TRADING ACTIVITY IN THE TREASURY FUTURES MARKET AND ITS ROLE IN FUTURES PRICE FLUCTUATIONS

by

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A dissertation submitted to the Graduate Faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2008

This manuscript has been read and accepted for the
Graduate Faculty in Economics in satisfaction of the
dissertation requirement for the degree of Doctor of Philosophy.

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Abstract

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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 Chapter 1 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. Significance relation can not be said of the hedgers and the price volatility; available evidence at best suggests a weak relation between hedging activity 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.

I review in Chapter 2 the classes of models in theorizing the volume-volatility relation. The strategic trading model of private information by Kyle (1985) and "differences of opinion" model of public information by Harris and Raviv (1993) are discussed. I propose that the "differences of opinion" models are more suitable in studying Treasury futures trading, since virtually all diligent analysts are exposed to the same set of public data (such as Federal Open Market Committee announcements, "Fed watchers'" studied guesses, or quarterly GDP growth rates and monthly nonfarm payrolls for general economic outlook), but they nonetheless infer their interest rate expectations with different interpretations of data. Unlike the cases in stock or corporate bond markets where differential accesses to private information are essential, differences in interpretation are more significant in Treasury futures trading and private information is less distinctive for individual contracts. The main predictions of the Harris and Raviv model are compared with my VAR results from Chapter 1; it is especially notable that the positively autocorrelated volume pattern is confirmed by the surprisingly strong VAR evidence. I then conclude with the recent episode (09/2006) of "market squeeze" warnings to financial institutions (essentially primary dealers) in the Treasury market. Implications on Treasury futures trading in terms of regulating the market are discussed.

Acknowledgements

My sincere gratitude to the Graduate Center of the City University of New York, the Georgetown University, and the University of Chicago that have provided me with the training grounds along the journey of an intellectual apprentice. Furthermore, the CUNY system offers me the valuable teaching experience and a tremendous platform that has assured me of a solid first step in this used-to-be-foreign, interesting American society. I would like to express my gratitude to the many people who have been kind and helpful on my path to a doctoral dissertation. I especially thank my family to be ever supportive of my endeavors. While in this volume all errors and omissions remain my sole responsibility, I thank Professors Thom Thurston, Nusret Cakici, Michael Grosssman, and Salih Neftci at the CUNY-Graduate Center for the advising along the Ph.D. program, and Professor Yau-De Wang at Taiwan's National Chiao Tung University for his answers to my questions since college years.

Wenchao Liao
August 2008

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CHAPTER 1: 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 (narrowly defined, that is, a market with a higher price volatility). 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 well 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; henceforth, in contrast, open interest primarily reflects the hedging activity and thus the proxy for the amount of uninformed trading. Second, Bessembinder and Seguin (1993) partitions the open interest into expected and unexpected components, and it is documented that futures price volatility is negatively related to the expected level of open interests in all 8 futures markets studied (yen, Deutsch mark, T-Bond, T-Bill, wheat, cotton, gold, silver). This could be interpreted as: Higher expected level of open interests leads to lower futures price volatilities and a more stable futures market. The expected level of open interest represents the un-informed trading activity, i.e. hedging activity of "hedgers". The expected portion reflects open interest as of the "beginning" of the trading day. The unexpected portion of open interest captures unanticipated changes in net contact formation. Since, as the paper found out, the explanatory power of other variables (variables other than past open interests) on the current open interest is small, we may infer that the expected open interest is approximately equal to yesterday's level, while unexpected open interest is approximately equal to the change in open interest during the current day.[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 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

[1] I did not partition open interest into expected or unexpected components. In fact, the "yesterday's" closing open interest (instead of today's open interest) can be used to run the VAR if this aspect is to be taken care of, in accordance with Bessembinder and Seguin (1993).

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 this issue of whether speculation activity is a stabilizing or destabilizing factor. 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.

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 unanticipated 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). Above all, the 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 in which various markets are combined (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 examine some of the Treasury market's institutional features in 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 from

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[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.

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

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

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

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

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

good measure for currency futures market (according to Bhargava and Malhotra (2007)). The AR(m)-GARCH(p,q) specification is the following:

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

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]

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

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[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.

[5] Another traditional volatility measure is from Garman-Klass (1980). The measure is defined as Volatility = $[0.5\,[\ln(High) - Ln(Low)]^2 - [2\ln(2) - 1]\,[\ln(Open) - \ln(Close)]^2\,]^{0.5}$, 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.

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 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.

[6] For discussion on the AIC and BIC information criteria and estimation issues, see Appendix to Chapter 1.
[7] See discussion on the stationary of series in the VAR section of Appendix to Chapter 1.

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

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[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.

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. 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]

[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.

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

[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.

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 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

[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.
[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.

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

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[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.

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

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 futures case)

[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.

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.

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

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 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

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[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.

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.

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[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] Granger causality is a causality *in the statistical sense*. Inferences on causality in non-experimental research should rely on considerations external to the collected data, in order to determine whether a factor should be endogenous or exogenous to the model. Granger causality simply looks at the "causality" *within* the collected data, determined purely by time series techniques with no specific economic reasoning attached. Also see the Appendix on the Granger causality.

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 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

[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).

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.

[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, F. R. (1999). Also, see MacKenzie (2003; 2006) for the sociological aspects surrounding the event and the interplay between arbitrage models and the markets.

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.

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.[25] 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).

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

[25] It is my impression that the 70-75% of VAR results are the same by either "aggregate" or "active contact" amounts. 15-20% of the results are diverging, while 5-15% are opposite. Readers are referred to the discussions on VAR results.

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 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

[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).

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 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

[27] However, when GARCH volatility is used, as later in Table 8A and 8B, coefficients are not significant for each contract.

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.

[28] I am still yet to find an explanation.

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 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

[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 Appendix to Chapter 1 for discussions on GARCH estimation.
[30] Again, no explanation can be offered for now.

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]

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.

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[31] The forecast plots for volatility and trading activity from VAR are available. See Figure 2A and 2B for an example.

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 active amount is in the positive. Aggregate amount clearly declines eventually to the

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

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 decay to zero. The GARCH

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

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. 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.

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

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 activities 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. For GARCH volatility, there is no evidence on the change in demand on futures as speculators face a more volatile market.

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.) Nonetheless, when GARCH volatility is used, the interesting result occurs 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. The GARCH volatility is by design the "most sophisticate/correct" measure. The diverging estimation results between historical and GARCH volatilities—both are of a longer-term nature in terms of information contained—unlike the short-term intraday volatility—show promises of differentiating or validating economic reasoning for future research on market trading.

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.

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

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 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 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: FURTHER DISCUSSIONS ON GARCH VOLATILITY AND VAR 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. Moreover, I will discuss the VAR estimation with its variant forms and some technical aspects of information criteria, Granger causality, and impulse responses.

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:

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

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) 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.

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

[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.

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

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[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.

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.

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.

[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.

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).

Vector Autoregressive (VAR) Model

What precisely is the effect of a change in volume in the Treasury futures market on the price volatility of futures? How big a drop in open interest is needed in order to offset the volatility increase caused by an increase in the trade volume? How well do speculators respond to the demand change for Treasury futures by hedgers? What fraction of the variation in futures price in the past 4 days is due to the trading activity? And as trading is concerned, how much of it is attributable to speculative motive (as opposed to hedging motive) of traders? By using the VAR techniques, we can know the answers to these questions, with perhaps a modest range of uncertainty. We can take a quantitative look of these and related questions with three basic varieties of VAR models: the reduced-form, recursive, and structural models. (See Stock and Watson (2001) for a review.) I restricted the following discussions to linear models of VAR; modeling issues of nonlinear specification and further extensions along nonlinear techniques (such as Gibbs sampler) are referred to Waggoner and Zha (2003) and Hasbrouck (2006).

Bhargava and Malhortra (2007) sets up a *reduced-form* VAR, which expresses each variable as a linear function of its own past values, the past values of all other variables being considered, and a serially uncorrelated error term. The VAR involves only two equations: current volatility as a function of past values of volatilities and trading activity; and current trading activity as a function of past values of trading activities and volatility. Trading activity is proxied by volume and open interest respectively for comparison. Each equation is estimated by ordinary least squares regression:

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

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

The number of lagged values to include in each of the two equations can be determined by a number of different information criteria; the common practice used (as well as a default in statistical programs) is Akaike (AIC) or the Bayes (BIC). Bhargava and Malhortra (2007) reports that the majority of the AIC results give a lag length of four, and they settle at four lags for all estimations for the purpose of consistency. Error terms in the regressions are the “surprise” movements in the variables after taking into account its past values. When different variables are correlated with each other—they usually are—then the error terms are themselves correlated across equations in the reduced-form model.

By contrast, a *recursive* VAR constructs the error terms in each regression equation to be uncorrelated with the error term of the preceding equation. It is done in a larger model by judiciously including some contemporaneous values as regressors; in our two-equation model, the only change in specification is to include the contemporaneous value of volatility, Vol_t, in the regression on trading activity:

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

$$TA_t = a_{0t} + \sum_{j=1}^{k} a_j TA_{t-j} + \sum_{j=1}^{k} b_j Vol_{t-j} + b_0 Vol_t + e_t$$

Estimating each equation by ordinary least squares produces residuals which are uncorrelated across equations. The recursive algorithm is equivalent to estimating the reduced form VAR coefficients first, and then computing the Cholesky factorization of the coefficients. However, the VAR results depend on the order of the variables. Once the recursive model is specified in a different order of variables, the models, coefficients and residuals changes as well. For the number of *n* variables, there are *n*! possible representations of recursive VAR.

A *structural* VAR tries to identify the relations among contemporaneous variables by using economic/financial theories. Theories impose restrictions on the form and parameters of the model, and these identifying assumptions allow correlations to be causally interpreted. Identifying assumptions can involve the entire VAR and therefore spell out all of the causal links in the model, or they can involve just a single equation—with possible parameter restrictions as well—that specify only a specific causal link. This produces instrumental variables (IVs) which are used to estimate the links of contemporaneous variables in the instrumental variable regression. A different "theory" (a set of assumptions) gives rise to a different model, and the key is to look for "correct" identifying assumptions. Blanchard and Quah (1989) and Blanchard (1989) are the classical examples for structural VAR modeling. For a further extension to my study, we can consider two related structural models, each incorporates a different assumption that identifies the causal influence of a third factor (or a condition) other than trading activity and volatility on trading activity and price volatility. The variables may be backward looking or forward looking, depending on assumptions.

VAR vs. VEC Models

Stationarity of variables is a delicate issue in VAR estimation. Sims (1980) and others suggest against differencing and de-trending of time series even if the variable has a unit root, since the goal of a VAR analysis is to determine the interrelationships among various variables rather than to determine the parameter estimates—differencing or de-trending throws away information concerning the comovements in data (such as cointegrating relationships). Moreover, a trending variable in the VAR can be well-approximated by a unit root plus drift. The usual practice, however, especially on estimating a structural model, to make a series stationary, so that the form of a variable in VAR mimics a true data generating process in the real world.

Augmented Dickey-Fuller and Phillips-Perron are two common tests for stationarity of data series in the VAR model.[41] As mentioned, VAR model is suitable when the series are stationary. If the series are not stationary, the vector error correction model (VECM)

[41] SAS does not provide the Phillips-Perron test.

may be more appropriate. Dependent variables and regressors are differenced in the VECM, so it can also be used as component series are not stationary. The VECM has an equivalent VAR representation, along with a specified parameterization.

Akaike Information Criterion

We test for the lag length in order to determine the order in VAR estimation. Akaike (AIC) and Bayesian (BIC) information criteria are used. As we conduct the estimation, we encounter two types of errors using a finite sample: 1) "variance", which is caused by wrong specification of the admitted (restricted) parameter space of the model and, 2) "bias", which is the error in terms of the distance between the restricted parameter space and the true parameter vector of the model (Bozdogan, 2000). Simply, estimation risk can be expressed as the sum of the "variance" and the "bias". The "variance"—which is captured by the log-likelihood function—tells if the correct specification on the probability distribution of model parameters is used by comparing with the data at hand. "Bias" penalizes the increased unreliability for the goodness of fit when additional free parameters are included.

AIC is developed to measure the estimation error; the smaller the AIC, the smaller the estimation error. In general, the AIC is

$$AIC = 2\,k - 2\ln(L)$$

,where k is the number of parameters and L is the likelihood function.[42] As is evident, AIC attempts to fit the data with a minimum number of model parameters: AIC not only

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[42] When we assume that the model errors are normally and independently distributed, the AIC is reduced to: $AIC = 2\,k + n\ln(RSS/n)$, where RSS is the residual sum of squares and n is the number of observations.

rewards goodness of fit, but also includes a penalty that is an increasing function of the number of estimated parameters. Since increasing the number of free parameters to be estimated improves the goodness of fit, this penalty discourages overfitting.

The Akaike information criterion (AIC) seeks to measure the closeness of an estimated model to the true data-generating process over the domain of y using the Kullback-Leibler information measure,

$$I = \int [\ln g(y) - \ln f(y \mid \theta)] g(y) dy,$$

where **θ** is a vector of unknown parameters characterizing the density of the postulated model, f(y|**θ**), and g(y) is the true density of y. This measure is positive unless g(y) = f(y|**θ**) almost everywhere[43]. AIC selects the model specification that minimize information measure *I*. In our linear model specification, **y** = **x β** + **u** —which specifies a causal relationship among the dependent variable y, the explanatory variables of the vector **x**, and the stochastic error u—the information measure reduces to

$$AIC = \log \hat{\sigma}^2 + \frac{2k}{n},$$

where $\hat{\sigma}^2$ is the maximum likelihood (biased) estimator of the unknown variance of error term u, k is the number of exogenous variables of the vector **x** = $\{x_1, \ldots x_k\}$, with which the coefficients vector $\boldsymbol{\beta}_{1\square k} = \{\beta_1, \ldots, \beta_k\}$ is to be estimated in the linear model, and n is the number of observations. In addition, **u** = $\{u_1, \ldots, u_n\}$ and **y** = $\{y_1, \ldots, y_n\}$.

Granger Causality

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[43] A property holds almost everywhere if the set of elements for which the property does not hold is a null set, i.e. is a set with measure zero.

I want to determine whether trading activity causes volatility. For the multivariate time series that are considered simultaneously, the complicated cross-correlation patterns could arise from different possible models. In choosing the appropriate model specification, a large of number of unknown parameters are required to be estimated with complicated procedures. To narrow down possible choices of model, the interrelationships among multiple time series can be exploited with statistical procedures, and causal relationships (in a statistical sense[44]) among economic variables are identified. Granger causality can be employed to infer causal relations among variables if one were to assume that (1) the future can not cause the past (i.e. causality can only occur with the past causing the present or the future and (2) the cause contains information which is unique to the effect; information on this effect is not available from elsewhere. In mathematical terms, let F(A | B) denote the conditional distribution function of A given B, and Ω_t denote the information set at time t, which also includes the past values of x_t and y_t, denoted by $X_t = \{\dots, x_{t-2}, x_{t-1}\}$ and $Y_t = \{\dots, y_{t-2}, y_{t-1}\}$, respectively. Then if

$$F(y_{t+j} \mid \Omega_t) = F(y_{t+j} \mid \Omega_t - X_t) \quad \text{for all } j \geq 0,$$

where $\Omega_t - X_t$ denotes the information set Ω_t other than X_t , then we can say that x does not cause y, relative to the information set Ω. If the above relation does not hold, then x (Granger) causes y.

Meanwhile, we can define the Granger causality in operational terms. Let $\Omega_t = \{ \mathbf{w}_{t-j}, j=1, 2, \dots\}$, where w_t is a stationary n-dimensional vector of random variables, including y_t

[44] Inferences in non-experimental research on causality tends to rely on considerations external to the data, such as determining which variables should be endogenous or exogenous to the model. The causalities discussed here, however, are determined purely by time series techniques with no specific economic reasoning attached.

and x_t. Let σ^2 (A | B) denotes the minimum mean-squared prediction error of A given B. If the prediction of y using past x is more accurate than such prediction of y without using past x, that is, $\sigma^2(y_t | \Omega_t) < \sigma^2(y_t | \Omega_t - X_t)$, then x Granger causes y, by definition. If $\sigma^2(y_t | \Omega_t) < \sigma^2(y_t | \Omega_t - X_t)$ and $\sigma^2(x_t | \Omega_t) < \sigma^2(x_t | \Omega_t - Y_t)$, then the feedback occurs. (Causality may include the feedback; when feedback does not occur, then x is said to be exogenous to the system. Exogeneity is a stronger condition, and Hausman test can be performed for testing the exogeneity specification.) Since Granger causality test is very sensitive to the choice of the order of lagged variables in the preliminary unconstrained model, Hsiao (1982; p.411-2) suggests a system identification procedure in order to avoid having the test result contingent upon an arbitrary choice of the lag order.

Putting Granger causality test in VAR estimation, the null hypothesis is "H_0: GROUP1 variable is an independent variable", that is, GROUP1 is influenced only by itself, and not by GROUP2 variables. A small p-value (<0.05) indicates that you can reject Granger causality from GROUP2 variables to the GROUP1 variables. In other words, you can say that the GROUP1 variable is influenced by GROUP2 variable, at the 0.05 significance level of the Granger test. If the test fails to reject the null, the GROUP1 variable may be considered as independent variable—GROUP1 variable causes GROUP2 variables, but the GROUP2 variables do not cause the GROUP1 variable. Briefly, in the VAR model as specified:

$$\begin{bmatrix} \Phi_{11}(B) & \Phi_{12}(B) \\ \Phi_{21}(B) & \Phi_{22}(B) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

If $\Phi_{12}(B) = 0$, the GROUP1 variables in the vector y_{1t} are said to cause the variables in y_{2t}, but y_{2t} do not cause y_{1t}. $\Phi_{ij}(B)$, for i,j=1,2, are partitioned coefficients. The implication is that the future values of the process y_{1t} are influenced only by its own past but not by the past of y_{2t} , where future values of y_{2t} are influenced by the past of both y_{1t} and y_{2t} .

The traditional linear Granger causality test has higher power in uncovering linear causal relations, but their power against non-linear causal relations may be low. Traditional test might overlook a significant non-linear relation between trading volume and price volatility, and the causality is uni-directional. A version of non-linear Granger tests is developed by Baek and Brock (1992), in which non-parametric estimators of temporal relation within and across time series provide bi-directional causality specification. When applied to the residuals of vector autoregressions, the Baek and Brock test can be used to determine whether non-linear relations exist between given time series. For a detailed study on volume-volatility relation using the non-linear Granger causality test, see Hiemstra and Jones (1994).

Impulse Response Functions

Dynamic models such as a VAR are best at describing the impact of an exogenous shock in one variable on the whole system. An impulse response function is used to simulate the effects of an innovation to one variable on the conditional forecasts of other variables in this system. A shock of one standard deviation (one "unit") is introduced at time *t* to the *k*th variable; the *k*th variable then returns to the previous level without the temporary, one-period shock. The effect on the *m*th variable is examined over the time horizon, holding all other variables constant at all times. 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.[45]

[45] Price volatility is measured by the intra-day volatility, historical volatility, and the GARCH volatility, respectively.

CHAPTER 2: VOLUME AND VOLATILITY: THE RELATION, TWO MODELS, AND REGULATING MARKET SQUEEZES OF TREASURY FUTURES TRADING

The role of information is critical in studying the relation of volume and volatility. My vector autoregressive (VAR) empirical results shed light on Treasury futures trading behavior, while providing insights into how trading activity of both hedgers and speculators influence price volatility and thus the market stability (see Chapter 1). This line of inquiry on the process of exchanging assets and outcomes (which includes prices and volumes) under explicit trading rules is well situated within the market microstructure literature. Prices emerge from trading mechanisms and conditions as buyers and sellers trade with one another—be they hedgers or speculators. Meanwhile, volume and volatility provides measures of how significant the role of information is for the market.

Chapter 2 intends to illuminate the behavior of prices and volumes by looking at how specific trading mechanism affects the price formation process and trading activity. Two major classes of models—which treat the nature of information differently—as well as empirical evidence are discussed. A hands-on application in terms of regulating the market is the recent episode (since 09/2006) of "market squeeze" warnings to financial institutions (essentially primary dealers) in the Treasury market.[46] Liquidity in the

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[46] James Clouse, a deputy assistant secretary from the U.S. Treasury, cautioned to members of the Bond Market Association (Government Securities and Funding Division) in a scheduled event on September 27, 2006, that number of questionable practices among 22 primary dealers of Treasury securities increased in the last two years (*The Economist*, November 2, 2006). In response, Treasury Market Practices Group (TMPC), created thereafter by market participants and joined by officials, recently publishes the "Treasury

Treasury market involves the important element of “network externality”, of which investors trade and take positions in the Treasury market in part because many other investors are doing so as well. This self-reinforcing process increases the number of potential counterparties and tends to reduce trading cost, which in turn draws in more investors and further reduce trading costs. Manipulative practices may drive away investors as they migrate to other instruments and start a reverse, harmful cycle.

Of the role of information, one major class of theoretical models relies on the basic assumption of private (or asymmetric) information among traders. These rational expectation models (competitive and strategic) generate disagreements on asset valuation through differential information, relating prices to private information while treating the volume as by-product of market mechanism. Traders are usually categorized as either informed or uninformed (“liquidity/noise traders”). The market makers (“specialist”) may as well play a critical role in determining price and volume. The long literature includes Grossman and Stiglitz (1976, 1980), Diamond and Verrecchia (1981), Kyle (1984, 1985, 1989), Admati and Pfleiderer (1988a), Grundy and McNichols (1989), Kim and Verrecchia (1991), Brock and Kleidon (1992), Admati, Pfleiderer and Zechner (1993), Foster and Viswanathan (1993a), Shalen (1993), Wang (1994), and Suominen (2001), to mention only a few.

As examples, Kyle (1985) and Admati and Pfleiderer (1988a) associate the timing of informed trading with uninformed traders’ trading volume. Foster and Viswanathan

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Market Best Practice” on May 11, 2007 (TMPC, 2007). See also James Clouse’s remarks at the Bond Market Associations (Clause, 2006).

(1993b) tests on the different predictions and find that trading volume, adverse selection costs, and return volatility are higher in the first half hour of trading, which is inconsistent with Admati and Pfleiderer (1988a). Brock and Kleidon (1992) predicts that transaction demands of high volume are concurrent with wide bid-ask spreads, suggesting that market makers can exercise price discrimination power by charging higher prices at the peak demand periods. They ascribe the intra-day U-shaped volume and volatility curve to the daily market open and closure.

The second class of models explores the idea that the market participants hold different opinions/beliefs on common knowledge. Harrison and Kreps (1978) and Varian (1989) are early attempts in exploring this aspect of market trading behavior. The important role of public information has long been noticed (for example, see the often-cited Ederington and Lee (1993) study, which examines the impact of macroeconomic news announcements on interest rate as well as foreign exchange futures market). And even those public announcements generating no price change are often associated with significant trading (Bamber and Cheon (1995), and Kandel and Pearson (1995)). Therefore, trader's differential interpretations on public information should be an important factor in understanding trading activity.

Harris and Raviv (1993), Kandel and Pearson (1995), and Odean (1998) are more recent studies that emphasize the role of difference of opinions in the volume of trade. Bamber et al. (1999) provides empirical evidence of which traders' differential interpretations explain a significant amount of trading (in particular when trading volume is unexpectedly high). Differences of opinion can also be interpreted as a form of "overconfidence", by which each investor (incorrectly) thinks his own judgment is more precise than the other's; Odean (1998) discusses market overconfidence "when all traders are above the average". In addition, differences of opinion can also be thought of as reflecting a type of bounded rationality in which investors are simply unable to make inferences from market price (Hong and Stein, 1999). In the more recent study by Hong and Stein (2003), differences of opinion model is extended in order to explain market crash by explicitly modeling the increased correlations among assets (or the "contagion effect").

A third category of volume-volatility models that receives broad attentions are models based on the "mixture of distribution" hypothesis (MDH); they are primarily statistical in nature. MDH models are unappealing from the standpoint of my study. Being statistical, they do not "explain" the economic behavior of market participants, although they offer essential insights and practical implications. I provide a short review in the Appendix to Chapter 2.

In the following sections, I discuss the Kyle (1985) model of private information and the model of Harris and Raviv (1993), a public information model based on differences in beliefs. I then use the recent (September 2006) squeeze warnings episode as implications of volume-volatility relation in regulating the Treasury (in particular the futures) market.

Private Information Models

Volume has been used as a measure of the “information content” of financial and macroeconomic events. In the private information models, volume is related to volatility because it reflects the extent of disagreement about an asset’s value based on different information set. Informed traders would trade when they know there is an above-average probability of a certain favorable price move, and they would hold off trading when they know there is a below-average probability of a favorable price move, as they may decide it is too expensive to be worth trading. In this way, the 'better informed' investors will obtain a trading advantage (i.e., a trading premium) over the uninformed, average traders. These models (typically called the “asymmetric information” models) can be categorized as either competitive or strategic. In the competitive models, informed traders prefer to trade a larger amount of assets at any price than uninformed traders, and thus introduce into securities trading the adverse-selection problem faced by market makers. See Admati and Pfleiderer (1988a) for discussion. The adverse selection problem may not be alleviated in the strategic models, as a monopolist informed trader breaks one large trade into several small-sized trades, where uninformed traders incidentally provide camouflage which conceals the informed trader’s trading from the market maker (Kyle, 1985). The sole informed trader makes profits by exploiting his market power.

Volume and price volatility are positively correlated in both the competitive and strategic models, as a result of the assumption that trading volume is positively related to the quality (precision) of information. As one large single bulk of trade is split into small chunks, however, strategic behavior of the monopolist informed trader may attenuate this positive relation in the strategic model. Nonetheless, Holden and Subrahmanyam (1992) shows that in the more realistic setting where multiple informed traders are present, noncooperative informed traders choose a larger quantity to trade than a monopolist (or, equivalently, collusive agents), and therefore the positive relation between volume and volatility are present and the distinction between competitive and strategic models are blurred.

Moreover, an information owner may wish to sell information where the alternative is to trade on the private information. In the context of institutional investors vs. small investors, mutual funds or investment advisory services can either sell security analysis or trade on his own his own account on the basis of the information. He is strategic in trading in terms of taking into account the impact his decision would have on the asset price. For example, Admati and Pfleiderer (1988b) extends the Kyle (1985) model and concludes that it would be more desirable for a (monopolistic) risk-averse information owner to sell information than to trade assets based on the information. An institutional investor creates a portfolio based on his private information and then sells shares to individuals, aside from directly selling information. Admati and Pfleiderer (1990) devises a private information model in which indirect sale allows the seller to control more effectively the buyer's information to the information.

Strategic Trading Model (Kyle, 1985)

Kyle's seminal model on strategic trading in the speculative market is discussed here (Kyle, 1985). We look at the sequential auction equilibrium, in which a number of auctions (or rounds of trading) take place sequentially. Equilibrium price at each round reflects the information contained in the past and current order flows, as the informed trader maximizes his expected payoffs. The informed trader takes into account his effect on prices in both the current and future rounds.

Kyle's model describes the volume-volatility relation in its pure form. Price fluctuation is purely a consequence of order flow innovation. Order flow is the *aggregate* quantity of combined volumes traded by both the informed and uninformed traders ("noise traders"). The market maker is able to observe the aggregate quantity but not the volume of each type of traders; as a consequence, price fluctuates with the order flow innovation (the combined volume), without the information from individual traders separately. At each auction, trading takes place in two steps: At step one, the informed and noise traders place the market orders, choosing simultaneously the quantities they intend to trade. At step two, the market maker set a price that clears the market such that both informed and noise traders' market orders (in quantity) are met. The market maker's information consists of observations of current and past order flows (the aggregate quantity), while at step one the informed trader knows his own private observation of the underlying asset value and the past quantities and prices traded by himself. The informed trader, however, does not observe current and future prices and quantities made by noise traders (although noise traders *past* prices and quantities are of common knowledge). The noise traders' current quantity is random and is independently distributed from the informed trader's past and current quantities, as well as from noise traders' past quantities.

The risk-neutral informed trader is assumed to maximize his expected profits. There are totally N rounds, and we denote each round by 1, 2,…,n,…,N. Let $\tilde{u}_n$ denote the quantity held by noise traders at the auction round n, so that $\Delta\tilde{u}_n = \tilde{u}_n - \tilde{u}_{n-1}$ denotes the quantity *traded* by noise traders at the n-th auction. Brownian motion is assumed so that $\Delta\tilde{u}_n$ is normally distributed with zero mean and a specified variance, and that the quantity traded in one auction is independent of the quantity traded at other auctions. Let $\tilde{v}$ denote the *ex post* (realized) liquidation value of the risky asset, which is assumed to be normally distributed with constant mean and variance. Let $\tilde{x}_n$ denote the aggregate position of the informed trader at auction round n, so that $\Delta\tilde{x}_n = \tilde{x}_n - \tilde{x}_{n-1}$ denotes the quantity traded by the informed trader at the n-th auction. Let $\tilde{p}_n$ denote the market clearing price at the n-th auction. We interpret the trading rules and pricing rules as functions of relevant informations: At step one, the informed trader chooses the quantity to hold as he observes the liquidation value of the asset and past equilibrium prices. Accordingly, his position after the n-th auction is given by

$$\tilde{x}_n = X_n(\tilde{p}_1,...\tilde{p}_{n-1},\tilde{v}),$$

from which the actual quantity traded is determined by the difference of current and last period position. At step two, the market maker sets a market equilibrium price as he observes not only the current value of the order flow, but also the past values of the order flow as well. Accordingly, the market clearing price is determined by

$$\tilde{p}_n = P_n(\tilde{x}_1 + \tilde{u}_1,...,\tilde{x}_{n-1} + \tilde{u}_{n-1}, \tilde{x}_n + \tilde{u}_n).$$

Define the informed trader's "trading strategy" *X* as a vector of functions X_1 to X_n, and the market maker's "pricing rule" *P* as a vector of functions P_1 to P_n:

$$X = \langle X_1,..., X_n \rangle , \qquad P = \langle P_1,..., P_n \rangle \ .$$

Now we define the informed trader's expected profit at the n-th auction on his acquired positions (from n- to N-th rounds) of risky asset, with the *ex post* liquidation value $\tilde{v}$, as:

$$\tilde{\pi}_n = \sum_{k=n}^{N} (\tilde{v} - \tilde{p}_k)\tilde{x}_k \ .$$

Since $\tilde{\pi}_n$ is dependent on trading strategy X and pricing rule P , we may write

$$\tilde{\pi}_n = \tilde{\pi}_n (X, P) .$$

A sequential auction equilibrium is defined as a pair (X, P) such that the following two conditions hold:

(i) Profit maximization:

For all n = 1,…,N and for all trading strategies $X' = \langle X_1 ',..., X_n ' \rangle$ such that $X_1 ' = X_1,..., X_{n-1} ' = X_{n-1}$, but $X_n ' \neq X_n$, we have

$$E\{\tilde{\pi}_n (X, P) | \tilde{p}_1,...\tilde{p}_{n-1}, \tilde{v}\} \geq E\{\tilde{\pi}_n (X', P) | \tilde{p}_1,...\tilde{p}_{n-1}, \tilde{v}\} .$$

(ii) Market Efficiency:

For all n = 1,…,N, we have

$$\tilde{p}_n = E\{\tilde{v} | \tilde{x}_1 + \tilde{u}_1,..., \tilde{x}_n + \tilde{u}_n\} .$$

At the equilibrium, market makers by assumption can not distinguish between the trading volume of the informed trader and that of noise traders, and the market price determined by market makers are assumed to equal the expected value of the underlying asset, conditional on market makers' information at the dates the prices are determined (the “market efficiency” condition). Market makers, therefore, earn zero profits on average, while the informed trader makes profits at the expense of noise traders. At the same time, noise traders provide the “camouflage” for the informed trader, in the sense that their trading volumes are indistinguishable from that of the informed trader, as seen from the perspective of market makers. The informed trader acts as the monopolist of asset market in the inter-temporal decision problem; he explicitly considers the effect his trading volume decision would have on the market price at one auction, and on future trading opportunities which the informed trader over the remaining rounds would maximize expected profits.

The discreet dynamic model can be further extended to a continuous-time model, and the sequential auction equilibrium converges to the continuous auction equilibrium. At the continuous equilibrium, volatility of trading prices is constant over time, and information is therefore incorporated gradually into prices at a constant rate. Trading volume of the informed trader looks to be small, since the volatility of prices is determined by noise traders and not by the informed trader. Nonetheless, at the end of trading the insider determines the price—despite his small trading volume—because his trade volumes are positively correlated from period to period, while the trade volumes of noise traders are uncorrelated.

In the continuous auction equilibrium, the informed trader’s (ex ante) expected profits can be shown to exactly double the expected profit in the single auction equilibrium. An ex ante doubling of the trading volume of noise traders induces the informed trader and market makers to double their volumes, too; and since the equilibrium market price is not affected, the informed trader's profit doubles. The continuous auction equilibrium essentially describes Black's intuitions of a liquid market (Black, 1971), but the characteristics are explicitly modeled in the context of maximizing behaviors.

This model of sequential arrival of information implies that traders not yet informed with new information can not perfectly infer from the presence of informed trading, as new information is disseminated from informed to uninformed traders ("noise traders") sequentially. Both trading volume and price movement are increased as a consequence with sequential arrivals of new information to the market, and the effect is more significant during the period of more information shocks.

Rate of Incorporating Private Information

The pattern of price volatility over time reflects the rate at which the insider's private information is incorporated into trading prices, and the distribution functions for the pricing process is characterized by a sequence of variance parameters—which we assume for each auction round for the martingale process of price increment—the parameters measuring the price fluctuations from auction to auction. Market price is the expected value of underlying asset price, conditional on order flow (the combined quantity of noise traders and insider).

Comparing the sequential auction equilibrium with the continuous auction equilibrium may shed light on this rate of incorporating information into trading prices. In the sequential[47] auction equilibrium, since the trading price follows a martingale process—therefore, the price increments are normally and independently distributed with zero means—price volatility varies with the varying assumptions on variance of the normal distribution of price increments at each auction. (At each auction, different types of martingales process may be assumed, by varying the variance parameter of the normal distribution for the price increments.)

In the continuous auction equilibrium, all of the insider's private information is incorporated into prices by the end of trading; while the trading price converges to the underlying asset value, price volatility gradually decreases until in the limit a volatility of zero is attained. The rate of change in the price volatility (the slope)—unlike the case in the sequential auction equilibrium—is constant over time, implying a constant rate of information incorporation into trading prices. The market efficiency condition, with the assumption that trading occurs at the end of the infinitesimal instant, gives rise to the zero profit for market makers, while at the same time requiring that noise traders bear the loss to the insider's gain, by virtue of the fact that they trade against themselves as they drive the trading price reversely to their own disadvantage. This equilibrium price actually follows a Brownian motion process—due to the normality and martingale properties inherent in the market efficiency condition—with the constant, prior variance (the given initial boundary condition). To market makers, who do not observe the realization of random variable of the underlying asset value, price fluctuations *appear* to have no drift.

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[47] Kyle (1985) assumes this sequential equilibrium to be a linear one, in the sense that the component functions of 1) the insider's trading strategy $X = \{x_t\}_t$ (the collection of trading volumes over time by the insider) and 2) $P = \{p_t\}_t$ (the collection of trading prices with the innovation structure (a linear one) as $p_t = p_{t-1} + \lambda_t (\Delta x_t + \Delta u_t)$), are both linear. x_t is the insider's trading volume, while u_t is noise traders' trading volume.

But, for the insider with the private knowledge of the true underlying value of asset, he knows the exact level to which trading prices would eventually converge, and his trading volumes are correlated positively from period to period. At the end of trading, it is the insider who determines the equilibrium price level. Even though the noise traders *determine* the volatility of price, their trades only cause the price to wander aimlessly, not affecting the equilibrium price level.

The market efficiency condition of the insider's optimization problem implies that the market makers' profits are driven to zero. In an earlier study, Kyle discusses an imperfect competition model of market makers in a market where many insiders with different information participate, and market makers may earn positive profits arising from transaction frictions (Kyle, 1984). As such, the existence of market makers is explained. But since the purpose is to study how price formation is influenced by the insider, this model here considers the insider's profit-maximization behavior with the simplified assumption of homogeneous market makers.

Kyle's model shows that modeling the price innovation as a function of quantity traded is consistent with modeling price innovations as the consequence of new information. The informed trader is allowed to choose the quantity but with no possibility to condition on price the quantity of his choosing, i.e. he is allowed to chooses the "market orders" (quantity) but not the "limit orders" (the demand function).[48] Nonetheless, trading

[48] Kyle (1989) extends the strategic model to include many informed traders as imperfectly competitors who choose the "limit orders" and then submit to an auctioneer. The auctioneer aggregates the demand schedules by both uninformed and informed traders, calculates a market clearing price, and allocate quantities to satisfy each trader's demand. The equilibrium looks a perfectly competitive one, from the

volume does play an important role in learning. Campell et al. (1993) and Wang (1994) use trading volume to help an econometrician to learn the expected returns on the assets, although traders themselves do not learn anything from trading volume itself. Blume et al. (1994) and Bernardo and Judd (1999) extend the framework and assume that traders make inferences about the quality of informed trader's signals and estimate the payoff to the asset. Souminen (2002) develops a model in which informed traders, by using past periods' trading volume, estimate the probability of the new private information arrival in this period and adjust their strategies accordingly.

Private information models are especially suitable to study informed trading behavior in speculative markets, such as the effect of insider trading on price volatility. Other topics include the implications of market manipulation on the information content of prices and on the market liquidity. While liquidity characteristics ("tightness", "depth", "resiliency") are derived from dynamic trading with underlying assumption of information asymmetry among the insider, noise traders and market makers, these models capture the features of trading in organized exchanges where significant private information are prevalent. These models are more suitable to stock and corporate bond markets where uncertainties mainly stem from private information such as a firm's output, the launch of a new product development, or profitability of a recent acquisition. Nonetheless, the dominantly public information nature of the Treasury cash and futures trading precludes the use of private

auctioneer's perspective, but it is in fact imperfectly competitive, because each trader acknowledges that the equilibrium price may change if he submits a different demand schedule. Imperfect competition, therefore, exists not as the market-clearing rules themselves, but rather as the *manner* in which traders determine what schedule to submit by exploiting these rules.

information models. In the next section, I will discuss the more suitable class of models based on traders' differences of opinion/belief.

Differences of Opinion: A Public Information Model

As mentioned, private information models do not provide an adequate description about treasury futures trading. Now I turn to a class of models call the “differences of opinion”. It builds on the idea that traders interpret the same, common data differently, a taken-for-granted proposition but less-frequently explored. It is especially the case in the Treasury futures market, where private information on individual contracts is less significant and less distinctive (unlike the cases in the equity or corporate bond markets[49]). What really matters to an investor—be it coming out of readings on Federal Open Market Committee (FOMC) minutes and announcements, on “Fed watchers’” smart, studied guesses, on the quarterly GDP growth rates and monthly non-farm payrolls (the “king of statistics”) as for general economic outlook—is his expectations on interest rate movements in the future. Virtually all diligent analysts are exposed to the same set of public data (qualitative as well as quantitative), but they choose to interpret the common data with their own judgments. Speculators’ beliefs and opinions are different, instead of their differential accesses to private information.

Now I use the Harris and Raviv (1993) model to describe the trading activity in Treasury futures market. Their model assumes in a more refined manner that all traders agree on whether a piece of information is favorable or unfavorable, but the two groups disagree on the extent to which this information is important to asset valuation. Future interest rates may be up or down, and probabilities of either direction are agreed on by traders,

[49] See Edwards (2006), Edwards et al. (2006), and Edwards et al. (2007) for interesting discussions on corporate bond market microstructure.

but they have different opinions about the actual impact of high (or low) interest rate on the final payoff of Treasury securities.

Harris and Raviv (1993) model assumes that all traders receive the same information but differ in the way in which they interpret the information. Traders share common prior beliefs about a particular asset's returns (high and low, with equal probability). Each trader updates his belief on the returns as the public news is available. Nonetheless, he updates his belief according to his own likelihood function, which depicts his "model" on the relationship between the news and asset returns. Two different values are assigned to the likelihood function parameter θ: the low-θ ("responsive") traders and the high-θ ("unresponsive") traders. Upon receiving favorable (unfavorable) news, speculators in the responsive group increase (decrease) their probability of high return more than those in the unresponsive group. With a cumulative impact of past information to be favorable, responsive speculators thus value the assets more highly and will want to own all of it. Trading occurs when (and only when) *cumulative* information switch from favorable to unfavorable or vice versa.

To see it clearly, let final payoff, R, be either high (H) or low (L) with equal probabilities. We assume that traders realize that the true prior probabilities are equal. New public information in the form of a signal, s_t, is revealed at each date t = 1,…,T, and then speculators update their beliefs, which may result in a trade at price p_t. Given a final payoff $R \in \{H, L\}$, we denote the true probability density of signal s by $\sigma_R^0(s)$.

The likelihood function is assumed to be exponential:

$$\text{(1)} \qquad \sigma_H^0(s) = \sigma_L^0(-s) = \begin{cases} k_0 a_0^s & for \quad s \geq 0, \\ k_0 b_0^{-s} & for \quad s < 0, \end{cases}$$

,where the same k_0 is assigned to either $s \geq 0$ or $s < 0$ case for simplicity; k_0 can be seen as a scale parameter without much significance. Also, a_0 and b_0 are strictly between 0 and 1. The symmetric assumption $\sigma_H^0(s) = \sigma_L^0(-s)$ indicates that the probability of high final payoff for a particular signal is the same as the probability of low final payoff for a reverse signal. Signals s's become "additive" because of the symmetric exponential form specification of likelihood function as well as the conditionally independent signals (independent and identically distributed, i.i.d).

With a history of signals from period 1 to period t, $s^t \equiv \{s_1, s_2, \ldots, s_t\}$, the true posterior probability for high realized return, R = H, is:

$$\text{(2)} \qquad \pi_{Ht}^0(s^t) = \frac{\prod_{\tau=1}^t \sigma_H^0(s_\tau)}{\sum_{R=H,L} \prod_{\tau=1}^t \sigma_R^0(s_\tau)} = [1 + \theta_0^m]^{-1} \equiv \pi_H^0(m)$$

,where m is the cumulative signal defined as $m = s_1 + \ldots + s_t$. Here, the Bayes' rule is applied in order to obtain the above result. The posterior probability depends only on the cumulative signal m, so the signal history s^t is substituted with m in the result. And the probability of low realized return, R = L, is $\pi_L^0(m) = 1 - \pi_H^0(m)$. Meanwhile, "additive" signals implies that only the aggregate influence matters; a signal (s) of 5 is equivalent to 5 signals of 1 each (or a signal of 8 combines with another signal of -3).

θ_0 is an inverse measure of the quality of the signal. θ_0 is defined as:

$$\theta_0 \equiv \frac{b_0}{a_0}$$

,where a_0 and b_0 are likelihood function parameters. [*explain the meaning of a and b*]. For convenience, the model assumes the posterior probability of high return is increasing in m, so that a larger value of m denotes a more favorable information; the relation $[1+\theta_0^m]^{-1} \equiv \pi_H^0(m)$ implies that the $\theta_0 < 1$. θ_0 thus can be interpreted as an inverse measure of signal quality: A very high-quality signal (i.e. θ_0 close to 0) would result in a posterior that has probability close to 1 for high return R = H, and probability 0 for low return R = L, when the news is very favorable (very large, positive m). Meanwhile, a very unfavorable news (very negative m) gives rise to a high return probability close to 0, while the low return probability is close to 1. The signal therefore conveys "correct" information with a θ_0 close to 0. Conversely, a θ_0 close to 1 implies a favorable news would result in a posterior in which high and low return probabilities are close to 1/2, and thus the information is of bad quality in distinguishing the two outcomes of return.

Shares of risky assets are traded for a riskless asset[50] by two groups of speculators, in which one group is "responsive" to signals and the other group "unresponsive". The two groups are distinguished by the parameter value of θ in the likelihood function, which describes the relation between signals and final payoff. Denote the two groups as 1 and 2, and their belief is described by θ_1 and θ_2 in the likelihood function. Differences of opinion are generated by assuming that the two groups of speculators interpret the signal

[50] Discounting is neglected for simplicity, and therefore the rate of return on riskless asset is zero. Moreover, riskless asset only serves an auxiliary role with the assumption of risk-neutral speculators. It will be prominent in the maximization problem in the case of risk-adverse speculators. See Harris and Raviv (1993), p.489.

differently; after observing a signal, each speculator revises his beliefs regarding the final payoff R according to his own "model" (i.e. the likelihood function).

Assume $\theta_1 < \theta_2$. Given the interpretation of θ as signal quality, group 1 believes more than group 2 that the signal is of high quality, and therefore group 1 responds to a given signal history with a greater reaction. That is to say, when the cumulative signal history m is positive, group 1 is more optimistic in its evaluation than group 2. When the cumulative signal history is negative, group 1 is more pessimistic. When the cumulative signal history is neutral ($m = 0$), both groups revert to their prior belief that the high and low returns occurs with probability 1/2 each. In this setup, group 1 is the "responsive" group and group 2 is "unresponsive". Trading of the risky assets occur when (and only when) the two groups "switch sides" on their evaluations of return probability; say, although both see the same favorable information, one group becomes ever more optimistic as to surpass the other group's optimistic judgment. In this case, the overly-optimistic group would buy risky securities from the less-optimistic group. If its reassessment does not surpass the other group's, however, there will be no trade.

The above is the direct consequence of risk neutrality[51] assumption on investors. Since Harris and Raviv (1993) model primarily looks at volume generated by speculative purposes, without regards to life-cycle or hedging motives, risk neutrality is an appropriate assumption. Short sales can not be allowed, because risk neutrality also

[51] Risk neutrality is used to describe an individual who cares only about the expected outcome of an investment, and not the risk (variance of outcomes or the potential gains or losses). A risk-neutral person will neither pay to avoid risk nor actively take risks, say, he is as happy to be given $1 as to play a game in which he wins nothing with probability 1/3 and wins $1.50 with probability 2/3.

implies an infinitely elastic demand function; any trader will seek to buy (sell) an infinite amount of shares at any price below (above) his reservation price. Thus, it is necessary to assume a fixed number of available shares, as all available shares would be purchased by the more optimistic group. It is worth pointing out again that the two groups have access to exactly the same information—only the "belief" of each group of speculators and the switch of belief make the trade volume.

The Harris and Raviv model make the important assumption that in each period one group has sufficient market power to offer a "take-it-or-leave-it" price to the other group. Market price will be set equal to the "price-taking" group's reservation price, which is its expectation of next period's equilibrium price and, by successive iteration to the last period T, is equal to its current expectation of the final payoff. This model mimics the Treasury futures market structure where institutional investors hold the sway against small, individual investors. One interpretation is to treat the price-setting group as a collection of institutional investors, and market maker (CBOT) gives preferential treatment to the large traders by filling their orders at the reservation price of small, individual traders.

Suppose the cumulative signal at date t is m, then the current expectation of the final payoff by price-taking group—which is its today's reservation price as well as the price of risky asset at period t—is the following:

$$p_t = p(m) = H\pi_H(m) + L\pi_L(m) = (H - L)\pi_H(m) + L$$

, where $\pi_H(m)$ is given by the posterior probability equation (2). The beliefs depend on the signal history only through the cumulative signal m; so does the market price. Since either group 1 or 2 may become the price-taking group in each period, the subscript "1" or "2" is dropped. This completes the model descriptions on how trades occur and what trading volume and trading price are.

Model Predictions

I now compare the main predictions of the difference of opinion model by Harris and Raviv (1993) with my VAR results on Treasury futures market. It is especially notable that the positively autocorrelated volume pattern is confirmed by the surprisingly strong evidence from VAR estimation.

Theorem 1 Price changes and volume are positively correlated. All of the correlations between volume and the three volatility measures in my VAR results are all positive. See Table 2A by aggregate amount and Table 2B by active contract amount. Although many empirical studies confirm the prediction, however, several studies obtain mixed results. For example, Foster and Viswanathan (1993b) provides the empirical evidence that trading volume is high when volatility is high in the intraday case (as the market opens in the morning), but not in the interday case, in which return volatility has no significant variations.

Theorem 2 Revisions in forecasts are related to changes in speculator's belief about the probability of high payoff. Changes in the "mean forecast of the final payoff" and volume are positively correlated. Both variables are driven by the “signal”, a third, exogenous factor. My study is not able to verify this proposition.

<u>Theorem 3</u> Consecutive transaction price changes exhibit negative serial correlation, in the two senses of transaction-to-transaction and period-to-period transition in the model. A positive change in price will be followed by a negative change. If speculators overestimate (underestimate) the true quality of the signal, then consecutive price changes exhibit negative (positive) serial correlation. This theorem deals with the first moment of price (price change, defined by the distance of two consecutive prices), but not the second moment (volatility of price). It can not be verified if my result is consistent with the model prediction; my study has only the VAR result on autocorrelation of market volatility and of trading volume, respectively, but not the autocorrelation of price change. The well-documented empirical relation can be tested, though, with my dataset.

<u>Theorem 4</u> Volume is positively autocorrelated; high (low) volume this period tends to be followed by a high (low) volume next period. The intuition is as follows: In this model, positive volume occurs only when the two groups of speculators “switch sides”. As such switch occurred in the last period, the two groups are more likely to have similar opinion in the beginning of this period. When the current news is announced, opinions of the two groups, again, are more likely to reverse and the trade will occur in the end of this period. Thus, last period’s trading leads to this period’s trading, and volume is positively autocorrelated. In my VAR results on the Treasury futures market, evolutions of volume exhibit surprisingly the exact prediction. Of each of the Treasury futures contracts, the four volume lag coefficients (from t-1 to t-4) are not only positive, but also they are all strongly significant. This applies to either the "aggregate amount" or the "active contract amount" construction. See the upper-right block in each panel in Table 3A and 3B, 5A and 5B, 7A and 7B. Impulse responses also confirm the result that the speculative trading follows the positive autocorrelative pattern. (Nonetheless, open interest doe not exhibit the same positive and significant coefficients; hedging activity is not positively autocorrelated. See the upper-right block in each panel in Table 4A and 4B, 6A and 6B, 8A and 8B.) The two models of Wang (1992) and Foster and Viswanathan (1993a) offer the same prediction, whereas Harris (1987) and others provide the consistent empirical evidence. Harris (1987) obtains a median correlation coefficient of 0.586 between the numbers of transactions of previous day and today, and an autocorrelation in daily volume of 0.347.

The adage of "Liquidity begets liquidity" suggests the positively autocorrelated volume pattern (Chowdhry and Nanda, 1991). Liquidity anomaly is self-perpetuating; traders would avoid trading illiquid periods as they find out about a liquidity anomaly. Chordia et al. (2001) offers the more recent evidence in the stocks market. Interestingly, my study on Treasury futures trading also strongly confirms this empirical regularity.

<u>Theorem 5</u> Volume is larger than usual right at the opening of the market (say, after the overnights, weekends, and holidays). My study does not deal with this issue. See Jain and

Joh (1988), Amihud and Mendelson (1991), and Foster and Viswanathan (1993b) for relevant studies.

Critiques on the Harris and Raviv (1993) Model

Harris and Raviv model emphasizes the role of volume (as speculators' trading activity) in explaining asset prices and market behaviors, and it generates disagreements through public information but with traders' different prior beliefs or interpretations. As mentioned, this differences of opinion model suites well to the public information nature of Treasury futures trading, whereas rational expectations models of private information generate trading activity by exploiting informational advantages.

However, there are several deficiencies in applying this model to Treasury futures market. First, short-sales are not allowed in the model, but they are used as often in practice as to hedge the long positions in cash Treasuries. This type of trading strategy ("short hedge")[52] is essential, but the Harris and Raviv model with risk-neutral assumption does not allow short sales as it has to assume a fixed number of shares available, and the trading is either all or nothing. This causes a problem in describing the trading behavior in the Treasury futures market. Although risk adverse version of the model—which produces volume activities as one group's belief changes "relative to" the other's (instead of "switching sides" from optimistic to pessimistic and vice versa)—allows for short

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[52] One basic way in building up an arbitrage is to buy Treasury futures contract while short-sale Treasury cash notes and bonds. It is called the "long hedge". The reverse trading strategy where futures are sold short is the "short hedge". Readers are referred to CBOT website for introduction on basic trading strategies: http://cbot.com/cbot/pub/page/0,3181,1413,00.html

sales, it also adds considerable complexities and further simplifying assumptions have to be made on the original model.

Another deficiency of Harris and Raviv model in describing Treasury futures trading is the volume generated solely by speculation, as opposed to hedging or life-cycle considerations. Trading activity occurs only for speculative motives. A model with endogenized speculative and hedging activities is needed, so that open interest (the proxy of hedging activity) can be explained and tested, and that trading occurs for both speculative and hedging purpose. Hedgers' behavior can therefore be explained.

Position Limits and Futures Market Squeezes

Treasury securities market (including its derivatives) is the world's deepest and most liquid.[53] It has a daily volume many times more than U.S. equity markets. It is where the U.S. government borrows and especially where the Federal Reserve implements its monetary policy. And it provides the crucial risk-free benchmark rates against other credits. Thus, the issue of questionable trading practices in Treasury market (cash and derivatives) is a testy one not least from the regulatory perspective. Economic studies usually theorize futures contracts as a hedging medium, which would increase the speed of price discovery, improves market efficiency, and help with stabilizing the market. But, of course, speculative behavior and day trading activity are well known facts in the futures market. As a result of profit-seeking behaviors of such traders, the existence of the risk-hedging instruments such as the Treasury futures may therefore have destabilized the market.

Recent incidents have raised the concerns of regulators on the proper functioning of this important market. An indicator is the sharp increase in the Treasury settlement "fails" (defined as a failure to return Treasury securities on time to the lender) in the last two years; the phenomenon was particularly prominent when the repo rate was low and bonds were scarce. James Clouse, a deputy assistant secretary from the U.S. Treasury, cautioned to members of the Bond Market Association in a scheduled event in late September 2006 that the number of questionable practices among 22 primary dealers of Treasury securities increased in the last two years. *The Economist* magazine reported an interesting

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[53] Dupont and Sack (1999) offers a concise introduction to the fundamentals of Treasury securities market (with focus on the cash market).

fall in the number of bonds in short supply after Mr. Clouse's speech. In the following meeting with its 22 primary dealers on November 6, 2006, the New York Federal Reserve aired concerned about problematic behaviors (NY Fed, Nov. 6, 2006). In the after-meeting statement, it re-emphasized that to put strong oversight and compliance "into day-to-day operations is consistent with a competitive open market and should not limit or constrain legitimate trading activities" (*The Economist*, November 2, 2006). In response, the Treasury Market Practices Group (TMPC) was created thereafter by market participants and joined by officials. On May 11, 2007, it published the "Treasury Market Best Practice" guidelines (TMPC, 2007).

The concern was on "market squeezes". Strategic trading behavior in the Treasury market is viewed by some as part of the "game", and the potential gain from controlling an issue is simply the reward for dealers and others to assume risk and make markets.[54] Salomon Brothers' illegal bidding behavior in the May of 1991 "cornered" the auction on Treasury (cash) notes. (For discussions on squeeze-related issues in the context of auctions, see Jegadeesh (1993) and Bikhchandani and Huang (1993). For an example on the Japanese government bonds market, see Hamao and Jegadeesh (1998).[55]) Market squeezes can occur in securities auctions and in trading. In this section, I will discuss squeezes occurred in trading, which better describe the Treasury futures securities market. A previous incident was the squeeze pressures in CBOT's 30-year bond futures through 1993 and 1994. Merrick et al. (2005) provides an excellent and detailed discussions on

[54] See Chatterjea and Jarrow (1998) for a theoretical model on market manipulation.

[55] Incidents of market manipulation in government debt markets outside the United States: The three well-publicized examples are the Japanese government bond futures squeeze at the TSE (Tokyo Stock Exchange) in September 1986, the Italian government bond futures at the LIFFE (London International Financial Futures and Options Exchange), the Eurex BOBL squeeze in March 2001, and the alleged cornering of 2016 U.S. Treasury bond issuance by Japanese investors in the February auction of 1986.

futures market squeeze using the example from the U.K. government bond during March 1998. Market squeeze in Treasury cash and futures markets and the best practice guideline of the newly-formed Treasury Market Practices Group will be discussed, so are the implications for squeezes that arise during the course of trading Treasury futures.

"Futures Squeezes"

In a "futures squeeze", for example, a trader requires control in the repo or cash market over a security that is cheapest-to-deliver into a Treasury futures contract. In addition, the trader then establishes a futures position on which it is due to receive securities at settlements. In usual cases, traders close out their open position in an expiring Treasury futures contract and roll into the subsequent contract. But a trader may instead attempt a "futures squeeze" and insists on taking delivery at settlement, in order to use the control over the cheapest-to-deliver security to force other market participants to settle their futures obligations and deliver more expensive securities. Futures squeezes have been observed in several countries over the years. Manipulators usually build up a substantial long position in a bond futures contract and also a sizable amount of its cheapest-to-deliver bond issue. The squeezer attempts to profit by restricting the supply of the cheapest deliverable issue, which increases the price of it and at the same time forces holders of short futures position either to deliver more highly valued bond issues or to buy back their futures position at an inflated price.[56]

In response to concerns with respect to settlement of contracts, the CBOT establishes position limits for all Treasury futures contract during the last ten days of trading of each

[56] In the U.S., the Fenchurch Capital Management case in 1993 is perhaps the most prominent recent example.

contract (Willkie Farr & Gallagher, LLP; "Client Memorandum"). Position Limit is the designated maximum position, either net long or net short, in one commodity future (or option) or in all futures (or options) of one commodity combined that may be held or controlled by one person (other than a person eligible for a hedge exemption) as prescribed by an exchange and/or by the CFTC. Position limits are put in place to ensure that entities cannot establish a dominant and potentially destabilizing position in a product by "cornering" (or "squeezing") the market. (See the "June Amendment" (2005) on CBOT regulation 425.01, effective beginning with the December 2005 contact expiration cycle.) And unlike other speculative position limits, there is no exemption from the limits for hedging position. Subsequent revision on the position limits during last ten trading days. The most recent revision on position limits; effective on June 6, 2007 for 30- and 10-year Treasury futures contract and June 15, 2007 for 5- and 2-years. Positions are aggregated in accounts for which a trader has direct and indirect controls. (CBOT; "Reminder Notice", May 29, 2007).[57]

A bank's compliance department should beware when a trading desk is generating abnormally high profits on a position of an issue in which the desk is exercising significant control over the floating supply. From the funding side, when the trading desk continuously finances a large portion of its holdings of a scarce security in, say, a tri-

[57] "Repo squeeze" is another type of Treasury market manipulation. Firms reverse in very large positions in highly sought-after securities in the term repo market. At the same time, they limit the availability of the security to other market participants by financing only a portion of their term repo position in the "specials" market. (For discussions on special repo rates see Duffie (1996) and the empirical Jordan and Jordan (1997) study.) The balance of their position is financed at higher rates in tri-party repo or similar arrangements. In tri-party repo, the custodian ensures that the collateral pledged by a firm borrowing cash is immobilized and thus not available to be circulated in the market. The firm intentionally a large portion of a position in a scarce security at the general collateral rate rather than obtaining low-cost funding in the specials market. The firm may be engaging in intentionally choosing the portions of its total position to finance so as to minimize the combined cost of funds. It can be an exercise in monopoly pricing power. See Fisher (2002).

party financing, at a rate well-above the prevailing rate in the “specials” market, compliance officers may need to see the factors that give rise to this funding choice. SEC (Securities and Exchange Commission) is charged with enforcing the anti-manipulation prohibitions in federal securities law, and the CFTC (Commodity Futures Trading Commission) is the relevant enforcing agency on matters pertaining to futures markets. Meanwhile, joint surveillance programs are established by regulatory agencies.

Market Depth

Liquidity characteristics of market are specified in Kyle (1985). The continuous auction equilibrium in Kyle’s (1985) seminal model of informed trading fully characterizes Black (1971)’s intuitive description of a “liquid market”. Black (1971) describes that the “liquid market is a continuous market, in the sense that almost any [security] can be bought or sold immediately, and an efficient market, in the sense that small amounts of [security] can always be bought and sold very near the current market price, and in the sense that large amounts can be bought or sold over long periods of time at prices that, on average, are very near the current market price.” As Kyle (1985) elaborates using a continuous auction equilibrium, “market liquidity” refers to several different elements of transaction costs (including “tightness”, “depth” and “resiliency”, and a liquid market so defined by Black refers roughly to one which is almost infinitely tight, not infinitely deep, and resilient enough (so that the prices tend to converge to the underlying value of the security).[58]

[58] “Tightness” refers to the cost of turning over a position in a short period of time. The market is infinitely tight in the continuous auction equilibrium, in the sense that turning over a position is quick and costless. “Market resilience” refers to the convergence speed at which the price moves toward the underlying value (the liquidation value) of asset; that is, resilience is measured as the speed at which prices recover from a

"Market depth" refers to the ability of the market to absorb quantities without having a large effect on price; depth of the market is constant in the continuous auction equilibrium. Kyle (1985) Theorem 3, the constancy of market depth in the continuous auction equilibrium. Behavior of the informed trader ("insider") is not consistent with an increasing market depth or a decreasing one: If the depth ever increases, the insider would want to destabilize prices before the depth increase, so as to generate unbounded profits; if the depth ever decreases, the insider would want to immediately incorporate into the price all of his private information. The behavior of an informed trader is "stable" enough to sustain an equilibrium. Constancy of market depth also explains why the price volatility is constant over time in a continuous auction equilibrium—at which the depth is constant—and not in a sequential auction equilibrium, where the non-constant market depth results in the varying price volatility.

In the market microstructure literature, the market depth is adversely affected by the strategic trading behavior of market participants. Pirrong (1995) shows that the delivery squeezes erode market depth and randomly penalize traders who "consume" liquidity (i.e. hedgers). Naik and Yadav (2003) offers an estimation framework for market depth. They find that the U.K. government bond market in London is actually very deep, and that the depth is affected only in certain special circumstances. By extending the Naik and Yadav framework, Merrick et al. (2005) finds that market squeezes do penalize hedgers, and that depth erosion is not the most negative impact of market squeezes but instead the major cost lies in loss of liquidity. Hedgers would curtail their use of government bond futures

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random, uninformative shock. Noise traders, who are uninformed, cause the price to wander aimlessly without a tendency to return to the underlying value. The resilience of price in the market, however, is determined by the trading of the insider, who has the private information.

for fear of large sudden contract price changes that are unrelated to term structure fundamentals. The period of sustained mispricing and the associated uncertainty would turn away hedging activity, since a short-term hedger using a short (long) position in the futures market would face a loss due to a large change in price relations if the squeeze succeeded (collapsed) (the "peso problem").

Merrick et al. (2005) recommends that Treasury futures exchanges should remove the sources of opportunities for squeezes. They should mark-to-market the specifications of their bond contracts much more frequently than they do in the past. They also recommend the elimination of discrepancy in settlement penalties between cash and futures market in order to lessen price distortions. Futures exchanges levy heavy fines on contract shorts that fail to delivery. No such penalty exists for traders who fail to deliver in the cash bond and bond repurchase agreement markets. Cross-market cash-futures arbitrage; during a squeeze, arbitragers can not feel confident using a standard repo agreement to finance the cash market position because the repo counterparty may fail on the timely return of the collateralized bond. Arbitrage traders may begin to leave the market.[59]

In the context of market squeezes, differences of opinion can be interpreted as divergent beliefs between two groups of traders: the optimistic squeezers who believe the squeeze will succeed and that the price of the scarce Treasury issue will rise even further, as opposed to "contrarians" who believe the squeeze will fail and that the price of the scarce Treasury issue will fall. Merrick et al. (2005) measures the fractions of trade that take

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[59] In my VAR study (Chapter 1), I classified traders as speculators and hedgers. The cross-market arbitragers discussed here can be seen as speculators of Chapter 1.

place between the two groups, among different squeezers, and among different contrarians. They find that about 89% of the trading takes place between the squeezers and the contrarians, mainly during the later unwinding and profit-reaping phases of squeezes. Trading among contrarians (1%) is virtually zero as most of them maintained their short positions throughout the squeezes. Trading between squeezers and contrarians is overall statistically highly significant that substantially trading volumes occurred than one would expect if trading is randomly distributed across different market participants; difference of opinion among traders clearly generate trading.

TMPG "Best Practices" Report—Treasury dealers' proclaimed self-restraints on squeeze practices—intends to promote market making and liquidity. "All market participants should believe in a manner that is consistent with supporting market liquidity. Dealers, in particular, should promote market making, and all market participants should avoid trading strategies that hinder market clearance. Examples of strategies to avoid include those that cause or exacerbate settlement fails, those that inhibit the provision of liquidity by others, or those that restrict the floating supply of a particular issue in order to generate price movements in that security or related market. In particular, three key points in this report are related to market squeezes:

1. When a participant controls a significant percentage of the floating supply of an issue that is trading deeply special, it should ensure that it is making a good faith attempt to lend the security into the specials market rather than choosing to finance large portions of this collateral in relatively more expensive funding arrangements.

2. Market participants with particularly large short positions of an issue should ensure that they are making a good faith attempt to borrow needed securities in order to make timely delivery of securities. Market participants should avoid the practice of "strategic fails"—that is, the practice of selling short a security in the repo market at or near zero percent with little expectation of being able to obtain the security to make timely delivery.
3. "Holding the box"—holding settlement of an executed trade for a period of time—is appropriate only in very specific and limited circumstances, such as ensuring a futures contract delivery obligation, and the request to "hold the box" shod be appropriately approved by trading management, settlement staff and compliance officers.

Concluding Remarks

Chapter 2 provides a literature review along the line of privately-held trading information and public information. Volume-volatility relation is explored in the context of Treasury futures trading, and the "differences of opinion" model (a public information model) is considered to be a proper description. The strategic trading model of Kyle (1985) and the Harris and Raviv (1993) differences of opinion model are reviewed. Major predictions of the Harris and Raviv model are also compared with the empirical VAR (vector autoregressive) study in Chapter 1.

The recent episode (since 09/2006) of "market squeeze" warnings to financial institutions (essentially primary dealers) in the Treasury market is discussed. Merrick et al. (2005) shows how prices of squeezed bonds relate to trading flows of market participants, while looking at the order flow information between individual dealers and their customers, and finds evidence of learning and concerted action, and of the way the information on a potential squeeze is disseminated to the broader market. As a result of profit-seeking behaviors of such traders, the existence of the risk-hedging instruments such as the Treasury futures may therefore have destabilized the market.

Speculators may disagree on the interpretation of public news—or may simply hold different private information—so they conclude on different evaluations on the relation between public news and his own belief in securities performance. The relationships between information, volatility, volume (along with return and time[60]) can be further explored in the "differences of opinion" framework in the study of Treasury futures

[60] See Manganelli (2005) on the modeling of the "durations" of trade.

trading.

APPENDIX: MODELS OF MIXTURE OF DISTRIBUTIONS (MDH)

A third category of volume-volatility models that receives broad attention is these models based on the "mixture of distribution" hypothesis (MDH). They take the more empirically-oriented approach by estimating statistical models in order to explain regularities in volume and volatility. See the seminal Clark (1973) model. See also Epps and Epps (1976), Tauchen and Pitts (1983) and Harris (1986, 1987).

For the MDH models, price movements are caused primarily the arrival of new information and the process that incorporate this information into asset prices. Based on the assumption that the variance per transaction is monotonically related to volume of that transaction. It further assumes that a mixing (or latent) variable causes the volume-volatility relation. Number of information arrivals is usually taken to be the mixing variable, so are the volume per transaction and the number of transactions. In these models, dynamic features are governed by information flow modeled as a stochastic volatility process.

Clark (1973) model implies that all groups who trade on information will have a similar volume-volatility relation. Epps and Epps (1976) model, however, is based on the disagreement between traders, and the trading volume increases as they disagree further. Epps and Epps model suggests a causal relation from volume to volatility.[61] Harris (1987) and Tauchen and Pitts (1983) model the volume-volatility relation as a mixture of bivariate normal distributions, and investigate whether MDH can explain the

[61] Perhaps a hybrid model (an MDH model combined with a "difference of opinions" model) can be developed to explain Treasury futures trading.

characteristics of return distribution (normality of returns and the autocorrelation in returns and squared returns). Both confirm the prediction in the Epps an Epps model that the volatility causes the volume.[62] Harris (1987) also shows that the number of daily transactions may be a useful instrument variable for the number of information arrivals in a day.

Since volatility and volume are correlated only because both are related to the number of daily information arrivals (the latent variable), the number of daily transactions should be proportional to the number of information arrivals, as when a fixed number of traders who all trade at a fixed number of times is assumed. The volume-volatility relation should therefore be rendered statistically insignificant when volatility is conditioned on the number of transactions. This interpretation of MDH is confirmed in Jones et al. (1994).

Since MDH is associated with ad hoc specifications which posit a joint dependence of returns and volume on an underlying latent variable or an information flow variable, Lamoureux and Lastrapes (1990) tests if volume is driven by some identical factors that generate volatility. It finds that the volume variable is strongly significant in estimation as the volume variable is directly inserted into the ARCH (autoregressive conditional heteroskedasticity) variance process, while at same time past return shocks become insignificant. Andersen (1996) develops a model of volume-volatility relation from an information flow perspective by specifying a stochastic volatility process on which the

[62] It should be noted that the Granger causality test does not show the causation direction, even if causality can be established by the test in my VAR study in Chapter 1.

latent driving process is emphasized. The information flow represents a stochastic volatility process that drives both the asset return and volume, so that the two series will provide information regarding that state of the *un*observed volatility process. This separates from the ARCH modeling strategy in which the return volatility, when conditional on parameter estimates, is observable ex post. It is also a variant of private information model. Although the arrival of public information has an immediate impact on asset price, public information does not induce any additional trading activity.

Andersen (1996) argues that the general framework of the MDH still provides a useful basis for structural modeling of the interaction of market variables in response to information flows. He modifies the MDH in a simple microstructure setting where informed and uninformed traders (along with market makers) trade in a single competitive market with a random asset liquidation value. The modified MDH model provides an acceptable characterization of empirical relations.

Mixed distribution models are primarily statistical in nature. Being statistical, they do not provide fully-specified theories in “explaining” the economic behavior of market participants. Although unappealing from this standpoint, this class of models complements and reinforces the insights obtained from behavior models.

Figure 1A: Futures Contract Specs: 10 Year U.S. Treasury Notes Futures

(Source: CBOT)

Contract Size
One U.S. Treasury note having a face value at maturity of $100,000 or multiple thereof.
Deliverable Grades
U.S. Treasury notes maturing at least 6 1/2 years, but not more than 10 years, from the first day of the delivery month. The invoice price equals the futures settlement price times a conversion factor plus accrued interest. The conversion factor is the price of the delivered note ($1 par value) to yield 6 percent.
Tick Size
One half of 1/32 of a point ($15.625/contract) rounded up to the nearest cent; par is on the basis of 100 points.
Price Quote
Points ($1,000) and one half of 1/32 of a point; i.e., 84-16 equals 84 16/32, 84-165 equals 84 16.5/32
Contract Months
Mar, Jun, Sep, Dec
Last Trading Day
Seventh business day preceding the last business day of the delivery month.
Last Delivery Day
Last business day of the delivery month.
Delivery Method
Federal Reserve book-entry wire-transfer system
Trading Hours
Open Auction: 7:20 am - 2:00 pm, Central Time, Monday – Friday Electronic: 7:00 pm - 4:00 pm, Central Time, Sunday - Friday Trading in expiring contracts closes at noon, Chicago time, on the last trading day.
Ticker Symbols
Open Auction: TY Electronic: ZN
Daily Price Limit
None

Figure 1B: Roll-Over Method

(Source: CBOT)

Rollover Method

Select Rollover Method allows you to choose the method you would like to use to continue (rollover) your data from the expiring contract to the next contract. Rollover is the period of time when the front-month contract approaches expiration and the next deferred contract begins to become the new active contract. Select from:

Daily Volume: When you select Daily Volume as the rollover method, the contract with the greatest daily volume is designated the active contract. Once the daily volume for another contract exceeds the daily volume for the current active contract, the former contract becomes the active contract. When this condition is set, your data will advance to the new active contract. Rollover will occur on the same day the new active contract's daily volume exceeds the former active contract's daily volume.

Daily Open Interest: When you select "Daily Open Interest" as the rollover method, the contract with the greatest daily open interest is designated the active contract. Once the daily open interest for another contract exceeds the daily open interest for the current active contract, the former contract becomes the active contract. When this condition is set, your data output will advance to the new active contract. This occurs on the same day the new active contract's daily open interest exceeds the former active contract's daily volume.

Specific Number of Days Before Expiration: When you select "Specific Number of Days Before Expiration" as the rollover method, the number of day's you specify before the contract expires is the day which rollover will occur to the next contract. The expiration day is the same as last trading day. If you select "0", rollover will occur on the expiration day. The CBOT *DataExchange* uses "trading days" not "calendar days." Trading days are Monday – Friday, except holidays.

Specific Number of Days Before Delivery: When you select "Specific Number of Days Before Delivery" as the rollover method, the number of day's you specify before delivery is the day which rollover will occur to the next contract. Delivery is defined as the first delivery day for the contract. If you select "0", rollover will occur on the first delivery day. This option uses "trading days" not "calendar days." Trading days are Monday – Friday, except holidays.

Specific Date: When you select "Specific Date" as the rollover method, the date you specify is the date on which rollover occurs. For example, if you select: Months to Delivery = –1 and Day of Month = 20, the rollover will occur on the 20^{th} calendar date of the month preceding the delivery month. This option uses "trading days" not "calendar days."

Figure 1C-1: Sample Original Data

2 Year U.S. Treasury Notes Futures

Date	Symbol	Month Code	Year Code	Open	High	Low	Close	Settlement	Volume	Open Interest
19910102	TU	H	1991	101.3125	101.5	101.3047	101.4844	101.4844	2344	7281
19910103	TU	H	1991	101.5	101.5625	101.4844	101.4844	101.4844	1993	8313
19910104	TU	H	1991	101.5234	101.5234	101.2656	101.3125	101.3125	578	8522
19910107	TU	H	1991	101.25	101.2813	101.2109	101.2344	101.2344	343	8566
19910108	TU	H	1991	101.2266	101.4688	101.2266	101.2969	101.2969	1730	7652
19910109	TU	H	1991	101.4375	101.4531	101.25	101.2656	101.2656	1555	8203
19910110	TU	H	1991	101.3125	101.375	101.3125	101.3594	101.3594	303	8207
19910111	TU	H	1991	101.3438	101.375	101.2969	101.3281	101.3281	586	7923
19910114	TU	H	1991	101.25	101.3281	101.2422	101.3125	101.3125	562	7452
19910115	TU	H	1991	101.3125	101.3281	101.2891	101.2969	101.2969	186	7477
19910116	TU	H	1991	101.1563	101.2266	101.1563	101.2188	101.2266	238	7506
19910117	TU	H	1991	101.4063	101.4063	101.2266	101.2813	101.2813	1214	8009
19910118	TU	H	1991	101.2813	101.375	101.2656	101.3594	101.3594	578	8052
19910121	TU	H	1991	101.3438	101.3984	101.3125	101.3828	101.3828	423	8219
19910122	TU	H	1991	101.3906	101.3984	101.3359	101.3516	101.3516	925	7704
19910123	TU	H	1991	101.3438	101.4219	101.3281	101.4219	101.4219	224	7696
19910124	TU	H	1991	101.4531	101.5156	101.4531	101.5156	101.5156	144	7696
19910125	TU	H	1991	101.5156	101.5156	101.3594	101.4063	101.4063	166	7723
19910128	TU	H	1991	101.3906	101.3984	101.3594	101.3906	101.3906	103	7721
19910129	TU	H	1991	101.4063	101.4219	101.3828	101.4219	101.4219	86	7674

Figure 1C-2: CBOT Treasury Futures Month Code

Month	***Code***
January	F
February	G
March	H
April	J
May	K
June	M
July	N
August	Q
September	U
October	V
November	X
December	Z

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.

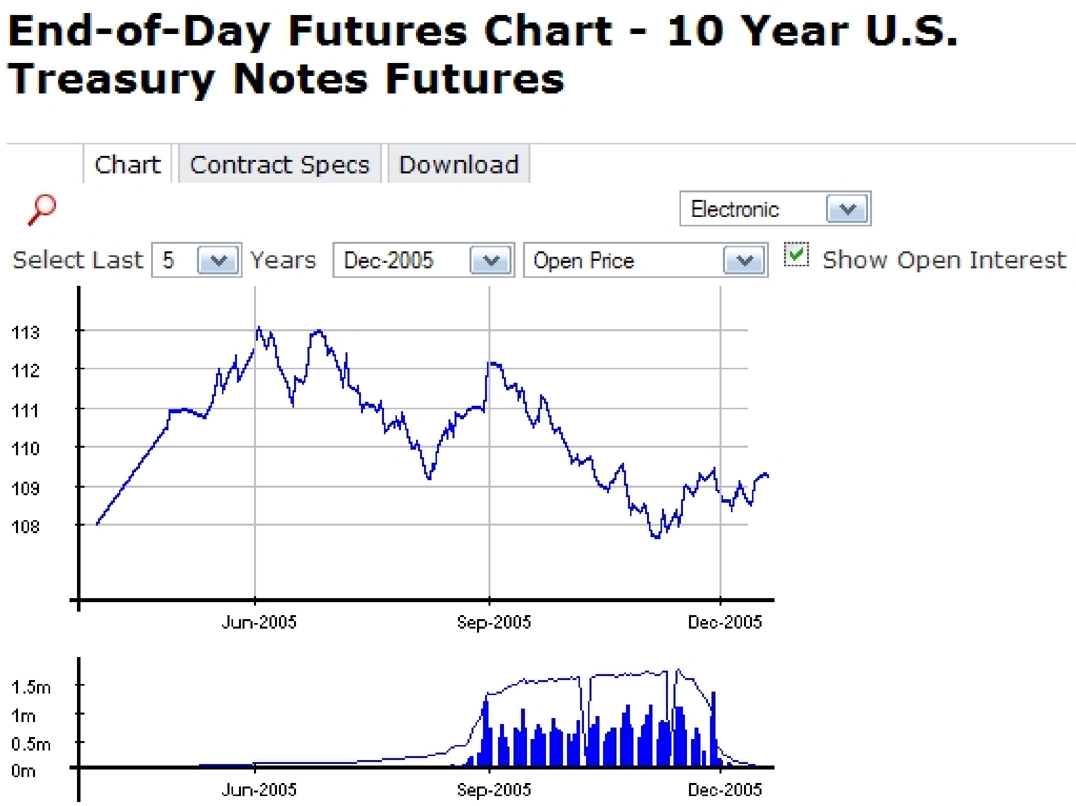


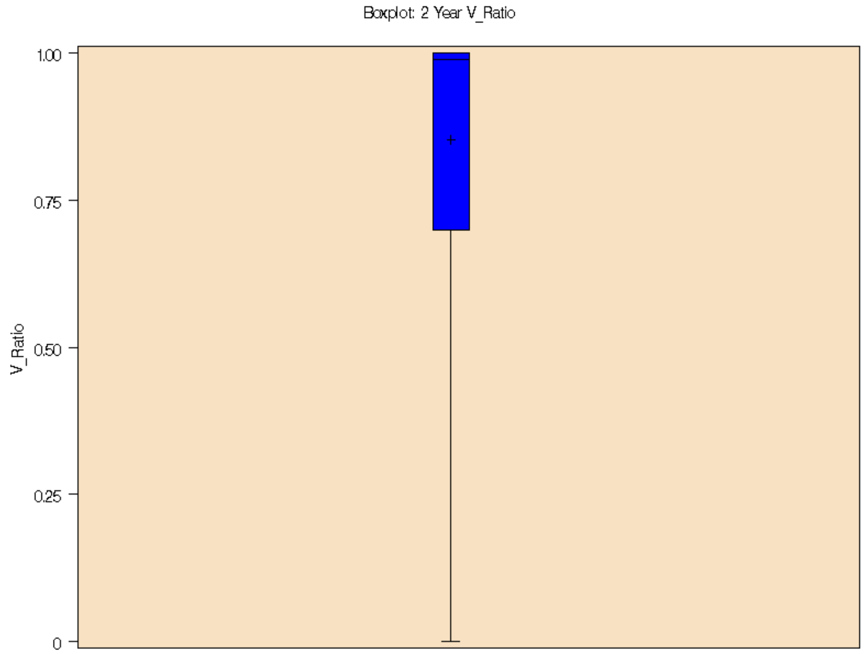
Figure 1E: "Active Contract" Time Table, Using Year 1992 as Example

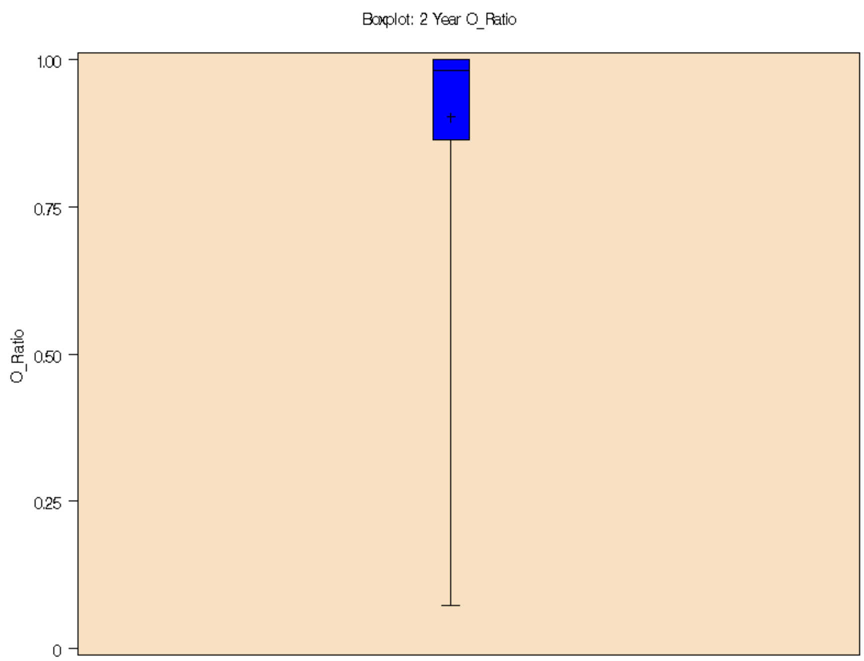
Contract	"Active" period
…	…
H 92	12/01/1991 to 02/28/1992
M 92	03/01/1992 to 05/31/1992
U 92	06/01/1992 to 08/31/1992
Z 92	09/01/1992 to 11/30/1992
H 93	12/01/1992 to 02/28/1993
…	…

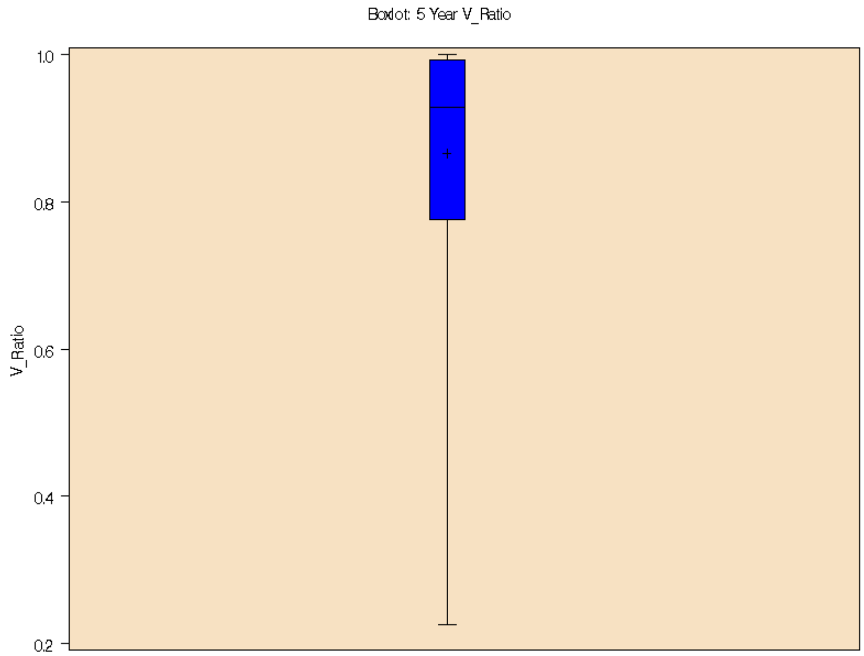
Table 1A
Summary Statistics of V_Ratio and O_Ratio

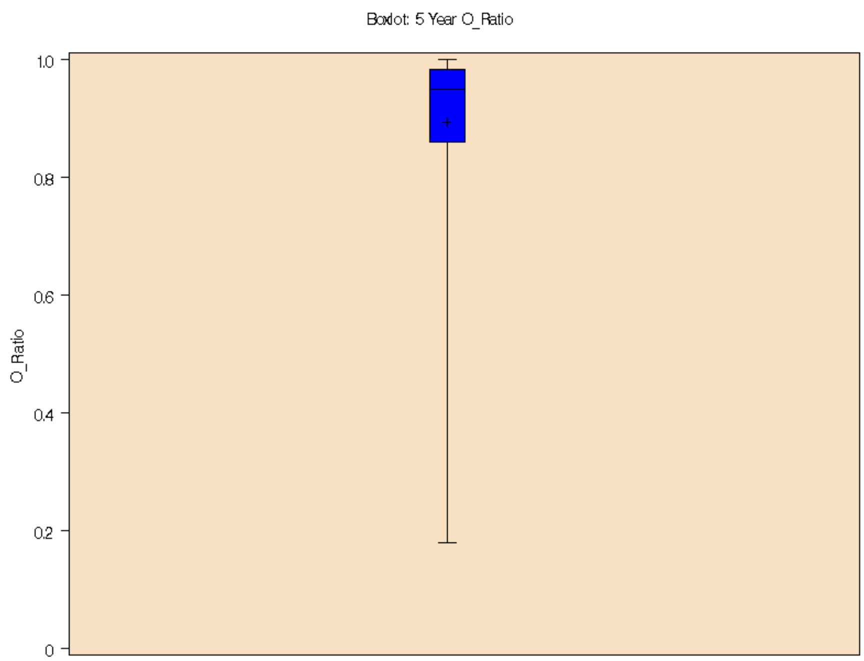
	Mean	Std Dev	N	Minimum	Maximum	Median
2 Year						
V_Ratio	0.8527774	0.1959624	4032	0	1	0.9886192
O_Ratio	0.9019683	0.1551922	4034	0.0723660	1	0.9807020
5 Year						
V_Ratio	0.8657134	0.1524070	4015	0.2261302	1	0.9285141
O_Ratio	0.8933798	0.1359528	4036	0.1803906	1	0.9487087
10 Year						
V_Ratio	0.8662879	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

Figure 1F: Boxplots for V_Ratio and O_Ratio

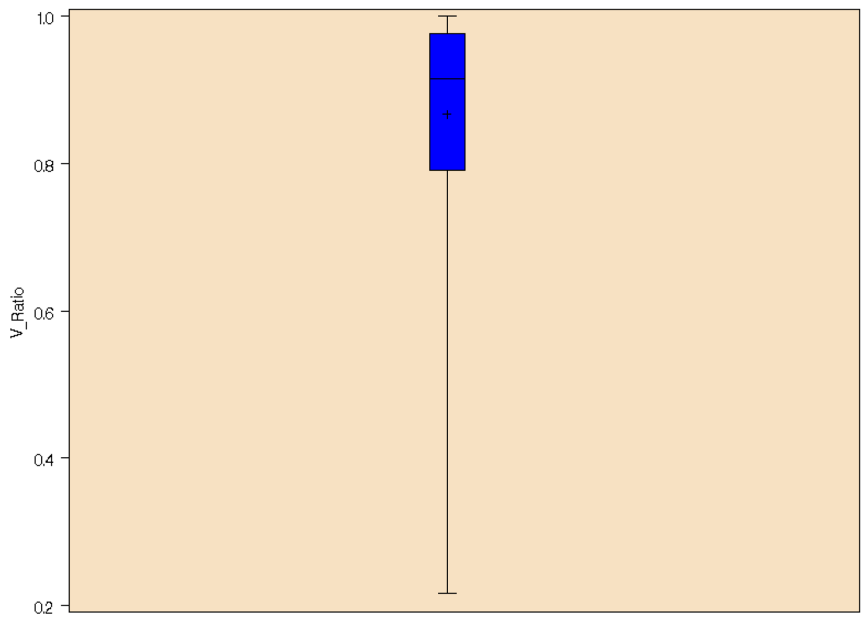




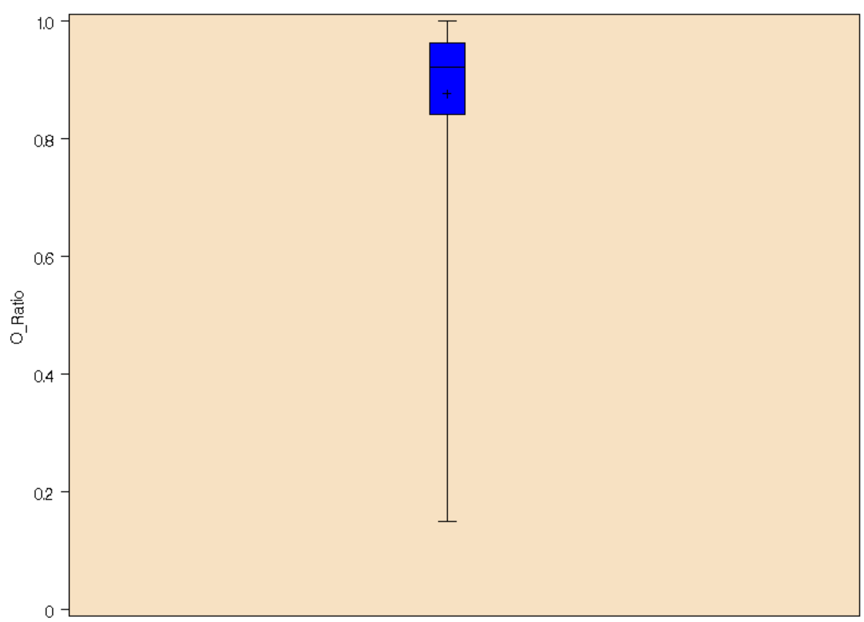

Boxplot: 5 Year V_Ratio
V_Ratio
1.0
0.8
0.6
0.4
0.2

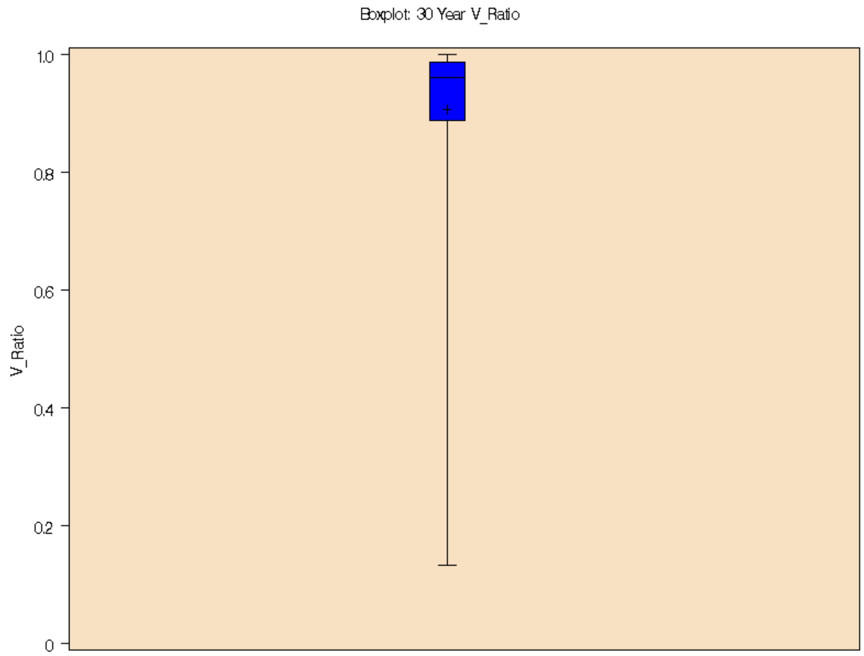

Boxplot: 5 Year O_Ratio
O_Ratio
1.0
0.8
0.6
0.4
0.2
0

Boxplot: 10 Year V_Ratio



Boxplot: 10 Year O_Ratio




Boxplot: 30 Year V_Ratio
V_Ratio
1.0
0.8
0.6
0.4
0.2
0

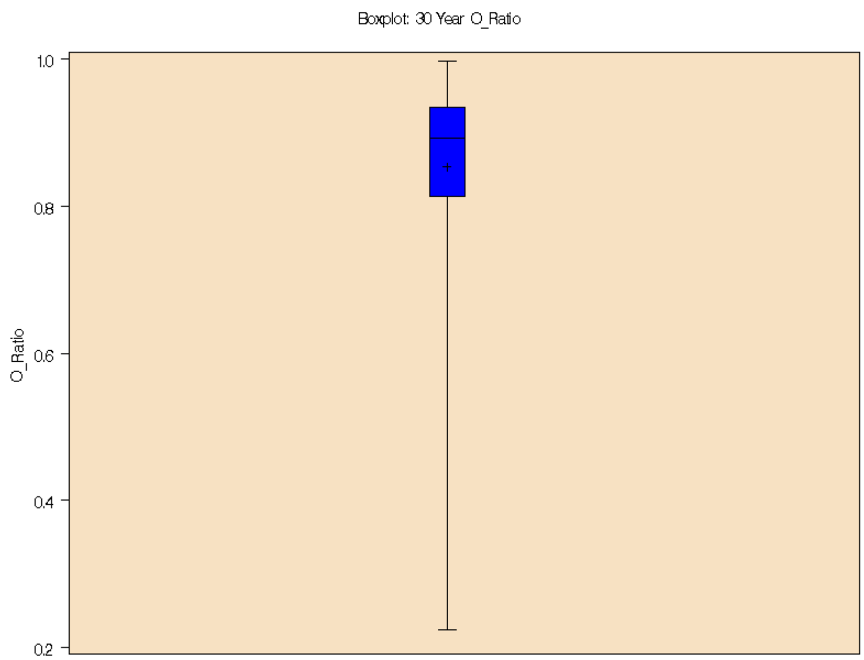

Boxplot: 30 Year O_Ratio
O_Ratio
1.0
0.8
0.6
0.4
0.2

Figure 1G: Test for Autocorrelation with Durbin-Watson Test

Two Year Futures as Example

Test for Autocorrelation

The AUTOREG Procedure

Dependent Variable return

Ordinary Least Squares Estimates

SSE	0.00697948	DFE	3987
MSE	1.75056E-6	Root MSE	0.00132
SBC	-41538.491	AIC	-41544.782
Regress R-Square	0.0540	Total R-Square	0.0540

NOTE: No intercept term is used. R-squares are redefined.

Durbin-Watson Statistics

Order	DW	Pr < DW	Pr > DW
1	1.9300	0.0136	0.9864
2	2.0885	0.9975	0.0025
3	2.0731	0.9904	0.0096
4	2.0647	0.9819	0.0181

NOTE: Pr<DW is the p-value for testing positive autocorrelation, and Pr>DW is the p-value for testing negative autocorrelation.

Variable	DF	Estimate	Standard Error	Approx t Value	Pr > |t|
average_return	1	1.0321	0.0684	15.09	<.0001

Figure 1H: Stepwise Autoregression (to determine the order of autocorrelation)

Two Year Futures as Example

Stepwise Autocorrelation: Determine the AR(m) order

The AUTOREG Procedure

Dependent Variable return

Ordinary Least Squares Estimates

SSE	0.00697986	DFE	3988
MSE	1.75022E-6	Root MSE	0.00132
SBC	-41546.563	AIC	-41546.563
Regress R-Square	0.0540	Total R-Square	0.0540
Durbin-Watson	1.9327		

NOTE: No intercept term is used. R-squares are redefined.

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
average_return	1	1.0000	0	Infty	<.0001

Restriction	DF	L Value	Standard Error	t Value	Approx Pr > |t|
RESTRICT	-1	0.0000120	0.0000256	0.47	0.6393

Estimates of Autocorrelations

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0     1.75E-6      1.000000    |                    |********************|
  1    5.886E-8      0.033631    |                    |*                   |
  2    -8.09E-8     -0.046245    |                   *|                    |
  3    -6.73E-8     -0.038444    |                   *|                    |
  4    -5.96E-8     -0.034071    |                   *|                    |
  5    -4.08E-8     -0.023315    |                    |                    |
  6    -2.68E-8     -0.015317    |                    |                    |
```

(continue: Stepwise Autoregression)

Backward Elimination of Autoregressive Terms

Lag	Estimate	t Value	Pr > |t|
6	0.018417	1.16	0.2451
5	0.024633	1.56	0.1200

Preliminary MSE 1.74E-6

Estimates of Autoregressive Parameters

Lag	Coefficient	Standard Error	t Value
1	-0.032352	0.015834	-2.04
2	0.047749	0.015833	3.02
3	0.034203	0.015833	2.16
4	0.033885	0.015834	2.14

Algorithm converged.

Maximum Likelihood Estimates

SSE	0.00693956	DFE	3984
MSE	1.74186E-6	Root MSE	0.00132
SBC	-41536.478	AIC	-41561.642
Regress R-Square	0.0564	Total R-Square	0.0594
Durbin-Watson	2.0016		

NOTE: No intercept term is used. R-squares are redefined.

Variable	DF	Estimate	Standard Error	Approx t Value	Pr > |t|
average_return	1	1.0000	0	Infty	<.0001
AR1	1	-0.0323	0.0158	-2.04	0.0412
AR2	1	0.0478	0.0158	3.02	0.0026
AR3	1	0.0343	0.0158	2.16	0.0306
AR4	1	0.0339	0.0158	2.14	0.0323

Figure 1I: Test for Heteroskadasticity

The AUTOREG Procedure

Dependent Variable return

Ordinary Least Squares Estimates

SSE	0.00697986	DFE	3988
MSE	1.75022E-6	Root MSE	0.00132
SBC	-41546.563	AIC	-41546.563
Regress R-Square	0.0540	Total R-Square	0.0540
Durbin-Watson	1.9327		

NOTE: No intercept term is used. R-squares are redefined.

Q and LM Tests for ARCH Disturbances

Order	Q	Pr > Q	LM	Pr > LM
1	0.0008	0.9775	0.0008	0.9775
2	0.4437	0.8010	0.4426	0.8015
3	0.4862	0.9219	0.4847	0.9222
4	0.5770	0.9656	0.5710	0.9662
5	0.5787	0.9890	0.5723	0.9892
6	0.6312	0.9959	0.6216	0.9960
7	0.6799	0.9985	0.6691	0.9986
8	0.6801	0.9996	0.6694	0.9996
9	0.6806	0.9999	0.6702	0.9999
10	0.6836	1.0000	0.6735	1.0000
11	0.6850	1.0000	0.6750	1.0000
12	0.6850	1.0000	0.6750	1.0000

Variable	DF	Estimate	Standard Error	Approx t Value	Pr > |t|
average_return	1	1.0000	0	Infty	<.0001

Restriction	DF	L Value	Standard Error	Approx t Value	Pr > |t|
RESTRICT	-1	0.0000120	0.0000256	0.47	0.6393

(continue: Test for Heterskedasticity)

Estimates of Autocorrelations

```
Lag   Covariance    Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 0     1.75E-6       1.000000    |                    |********************|
 1     5.886E-8      0.033631    |                    |*                   |
 2     -8.09E-8     -0.046245    |                   *|                    |
 3     -6.73E-8     -0.038444    |                   *|                    |
 4     -5.96E-8     -0.034071    |                   *|                    |
```

Preliminary MSE 1.74E-6

Estimates of Autoregressive Parameters

Lag	Coefficient	Standard Error	t Value
1	-0.032352	0.015834	-2.04
2	0.047749	0.015833	3.02
3	0.034203	0.015833	2.16
4	0.033885	0.015834	2.14

Yule-Walker Estimates

SSE	0.00693956	DFE	3984
MSE	1.74186E-6	Root MSE	0.00132
SBC	-41536.477	AIC	-41561.642
Regress R-Square	0.0564	Total R-Square	0.0594
Durbin-Watson	2.0016		

NOTE: No intercept term is used. R-squares are redefined.

Variable	DF	Estimate	Standard Error	Approx t Value	Pr > |t|
average_return	1	1.0000	0	Infty	<.0001

Restriction	DF	L Value	Standard Error	Approx t Value	Pr > |t|
RESTRICT	-1	-6.995E-6	0.0000273	-0.26	0.7981

Figure 1J: Determine the AR(m)-GARCH(p,q) Specification

AR(1)-GARCH(1,1) on Two Year Futures as Example

AR(1)-GARCH(1,1)

The AUTOREG Procedure

Dependent Variable return

Ordinary Least Squares Estimates

SSE	0.00697986	DFE	3988
MSE	1.75022E-6	Root MSE	0.00132
SBC	-41546.563	AIC	-41546.563
Regress R-Square	0.0540	Total R-Square	0.0540
Durbin-Watson	1.9327		

NOTE: No intercept term is used. R-squares are redefined.

Variable	DF	Estimate	Standard Error	Approx t Value	Pr > |t|
average_return	1	1.0000	0	Infty	<.0001

Restriction	DF	L Value	Standard Error	Approx t Value	Pr > |t|
RESTRICT	-1	0.0000120	0.0000256	0.47	0.6393

Estimates of Autocorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	1.75E-6	1.000000	| |********************|
1	5.886E-8	0.033631	| |* |

Preliminary MSE 1.748E-6

Estimates of Autoregressive Parameters

Lag	Coefficient	Standard Error	t Value
1	-0.033631	0.015828	-2.12

Algorithm converged.

AR(1)-GARCH(1,1)

GARCH Estimates

SSE	0.00703843	Observations	3988
MSE	1.7649E-6	Uncond Var	2.29902E-6
Log Likelihood	20806.002	Total R-Square	0.0460
SBC	-41578.84	AIC	-41604.004
Normality Test	1964253.89	Pr > ChiSq	<.0001

NOTE: No intercept term is used. R-squares are redefined.

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
average_return	1	1.0000	0.0000693	14420.9	<.0001
AR1	1	-0.1312	0.0209	-6.29	<.0001
ARCH0	1	7.3745E-7	3.5612E-8	20.71	<.0001
ARCH1	1	0.2978	0.0185	16.11	<.0001
GARCH1	1	0.3814	0.0200	19.07	<.0001

Figure 1K: SAS Sample Program on GARCH Specification

```
data two_year;
  input return average_return;
  cards;

0.000461965   3.66592E-06
0.003151056   0.000153716
0.000613685   ......
;
run;

proc print data=two_year;
  *title 'Return and Average_Return';
run;


/*Assuming the AR(2)*/
proc autoreg data=two_year;
        model return = average_return / noint nlag=2 method=ml;
        restrict average_return = 1;
        title 'Assuiming the AR(2)'
run;

/*Testing for Autocorrelation; do not restrict the main regression with restrict
average_return=1[so that p-values are shown], but still specify noint*/
proc autoreg data=two_year;
        model return = average_return / noint dw=4 dwprob;
        restrict average_return = 1;
        title 'Test for Autocorrelation';
run;

/*Stepwise Autocorrelation: Determine the AR(m) order*/
proc autoreg data=two_year;
        model return = average_return / method=ml noint nlag=6 backstep;
        restrict average_return = 1;
        title 'Stepwise Autocorrelation: Determine the AR(m) order';
run;


/*Testing for Heteroskadasticity*/
proc autoreg data=two_year;
        model return = average_return / noint nlag=4 archtest dwprob;
        restrict average_return = 1;
        title 'Testing for Heteroskadasticity';
run;
```

```
/*GARCH: AR(0 or 1 or 4) and GARCH(p,q):(1,1),(1,2),(2,1),(2,2)*/
proc autoreg data=two_year;
	model return = average_return / noint nlag=4 garch=(p=2,q=2);
	restrict average_return = 1;
	title 'AR(m=4)-GARCH(p=2,q=2)';
run;

proc print data=out noobs;
	var vhat;
	title 'Estimated Conditional Error Variance';
run;
```

Figure 1L: SAS Sample Program on VAR Estimation

Two Year Futures: Log Aggregate Volume vs. GARCH Volatility as Example

```
data two_year;
  input TA VOL; /*TA: trading activity; VOL: volatility*/
  cards;

4.510859507   0.001362173
6.64509097    0.00128963
5.105945474   ......

;
run;

proc print data=two_year;
  title 'trading_activity and volatility';
run;


ods html;
ods graphics on;
proc varmax data=two_year;
        model VOL TA / p=4 dftest print=(impulse);
        title '2 Year Log_Aggr_Volume Vol_GARCH VAR(4)';
        causal group1=(VOL) group2=(TA);
        causal group1=(TA) group2=(VOL);
        output lead=12;
run;

ods graphics off;
ods html close;
```

Figure 1M: SAS Output on VAR Estimation

Two Year Futures: Log Volume vs. Historical Volatility as Example

2 Year Log_Volume Vol_Historical VAR(4)

The VARMAX Procedure

Number of Observations	3985
Number of Pairwise Missing	0

Simple Summary Statistics

Variable	Type	N	Mean	Standard Deviation	Min	Max
VOL	Dependent	3985	0.00119	0.00065	0.00034	0.00772
TA	Dependent	3985	7.86265	1.08682	2.30259	11.31617

Dickey-Fuller Unit Root Tests

Variable	Type	Rho	Pr < Rho	Tau	Pr < Tau
VOL	Zero Mean	-38.75	<.0001	-4.39	<.0001
	Single Mean	-173.49	0.0001	-9.31	<.0001
	Trend	-174.41	0.0001	-9.34	<.0001
TA	Zero Mean	-9.37	0.0338	-2.14	0.0315
	Single Mean	-668.03	0.0001	-18.30	<.0001
	Trend	-1007.0	0.0001	-22.43	<.0001

Granger-Causality Wald Test

Test	DF	Chi-Square	Pr > ChiSq
1	4	30.06	<.0001
2	4	7.96	0.0929

Test 1: Group 1 Variables: VOL
Group 2 Variables: TA

Test 2: Group 1 Variables: TA
Group 2 Variables: VOL

2 Year Log_Volume Vol_Historical VAR(4)

Type of Model	VAR(4)
Estimation Method	Least Squares Estimation

Constant Estimates

Variable	Constant
VOL	-0.00006
TA	1.27576

AR Coefficient Estimates

Lag	Variable	VOL	TA
1	VOL	0.96354	-0.00001
	TA	-106.14844	0.34717
2	VOL	0.00944	0.00001
	TA	54.00386	0.22207
3	VOL	0.00067	0.00001
	TA	-62.38476	0.16028
4	VOL	-0.02081	0.00001
	TA	80.97935	0.11349

Schematic Representation
of Parameter Estimates

Variable/ Lag	C	AR1	AR2	AR3	AR4
VOL	-	+-	..	.+	..
TA	+	.+	.+	.+	.+

+ is > 2*std error, - is < -2*std error, . is between, * is N/A

2 Year Log_Volume Vol_Historical VAR(4)

Model Parameter Estimates

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|	Variable
VOL	CONST1	-0.00006	0.00003	-2.21	0.0272	1
	AR1_1_1	0.96354	0.01588	60.66	0.0001	VOL(t-1)
	AR1_1_2	-0.00001	0.00000	-2.05	0.0401	TA(t-1)
	AR2_1_1	0.00944	0.02208	0.43	0.6690	VOL(t-2)
	AR2_1_2	0.00001	0.00000	1.56	0.1183	TA(t-2)
	AR3_1_1	0.00067	0.02208	0.03	0.9760	VOL(t-3)
	AR3_1_2	0.00001	0.00000	2.34	0.0194	TA(t-3)
	AR4_1_1	-0.02081	0.01585	-1.31	0.1892	VOL(t-4)
	AR4_1_2	0.00001	0.00000	1.59	0.1129	TA(t-4)
TA	CONST2	1.27576	0.10270	12.42	0.0001	1
	AR1_2_1	-106.14844	62.96302	-1.69	0.0919	VOL(t-1)
	AR1_2_2	0.34717	0.01579	21.99	0.0001	TA(t-1)
	AR2_2_1	54.00386	87.51957	0.62	0.5372	VOL(t-2)
	AR2_2_2	0.22207	0.01655	13.41	0.0001	TA(t-2)
	AR3_2_1	-62.38476	87.50908	-0.71	0.4760	VOL(t-3)
	AR3_2_2	0.16028	0.01656	9.68	0.0001	TA(t-3)
	AR4_2_1	80.97935	62.82270	1.29	0.1975	VOL(t-4)
	AR4_2_2	0.11349	0.01579	7.19	0.0001	TA(t-4)

Covariances of Innovations

Variable	VOL	TA
VOL	0.00000	0.00001
TA	0.00001	0.55696

Information Criteria

AICC	-17.7389
HQC	-17.7289
AIC	-17.7389
SBC	-17.7105
FPEC	1.977E-8

2 Year Log_Volume Vol_Historical VAR(4)

Cross Covariances of Residuals

Lag	Variable	VOL	TA
0	VOL	0.00000	0.00001
	TA	0.00001	0.55570
1	VOL	-0.00000	-0.00000
	TA	-0.00000	-0.00622
2	VOL	-0.00000	-0.00000
	TA	-0.00000	-0.01214
3	VOL	-0.00000	-0.00000
	TA	-0.00000	-0.02097
4	VOL	0.00000	0.00000
	TA	-0.00000	-0.03695
5	VOL	0.00000	0.00000
	TA	0.00000	0.02673
6	VOL	0.00000	-0.00000
	TA	0.00001	-0.00331
7	VOL	0.00000	-0.00000
	TA	0.00000	0.00740
8	VOL	0.00000	0.00000
	TA	-0.00000	-0.00152
9	VOL	0.00000	-0.00000
	TA	-0.00000	-0.01690
10	VOL	0.00000	-0.00000
	TA	-0.00000	0.01423
11	VOL	0.00000	-0.00000
	TA	0.00000	0.00044
12	VOL	0.00000	-0.00000
	TA	-0.00000	0.00723

Cross Correlations of Residuals

Lag	Variable	VOL	TA
0	VOL	1.00000	0.05379
	TA	0.05379	1.00000
1	VOL	-0.00085	-0.00256
	TA	-0.00104	-0.01119
2	VOL	-0.00208	-0.00537
	TA	-0.00392	-0.02184
3	VOL	-0.00206	-0.00615

	TA	-0.00301	-0.03774
4	VOL	0.02359	0.00043
	TA	-0.00123	-0.06650
5	VOL	0.02498	0.00047
	TA	0.02001	0.04811
6	VOL	0.02537	-0.00269
	TA	0.04290	-0.00595
7	VOL	0.01946	-0.01574
	TA	0.00256	0.01332
8	VOL	0.01677	0.00218
	TA	-0.01755	-0.00274
9	VOL	0.01832	-0.00548
	TA	-0.00792	-0.03041
10	VOL	0.00998	-0.01306
	TA	-0.00443	0.02561
11	VOL	0.01988	-0.01038
	TA	0.01890	0.00079
12	VOL	0.00656	-0.00192
	TA	-0.00601	0.01301

Schematic Representation of Cross Correlations of Residuals

Variable/ Lag	0	1	2	3	4	5	6	7	8	9	10	11	12
VOL	++	..	..	..	..	..	..	..	..	..	..	..	..
TA	++	..	..	.-	.-	.+	+.	..	..	..	..	..	..

+ is > 2*std error, - is < -2*std error, . is between

Portmanteau Test for Cross Correlations of Residuals

Up To Lag	DF	Chi-Square	Pr > ChiSq
5	4	40.97	<.0001
6	8	50.76	<.0001
7	12	54.20	<.0001
8	16	56.71	<.0001
9	20	62.05	<.0001
10	24	66.13	<.0001
11	28	69.50	<.0001
12	32	70.58	<.0001

2 Year Log_Volume Vol_Historical VAR(4)

Univariate Model ANOVA Diagnostics

Variable	R-Square	Standard Deviation	F Value	Pr > F
VOL	0.9174	0.00019	5512.59	<.0001
TA	0.5272	0.74630	553.73	<.0001

Univariate Model White Noise Diagnostics

Variable	Durbin Watson	Normality Chi-Square	Normality Pr > ChiSq	ARCH F Value	ARCH Pr > F
VOL	2.00170	9999.99	<.0001		
TA	2.02157	964.82	<.0001	46.45	<.0001

Univariate Model AR Diagnostics

Variable	AR1 F Value	AR1 Pr > F	AR2 F Value	AR2 Pr > F	AR3 F Value	AR3 Pr > F	AR4 F Value	AR4 Pr > F
VOL	0.00	0.9572	0.01	0.9900	0.01	0.9981	0.56	0.6903
TA	0.50	0.4801	1.19	0.3038	2.74	0.0418	6.69	<.0001

2 Year Log_Volume Vol_Historical VAR(4)

Simple Impulse Response

Lag	Variable	VOL	TA
1	VOL	0.96354	-0.00001
	TA	-106.14844	0.34717
2	VOL	0.93873	-0.00000
	TA	-85.12680	0.34346
3	VOL	0.91427	0.00001
	TA	-163.11970	0.35662
4	VOL	0.86937	0.00001
	TA	-118.03263	0.36896
5	VOL	0.82528	0.00002
	TA	-126.33586	0.30014
6	VOL	0.78261	0.00002
	TA	-127.54955	0.28041
7	VOL	0.74146	0.00003
	TA	-128.47081	0.26165
8	VOL	0.70251	0.00003
	TA	-124.09538	0.24132
9	VOL	0.66538	0.00004
	TA	-122.91433	0.21902
10	VOL	0.63010	0.00004
	TA	-120.86828	0.20152
11	VOL	0.59661	0.00004
	TA	-118.46178	0.18514
12	VOL	0.56483	0.00004
	TA	-115.67408	0.16972

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.

Figure 2A: Sample Forecast Plot for Volatility

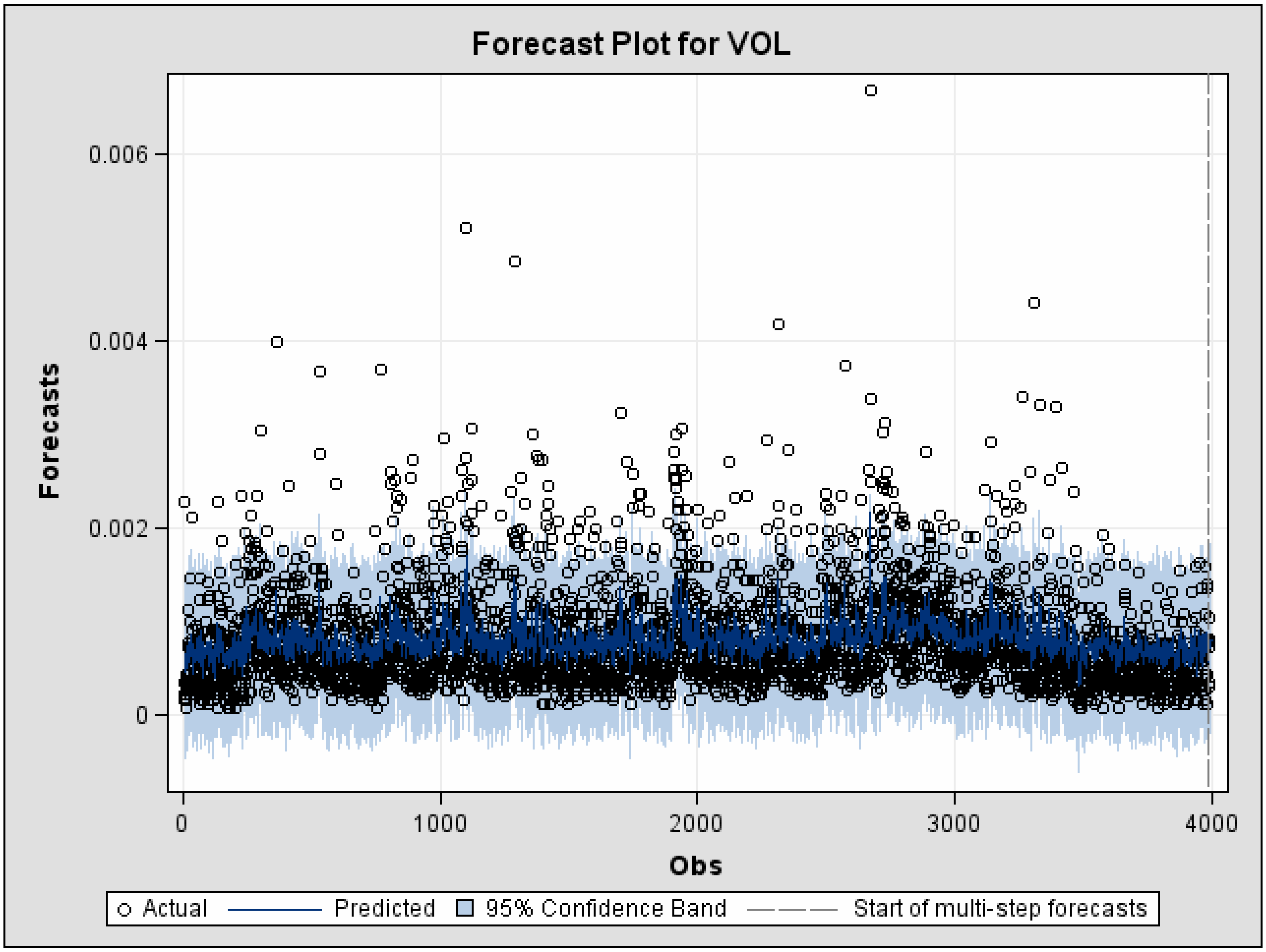


Figure 2B: Sample Forecast Plot for Trading Activity

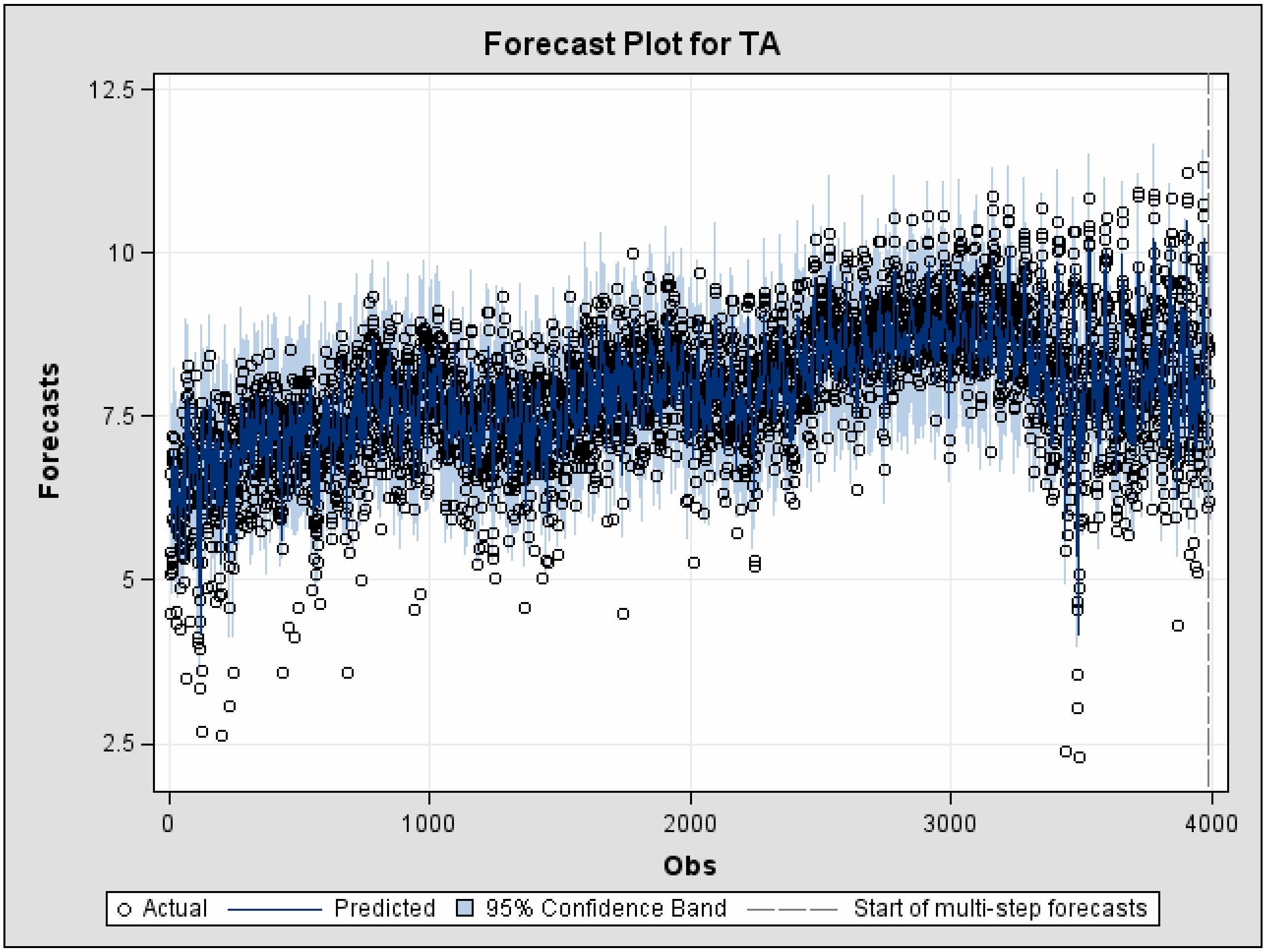
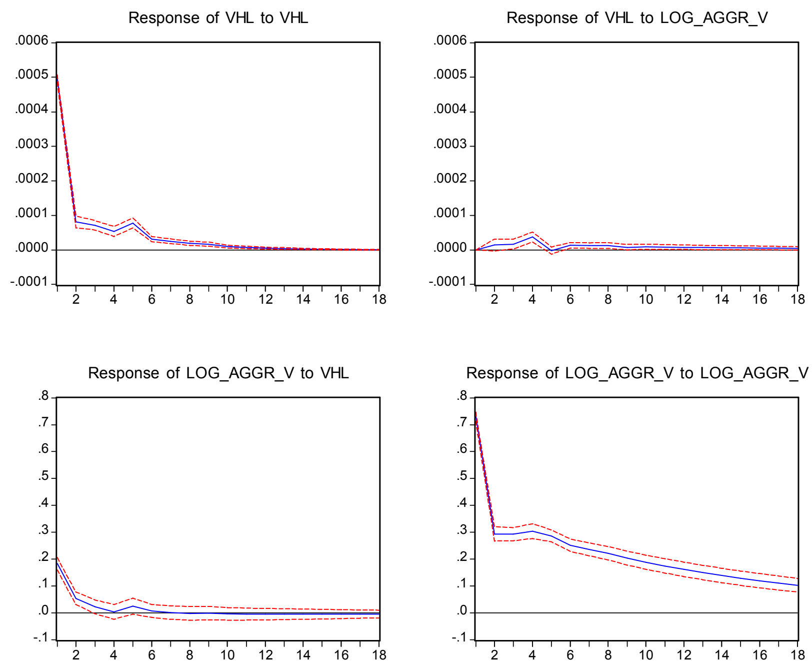


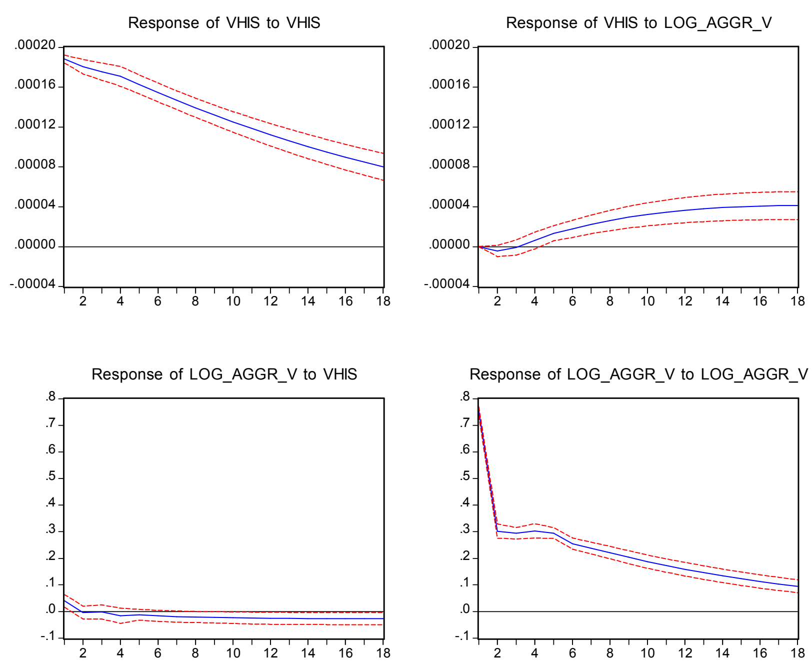
Figure 3: Impulse Responses (produced in EView)

2 Year Futures, with Aggregate Amount

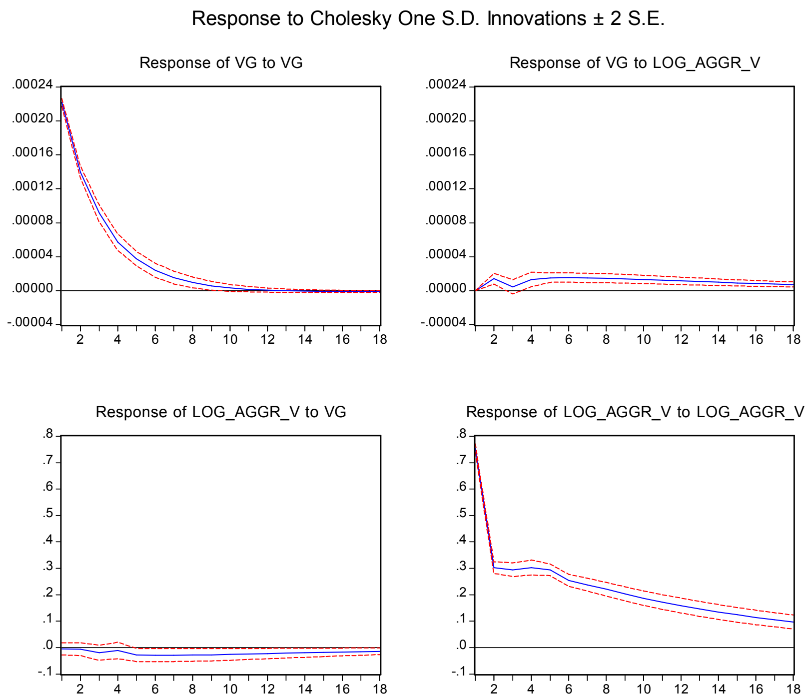
Response to Cholesky One S.D. Innovations ± 2 S.E.

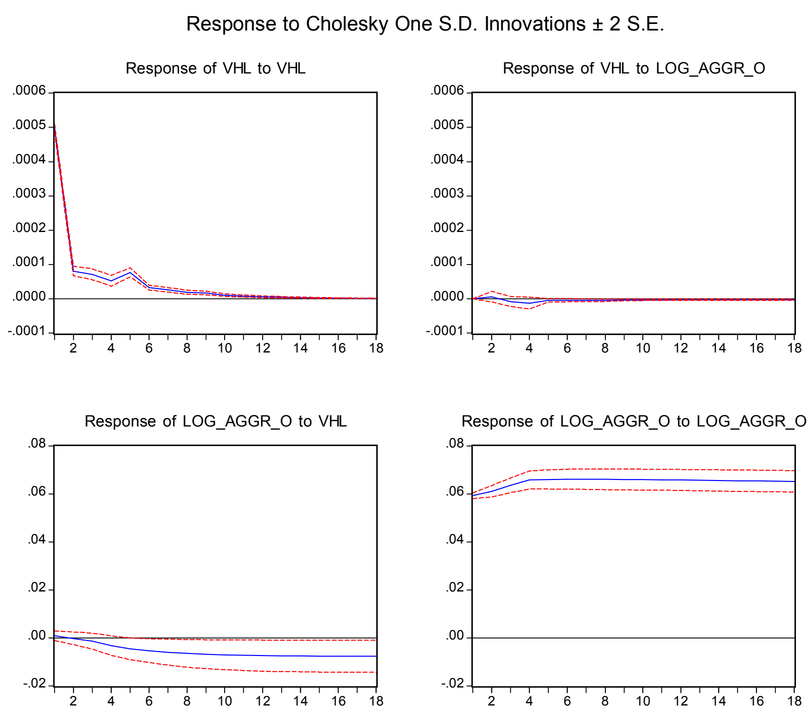


Response to Cholesky One S.D. Innovations ± 2 S.E.

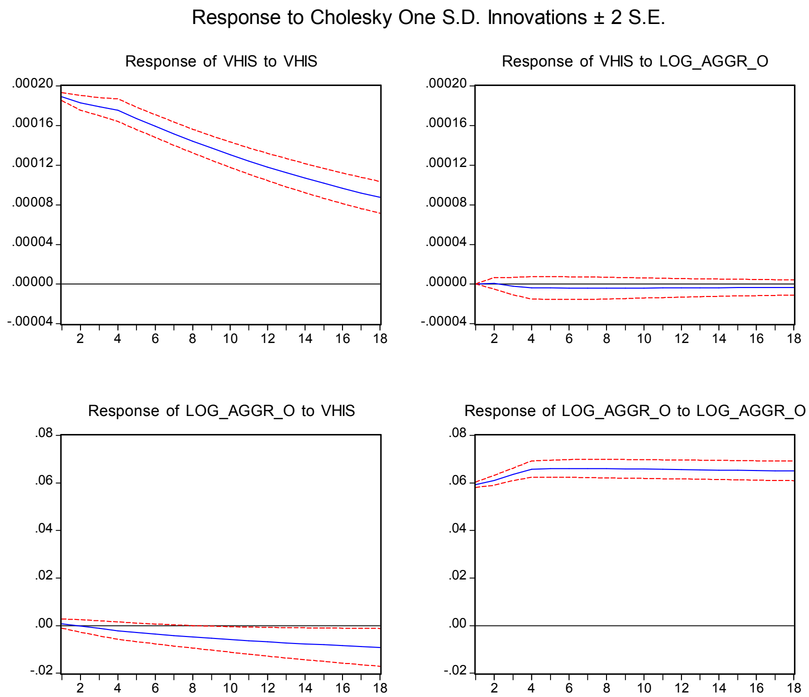


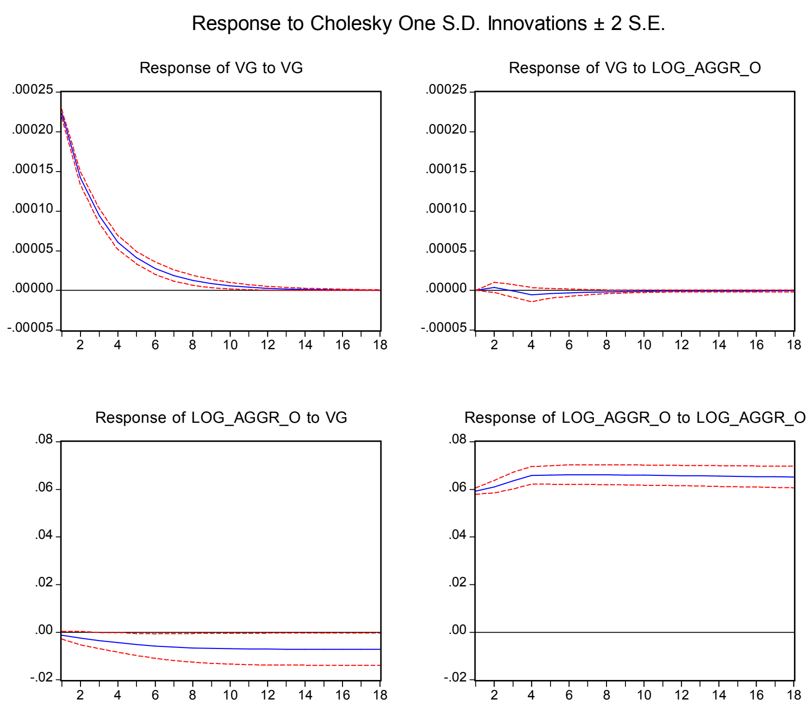
(2 Year Futures, with Aggregate Amount)



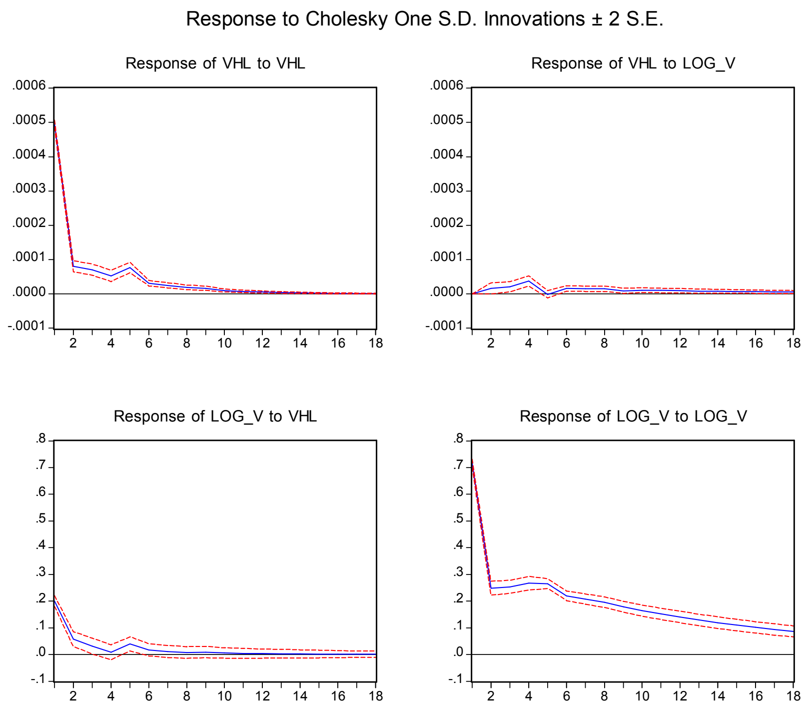


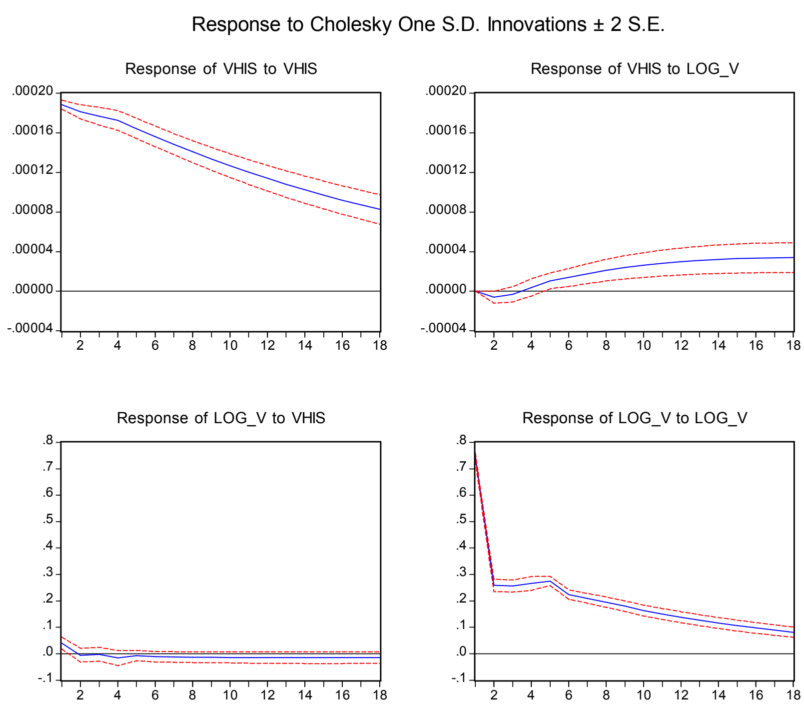
(2 Year Futures, with Aggregate Amount)





2 Year Futures, with Active Contract Amount





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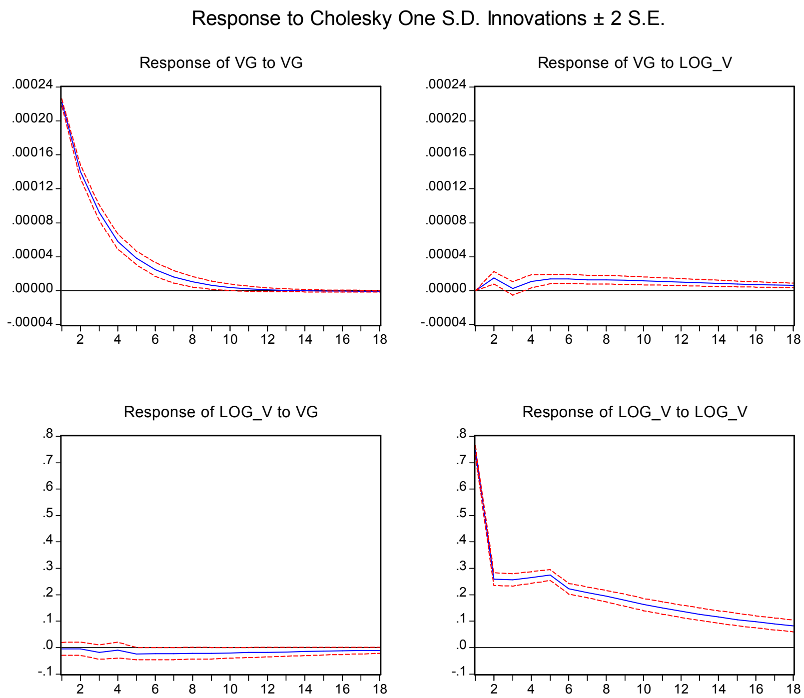

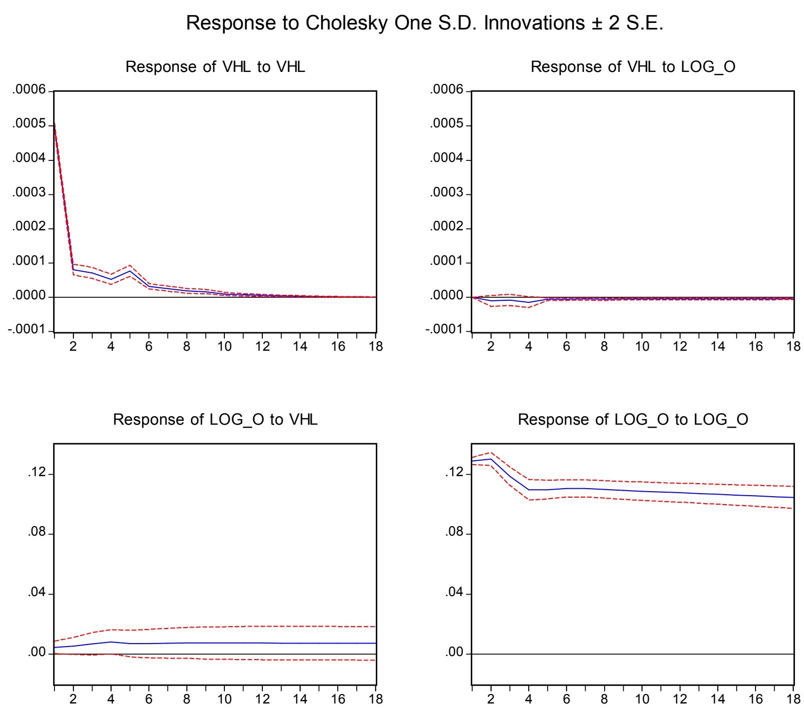

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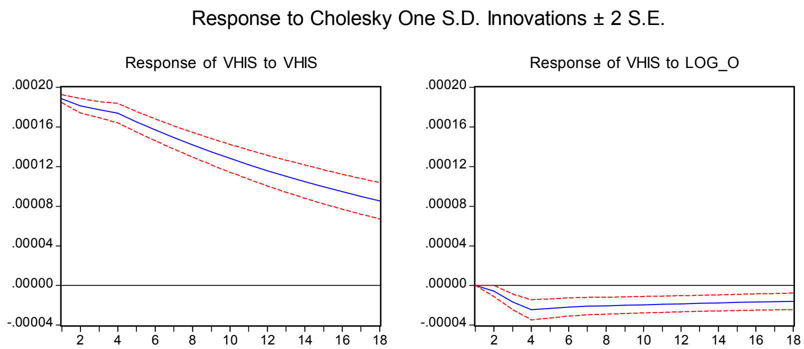
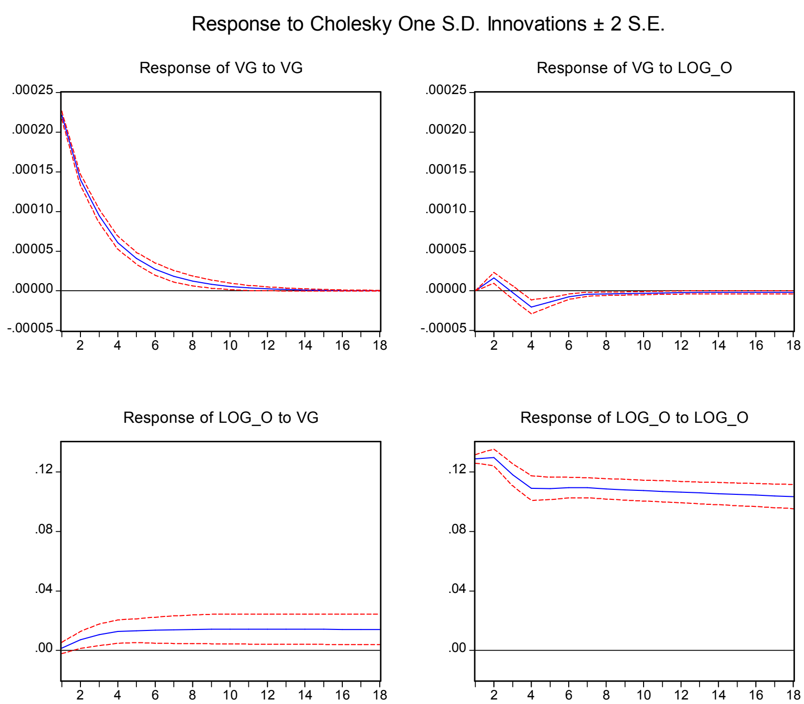
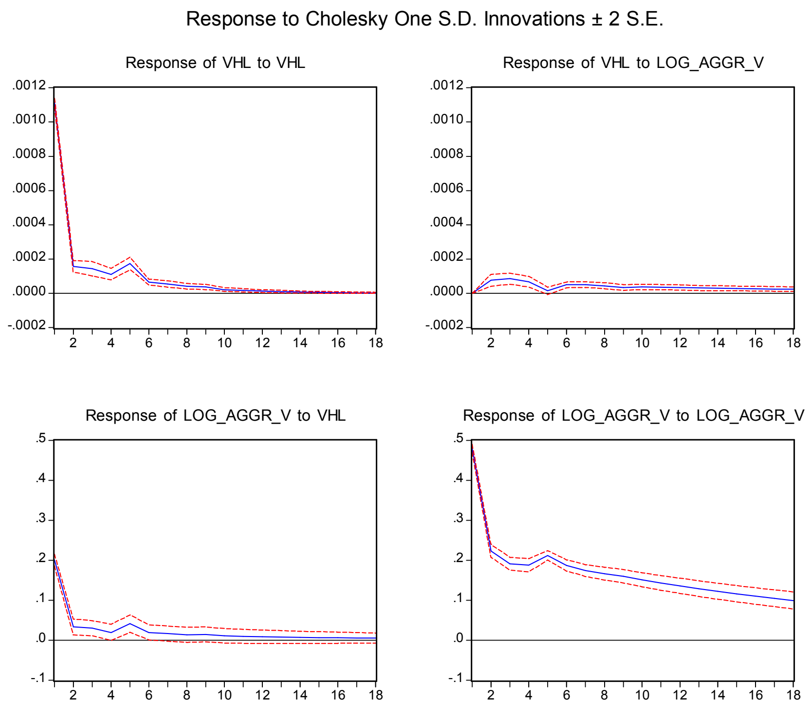
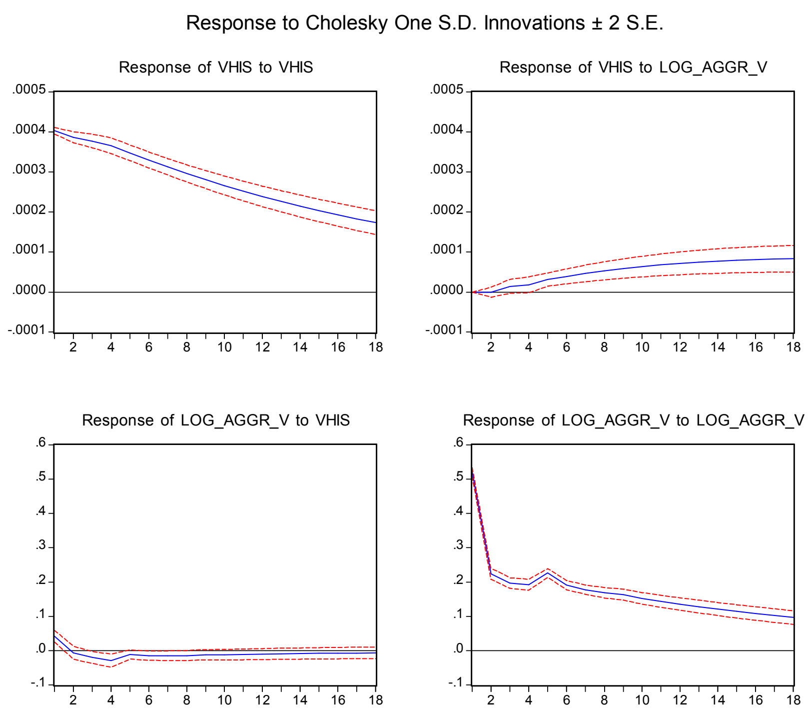




5 Year Futures, with Aggregate Amount





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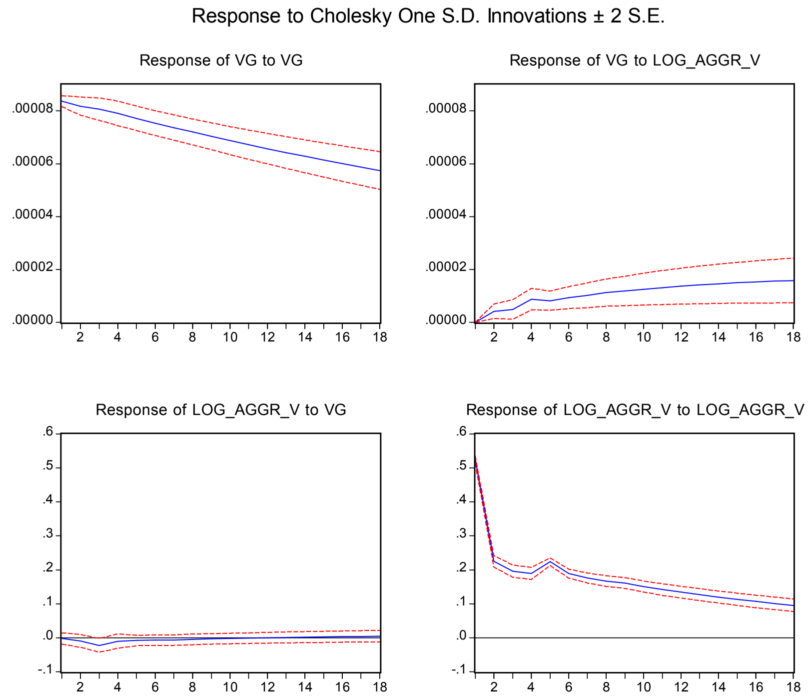

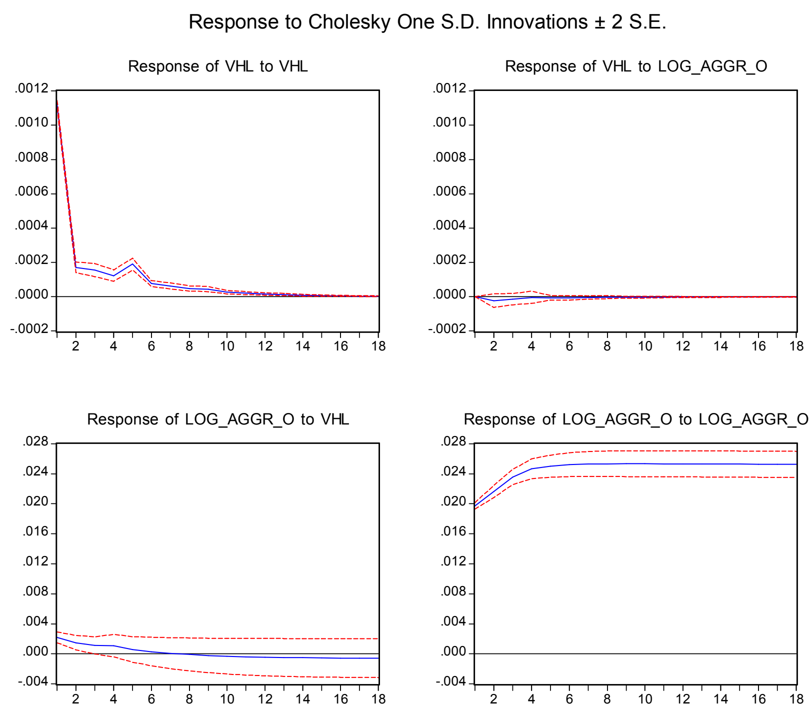

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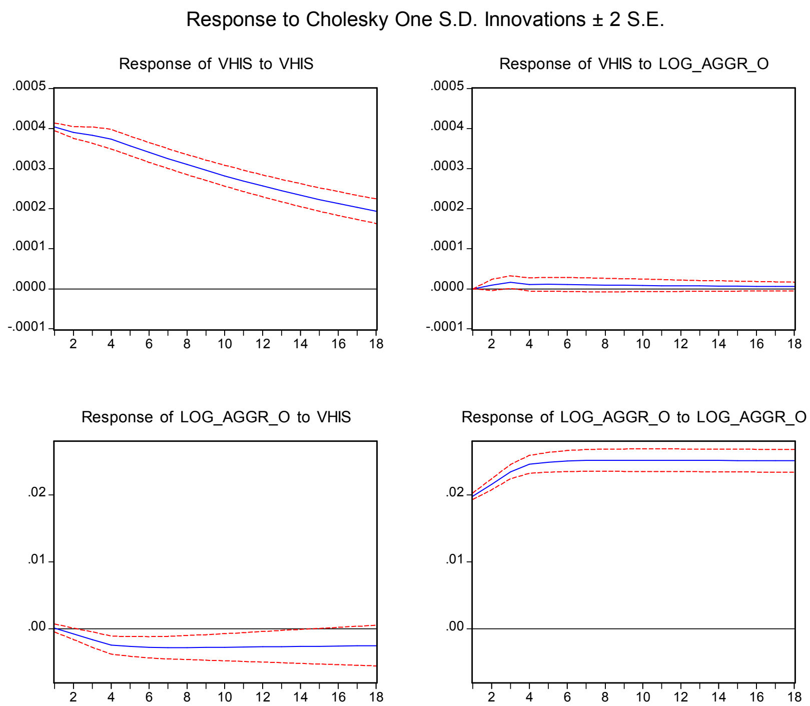
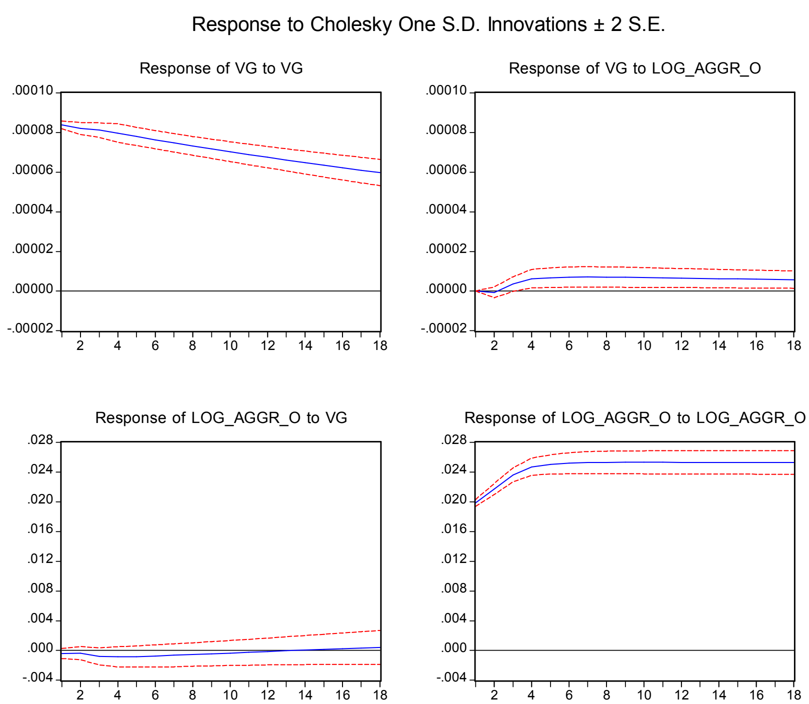
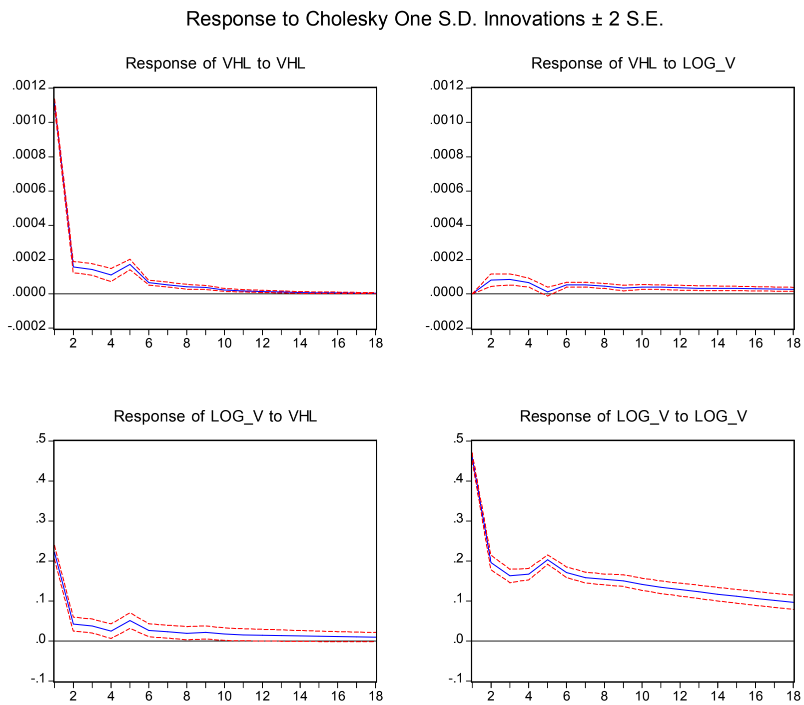
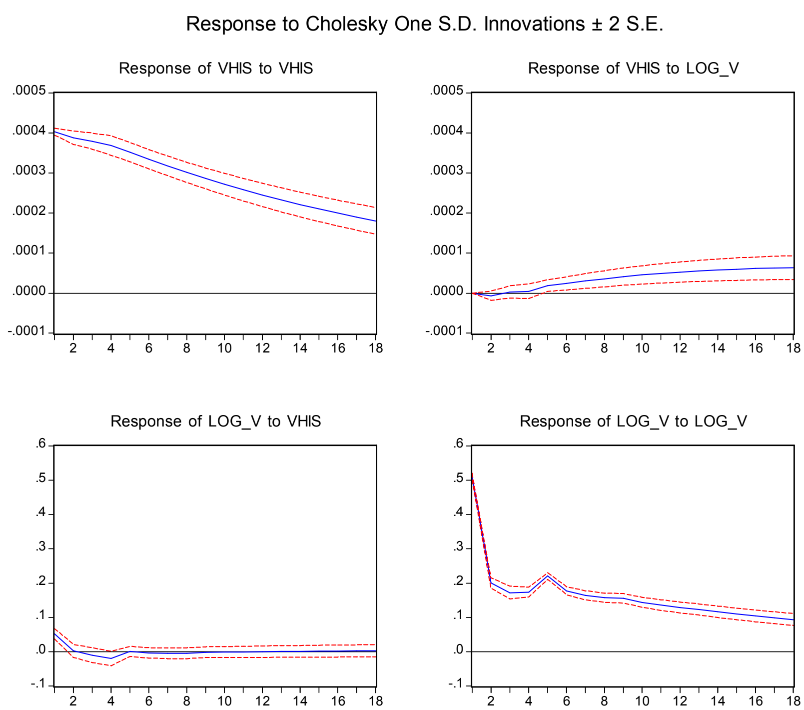




5 Year Futures, with Active Contract Amount





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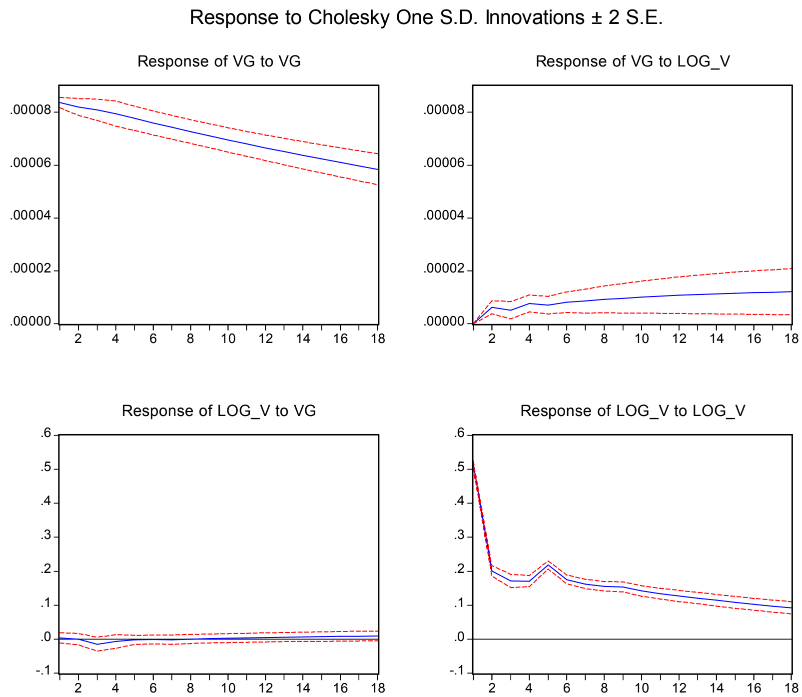

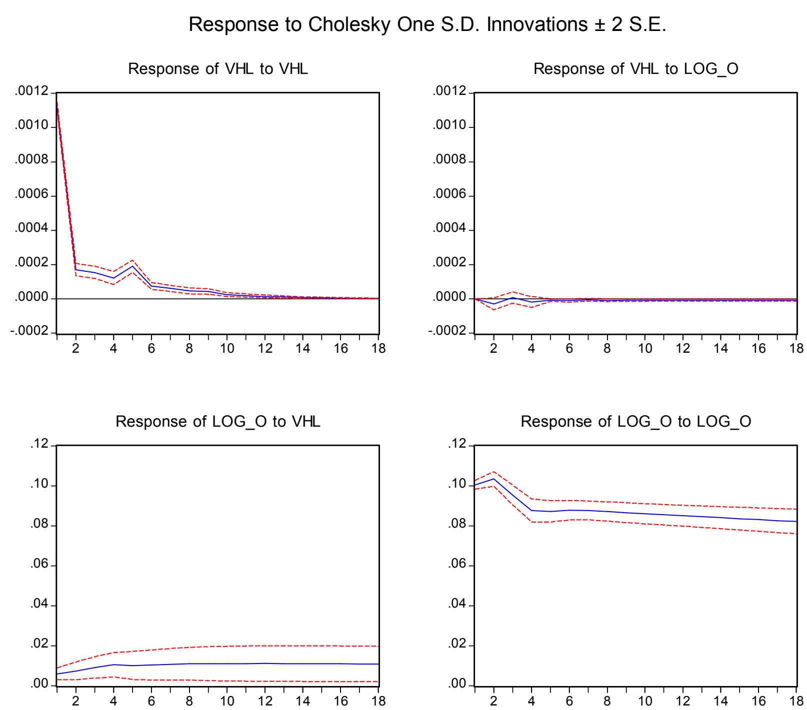

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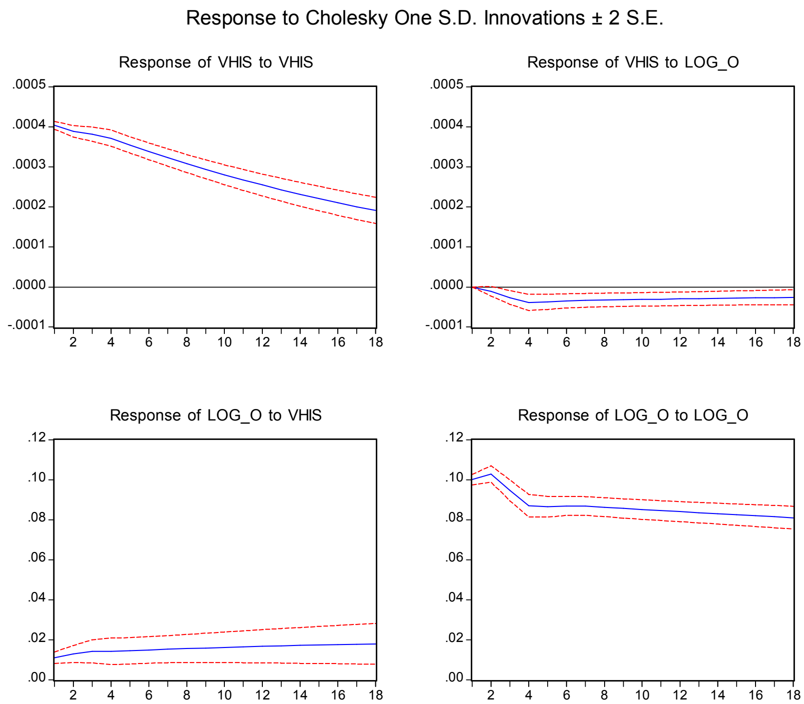
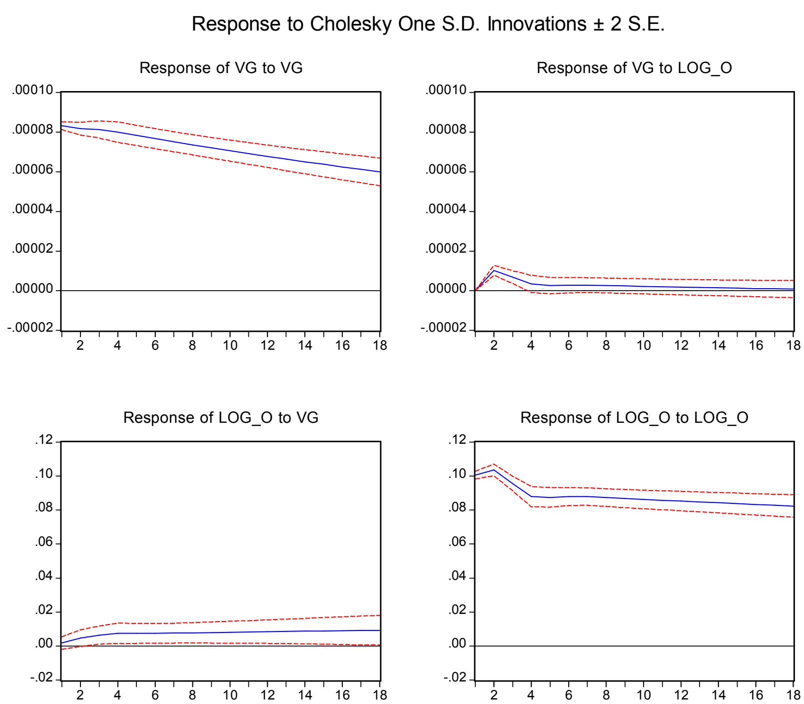
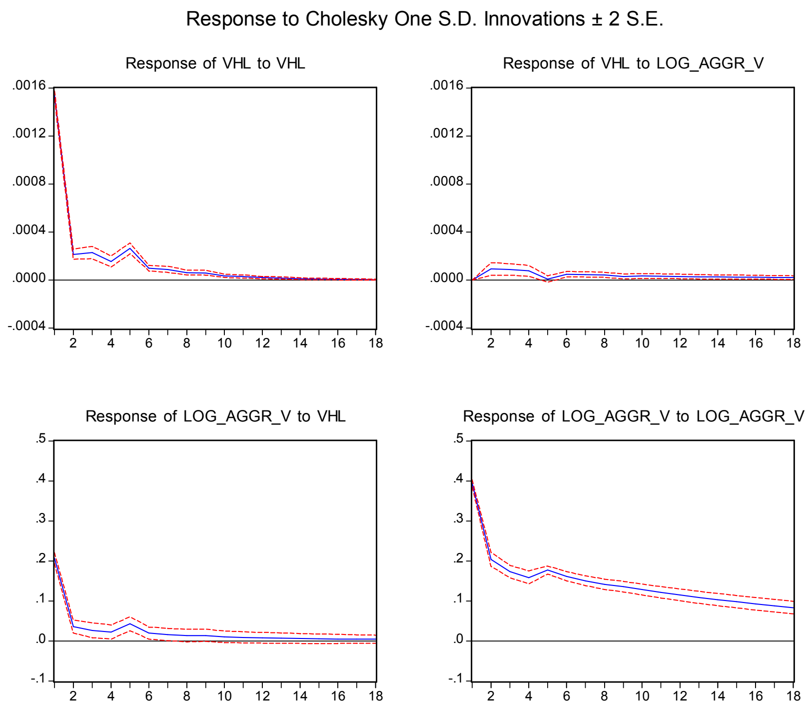
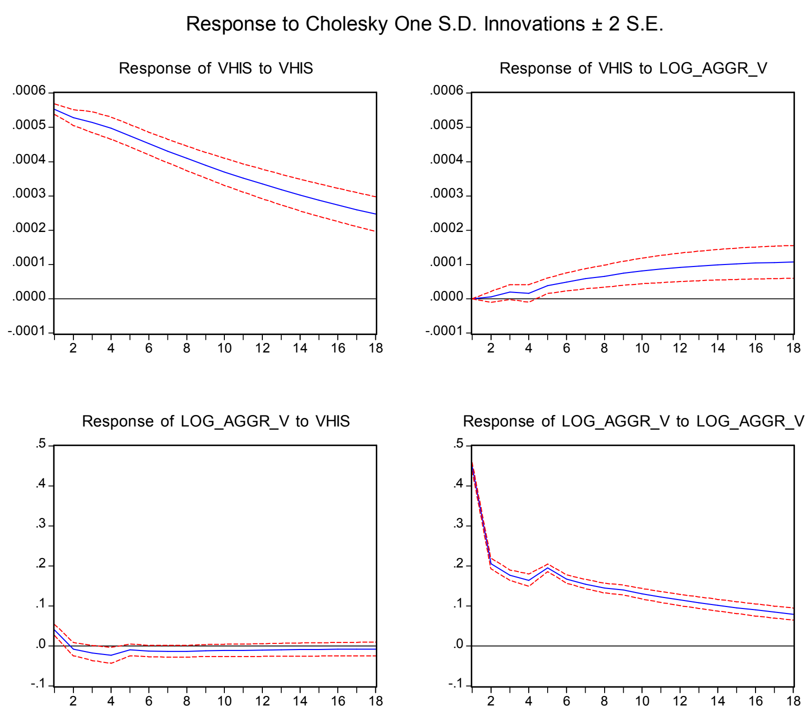




10 Year Futures, with Aggregate Amount





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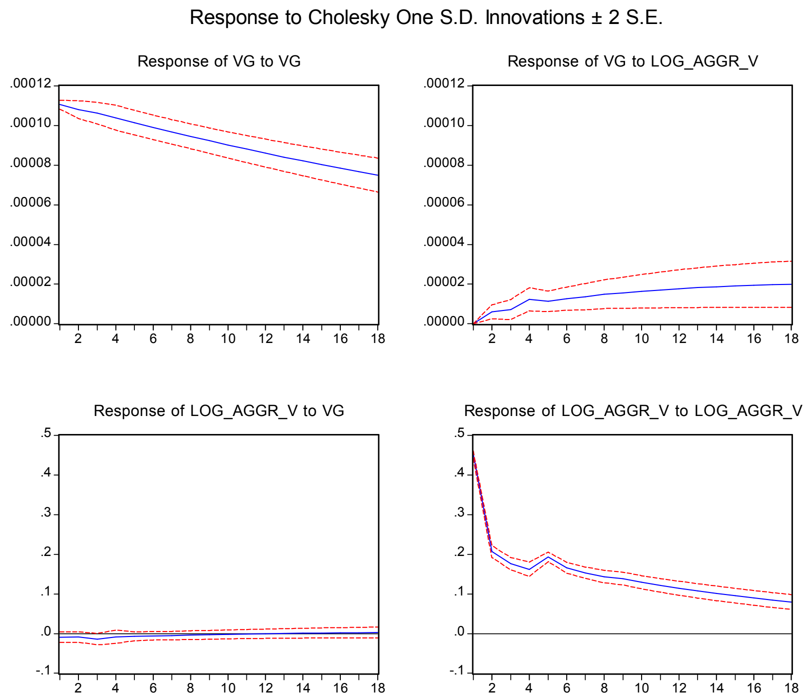

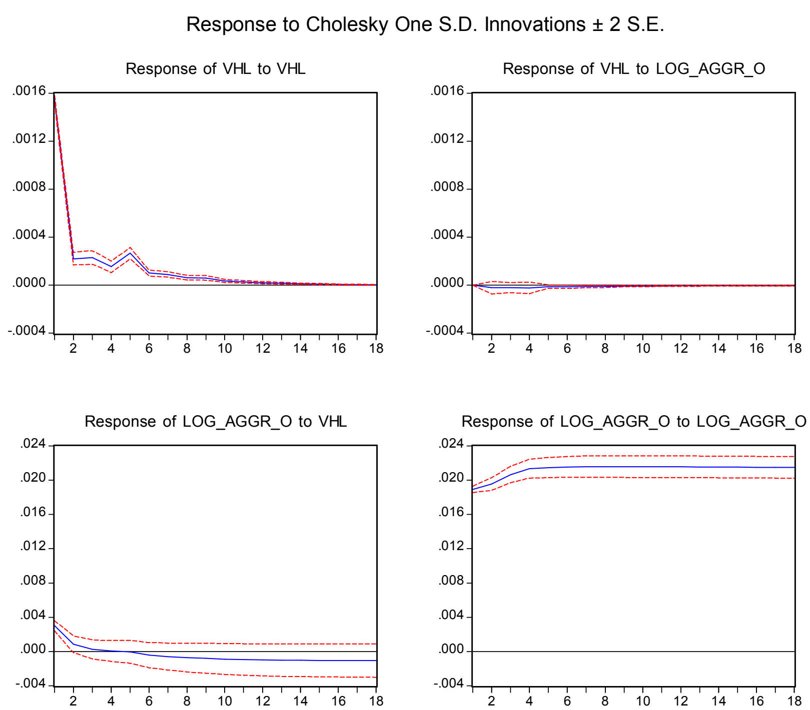

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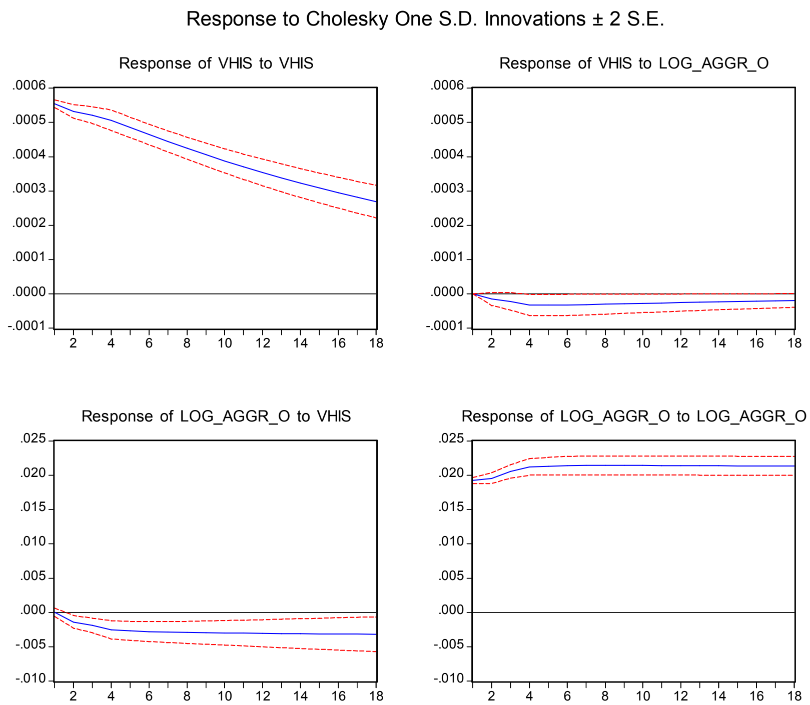
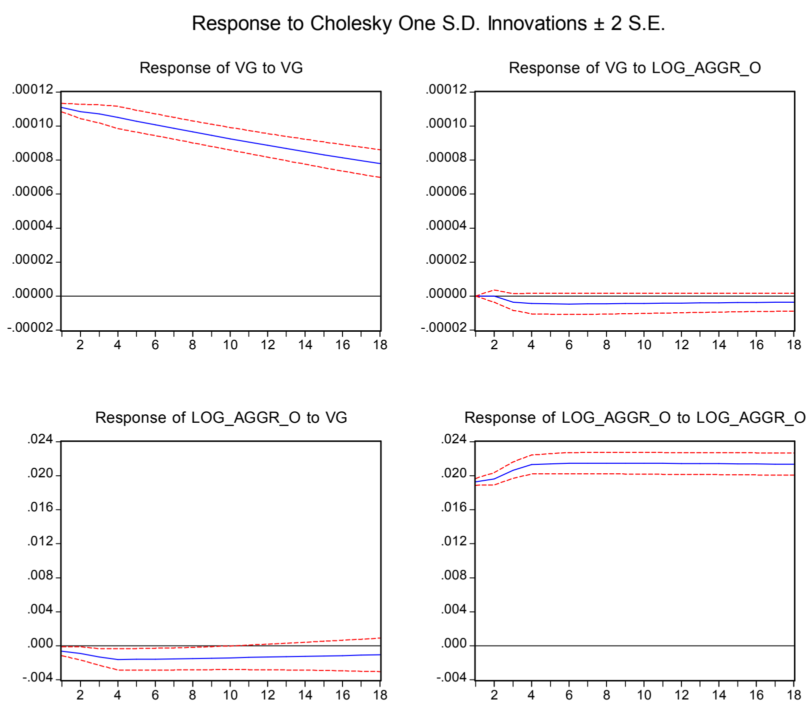
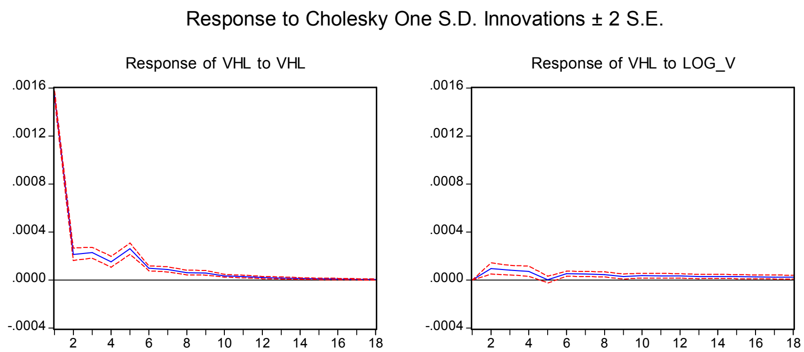
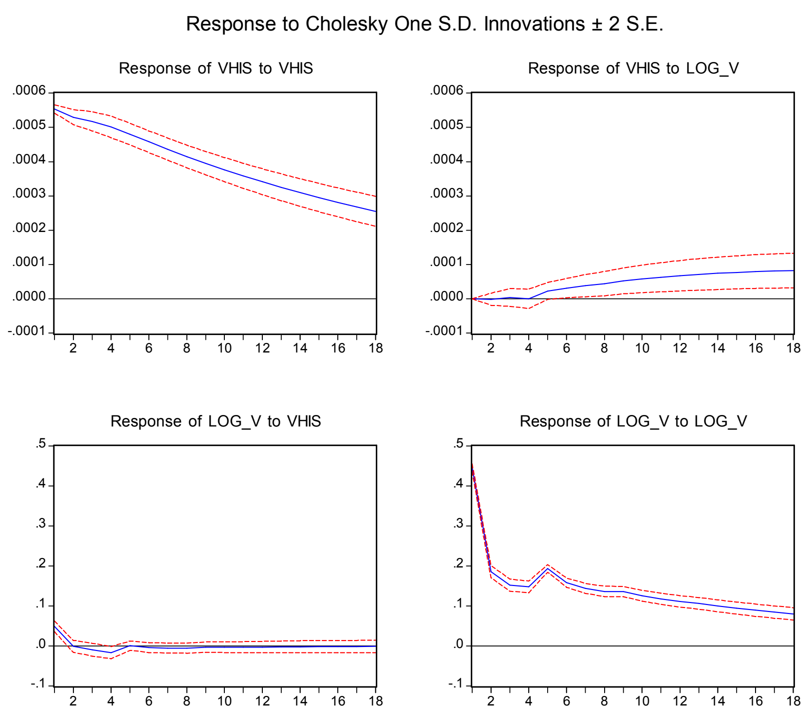




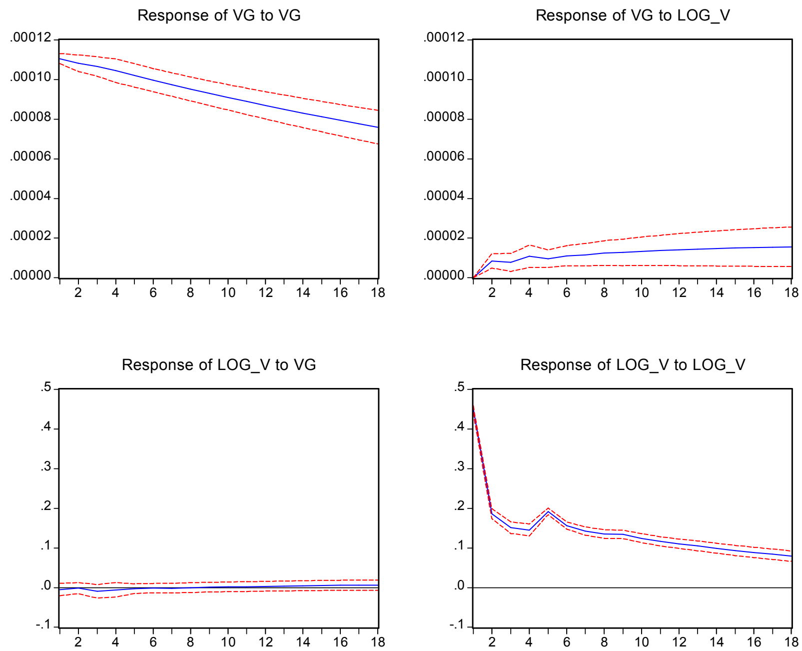
10 Year Futures, with Active Contract Amount



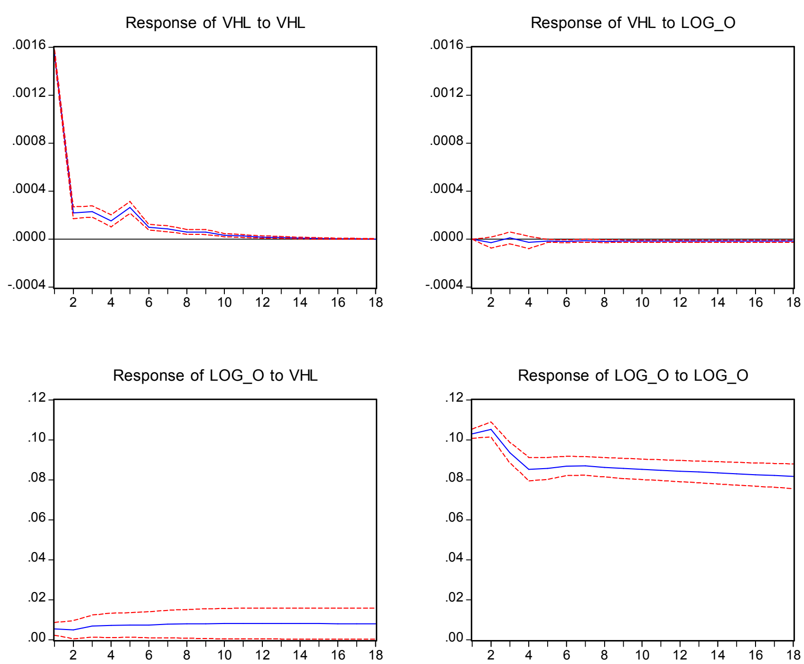


(10 Year Futures, with Active Contract Amount)

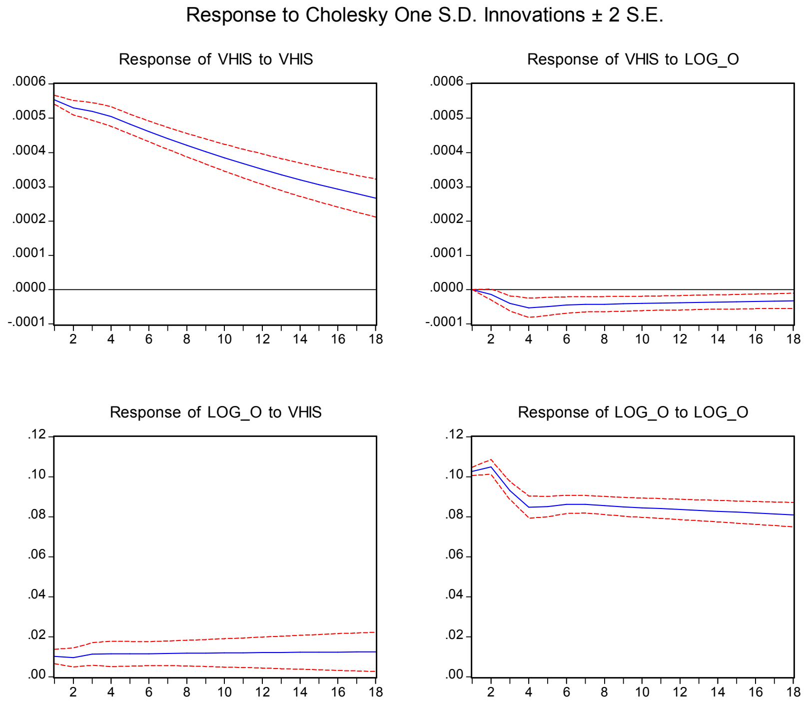
Response to Cholesky One S.D. Innovations ± 2 S.E.

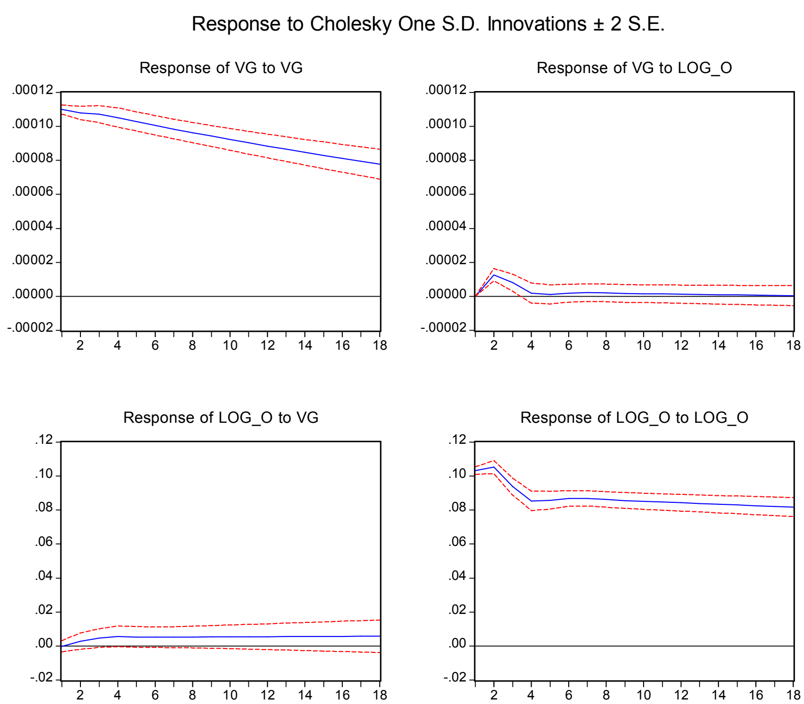


Response to Cholesky One S.D. Innovations ± 2 S.E.



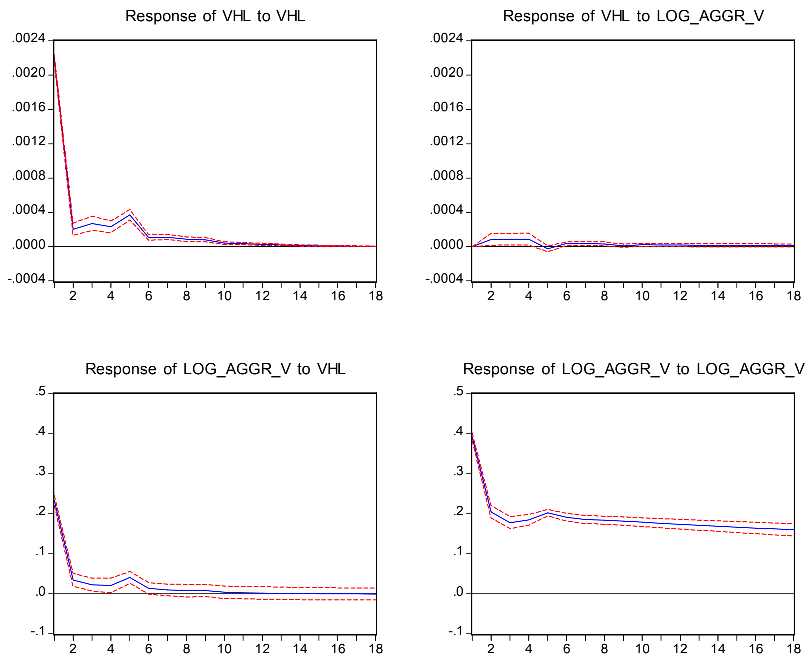
(10 Year Futures, with Active Contract Amount)



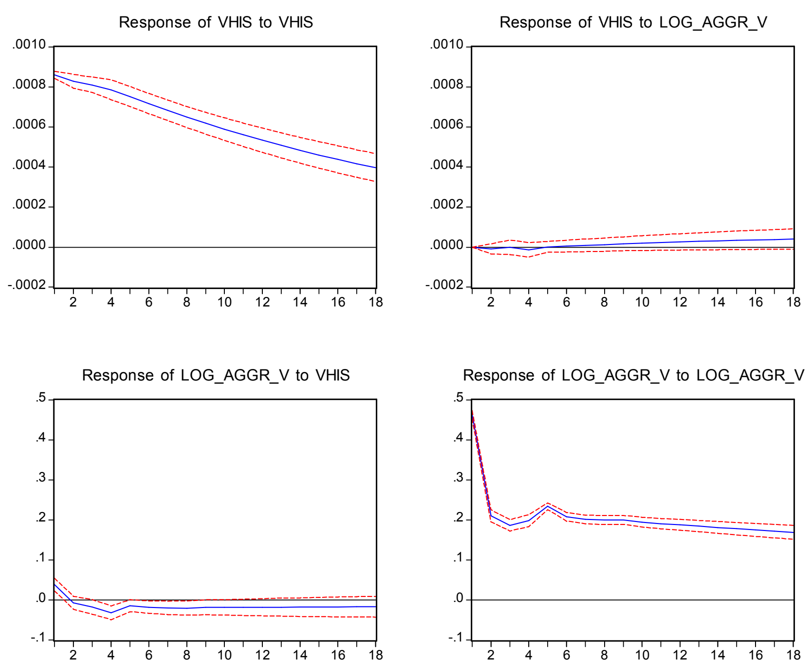


30 Year Futures, with Aggregate Amount

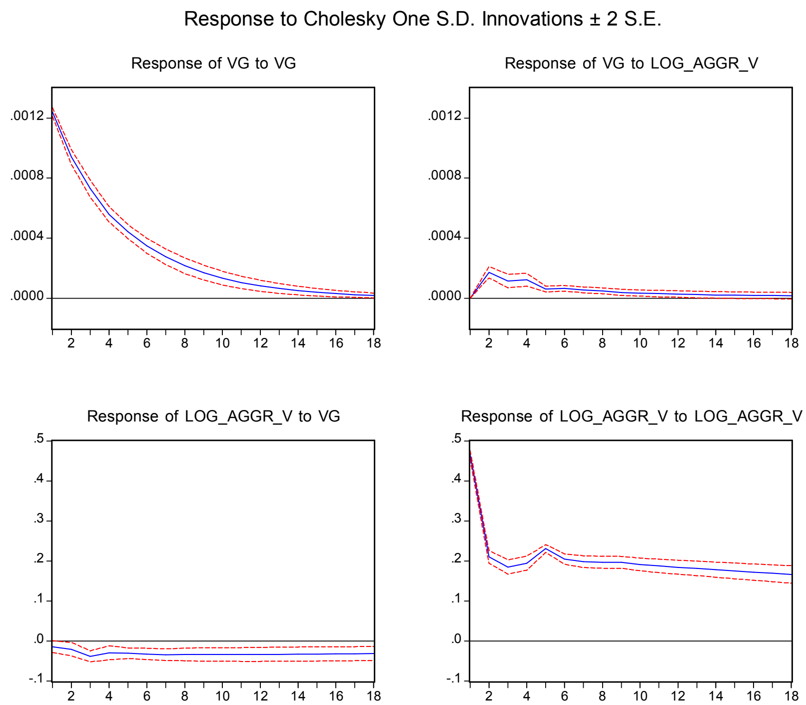
Response to Cholesky One S.D. Innovations ± 2 S.E.

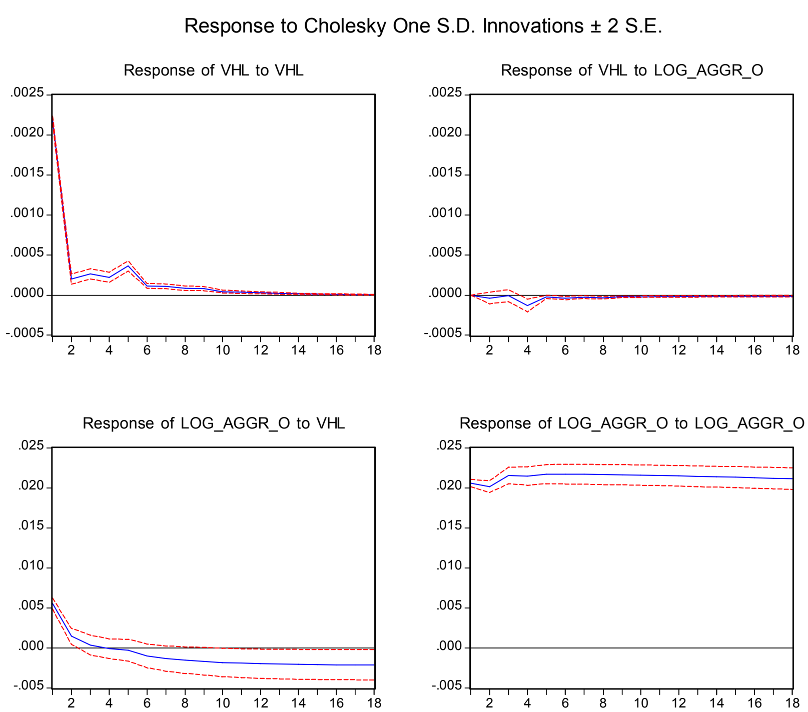


Response to Cholesky One S.D. Innovations ± 2 S.E.

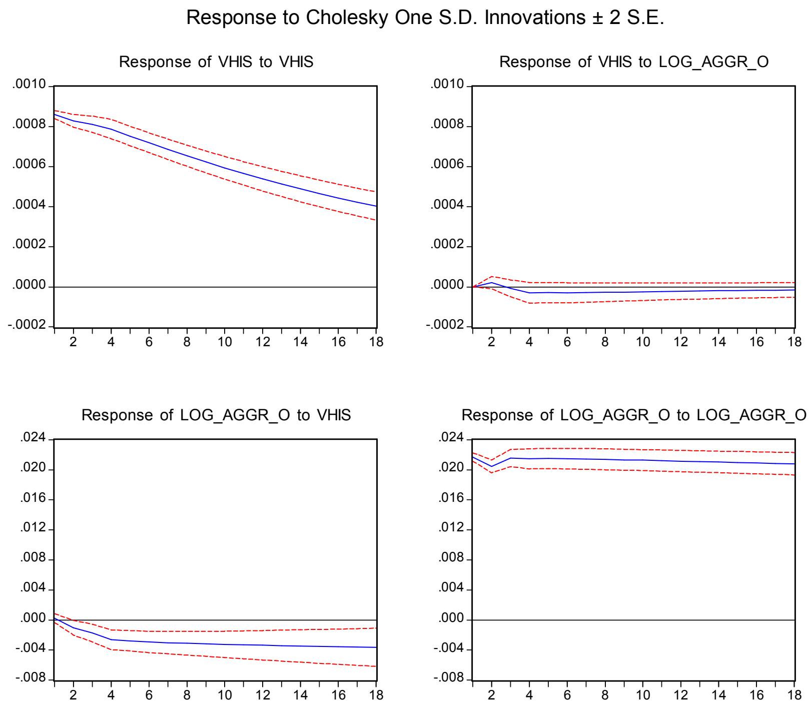


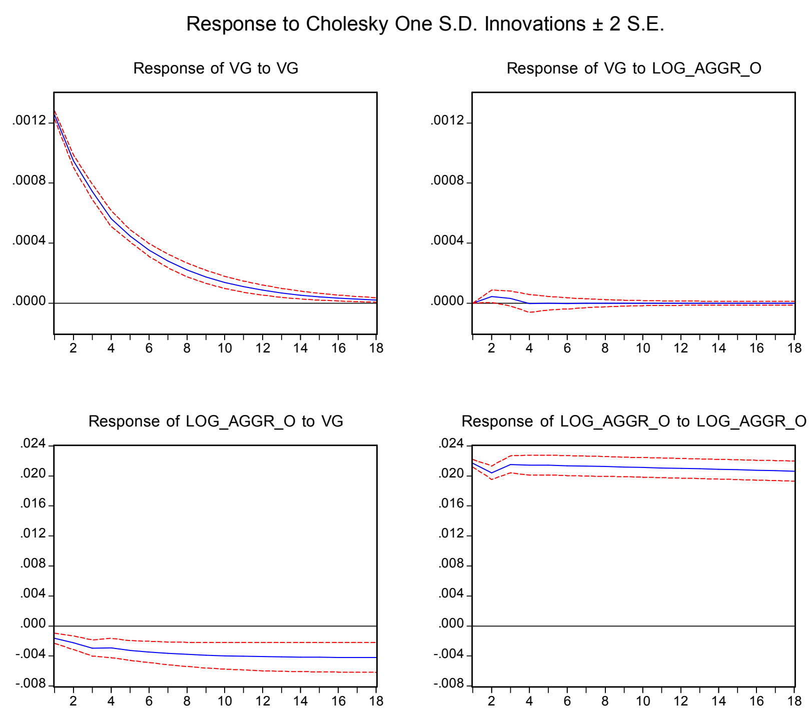
(30 Year Futures, with Aggregate Amount)



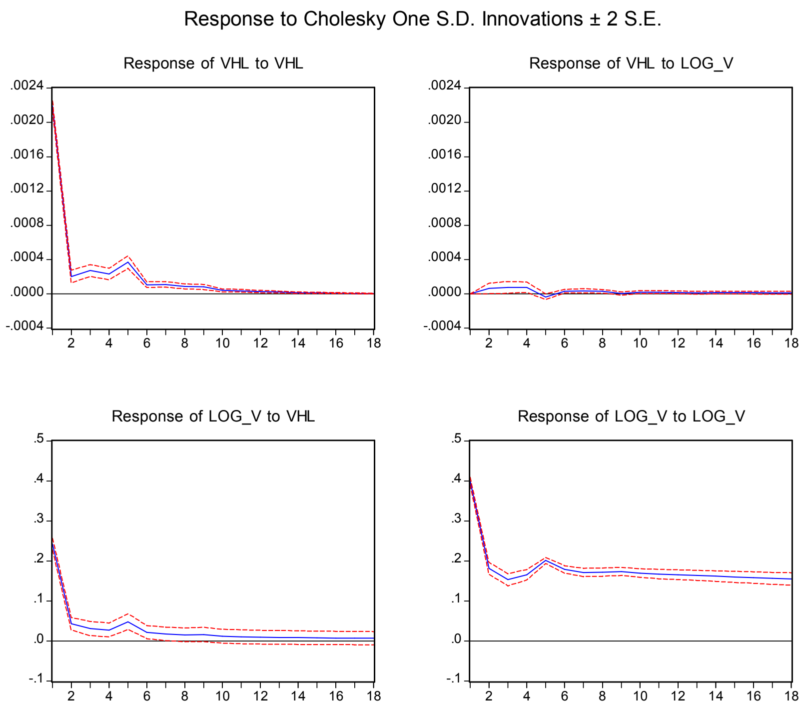


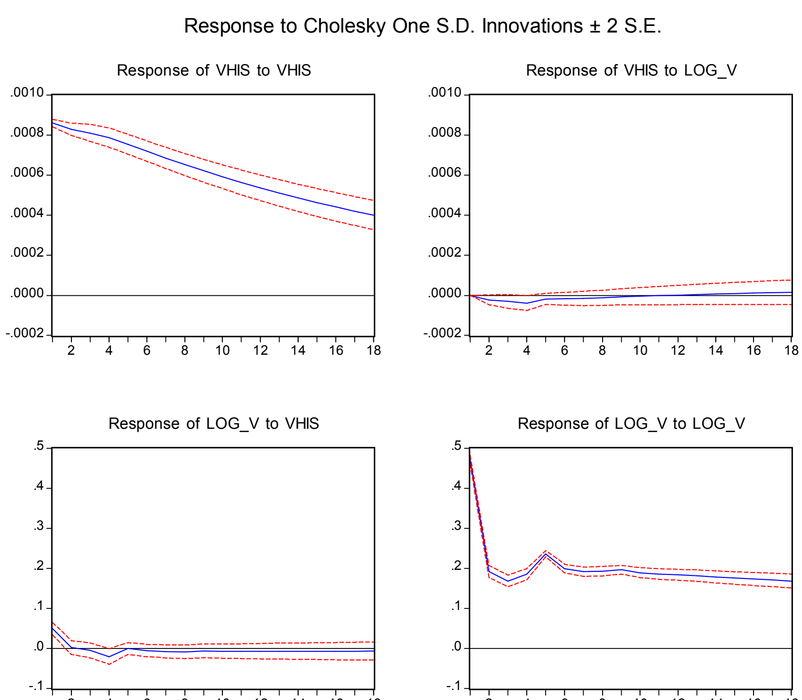
(30 Year Futures, with Aggregate Amount)



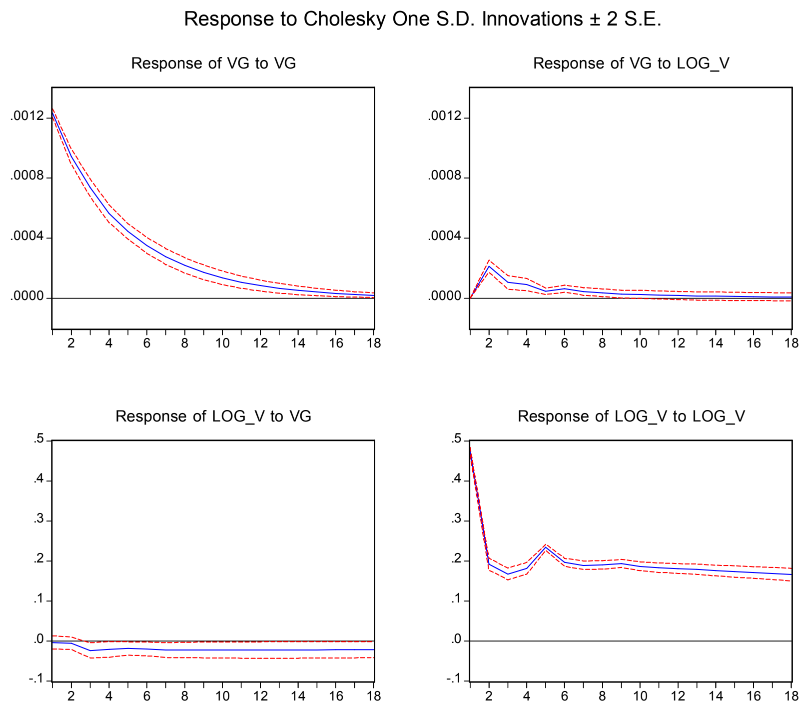


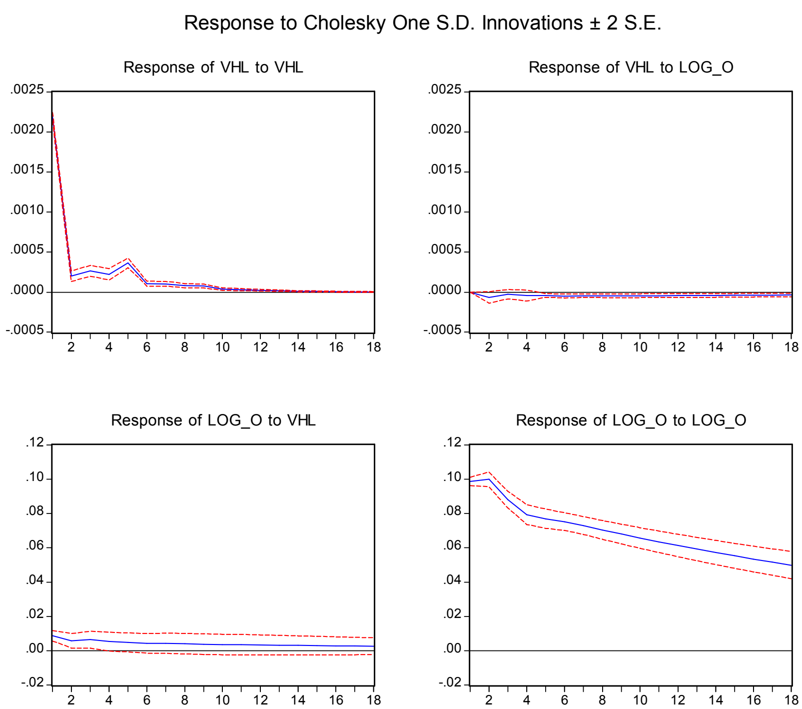
30 Year Futures, with Active Contract Amount





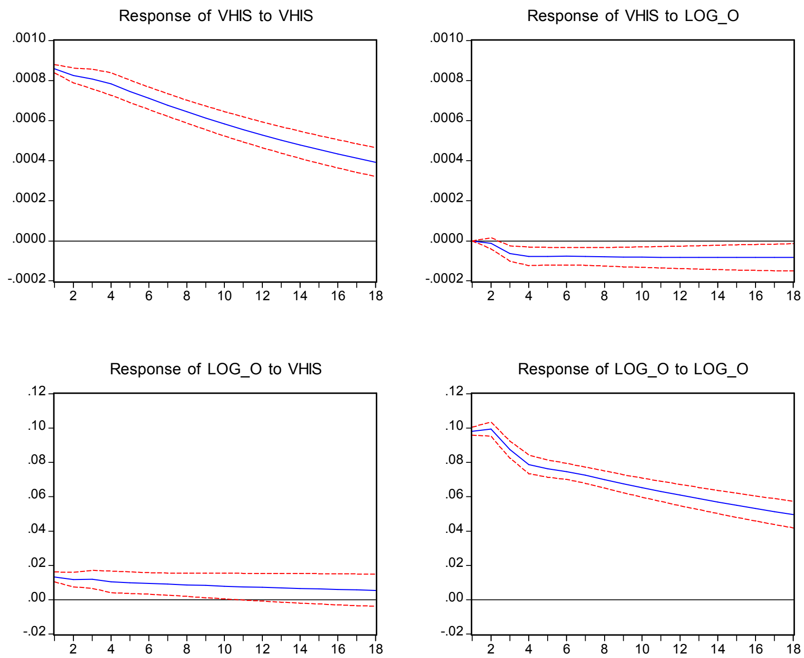
(30 Year Futures, with Active Contract Amount)





(30 Year Futures, with Active Contract Amount)

Response to Cholesky One S.D. Innovations ± 2 S.E.



Response to Cholesky One S.D. Innovations ± 2 S.E.

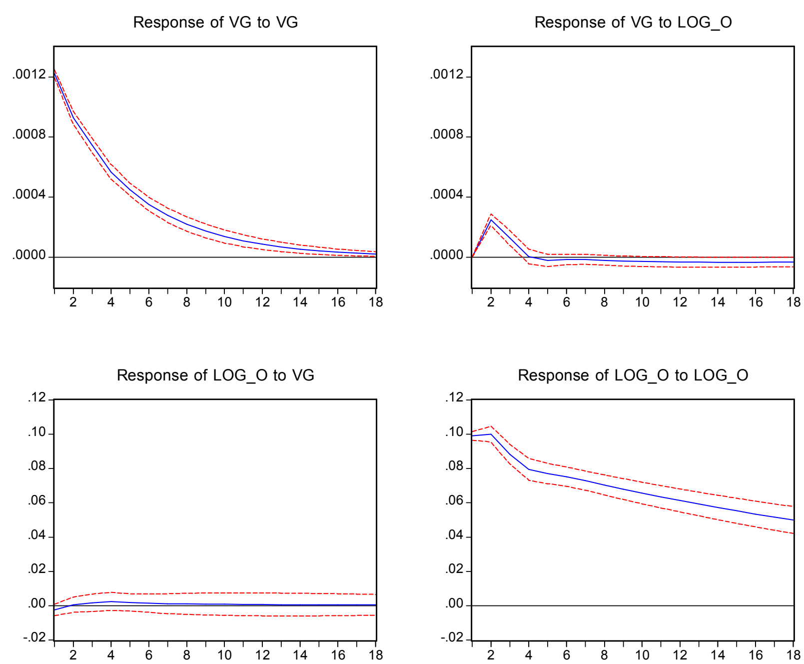


Figure 4: Log Amount Table

AMOUNT	LOG_AMOUNT	Difference
10	2.3026	
100	4.6052	2.3026
1000	6.9078	2.3026
10000	9.2103	2.3026
100000	11.5129	2.3026
1000000	13.8155	2.3026
10000000	16.1181	2.3026
100000000	18.4207	2.3026

Example: from e^9.21 to e^11.51		Difference
(2.72)^9.21	10054.94	
(2.72)^9.4	12160.40	2105.45
(2.72)^9.6	14854.62	2694.22
(2.72)^9.8	18145.76	3291.15
(2.72)^10	22166.09	4020.32
(2.72)^10.2	27077.14	4911.05
(2.72)^10.4	33076.28	5999.13
(2.72)^10.6	40404.56	7328.28
(2.72)^10.8	49356.48	8951.92
(2.72)^11	60291.76	10935.28
(2.72)^11.2	73649.83	13358.07
(2.72)^11.4	89967.47	16317.64
(2.72)^11.51	100435.69	10468.22

Figure 5: CBOT Volume-at-Price Sample Data

10 Year U.S. Treasury Notes Futures

Period: 01-Apr-2004 - 07-Apr-2004

ExchCode	Commodity	Year	Month	TradeDate	TradePrice	Volume
XCBT	ZN	2004	M	20040401	114245	962
XCBT	ZN	2004	M	20040401	114250	9098
XCBT	ZN	2004	M	20040401	114255	16930
XCBT	ZN	2004	M	20040401	114260	30506
XCBT	ZN	2004	M	20040401	114265	40882
XCBT	ZN	2004	M	20040401	114270	50284
XCBT	ZN	2004	M	20040401	114275	72556
XCBT	ZN	2004	M	20040401	114280	92958
XCBT	ZN	2004	M	20040401	114285	119182
XCBT	ZN	2004	M	20040401	114290	91650
XCBT	ZN	2004	M	20040401	114295	59134
XCBT	ZN	2004	M	20040401	114300	64438
XCBT	ZN	2004	M	20040401	114305	60848
XCBT	ZN	2004	M	20040401	114310	31560
XCBT	ZN	2004	M	20040401	114315	32210
XCBT	ZN	2004	M	20040401	115000	31490
XCBT	ZN	2004	M	20040401	115005	28426

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	0.008807		0.9702	
							(<.0001)*	(<.0001)*		(<.0001)*	
		2					5.4595E-6	0.006708	0.4883	0.0355	
							(<.0001)*	(0.4635)	(<.0001)*	(0.0397)*	
	2	**1**					1.7063E-7	0.008098		1.0530	-0.0804
							(<.0001)*	(<.0001)*		(<.0001)*	(<.0001)*
		2					4.8411E-6	0.002963	0.5152	0.0285	0.0660
							(<.0001)*	(0.7025)	(<.0001)*	(0.0553)	(0.0003)*
1	**1**	**1**	-0.0680				3.2554E-6	0.1083		0.5329	
			(0.0016)*				(<.0001)*	(<.0001)*		(<.0001)*	
		2	-0.0155				5.5085E-6	0.0121	0.4846	0.0274	
			(0.3024)				(<.0001)*	(0.2528)	(<.0001)*	(0.1168)	
	2	**1**	-0.0348				1.9775E-6	0.0269		0.9880	-0.2440
			(0.0735)				(0.0531)	(0.1157)		(0.0796)	(0.5829)
		2	-0.00686				4.8517E-6	0.007233	0.5156	0.0252	0.0649
			(0.6402)				(<.0001)*	(0.4407)	(<.0001)*	(0.0996)	(0.0004)*
4	**1**	**1**	-0.0612	0.0352	0.0334	0.0453	3.0967E-6	0.0973		0.5580	
			(0.0047)*	(0.0547)	(0.0894)	(0.0107)*	(<.0001)*	(<.0001)*		(<.0001)*	
		2	-0.007406	0.0678	0.0219	0.0505	5.4695E-6	0.007676	0.5145	0.0213	
			(0.6140)	(0.0003)*	(0.1336)	(<.0001)*	(<.0001)*	(0.4085)	(<.0001)	(0.1649)	
	2	**1**	-0.0300	0.0465	0.0423	0.0454	8.4009E-6	0.006025		7.1702E-6	-1.28E-11
			(0.0923)	(0.0033)*	(0.0119)*	(0.0027)*	(0.1225)	(0.6017)		(1.0000)	(1.0000)
		2	-0.0300	0.0465	0.0423	0.0454	7.6523E-6	0.0246	0.0256	1.208E-13	7.8849E-7
			(0.1023)	(0.0053)*	(0.0090)*	(0.0020)*	(<.0001)*	(0.0619)	(0.0110)*	(1.0000)	(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	-5.32E-23		9.9868E-7	
							(<.0001)*	(1.0000)		(<.0001)*	
		2					0.0000124	0.000552	0.3849	0.0192	
							(<.0001)*	(0.9461)	(<.0001)*	(0.2902)	
	2	**1**					0.0000175	8.6554E-7		1.6691E-6	6.7122E-7
							(<.0001)*	(0.9999)		(1.0000)	(1.0000)
		2					0.0000109	3.626E-21	0.4059	0.0175	0.0781
							(<.0001)*	(1.0000)	(<.0001)*	(0.2523)	(0.0012)*
1	**1**	**1**	-0.0276				4.1394E-7	0.008139		0.9686	
			(0.1415)				(0.0006)*	(<.0001)*		(<.0001)*	
		2	-0.0153				0.0000125	0.001745	0.3816	0.0146	
			(0.3150)				(<.0001)*	(.8373)	(<.0001)*	(0.4617)	
	2	**1#**	-0.0269				3.4493E-7	0.006860		1.1435	-0.1697
			(0.1488)				(0.0004)*	(<.0001)*		(<.0001)*	(<.0001)*
		2	0.000402				0.0000109	-3.92E-21	0.4061	0.0176	0.0781
			(0.9773)				(<.0001)*	(1.0000)	(<.0001)*	(0.2725)	(0.0013)*
4	**1**	**1**	-0.0235	0.0406	0.0437	0.0611	3.8868E-7	0.008783		0.9695	
			(0.2117)	(0.0222)*	(0.0238)*	(0.0006)*	(0.0003)*	(<.0001)*		(<.0001)*	
		2	-0.0117	0.0237	0.0351	0.0649	0.0000126	0.000180	0.3966	-2.45E-11	
			(0.4078)	(0.2437)	(0.0157)*	(<.0001)*	(<.0001)*	(0.9691)	(<.0001)*	(0.9996)	
	2	**1**	-0.0206	0.0409	0.0430	0.0522	0.0000173	0.001626		6.5792E-6	1.208E-12
			(0.2308)	(0.0084)*	(0.0104)*	(0.0007)*	(0.7027)	(0.8656)		(1.0000)	(1.0000)
		2	-0.0206	0.0409	0.0430	0.0522	0.0000156	0.0157	0.0420	1.079E-13	9.5071E-7
			(0.2531)	(0.0185)*	(0.0083)*	(0.0005)*	(<.0001)*	(0.1532)	(0.0001)*	(1.0000)	(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.

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