series ("aggregate" and "active contract" amounts) in the same study, and the results are compared. On the volume-volatility relation, it is among the few studies that explicitly focus on individual contract instead of an all-as-one approach. The long period of data (from year 1991 to 2006) is applied to the VAR framework. In addition, GARCH volatility specifications are comprehensively tested and the GARCH(1,1) volatility specification—commonly-used in the currency futures market—is conveniently arrived at, so possible cross-market comparisons may be fruitful for future applications.

Keywords: volume-volatility relation, vector autoregression (VAR), GARCH volatility, Treasury futures trading, hedging, speculation, market microstructure

---

* The Graduate Center, City University of New York (Economics), 365 Fifth Avenue, New York, NY 10016. Contact: wenc.liao@gmail.com, 201-232-1950.

** Chapter 1 of Liao, W. (2008), "Trading Activity in the Treasury Futures Market and Its Role in Futures Price Fluctuations" (available at SSRN: http://ssrn.com/abstract=1028432). I express my sincere gratitude to Professors Thom Thurston, Nusret Cakici, Michael Grossman, and Salih Neftci at the CUNY-Graduate Center. All errors and omissions are my sole responsibility.

TRADING TREASURY FUTURES: A VECTOR AUTOREGRESSIVE (VAR) ANALYSIS ON THE VOLUME-VOLATILITY RELATION

This paper intends to explore the relationship between trading activity and price volatility existing in the U.S. Treasury futures market. Measuring the trading activity requires of distinguishing between traders by behavior types—in this paper, they are simply either speculators (i.e. day traders) or hedgers. The fact that the Treasury futures contracts have been the choice instruments of fixed-income portfolio hedging as they are traded in a liquid and transparent market will be closely looked at in this paper. Some studies find that the futures market provides a medium for hedging, helping the price discovery and improving the efficiency of the market; the market is stabilized in the process. Nonetheless, studies also suggest that futures market provides another means exploited by profit-seeking speculators, and hence leads to a destabilizing market exemplified by a more volatile market. This paper will look into the interplay between trading activity and price volatility in the Treasury futures market.

As for price volatility of futures, three measures will be used, including (1) the extreme value estimator that measures intra-day volatility; (2) historical volatility; and (3) conditional volatility from AR(m)-GARCH(p,q) process. We will explore the price volatility of Treasury futures contracts in order to infer the behavior of traders, and discuss how trading activity on Treasury futures is affected. Are speculators (i.e. day traders) destabilizing the futures trading market? Are hedgers helpful in stabilizing the market, or—on the contrary—do they contribute further to market turbulences? And does futures trading lead to higher speculation, and therefore the trading on the whole destabilize the futures market? It too should be helpful to examine to what extent my methodology can distinguish between the two types of traders (speculators and hedgers) as I have defined in the futures market of Treasury securities.

Why do we distinguish between speculators and hedgers with the proxies of volume and open interest? What are the implications? On examining the data, for a particular contract, the open interest grows ("accumulates") to a very large number, then decrease somewhat when the contract approaches its maturity. Volume, in contrast, is a number that "does not accumulate"—that is, the number is not added on the previous day's amount. Thus, volume is suitable to capture the daily activity of a particular group of traders who trades with a short, instant time frame; it may serve as the proxy for the trading behavior of day traders/speculators.

Open interest is the number of contracts outstanding in the market for a particular maturity of futures contract. Open interest measures the hedgers' trading activity for two reasons. First, day traders are mainly speculators, who do not hold open positions overnight; therefore, open interest primarily reflects the hedging activity and hence the uninformed trading. Second, according to Bessembinder and Seguin (1993), the willingness and ability of traders to risk capital and take positions—in response to a perceived deviation of price from intrinsic value—determines the market depth, and willingness is partly a result of the trader's degree of risk aversion/taking, while ability is partly a result of trader's wealth constraints. A variable constructed from open interest is supposed to contain the information on current market depth, when the trader's risk aptitude and wealth do not change drastically.[1] Thus, open interest gives a measure of hedging position of hedgers. Volume and open interest data provides insights into the effects of market activity on futures price, and distinguishing effects that are generated by trading of speculators (who are informed) or hedgers (who are uninformed).

Volume-Volatility Relation

I will provide a more comprehensive review on the volume-volatility relation in the Chapter 2. Here I briefly discuss the issue. Volume-volatility relation is directly related to the role of information in price formation. Volatility and volume provide measures on how the market information is reflected in trading, while investigating the relationship among information, volume, volatility and return is usually the starting point to understand the market. This study, in particular, looks at the empirical evidence on the positive or negative relation between volume and volatility so as to understand how trading affects the market and in turn how traders react. Volume and volatility are usually assumed to be the primary variables through which the information is conveyed.

Karpoff (1987) reports an early empirical regularity on the positive contemporaneous correlation between trading volume and price volatility. Particularly for the futures market, volume-volatility relation has a bearing on the issue of whether speculation activity is a stabilizing or destabilizing factor. The time to delivery of a futures contract may affect the trading volume, too, and through the effect to the variability of futures price. Volume-volatility relation can also be used to distinguish the information sources (say, public or private) on the demand for futures (see Harris and Raviv (1993) and Shalen (1993)).

Volatility of prices may respond to volume shocks asymmetrically, depending on whether the volume is above (positive shock) or below (negative shock) its expected value. Positive price shocks are usually associated with larger volumes while the negative shocks with smaller ones. Bessembinder and Seguin (1993) further partitions volume (and open interest) into expected and unexpected components. Allowing each component to have its own effect on the observed price volatility, they are able to tell if the volume-volatility relation would have changed with a different source of volume generation. They find that futures price volatility is positively related to both the unexpected and expected components of volume, while the magnitude of volatility change is six times larger on average with the unexpected component of volume shock. Also, they find that the unexpected component asymmetrically affects the contemporaneous volatility—the positive unexpected volume shocks have a largest effect on volatility—when positive and negative volume shocks of expected component affect price volatility in symmetry. Moreover, even as volume is included in model specification, the daily change in open interest clearly has explanatory power.

---

[1] Also, the *un*expected change in open interest during a time period should be a proxy for the trader's current willingness to risk his capital. See Bessembinder and Seguin (1993).

Distinguishing trading activity further would be helpful. It is often argued that the market depth varies with recent trading activity, and that the observed price volatility is lower when the open interest (as proxy for uninformed trading) is large, conditional on contemporaneous volume. Kyle (1985) defines the market depth as the volume of *un*anticipated order flow required to move market price by one unit; his model shows that larger volumes would come from the support of informed trading (speculation), and that the market depth varies with the level of non-informational trading activity (hedging). Empirical relations can be tested by incorporating the persistence of trading activity into a dynamic system such as vector autoregression (VAR). Volume-volatility relation provides insights into the structure of financial markets—how the information is disseminated, whether the change in dissemination rate propagates to price fluctuation, to what extent institutional features such as introduction of short-sale constraints transform the market, and indeed what effects the various types of traders and information present.

Most of the volume-volatility based hypotheses in futures market are tested on stocks; see Bae et al. (2002), Chang et al. (2000), Chatrath et al. (2003), Darrat et al. (2002) and Gulen and Mayhew (2000) for examples. A few tests this relation in the futures markets of commodities and currency; see Yang et al. (2005) on the commodity futures, and Clifton (1985), Chatrath et al. (1996), Adrangi and Chatrath (1998), Bhargava and Malhorta (2007) on currency futures. Wiley and Daigler (1999) deals with the interest rate market (the Treasury futures), so does one part of Bessembinder and Seguin (1993). Tauchen and Pitts (1983) provides one of the early studies on volume-volatility in Treasury futures market, using the first Treasury contract—the 90-day T-bills futures—with data from the very first trading day on January 6, 1976 until June 30, 1979. Meanwhile, some studies work along the dimension of volume-volatility relation for various markets (such as Besssembinder and Seguin (1993)); while a well-established methodology and legitimate in itself–in particular in current investment landscape where trading and arbitrage are constructed across asset classes and markets—I would want to put the volume-volatility relation into the context of a specific market. With the use of econometric tools, my study concentrates on the Treasury markets of medium- and long-term maturities.[2] The natures and characteristics of the Treasury market that distinguish it from other markets will be discussed. I will examine some of the Treasury market's institutional features in the Chapter 2. The underlying *belief* is that the market nature makes a difference, although this study will not be as extensive as to confirm the characteristics of other markets. It will be interesting to see whether the nature of the Treasury market itself makes different conclusions on volume-volatility relation, in contrast to stock, currency, commodities or other markets.

Measures of Volatility

Following Bhargava and Malhotra (2007) here—whose research design I follow as well—I use the three different measures of volatility: (1) the extreme value estimator that measures intra-day volatilities; (2) historical volatility; and (3) conditional volatility

[2] Because of data availability, I exclude the futures contract on short-term Treasury bills (with maturities equal to or less than one year) from this study.

from the GARCH process. Parkinson (1980) developed this extreme value estimator for intra-day volatility (to avoid the need of using high-frequency tick-by-tick data):

$$(1) \qquad \sigma_{HL,t} = \sqrt{0.3607[\ln(\frac{H_t}{L_t})]^2}$$

where H_t is the highest price of the futures contract on day t, and L_t is the lowest price of the futures contract on day t. This estimator measures the volatilities coming from trading of speculators (and day traders).

The second volatility measure calculates the standard deviation from historical futures prices. The following formula is used:

$$(2) \qquad HSD_t = \sqrt{\sum_{i=t-20}^{t} \frac{(R_i - \overline{R}_t)^2}{21-1}}$$

where $R_t = \ln\left(\frac{F_t}{F_{t-1}}\right)$, $\qquad \overline{R}_t = \sum_{i=t-20}^{t} \frac{R_i}{21}$.

F_t is the futures price, and I use the current day and the last 20 consecutive days of prices (thus, from date t-20 to t-1 and to the current date t; at a total of 21 observations[3]) to calculate $\overline{R}_t$, the average return at day t. Historical volatility is then obtained.

The third volatility measure is derived from the GARCH model, where I obtain the conditional variance of return on Treasury futures. I extend the GARCH(1,1) specification of Bhargava and Malhotra (2007) to the general form AR(m)-GARCH(p,q). It is interesting to investigate whether the conditional variance from GARCH(1,1) is also the appropriate measure of the Treasury future market, since numerous studies find it a good measure for currency futures market (according to Bhargava and Malhotra (2007)). The AR(m)-GARCH(p,q) specification is the following:

$$R_t = \overline{R}_t + v_t$$
$$v_t = \varepsilon_t - \varphi_1 v_{t-1} - \varphi_2 v_{t-2} - \ldots - \varphi_m v_{t-m}$$
$$\varepsilon_t | I_{t-1} \approx N(0, \sigma_t^2)$$
$$(3) \qquad \sigma_t^2 = \omega + \sum_{j=1}^{p} \gamma_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where $\overline{R}_t$ is the mean of R_t conditional on past information, and σ_t is the volatility measure derived from AR(m)-GARCH(p,q).[4] [5]

[3] 21 days is the approximate number of business trading days for one month.

[4] The main regression has two restrictions: 1) no intercept; and 2) coefficient = 1. In SAS program, use "noint" as model option for no intercept, and add "restrict" command for the coefficient to be 1.

Vector Autoregressive (VAR) Analysis

I use both the volume (to capture speculative activity) and open interest (to capture hedging activity) as proxies for demand for Treasury futures. The purpose is to examine the relationship between futures price volatility and the hedging and speculation demands for Treasury futures. In specific, the paper examines the impact of an increase (decrease) in volatility on the demand of futures by hedgers and speculators. The VAR (vector autoregressive) approach is suited for this purpose.

Impulse response functions will show how the conditional forecast of one variable would change in response to the shock in another variable of the VAR system. The Granger causality tests (Intriligator, Bodkin and Hsiao, 1996) will be conducted to see if causal relations can be inferred between trading activity (speculative or hedging) and the volatility in futures price.

We use VAR to determine the relationship between trading activity and futures market volatility. (Also see the Appendix on VAR discussion.) I will take the *reduced form* VAR approach:

$$Vol_t = \alpha_{0t} + \sum_{j=1}^{k} \alpha_j Vol_{t-j} + \sum_{j=1}^{k} \beta_j TA_{t-j} + \varepsilon_t$$

$$TA_t = a_{0t} + \sum_{j=1}^{k} a_j TA_{t-j} + \sum_{j=1}^{k} b_j Vol_{t-j} + e_t$$

The reduced form VAR expresses each variable as a function of its own past values, the past values of the other variable, and a serially uncorrelated error term: current volatility as a function of past values of volatilities and trading activity; current trading activity as a function of past values of trading activities and volatility. In the two equations, α_j and a_j are the coefficients of own past values and β_j and b_j are the coefficients of the lagged independent variables; Vol_t is the futures price volatility and TA_t the trading activity (natural logarithm of volume or open interest). The number k is number of lags. By treating every endogenous variable in the system as a function of lagged values of all the endogenous variables in the system, the reduced form model sidesteps the need for structural specification.

Each equation is then estimated by ordinary least squares regression. The number of lagged values to include in each of the two equations will be determined by Akaike (AIC) or the Bayes (BIC) information criteria.[6] The majority of AIC results gives a lag

---

[5] Another traditional volatility measure is from Garman-Klass (1980). The measure is defined as Volatility = $[0.5\,[\ln(\text{High}) - \text{Ln}(\text{Low})]^2 - [2\ln(2) - 1]\,[\ln(\text{Open}) - \ln(\text{Close})]^2\,]^{0.5}$,where High, Low, Open, Close denotes the high, low, open, and closing prices in the day for a particular contract. Also see Wiley and Daigler (1999) for the application in a GARCH model.

[6] For discussion on the AIC and BIC information criteria and estimation issues, see Appendix to Chapter 1 of Liao, W. (2008), "Trading Activity in the Treasury Futures Market and Its Role in Futures Price Fluctuations" (available at SSRN: http://ssrn.com/abstract=1028432)

length of four, so I settle at four lags for all estimations for the purpose of consistency. Trading activity is proxied by volume and open interest respectively, and the VAR results of the two different proxies will be used to infer and compare the behavior of hedgers and speculators. The two error terms may be themselves correlated across equations in the reduced form VAR, if the trading activity and price volatility are correlated with each other. In addition, I will test for stationarity of all time series using the Dickey-Fuller test for unit roots, since VAR model is suitable when the series are stationary. If the series are not stationary, the vector error correction (VEC) model may be more appropriate.[7]

Impulse response functions are used to analyze the impact of change in volume (or change in open interest) on the price volatility of Treasury futures, which is in turn measured by the intra-day volatility, historical volatility, and the GARCH volatility, respectively. An impulse response function is used to simulate the effects of an innovation to one variable on the conditional forecasts of other variables in a dynamic model. A sudden shock of one standard deviation (one "unit") is introduced at day 0 to one variable, and then the shock disappears. The effect of the temporary, one-period volume shock on the volatility is examined over the time horizon.

---

[7] See discussion on the stationary of series in Appendix to Chap.1 of Liao, W. (2008), "Trading Activity in the Treasury Futures Market and Its Role in Futures Price Fluctuations" (available at SSRN: http://ssrn.com/abstract=1028432).

DATA AND ESTIMATION

Daily settlement prices, trading volumes, open interests, daily high and low prices for 2-year, 5-year, 10-year notes and 30-year bonds in the Treasury futures market are obtained from the CBOT DataExchange. [8] I use the Treasury futures data from 01/01/1991 to 12/31/2006. No special reason is attached except that this period is the greatest overlap of available data on the four types of Treasury futures contract. Meanwhile, since the same period is used, other exogenous variables (macroeconomic and Treasury-market-specific) should be controlled. Data are specified for an individual contract by the month and year codes. As a result, 16,147 observations are created and examined based on 256 contracts.

Issues arise on how to merge data and create series. For a certain type of Treasury futures (say, futures on 10-year note), since three to four contracts of different delivery months exits simultaneously on a particular date, the series of price and volume (and open interest) may be generated judiciously. Bessembinder and Seguin (1993) aggregates the data (including the Treasury futures) for a particular day for all available contracts. So does Bhagarva and Malhortra (2007) proceed the analysis with aggregate data. Since market microstructure studies may be advanced either by examining the transaction data in a more segregated time period (ie. the "high-frequency", tick-by-tick data) or by limiting horizontally the "scope" of the data to individual contract instead of aggregation, I construct the "active contract" data series.[9] To my knowledge, my study is one of the few studies that examine the volatility-volume relation of a particular market by individual contracts. At the same time, I do the aggregate data analysis as well. I hope to see how the results correspond to 1) the results based on individual contract data; and 2) the results from other markets (currency, commodity, equity) obtained based on aggregate data. In the following sections, I will discuss data series generation and rationales for different ways of construction. It ought to be kept in mind, however, that the intention is to create data series well-suited for exploring volatility-volume relations in the Treasury futures market.

Constructing Volume and Open interest

On examining the Treasury futures data at hand, there are (at least) three ways to generate the volume and open interest series for the purpose of studying volume-volatility relation. (See Figure 1C for a sample of original data and CBOT month codes.) First, volumes and open interests of a type of contract (say, 10-year note futures) are to be summed across all outstanding maturities for a particular day, in order to obtain an aggregate measure of market activity. Bessembinder and Seguin (1993) uses this approach. For each available contract in a period, however, the delivery month (expiry) is different. Second, Bhargava and Malhorta (2007) suggests that, for a particular day, futures contracts with the highest open interests (or volumes) are used. Open interest is usually highest for contracts closest to maturity, except for a few days prior to expiration.

---

[8] See the contract specifications and sample data in Figure 1A.

[9] The "active contract" concept is inspired by the roll-over method specified by CBOT. See Figure 1B.

Nonetheless, this method is biased toward the high-trading end of all contracts. Another way is to use the volume and open interest associated with same observations that are selected for generating the price series, which I call the “active contract” method.[10]

As for the first approach, market activity at the aggregate level seems to offer a convincing way of describing the market, a view not possibly obtained by looking at one of existing individual contracts. For my own purpose, I intend to compare the results of the first and third approaches. I also want to compare my results with those of Bessembinder and Seguin (1993), one of the few volume-volatility studies which include Treasury futures market.

Constructing Returns

I use the “settlement price” instead of the “close price” from the dataset, because it is the settlement price that is used to calculate a trader’s gains and losses and the margin calls. [11] Moreover, it is calculated for each trading day as the average price at which a contract trades, and therefore, it is suitable for a study on daily series. Since the volume and open interest tend to be very low within the delivery month of the maturing contract, prices of the *second-nearest* contract are then used. We want to construct a price series that are representative of actively-traded futures contracts.

I use the “near returns” (Bessembinder and Seguin, 1993) to construct the return series. Clark (1973) suggests the more complex “composite return” method; the idea is to define a “contract” that matured a fixed distance in the future, and the distance is constructed by taking the average maturity of all futures in the market with a weight function. Both methods aim to generate longer return series that always represent prices of an “active” market. Although sound in theory, the composite return method requires much more efforts with limited gains.[12]

By examining the volume/open interest charts on CBOT website (see Figure 1D), I see that activities are most prominent in the three months prior to the end-date of the delivery month of futures contract. For example, the 10-year Treasury note futures contract with delivery month of December 2005 (Code: Z 05) is relatively inactive until the late August 2005, when the volume suddenly went up, as traders (both hedgers and

[10] It should be noted that the second method, while choosing the highest volume (or open interest), may generate a series not too different from the third. To have “active” contracts is exactly the rationale to form the series using the second and the third methods.

[11] A quick note on Treasury *bills* futures: We use the “delivery price” in Treasury bill futures (instead of a settlement price) to calculate the returns. The quoted price, Q, on the T-bill futures must be converted to the implied delivery price, D = (75 + (Q/4)). The quoted price obligates the seller to delivery 13-week T-bills at contract maturity for a price such that the *annualized* return to the buyer over the 13 weeks is (100 - Q) percent. The CME’s 13-week Treasury bill futures contract is the only one futures contract on T-bills. It was launched in 1976 and was the first interest rate futures contract. T-bills are the short-term (less than one year) cash management tools. Tauchen and Pitt (1983) offers the early empirical study on the Treasury bill futures, using data from 01/01/1976 to 06/30/1979.

[12] Bessembinder and Seguin (1993) finds that the near returns are very highly correlated with the returns calculated with Clark’s composite contracts. Empirical results should be robust with either return series.

speculators) switched ("rolled") into the December contract. The September contract volume ceased to be "active" since early September, 2005, and it expired when reached the last delivery date on September 21, 2005. The December 2005 contract remained active until late November, 2005, but the volume dropped in December. Traders had rolled into the "second-nearest" contract, that is, the contract with the delivery month of March, 2006.

Therefore, in order to construct a price series at which contracts are traded actively, I use the settlement prices of the contract close to expiration, except within the delivery month of that contract, of which the second-nearest (next) contract is used (following Bessembinder and Seguin (1993) and others).[13] The return series is then calculated as the series of percentage change on successive "active prices".[14] This is a desirable feature since the returns are more likely to be representative of an active contract with reasonable amount of quantities being transacted at all times. Moreover—in practice—traders can easily roll into the second-nearest contract at the beginning of the delivery month.

I then decide on how to deal with the zero volume and zero open interest observations in dataset. On inspecting the observations with zero volume and/or zero open interest on the active and aggregate data, most of them are zero in volume but not in open interest: 2-year and 10-year notes futures data has 23 and 21 records, respectively, with zero volume, while one of the 23 has a zero open interest; there are no other zero volume records. 5- and 30- year notes futures data has 18 records with zero volume; no record has zero open interest. A zero open interest on a trading day while the adjacent two trading days have a non-zero open interest during a contract's active life is outright wrong, so I treat the specific observations (2004/12/23, H05) in 10-year notes as missing data. I use the average of the two adjacent open interests; the volume is also calculated as such. The observation in the 2-year notes (2004/12/30, Z 04) happens on the expiring date of the contract, so I simply exclude this observation.[15]

On inspecting the zero volume observations, I find it hard to exclude them, since 1) the volumes in adjacent observations are varied; and 2) at times, even though two (or three) contracts exist, both of them have zero volumes. Therefore, observations with zero volume are kept intact. In the end, 16,147 observations are created from available Treasury futures data for the four types of contracts.

Analyzing V_Ratio and O_Ratio

---

[13] See the "active" contract time table in Figure 1E. There is one exception, however: I use the December 2004 (Code: Z 04) contract data for the month of December 2004, because it was the only contract existing–even when the contract was about to expire in the end of the same month. Activity of this contract was still active during this period, so the result should be not much affected.

[14] The natural-log return is calculated: $R_t = \ln\left(\frac{F_t}{F_{t-1}}\right)$.

[15] See also footnote 13 about this particular contract.

On comparing the volumes of both the active contract and aggregate contract, I do not find significant deviation. During a period, usually one major contract is actively traded while other existing contracts are thinly traded, and the aggregate volume in the period concentrate heavily in one contract—in effect, in the one "active contract" specifically constructed in the third approach. Futures markets are usually reported to have this "concentration of liquidity" feature, where the trading volume is highly concentrated on one contract (usually the one close to expiration). Fleming and Sarkar (1999), using tick-by-tick data of the one year 1993, provides a quick evidence on liquidity concentration (with the exception of the 13-week Treasury bill futures), and it also shows that the more active the concentration on one particular contract, the less active the more distant contracts. They also reports the concentration by maturity, where the vast majority of futures trading volume is in longer maturity instruments, especially in the 30-year bond futures.

In order to see it more clearly in my dataset, I design the "V_Ratio" and "O_Ratio" statistics; simply, they represent the portion of trading concentrating on the heavily-traded, "active" contract, respectively in volume and open interest. For the case with only one contract (the active contract) exists but with zero volume, I assign "1" for either V_Ratio or O_Ratio; it means trading on the particular date can be fully explained by one contract. A minimum of zero means the active contract actually has no trading volume, while other contracts exists and the aggregate trading volume is nonzero, such as the minimum value of zero in the V_Ratio of 2-year note futures.

Summary statistics of the V_Ratio and O_Ratio are reported in Table 1A. Boxplots are also included; the two-year note futures, for example, has an inter-quarter range (3Q - 1Q) of about 0.3 (see Figure 1F). Some of the "active contracts" as so defined has very small ratio on the aggregate trading volume: Although these data points are treated as outliers on boxplots, they are in fact those trading dates when the active contract's volume is a minor fraction of aggregate volume. The minimum of the 4 types of contracts are all less than one-forth of aggregate volume; thus there are days the volume can not be truly "representative" by an active contract. (However, I define active contracts in order to construct the *price* series.) Since the "outliers" are many and distant from the inter-quarter range (Q3 – Q1; see the boxplots), the medians of V_Ratio and O_Ratio should be a better measure for how well the active contracts represent the aggregate trading volume from year 1991 to 2006. Except for the 2-year futures contract (with median 0.98), other three have a median around 0.90.[16] This result should come from the fact that a futures contract type with a longer-maturity underlying has longer contract life (as designed by CBOT). Therefore, active contract's volume represent a smaller fraction of aggregate volume of the day, since several (three to five in the 30-year

[16] The anomaly is the 30-year contract's V_Ratio, which has a large median of 0.96. One possible explanation is that, while a lot of periods have seen overlapping contracts, a lot more periods has only one or two contracts existing (and only one is actively-traded) in the long duration of the 30-year futures contract life, which usually ranges from 2 to 3 years. In addition, in terms of volume, usually the active contract dominates the volume but not the open interests, so that the fraction of the "active contract" in the aggregate volume (of the one or two existing contracts) is bigger.

futures case) contracts existed at the same time and were actively traded at overlapping period. Moreover, I find that the longer the maturity of underlying Treasury security, the smaller the standard deviations of V_Ratio and O_Ratio. I believe this feature is also a result of overlapping contracts. From the V_Ratio and O_Ratio analysis, I see that using aggregate volume or active contract volume does not seem to make a difference for the vector autoregression (VAR) results. I will obtain the result and see if my conjecture is right.

Obtaining Volatilities

I construct the three time series of volatilities (intra-day, historical, and GARCH) accordingly. At some days, trading does not occur (volume is zero, although open interest is usually non-zero)[17], and hence those observations lacking either the settlement price or the high and low prices (or all three) are to be omitted. The intra-day volatility using high and low prices are then constructed according to the extreme-value measure specified in Parkinson (1980).

The historical volatility is constructed based on a return series of a consecutive 21-day period. On examining the pattern, for the (current) benchmark 10-year notes futures, the highest three periods are 12/01/1999 to 12/30/1999, 11/29/2001 to 12/28/2001 and 09/02/2003 to 09/30/2003, where the highest (first period) is abnormally high (about 3 times the second highest (third period)). As for the price volatility of the old benchmark the 30-year Treasury bond futures, the highest three periods are 12/01/1999 to 12/29/1999, 12/18/2001 to 12/14/2001; 08/06/2003 to 09/30/2003.

The GARCH volatility is estimated with the AR(m)-GARCH(p,q) specification. For each contract type, 12 specifications are estimated and examined (where m = 0, 1 or 4; p = 1 or 2; q = 1 or 2). Appendix offers considerations on obtaining the GARCH volatility measure. In the end, I settle for the AR(0)-GARCH(1,1) form, since the results are fairly consistent across the four contract types. For more details on estimation, please see the Appendix to Chapter 1.

VAR Estimation

I use the most basic form of a VAR, which treats all variables as symmetric without making assumptions on whether each individual variable is dependent or independent. The Dickey-Fuller tests of stationarity for are performed. Each time series (volume, open interest, aggregate volume, aggregate open interest, intra-day volatility, historical volatility, GARCH volatility) is tested against models of the mean, single-mean and trend, and the test statistics (rho and tau) rejects that the individual series has a unit

---

[17] But notice that I may have assigned “1” to R_Ratio and V_Ratio on these days; most often only one contract existed.

root.[18] I restrict the selection of the order of VAR to between one and four, although it is theoretically possible to estimate the reduced-form VAR model with five or more lags. Difficulty in obtaining a non-singular[19] variance-covariance matrix in estimation arises in high orders, and valuable, meaningful analysis can not be performed. For example, variance decomposition on forecast errors can specify the proportion of movements in a sequence due to its own shocks versus shocks of other variables. The VAR order with the smallest information criterion on model specification is then chosen to be the best-fit.[20]

Evidence from the Akaike (AIC) and Bayesian (BIC)[21] information criteria on estimating the reduced-form VAR suggest an order of three or four. The majority of the smallest (most negative) information criteria occur at order four. In addition, I want to compare across contract types with consistency. Given these considerations, I estimate the reduced-form VAR for each contract type with the number of four lags. Meanwhile, in order to determine whether trading activity causes volatility, I test for Granger causality between volume and volatility variables.[22] Causal relationships (in a statistical sense) among economic variables may be identified, if one were to assume that the future can not cause the past, and the information on this effect is not available from elsewhere. As for impulse responses, the size of shocks applied to the VAR system is a one-standard deviation shock of the error. As common practice in the VAR literature, the sixty-eight percent confidence band is also drawn.

[18] The idea of a VAR analysis is to determine the interrelationships among various variables, rather than to determine the parameter estimates, as Sims (1980) and others argues. However, the test for stationarity has become the common practice in VAR estimation. See Appendix for discussion.

[19] A non-singular matrix should be inversible, or equivalently, should have a non-zero determinant.

[20] Also see the determination of VAR order in Buckle et. al. (2002).

[21] Denoted as SBC (Sawa's Baysesian information criterion) in the SAS.

[22] For estimation issues with Granger causality, see Appendix to Chapter 1 of Liao, W. (2008), "Trading Activity in the Treasury Futures Market and Its Role in Futures Price Fluctuations" (available at SSRN: http://ssrn.com/abstract=1028432)

VAR RESULTS

Table 1B provides the summary statistics of the mean, median, standard deviation (S.D.), minimum, and maximum for the following variables: daily log return, aggregate volume and aggregate open interest, active contract's volume and open interest, and the three measures of volatility. (See Figures 1L and 1M for SAS program.) Returns on average for the data period are positive for each contract type. Dispersion in returns (in terms of standard deviation of returns) in the 30-year bond futures is the largest, followed by 10-year, 5-year, and 2-year futures. Long maturity of futures seems to add more variation on the returns. Depending on its chosen data of issuance, a 2-year notes futures contract (futures contract on 2-year Treasury notes) usually has a life span of 4 to 6 months. A 5-year futures has a life of 7 to 10 months, and a 10-year futures 8 months to 1 year. 30-year bond futures contract has a life spanning from 10 months to 2.75 years, although the majority of life is more than 2 years. Albeit at regular issuance frequencies, the CBOT judiciously chooses the type of contract to be issued and determines how long the contract is to expire, depending on its judgment on market liquidity and needs. Interestingly, the average return during this period (from year 1991 to 2006) also decreases along with underlying maturity.

Also, based on volume and open interest, 2-year contract is the least active contract. As the benchmark of fixed income securities shifted from 30-year bonds to 10-year notes on May 3, 2000, when the Wall Street Journal officially declared the change of daily statistics publication, the Treasury futures market would have reflected some of the reality[23]. It will be interesting to take a look at the VAR results before and after the benchmark shift in the respective 10-year and 30-year bonds markets. It is essential to distinguish between the mean and median. Across the four markets, the volume of zero appear more than a few times even the active contracts are chosen to be representative, and extremely high volume and open interests occurred from time to time. Simply looking at the means may be misleading. The means are all above the medians, indicating upward biases in volume and open interests. In terms of volume (both in aggregate amount and in the representative "active contract"), the 30-year futures market is unequivocally the most active, which has three times the volume of the next active 10-year market, four times the 5-year market, and about forty times the least active 2-year market. As for open interests, the results are similar, only that the 10-year and 30-year markets have about the same level. (In fact, the mean and median open interests in 10-year market are higher.)

In terms of dispersions on trading volume and open interest (standard deviation as percentage of the mean), the 30-year market is the most concentrated (i.e. smallest

[23] The 30-year Treasury bonds became the fixed-income market's benchmark during the period of heaviest Treasury borrowing from the mid-1980s through the early 1990s, along with the surge in sales and trading. However, beginning in September 1999, futures contracts on the 10–year Treasury notes pulled ahead to gain more open interests. Since the open interest, or contracts outstanding, represents investor's interests in a particular futures contract prior to sale or expiration, a rising open interests implies increasing investor preference and rising trading activity. In May 2000, the 10-year notes rate was already the basis for the rate charged on most home mortgages. See accounts on the benchmark shift in Jones (2000) and Wojnilower (2000).

dispersion). The highest trading volume occurs in the 30-year market (1,121,634 contracts in aggregate) on 09/27/1998, while days of 8/21/1998, 8/28/1998, 09/01/1998, 09/10/1998 are among the top ten trading volumes. Evidently, the August and September of 1998 have seen heavy activities due to Russian bond defaults and the LTCM crisis. It's also interesting to notice that all of the top ten open interests (both in aggregate amount and in the "active contract") occurred spanning from late June to early July of 1998, indicating heavy speculation activities in the Treasury futures market before the LTCM exploded, and then jumped up again in late August. In fact, from year 1991 to 2006, the 79 of the top 80 days of highest open interests occurred during the period of mid-May to early September of 1998, when the Russian government defaulted on government bonds (GKOs) and panicked investors sold Japanese and European bonds to buy U.S. Treasury bonds. LTCM exploded due to the breakdown of bond "convergence trades". [24] Amazingly (but without surprises), Treasury futures market (along with the cash market) absorbed most of the demands in hedging and speculation.

Moreover, comparing the aggregate amount with "active contract" by the mean and median, we can see that more than three-fourths of the aggregate amount is due to the trading in one active contract. It *looks* that the active contract approach is quite representative of the aggregate approach.

Across the four contract types, the intra-day volatility measure consistently provides the lowest value for the estimate of volatility, the GARCH volatility comes the highest, while the historical volatility comes in the middle. Historical volatility estimate has a higher standard deviation than the historical volatility estimate. GARCH volatility estimate, however, is substantially the least dispersed in terms of standard deviation in four contract types, perhaps thanks to its upward-biased estimates. As comparison to the currency futures markets (reported in Bhargava and Malhortra (2007)), the difference is in the GARCH volatility, as it comes the lowest in all currency markets, even though the least dispersion still occurs in the GARCH volatility. But the interesting thing to notice is the consistency exhibited in the three estimates in the respective currency and treasury futures markets; this would imply the construction of volatility measures is a major determinant to the upward- or downward-bias in level and standard deviation.

[24] LTCM (Long Term Capital Management) had developed complex mathematical model to take advantage of fixed income arbitrage deals usually with U.S., Japanese, and European government bonds. The basic idea was that while over time the value of long-dated bonds issued a short-time apart tend to become identical, the more heavily traded bonds such as U.S. Treasury bonds would approach long-term price more quickly than less heavily traded and less liquid bonds, and thus an arbitrage opportunity should occur. As the bond markets experienced the "flight to liquidity" (to the on-the-run U.S. Treasuries) in the late summer of 1998, LTCM's highly-leveraged position was no longer sustainable since the convergence trades broke down: spread between on- and off-the-run Treasury widened. Marketwide repricing of risks rendering the benefit of LTCM's diversification strategy impossible to realize, since all of the positions in its portfolio has then moved in the same direction. Even though LTCM's directional bets in the end was correct, in the sense that the values of government bonds did eventually converge, the company has been too leveraged to stay solvent. (So an oft-quoted Keynesian wisdom goes: "The market can stay irrational longer than you can stay solvent.") See Edwards (1999). Also, see MacKenzie (2003; 2006) for the sociological aspects surrounding the event and the interplay between arbitrage models and the markets.

Table 1C provides the correlation of activities (between aggregate amount and "active contract" amount). Except for the open interest in the 30-year bond futures, aggregate and "active contract" amounts are highly correlated (over 0.95) over the period of 1991 to 2006. 30-year bond futures market is the most interesting, where the aggregate and active contract volumes are highest correlated (0.987), while the two amounts in open interest is least correlated (0.845) (although it's still high). 30-year futures has a longer maturity (usually 10 months to 2.75 years) and more contracts (four or five) were alive at the same time. The active contract activity is supposedly to be a smaller fraction of the aggregate amount, and thus the aggregate and active contract amounts could be less correlated. It is the case in open interest, which implies hedgers (proxied by open interest) relies more on non-active contracts at the same time. However, speculation activities (proxied by volume) concentrated more heavily on the only "active contract" of the time—so that aggregate and "active contract" amounts are highly correlated. This fact may imply the usually hard-to-distinguish hedging and speculation activities may be better studied in the 30-year futures market, among the four Treasury futures markets.

Compared with the currency futures markets (Bhargava and Malhortra (2007)), the correlations between volume and open interests are substantially lower in the Treasury futures markets (both in the aggregate and active contract amounts). 2-year futures has the highest correlation (0.474 in aggregate amount and 0.415 in active contract amount), while the 5-year is the least correlated (but still positive). 30-year bond futures has a negative correlation (-0.273 in aggregate amount and -0.375 in active contract amount). (In the currency markets, nonetheless, volume and open interests are all positively correlated.) Since negatively correlated volume and open interest may indicate diverges in the behavior of speculators and hedgers, the 30-year market may suggest a more prominent result. It looks to be congruent with the above analysis on the correlation between aggregate and active contract amounts, as the 30-year market has the most divergent correlations (see previous paragraph).

Tables 2A and 2B provide the correlations between the two measures of trading activity and the three measures of futures price volatility. As expected, the speculators' activities destabilize the market: Correlations between volume and the measures of volatility are all positive, both in the aggregate amount and the active contract amount. Interestingly, however, negative correlations between open interest and volatility show up in most cases (except for correlations between the 5-year and 10-year and GARCH volatility), which implies that hedgers do not destabilize the markets, since the open interest increases as volatility decreases. It may be further inferred that the hedgers help stabilize the futures market as they participate in the activity. Correlations between the three measures of volatility are all positive as expected; historical volatility and GARCH volatility are more highly correlated. Results are not much different between aggregate amount and active contract amount.

Tables 3 to 8 give the VAR and Ganger causality results. "A" or "B" indicate that trading activity is proxied, respectively, by the aggregate amount or by the active contract amount. Tables 3A and 3B indicate that volatility Granger causes volume strongly in all contract types. When the VHL (intra-day volatility) is in the dependent variable column, the null hypothesis becomes H_0: intra-day volatility is independent, i.e., volume does not Granger-causes intra-day volatility. Volume does Ganger-cause intra-day volatility, as the Granger test rejects the null at the 5% significance level (each Granger p-value < 0.05). Similarly, intra-day volatility Granger-causes volume (each Granger p-value < 0.05).[25]

To see whether day traders (i.e. speculators, proxied by volume) destabilize the market, we look at the lower-right quarter of the Panel A, B, C, D in Table 3A. For each of the four contract types, day t-1 coefficient for volume is positive and significant (except for the 2-year market where it is weakly significant at p=0.0669). Day traders clearly destabilize the market of the next day: As volume rises, volatility of next day also rises. Day t-2 and t-3 coefficients for volume are mostly not significant. Nonetheless, all of the day t-4 coefficients in the four contract types are strongly significant and negative, indicating that speculation activity in market four days ago actually help with stabilizing the current market, even though it caused the turmoil on the first following day. Meanwhile, since all the lags of volatility on itself in four contract types are all positive and strongly significant, an increase (or decrease) in volatility clearly increases (or decreases) the volatilities in the following days. The VAR with active contract (Table 3B) also gives the same result.

When volume is used as the dependent variable, we can infer the momentum in trading and the feedback effect from the VAR results (see the upper part in each panel). Trading momentum is strong in each contract type, as the four lag volume coefficients are all strongly significant and positive. Day traders' high volume of trading today leads to high volumes in next days. Intra-day volatility Granger causes the volume significantly in each contract types, which shows strong feedback from intra-day volatility to volume. Moreover, since almost all of the t-1 to t-3 lag volatility coefficients are negative and significant for each contract type (while all t-4 coefficients are positive but none of them are significant), we can infer that the speculators (day traders) demand fewer of the Treasury futures in the period of high intra-day volatility for each contract types. With the negative feedback, speculation activity by itself deters future speculation.

Table 4A and 4B give the VAR result for hedging activity (proxied by open interest), while using the intra-day volatility measure. Except for the 5-year Treasury futures market, the Granger causality is significant: open interest Granger causes intra-day volatility. (Similarly, intra-day volatility Granger causes open interest, except for the weak causality in the 2-year contract.) Does hedging activity stabilize or destabilize the market? We can not clearly infer from the lag coefficients of open interest, since almost all of them are not significant (except for t-3 and t-4 coefficients in the 30-year contract). It looks, though, that hedging may be weakly stabilizing for the following one day—5-, 10-, and 30-year markets have negative t-1 lag coefficients with the aggregate amount (Table 4A), and all of them have negative one lag coefficients with the active contract

---

[25] For the discussion on Granger causality, see Appendix to Chapter 1 of Liao, W. (2008), "Trading Activity in the Treasury Futures Market and Its Role in Futures Price Fluctuations" (available at SSRN: http://ssrn.com/abstract=1028432)

amount (Table 4B). Intra-day volatility increases are followed by increased volatility for the next several days, for the lag coefficients are all positive and strongly significant.

As we look at the upper part of each panel (where open interest is the dependent variable), feedback effects are significant only on the first lag (while it's not even significant in the 2-year contract). Negative coefficient on the first lag indicates that the hedgers' demand for Treasury futures decreases as intra-day volatility increases; hedging activity is restrained if the intra-day price movement of previous day increased. Hedgers' reluctance to engage in a volatile market before sufficient information is available may help explain the result. We will later compare with the historical volatility result, where presumably the increase in *historical* volatility should increase hedgers' demand for Treasury futures.[26] Notice that the feedback effects are almost non-existent when active contract's open interest is used, although the first lag in the 30-year bond futures is significant (and negative). Unlike the case of speculators in Table 3A and 3B, the momentum is less perpetuating, as only the first lag (upper-right in panel) is positive and significant across contract types (Table 4A). However, when active contract is used (in Table 4B), the interesting pattern emerges: In every contract type, the first, second, and fourth lag coefficients are all significant, where the first and fourth lags are positive and the second lag is negative. Thus, we may infer that the second day re-adjustment (opposite) in hedging activity occurs on the active contract in each contract type.

In Table 5A and 5B, the historical volatility is used for VAR. Volume Granger causes volatility in all but the 30-year bond futures contract. (Same results with both the aggregate and active contract amounts.) Furthermore, all volume lag coefficients in the 30-year contract are all insignificant. Historical volatility, constructed on a long-term (20 days) basis, shows in VAR how the trading activity reacts to long-term previous activity. It looks that speculators, in the long term, do not have much impact on the 30-year futures contract, which has been the most liquid (at least before the benchmark shift in May 2000) in the Treasury market. For the 2-, 5-, and 10-year contracts, speculation activity does destabilize the market: The t-3 coefficient, t-2 coefficient, and t-4 coefficient, respectively, are positive and significant. Moreover, in each contract, the t-1 lag coefficient of historical volatility is significant (as well as positive), suggesting that an increase (or decrease) in volatility clearly increases (or decreases) the volatilities in the next day, but not to following days. Speculators (as well as hedgers, in Table 6A and 6B) seem to be good at incorporating long-term volatility information. The VAR with active contract (Table 5B) gives the same result.

When volume is the dependent variable, I find a strong trading momentum for speculators in every contract type, as the four lag volume coefficients are all strongly significant and positive. High volume today (proxy to speculation activity) leads to high volumes in next days. No feedback effect is detected in the 2-year contract, but I find consistent pattern in other three contracts. The first lag is negative and significant (same

---

[26] Historical volatility is calculated from returns of past 20 days; hedgers presumably would decide whether to increase or decrease the hedge according to the past available information. Intra-day volatility is calculated from a one-day extreme movement of price (highest and lowest levels).

as in Table 3A and 3B when intra-day volatility is used)[27], and the fourth lag is positive and significant. As the long-term volatility is considered, a decrease in volatility immediately follows a volatility increase on the first day, and then increases again on the fourth day. The result is the same in Table 5B with the active contract.

Table 6A and 6B describes the VAR result for hedging activity, when the historical volatility is used. When the aggregate amount is used, as in Table 6A, open interest does not Granger cause the volatility in the 2-year, 5-year, and 10-year futures contract, and it only weakly Granger causes (p-value = 0.0508) the volatility in the 30-year futures. Moreover, volatility Granger causes the open interest in 5-, 10-, and 30-year contracts, but not in the 2-year contract. As to whether hedging stabilize or destabilize the market, none of the lag coefficients are significant in each market except for the t-2 lag in the 30-year market (i.e. only in the 30-year contract, hedging helps stabilize the market, at the following second day.) The result is quite different, when the active contract amount is used (as in Table 6B).[28] Open interest strongly Granger causes volatility in all contract types, while volatility does not Granger causes the open interest. Therefore, open interest has an impact on the volatility, but the reverse is not true. Furthermore, the result is mixed on whether hedging stabilizes the market. In the 2-year and 5-year futures contracts, only the t-4 lag is significant and positive, which implies open interest destabilize the market on the fourth day. In the 10-year contract, however, no lag coefficient is significant. In the 30-year contract, only the t-2 lag is significant but negative, which implies hedging help stabilize the market on the following second day. Since none of the VAR lag coefficients using intra-day volatility with active contract amount is significant (in Table 4B), hedgers seem to influence the market stability more by incorporating more long term volatility information. (Even though the result is different for each contract.)

One would expect that the hedging activity increases with an increase in historical volatility; hedgers are able to determine the extent of hedging, as long-term volatility information is available. By checking the feedback effect (upper-left of each panel), the effect is either reverse (with aggregate amount, Table 6A) or not significant (with active contract amount, Table 6B). The momentum does not seem to be consistent in each of the contracts, as the significant lags may have opposite signs (upper-right in each panel). All the first lags of momentum, however, are positive and significant.

In Table 7A and 7B, the GARCH volatility measure is used in the VAR.[29] In each contract, volume strongly Granger causes volatility. We infer that the speculation activity has an impact on the market. In addition, volatility does not Granger cause volume except in the 30-year contract. Speculators seem to destabilize the market, as the first lags of the four contracts are all positive and significant (lower-right in the panel). However, the

[27] However, when GARCH volatility is used, as later in Table 8A and 8B, coefficients are not significant for each contract.
[28] I am still yet to find an explanation.
[29] GARCH volatility is supposedly to be the most "accurate" volatility measure, as it takes account of autocorrelated and heteroskedastic errors of time series data; information contained in the non-spherical errors is exploited. See Chapter 3 for discussion on GARCH estimation.

other significant lags are mostly negative (notably the fourth lag); the market is then stabilized within several days. In each contract, volatility increases after a rising volatility only for the first day, as the first lags are significant but not the other lags (lower-left in the panel). Results are the same with both aggregate and active contract amounts.

When the volume is in the dependent variable, the lag coefficients show the strong momentum in each contract (upper-right in the panel). I find consistent and strong evidence that the speculation activity perpetuates for the four days (see Table 3A and 3B; Table 5A and 5B), with both the aggregate and active contract amounts. As for the feedback effect, no lag coefficients are significant in each market; demand on futures by speculators is not significantly affected.

Table 8A and 8B examines hedging activity (proxied by open interest) using the GARCH volatility in VAR. The aggregate amount (Table 8A) and active contract amount (Table 8B) give very different results.[30] Open interest Granger causes volatility only in the 5-year market, when the aggregate amount is used. However, open interest Grangers causes volatility in all four contracts, when active contract amount is used. Furthermore, I find only weak evidence that the hedging activity destabilize the market in Table 8A, since only the second lag in the 5-year contract and the first lag in 30-year are significant, and both are positive. Table 8B, however, shows a consistent pattern in which the first lag is positive (and significant) and the second lag is negative (and significant) in each futures contract. The fourth lag is significant in the 2-year and 30-year contracts. Thus, we may infer that hedging destabilize the market on the first day, and help stabilize the market on the second day. It goes on to destabilize the market in 2- and 30-year contracts on the fourth day. An increasing volatility would have increased the volatility on the first day, as the first lags are all significant (lower-left in the panel; for both Table 8A and 8B), but not on other days. In addition, open interest strongly Granger causes volatility in all contract types, while volatility Granger causes open interest (albeit strongly) only for the 2-year contract. Open interest impacts the market volatility, but the reverse is not evident.

I then check the momentum and the feedback effect, in which open interest is the dependent variable. Momentum is positive and significant on the first lag for each contract (upper-right in the panel), but most of the other significant lags are negative (except for the fourth lags of 10-year and 30-year contracts in Table 8B). We can not infer that the momentum lasts longer than a day. With the aggregate amount (Table 8A), only the first lag of the 30-year contract is significant in the feedback effect. With the active contract amount (Table 8B), however, the first lags of the four contracts are all significant and positive (although the 30-year is weakly significant at p-value = 0.0524). Volatility increase, therefore, increases hedgers' demand for futures on the first day in each market when the active contract amount is used.[31]

---

[30] Again, no explanation can be offered for now.

[31] Examples on forecast plots for volatility and trading activity from VAR are available upon request.

Impulse responses

Impulse response is the dynamic response of the level of each of the endogenous variables to innovations in the trading activities and volatilities. Figure 3 provides the impulse response graphs. We first look at the response of volatility to a shock of trading activity, for four contract types with both the aggregate and active contract amount. Each figure gives both the point estimate and 68% confidence bands obtained by Monte Carlo simulations. The change in volatility (in percentage) can be quantified from the graph. We then look at the response of trading activity to a shock of volatility. The quantitative aspect in trading activity is misleading on the graph, however, since taking logarithm on volume and open interest distorts the measurement scale. Instead, we look at the qualitative properties on the graph. In the log amount table (in the appendix), for example, an increase of 0.2 within the [9.21, 11.51] interval (denoting the contract amount from 10,000 to 100,000) gives uneven scale for the contract number increase. Similarly, a 0.2 increase at interval [9.21, 11.51] is quite smaller than a 0.2 increase at interval [11.51, 13.81]. Hence, we should be careful not to interpret the y-axis of trading activity simply of the same quantitative scale. Third, we look at how volatility itself propagates in response to a shock in volatility, and then examine the similar own-response with trading activity.

Response of volatility to trading activity

The response of intra-day volatility measure (VHL) to the volume trading shock (Log_Aggr_V and Log_V) [32] are very similar across four contract types. With a small initial increase (0.01 percent) up to the third day, the effect disappears at day 5. It is not clear why the responses are consistent across different contracts, and the results are the same with either the aggregate amount or active contract amount. A sudden increase of speculators' demand on futures causes a small disturbance in the intra-day volatility, and the effect is essential gone on the fifth day. The response of intra-day volatility to a shock in open interest (Log_Aggr_O and Log_O) is quite minor across the four contracts (perhaps except in the 30-year futures), and the effect is gone after the fifth day; increase in hedging activity hardly has an effect on the intra-day volatility.

The response of historical volatility (VHIS) to the shock in trading activity behaves very differently from the response of intraday volatility (VHL). The effect is persistent and lasting in the case of historical volatility. Responding to the volume shock, historical volatility increases gradually and end up at a higher level. Since the historical volatility captures the long term effect, the pattern is not surprising. However, historical volatility in response to open interest shock ends up at a lower level (a small 0.005 percent). The effect is positive, though, in the 5-year contract, but the effect is minor. We may infer that the long-term volatility is increased persistently by speculation demand shock, but is decreased persistently by the hedging demand shock. The same pattern, again, appears across the four contracts, both with aggregate and active contract amounts. The result confirms that the hedging seems to stabilize the market, while speculation destabilizes it.

---

[32] The upper-right graph among the four in each set. See Appendix for impulse responses.

When the GARCH volatility (VG) measure is used, response of volatility to a trading activity shock gives mixed results. Interestingly, speculation activity (proxied by volume) destabilized the market in the first five days for the 2-year and 30-year contracts, in which volatility peaks at 0.02 percent on the second day, but the effect eventually declines and smoothes out to zero. The 5-year and 10-year market, in contrast, see a rise in volatility first and then reaches an even higher level (0.02 percent and higher). Hence, speculation in futures in the end destabilizes the 5-year and 10-year contracts, but not the 2-year and 30-year. Hedging activity (proxied by open interest) in the 5-year contract still destabilizes the market eventually, but for the 10-year contract it stabilizes the market, resulting in a lower volatility level at 0.01 percent. Meanwhile, hedging in the 2-year and 30-year contracts has no obvious effect on the market volatility. Moreover, with the active contract amount used, we obtain the same results for the speculation activity for each contract type. As for hedging activity (Log_Aggr_O vs. Log_O), we obtain very different results: While for the 2-year and 30-year contracts no obvious effects show up with aggregate amount, hedging does immediately destabilize the market (a minor 0.002 percent in 2-year and a significant 0.03 percent in 30-year) when active contract amount is used. The 5-year and 10-year contracts are too destabilizing the market a bit (0.0015 percent), all with the peak on the second day; the effects declines quickly to zero. A special case arises in the 2-year contract, where the market sees further decreased volatility, with the trough at 0.002 percent on the fourth day, and then smoothes out to zero. We can see that by constructing the amount according to the aggregate method or the “active contract” method indeed gives different results at times.

Response of trading activity to volatility

This “feedback effect” [33] where market disturbances in turn cause hedgers and speculators to adjust the futures demand has been briefly discussed in VAR tables. In addition, since the log scale would distort quantitative interpretations as mentioned earlier, we focus on the qualitative properties. The responses of volume (Log_Aggr_V and Log_V) to intra-day volatility shock (VHL) in the 2-year contract are almost identical; a volatility shock significantly increases speculation demand for futures on the first day, but the effect declines quickly and eventually returns to zero. However, the response of open interest to intra-day volatility is quite different when either aggregate amount (Log_Aggr_O) or active contract amount (Log_O) is used: aggregate open interest smoothes out to the negative, while the active contract amount smoothes out to the positive. Again, the same shock gives two different results when trading activity is constructed according to each different concept. Hedging demands, though, would be permanently increased or decreased. For 5-year, 10-year, and 30-year contracts, the responses of speculation demand (proxied by volume) are similar with aggregate and active contract amount, while all four contracts in fact have the similar effect that the speculation demands spikes on day 1 and quickly goes back and decays to zero. As for the 5-year contract with aggregate amount, the increase in intra-day volatility never leads to a proportional increase in hedging demand (Log_Aggr_O)—although the confidence bands are so large that a full adjustment in either upward or downward can not be rejected; the active contract amount (Log_O) clearly rises up and smoothes out. For 10-year contract, aggregate amount almost clearly smoothes out to the negative, while the

[33] The lower-left graph among the four in each set. See Appendix for impulse responses.

active amount is in the positive. Aggregate amount clearly declines eventually to the negative for the 30-year contract, although the active amount smoothes out to the positive (albeit with gradual decay). Therefore, we can not infer whether hedging demand for futures increases or decreases in respond to intra-day volatility shock—in general, aggregate open interest adjusts downward and active contract open interest adjusts upward—but the effect nonetheless exists.

The response of trading activity to historical volatility (VHIS) shock gives the similar results as the response to the intra-day volatility. The volume (both in aggregate and active contract amounts) rises on the first day and then gradually vanishes with a slight rise on the fifth day, although the initial peak and drop is not as dramatic as in the intra-day volatility case. Apparently, the long-term perspective embedded in the historical volatility smoothes the feedback effect, in which speculators react with less demand change. The difference, though, between responses to the two volatilities is also clear: intra-day volatility result uniformly in positive adjustments over time in speculators' demand on futures, while historical volatility result in negative (although the 68% confidence bands could not rule out adjustments to the positive). As for hedgers' demand (proxied by open interest), aggregate amount (Log_Aggr_O) adjusts downward and the active contract amount (Log_O) adjusts upward for all contract types, a response which is similar to the response to intra-day volatility. Therefore, we can not say for certain how hedging activity adjust, but adjust it sure does. One notable anomaly is in the 30-year contract, where active contract open interests (Log_O) decays instead of gradually increasing, although the adjustments are still in the positive just as other three contract types.

The response of volume to GARCH volatility (VG) is has seen a less pronounced effect than both the responses to intra-day volatility and to historical volatility, although with similar patterns. Negative adjustments occur significantly in the 30-year contract (in both the aggregate and active contract amounts). The negative adjustments are less significant in 2-year, 5-year, and 30-year contracts; in fact, the trends clearly move upward (though still in the negative) after the eighth day. The response of open interest to GARCH volatility still follows the general pattern as in the other two volatility measures: when aggregate amount (Log_Aggr_O) is used, open interests smoothes out to the negative; when active contract amount (Log_O) is used, open interest smoothes out to the positive. However, with aggregate amount the 5 year contract can not reject either an upward or a downward adjustment, although the large confidence bands ensure a likely full adjustment. (In the 5-year contract, the response to intra-day volatility with aggregate amount is similar here, but the response to historical volatility is a sure downward adjustment.) In the same token, with active contract amount the 30-year contract ensures a likely full adjustment, but the adjustment can be either upward or downward. The other three contracts with active amount show a clear gradual increase in hedging demand for futures over time.

Own effects in impulse response

We first look at the own response of volatility (response of volatility to volatility[34]). The response eventually returns to zero for the three volatility measures in all contract types. The speed, however, diverges as intra-day volatility drops quickly on the second day, while the historical and GARCH volatilities gradually decays to zero. The GARCH volatility is in general more convex than historical volatility (i.e. GARCH volatility decays faster). Looking into the detail in each contract, I find that the intra-day volatility (VHL) amazingly all follow the same pattern: it peaks on the first day, drops quickly on second day, reach the lowest on the fourth day, hike a bit on the fifth day, and smoothes out to zero. It is not clear why all of the intra-day volatility responses follow the exact pattern, which holds for speculation (proxied by volume) and hedging (proxied by open interest), and with both aggregate and active contract amounts. Quantitative changes are also consistent for speculation or hedging activities (and with both aggregate and active contract amounts) in each contract type. Across the contract types, the quantitative scale of change follows the underlying bond maturity of futures contract: 30-year contract sees a 0.2 percent first day response, 10-year sees a 0.16 percent, 5-year sees a 0.11 percent, and 2-year sees a 0.05 percent. Responses in following days accordingly adjust to scale.

The historical volatility (VHIS) also has the same pattern across contract types. Based on its long-term (20-day) construction, historical volatility naturally declines slowly and persistently at a long horizon. The order of quantitative scale is the same as in the intra-day volatility: the largest change (0.082 percent) occurs in 30-year contract, followed by 0.05 percent in 10-year, 0.04 percent in 5-year, and 0.016 percent in 2-year. The reason to the congruence of ordering with underlying security's maturity is not clear. The rate of decline (slope) is similar across contract types.

Response of GARCH volatility (VG) to own shock is interesting. 2-year and 30-year contracts have a convex shape of response, which implies the rate of decrease in volatility becomes slower and slower in time, after the first day peak. The 5-year and 10-year contracts, however, have a shape of straight line, which implies the rate of decrease is constant. Quantitatively, the 30-year has the highest first day volatility peak at 0.12 percent, which is 10 times larger than the following 2-year contract at 0.022 percent. The 10-year contract has a 0.011 percent peak, and the 5-year has a 0.008 percent peak at first day.

The own response in trading activity[35] diverges in the shape between the volume and open interest. As for volume response, the jump at the first day soon gives away to the immediate drop on the second day. (For the 30-year contract, the volume drops for another day on day3.) The volume then climbs up slightly until day 5 (except for the 2-year contract, until day 4), and smoothes out to a lower level. Open interest instead follows a different pattern, and the construction of aggregate amount or active contract amount also affects the shape. With the aggregate amount, 2-year, 5-year, and 10-year contracts gradually increase after the first day jump and reach a higher plateau. The 30-year contract sees a minor drop on the second day, and then follows the same pattern.

[34] The upper-left graph among the four in each set. See Appendix for impulse responses.
[35] The lower-right graph among the four in each set. See Appendix for impulse responses.

Hedging activity apparently propagates over time. With the active contract amount, while hedging propagates and reaches a higher (than original) level, open interest nonetheless slides as well as smoothes out over time. There is a temporary jump on the second day, and a minor drop on the fourth day, and the 30-year contract slides down faster than other three contracts. The quantitative scale is distorted by the logarithm transformation as mentioned earlier.

DISCUSSIONS

While the results are mixed, we may roughly conclude that speculators destabilize the Treasury futures market, causing a more turbulent market as evident in the increased price volatility. However, the same can not be said of hedgers. Available evidence at best suggests a weak relation between hedging and a decreased price volatility (indicating a market being stabilized). Intricacies arise as we take into account the time lag dynamics in the VAR. When the intra-day volatility is used, speculation activity also help to stabilize the market on the fourth day, although speculators destabilize the market on the first day. Hedging seems to stabilize the market at least for the first day. Historical volatility results provide the interesting observation that in the longer term, speculators do not have much impact on the 30-year contract which uses the most liquid 30-year Treasury bonds as underlying. Speculators can destabilize the other contracts which use less liquid underlying Treasury securities. Meanwhile, hedgers seem to be able to incorporate longer-term volatility information better than the one-day intra-day volatility measure, as more than a few lag coefficients in the VAR using historical volatility measure are significant. GARCH volatility provides the similar result (as intra-day volatility) that the speculation activity destabilizes the market on the first day, but the market is then stabilized instead on later days.

My study also compares the results with different ways of constructing data (aggregate vs. active contract). Sharp contrasts appear in the two cases on hedging activity either by using the historical volatility (Table 6A, 6B) or by using the GARCH volatility (Table 8A, 8B). When aggregate amount is used, open interest weakly—and only rarely—Granger causes volatility; hedging activity hardly impacts the market. However, when the active contract amount is used, the causality is strong in all contracts. In the similar vein, most of the lag coefficients in VAR are insignificant when aggregate amount is used, indicating that hedging activity only weakly (if any) stabilize the market. As the active contract amount is used, it is much more clear that hedgers do influence the market volatility, since most (but not all) of lag coefficients are significant. Nonetheless, the results are mixed as to whether the market is destabilized or stabilized by hedging activity. The market is to be destabilized on the first day and then to be stabilized on the second day, as in the GARCH volatility case in Table 8B. Hedging destabilizes the market in the 2-year and 5-year contracts, stabilizes the 30-year market, but none can be said about the 10-year market, as in the historical volatility case in Table 6B. Aggregate or active contract amount, the strong and significant trading momentum is especially notable; positive autocorrelated volume patterns are confirmed in Treasury futures trading—surprisingly without any ambiguity.

Furthermore, my study draws inferences from investor's reaction to the increased market volatility by answering the question of whether the demand for Treasury futures is positively or negatively correlated with an increased volatility. Speculators' demand for futures goes down when intra-day volatility increases for each of the contracts; speculation itself deters future speculation. Hedging activity also decreases in a period of high intra-day volatility, since hedgers may be reluctant to engage in a volatile market before sufficient information is available. Historical volatility reflects a longer-term consideration on demand for futures, when market participants can incorporate more volatility information. Speculators decrease their demand for futures as historical volatility rises, similar to the response with intra-day volatility. The minor difference is that their demand for futures increases on the fourth day, supposedly to take advantage of market turbulence. With available longer-term information, therefore, speculators respond to a more volatile market with a rise in futures trading activity. As for hedging, the usual conjecture is that hedgers increase the demand for futures in response to an increase in historical volatility, while hedgers are able to determine the extent of hedging with the available longer-term volatility information. The VAR results, however, do not support the conjecture: as historical volatility increases, hedgers' demand for futures either decreases or do not change significantly. (The result is in fact in line with the intra-day volatility.) The GARCH volatility is by default the "most correct" measure. There is no evidence on the change in demand on futures as speculators face a more volatile market. There is, however, one thing interesting about hedging activity: Unlike the intra-day or historical volatility cases, hedgers increase their demand on futures as GARCH volatility rises; when the GARCH volatility is used, hedgers do respond to market turbulence with their increasing need of hedging.

Impulse responses give the graphic representation of the VAR dynamics. We see that the increase in speculation causes a small turbulence in the intra-day activity, but the effect fades away on the fifth day. Increase in hedging activity has little effect on intra-day volatility. Historical volatility persistently rises by the increase in speculation demand, but persistently falls by the increase in hedging demand. GARCH volatility has mixed results, and the construction with aggregate or active contract amount gives some different results. As the "feedback effect" is concerned, intra-day volatility shock significantly increases speculation activity, but the effect quickly declines and eventually returns to zero. Nonetheless, hedging activity would be permanently decreased or increased, depending on aggregate or active contract amount. (In general, aggregate open interest adjusts upward and active contract open interest adjusts downward.) Feedback effect with the historical volatility gives the similar results—while the longer-term aspect embedded in it smoothes the effect—but difference in speculators' demand on futures occurs. The GARCH volatility also has similar patterns, although the effect is less pronounced. As for own-response in volatility, the three volatilities eventually return to zero; however, intra-day volatility drops quickly while historical and GARCH volatilities gradually decay. The own-response in trading activity diverges in shape between volume and open interest. Volume quickly drops, but open interest instead follows different patterns, depending on construction of aggregate or active contract amount.

To my knowledge, this study is the first in applying the VAR technique to the context of Treasury futures trading, and the first in comparing the three different volatility measures (intra-day, historical, and GARCH) simultaneously on Treasury futures. It is also the first in examining the volume and open interest by constructing the aggregate or "active contract" amount in the same study, while the results are compared. (And the V_Ratio and O_Ratio are also constructed and examined.) GARCH volatility specifications are comprehensively tested and (conveniently) arrived at the conclusion of the commonly-used GARCH(1,1). On volume-volatility relation, it is probably among the few which have a specific focus on examining an individual futures contract of Treasury securities, while applying a longer period of data (16 years) to the vector autoregressive (VAR) framework. As concluded, this study suggests that speculators do destabilize the Treasury futures market (although the results are somewhat mixed), while it merely infers a weak relation at best between hedging activity and a Treasury futures market being stabilized.

Future Extensions

There are several possible extensions based on my current study. Interactions among the four types of futures contracts are certainly interesting to look at. As is well known, hedging as well as speculation involves all four types of Treasury futures contracts (and more).[36] The volume-volatility study usually does not consider the interactions among instruments; in my study, I treat each futures contract independent with one another, but they are of course correlated. A study which includes interaction among contracts should be a significant extension. Naturally, interactions among Treasury, currency, commodities, and other markets are also worth studying, although the scope needs to be further refined as to be realistic.

We may also examine the relationship between the cash and futures prices in the Treasury market. My study only looks at activities in the futures market; further work should see how the cash securities trading affects the trading in Treasury futures (and vice versa). Among several common usages, futures contracts are a low cost alternative to selling the portfolio's cash bond securities, and the ability to use futures to protect against interest rate moves allows investors to make larger transactions in the spot market. Therefore, futures trading will have impact on the cash bond prices (and vice versa). The seminal paper by Grossman (Grossman, 1988) provides theoretical underpinning to the interaction between cash and futures price, whereas the informational role played by cash securities is emphasized. Jordan and Kuiper (1997) shows the direct evidence that the underlying Treasury bond price is distorted as the bond becomes the cheapest to delivery against Treasury futures contracts. Fleming and Sarkar (1999) provides a quick look at the spot-futures price linkage in the Treasury market. On evidence of stock index futures, Darrat et al. (2002) finds that futures market volatility is an outgrowth of a turbulent cash market. For a commodities market example, see Yang et al. (2005).

A problem with this type of VAR exercise is that, unlike macroeconomic studies, there is not an underlying theory behind the VAR regression. Therefore, to go beyond the simple graphical and numerical results is over-stretching. We can not infer theories (not as sound) comparable to the supply shock/demand shock distinction and provide evidence for or against a Keynesian theory, for example, as in Blanchard and Quah (1989) and Blanchard (1989). Or we can not inform the change in volatility and trading activity with external factors, unlike the case in structural VAR estimation (see Buckle et al., 2002). Technically, we can add exogenous variables to the VAR system, since a VAR

[36] For currency futures, cross-hedge among currencies is also common.

process can be extended to other observable variables of interest (and their lag values) that are determined outside the system.

Likewise, we may go beyond the techniques of a multivariate linear model (such as the VAR). One limitation of VAR is that, without modification, standard VARs miss nonlinearities, conditional heteroskedasticity, and drifts or breaks in parameters (Stock and Watson, 2001). Estimations involves nonlinear filtering and Bayesian techniques such as Gibbs sampler are usually quicker and simpler. See Waggoner and Zha (2003) for applying the Gibbs sampler technique to VARs. Furthermore, most market microstructure models—such as the classic Roll's model of transaction costs (Roll, 1984)—are dynamic over time and they include latent (hidden, unobservable) variables. For example, a trade indicator variable of "buy or sell" may not be observed from data. Meanwhile, the latent variables are often non-Gaussian. Gibbs sampler is suitable as we formulate a dynamic latent variable model in state-space form and estimated via maximum-likelihood. Studies by Hasbrouck (2004, 2006a; in addition, 2006b) provide the applications of Gibbs samplers on market trading activity.

A quick note on CBOT databases. CBOT began to publicly offer the "trader type" data as Liquidity Data Bank (LDB), classifying traders into four types (hedgers, large speculators, small traders and spreaders). Therefore, further research can offer more accurate insights on trading behavior. See an example by Daigler and Wiley (1999) and also Wiley and Daigler (1999) on a previous study (before the dataset is made public). Chatrath et al. (2003) offers another example in the market of S&P 500 index futures by extending the dichotomous framework to the trading activity of the four groups of traders. CBOT also offers "volume-at-price" data for each trading day, which provides the total volume traded at each price during a trading day for all Treasury futures contracts. (See the sample in Figure 5). And, of course, the tick-by-tick data is available for use in high frequency studies.

APPENDIX: DISCUSSIONS ON GARCH VOLATILITY ESTIMATION

In this appendix, I will discuss the GARCH volatility measure and explain in detail how I settle for the AR(0)-GARCH(1,1) specification.

GARCH Volatility Measure

Most of the time the regression errors of time series data are not independent through time, and the Treasury futures data is no exception. Efficiency of ordinary least square (OLS) estimator is affected, standard deviation estimates are biased, and the statistical tests on the significance of the parameters and the confidence band for predicted values are incorrect. Since I want to estimate a linear regression model for time series data when the errors are autocorrelated or heteroskedastic, I use the autoregressive error model (AR) in order to correct autocorrelation, and the generalized autoregressive conditional heteroskedasticity (GARCH) model and variants in order to correct for heteroskedasticity. Information contained in non-spherical error terms can then be exploited.

Specifying the Appropriate AR(m)-GARCH(p,q)

Past studies show that the conditional variance from the GARCH(1,1) model is the appropriate volatility measure for currency futures markets (Bhargava and Malhotra, 2007). However, it's not clear whether GARCH(1,1) is the appropriate model for the use in Treasury futures market. To start with, I want to specify an appropriate AR(m)-GARCH(p,q) model for the data at hand; after settle on a "correct" specification, I then obtain the conditional volatility. This volatility measure is to be used in VAR estimation.

For consistency, I will later decide on a common specification. GARCH volatility is estimated from this AR(m)-GARCH(p,q) specification:

$$R_t = \overline{R}_t + \nu_t$$

$$\nu_t = \varepsilon_t - \varphi_1 \nu_{t-1} - \varphi_2 \nu_{t-2} - \ldots - \varphi_m \nu_{t-m}$$

$$\varepsilon_t | I_{t-1} \approx N(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \gamma_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where $R_t = \ln\left(\frac{F_t}{F_{t-1}}\right)$, $\overline{R}_t = \sum_{i=t-20}^{t} \frac{R_i}{21}$, and F_t is the futures price.

Although assuming that the mean return[37] of previous period is the only regressor in the main regression is extremely naïve ($R_t = \overline{R}_t + \nu_t$), efforts can be much simplified as we focus on obtaining the volatility measure from the best AR(m)-GARCH(p,q)

[37] Average of the returns from the past 20 days and the current day (at total 21 days).

specification.[38] Durbin-Watson test is conducted to test for autocorrelation. Stepwise autoregression is then performed to determine the AR order, while the Yule-Walker method is used for this stepwise procedure. The maximum likelihood estimates are produced after the order is determined from significant tests of Yule-Walker.

Q test (McLeod and Li, 1983) and Engle's LM test (Engle, 1982) for ARCH disturbances are conducted to detect heteroskedasticity. Maximum likelihood method is used in estimating the GARCH model, while the log likelihood function is computed from the product of all conditional densities of the prediction errors. Also, Engle's LM test and Bera-Jarque normality test (Jarque and Bera, 1980) is conducted. As a note, my Treasury futures dataset involves a large sample period (from year 1991 to 2006), which correspons to the suggestion by Engle and Mezrich (1995) on using at least eight years of daily data for the GARCH model to be used properly.

I decide to estimate the following 12 specifications of AR(m)-GARCH(p, q), where m = 0, 1 or 4; p = 1 or 2; q = 1 or 2. Take the two-year Treasury futures for example (other three types follow a similar procedure). Durbin-Watson test shows that positive autocorrelation is present (p-value in order 1 is 0.0136; see Figure 1G).[39] The stepwise autoregression is then conducted to determine the number of autoregressive lags (Figure 1H). The method initially fits a higher-order model with 6 autoregressive lags and then sequentially removes autoregressive parameters until all remaining autoregressive parameters have significant t-tests. Backward elimination shows that the autoregressive parameters at lags 5 and 6 are insignificant (at the 0.05 level) and eliminated, resulting in a model with 4 lags.[40]

Since models that take into account heteroskadasticity can make more efficient estimators, the test for heteroskadasticity is conducted. See Figure 1I for SAS results. The Q statistic tests for changes in variance across time using lag windows ranging from 1 through 12. The LM test (Engle (1982)) also helps to determine the order of the ARCH model appropriate for modeling the heteroskedasticity. No heteroskedastisity is detected by either test. The AR order should be 4, but in the stepwise GARCH analysis, the coefficients of order 2, 3, and 4 are not significant. Therefore, I estimate the AR order of m = 0, 1, and 4.

---

[38] The univariate framework is parsimonious, which allows to capture the more salient features of the data. For a multivariate GARCH example, see Gulen and Mayhew (2000). Multivariate specification are used to study the dynamic interaction between individual volatilities and the conditional covariances.

[39] Ordinary (first-order) and generalized (higher-order) Durbin-Watson (DW) statistics test for the presence of autocorrelation. *Generalized* DW test should not be used to decide on the autoregressive order, since tests of higher orders assume the absence of lower-order autocorrelation. Only when the first-order DW test indicates no first-order autocorrelation, we then look at the second-order ("generalized") test statistic for checking the second-order autocorrelation. However, if the first-order autocorrelation is detected, we do not look at the second (and higher) -order test results. They are not appropriate to decide that an order higher than 1 be used.

[40] It should be noted that I do not account for the seasonality in the data. An interesting topic for future research would be to investigate whether accounting for seasonality, and *which* seasonality, has a significant impact on the results.

Moreover, I examine the GARCH(1,1), GARCH(1,2), GARCH(2,1), GARCH(2,2) specifications with the three different AR orders. (See Figure 1J and 1K.) Estimates in the AR order of 4 are mostly insignificant, so I ignore the AR order higher than 1. Empirical studies usually settle on one of these four simple GARCH specifications; for example, it has been shown that GARCH(1,1) performs well for currency futures. Judging from the significance of estimates, the three better specifications are: AR(0)-GARCH(1,1), AR(0)-GARCH(1,2), AR(1)-GARCH(1,1). I then use a similar procedure to determine the better specifications in the 5-, 10-, and 30-year Treasury futures. Both AR(0)-GARCH(1,1) and AR(1)-GARCH(1,1) seem to give consistent results across contract types. Besides, I find that the specification results are fairly consistent for the four contract types.

To decide on one common specification for consistency, I choose the specification of AR(0)-GARCH(1,1). The AR(1)-GARCH(1,1) is dropped because 5- and 10-year futures give a slightly different estimation results. (See Tables 9A-9D for the determining the specification in three types of contracts.) Besides, AR(0)-GARCH(1,1) also has the advantage in comparing results from various markets (currency, equity, and commodities).

Estimation problems occur as I estimate the specifications of AR(m)-GARCH(p=1,q=2), where m=0, 1, 4: the GARCH estimates do not converge. Estimations have exceeded the maximum allowable number of iterations (50) for all iterative computation processes in the SAS program. After I eliminate the restriction on the coefficient to be 1 in the main regression $R_t = \overline{R}_t + \nu_t$, the GARCH estimates are able to converge. For each m, the estimated coefficient is close to 1, and is significant. It looks no different as GARCH estimation is concerned. Another estimation problem occurs when I try to obtain the estimated conditional error variance in the SAS program for the ten-year futures: The specification AR(0)-GARCH(1,1) gives the same error variance (0.000017474) for all observations. ARCH0 estimate in the ten-year GARCH is not significant, and it is the only one anomaly in this specification among the four contract types. It is not clear whether the insignificance of ARCH0 contributes to this problem. I decide to use AR(1)-GARCH(1,1) for ten-year contract, but still keep the AR(0)-GARCH(1,1) for all other contracts, since more problem would occur as ten- and thirty-year futures do not support the AR(1)-GARCH(1,1) specification. In addition, comparisons can be easily made across different futures markets. This study seems to be the first in identifying AR(0)-GARCH(1,1) (along with perhaps the AR(1)-GARCH(1,1)) as the appropriate specification of volatility measure.

In the parameter estimates table, ARCH0 represents the estimate for the parameter ω, ARCH1 represents the estimate for α_1, GARCH1 represents the estimate for γ_1, and so on. The Bera-Jarque normality test on each of the contract has a significant p-value ($p < 0.0001$), indicating that the null hypothesis of normally-distributed residuals, ϵ_t / σ_t, from the GARCH model is rejected. The R-square values are low (around 0.0540).

References

Adrangi, B., Chatrath, A. "Futures Commitments and Exchange Rate Volatility." *Journal of Business Finance and Accounting*, 25 (1998), 501-520.

Bae, S.; T. Kwon; and J. Park. "Futures Trading, Spot Market Volatility, and Market Efficiency: The Case of the Korean Index Futures Markets." *Journal of Futures Markets*, 24 (2004), 1195-1229.

Bessembinder, H., and P. J. Seguin. "Price Volatility, Trading Volume, and Market Depth: Evidence from Futures Markets." *Journal of Financial and Quantitative Analysis*, 28 (March 1993), 21-39.

Bhargava, V., and D. K. Malhotra. "The Relationship Between Futures Trading Activity and Exchange Rate Volatility, Revisited." *Journal of Multinational Financial Management*, 17 (2007), 95-111.

Blanchard, O. J. "A Traditional Interpretation of Macroeconomic Fluctuations." *American Economic Review*, 79 (Dec. 1989), 1146-1164.

Blanchard, O. J., and D. Quah. "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *American Economic Review*, 79 (Sept. 1989), 655-673.

Buckle, R. A.; K. Kim; H. Kirkham; N. McLellan; and J. Sharma. "A Structural VAR Model of the New Zealand Business Cycle." New Zealand Treasury Working Paper 02/26 (December 2002).

Chang, E.; R. Y. Chou; and E. F. Nelling. "Market Volatility and the Demand for Hedging in Stock Index Futures." *Journal of Futures Markets*, 20 (2000), 105-125.

Chatrath, A.; S. Ramchander; and F. Song. "The Role of Futures Trading Activity in Exchange Rate Volatility." *Journal of Futures Markets*, 16 (1996), 561-584.

Chatrath, A.; F. Song; and B. Adrangi. "Futures Trading Activity and Stock Price Volatility: Some Extensions." *Applied Financial Economics*, 13 (Sept. 2003), 655-664.

Clark, P. K. "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices." *Econometrica*, 41 (Jan. 1973), 135-155.

Clifton, E. V. "The Currency Futures Market and Interbank Foreign Exchange Trading." *Journal of Futures Markets*, 5 (1985), 375-384.

Daigler, R. T., and M. Wiley. "The Impact of Trader Type on the Futures Volatility-Volume Relation." *Journal of Finance*, 54 (Dec. 1999), 2297-2316.

Darrat, A. F.; S. Rahman; and M. Zhong. "On the Role of Futures Trading in Spot Market Fluctuations: Perpetrator of Volatility or Victim of Regret?" *Journal of Financial Research*, 25 (2002), 431-445.

Edwards, F. R. "Hedge Funds and the Collapse of Long Term Capital Management." *Journal of Economic Perspective*, 13 (Spring 1999), 189-210.

Engle, R. F. "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica*, 50 (1982), 987-1007.

Engle, R., and Mezrich, J. "Grappling with GARCH." *Risk*, 8 (1995), 112-117.

Fleming, M.; and A. Sarkar. "Liquidity in the U.S. Treasury sport and futures markets." BIS Committee on Global Financial System Publication No. 11 (May 1999).

Garman, M., and M. Klass. “On the Estimation of Security Price Volatilities from Historical Data.” *Journal of Business*, 53 (1980), 67-78.

Grossman, S. J. “An Analysis of the Implications for Stock and Futures Price Volatility of Program Trading and Dynamic Hedging Strategies.” Journal of Business, 61 (1988), 275-298.

Gulen, H., and S. Mayhew. “Stock Index Futures Trading and Volatility in International Equity Markets.” *Journal of Futures Markets*, 20 (2000), 661-685.

Harris, M., and A. Raviv. “Differences of Opinion Make a Horse Race.” *Review of Financial Studies*, 4 (1993), 473-506.

Hasbrouck, J. “Trading Costs and Returns for U.S. Equities: The Evidence from Daily Data.” New York University, Stern School of Business (2006a).

____________________. “Gibbs Estimation of Microstructure Models: Teaching Notes.” (October 2006b). http://pages.stern.nyu.edu/~jhasbrou/

____________________. “Liquidity in the Futures Pits: Inferring Market Dynamics from Incomplete Data.” *Journal of Financial and Quantitative Analysis*, 39 (2004).

Jarque, C. M., and A. K. Bera. “Efficient Tests for Normality, Homoskedasticity and Serial Independence of Regression Residuals.” *Economic Letters*, 6 (1980), 255-259.

Jones, D. M. “The Demise of the 30-Year Treasury Bond as a Benchmark or Pricing Fixed Income Securities.” *Business Economics* (October 2000),

Jordan, B. D., and D. R. Kuiper. “Negative Option Values are Possible: The Impact of Treasury Bond Futures on the Cash U.S. Treasury Market.” *Journal of Financial Economics*, 46 (1997), 67-102.

Karpoff, J. M. “The Relation Between Price Changes and Trading Volume: A Survey.” *Journal of Financial and Quantitative Analysis*, 22 (March 1987), 109-126.

Kyle, A. S. “Market Structure, Information, Futures Markets, and Price Formation.” *International Agricultural Trade: Advanced Readings in Price Formation, Market Structure, and Price Instability*, ed. by G. G. Storey, A. Schmitz, and A. H. Sarris (1984), 45-64. Westview Press.

MacKenzie, D. *An Engine, Not a Camera: How Financial Models Shape Market.* MIT Press (May 2006).

____________________. “Long-Term Capital Management and the Sociology of Arbitrage.” *Economy and Society*, 32 (August 2003), 349-380.

McLeod, A. I., and W. K. Li. “Diagnostic Checking ARMA Time Series Models Using Squared-Residual Autocorelations.” *Journal of Time Series Analysis*, 4 (1983), 269-273.

Parkinson, M. “The Extreme Value Method for Estimating the Variance of the Rate of Return.” *Journal of Business*, 53 (1980), 61-66.

Roll, R. “A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market.” *Journal of Finance*, 39 (Sep. 1984), 1127-1139.

Shalen, C. T. “Volume, Volatility, and the Dispersion of Beliefs.” *Review of Financial Studies*, 6 (1993), 405-434.

Sims, C. A. “Comparison of Interwar and Postwar Business Cycles: Monetarism Reconsidered", *American Economic Review* 70 (May 1980), 250-257.

Stock, J. H., and M. W. Watson. "Vector Autoregressions." *Journal of Economic Perspectives*, 15 (2001), 101-115.

Tauchen, G. E., and M. Pitts. "The Price Variability-Volume Relationship on Speculative Markets." *Econometrica*, 51 (1983 March), 485-505.

Waggoner, D. F., and T. Zha. "A Gibbs Sampler for Structural Vector Autoregressions." *Journal of Economic Dynamics and Control*, 28 (2003), 349-366.

Wiley, M. K., and R. T. Daigler. "A Bivariate GARCH to the Futures Volume-Volatility Issue." Conference paper, Eastern Finance Association Meetings (April 1999).

Wojnilower, A. M. "Life Without Treasury Securities." *Business Economics* (October 2000), 10-15.

Yang, J.; B. Balyeat; and D. Leatham. "Futures Trading Activity and Commodity Cash Price Volatility." *Journal of Business Finance and Accounting*, 32 (2005), 297-324.

Figure 1D: Sample Chart of Futures Price and Trading Volume
(Source: CBOT) This chart shows that a contract is usually heavily traded three months before expiry. Accordingly, we may define the "active contract", and then construct data series. The 10-year Treasury note futures with December 2005 expiry (Z 05) is used in the sample chart, and it shows the price, volume and open interest. The contract is "active" from mid-August to the end-of-December in year 2005.

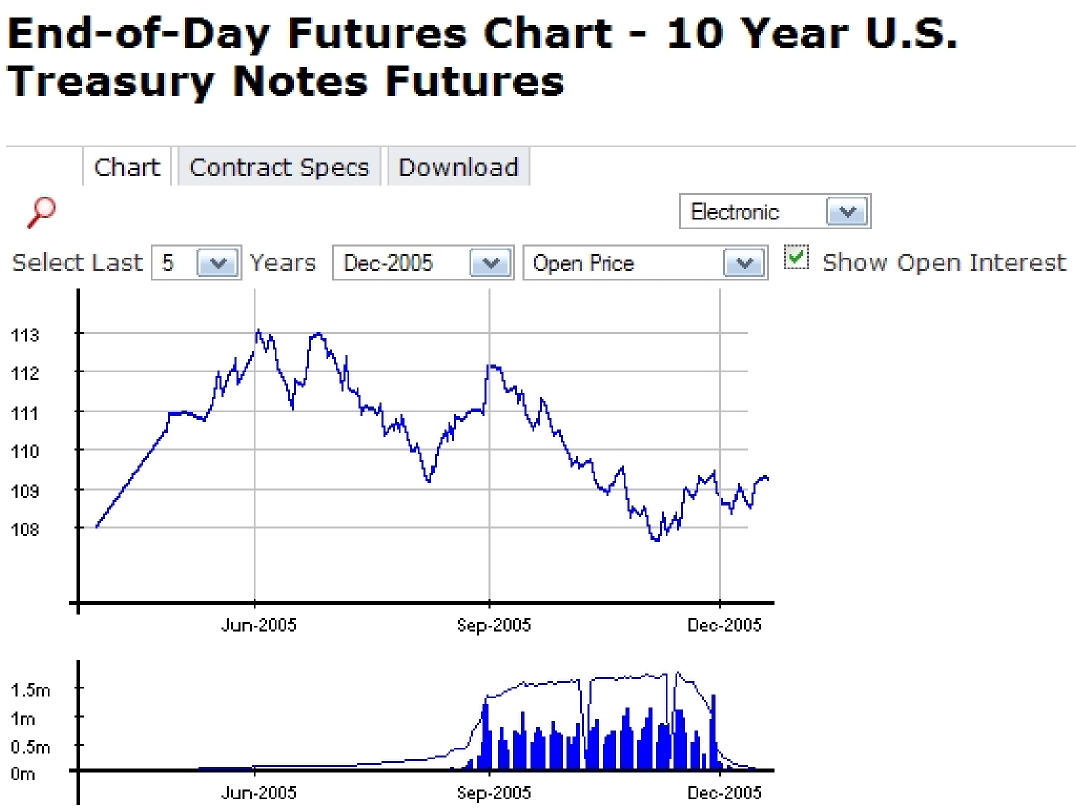

Figure 1E: "Active Contract" Time Table, Using Year 1992 as Example

Contract	"Active" period
…	…
H 92	12/01/1991 to 02/28/1992
M 92	03/01/1992 to 05/31/1992
U 92	06/01/1992 to 08/31/1992
Z 92	09/01/1992 to 11/30/1992
H 93	12/01/1992 to 02/28/1993
…	…

Table 1A
Summary Statistics of V_Ratio and O_Ratio

	Mean	Std Dev	N	Minimum	Maximum	Median
2 Year						
V_Ratio	0.8527774	0.1959624	4032	0	1	0.9886192
O_Ratio	0.9019683	0.1551922	4034	0.0723660	1	0.9807020
5 Year						
V_Ratio	0.8657134	0.1524070	4015	0.2261302	1	0.9285141
O_Ratio	0.8933798	0.1359528	4036	0.1803906	1	0.9487087
10 Year						
V_Ratio	0.8662879	0.1383341	4035	0.2163342	1	0.9141577
O_Ratio	0.8759191	0.1299952	4036	0.1504096	0.9997018	0.9208492
20 Year						
V_Ratio	0.9068490	0.1331673	4036	0.1327326	1	0.9600990
O_Ratio	0.8531430	0.1280768	4036	0.2236310	0.9976102	0.8930055

Table 1B
Summary Statistics of Futures Returns, Volumes (Aggregate and Active Contract), and Volatilities

	R_t	Aggr_V	Aggr_O	Active_V	Active_O	VHL	VHIS	VG
PANEL A: 2-Year Treasury Notes								
Mean	0.00000140	6352.75	118460.35	4456.93	98773.18	0.000810287	0.001189759	0.001330581
Median	0	3204.50	40693.50	2684.50	38095.00	0.000681191	0.001049136	0.001267366
S.D.	0.00136034	11367.24	207063.74	5776.10	144226.02	0.000521685	0.000653904	0.000292007
Minimum	-0.03526969	0	7347.00	0	3403.00	0.000088282	0.000338983	0.001191944
Maximum	0.00000185	191582.00	1395757.00	82139.00	717954.00	0.006695432	0.007724078	0.011891310
PANEL B: 5-Year Treasury Notes								
Mean	0.00000949	53296.72	486319.67	43546.13	434454.11	0.002042513	0.002650376	0.002934169
Median	0	42619.00	288913.00	37508.00	262654.00	0.001744916	0.002391333	0.002864986
S.D.	0.00300747	43818.60	415047.00	31104.68	379112.65	0.001173678	0.001419314	0.000423269
Minimum	-0.08248347	0	62638.00	0	27557.00	0.000355322	0.000810002	0.002587669
Maximum	0.01142200	342202.00	1712504.00	214355.00	1461839.00	0.011584947	0.018071908	0.007846812
PANEL C: 10-Year Treasury Notes								
Mean	0.00001985	93306.59	696738.02	77760.20	615699.99	0.003089416	0.003828566	0.004182462
Median	0.00006797	80239.00	517245.00	69871.00	451408.00	0.002711878	0.003509524	0.004091603
S.D.	0.00429428	66082.72	604995.17	49478.45	556003.32	0.001624228	0.001958311	0.000545384
Minimum	-0.11587196	144.00	67129.00	144.00	34280.00	0.000553873	0.001273298	0.003736067
Maximum	0.01422094	497385.00	2575893.00	352937.00	2449955.00	0.014715876	0.025448321	0.010725665
PANEL D: 30-Year Treasury Bonds								
Mean	0.00003695	232683.16	518021.21	214033.00	441601.40	0.004736970	0.005750593	0.006346455
Median	0.00027031	215638.00	476807.00	196611.00	414975.00	0.004267038	0.005351704	0.006020318
S.D.	0.00646685	179834.20	161315.96	169719.09	151802.71	0.002274539	0.002980519	0.001964556
Minimum	-0.18708014	173.00	236530.00	152.00	86689.00	0.001000139	0.002195475	0.005037365
Maximum	0.02131253	1121634.00	1138994.00	1065484.00	955730.00	0.025172261	0.041067947	0.074023241

Aggr_V and Aggr_O stand for the volume and open interest obtained by the aggregate amount. Active_V and Active_O stand for the volume and open interest obtained by the "active contract" amount. VHL stands for the intra-day (high-low) measure of volatility. VHIS stands for the historical standard deviation. VG stands for the volatility estimated by GARCH(1,1). $R_t = \ln (F_t / F_{t-1})$ is the log daily return.

Table 1C
Correlation of Activities

	Aggr_V	Aggr_O	Active_V	Active_O
Two Year Notes				
Aggr_V	1			
Aggr_O	0.474	1		
Active_V	0.967	0.462	1	
Active_O	0.395	0.979	0.415	1
Five Year Notes				
Aggr_V	1			
Aggr_O	0.046	1		
Active_V	0.972	-0.018	1	
Active_O	-0.039	0.974	-0.063	1
Ten Year Notes				
Aggr_V	1			
Aggr_O	0.119	1		
Active_V	0.967	0.043	1	
Active_O	0.040	0.977	0.006	1
Thirty Year Bonds				
Aggr_V	1			
Aggr_O	-0.273	1		
Active_V	0.987	-0.297	1	
Active_O	-0.417	0.845	-0.375	1

Aggr_V and Aggr_O stand for the volume and open interest obtained by the aggregate amount. Active_V and Active_O stand for the volume and open interest obtained by the "active contract" amount.

Table 2A
By Aggregate:
Correlation Coefficients Between Trading Activity and Price Volatility

	Volume	Open Interest	VHL	VHIS	VG
PANEL A: 2-Year Treasury Notes					
Volume	1				
Open Interest	0.474	1			
VHL	0.231	-0.077	1		
VHIS	0.064	-0.105	0.192	1	
VG	0.108	-0.039	0.093	0.487	1
PANEL B: 5-Year Treasury Notes					
Volume	1				
Open Interest	0.046	1			
VHL	0.368	-0.035	1		
VHIS	0.149	-0.013	0.207	1	
VG	0.177	0.023	0.123	0.755	1
PANEL C: 10-Year Treasury Notes					
Volume	1				
Open Interest	0.119	1			
VHL	0.381	-0.091	1		
VHIS	0.116	-0.040	0.215	1	
VG	0.152	0.002	0.133	0.781	1
PANEL D: 30-Year Treasury Bonds					
Volume	1				
Open Interest	-0.273	1			
VHL	0.249	-0.063	1		
VHIS	0.037	-0.065	0.193	1	
VG	0.037	-0.024	0.092	0.625	1

VHL stands for the intra-day (high-low) measure of volatility. VHIS stands for the historical standard deviation. VG stands for the volatility estimated by GARCH(1,1). Volume and open interest are in natural logarithm.

Table 2B
By Active Contract:
Correlation Coefficients Between Trading Activity and Price Volatility

	Volume	Open Interest	VHL	VHIS	VG
PANEL A: 2-Year Treasury Notes					
Volume	1				
Open Interest	0.415	1			
VHL	0.271	-0.074	1		
VHIS	0.060	-0.112	0.192	1	
VG	0.088	-0.061	0.093	0.487	1
PANEL B: 5-Year Treasury Notes					
Volume	1				
Open Interest	-0.063	1			
VHL	0.411	-0.036	1		
VHIS	0.161	-0.008	0.207	1	
VG	0.193	0.030	0.123	0.755	1
PANEL C: 10-Year Treasury Notes					
Volume	1				
Open Interest	0.006	1			
VHL	0.421	-0.090	1		
VHIS	0.130	-0.032	0.215	1	
VG	0.168	0.010	0.133	0.781	1
PANEL D: 30-Year Treasury Bonds					
Volume	1				
Open Interest	-0.375	1			
VHL	0.250	-0.058	1		
VHIS	0.040	-0.039	0.193	1	
VG	0.036	-0.013	0.092	0.625	1

VHL stands for the intra-day (high-low) measure of volatility. VHIS stands for the historical standard deviation. VG stands for the volatility estimated by GARCH(1,1). Volume and open interest are in natural logarithm.

Table 3A
VAR with Aggregate: Volume vs. VHL

Dependent Variable	Independent Variable	Lag	VHL	p-value	Volume	p-value
PANEL A: 2-Year Treasury Notes						
Volume (Granger p<0.0001)	VHL	-1	-39.48772	0.1085	0.40174	0.0001
		-2	-81.26104	0.0011	0.23995	0.0001
		-3	-77.17747	0.0019	0.16129	0.0001
		-4	21.69039	0.3790	0.06889	0.0001
VHL (Granger p<0.0001)	Volume	-1	0.15643	0.0001	0.00002	0.0669
		-2	0.11146	0.0001	0.00001	0.2986
		-3	0.05282	0.0013	0.00003	0.0044
		-4	0.12628	0.0001	-0.00004	0.0002
PANEL B: 5-Year Treasury Notes						
Volume (Granger p <.0001)	VHL	-1	-53.89469	0.0001	0.46556	0.0001
		-2	-13.50700	0.0941	0.19065	0.0001
		-3	-14.90470	0.0648	0.12855	0.0001
		-4	4.91660	0.5385	0.13658	0.0001
VHL (Granger p <.0001)	Volume	-1	0.11304	0.0001	0.00016	0.0001
		-2	0.09308	0.0001	0.00009	0.0286
		-3	0.06551	0.0001	0.00000	0.9583
		-4	0.13901	0.0001	-0.00011	0.0027
PANEL C: 10-Year Treasury Notes						
Volume (Granger p <.0001)	VHL	-1	-46.13684	0.0001	0.51802	0.0001
		-2	-12.87895	0.0140	0.18338	0.0001
		-3	-2.75020	0.5999	0.09370	0.0001
		-4	5.14289	0.3177	0.12497	0.0001
VHL (Granger p <.0001)	Volume	-1	0.10827	0.0001	0.00024	0.0001
		-2	0.11776	0.0001	0.00008	0.2510
		-3	0.06210	0.0006	-0.00000	0.9905
		-4	0.15269	0.0001	-0.00017	0.0062
PANEL D: 30-Year Treasury Bonds						
Volume (Granger p <.0001)	VHL	-1	-39.71008	0.0001	0.52292	0.0001
		-2	-14.36008	0.0002	0.18895	0.0001
		-3	-8.48290	0.0286	0.14827	0.0001
		-4	3.34455	0.3782	0.11981	0.0001
VHL (Granger p = 0.0005)	Volume	-1	0.06920	0.0001	0.00022	0.0129
		-2	0.10413	0.0001	0.00009	0.3402
		-3	0.07987	0.0001	0.00004	0.7141
		-4	0.16918	0.0001	-0.00029	0.0011

Volume is in natural logarithm. VHL is the intra-day (high-low) measure of volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 3B
VAR with Active Contract: Volume vs. VHL

Dependent Variable	Independent Variable	Lag	VHL	p-value	Volume	p-value
PANEL A: 2-Year Treasury Notes						
Volume (Granger p < 0.0001)	VHL	-1	-23.28183	0.3422	0.34635	0.0001
		-2	-68.74555	0.0055	0.23366	0.0001
		-3	-87.06949	0.0004	0.17141	0.0001
		-4	23.61173	0.3362	0.10416	0.0001
VHL (Granger p < 0.0001)	Volume	-1	0.15335	0.0001	0.00002	0.0405
		-2	0.10802	0.0001	0.00002	0.1249
		-3	0.05067	0.0021	0.00003	0.0051
		-4	0.12621	0.0001	-0.00004	0.0003
PANEL B: 5-Year Treasury Notes						
Volume (Granger p <.0001)	VHL	-1	-46.86813	0.0001	0.42670	0.0001
		-2	-11.76980	0.1450	0.17984	0.0001
		-3	-20.53074	0.0110	0.14664	0.0001
		-4	-0.71893	0.9285	0.17351	0.0001
VHL (Granger p <.0001)	Volume	-1	0.10593	0.0001	0.00017	0.0001
		-2	0.08856	0.0001	0.00009	0.0248
		-3	0.06202	0.0004	0.00001	0.8602
		-4	0.13923	0.0001	-0.00011	0.0028
PANEL C: 10-Year Treasury Notes						
Volume (Granger p <.0001)	VHL	-1	-37.99912	0.0001	0.46663	0.0001
		-2	-10.64187	0.0453	0.16513	0.0001
		-3	-6.63353	0.2121	0.11789	0.0001
		-4	-1.07732	0.8368	0.17572	0.0001
VHL (Granger p<.0001)	Volume	-1	0.10276	0.0001	0.00026	0.0001
		-2	0.11580	0.0001	0.00007	0.2890
		-3	0.05842	0.0015	0.00001	0.8418
		-4	0.15280	0.0001	-0.00017	0.0060
PANEL D: 30-Year Treasury Bonds						
Volume (Granger p <.0001)	VHL	-1	-30.56653	0.0001	0.45373	0.0001
		-2	-11.97364	0.0023	0.18259	0.0001
		-3	-10.78816	0.0061	0.16531	0.0001
		-4	-3.67631	0.3417	0.18070	0.0001
VHL (Granger p = 0.0026)	Volume	-1	0.07568	0.0001	0.00016	0.0651
		-2	0.10222	0.0001	0.00011	0.2384
		-3	0.07637	0.0001	0.00005	0.5663
		-4	0.16636	0.0001	-0.00026	0.0022

Volume is in natural logarithm. VHL is the intra-day (high-low) measure of volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 4A
VAR with Aggregate: Open Interest vs. VHL

Dependent Variable	Independent Variable	Lag	VHL	p-value	Open Interest	p-value
PANEL A: 2-Year Treasury Notes						
Open Interest (Granger p = 0.0526)	VHL	-1	-2.26934	0.2269	1.03075	0.0001
		-2	-1.94539	0.3056	0.01054	0.6436
		-3	-3.05302	0.1075	-0.00581	0.7988
		-4	-1.31534	0.4833	-0.03713	0.0192
VHL (Granger p = 0.0237)	Open Interest	-1	0.16286	0.001	0.00011	0.4070
		-2	0.11792	0.001	-0.00026	0.1686
		-3	0.06367	0.001	-0.00005	0.8006
		-4	0.11040	0.001	0.00018	0.1710
PANEL B: 5-Year Treasury Notes						
Open Interest (Granger p = 0.0076)	VHL	-1	-0.82444	0.0033	1.09717	0.0001
		-2	-0.30496	0.2817	-0.00928	0.6951
		-3	0.14673	0.6401	-0.05174	0.0289
		-4	-0.28796	0.3016	-0.03663	0.0215
VHL (Granger p = 0.4261)	Open Interest	-1	0.15478	0.0001	-0.00116	0.1962
		-2	0.11491	0.0001	0.00073	0.5847
		-3	0.06975	0.0001	0.00062	0.6417
		-4	0.12610	0.0001	-0.00022	0.8076
PANEL C: 10-Year Treasury Notes						
Open Interest (Granger p <.0001)	VHL	-1	-1.45669	0.0001	1.03270	0.0001
		-2	-0.24925	0.2146	0.02312	0.3167
		-3	0.16214	0.4193	-0.02497	0.2795
		-4	0.16969	0.3882	-0.03157	0.0490
VHL (Granger p = 0.0134)	Open Interest	-1	0.14488	0.0001	-0.00110	0.3937
		-2	0.12920	0.0001	0.00024	0.8957
		-3	0.05953	0.0002	0.00006	0.9746
		-4	0.12865	0.0001	0.00071	0.5859
PANEL D: 30-Year Treasury Bonds						
Open Interest (Granger p <.0001)	VHL	-1	-1.81148	0.0001	0.97832	0.0001
		-2	-0.54113	0.0008	0.08580	0.0002
		-3	0.17760	0.2739	-0.06684	0.0037
		-4	0.18193	0.2470	-0.00114	0.9445
VHL (Granger p = 0.0003)	Open Interest	-1	0.09615	0.0001	-0.00175	0.2986
		-2	0.10911	0.0001	0.00157	0.5059
		-3	0.09401	0.0001	-0.00574	0.0150
		-4	0.12446	0.0001	0.00558	0.0009

Open interest is in natural logarithm. VHL is the intra-day (high-low) measure of volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 4B
VAR with Active Contract: Open Interest vs. VHL

Dependent Variable	Independent Variable	Lag	VHL	p-value	Open Interest	p-value
PANEL A: 2-Year Treasury Notes						
Open Interest (Granger p = 0.7391)	VHL	-1	1.70054	0.6775	1.00980	0.0001
		-2	3.40032	0.4109	-0.09865	0.0001
		-3	2.72536	0.5092	0.02119	0.3475
		-4	-3.09375	0.4481	0.06241	0.0001
VHL (Granger p = 0.0177)	Open Interest	-1	0.16348	0.0001	-0.00008	0.1904
		-2	0.11719	0.0001	0.00003	0.6875
		-3	0.06467	0.0001	-0.00005	0.5618
		-4	0.11152	0.0001	0.00007	0.2210
PANEL B: 5-Year Treasury Notes						
Open Interest (Granger p = 0.3950)	VHL	-1	1.18350	0.4032	1.02901	0.0001
		-2	1.77262	0.2147	-0.10985	0.0001
		-3	1.16214	0.4155	0.00955	0.6753
		-4	-0.64586	0.6473	0.06517	0.0001
VHL (Granger p = 0.1382)	Open Interest	-1	0.15439	0.0001	-0.00029	0.1034
		-2	0.11400	0.0001	0.00042	0.0963
		-3	0.07198	0.0001	-0.00032	0.2091
		-4	0.12633	0.0001	0.00015	0.4075
PANEL C: 10-Year Treasury Notes						
Open Interest (Granger p = 0.6004)	VHL	-1	-0.36871	0.7258	1.02057	0.0001
		-2	1.64658	0.1204	-0.13329	0.0001
		-3	0.22320	0.8332	0.03718	0.1011
		-4	0.07529	0.9428	0.06986	0.0001
VHL (Granger p = 0.0035)	Open Interest	-1	0.14385	0.0001	-0.00027	0.2464
		-2	0.12810	0.0001	0.00043	0.2056
		-3	0.06093	0.0001	-0.00043	0.2055
		-4	0.12999	0.0001	0.00017	0.4646
PANEL D: 30-Year Treasury Bonds						
Open Interest (Granger p = 0.2505)	VHL	-1	-1.40980	0.0480	1.01283	0.0001
		-2	0.92688	0.1943	-0.13421	0.0001
		-3	-0.24939	0.7267	0.03601	0.1123
		-4	-0.09081	0.8981	0.04795	0.0026
VHL (Granger p = 0.0033)	Open Interest	-1	0.09383	0.0001	-0.00067	0.0570
		-2	0.11244	0.0001	0.00048	0.3431
		-3	0.08150	0.0001	-0.00021	0.6696
		-4	0.13679	0.0001	0.00003	0.9241

Open interest is in natural logarithm. VHL is the intra-day (high-low) measure of volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 5A
VAR with Aggregate: Volume vs. VHIS

Dependent Variable	Independent Variable	Lag	VHIS	p-value	Volume	p-value
PANEL A: 2-Year Treasury Notes						
Volume (Granger p = 0.0261)	VHIS	-1	-109.5856	0.0857	0.40101	0.0001
		-2	54.82373	0.5356	0.22812	0.0001
		-3	-61.21137	0.4891	0.15423	0.0001
		-4	65.36276	0.3040	0.07935	0.0001
VHIS (Granger p < 0.0001)	Volume	-1	0.96061	0.0001	-0.00001	0.1421
		-2	0.00972	0.6595	0.00001	0.1158
		-3	0.00094	0.9660	0.00001	0.0336
		-4	-0.01896	0.2315	0.00001	0.1201
PANEL B: 5-Year Treasury Notes						
Volume (Granger p <.0001)	VHIS	-1	-60.26742	0.0035	0.43000	0.0001
		-2	-4.79140	0.8674	0.19258	0.0001
		-3	-0.25378	0.9929	0.12468	0.0001
		-4	57.59389	0.0052	0.15194	0.0001
VHIS (Granger p <.0001)	Volume	-1	0.95958	0.0001	-0.00000	0.9264
		-2	0.01259	0.5688	0.00003	0.0270
		-3	-0.00314	0.8871	-0.000000	0.7882
		-4	-0.01662	0.2955	0.00002	0.1459
PANEL C: 10-Year Treasury Notes						
Volume (Granger p <.0001)	VHIS	-1	-47.66700	0.0002	0.45960	0.0001
		-2	7.12474	0.6919	0.18389	0.0001
		-3	4.97334	0.7820	0.10278	0.0001
		-4	29.55925	0.0226	0.14903	0.0001
VHIS (Granger p <.0001)	Volume	-1	0.95473	0.0001	0.00001	0.5013
		-2	0.01738	0.4311	0.00003	0.2346
		-3	-0.00380	0.8632	-0.00002	0.2673
		-4	-0.01368	0.3900	0.00005	0.0136
PANEL D: 30-Year Treasury Bonds						
Volume (Granger p <.0001)	VHIS	-1	-28.42188	0.0009	0.45457	0.0001
		-2	2.22348	0.8526	0.19555	0.0001
		-3	-8.63513	0.4705	0.15646	0.0001
		-4	30.42352	0.0004	0.16034	0.0001
VHIS (Granger p = 0.2548)	Volume	-1	0.96409	0.0001	-0.00002	0.5240
		-2	0.01217	0.5830	0.00002	0.4512
		-3	-0.00505	0.8197	-0.00003	0.3473
		-4	-0.01616	0.3107	0.00004	0.1373

Volume is in natural logarithm. VHIS is the historical volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 5B
VAR with Active Contract: Volume vs. VHIS

Dependent Variable	Independent Variable	Lag	VHIS	p-value	Volume	p-value
PANEL A: 2-Year Treasury Notes						
Volume (Granger p = 0.0929)	VHIS	-1	-106.1484	0.0919	0.34717	0.0001
		-2	54.00386	0.5372	0.22207	0.0001
		-3	-62.38476	0.4760	0.16028	0.0001
		-4	80.97935	0.1975	0.11349	0.0001
VHIS (Granger p < .0001)	Volume	-1	0.96354	0.0001	-0.00001	0.0401
		-2	0.00944	0.6690	0.00001	0.1183
		-3	0.00067	0.9760	0.00001	0.0194
		-4	-0.02081	0.1892	0.00001	0.1129
PANEL B: 5-Year Treasury Notes						
Volume (Granger p = 0.0005)	VHIS	-1	-45.13790	0.0261	0.39295	0.0001
		-2	-7.48864	0.7908	0.18267	0.0001
		-3	-8.64888	0.7592	0.13669	0.0001
		-4	58.20951	0.0041	0.18338	0.0001
VHIS (Granger p = 0.0004)	Volume	-1	0.96370	0.0001	-0.00001	0.2878
		-2	0.01091	0.6229	0.00002	0.0717
		-3	-0.00385	0.8620	-0.00000	0.9328
		-4	-0.01781	0.2634	0.00002	0.0451
PANEL C: 10-Year Treasury Notes						
Volume (Granger p = 0.0003)	VHIS	-1	-38.57227	0.0029	0.41678	0.0001
		-2	6.03194	0.7370	0.16671	0.0001
		-3	-2.86268	0.8734	0.12062	0.0001
		-4	31.68087	0.0143	0.18959	0.0001
VHIS (Granger p = 0.0011)	Volume	-1	0.95768	0.0001	-0.00000	0.8862
		-2	0.01715	0.4389	0.00001	0.5545
		-3	-0.00554	0.8026	-0.00001	0.5590
		-4	-0.01440	0.3666	0.00005	0.0059
PANEL D: 30-Year Treasury Bonds						
Volume (Granger p = 0.0002)	VHIS	-1	-20.51629	0.0195	0.40775	0.0001
		-2	2.10373	0.8634	0.19040	0.0001
		-3	-14.18366	0.2463	0.16901	0.0001
		-4	29.07661	0.0009	0.20216	0.0001
VHIS (Granger p = 0.1302)	Volume	-1	0.96581	0.0001	-0.00005	0.0919
		-2	0.01228	0.5804	0.00000	0.9575
		-3	-0.00730	0.7424	-0.00000	0.9196
		-4	-0.01574	0.3238	0.00006	0.0314

Volume is in natural logarithm. VHIS is the historical volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 6A
VAR with Aggregate: Open Interest vs. VHIS

Dependent Variable	Independent Variable	Lag	VHIS	p-value	Open Interest	p-value
PANEL A: 2-Year Treasury Notes						
Open Interest (Granger p =0.1112)	VHIS	-1	-5.26589	0.2899	1.03091	0.0001
		-2	-0.29380	0.9662	0.01011	0.6572
		-3	0.44925	0.9483	-0.00629	0.7824
		-4	1.44306	0.7718	-0.03628	0.0222
VHIS (Granger p =0.8063)	Open Interest	-1	0.96719	0.0001	0.00001	0.8275
		-2	0.01194	0.5888	-0.00006	0.4310
		-3	0.00034	0.9876	0.00002	0.8216
		-4	-0.02524	0.1117	0.00003	0.5785
PANEL B: 5-Year Treasury Notes						
Open Interest (Granger p =0.0008)	VHIS	-1	-2.21348	0.0045	1.09065	0.0001
		-2	0.18991	0.8606	-0.00339	0.8850
		-3	0.25722	0.8120	-0.04627	0.0484
		-4	1.58326	0.0421	-0.04141	0.0089
VHIS (Granger p = 0.3611)	Open Interest	-1	0.96511	0.0001	0.00048	0.1363
		-2	0.01809	0.4120	-0.00014	0.7633
		-3	-0.00700	0.7507	-0.00069	0.1491
		-4	-0.01951	0.2190	0.00035	0.2751
PANEL C: 10-Year Treasury Notes						
Open Interest (Granger p <.0001)	VHIS	-1	-2.53135	0.0001	1.01658	0.0001
		-2	1.52748	0.0457	0.03230	0.1531
		-3	-0.09581	0.9003	-0.01785	0.4296
		-4	0.84264	0.1267	-0.03153	0.0462
VHIS (Granger p = 0.2680)	Open Interest	-1	0.95980	0.0001	-0.00077	0.0906
		-2	0.01712	0.4367	0.00039	0.5453
		-3	-0.00745	0.7352	-0.00014	0.8238
		-4	-0.01246	0.4326	0.00052	0.2522
PANEL D: 30-Year Treasury Bonds						
Open Interest (Granger p <.0001)	VHIS	-1	-1.46755	0.0002	0.94268	0.0001
		-2	0.49052	0.3776	0.10695	0.0001
		-3	-0.11036	0.8425	-0.05003	0.0216
		-4	0.82643	0.0390	-0.00248	0.8754
VHIS (Granger p = 0.0508)	Open Interest	-1	0.96320	0.0001	0.00097	0.1221
		-2	0.01759	0.4247	-0.00218	0.0117
		-3	-0.01081	0.6234	0.00001	0.9935
		-4	-0.01490	0.3476	0.00120	0.0545

Open interest is in natural logarithm. VHIS is the historical volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 6B
VAR with Active Contract: Open Interest vs. VHIS

Dependent Variable	Independent Variable	Lag	VHIS	p-value	Open Interest	p-value
PANEL A: 2-Year Treasury Notes						
Open Interest (Granger p = 0.1519)	VHIS	-1	9.38677	0.3874	1.00818	0.0001
		-2	13.29794	0.3782	-0.09877	0.0001
		-3	-9.97403	0.5085	0.02328	0.3024
		-4	-8.48796	0.4333	0.06225	0.0001
VHIS (Granger p <.0001)	Open Interest	-1	0.96427	0.0001	-0.00004	0.0597
		-2	0.01689	0.4437	-0.00004	0.1909
		-3	0.00266	0.9040	0.00002	0.5944
		-4	-0.02885	0.0685	0.00006	0.0056
PANEL B: 5-Year Treasury Notes						
Open Interest (Granger p = 0.3503)	VHIS	-1	3.83738	0.3348	1.02789	0.0001
		-2	1.72492	0.7550	-0.11006	0.0001
		-3	-3.09420	0.5756	0.01133	0.6208
		-4	-0.68536	0.8630	0.06463	0.0001
VHIS (Granger p = 0.0068)	Open Interest	-1	0.96581	0.0001	-0.00011	0.0971
		-2	0.02004	0.3658	-0.00005	0.5816
		-3	-0.00662	0.7653	0.00002	0.8133
		-4	-0.02177	0.1715	0.00013	0.0495
PANEL C: 10-Year Treasury Notes						
Open Interest (Granger p = 0.4262)	VHIS	-1	-1.38985	0.6401	1.02091	0.0001
		-2	6.65331	0.1066	-0.13545	0.0001
		-3	-3.73203	0.3655	0.03846	0.0913
		-4	-0.92308	0.7558	0.07020	0.0001
VHIS (Granger p = 0.0046)	Open Interest	-1	0.96047	0.0001	-0.00013	0.1150
		-2	0.02323	0.2932	-0.00012	0.3194
		-3	-0.00906	0.6818	0.00011	0.3728
		-4	-0.01647	0.3005	0.00014	0.1091
PANEL D: 30-Year Treasury Bonds						
Open Interest (Granger p = 0.6079)	VHIS	-1	-2.02564	0.2724	1.01215	0.0001
		-2	4.06513	0.1130	-0.13368	0.0001
		-3	-2.65104	0.3014	0.03525	0.1219
		-4	0.44493	0.8092	0.04920	0.0021
VHIS (Granger p = 0.0011)	Open Interest	-1	0.96306	0.0001	-0.00013	0.3574
		-2	0.02223	0.3175	-0.00039	0.0493
		-3	-0.01328	0.5505	0.00034	0.0867
		-4	-0.01658	0.2994	0.00009	0.5068

Open interest is in natural logarithm. VHIS is the historical volatility. a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 7A
VAR with Aggregate: Volume vs. VG

Dependent Variable	Independent Variable	Lag	VG	p-value	Volume	p-value
PANEL A: 2-Year Treasury Notes						
Volume (Granger p = 0.2044)	VG	-1	-18.85819	0.7271	0.40074	0.0001
		-2	-62.44272	0.3282	0.22938	0.0001
		-3	43.53342	0.4951	0.15379	0.0001
		-4	-78.18992	0.1456	0.07763	0.0001
VG (Granger p < 0.0001)	Volume	-1	0.63137	0.0001	0.00002	0.0001
		-2	0.1349	0.4718	-0.00001	0.0071
		-3	-0.00883	0.6375	0.00001	0.0190
		-4	0.00674	0.6691	0.00000	0.6303
PANEL B: 5-Year Treasury Notes						
Volume (Granger p = 0.1055)	VG	-1	-97.41910	0.3267	0.42939	0.0001
		-2	-120.25985	0.3863	0.19071	0.0001
		-3	231.94502	0.0948	0.12035	0.0001
		-4	7.02389	0.9436	0.14999	0.0001
VG (Granger p < .0001)	Volume	-1	0.97747	0.0001	0.00001	0.0016
		-2	0.00929	0.6751	-0.00000	0.4952
		-3	-0.00449	0.8394	0.00001	0.0474
		-4	-0.00447	0.7780	-0.00001	0.0373
PANEL C: 10-Year Treasury Notes						
Volume (Granger p = 0.5545)	VG	-1	-39.79935	0.5388	0.45801	0.0001
		-2	-40.52289	0.6544	0.18135	0.0001
		-3	85.86414	0.3429	0.09872	0.0001
		-4	5.99487	0.9261	0.14847	0.0001
VG (Granger p <.0001)	Volume	-1	0.97825	0.0001	0.00001	0.0006
		-2	0.00568	0.7978	-0.00000	0.4339
		-3	-0.00337	0.8793	0.00001	0.0535
		-4	-0.00333	0.8336	-0.00001	0.0190
PANEL D: 30-Year Treasury Bonds						
Volume (Granger p = 0.0013)	VG	-1	-11.15845	0.0607	0.45180	0.0001
		-2	-12.66111	0.0907	0.19753	0.0001
		-3	11.36662	0.1284	0.15694	0.0001
		-4	0.40371	0.9455	0.16010	0.0001
VG (Granger p <.0001)	Volume	-1	0.76351	0.0001	0.00037	0.0001
		-2	0.01370	0.4918	-0.00020	0.0001
		-3	-0.00163	0.9346	0.00002	0.7212
		-4	0.00683	0.6643	-0.00015	0.0002

Volume is in natural logarithm. VG is the volatility estimated by GARCH(1,1). a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 7B
VAR with Active Contract: Volume vs. VG

Dependent Variable	Independent Variable	Lag	VG	p-value	Volume	p-value
PANEL A: 2-Year Treasury Notes						
Volume (Granger p = 0.3480)	VG	-1	-12.68904	0.8122	0.34629	0.0001
		-2	-59.68430	0.3449	0.22319	0.0001
		-3	32.57611	0.6057	0.15991	0.0001
		-4	-59.71436	0.2608	0.11252	0.0001
VG (Granger p <.0001)	Volume	-1	0.63398	0.0001	0.00002	0.0001
		-2	0.01353	0.4712	-0.00002	0.0009
		-3	-0.00857	0.6477	0.00001	0.0252
		-4	0.00741	0.6384	0.00000	0.4261
PANEL B: 5-Year Treasury Notes						
Volume (Granger p = 0.1385)	VG	-1	-16.72146	0.8638	0.39124	0.0001
		-2	-168.07350	0.2180	0.18044	0.0001
		-3	161.26018	0.2370	0.13351	0.0001
		-4	54.47993	0.5756	0.18269	0.0001
VG (Granger p < .0001)	Volume	-1	0.97983	0.0001	0.00001	0.0001
		-2	0.00731	0.7418	-0.00001	0.0134
		-3	-0.00324	0.8837	0.00000	0.1642
		-4	-0.00570	0.7189	-0.00000	0.0922
PANEL C: 10-Year Treasury Notes						
Volume (Granger p = 0.4870)	VG	-1	4.91062	0.9393	0.41403	0.0001
		-2	-78.70164	0.3835	0.16427	0.0001
		-3	65.01879	0.4714	0.11743	0.0001
		-4	26.34681	0.6825	0.19000	0.0001
VG (Granger p <.0001)	Volume	-1	0.98030	0.0001	0.00002	0.0001
		-2	0.00382	0.8632	-0.00001	0.0265
		-3	-0.00254	0.9089	0.00000	0.2630
		-4	-0.00409	0.7958	-0.00001	0.0626
PANEL D: 30-Year Treasury Bonds						
Volume (Granger p = 0.0364)	VG	-1	-3.40945	0.5759	0.40492	0.0001
		-2	-14.04558	0.0675	0.19093	0.0001
		-3	5.00722	0.5131	0.17005	0.0001
		-4	2.80647	0.6412	0.20315	0.0001
VG (Granger p <.0001)	Volume	-1	0.76622	0.0001	0.00045	0.0001
		-2	0.01156	0.5625	-0.00030	0.0001
		-3	-0.00229	0.9085	-0.00002	0.6711
		-4	0.00683	0.6626	-0.00011	0.0080

Volume is in natural logarithm. VG is the volatility estimated by GARCH(1,1). a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 8A
VAR with Aggregate: Open Interest vs. VG

Dependent Variable	Independent Variable	Lag	VG	p-value	Open Interest	p-value
PANEL A: 2-Year Treasury Notes						
Open Interest (Granger p =0.3449)	VG	-1	-5.44841	0.1965	1.03112	0.0001
		-2	-0.76820	0.8778	0.01051	0.6448
		-3	-0.02184	0.9965	-0.00633	0.7812
		-4	-1.90146	0.6520	-0.03672	0.0207
VG (Granger p=0.3253	Open Interest	-1	0.63514	0.0001	0.00006	0.2923
		-2	0.01901	0.3117	-0.00011	0.1808
		-3	-0.00949	0.6134	-0.00004	0.6826
		-4	0.00898	0.5712	0.00008	0.1584
PANEL B: 5-Year Treasury Notes						
Open Interest (Granger p = 0.4448)	VG	-1	0.77392	0.8369	1.09323	0.0001
		-2	-5.60538	0.2865	-0.00668	0.7762
		-3	4.79439	0.3617	-0.04839	0.0395
		-4	1.01370	0.7872	-0.03860	0.0150
VG (Granger p = 0.0048)	Open Interest	-1	0.97783	0.0001	-0.00004	0.5952
		-2	0.01339	0.5460	0.00025	0.0119
		-3	-0.00902	0.6839	-0.00009	0.3637
		-4	-0.00249	0.8749	-0.00012	0.0642
PANEL C: 10-Year Treasury Notes						
Open Interest (Granger p = 0.5108)	VG	-1	-2.07286	0.4531	1.01830	0.0001
		-2	-1.48232	0.7013	0.03401	0.1330
		-3	1.30805	0.7350	-0.02009	0.3748
		-4	2.48560	0.3682	-0.03270	0.0392
VG (Granger p = 0.3826)	Open Interest	-1	0.97885	0.0001	-0.00000	0.9693
		-2	0.00759	0.7324	-0.00018	0.1773
		-3	-0.00734	0.7408	0.00013	0.3049
		-4	-0.00010	0.9950	0.00005	0.6174
PANEL D: 30-Year Treasury Bonds						
Open Interest (Granger p = 0.0470)	VG	-1	-0.56581	0.0404	0.94231	0.0001
		-2	-0.08636	0.8030	0.10672	0.0001
		-3	0.39895	0.2490	-0.04793	0.0284
		-4	-0.23688	0.3893	-0.00396	0.8029
VG (Granger p = 0.1313)	Open Interest	-1	0.75920	0.0001	0.00210	0.0220
		-2	0.01966	0.3241	-0.00213	0.0901
		-3	-0.01617	0.4173	-0.00130	0.3003
		-4	0.01590	0.3158	0.00134	0.1414

Open interest is in natural logarithm. VG is the volatility estimated by GARCH(1,1). a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Table 8B
VAR with Active Contract: Open Interest vs. VG

Dependent Variable	Independent Variable	Lag	VG	p-value	Open Interest	p-value
PANEL A: 2-Year Treasury Notes						
Open Interest (Granger p = 0.0142)	VG	-1	24.35365	0.0082	1.00753	0.0001
		-2	0.58906	0.9569	-0.10099	0.0001
		-3	1.73263	0.8731	0.02492	0.2707
		-4	-2.40152	0.7931	0.06356	0.0001
VG (Granger p <.0001	Open Interest	-1	0.63217	0.0001	0.00013	0.0001
		-2	0.02428	0.1951	-0.00022	0.0001
		-3	-0.00927	0.6191	-0.00004	0.3162
		-4	0.01016	0.5184	0.00013	0.0001
PANEL B: 5-Year Treasury Notes						
Open Interest (Granger p = 0.2227)	VG	-1	32.88455	0.0867	1.02905	0.0001
		-2	-9.77329	0.7161	-0.11295	0.0001
		-3	-5.93986	0.8239	0.01165	0.6116
		-4	-12.65397	0.5062	0.06598	0.0001
VG (Granger p <.0001)	Open Interest	-1	0.97979	0.0001	0.00010	0.0001
		-2	0.01268	0.5680	-0.00014	0.0001
		-3	-0.00976	0.6581	0.00001	0.5895
		-4	-0.00262	0.8675	0.00002	0.0755
PANEL C: 10-Year Treasury Notes						
Open Interest (Granger p = 0.2705)	VG	-1	27.39105	0.0657	1.01957	0.0001
		-2	-11.34166	0.5867	-0.13474	0.0001
		-3	-3.92522	0.8497	0.03854	0.0914
		-4	-10.09711	0.4940	0.07074	0.0001
VG (Granger p <.0001)	Open Interest	-1	0.98128	0.0001	0.00012	0.0001
		-2	0.00931	0.6752	-0.00017	0.0001
		-3	-0.01028	0.6413	0.00000	0.9359
		-4	-0.00112	0.9429	0.00004	0.0120
PANEL D: 30-Year Treasury Bonds						
Open Interest (Granger p = 0.3438)	VG	-1	2.49238	0.0524	1.00985	0.0001
		-2	-1.22204	0.4503	-0.13489	0.0001
		-3	0.17066	0.9143	0.03857	0.0963
		-4	-0.82536	0.5102	0.04981	0.0022
VG (Granger p <.0001)	Open Interest	-1	0.76502	0.0001	0.00252	0.0001
		-2	0.02016	0.3126	-0.00319	0.0001
		-3	-0.01881	0.3362	-0.00002	0.9417
		-4	0.01513	0.3275	0.00061	0.0024

Open interest is in natural logarithm. VG is the volatility estimated by GARCH(1,1). a, b, and c are significant levels at 1, 5, and 10%, respectively. p-values of VAR results are presented. The p-values for Granger causality test are also included, with hypothesis H_0: independent variable does not Granger-cause the dependent variable and H_1: independent variable Granger-causes the dependent variable.

Note: Graphs on Impulse Responses are available from Liao, W. (2008), "Trading Activity in the Treasury Futures Market and Its Role in Futures Price Fluctuations" (available at SSRN: http://ssrn.com/abstract=1028432).

Table 9A
Choosing an AR(m)-GARCH(p, q) Specification: Two Year Note Futures

m	p	q	AR1	AR2	AR3	AR4	ARCH0	q		p	
								ARCH1	ARCH2	GARCH1	GARCH2
0	**1**	**1**					7.0801E-7	0.1249		0.5006	
							(<.0001)*	(<.0001)*		(<.0001)*	
		2					1.242E-6	0.0219	0.3508	0.0490	
							(<.0001)*	(0.0254)*	(<.0001)*	(0.0403)*	
	2	**1**					4.8191E-7	0.0307		0.8977	-0.2015
							(<.0001)*	(<.0001)*		(<.0001)*	(0.0303)*
		2					1.1302E-6	0.0103	0.3833	0.0276	0.0748
							(<.0001)*	(0.2393)	(<.0001)*	(0.1410)	(<.0001)*
1	**1**	**1**	-0.1312				7.3745E-7	0.2978		0.3814	
			(<.0001)*				(<.0001)*	(<.0001)*		(<.0001)*	
		2	-0.0346				1.279E-6	0.0470	0.3174	0.0262	
			(0.0418)*				(<.0001)*	(0.0012)*	(<.0001)*	(0.2770)	
	2	**1**	-0.0638				6.1889E-7	0.0435		0.7492	-0.1403
			(0.5150)				(0.9008)	(0.9352)		(0.9468)	(0.9859)
		2	-0.0155				1.1451E-6	0.0229	0.3736	0.0199	0.0698
			(0.3160)				(<.0001)*	(0.0422)*	(<.0001)*	(0.3017)	(0.0003)*
4	**1**	**1**	-0.1246	0.0275	0.00394	0.0221	7.5068E-7	0.2668		0.3902	
			(<.0001)*	(0.0979)	(0.8306)	(0.1738)	(<.0001)*	(<.0001)*		(<.0001)*	
		2	-0.0177	0.0514	0.00962	0.0268	1.2611E-6	0.0259	0.3506	0.0347	
			(0.2763)	(0.0124)*	(0.5225)	(0.0221)*	(<.0001)*	(0.0154)*	(<.0001)*	(0.1347)	
	2	**1**	-0.0797	0.0431	0.0261	0.0276	5.4322E-7	0.0485		0.8119	-0.1648
			(0.0001)*	(0.0169)*	(0.1788)	(0.1219)	(<.0001)*	(<.0001)*		(<.0001)*	(0.1383)
		2	-0.0133	0.0528	0.0186	0.0213	1.1288E-6	0.0196	0.3879	0.0169	0.0771
			(0.3819)	(0.0154)*	(0.1932)	(0.1453)	(<.0001)*	(0.0556)	(<.0001)*	(0.3521)	(0.0001)*

Estimates of coefficient and p-value (in parenthesis). Blank: not applicable. *: significant at the level of 5%. A SAS output example is provided in the Appendix. Notice that the sequence of p, q is expressed in reverse for the convenience of reading SAS outputs.

Table 9B
Choosing an AR(m)-GARCH(p, q) Specification: Five Year Note Futures

m	p	q	AR1	AR2	AR3	AR4	ARCH0	q		p	
								ARCH1	ARCH2	GARCH1	GARCH2
0	**1**	**1**					1.8568E-7 (<.0001)*	0.008807 (<.0001)*		0.9702 (<.0001)*	
		2					5.4595E-6 (<.0001)*	0.006708 (0.4635)	0.4883 (<.0001)*	0.0355 (0.0397)*	
	2	**1**					1.7063E-7 (<.0001)*	0.008098 (<.0001)*		1.0530 (<.0001)*	-0.0804 (<.0001)*
		2					4.8411E-6 (<.0001)*	0.002963 (0.7025)	0.5152 (<.0001)*	0.0285 (0.0553)	0.0660 (0.0003)*
1	**1**	**1**	-0.0680 (0.0016)*				3.2554E-6 (<.0001)*	0.1083 (<.0001)*		0.5329 (<.0001)*	
		2	-0.0155 (0.3024)				5.5085E-6 (<.0001)*	0.0121 (0.2528)	0.4846 (<.0001)*	0.0274 (0.1168)	
	2	**1**	-0.0348 (0.0735)				1.9775E-6 (0.0531)	0.0269 (0.1157)		0.9880 (0.0796)	-0.2440 (0.5829)
		2	-0.00686 (0.6402)				4.8517E-6 (<.0001)*	0.007233 (0.4407)	0.5156 (<.0001)*	0.0252 (0.0996)	0.0649 (0.0004)*
4	**1**	**1**	-0.0612 (0.0047)*	0.0352 (0.0547)	0.0334 (0.0894)	0.0453 (0.0107)*	3.0967E-6 (<.0001)*	0.0973 (<.0001)*		0.5580 (<.0001)*	
		2	-0.007406 (0.6140)	0.0678 (0.0003)*	0.0219 (0.1336)	0.0505 (<.0001)*	5.4695E-6 (<.0001)*	0.007676 (0.4085)	0.5145 (<.0001)	0.0213 (0.1649)	
	2	**1**	-0.0300 (0.0923)	0.0465 (0.0033)*	0.0423 (0.0119)*	0.0454 (0.0027)*	8.4009E-6 (0.1225)	0.006025 (0.6017)		7.1702E-6 (1.0000)	-1.28E-11 (1.0000)
		2	-0.0300 (0.1023)	0.0465 (0.0053)*	0.0423 (0.0090)*	0.0454 (0.0020)*	7.6523E-6 (<.0001)*	0.0246 (0.0619)	0.0256 (0.0110)*	1.208E-13 (1.0000)	7.8849E-7 (1.0000)

Estimates of coefficient and p-value (in parenthesis). Blank: not applicable. *: significant at the level of 5%. A SAS output example is provided in the Appendix. Notice that the sequence of p, q is expressed in reverse for the convenience of reading SAS outputs.

Table 9C
Choosing an AR(m)-GARCH(p, q) Specification: Ten Year Note Futures

m	p	q	AR1	AR2	AR3	AR4	ARCH0	q		p	
								ARCH1	ARCH2	GARCH1	GARCH2
0	1	1					0.0000175 (<.0001)*	-5.32E-23 (1.0000)		9.9868E-7 (<.0001)*	
		2					0.0000124 (<.0001)*	0.000552 (0.9461)	0.3849 (<.0001)*	0.0192 (0.2902)	
	2	1					0.0000175 (<.0001)*	8.6554E-7 (0.9999)		1.6691E-6 (1.0000)	6.7122E-7 (1.0000)
		2					0.0000109 (<.0001)*	3.626E-21 (1.0000)	0.4059 (<.0001)*	0.0175 (0.2523)	0.0781 (0.0012)*
1	1	1	-0.0276 (0.1415)				4.1394E-7 (0.0006)*	0.008139 (<.0001)*		0.9686 (<.0001)*	
		2	-0.0153 (0.3150)				0.0000125 (<.0001)*	0.001745 (.8373)	0.3816 (<.0001)*	0.0146 (0.4617)	
	2	1#	-0.0269 (0.1488)				3.4493E-7 (0.0004)*	0.006860 (<.0001)*		1.1435 (<.0001)*	-0.1697 (<.0001)*
		2	0.000402 (0.9773)				0.0000109 (<.0001)*	-3.92E-21 (1.0000)	0.4061 (<.0001)*	0.0176 (0.2725)	0.0781 (0.0013)*
4	1	1	-0.0235 (0.2117)	0.0406 (0.0222)*	0.0437 (0.0238)*	0.0611 (0.0006)*	3.8868E-7 (0.0003)*	0.008783 (<.0001)*		0.9695 (<.0001)*	
		2	-0.0117 (0.4078)	0.0237 (0.2437)	0.0351 (0.0157)*	0.0649 (<.0001)*	0.0000126 (<.0001)*	0.000180 (0.9691)	0.3966 (<.0001)*	-2.45E-11 (0.9996)	
	2	1	-0.0206 (0.2308)	0.0409 (0.0084)*	0.0430 (0.0104)*	0.0522 (0.0007)*	0.0000173 (0.7027)	0.001626 (0.8656)		6.5792E-6 (1.0000)	1.208E-12 (1.0000)
		2	-0.0206 (0.2531)	0.0409 (0.0185)*	0.0430 (0.0083)*	0.0522 (0.0005)*	0.0000156 (<.0001)*	0.0157 (0.1532)	0.0420 (0.0001)*	1.079E-13 (1.0000)	9.5071E-7 (1.0000)

Estimates of coefficient and p-value (in parenthesis). Blank: not applicable. *: significant at the level of 5%. A SAS output example is provided in the Appendix. Notice that the sequence of p, q is expressed in reverse for the convenience of reading SAS outputs.

#: anomaly in the longer term data.

Table 9D
Choosing an AR(m)-GARCH(p, q) Specification: Thirty Year Bond Futures

m	p	q	AR1	AR2	AR3	AR4	ARCH0	q		p	
								ARCH1	**ARCH2**	**GARCH1**	**GARCH2**
0	**1**	**1**					9.0727E-6	0.1792		0.6390	
							(<.0001)*	(<.0001)*		(<.0001)*	
		2					0.0000249	0.000276	0.4236	0.0541	
							(<.0001)*	(0.9786)	(<.0001)*	(0.0405)*	
	2	**1**					0.0000104	0.0955		0.8301	-0.1723
							(<.0001)*	(<.0001)*		(<.0001)*	(0.2224)
		2					0.0000156	0.0000539	0.4313	0.0790	0.2019
							(<.0001)*	(0.9942)	(<.0001)*	(.0024)*	(<.0001)*
1	**1**	**1**	-0.0219				9.3733E-6	0.1808		0.6259	
			(0.3479)				(<.0001)*	(<.0001)*		(<.0001)*	
		2	0.0202				0.0000247	-1.48E-10	0.4224	0.0585	
			(0.1806)				(<.0001)*	(1.0000)	(<.0001)*	(0.0296)*	
	2	**1#**	0.001722				4.1619E-6	0.0254		1.2800	-0.4096
			(0.9310)				(0.0020)*	(0.0125)*		(<.0001)*	(0.0391)*
		2	0.0236				0.0000154	1.163E-21	0.4288	0.0818	0.2054
			(0.1235)				(<.0001)*	(1.0000)	(<.0001)*	(0.0016)*	(<.0001)*
4	**1**	**1**	0.002947	0.0234	0.0294	0.0436	0.0000395	-1.76E-23		1.0483E-6	
			(0.8602)	(0.0488)*	(0.0704)	(0.0035)*	(< .0001)*	(1.0000)		(0.9999)	
		2	0.0230	0.0291	0.0451	0.0585	0.0000269	-2.74E-10	0.4225	-2.74E-10	
			(0.1321)	(0.1506)	(0.0012)*	(<.0001)*	(<.0001)*	(1.0000)	(<.0001)*	(<.0001)*	
	2	**1**	0.002949	0.0234	0.0294	0.0436	0.0000395	7.6007E-7		3.966E-12	9.8984E-7
			(0.8746)	(0.0496)*	(0.0713)	(0.0035)*	(<.0001)*	(0.9999)		(1.0000)	(0.9999)
		2	0.0266	0.0400	0.0590	0.0801	0.0000123	-4.75E-21	0.4112	0.1211	0.2526
			(0.0873)	(0.0772)	(0.0005)*	(<.0001)*	(<.0001)*	(1.0000)	(<.0001)*	(<.0001)*	(<.0001)*

Estimates of coefficient and p-value (in parenthesis). Blank: not applicable. *: significant at the level of 5%. A SAS output example is provided in the Appendix. Notice that the sequence of p, q is expressed in reverse for the convenience of reading SAS outputs. #: anomaly in the longer term data.