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MACROECONOMIC ANNOUNCEMENTS AND VOLATILITY OF  
TREASURY FUTURES

BY

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# MACROECONOMIC ANNOUNCEMENTS AND VOLATILITY OF TREASURY FUTURES<sup>1</sup>

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## Abstract

Utilizing open-close returns, close-close returns and volume data, we examine the reaction of the Treasury futures market to the periodically scheduled announcements of prominent U.S. macroeconomic data. Heterogeneous persistence from scheduled news vs. non-scheduled news is revealed. Strong asymmetric effects of scheduled announcements are presented: positive shocks depress volatility on consecutive days, while negative shocks increase volatility. Announcement-day shocks have small persistence, but great impacts on volatility in the short run. Investigation into volume data shows that announcement-day volume has lower persistence than non-announcement-day volume. No statistically significant risk premium manifests on the release dates. Compared with the implied volatility and realized volatility data, we find our model successful in forming both in-sample and out-of-sample multi-step forecasts. Distinctions are made and tested among microstructure theories that differ in predictions of the impact of scheduled macroeconomic news on volatility and volatility persistence. Asymmetric effects between positive and negative shocks from scheduled news call for further exploration of microstructure theory.

*JEL classification:* C32; G12; G13; G14

*Keywords:* Volatility; Implied Volatility; Information; Announcements; GARCH; Risk

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"Among the most puzzling issues is the behavior of volatility, while the general properties of volatility remain elusive, the most intriguing feature revealed by empirical work on volatility is its long persistence. Such behavior has sparked a search, almost akin to that for the Holy Grail, for the perfect GARCH model, but the underlying question of why such volatility persistence endures remain unanswered." (Goodhart and O'Hara,1996)

## I. INTRODUCTION

The fact that volatility in financial markets is correlated over time has been well documented in financial literature<sup>2</sup>. In contrast with the remarkable progress made in modeling the autocorrelated volatility process empirically, relatively little is known about why financial market volatility is autocorrelated.

Various theories have been provided as explanations of the volatility autocorrelation. The difficulty in distinguishing the true reasons lies in the fact that we do not directly observe information arrivals, nor can we measure the information content of news accurately. Analysis of public announcement effects provides a good starting point for the solution of this question. Macroeconomic announcements are known to drive up return volatility on the announcement days, e.g. Harvey and Huang (1991) and Ederington and Lee (1993). Besides the known type and risk, the timing of macroeconomic announcements is exogenously predetermined. Most macroeconomic news is released once a month, thus, the arrivals are neither in clusters, nor positively related. The announced macroeconomic news is instantaneously available to all traders. Moreover, the periodically released news is widely expected. Some empirical work<sup>3</sup> has shown that the market anticipation of the macroeconomic data is unbiased. These features of macroeconomic announcements would lead to a different incorporating process than

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<sup>2</sup> For an earlier discussion, see Fama (1970), and for a comprehensive survey of recent work, see Bollerslev, Chou and Kroner (1992).

private information or information of poor quality. As a result, we would expect heterogeneous persistence of volatility immediately following the announcement.

In the case of Treasury bonds, in which cash flows are fixed in nominal terms and the underlying variables likely to be relevant for pricing are those that characterize the general macroeconomic environment. Unlike with stocks or corporate bonds, there is little, if any, asset-specific information concerning T-bonds. Contrary to the findings of French and Roll (1986) and Stoll and Whaley (1990), that private information is the dominant factor in stock return volatility, Ederington and Lee (1993) point to the public announcements as a major source of price volatility in the T-bond market. Fleming and Remolona (1997) conclude, “public information clearly plays the dominant role in the bond market, precisely because much of the relevant information is revealed to the public at large by means of the regularly scheduled announcements.” Compared with stock markets, studying how T-bond markets process scheduled announcements provides more straightforward evidence for market efficiency, volatility persistence, and the size and the speed of market adjustment to news. The understanding of the T-bond market’s response to macroeconomic announcements -- a major source of price volatility -- is also crucial to the volatility forecast of the T-bond market. In the hope of shedding some light on the sources of persistence in asset price volatility, this paper studies how public information about macroeconomic fundamentals moves prices of T-bond futures.

In the few studies of market reaction to announcements in terms of volatility, market expectations are rarely used. Conditional volatility incorporates information already available to the market, and ARCH models provide approximates of conditional

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<sup>3</sup> For examples, see Pearce and Roley (1985) and Balduzzi, Elton and Green (1996).

volatility for a wide variety of volatility processes<sup>4</sup>. Jones, Lamont and Lumsdaine (1998) (hereafter JLL) examine the reaction of conditional volatility implied by ARCH models to the news release in the Treasury bond cash market. They find a risk premium on the release dates and a lack of persistence of announcement-day volatility. Their evidence supports the mixture of distribution hypothesis (MDH), *i.e.* volatility persistence stems from clustering information arrival. In this paper, we follow JLL's insightful analysis to focus on conditional volatility within a generalized ARCH framework and to decompose volatility on announcement days into two parts, transitory and non-transitory.

This study reveals heterogeneous persistence from scheduled announcements vs. non-scheduled announcements. Further in this research, we distinguish negative shocks from positive ones and investigate their effects separately. Evidence suggests that positive shocks on announcement days depress volatility on successive days, while negative shocks on announcement days increase volatility. We find announcement-day volatility plays a substantial role in short-term volatility forecasts. This is contrary to JLL's findings that the announcement-day shocks do not have subsequent impact on daily volatility. We then extend our research to volume data and find that announcement days have higher volume and less volume persistence. In contrast with the findings of JLL, our study on the volatility and volume data indicates the inadequacy of the mixture of distributions hypothesis in explaining volatility persistence, and we do not find strong evidence that the scheduled announcement increases the expected open-close daily return significantly. Our findings do show support of the view that the market learns the content of scheduled announcements more quickly. In this paper, we make a first attempt at incorporating

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<sup>4</sup> See Nelson (1990) and Nelson and Foster (1994).

survey data as market expectation, along with the knowledge of the timing of scheduled announcements, into a GARCH model in forming market participants' volatility expectations. Compared with the implied volatility and realized volatility data, we find our model successful in forming both in-sample and out-of-sample multi-step forecasts. Although we focus our research on Treasury bonds since public information plays the dominant role in the bond market, the research presented here leads us to believe that we provide a general approach, which could be applied to modeling heterogeneous news impacts on volatility for other financial instruments.

The paper is organized as follows: in section II, we discuss related theory and propose a few hypotheses to test in our empirical work. In section III, we describe the data, while in section IV we provide preliminary analysis. In section V, we develop models of daily conditional volatility persistence. In section VI, in-sample and out-of-sample forecasts are conducted and evaluated. Section VII presents conclusions and suggestions for future work.

## **II. THEORY AND HYPOTHESIS**

One appealing theory explaining the positive autocorrelation of volatility is the mixture of distribution hypothesis (MDH) proposed by Clarke (1973) and Harris (1987). This model assumes that individual price changes and the trading size are instantaneous responses to information arrivals. Volatility and volume are jointly distributed as a function of the time dependent mixing variable - the rate of information arrival. Therefore, if the news arrives in clusters, we would expect financial markets to exhibit positively autocorrelated volatility. Ederington and Lee (1993), Mitchell and Mulherin (1994) and

Berry and Howe (1994) suggest the number of news items reported in a given period a meaningful news measure. Utilizing the dataset collected by Mitchell and Mulherin, JLL find evidence of positive and statistically significant autocorrelation in the news generating process at daily frequencies. Most macroeconomic news is released once a month, but there is a possibility that policymakers may react to the news after some delay. JLL find no evidence that the Fed target changes are more likely to occur on days immediately following announcement days. Therefore, the news arrivals are neither in clusters nor positively correlated in this case. If as claimed, the public announcements play a dominant role in the bond market and the clustering of news arrival is the sole underlying reason, we would not expect conditional volatility or volume to be positively correlated shortly after an announcement. Also, we would expect to see the market react to news instantaneously, thus reaching a new equilibrium without triggering higher volume on announcement days.

The sequential information model (SIM) suggested by Copeland (1976) assumes that new information is not simultaneously received by all the traders in the market, and it is the different degrees of information that traders have that generates volume. In the case of a macroeconomic announcement, the content is immediately available to the public, but the true implication of the news may not be. Once new information arrives at the market, a series of trades take place, representing many incomplete equilibria. The market will reach equilibrium when all traders finally have received the information. Thus, SIM suggests higher volume after the news arrivals as well as a stronger autocorrelation structure for both volatility and volume.

Blume, Easley and O'Hara (1994) stipulate a market consisting of informed and uninformed traders. Traders receive information with differing precision and quality,



informed traders reveal their private information to the market through trades, and all traders condition their price expectation on the past trades. Prices alone do not contain the full information; volume yields additional information on the precision and dispersion of an information signal. This is contrary to the limitation of SIM that uninformed traders can not infer the new information signal from informed traders' actions. When prices are noisy and do not fully reveal all of the traders' information, the convergence to a consensus price is slow, hence, volume and volatility persist even when the arrival of information does not. In He and Wang's (1995) model, differently informed investors trade for several rounds after they receive information; in Brock and LeBaron's (1995) model, learning gives rise to positively autocorrelated volatility when fundamentals follow a homoskedastic random walk. This line of research (referred to as the learning model throughout this paper), suggests that the more widely an information signal is perceived and the higher the precision of the signal, the smaller the probability of making profitable trades due to private information. Thus the new equilibrium will be reached faster and the persistence of volatility and trading volume will be lower.

In particular, Kim and Verrecchia (1991a) (hereafter KV) analyze how the anticipation of a forthcoming public announcement affects the market reaction to that announcement. In the pre-announcement period, investors trade based on common prior beliefs as well as private signals with different levels of precision. By forcing investors to revise their expectations, a public announcement creates the incentive for them to endogenously acquire private information. They conclude that information asymmetry is greater when imperfect disclosure is anticipated than when either a perfect announcement or no announcement at all is anticipated. Meanwhile, they point out that the variance of

the price change is greater for a more precise announcement. Also, they claim that if the average precision of pre-announcement information acquisition is low, the price reaction at the time of disclosure will be strong. They confirm the intuition that a price change reflects the average change in investors' beliefs due to the arrival of information, whereas volume arises due to differential belief revisions. An important feature in their model is that the ratio of volume to the absolute value of price change is a measure of the market's information asymmetry. KV (1991b) suggest that the average magnitude of market reaction differ with different types of announcements.

Compared with unscheduled interest rate news and policy announcements, DeGennaro and Shrieves (1997) find the regularly scheduled macroeconomic news releases result in a dramatic increase in the forex rate volatility. We study a subset of macroeconomic news announcements that cause significant belief revisions in this paper. MDH assumes the market clears instantaneously, hence there is no significant increment in volume on announcement days and no positive autocorrelation in volatility after a news disclosure. Though macroeconomic news is observed with high precision, its implication is nevertheless imperfectly revealed at the disclosure. Also the news impact is unlikely to dominate all beliefs and thus eliminate trading opportunities. SIM allows traders to understand the implication of news at different degrees but prevents traders from learning; it predicts stronger autocorrelation of volatility and volume after news arrival along with higher volume. The learning model suggests lower persistence in volatility and volume after the macroeconomic announcement. According to KV, the variance on the announcement day would be higher than average, the information asymmetry (ratio of volume to the absolute value of price change) would be lower on announcement days

while higher on pre-announcements days. Their work prompts two other hypotheses that the market reacts differently to good news versus bad news and that the market reacts more strongly to big shocks (when the average precision of pre-disclosure information is lower). In summary, these theories provide testable hypotheses. We will proceed to test them and incorporate the results in forming our own volatility forecasts.

### **III. DATA**

#### **A. Futures data**

The previous literature shows evidence that the futures market leads the cash market in its reaction to news. Thus, it is more interesting and relevant to study the futures market than the cash market. The US T-bond future is the most heavily traded long-term interest rate contract in the world. The T-bond contract, which calls for delivery of a US Treasury bond with fifteen or more years to maturity, possesses a March, June, September and December delivery cycle. During March, the prices of the June contract are taken for the continuous series until the first business day in June, when the September contract takes over even if the June contract is still trading. It has both a day and a night session. The night session was instituted for the Japanese market and operates when the cash bond market is closed in the United States. Most volume occurs during the day session, which is traded at the Chicago Board of Trade (CBOT). There are more than 1,000 registered traders in the market. As for the cash market, primary dealers conduct the majority of trades. Daigler (1997) indicates that a large portion of the trades in the futures market is traded as a hedge by traders in the cash market. This suggests a low noise level in the futures market as well. On November 7, 1988, CBOT moved the trade starting time

of T-bond futures from 9:00 <sub>AM</sub> Eastern time to 8:20 <sub>AM</sub> Eastern time, allowing one to better determine the effect of the macroeconomic public announcements made at 8:30 <sub>AM</sub> Eastern time. Until 1988, there was a clear upward-sloping trend in the trading volume of the T-bond futures, and the volume has stabilized since then.

In this study we use the daily data of the T-bond futures day session obtained from Data Stream. The data set begins November 9, 1988 and ends December 31, 1997.

#### B. Announcement data

Announcement effects of the consumer price index (CPI) are among those most frequently identified as significant in the bond market<sup>5</sup>. Announcements of the producer price index (PPI) have effects at least as significant as those of CPI, which have been documented by Ulrich and Wachtel (1984), Dwyer and Hafer (1989), McQueen and Roley (1993), Harvey and Huang (1993), JLL (1998) and Edison (1996). The recent studies by Cook and Korn (1991), Krueger (1996) and Edison (1996) emphasize the importance of employment numbers since the late 1980s. The sample of JLL runs from October 9, 1979 to December 31, 1993, and they find strong evidence that releases of employment data have an effect on bond cash market volatility. In this study we focus our interest on CPI, PPI and employment announcements. With only one exception, the employment report is issued on Friday. The PPI data is mostly issued on Thursday and Friday, while the CPI announcement is made almost evenly from Tuesday to Friday. For the time period we study, no announcements were observed on Mondays.

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<sup>5</sup> See for examples, Hardouvelis (1988), McQueen and Roley (1993), Harvey and Huang (1993), Becker, Finnerty and Kopercky (1996) and Edison (1996).

### C. Survey data

Theory suggests that it is the surprise in the announcement to which the market reacts. We are interested in testing whether big shocks cause different volatility persistence following the major announcements. The data on expectations are from Money Market Services (MMS), a San Francisco-based company, which has conducted telephone surveys normally one week or less before any news release since late 1977. Pearce and Roley (1985) find MMS forecasts unbiased and efficient. Balduzzi, Elton and Green (1996) conclude that the expectation-revision between the time of the survey by MMS and the time of the announcement does not substantially affect measure of surprise, and that the MMS survey data is an accurate representation of the consensus expectation in the market. We calculate the innovations by the difference between the survey and actual data. The unbiasedness cannot be rejected at the 5% level of significance for all of the data. To test for efficiency, we regress those shocks on the lagged values of all the announced data, and the coefficients are found to be insignificantly different from zero.

## IV. PRELIMINARY ANALYSIS

Table 1 gives summary statistics for open-close percentage returns. The mean of returns on the announcement days is higher than that of non-announcement days. Measured in both absolute value of the returns and square of the returns, the T-bond futures market volatility is far higher on release dates than on non-release dates. Taking a closer look at individual releases, we find that the mean of returns is higher only on PPI release dates than on non-announcement days, while on CPI and unemployment release dates, the mean is actually lower. Running an OLS regression on a dummy variable for

announcement day reveals a positive but statistically insignificant effect of announcements on expected open-close returns. Meanwhile, with no exception, volatility on all three kinds of release dates is much higher. Neither the level of returns nor the volatility exhibits positive autocorrelation in this dataset.

We turn next to simple OLS regressions for exploration of the relationship of announcement dates and return volatility proxies as well as investigation of the day-of-the-week effects on volatility. Table 2 documents the results. On announcement days, volatility is higher than average and statistically significant; this confirms that disclosure of news causes a shift in the fundamental asset values. If the full price implications of the information take longer than one day for the market to incorporate, we should expect consecutive shifts of the asset values, so days immediately following announcements would exhibit higher than average volatility as well. Table 2a shows the evidence against this hypothesis: post-release days actually have lower than average volatility, though not significantly. Reports that financial markets are particularly quiet on the days prior to these announcements are commonplace in such financial press as the Wall Street Journal. This phenomenon, called “calm before the storm” effect by JLL, is evident in Table 2a.

Volume and the ratio of volume to the absolute value of return data cast further light on market activity around announcements. On announcement days, we detect from Table 1 that volume shoots up. However, the volume-absolute-return ratio, as a measure of the information asymmetry, declines. The regression coefficients in Table 2a depict the same picture. The heightened volume on announcement days, which is again manifest in the coefficient of the dummy variable for announcement days in Table 2b, suggests that the new equilibrium is not reached instantaneously - a violation of the assumption of

MDH. The evidence presented here could be interpreted as the public announcement helping to dampen but not eliminate the asymmetry of private views. Apparently in Table 1a, volume is strongly autocorrelated, and Table 2b confirms this finding. Nevertheless, we find the persistence of volume is significantly lower after a macroeconomic announcement, which is in contrast to SIM but in favor of the learning model.

Table 2a shows that for the days following releases, volume is significantly lower. The volume-absolute-return ratio<sup>6</sup> is higher but statistically insignificant, which could be due to a few days with very low absolute returns. Judging from the median of the ratio data, we find that the ratio is actually lower on post-release days than on average days. On the pre-release days, volume declines insignificantly. In line with KV's argument, the ratio -- a measure of information asymmetry -- is significantly higher pre-release, which could explain the "calm before the storm" effect.

We further check the market activity for days following those releases that contain big shocks. A big shock is when the absolute value of the shocks is bigger than its standard deviation. Contrary with findings on average post-release days, we notice from Table 2a that on post-big-shock days there are small increases in terms of both absolute value of return and squared return, though both are statistically insignificant. This hints that volatility displays different behavior after a big shock, as suggested by KV. On days following a big news surprise, there is still a big drop in volume and thus, a decrease, though an insignificant one, in the volume-absolute-return ratio.

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<sup>6</sup> Days with zero  $R_t$  are deleted when calculate the ratio, announcement days have unproportionally low share among them.

The preliminary analysis so far suggests that the impact of disclosure is prevailing but not dominant enough to drive all beliefs to convergence immediately. News arrival clustering is unlikely to be the sole reason for the persistence of volatility in the T-bond futures market. Meanwhile, the evidence so far is in contrast to SIM but in favor of the KV model and the learning model.

Unlike the cash market, traders in the futures market take highly leveraged positions. Hence, we may observe the leverage effects documented in previous literature--bad news causes larger persistence of the increment in volatility. There could also be a volatility-feedback effect: traders demand higher future returns due to the increase of volatility, thus, price is pushed down and persistent high volatility is observed. KV's work also suggests asymmetry in volatility persistence corresponding to bad news vs. good news. Bad news, defined as news that lowers the returns, lifts the consecutive days' volatility, but with very small magnitude. However, there is distinct difference between bad news and good news from announcement-days. Compared with average non-announcement days, good news from news release days reduces successive days' volatility, while bad news increase successive days' volatility. We further examine whether bigger news produces a greater difference. News corresponding with returns lower than the 33% quantile ( $<0$ ) is denoted as big negative news; news corresponding with returns higher than the 67% quantile ( $>0$ ) is denoted as big positive news. A greater difference is shown for both open-close and close-close volatility data. For instance, the mean and median for absolute close-close returns on days after big positive news are 0.27 and 0.20 respectively, while on days after big negative news are 0.42 and 0.37 respectively and for average non-announcement days are 0.38 and 0.29. The volume-absolute-return



ratio data shows that information asymmetry is slightly higher on days after bad news than on days after good news, while the difference is much more prominent on days after macroeconomic announcements.

Previous studies provide voluminous evidence for the day-of-the-week effects on return volatility. A clear U-shaped curve over the week is not present in the Futures market as it is in the cash market. Table 2c indicates that volatility is higher on Thursdays and Fridays, compared with Mondays. We also run an OLS regression with the combined set of independent variables from Table 2a and Table 2c. The coefficients on variables appearing on Table 2a maintain the same signs and significance. However, Tuesday is no longer significant and the coefficients for Thursday and Friday are both positive, significant, and with similar size.

Compared with open-close return data, close-close return data shows similar patterns in preliminary analysis. For the regression of close-close return volatility, the coefficient for the dummy variable of days following announcements is negative, but unlike the case of open-close returns, it is significant. Close-close returns are more subject to influence from the quarterly switch from one future contract to another. Statistics shows that on the switching days returns are lower while variances are higher.

## **V. MODELING CONDITIONAL VOLATILITY**

### **A. GARCH models**

The GARCH(1,1) model proposed by Bollerslev (1986) has been widely used to model financial asset return volatility and has become a benchmark. We start this section by estimating a univariate GARCH(1,1) model with results reported in Table 3. We then

run modified GARCH(1,1) models by adding dummy variables for days around announcements and also dummy variables for day-of-the-week effects linearly into the variance equation. The modified GARCH(1,1) models could be expressed as follows:

$$(1) \quad r_t = c + \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$(2) \quad h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta_1 I_t + \delta_2 I_{t-1} + \delta_3 I_{t+1} + \delta_4 D_4 + \delta_5 D_5$$

where  $\Phi_{t-1}$  represents the information set available at the end of day t-1.  $D_4$  and  $D_5$  are dummy variables for Thursday and Friday respectively;  $I_t$  denotes the dummy variables for announcement days.  $I_{t+1}$  indicates pre-announcement days, while  $I_{t-1}$  represents post-announcement days.

We first include a dummy variable for the announcement day. As reported in Table 3, announcement days appear to significantly increase the conditional volatility and the log likelihood is considerably higher, however, the ARCH and GARCH effects become insignificant. Inclusion of dummy variables for pre-announcement days and post-announcement days produce another increase in log likelihood, while exhibiting significant coefficients for all dummy variables along with positive and significant ARCH and GARCH terms. Days prior to news disclosures show significantly lower conditional variance. Though days following announcements also present a significantly negative sign, the interpretation here is somewhat different. The negative sign here does not necessarily mean that these days have lower than average conditional volatility. The more probable reason for the negative sign is that a spike in the conditional variance on the announcement day does not carry over to the next day, and the negative coefficient offsets the persistent increment suggested by the significantly positive GARCH term. We further put dummy variables for Thursday and Friday, all the other terms in the variance equation

retain the same signs and change little in size. After controlling for announcement-day effects, Thursdays appear to have significant positive effects on volatility while Fridays do not. Due to the persistence found in both positive ARCH and GARCH terms, Thursdays' heightened volatility and conditional volatility have been incorporated into and help to push up the successive Fridays' conditional volatility, so that Friday-effects may be underestimated in this linear GARCH equation. If one does not control for announcement-day effects, both Thursdays and Fridays push up conditional volatility, however, the ARCH effect becomes insignificant while the GARCH effect is significantly diminished.

An interesting question is why the once highly significant ARCH effect disappear when we add in the linear dummy variable for announcement days or dummy variables for Thursday and Friday. The announcement effects on days around the release and the day-of-the-week effect cause structural breaks in conditional volatility. As pointed out by Andersen and Bollerslev (1997), the standard GARCH models imply a geometric decay in the volatility autocorrelation structure and cannot accommodate strong regular cyclical patterns. Hence, it will not be appropriate to use the benchmark GARCH (1,1) model to describe day-of-the-week effects and the announcement effects around disclosure days. We hypothesize that the volatility on announcement days has two components. One is transitory due to the shift of beliefs caused by the disclosure; the other one is non-transitory (persistent) due to the gradual convergence of beliefs supported by our findings in volume data. If the transitory component dominates, we will not be able to find any persistence with the standard GARCH framework. Without announcement clustering in the market and without continuous substantial belief shifts, consecutive big price

movements on the days after announcement are theoretically unlikely. Using tick data, Ederington and Lee (1993) and Becker, Finnerty and Kopecky (1997) document that major price shifts in the T-bond futures market occur within 15 minutes of the announcement. Becker et al. go on to conclude that the price changes which occur later on that day are independent of what happens within 15 minutes after the release. This, along with the evidence in our preliminary study, supports our hypothesis. The standard GARCH model does not suit our purpose of studying persistence of conditional volatility after announcements, so that decomposition of the variance is thus required.

#### B. GARCH models with filters

An appropriately designed filter may take care of cyclical patterns of day-of-the-week effects and announcement effects that we find here and may also remove the transitory part in volatility on the announcement days. Then only the non-cyclical and non-transitory part of volatility enters the GARCH equation.

Since preliminary analysis indicates asymmetry in volatility persistence from bad news versus good news, we test the asymmetric effects in the model. Letting  $r_t$  denote the daily open-close return, a filtered GARCH model can be expressed as follows:

$$(3) \quad r_t = c + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$(4) \quad F_t = (1 + \rho_1 I_t)(1 + \rho_2 I_{t-1})(1 + \rho_3 I_{t+1})(1 + \rho_4 D_4)(1 + \rho_5 D_5)$$

$$(5) \quad h_t = \bar{\omega} + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma_{t-1}^- \varepsilon_{t-1}^2$$

where  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise. The sign of  $\rho$  allows us to compare days of interest directly with average days, and there will be no ambiguity in judging announcement effects on the days following releases as well as the Friday effect. If the

shift in traders' beliefs is transitory, we will expect an insignificant  $\rho_2$ . Also, if there is indeed asymmetry in volatility persistence, we will expect a significant  $\gamma$ .

Table 4 demonstrates results from this model.  $\rho_2$  is insignificantly negative, so shifts in traders' beliefs appear to be transitory. Strong asymmetric effects are found. Nonetheless, ARCH effect is insignificant and enters with a negative sign; GARCH effect is positive and significant<sup>7</sup>. Announcement days give a large lift to conditional volatility, while pre-release days display smaller than average conditional volatility. Controlling for the announcement effects does not eliminate day-of-the-week effects, and vice versa.

### C. GARCH models with filters and heterogeneous persistence

#### C.A. With asymmetric effects

Being able to control the shift in beliefs by decomposing conditional variance into transitory and non-transitory parts, we then focus on how the market reacts to news. Preliminary analysis indicates that public news reduces information asymmetry after disclosure. Features of macroeconomic news would make the "learning" process shorter than private information or information with poorer quality that characterize non-announcement days. Thus, persistence of volatility and conditional volatility from announcement days should be smaller than that from non-announcement days.

Let  $X_t$  include the exogenous variables  $Z_t$  and the variables  $Y_{t-1} \in \sigma$ -algebra  $\mathcal{F}_{t-1}$ .  $f(X_t)$  and  $\lambda_j(X_t)$  stand for some functions of  $X_t$ . Allowing for heterogeneous persistence, we express the autocorrelation of conditional variance ( $h_t$ ) as:

$$(6) \quad h_t = f(X_t) + \sum_{j=1} \lambda_j \varepsilon_{t-j}^2$$

When  $\lambda_j = \alpha\beta^{j-1}$ , then the equation (6) reduces to GARCH(1,1). To allow for different volatility persistence on announcement and non-announcement days, we let  $\lambda_j(I_{t-j,A}, \bullet) = \alpha_A \beta_A^{j-1}$ , if  $I_{t-j,A} = 1$ ;  $\lambda_j(I_{t-j,N}, \bullet) = \alpha_N \beta_N^{j-1}$ , if  $I_{t-j,N} = 1$ . Equation (6) becomes

$$(7) \quad h_t = f(X_t) + \sum_{j=1} \alpha_A \beta_A^{j-1} \varepsilon_{t-j}^2 I_{t-j,A} + \sum_{j=1} \alpha_N \beta_N^{j-1} \varepsilon_{t-j}^2 I_{t-j,N}$$

Where  $I_{t-j,A}$  is the dummy variable for announcement on day t-j; and  $I_{t-j,A} = 1 - I_{t-j,N}$  is the dummy variable for no announcement on day t-j. Introducing heterogeneity to asymmetric effects into equation (7), and simplifying  $f(X_t)$  to be constant, we can rewrite (7) to be<sup>8</sup>

$$(8a) \quad h_t = \bar{\omega} + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$(8b) \quad h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$(8c) \quad h_t^N = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

Table 5 reports the results. GARCH terms are smaller on announcement days than on non-announcement days, indicating announcement-day shocks have smaller persistence. The ARCH coefficient on non-announcement days is insignificantly different from zero, and the one on announcement day is  $-0.115$  and significant<sup>9</sup>. With the log likelihood ratio test being significant at 1% critical level, the asymmetric effect is noteworthy here. Consistent with preliminary analysis, the asymmetric effects from announcement days are far more prominent than those from non-announcement days. On the post-announcement days, good news from releases reduces the conditional volatility; bad news increases the conditional volatility. With large ARCH coefficient ( $-0.115$ ) and asymmetric coefficient

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<sup>7</sup> without including the asymmetric effect, ARCH and GARCH effects are positive and significant.

<sup>8</sup> For details see Appendix 1.

<sup>9</sup> Without the asymmetric effects,  $\alpha_A$  would be insignificant, while  $\alpha_N$  would be 0.022 and statistically significant.

(0.277), shocks from announcement days generate great impacts on near-term future volatility. However, if we do not distinguish negative shocks from positive shocks, announcement-day volatility would appear not to persist at all and thus to have no impact on volatility forecasts. There is slightly stronger persistence after bad news, because of the leverage effect, volatility feedback effect, or a slower process for traders to comprehend the true information content in the release.

### C.B. A test for a macroeconomic risk premium and big-shock effects

Another interesting question remains: do T-bond futures earn positive risk premia on those days when they are exposed to macroeconomic risk? Preliminary analysis indicates “no” to this question. We further assess the question by adding ARCH-in-mean terms associated with announcements days into equation (3), which can be expressed as:

$$(3') \quad r_t = c + \eta I_{t,A} h_t + F_t \varepsilon_t$$

We also test for different effects on volatility persistence brought by big shocks, as suggested in the preliminary analysis. We conduct this test by allowing big shocks to have different ARCH effects on announcement days. Thus equation (8a) and (8b) turn into:

$$(8a') \quad h_t = \bar{\omega} + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$(8b') \quad h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

where  $I_{t,B}=1$ , if the absolute value of the shock is greater than its standard deviation; =0, otherwise.

From Table 6a, we find  $\varphi$  positive and significant. Also we observe an improvement in the log likelihood with the likelihood ratio test being significant at the 1% confidence level. The results hint that market participants take a longer time to achieve convergence facing a large shock. However, as long as the shock is non-negative, the

news that reveals a big shock still seems to push down information asymmetry. The insignificant suggests no macroeconomic risk premium and also casts doubt on the volatility-feedback effect as the reason for the asymmetric effects.

#### C.C. An explicit test of the volatility persistence

For an explicit test of the difference of coefficients of ARCH and GARCH terms on announcement days vs. non-announcement days, we modify equation (8a') & (8b') to:

$$(8a'') \quad h_t = \bar{\omega} + [(\alpha_N + \theta_1 + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + (\beta_N + \theta_2) h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$(8b'') \quad h_t^A = (\alpha_N + \theta_1 + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + (\beta_N + \theta_2) h_{t-1}^A$$

In Table 6b, we find  $\theta_1$  and  $\theta_2$  both negative and significant. We reject the hypothesis that persistence from announcement days vs. from non-announcement days is the same. This lends support to our hypothesis that the market learns more quickly about the price implications from the announcement data, and suggests that there is a tendency toward convergence among traders after news disclosure.

#### C.D. Tests of unemployment effect

Some researchers call the unemployment release the “king of announcements”. If the unemployment data is of special significance, we may see more substantial price movement and stronger convergence of private beliefs after its announcement. From Table 1, we find that volatility measured in terms of both absolute value and the squared value of return is higher on unemployment announcement days compared with that on CPI and PPI announcement days. Friday effects may contribute to part of the higher volatility. We test whether the unemployment report brings higher conditional volatility by modifying the filter equation (4) to:

$$(4') \quad F_t = (1 + \rho_1 D_4)(1 + \rho_2 D_5)(1 + \rho_3 I_t)(1 + \rho_4 I_{t+1})(1 + \rho_5 I_{t-1})(1 + \rho_6 I_{t,uem})$$



where  $I_{t,uem}$  represents a dummy variable for days with unemployment news. We then run regressions based on equations (3), (4'), (8a''), (8b'') and (8c). Table 7a displays the results.  $\rho_6$  is found to be positive but insignificant.

We proceed to test whether volatility from unemployment days has different persistence. This is done with equations (8a''') and (8b'''):

$$(8a''') h_t = \bar{\omega} + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + (\varphi I_{t-1,B} + \kappa I_{t-1,uem}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$(8b''') h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + (\varphi I_{t-1,B} + \kappa I_{t-1,uem}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

Table 7b gives out the result.  $\kappa$  is negative but again insignificant.

Evidence from Tables 7a and 7b shows that the unemployment report makes larger price movements and drives private views to further convergence. However, neither effect is significant. Similar tests are made on CPI and PPI, no report-specific effects are found.

#### C.E. Modeling with close-close return data

Studying close-close return data with our modified GARCH models will give us further understanding of how the market reacts to the news. Moreover, it will provide a robustness test for our modeling. Preliminary analysis shows that on the switching days returns are lower while variances are higher. Correspondingly, we include a dummy variable ( $I_{ch}$ ) representing a switching day into equation (3). Since the variance effect is purely transitory, we thus add the dummy variable to equation (4). Hence equation (3) and (4) become:

$$(3'') r_t = c + \lambda I_{ch} + F_t \varepsilon_t$$

$$(4'') F_t = (1 + \rho_1 D_4)(1 + \rho_2 D_5)(1 + \rho_3 I_t)(1 + \rho_4 I_{t+1})(1 + \rho_5 I_{t-1})(1 + \rho_7 I_{ch})$$

Both  $\lambda$  and  $\rho_7$  are found to be significant and carry the expected signs.

Similar to the results from open-close returns, we find both ARCH and GARCH terms are smaller on announcement days; when we test explicitly, we reject the hypothesis that the persistence of announcement vs. non-announcement days is the same. Also, we are unable to reject the hypothesis that big shocks have different effects on volatility persistence. No evidence for unemployment effects is shown, and we reject the hypothesis that T-bond futures earn an extra risk premium on announcement days. Once again, a significant asymmetric effect is demonstrated, and it is stronger on the announcement days. Consistent with our preliminary analysis, we find  $\rho_5$  is negative and significant. Table 8 reports the results for the regression using (3''), (4''), (8a'), (8b') and (8c).

#### D. Properties of the model

In this section, we evaluate the properties of the model by analysis of the impulse response function of shocks on forecasted volatility. Denoting the  $\tau$ -step forecasted volatility as  $H_{t-1,\tau}$ , we can write it as  $H_{t-1,\tau} = F_{t-1+\tau} \cdot (\varpi + h_{t-1,\tau}^A + h_{t-1,\tau}^N) \equiv F_{t-1+\tau} \cdot h_{t-1,\tau}$ . The one step forecasts for  $h_{t-1,1}^A$  and  $h_{t-1,1}^N$  are simply  $h_t^A$  and  $h_t^N$  respectively, as in the previous sections.

Based on the information set of t-1, we can write the  $\tau$ -step forecast as:

$$(9a) \quad h_{t-1,\tau} = \varpi + [(\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t+\tau-2,A}E_{t-1}\varepsilon_{t+\tau-2}^2 + \beta_A h_{t-1,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N)I_{t+\tau-2,N}E_{t-1}\varepsilon_{t+\tau-2}^2 + \beta_N h_{t-1,\tau-1}^N]$$

$$= \varpi + [(\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t+\tau-2,A}h_{t-1,\tau-1} + \beta_A h_{t-1,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N)I_{t+\tau-2,N}h_{t-1,\tau-1} + \beta_N h_{t-1,\tau-1}^N]$$

$$(9b) \quad h_{t-1,\tau}^A = (\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t-2+\tau,A}E_{t-1}\varepsilon_{t-2+\tau}^2 + \beta_A h_{t-1,\tau-1}^A = (\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t-2+\tau,A}h_{t-1,\tau-1} + \beta_A h_{t-1,\tau-1}^A$$

$$(9c) \quad h_{t-1,\tau}^N = (\alpha_N + 0.5\gamma_N)I_{t-2+\tau,N}E_{t-1}\varepsilon_{t-2+\tau}^2 + \beta_N h_{t-1,\tau-1}^N = (\alpha_N + 0.5\gamma_N)I_{t-2+\tau,N}h_{t-1,\tau-1} + \beta_N h_{t-1,\tau-1}^N$$

In the equations above, 0.5 comes from the percentage of negative shocks out of all shocks, and 0.322 is the percentage of big shocks out of all announcement-day shocks

over the sample period of November 9, 1988 to December 31, 1996. We employ the coefficients from equations (3''), (4''), (8a'), (8b') and (8c) with close-close return data for the sample period. Graph 1 depicts the impulse response function for the average impact of a one-unit increase of  $|\varepsilon_{t-1}|$  on  $h_{t-1,\tau}$ , over the sample with 2069 observations. Graph 2 presents the impulse response of a positive shock, while Graph 3 displays that of a negative shock. It is evident from Graphs 2 & 3 that negative shocks have higher impacts on forecasted volatility.

In Graphs 1 to 3, the portrayed impulse response is an average for impacts of shocks from both announcement-days and non-announcement-days. Notice that the percentage of announcement days out of the whole sample is only 14%, thus, the impacts of announcement-day shocks may be underrepresented by  $h_{t,\tau}^A$ ; therefore, we further demonstrate the impulse response for shocks from announcement days and non-announcement days separately. The one-step forecast from an announcement-day is:

$$(10a) \quad h_{t-1,1} \Big|_{I_{t-1,A}=1} \equiv h_t \Big|_{I_{t-1,A}=1} = \omega + h_t^A \Big|_{I_{t-1,A}=1} + h_t^N \Big|_{I_{t-1,A}=1} = (\alpha_A + \gamma_A I_{t-1}^- + \phi I_{t-1,B}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A + \beta_N h_{t-1}^N$$

$$\text{where } h_t^A \Big|_{I_{t-1,A}=1} = (\alpha_A + \gamma_A I_{t-1}^- + \phi I_{t-1,B}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A \quad , \quad h_t^N \Big|_{I_{t-1,A}=1} = \beta_N h_{t-1}^N$$

The one-step forecast from a non-announcement-day is:

$$(10n) \quad h_{t-1,1} \Big|_{I_{t-1,N}=1} \equiv h_t \Big|_{I_{t-1,N}=1} = \omega + h_t^A \Big|_{I_{t-1,N}=1} + h_t^N \Big|_{I_{t-1,N}=1} = (\alpha_N + \gamma_N I_{t-1}^-) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A + \beta_N h_{t-1}^N$$

$$\text{where } h_t^A \Big|_{I_{t-1,N}=1} = \beta_A h_{t-1}^A \quad , \quad h_t^N \Big|_{I_{t-1,N}=1} = (\alpha_N + \gamma_N I_{t-1}^-) \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

Apparently from Graph 4 and Graph 5, announcement-day shocks have smaller persistence but larger impacts on short-horizon volatility forecasts than non-announcement shocks. Graph 6 shows the curve of news impact on the one-step forecast, where announcement-day shocks manifest their significance. The pattern shown is consistent

with the preliminary findings of announcement-day shocks: bad news presents a larger distinction from good news when the magnitude is larger.

## **VI. FORECAST**

Market participants do not expect volatility to be constant over time but instead anticipate volatility to vary. Since the timing, though not the content of scheduled macroeconomic announcements, is known a priori, rational expectation of market uncertainty should compound the anticipated impact of important releases on price volatility. As important news releases heighten volatility significantly, correctly forecasted volatility should decline when the uncertainty from news disclosure is resolved.

Implied volatility (IMV) is a widely used measure of investors' volatility expectations. Ederington and Lee (1996) examine the impact of macroeconomic news disclosures on market uncertainty as measured by the implied standard deviation from the interest rate option markets. Their evidence indicates that IMV tends to fall on days with important scheduled news. However, we have to keep in mind that IMV is not a precise measure of market expectations. First, since it is a solution to nonlinear equations, IMV will not be an unbiased measure (Butler and Schachter (1986)). Second, since the IMV is obtained by solving the Black-Scholes model for observed option and future prices, it will reflect any factors that affect option prices but are not incorporated in the Black model (Canina and Figlewski (1993)). Third, price discreteness and bid-ask spreads will introduce error (Jorion (1995)). Our forecasted volatility should not be taken as a perfect measure of volatility expectation either. Nevertheless, if our modeling correctly incorporates the understanding of the impacts of news releases, we should be able to see

similar patterns in our forecasted volatility. In this section we compare the behavior of our forecasted volatility with that of the implied volatility and the realized volatility.

Let  $\sigma_t^2$  represent the mean of anticipated daily volatility from day t+1 to day t+T. In Ederington and Lee (1996), they have T as time to expiration of the option contract with the median being 38 trading days. For a better comparison, we calculate  $\sigma_{t-1}^2$  from our model as mathematical mean of one-step to 38-step (trading-day based) forecasted volatility, based on information available on day t-1. Similar to Ederington and Lee (1996), we obtained implied volatility (IMV) data from daily option closing prices for our comparison. IMV used here is a weighted average of IMV calculated for the most heavily traded contracts - the two nearest-the-money calls and the two nearest-the-money puts.

#### A. In-sample forecast <sup>10</sup>

Consistent with the findings of Ederington and Lee, the forward-looking implied volatility drop on announcement days for the sample period spanning from November 9, 1988 to December 31, 1996. The subsequently realized volatility also declines on news-release days. We expect our forecasts to show the same pattern, i.e.

$$E(\sigma_t^2 - \sigma_{t-1}^2 | I_{t,A} = 1) < 0.$$

The  $\tau-1$  step from time t forecast can be written in a version similar to (9a)-(9c):

$$(9a') \quad h_{t,\tau-1} = \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t+\tau-2,A}h_{t,\tau-2} + \beta_A h_{t,\tau-2}^A] + [(\alpha_N + 0.5\gamma_N)I_{t+\tau-2,N}h_{t,\tau-2} + \beta_N h_{t,\tau-2}^N]$$

$$(9b') \quad h_{t,\tau-1}^A = (\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t-2+\tau,A}E_t \varepsilon_{t-2+\tau}^2 + \beta_A h_{t,\tau-2}^A = (\alpha_A + 0.5\gamma_A + 0.322\phi)I_{t-2+\tau,A}h_{t,\tau-2} + \beta_A h_{t,\tau-2}^A$$

$$(9c') \quad h_{t,\tau-1}^N = (\alpha_N + 0.5\gamma_N)I_{t-2+\tau,N}E_t \varepsilon_{t-2+\tau}^2 + \beta_N h_{t,\tau-2}^N = (\alpha_N + 0.5\gamma_N)I_{t-2+\tau,N}h_{t,\tau-2} + \beta_N h_{t,\tau-2}^N$$

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<sup>10</sup> For further details, see Appendix 2.

If our one-step forecast  $h_t$  is unbiased, we will have  $h_{t-1,2}^A$  equal to  $h_{t,1}^A$  ( $h_{t+1}^A$ ) on average.

Similarly  $Eh_{t-1,2}^N = Eh_{t,1}^N$ , and thus  $Eh_{t-1,2} = Eh_{t,1}$ . Applying the equalities recursively, we

will have  $h_{t-1,\tau}^A$  equal to  $h_{t,\tau-1}^A$  on average. The same results apply to  $h_{t-1,\tau}^N$  and  $h_{t,\tau-1}^N$ ,  $h_{t-1,\tau}$  and

$h_{t,\tau-1}$ , and thus  $H_{t-1,\tau}$  and  $H_{t,\tau-1}$  ( $\cdot \cdot F_{(t-1)+\tau} = F_{t+(\tau-1)}$ ). Hence,

$$E\sigma_t^2 - E\sigma_{t-1}^2 = \frac{1}{38}E(H_{t,38} - H_{t-1,1}) = \frac{1}{38}E(H_{t,38}) - \frac{1}{38}E(F_t \cdot h_t) = 0$$

In Table 9a we test the hypothesis that  $h_t$  is an unbiased estimate of  $\varepsilon_t^2$ , evidence indicates that the hypothesis can not be rejected. Since our estimated  $\rho_I$  is  $>0$ ,

$E(F_t|I_{t,A} = 1) > EF_t$ , thus,  $E(H_t|I_{t,A} = 1) > EH_t$ . Since there is little effect on  $H_{t,38}$ , we

will have  $E(\sigma_t^2 - \sigma_{t-1}^2|I_{t,A} = 1) < 0$ . Table 9b reported evidence to confirm this hypothesis

in terms of both mean and median. The finding is actually in line with the findings of the

realized data and the implied volatility. Conversely,  $\sigma_t^2$  tend to rise on days with no

important macroeconomic announcements. We find support for it in terms of the mean but

not in terms of the median.

Since  $\rho_S < 0$ ,  $E(F_t|I_{t-1,A} = 1) < EF_t$ . With  $\alpha_A + 0.5\gamma_A + 0.322\phi \approx \alpha_N + 0.5\gamma_N$ , and

comparing (10a) and (10n), we will have  $E(h_t|I_{t-1,A}) \approx E(h_t)$ , thus  $E(H_t|I_{t-1,A}) < E(H_t)$

and  $E(\sigma_t^2 - \sigma_{t-1}^2|I_{t-1,A} = 1) > 0$ . We expect the forecasted volatility to rise on days following

scheduled announcements. Supporting evidence from both mean and median statistics is

reported in Table 9b; the realized data also presents the same pattern. However, we fail to

find this pattern for the implied volatility data.

Due to the day-of-the-week effect and the fact that macroeconomic announcements are clustered on Fridays and the weekly money supply figures are released after the markets close on Thursdays, the correctly anticipated  $\sigma_t^2$  should decrease on Fridays. Ederington and Lee (1996) find that the implied volatility tends to decline on Fridays. The subsequent realized volatility data exhibits the same tendency. Since  $E(F_t|D_5 = 1) > EF_t$  ( $\because \rho_2 > 0$  and  $\rho_3 > 0$ ), we predict similar findings, *i.e.*  $E(\sigma_t^2 - \sigma_{t-1}^2 | D_5 = 1) < 0$ , for the forecasted volatility. Indeed, we find the evidence for this Friday effect.

Table 9c presents the analysis from OLS regressions. All of the realized data, our forecasted volatility and the implied volatility decline on announcement days and on Fridays, while both the GARCH forecast and the realized volatility rise on days following announcements.

Examination of the term structure of the annualized forecasted standard deviation provides additional insights into forecasting properties. The term structure is constructed as  $\sqrt{\frac{252}{k} \sum_{\tau=1}^k H_{t,\tau}}$ . Graph 7 shows that it picks up pre-release, and returns towards the average level on release days. Graph 8 illustrates close co-movements between the GARCH forecasts and implied volatility.

## B. Out-of-sample forecast

As with the in-sample forecasts, the out-of-sample forecasts present a clear pattern around announcements. They decline on announcement days and on Fridays.

One particularly popular evaluation of the volatility forecast in the literature is obtained via the ex-post squared return regression:

$$(11) \quad r_t^2 = a + bH_{t-1,1} + \mu_t$$

If the model for the conditional volatility is correctly specified, it follows that, in population,  $a$  and  $b$  are equal to zero and unity, respectively. Our out-of-sample forecast window starts from January 1, 1997 and ends November 8, 1997, spanning 216 trading days. We estimate the coefficients in equations (3''), (4''), (8a'), (8b') and (8c) recursively and obtain a one-step-ahead volatility forecast for close-close returns. Applying equation (10), we test for the joint hypothesis that  $a=0$  and  $b=1$ . From the  $F$ -statistics and the  $\chi^2$  statistics reported in Table 10, we fail to reject the null.

The coefficient of multiple determination,  $R^2$  of the regression, provides a direct assessment of the variability in the *ex-post* volatility being explained by the particular estimates. Therefore,  $R^2$  is often interpreted as a simple measure of the degree of predictability in the volatility, and a guide to the accuracy of the volatility forecasts. The  $R^2$  from the regression in (10) for the one-step forecast is 0.062. The seemingly low  $R^2$  is in line with the evidence in the extant literature for other speculative returns with daily or lower frequency. Nonetheless, Andersen and Bollerslev (1997) point out that the use of  $R^2$  as a diagnostic for potential misspecification is problematic, since financial applications focus on the future volatility and not on the subsequent realized squared returns. Under the null hypothesis that the estimation constitutes a correct specification,  $R^2$  simply measures the extent of idiosyncratic noise in squared returns relative to the mean which is given by the (true) conditional return variance. Low  $R^2$ 's are not an anomaly but rather a direct implication of volatility models.



Use of the observed squared returns is justified to the extent that they provide an unbiased estimator of the underlying latent volatility. However, the realized squared returns are poor estimators of the day-by-day movements in volatility due to the large idiosyncratic component of daily returns. Implied volatility provides an alternative estimate of the latent volatility factors<sup>11</sup>. We compute  $\sigma_t^2$  recursively in the same way as we do for the in-sample forecasts.  $R^2$  is considerably higher and it accounts for more than fifty percent of the variability in the latent volatility as measured by the implied volatility. Graph 9 reveals the close co-movements of the implied volatility and our forecasted volatility, and the correlation between them is very high at 0.72. Nevertheless, we should bear in mind that IMV is not a precise measure for the latent volatility either, for the same reasons we discussed earlier in this section. The mean of IMV is higher than that of historic realized squared return. One may also acknowledge from Graph 7 that the mean of IMV is higher than the mean of our forecasted volatility. Thus it is no surprise that we reject the joint hypothesis that we have an unbiased forecast for the implied volatility.

In estimation of the level of returns, the asymmetric effects are found to be significant. We are interested in comparing the performance of forecasts with and without asymmetric effects. We estimate recursively equations (3''), (4''), (8a'), (8b') and (8c) with the restriction that  $\gamma_A = \gamma_N = 0$ , and then calculate  $\sigma_t^2$ . The correlation between  $\sigma_t^2$  and IMV is much lower (0.48), the co-movements are less manifest, and the  $R^2$  is smaller.

Through a comparison with the realized squared returns and implied volatility, we evaluate our in-sample and out-of-sample forecasts, and find the evidence indicating that

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<sup>11</sup> see the recent work of Canina and Figlewski (1993), Jorin (1995) and Lamoureux and Lastrapes(1993).

our GARCH model correctly incorporated the available information concerning news release into our forecasts.

## **VII. CONCLUSIONS AND FUTURE RESEARCH**

Understanding the determinants of asset prices and understanding the way that markets process new information about these determinants, are central questions in finance. In this paper, we follow JLL to focus on the study of a subset of asset price movements associated with observable announcements of identifiable types of risk, instead of trying to find ex-post explanations for all asset price movements.

We do not find statistically significant increase in expected open-close returns, *i.e.* macroeconomic risk premium, on the announcements days. Heightened volume on release-day indicates that news arrival clustering is not the sole reason for volatility persistence. Supporting the learning view, evidence on conditional volatility and volume shows that the market processes the information from scheduled news more quickly than nonscheduled news. Information asymmetry is decreased after news disclosure, nevertheless, convergence in beliefs does not happen instantaneously. A prominent finding is the strong asymmetric effects in the T-bond futures market where negative shocks increase conditional volatility on consecutive days. Furthermore, bad news from scheduled announcements brings stronger asymmetric effects than its counterpart from unscheduled announcements. This stylized fact calls for future exploration of the underlying microstructure theory. Interestingly, we find evidence that market participants take a longer time to arrive at convergence when facing a large shock. We do not, however, find evidence of heterogeneous effects on volatility persistence brought by

different types of announcements. Close-close returns show similar patterns to open-close returns<sup>12</sup>. Our study shows support of KV's view that anticipation of a news release affects the market reaction to that announcement.

Conducting in-sample and out-of-sample forecasts helps us to evaluate this model. Comparing the GARCH volatility forecast with the realized data and implied volatility, we find evidence that our model correctly incorporated the available information concerning news release into our forecasts. Hence, our model answers the critique that ARCH models base expected volatility solely on recent historical volatility. However, neither the observed squared returns nor the implied volatility is the ideal candidate for extracting information about the future latent volatility factor. Andersen (1996) and Gallant, Rossi and Tauchen (1992), suggest that information provided by the joint distribution of returns and trading volume would be a good source from which to extract information. Andersen and Bollerslev (1997) propose the use of intra-day data to help evaluate one-step forecasts. It would also be of interest to investigate evaluation criteria for the forecast horizon beyond one day. We leave these possibilities for future research.

Our empirical findings are quite different from those of JLL in two prominent aspects. First, we do not find a higher and statistically significant risk premium on announcement days. Second, the announcement-day volatility is important in forming conditional volatility. This raises an interesting issue for the possible difference between treasury bonds cash and future markets. There is evidence that the short and the long end of the yield curve behave somewhat differently (Duffie (1996)). To compare reactions to the news of T-bond futures with those of T-bill futures could be interesting as well.

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<sup>12</sup> Replicating empirical tests using returns in excess of the Treasury bill rate, similar results are found.

Although this study utilizes Treasury futures to analyze the heterogeneous persistence from scheduled announcements vs. non-scheduled announcements, we believe the approach provided here has a more general application. For example, the scheduled release of a company's quarterly reports or dividend earnings has large and varied effects than nonscheduled news on the company's stock returns. Therefore, when forecasting the conditional volatility of individual stocks, one could improve the forecast by incorporating the known timing and allowing for heterogeneity of scheduled announcements vs. non-scheduled announcements. Heterogeneous persistence could also exist among different kinds of scheduled announcements. For the study of T-bonds, it might exist between periodically scheduled macroeconomic announcements vs. other scheduled news such as the public auction of T-bonds; for the study of individual stocks, heterogeneous persistence might exist among the scheduled reports of a firm vs. the scheduled reports of companies relevant to that firm. We believe it would also be beneficial and important to allow heterogeneity of differentiated impacts among scheduled announcements. However, we leave this for future research.

## Appendix 1:

$$(6) \quad h_t = f(X_t) + \sum_{j=1} \lambda_j \varepsilon_{t-j}^2$$

Let  $\lambda_j = \alpha\beta^{j-1}$ , then

$$\begin{aligned} h_t &= f(X_t) + \sum_{j=1} \alpha\beta^{j-1} \varepsilon_{t-j}^2 = f(X_t) + \alpha\varepsilon_{t-1}^2 + \beta \sum_{j=1} \alpha\beta^{j-1} \varepsilon_{t-1-j}^2 = f(X_t) + \alpha\varepsilon_{t-1}^2 + \beta(h_{t-1} - f(X_{t-1})) \\ &= [f(X_t) + \beta f(X_{t-1})] + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} = g(X_t) + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \end{aligned}$$

where  $g$  is a function of  $X_t$ . When  $g$  reduces to constant, it is indeed GARCH(1,1).

Simplifying  $f(X_t)$  to be constant  $\bar{\omega}$ , let  $X_t = Z_t, I_{t-j,A}, I_{t-j,N}, I_{t-j}^-, \bullet, j = 1, 2, 3, \dots$ , and let

$\lambda_j(X_t) = \alpha_A \beta_A^{j-1}$ , if  $I_{t-j,A} = 1$ ;  $= \alpha_N \beta_N^{j-1}$ , if  $I_{t-j,N} = 1$ . Where  $I_{t-j,A}$  is the dummy variable for announcement on day  $t-j$ ; and  $I_{t-j,A} = 1 - I_{t-j,A}$  is the dummy variable for no announcement on day  $t-j$ .  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} > 0$ ;  $I_{t-1}^- = 0$ , otherwise. Equation (6) becomes

$$\begin{aligned} (7) \quad h_t &= \bar{\omega} + \sum_{j=1} \alpha_A \beta_A^{j-1} I_{t-j,A} \varepsilon_{t-j}^2 + \sum_{j=1} \alpha_N \beta_N^{j-1} I_{t-j,N} \varepsilon_{t-j}^2 \\ &= \bar{\omega} + (\alpha_A I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A \sum_{j=1} \alpha_A \beta_A^{j-1} I_{t-1-j,A} \varepsilon_{t-1-j}^2) + (\alpha_N I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N \sum_{j=1} \alpha_N \beta_N^{j-1} I_{t-1-j,N} \varepsilon_{t-1-j}^2) \\ &= \bar{\omega} + (\alpha_A I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A) + (\alpha_N I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N) \end{aligned}$$

$$(7a) \quad \text{where } h_t^A = \sum_{j=1} \alpha_A \beta_A^{j-1} I_{t-j,A} \varepsilon_{t-j}^2 = \alpha_A I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$(7b) \quad \text{and } h_t^N = \sum_{j=1} \alpha_N \beta_N^{j-1} I_{t-j,N} \varepsilon_{t-j}^2 = \alpha_N I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N \quad .$$

If further introduce heterogeneity to asymmetric effects into (7), i.e.,  $\lambda_j = (\alpha_A + \gamma_A) \beta_A^{j-1}$ ,

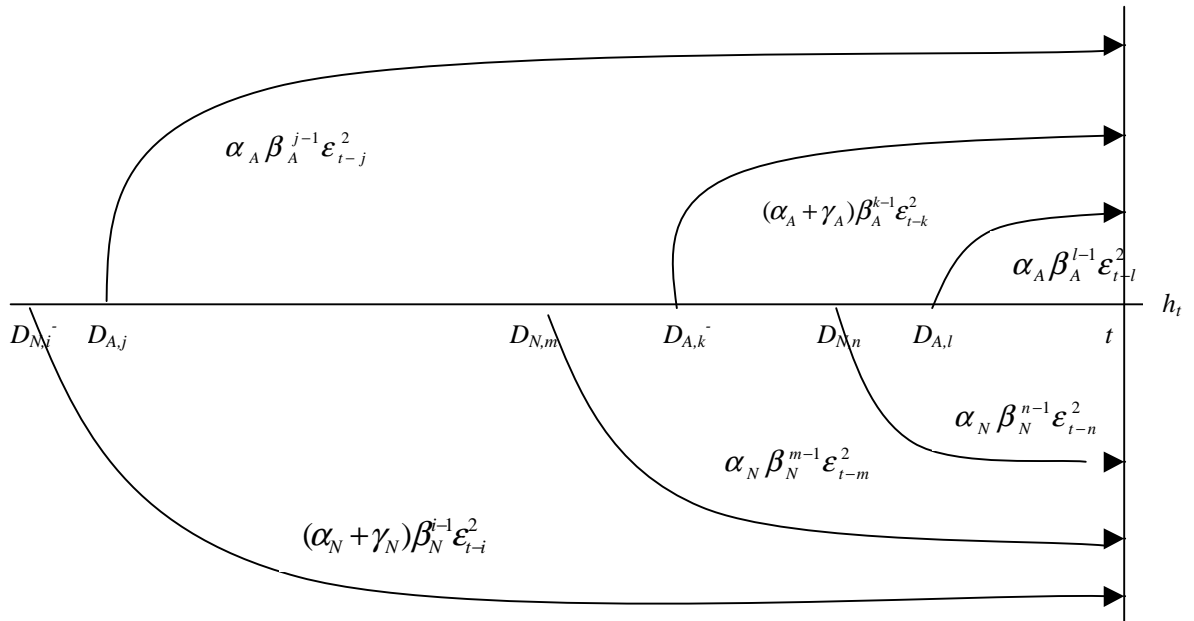
if  $I_{t-j,A} = 1$  and  $I_{t-j}^- = 1$ ;  $\lambda_j = (\alpha_N + \gamma_N) \beta_N^{j-1}$ , if  $I_{t-j,N} = 1$  and  $I_{t-j}^- = 1$ , we can rewrite it as

$$\begin{aligned} h_t &= \bar{\omega} + \sum_{j=1} (\alpha_A + \gamma_A I_{t-j}^-) \beta_A^{j-1} I_{t-j,A} \varepsilon_{t-j}^2 + \sum_{j=1} (\alpha_N + \gamma_N I_{t-j}^-) \beta_N^{j-1} I_{t-j,N} \varepsilon_{t-j}^2 \\ &= \bar{\omega} + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A \sum_{j=1} (\alpha_A + \gamma_A I_{t-j}^-) \beta_A^{j-1} I_{t-1-j,A} \varepsilon_{t-1-j}^2] \\ &\quad + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N \sum_{j=1} (\alpha_N + \gamma_N I_{t-j}^-) \beta_N^{j-1} I_{t-1-j,N} \varepsilon_{t-1-j}^2] \\ (8a) \quad &= \bar{\omega} + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N] \end{aligned}$$

$$(8b) \quad \text{where } h_t^A = \sum_{j=1} (\alpha_A + \gamma_A I_{t-j}^-) \beta_A^{j-1} I_{t-j,A} \varepsilon_{t-j}^2 = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$(8c) \quad \text{and } h_t^N = \sum_{j=1} (\alpha_N + \gamma_N I_{t-j}^-) \beta_N^{j-1} I_{t-j,N} \varepsilon_{t-j}^2 = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

The above can be best illustrated by a diagram. Let  $D_{A,j}$ ,  $D_{A,k}$ ,  $D_{A,l}$  denote announcement days  $j$ ,  $k$ ,  $l$  days before day  $t$ , respectively;  $D_{N,i}$ ,  $D_{N,m}$ ,  $D_{N,n}$  denote for non-announcement days  $i$ ,  $m$ ,  $n$  days before day  $t$ , respectively. Among these days,  $D_{A,k}$  and  $D_{N,i}$  are days with negative returns. The graph below depicts how the memory of past squared returns enter the construction of  $h_t$ .



## Appendix 2:

Based on  $\Phi_{t-1}$ , the two step forecast of  $h_{t-1,2}^A$  could be expressed as:

$$h_{t-1,2}^A = (\alpha_A + 0.5\gamma_A + 0.322\phi) I_{t,A} E_{t-1} \varepsilon_t^2 + \beta_A h_{t-1,1}^A = (\alpha_A + 0.5\gamma_A + 0.322\phi) I_{t,A} h_t + \beta_A h_t^A$$

Based on  $\Phi_t$ , the one step forecast of  $h_{t,1}^A$  is:

$$h_{t,1}^A \equiv h_{t+1}^A = (\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \phi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A$$

If  $h_t$  is an unbiased estimate of  $\varepsilon_t^2$ , i.e.  $Eh_t = E\varepsilon_t^2$ , then we will have  $Eh_{t-1,2}^A$  as:

$$Eh_{t-1,2}^A = E[(\alpha_A + 0.5\gamma_A + 0.322\varphi)I_{t,A}\varepsilon_t^2 + \beta_A h_t^A]$$

Since  $P(I_t^- = 1) = 0.5$  and  $P(I_{t,B} = 1 | I_{t,A} = 1) = 0.322$ , we can write  $Eh_{t+1}^A$  as:

$$Eh_{t+1}^A = [\alpha_A + \gamma_A E(I_t^- + \varphi I_{t,B} | I_{t,A} = 1)] E I_{t,A} \varepsilon_t^2 + E \beta_A h_t^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) E I_{t,A} \varepsilon_t^2 + E \beta_A h_t^A$$

So that  $Eh_{t-1,2}^A = Eh_{t,1}^A$ . Similarly  $Eh_{t-1,2}^N = Eh_{t,1}^N$ , and thus  $Eh_{t-1,2} = Eh_{t,1}$ .

The three-step forecast of  $h_{t-1,3}^A$  and the two-step forecast of  $h_{t,2}^A$  are as following:

$$h_{t-1,3}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+1,A} h_{t-1,2} + \beta_A h_{t-1,2}^A$$

$$h_{t,2}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+1,A} h_{t,1} + \beta_A h_{t,1}^A$$

$\therefore Eh_{t-1,2}^A = Eh_{t,1}^A$  and  $Eh_{t-1,2} = Eh_{t,1}$ ,  $\therefore Eh_{t-1,3}^A = Eh_{t,2}^A$ . Similarly, we have  $Eh_{t-1,3}^N = Eh_{t,2}^N$ ,

and thus  $Eh_{t-1,3} = Eh_{t,2}$ . Doing it recursively, we will have  $Eh_{t-1,\tau} = Eh_{t,\tau-1}$ , and hence,

$$EH_{t-1,\tau} = EH_{t,\tau-1}, \therefore H_{t,l} = F_{t+l} \cdot h_{t,l} \text{ and } F_{(t-1)+\tau} = F_{t+(\tau-1)}.$$

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**Table 1: Summary Statistics for Treasury Bond Futures Open-close Returns<sup>1</sup>**

(1a)

Statistics	Full Sample(2069)(11/9/88-12/31/96)					Announcement Days(292)					Non-announcement Days(1777)				
	$R_t$	$ R_t $	$R_t^2$	Volume	$VI/ R_t $	$R_t$	$ R_t $	$R_t^2$	Volume	$VI/ R_t $	$R_t$	$ R_t $	$R_t^2$	Volume	$VI/ R_t $
Mean	0.02407	0.414562	0.30679	313022	1650151.1	0.037787	0.643025	0.643372	429676	1442433	0.021975	0.377021	0.251482	293861	1684972
Median	0.030351	0.315458	0.099514	302650	847172.4	0.073403	0.545791	0.297888	424045	722284.8	0.029852	0.284394	0.08088	282770	872182.2
Max	2.490299	2.666053	7.107839	760890	19582417	2.294157	2.666053	7.107839	760890	16610896	2.490299	2.490299	6.201589	721620	19582417
Min	-2.66653	0	0	5308	15455.75	-2.66653	0	0	182730	121385.9	-2.481799	0	0	5308	15455.75
Std. Dev.	0.553491	0.367415	0.573981	126996.2	2257237	0.80259	0.480293	0.95705	113110.7	2017147	0.501139	0.330755	0.460277	118661.4	2293724
Skewness	-0.170189	1.601763	4.952546	0.430987	3.50066	-0.302608	1.164315	3.366066	0.346582	3.705018	-0.085537	1.544251	4.969004	0.45973	3.46434
Kurtosis	4.532168	6.756635	41.07717	2.991733	17.90224	3.252168	4.804123	18.52269	2.910719	19.87162	4.365717	6.462705	44.41824	3.115473	17.55403
Autocorrelation(1)	0	-0.028	-0.021	0.318**		0.081	-0.036	-0.064	0.346**		-0.036	0.02	0.011	0.419**	

(1b)

Statistics	CPI Announcement Days(97)					PPI Announcement Days (98)					Unemployment Announcement(97)				
	$R_t$	$ R_t $	$R_t^2$	Volume	$VI/ R_t $	$R_t$	$ R_t $	$R_t^2$	Volume	$VI/ R_t $	$R_t$	$ R_t $	$R_t^2$	Volume	$VI/ R_t $
Mean	0.001176	0.561262	0.466651	411635	1588888	0.1153539	0.578471	0.535253	416011	1472126	-0.004157	0.79006	0.929327	461377	1266285
Median	-8.34E-05	0.527329	0.278075	407820	754401.7	0.175091	0.474651	0.22535	420110	823435.5	0.078053	0.70012	0.490167	447360	677778.6
Max	1.518391	1.520941	2.313262	760890	10155578	2.294157	2.294157	5.263156	704440	11026845	1.702372	2.666053	-7.107839	737070	16610896
Min	-1.5202941	8.34E-05	6.96E-09	205590	278882.3	-1.894548	0	0	182730	246029.4	-2.666053	0	0	229850	121385.9
Std. Dev.	0.68666	0.391427	0.537322	108191.4	1985620	0.726144	0.450215	0.837533	111707.9	1899405	0.969015	0.555334	1.285638	113723.1	2165170
Skewness	0.046582	0.475944	1.513924	0.327889	2.63424	-0.121389	1.28172	3.116425	0.279121	3.126439	-0.43635	1.0696	2.732658	0.410068	4.950265
Kurtosis	2.287999	2.334604	5.031262	3.21079	10.01113	3.488767	4.87234	14.64	2.646218	13.32097	2.85676	4.187223	12.0083	2.669469	31.13582
Autocorrelation(1)	-0.071	-0.03	-0.068	0.19*		-0.017	0.16	0.207*	0.147		0.186*	0.225*	0.241*	0.245**	

Note<sup>1</sup>:  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent. \* denotes significance at 10% for Q-stat, while \*\* denotes significance at 5%.

$VI/|R_t|$  denotes for the ratio of volume to the absolute value of return. Days with zero  $R_t$  have been deleted, announcement days have unproportionally low share among them.

**Table 2. Analysis from OLS Regressions<sup>a</sup>**

(2a)<sup>1</sup>

	post-release ( $I_{t-1}$ )	release ( $I_t$ )	pre-release ( $I_{t+1}$ )	2-day-prior-to-release ( $I_{t+2}$ )	post-big shock ( $I_{t-1,B}$ )
$ R_t $	-0.032174 (-1.387086)	0.266004** (11.84521)	-0.069034** (-2.981167)	-0.047643** (-2.052155)	0.0102 (0.26234)
$R_t^2$	-0.023878 (-0.658719)	0.39189** (11.12892)	-0.108263** (-2.992753)	-0.064736* (-1.784485)	0.0013 (0.021709)
Volume	-34555.25** (-4.327445)	135766.6** (18.23684)	-6275.633 (-0.782494)	-4846.516 (-0.603399)	-41384 (-3.09327)**
$VI/ R_t $	11385.7 (0.07897)	-189021* (-1.814756)	234500.3** (2.255416)	151102.1 (1.435216)	-295898.3 (-1.434068)

Note<sup>1</sup>: the coefficients are corresponding to  $\beta$  in the two-variable regressions  $y_t = \alpha + \beta x_t$ . For  $VI/|R_t|$ , a few outliers due to extremely low absolute value of returns have been dismissed.

(2b)<sup>2</sup>

	$I_t$	lag1	$I_{t-1}$ *lag1	lag2	lag3	lag4	lag6	lag7	lag9	lag10	lag11
Volume <sup>3</sup>	56.938** (2.734731)	0.3318** (14.3733)	-0.2402** (-5.044097)	0.0796** (3.686723)	0.0824** (3.822812)	0.0817** (3.870038)	0.0378* (1.782825)	0.06** (2.827356)	0.0562** (2.680983)	-0.0637** (-2.952095)	0.0871** (15.13307)

Note<sup>2</sup>:  $I_t$  denotes dummy variable for announcement days,  $I_{t-1}$  denotes that for days following announcements.

Note<sup>3</sup>: volume is deseasonalized by day of the week and month of the year liquidity effects.

(2c)

	Tuesday	Wednesday	Thursday	Friday
$ R_t $	0.050866** (2.015765)	-0.002172 (-0.086069)	0.086169** (3.400971)	0.207897** (8.238725)
$R_t^2$	0.048241 (1.218603)	-0.014056 (-0.355071)	0.104433** (2.627352)	0.286077** (7.226466)

Note<sup>a</sup>: t-statistics shown in parentheses, \* denotes significance at 10%, \*\* denotes significance at 5%.

**Table 3. Benchmark GARCH(1,1) model<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + \varepsilon_t \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta_1 I_t + \delta_2 I_{t-1} + \delta_3 I_{t+1} + \delta_4 D_4 + \delta_5 D_5$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.

Mean Equation					
C	0.022125* (1.857597)	0.023048** (-1.995537)	0.025862** (2.29031)	0.030239** (2.72645)	0.029582** (2.558983)
Variance Equation					
$\omega$	0.006463** (2.24157)	0.252309** (17.01438)	0.216741** (4.050868)	-0.011754** (-1.987922)	0.094073** (2.623256)
$\alpha$	0.012683** (2.988117)	0.005359 (0.483575)	0.012768** (3.443631)	0.016092** (3.29473)	0.017463 (1.407261)
$\beta$	0.965789** (164.8616)	-0.010011 (-0.272653)	0.972745** (102.5614)	0.949748** (64.95862)	0.441693** (4.149666)
$\delta_2$			-0.383243** (-7.670261)	-0.352339** (-7.539449)	
$\delta_1$		0.392024** (7.713809)	0.416918** (7.870078)	0.427245** (8.230607)	
$\delta_3$			-0.049665** (-2.868078)	-0.081358** (-4.602952)	
$\delta_4$				0.119981** (7.276816)	0.145911** (5.799321)
$\delta_5$				-0.005293 (-0.223261)	0.196889** (8.110582)
log likelihood	-1701.127	-1642.853	-1626.689	-1612.417	-1663.713

Note<sup>a</sup>: t-statistics shown in parentheses, \* denotes significance at 10%, \*\* denotes significance at 5%.

**Table 4. Filtered GARCH Model with Leverage Effects<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t)(1 + \rho_2 I_{t-1})(1 + \rho_3 I_{t+1})(1 + \rho_4 D_4)(1 + \rho_5 D_5)$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma I_{t-1}^- \varepsilon_{t-1}^2$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.

	coefficient	robust t-stat
Mean Equation		
C	0.02885613	-1.03602
Variance Equation		
$\omega$	0.007708239	1.79951*
$\alpha$	-0.007460403	-0.99625
$\beta$	0.952661858	40.27074**
$\gamma^1$	0.041822092	2.8743**
Filter Equation		
$\rho_1$	0.451748334	6.98756**
$\rho_2$	-0.001569903	-0.0198
$\rho_3$	-0.136226622	-2.55578**
$\rho_4$	0.167830677	2.63963**
$\rho_5$	0.167238093	3.44749**
Residuals Sum of squares:	632.1377	
R <sup>2</sup> :	0.003429	
Ljung-Box(15):	12.0196	
log likelihood:	-1601.967044	

Note<sup>1</sup>: log-likelihood ratio test for asymmetric effects is 10.2, 1% significant with  $\chi^2(1)$   
 $\alpha, \beta$  would otherwise be 0.018, 0.961 respectively, both significant.

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.

**Table 5. Filtered GARCH with Heterogeneous Persistence<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t)(1 + \rho_2 I_{t-1})(1 + \rho_3 I_{t+1})(1 + \rho_4 D_4)(1 + \rho_5 D_5)$$

$$h_t = \omega + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$h_t^N = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,A}$  is the dummy variable for announcement on day t-1,  $I_{t-1,N} = 1 - I_{t-1,A}$ .

	coefficient	robust t-stat
Mean Equation		
C	0.030340802	1.27312
Variance Equation		
$\omega$	0.160495831	5.82303**
$\alpha_A$	-0.11476149	-8.14895**
$\alpha_N$	-0.004852544	-0.664
$\beta_A$	0.555454111	2.86141**
$\beta_N$	0.962453707	59.25967**
$\gamma_A^1$	0.277252373	2.22938**
$\gamma_N^1$	0.034753985	2.78168**
Filter Equation		
$\rho_1$	0.462712923	7.2393**
$\rho_2$	-0.033618735	-0.48311
$\rho_3$	-0.173372335	-4.8209**
$\rho_4$	0.19767383	2.99063**
$\rho_5$	0.144745834	3.01068**
Residuals Sum of squares:	632.1556	
R**2 :	0.003371	
Ljung-Box(15):	11.7948	
log likelihood:	-1598.438988	

Note<sup>1</sup>: likelihood ratio test for asymmetric effects are 14.3, 1% significant with  $\chi^2(2)$ .

$\alpha_A$  would otherwise be insignificant;  $\alpha_N$  would be 0.022, significant.

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.



**Table 6a. Filtered GARCH with Big Shocks<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + \eta I_{t,A} h_t + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t) (1 + \rho_2 I_{t-1}) (1 + \rho_3 I_{t+1}) (1 + \rho_4 D_4) (1 + \rho_5 D_5)$$

$$h_t = \omega + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \phi I_{t-1,B} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \phi I_{t-1,B} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$h_t^N = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day t-1;  $I_{t-1,B} = 0$ , otherwise.  $I_{t-1,A}$  is the dummy variable for announcement on day t-1,  $I_{t-1,N} = 1 - I_{t-1,A}$ .

	coefficient	robust t-stat
Mean Equation		
C	0.02316893	2.03719**
$\eta$	0.048466608	0.51737
Variance Equation		
$\omega$	0.166289902	6.05573**
$\alpha_A$	-0.191135516	-3.60635**
$\alpha_N$	-0.005939494	-0.82778
$\beta_A$	0.561742709	3.33368**
$\beta_N$	0.965316541	61.37579**
$\gamma_A$ <sup>1</sup>	0.322663668	2.47496**
$\gamma_N$ <sup>1</sup>	0.032498408	2.81889**
$\phi$ <sup>2</sup>	0.096385012	1.82607*
Filter Equation		
$\rho_1$	0.469785081	7.30347**
$\rho_2$	-0.027565009	-0.39494
$\rho_3$	-0.177910218	-3.78899**
$\rho_4$	0.207893337	3.07932**
$\rho_5$	0.140208444	2.89423**
Residuals Sum of squares:	633.3117	
R**2 :	0.0025	
Ljung-Box(15):	10.5777	
log likelihood:	-1593.146077	

Note<sup>1</sup>: likelihood ratio test for asymmetric effects are 14.3, 1% significant with  $\chi^2(2)$ .

$\alpha_A$  would otherwise be insignificant;  $\alpha_N$  would be 0.021, significant.

Note<sup>2</sup>: likelihood ratio test for big shocks is 10.6, 1% significant with  $\chi^2(1)$ .

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.

**Table 6b. Filtered GARCH with Big Shocks<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + \eta I_{t,A} h_t + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t) (1 + \rho_2 I_{t-1}) (1 + \rho_3 I_{t+1}) (1 + \rho_4 D_4) (1 + \rho_5 D_5)$$

$$h_t = \omega + [(a_N + \theta_1 + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + (\beta_N + \theta_2) h_{t-1}^A] + [(a_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$h_t^A = (a_N + \theta_1 + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + (\beta_N + \theta_2) h_{t-1}^A$$

$$h_t^N = (a_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day t-1;  $I_{t-1,B} = 0$ , otherwise.  $I_{t-1,A}$  is the dummy variable for announcement on day t-1,  $I_{t-1,N} = 1 - I_{t-1,A}$ .

	coefficient	robust t-stat
Mean Equation		
C	0.024471697	2.23184**
Variance Equation		
$\omega$	0.166044224	6.02263**
$\theta_1$	-0.180995517	-3.75748**
$\alpha_N$	-0.005822975	-0.80961
$\theta_2$	-0.4020016	-2.3856**
$\beta_N$	0.965401002	61.42687**
$\gamma_A$	0.325734032	2.43863**
$\gamma_N$	0.03228159	2.80504**
$\varphi$	0.092186358	1.83998*
Filter Equation		
$\rho_1$	0.477931673	7.43115**
$\rho_2$	-0.027110577	-0.38649
$\rho_3$	-0.17669006	-3.76044**
$\rho_4$	0.206615636	3.06432**
$\rho_5$	0.135599234	2.80902**
Residuals Sum of squares:	633.5362	
R**2 :	0.001952	
Ljung-Box(15):	10.4233	
log likelihood:	-1593.5462	

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.

**Table 7a. Test for Heterogeneity of Unemployment in Filter<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t) (1 + \rho_2 I_{t-1}) (1 + \rho_3 I_{t+1}) (1 + \rho_4 D_4) (1 + \rho_5 D_5) (1 + \rho_6 I_{t, uem})$$

$$h_t = \omega + [(\alpha_N + \theta_1 + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + (\beta_N + \theta_2) h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$h_t^A = (\alpha_N + \theta_1 + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + (\beta_N + \theta_2) h_{t-1}^A$$

$$h_t^N = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t, uem}$  denotes the dummy variable for days with unemployment news.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day t-1;  $I_{t-1,B} = 0$ , otherwise.  $I_{t-1,A}$  is the dummy variable for announcement on day t-1,  $I_{t-1,N} = 1 - I_{t-1,A}$ .

	coefficient	robust t-stat
Mean Equation		
C	0.024502091	2.23283**
Variance Equation		
$\omega$	0.16792935	6.11585**
$\alpha_A$	-0.174599984	-3.27811**
$\alpha_N$	-0.006107231	-0.82167
$\beta_A$	0.548363055	3.01668**
$\beta_N$	0.963810537	57.9055**
$\gamma_A$	0.313463293	2.30893**
$\gamma_N$	0.033118642	2.78592**
$\varphi$	0.090642222	1.67556*
Filter Equation		
$\rho_1$	0.43235066	6.09007**
$\rho_2$	-0.027967113	-0.3931
$\rho_3$	-0.175541164	-3.71973**
$\rho_4$	0.209575858	3.10021**
$\rho_5$	0.13051766	2.57673**
$\rho_6$	0.097326037	1.00665
Residuals Sum of squares:	633.5357	
R**2 :	0.001957	
Ljung-Box(15):	10.152	
log likelihood:	-1592.840735	

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.

**Table 7b. Test for Heterogeneity Persistence of Unemployment<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t) (1 + \rho_2 I_{t-1}) (1 + \rho_3 I_{t+1}) (1 + \rho_4 D_4) (1 + \rho_5 D_5)$$

$$h_t = \omega + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + (\varphi I_{t-1,B} + \kappa I_{t-1,uem}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + (\varphi I_{t-1,B} + \kappa I_{t-1,uem}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$h_t^N = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t,uem}$  denotes the dummy variable for days with unemployment news.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day t-1;  $I_{t-1,B} = 0$ , otherwise.  $I_{t-1,A}$  is the dummy variable for announcement on day t-1,  $I_{t-1,N} = 1 - I_{t-1,A}$ .

	coefficient	robust t-stat
Mean Equation		
C	0.024917922	2.2685**
Variance Equation		
$\omega$	0.16452463	5.94598**
$\alpha_A$	-0.167175834	-2.53695**
$\alpha_N$	-0.00558966	-0.77022
$\beta_A$	0.512323681	3.03106**
$\beta_N$	0.964917286	60.82589**
$\gamma_A$	0.351512216	2.49836**
$\gamma_N$	0.032609418	2.77975**
$\varphi$	0.084023671	1.49949
$\kappa$	-0.041542192	-0.74501
Filter Equation		
$\rho_1$	0.472539568	7.36339**
$\rho_2$	-0.023885692	-0.33301
$\rho_3$	-0.175227709	-3.7181**
$\rho_4$	0.201846738	3.04638**
$\rho_5$	0.135585756	2.85335**
Residuals Sum of squares:	633.5371	
R**2 :	0.002024	
Ljung-Box(15):	10.6373	
log likelihood:	1593.240911	

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.

**Table 8. GARCH with heterogeneity for Close-close Returns<sup>a</sup>**

Quasi-maximum likelihood estimates of the model

$$R_t = c + \lambda_{ch} + F_t \varepsilon_t, \text{ where } \varepsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$F_t = (1 + \rho_1 I_t)(1 + \rho_2 I_{t-1})(1 + \rho_3 I_{t+1})(1 + \rho_4 D_4)(1 + \rho_5 D_5)(1 + \rho_6 I_{ch})$$

$$h_t = \omega + [(\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A] + [(\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N]$$

$$h_t^A = (\alpha_A + \gamma_A I_{t-1}^-) I_{t-1,A} \varepsilon_{t-1}^2 + \varphi I_{t-1,B} \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$$

$$h_t^N = (\alpha_N + \gamma_N I_{t-1}^-) I_{t-1,N} \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$$

where  $R_t$  is the daily continuously compounded return of the Treasury futures expressed in percent,  $\Phi_{t-1}$  is information set available at the end of day t-1.  $I_{ch}$  indicates the dummy variable for the quarterly switches in futures contracts.  $I_t$  represents the dummy variables of the announcement days.  $I_{t+1}$  denotes for days prior to the announcements, while  $I_{t-1}$  for days immediately following the announcements.  $D_4$  and  $D_5$  stand for dummy variables of Thursday and Friday respectively.  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day t-1;  $I_{t-1,B} = 0$ , otherwise.  $I_{t-1,A}$  is the dummy variable for announcement on day t-1,  $I_{t-1,N} = 1 - I_{t-1,A}$ .

	coefficient	rob.tst
Mean Equation		
C	0.017043882	1.51588
$\lambda$	-0.567754126	-3.67252**
Variance Equation		
$\omega$	0.182644893	6.74652**
$\alpha_A$	-0.205159	-5.79377**
$\alpha_N$	-0.002203247	-0.26626
$\beta_A$	0.542508882	4.64492**
$\beta_N$	0.953163642	44.52611**
$\gamma_A^1$	0.341824651	2.58365**
$\gamma_N^1$	0.031350474	2.34844**
$\varphi$	0.180675005	2.22382**
Filter Equation		
$\rho_1$	0.472731621	7.31562**
$\rho_2$	-0.10155739	-1.59472
$\rho_3$	-0.139347731	-2.43957**
$\rho_4$	0.150123399	2.25695**
$\rho_5$	0.11130336	2.34446**
$\rho_6$	0.388551508	2.12313**
Residuals Sum of squares:	669.0185	
R**2 :	0.011631	
Ljung-Box(15):	17.6939	
log likelihood:	1656.458284	

Note<sup>1</sup>: likelihood ratio test for asymmetric effects are 23.8, 1% significant with  $\chi^2(2)$ .  $\alpha_A$  would otherwise be insignificant;  $\alpha_N$  would be 0.024, significant.

Note<sup>a</sup>: \*\* denotes significance at 5%, \* denotes significance at 10%.

**Table 9a. Unbiased test for one-step in-sample forecast**

Test for  $H_0: a=0, b=1$  in the OLS regression:  $R_t^2 = a + bH_{t-1,1} + \mu_t$

Where  $R_t^2$  is the squared return for the daily close-close returns, and  $H_{t-1,1}$  is the one-step forecast.

variable	coefficient	t-stat	F-test	F-test(joint)	$\chi^2$ test (joint)	$R^2$	Durbin-Watson
<i>a</i>	0.013195	0.482337	0.232649	0.127076	0.254152	0.075437	2.139247
<i>b</i>	0.963366	0.493835	0.243873				

**Table 9b. Basic Statistics for Log Difference of Forward Estimated, Implied and Realized Volatility<sup>1,4</sup>**

Statistics	All days			Announcement days			Days without announcements			Days following announcements		
	GARCH	Implied	Realized	GARCH	Implied	Realized	GARCH	Implied	Realized	GARCH	Implied	Realized
Mean ( $\mu$ )	-0.000127	-0.00016	-0.00010	-0.015824	-0.01654	-0.01298	0.002456	0.002551	0.002018	0.003426	-0.00101	0.00558
Std.	0.015746	0.034676	0.032425	0.014981	0.038316	0.046372	0.014307	0.033282	0.031816	0.020175	0.041178	0.034668
t-stat ( $\mu > 0$ )	-0.363487	-0.20145	-0.14316	-17.89437	-7.31301	-4.74271	7.736326	3.454268	2.85845	2.876834	-0.41347	2.726757
Median	-0.00207	0	-1.84E-05	-0.016029	-0.0117	-0.00434	-0.000961	0	0.00041	0.001572	0	0.001037
$P(\ln(\sigma_t/\sigma_{t-1}) > 0)$	39.54%	41.31%	49.31%	8.71%	22.61%	32.06%	44.67%	44.40%	52.12%	57.84%	42.86%	56.79%
Sign test <sup>2</sup>	-9.408294	-7.76498	-0.59911	-13.93064	-9.15435	-6.02087	-4.429947	-4.61347	1.795924	2.715294	-2.39046	2.361125

Note<sup>1</sup>: notice that the median for implied volatility is 0 except for announcement days. This causes  $P(\ln(\sigma_t/\sigma_{t-1}) > 0) < P(\ln(\sigma_t/\sigma_{t-1}) \geq 0)$ .

Note<sup>2</sup>: sign test =  $(n + 0.5 - 0.5 * N) / (0.5 * \sqrt{N})$  where N denotes number of observations, n denotes number of positive observations.

**Table 9c. Analysis from OLS Regression<sup>3,4</sup>**

	GARCH			Realized			Implied		
Constant	0.00246**	-0.00071*	0.00185**	0.00202**	-0.001039	0.00107	0.002551**	-1.59E-05	0.002651**
	(7.12046)	(-1.8955)	(5.057604)	(2.45970)	(-1.25455)	(1.22551)	(3.102502)	(-0.018955)	(3.024547)
Anno	-0.01828**		-0.01832**	-0.0150**		-0.01507**	-0.019091**		-0.019081**
	(-19.9225)		(-19.9225)	(-6.87558)		(-6.92049)	(-8.740887)		(-8.733569)
Anno(-1)		0.00414**	0.00432**		0.00662**	0.00677**		-0.000989	-0.000726
		(4.14165)	(4.7322)		(3.00570)	(3.10818)		(-0.442512)	(-0.330816)
Constant	0.00232**			0.00198**			0.00201**		
	(6.22015)			(2.31713)			(2.3352)		
Friday	-0.01202**			(-0.01025)**			(-0.01074)**		
	(-14.5505)			(-5.4041)			(-5.59742)		

Note<sup>3</sup>: Anno denotes dummy variable for announcement days, Anno(-1) denotes dummy for days following announcements.

t-statistics shown in parentheses, \* denotes significance at 10%, \*\* denotes significance at 5%.

Note<sup>4</sup>: volatility data is in terms of annualized (multiplying by the square root of 252 - the approximate number of trading days in one year) standard deviation.

**Table 10a. Unbiased test for one-step out-of-sample forecast<sup>1</sup>**

OLS estimates of the model  $R_t^2 = a + bH_{t-1,1} + \mu_t$

Where  $R_t^2$  is the squared return for the daily close-close returns, and  $H_{t-1,1}$  is the one-step forecast

$H_0: a=0, b=1$

variable	coefficient	t-statistics	F-test	F-test(joint)	$\chi^2$ test (joint)	$R^2$	Durbin-Watson
<i>a</i>	0.011138	0.168075	0.028249	1.488965	2.97793	0.66177	2.05762
<i>b</i>	0.802512	0.933381	0.871201				

**Table 10b. Implied volatility and multi-step out-of-sample forecast<sup>1, 2</sup>**

OLS estimates of the model  $\sigma_{IMV} = a + b\sigma_{GARCH} + \mu$

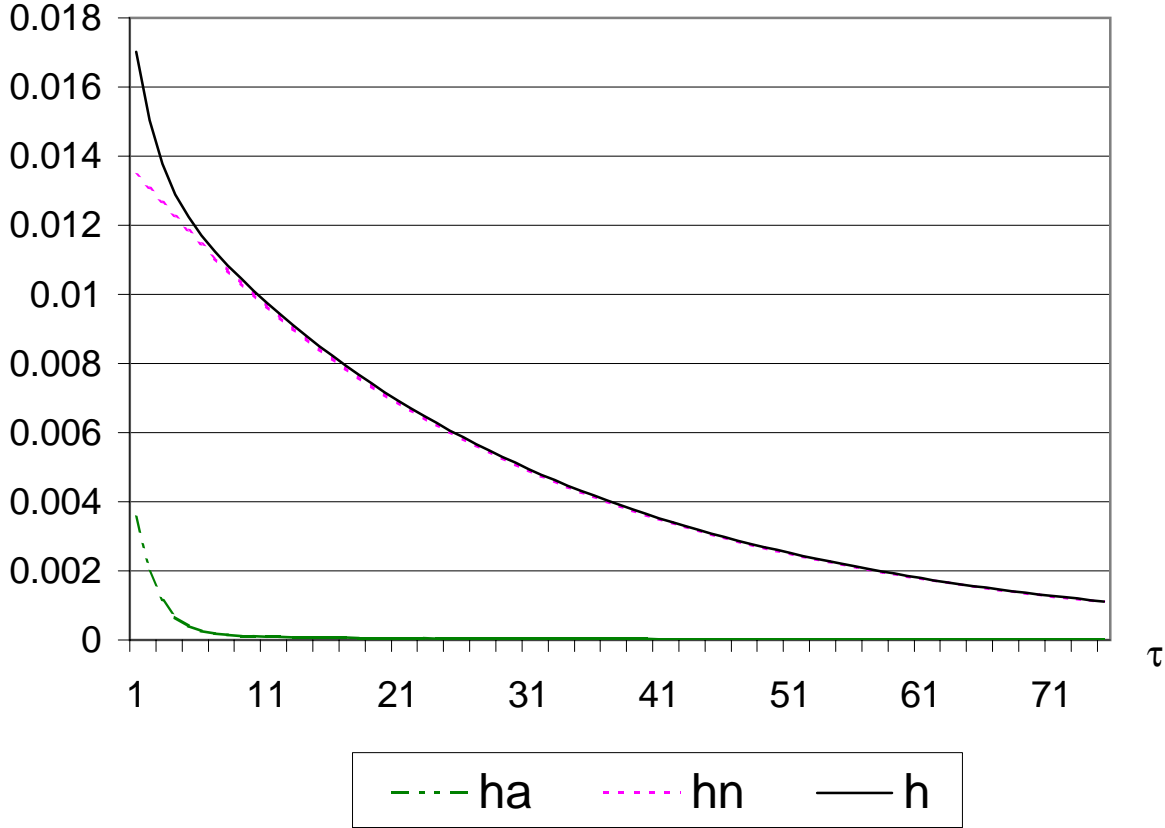
Where  $\sigma_{IMV}$  is the annualized square root of implied volatility, and  $\sigma_{GARCH}$  is the annualized square root of the mathematical mean of one-step to 38 step (trading-day based) forecasted volatility.

	Forecasts with asymmetric effects			Forecasts without asymmetric effects		
<i>a</i>	-5.559194** (-6.138501)	-4.513466** (-4.232337)	-3.264638** (-2.687821)	-3.177181** (-2.199088)	-1.916818** (-1.221566)	0.61574** (0.3631)
<i>b</i>	1.765648** (16.06283)	1.638627** (12.661)	1.486493** (-10.08364)	1.589419** (8.416623)	1.42465** (6.946588)	1.092919** (4.930657)
ma(1)		0.574052** (10.31)	0.660782** (10.62026)		0.661428** (12.95511)	0.779414** (13.2172)
ma(2)			0.363148** (5.842262)			0.461118** (7.867141)
$R^2$	0.544318	0.698676	0.732321	0.246966	0.580509	0.659244
D-W stat	0.677071	1.667546	1.906378	0.445242	1.450461	1.783782

Note<sup>1</sup>: \* denotes significance at 10%, \*\* denotes significance at 5%.

Note<sup>2</sup>: t-statistics shown in parentheses.

**Graph 1: impulse response of shocks over futures volatility**



Note: this graph depicts the average impulse response of one-unit of  $|\varepsilon_t|$  on the  $\tau$ -step volatility forecast of the dataset with 2069 observations. The 1-step forecast equation could be expressed as the following:

$$h_{t,1} \equiv h_{t+1} = \varpi + [(\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \varphi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A] + [(\alpha_N + \gamma_N I_t^-) I_{t,N} \varepsilon_t^2 + \beta_N h_{t,1}^N], \text{ where}$$

$$h_{t,1}^A \equiv h_{t+1}^A = (\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \varphi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A \quad h_{t,1}^N \equiv h_{t+1}^N = (\alpha_N + \gamma_N I_t^-) I_{t,N} \varepsilon_t^2 + \beta_N h_t^N$$

For  $\tau > 1$ , then the forecast equation could be expressed as the following:

$$h_{t,\tau} = \varpi + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N]$$

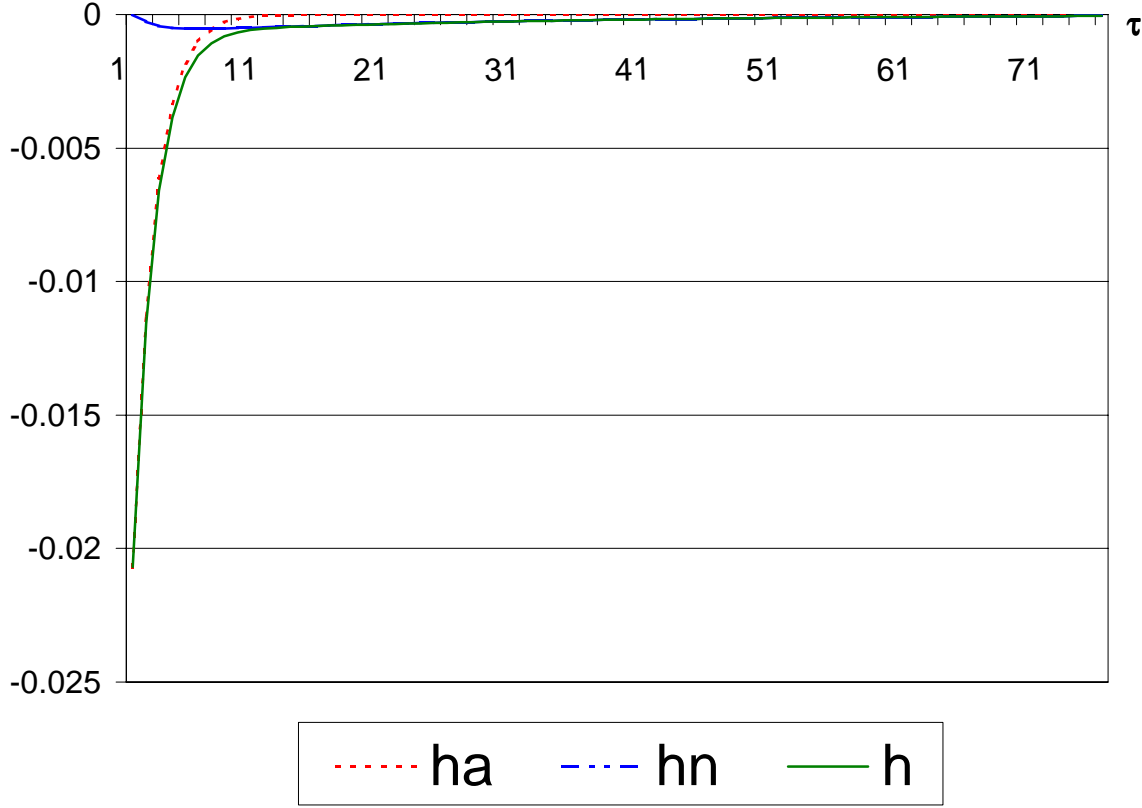
$$= \varpi + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} h_{t,\tau-1} + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} h_{t,\tau-1} + \beta_N h_{t,\tau-1}^N] \text{ where}$$

$$h_{t,\tau}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A, \quad h_{t,\tau}^N = (\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N.$$

In the equations above,  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day  $t-1$ ;  $I_{t-1,B} = 0$ , otherwise.  $I_{t,A}$  is the dummy variable for announcement on day  $t$ ,  $I_{t,N} = 1 - I_{t,A}$ . Notice that the impact on  $h^A$  (ha in the graph) is low due to the small percentage of announcement days out of the whole sample (14%) and that of the big-announcement days out of the announcement days (32%).



## Graph 2: impulse response of positive shocks over futures volatility



Note: this graph depicts the impulse response of one-unit increase of  $|\varepsilon_t|$  on the  $\tau$ -step volatility forecast, when  $\varepsilon_t$  is positive. The average impulse response of 2069 observations in the dataset is calculated. The one-step forecast equation could be expressed as the following:

$$h_{t,1} \equiv h_{t+1} = \bar{\omega} + [(\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \varphi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A] + [(\alpha_N + \gamma_N I_t^-) I_{t,N} \varepsilon_t^2 + \beta_N h_{t,1}^N], \text{ where}$$

$$h_{t,1}^A \equiv h_{t+1}^A = (\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \varphi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A \quad h_{t,1}^N \equiv h_{t+1}^N = (\alpha_N + \gamma_N I_t^-) I_{t,N} \varepsilon_t^2 + \beta_N h_t^N$$

For  $\tau > 1$ , then the forecast equation could be expressed as the following:

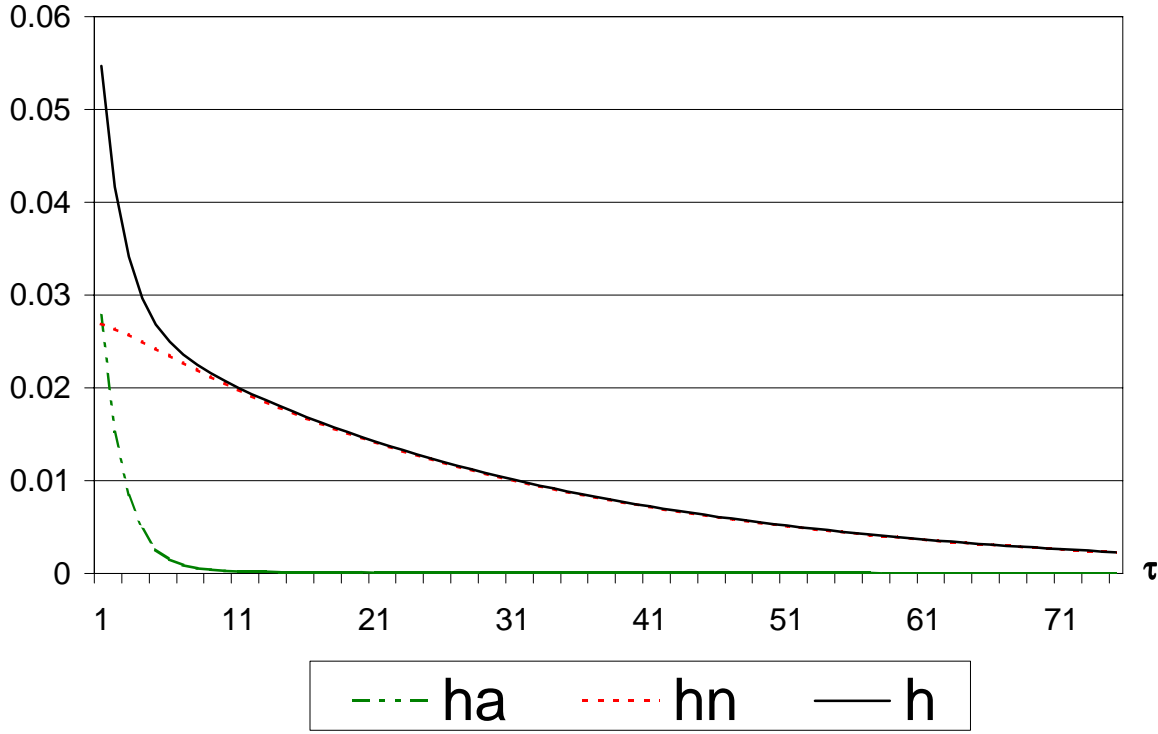
$$h_{t,\tau} = \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N]$$

$$= \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} h_{t,\tau-1} + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} h_{t,\tau-1} + \beta_N h_{t,\tau-1}^N] \text{ where}$$

$$h_{t,\tau}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A, \quad h_{t,\tau}^N = (\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N.$$

In the equations above,  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day  $t-1$ ;  $I_{t-1,B} = 0$ , otherwise.  $I_{t,A}$  is the dummy variable for announcement on day  $t$ ,  $I_{t,N} = 1 - I_{t,A}$ . Notice that if not for the small percentage (14%) of announcement days out of the whole sample and that (32%) of the big-announcement days out of the announcement days, the impact on  $h^A$  (ha in the graph) would be higher.

### Graph 3: Impulse response of negative shocks over futures volatility



Note: this graph depicts the impulse response of one-unit increase of  $|\varepsilon_t|$  on the  $\tau$ -step volatility forecast, when  $\varepsilon_t$  is negative. The average impulse response of 2069 observations in the dataset is calculated. The one-step forecast equation could be expressed as the following:

$$h_{t,1} \equiv h_{t+1} = \bar{\omega} + [(\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \varphi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A] + [(\alpha_N + \gamma_N I_t^-) I_{t,N} \varepsilon_t^2 + \beta_N h_t^N] , \text{ where}$$

$$h_{t,1}^A \equiv h_{t+1}^A = (\alpha_A + \gamma_A I_t^-) I_{t,A} \varepsilon_t^2 + \varphi I_{t,B} \varepsilon_t^2 + \beta_A h_t^A \quad h_{t,1}^N \equiv h_{t+1}^N = (\alpha_N + \gamma_N I_t^-) I_{t,N} \varepsilon_t^2 + \beta_N h_t^N$$

For  $\tau > 1$ , then the forecast equation could be expressed as the following:

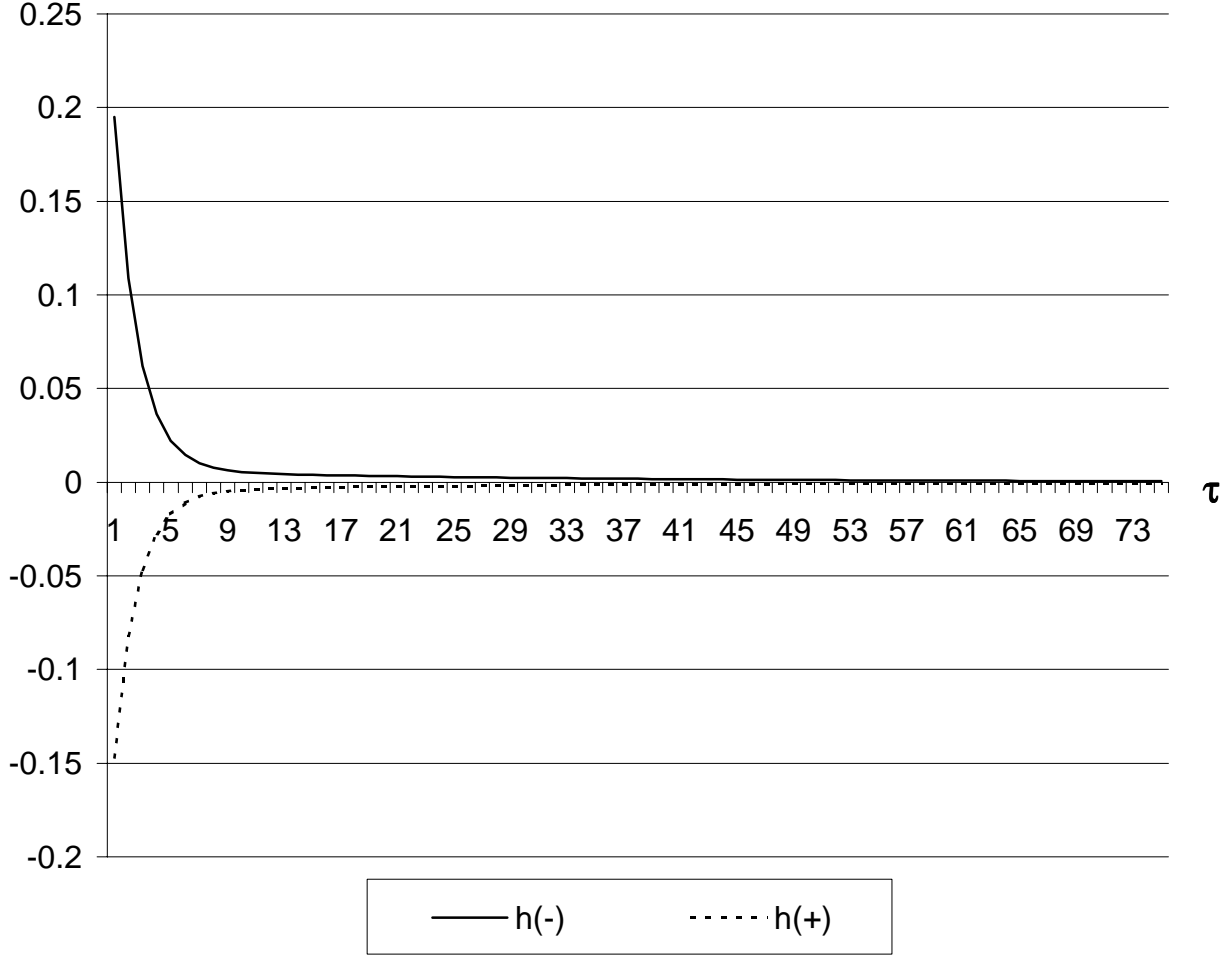
$$h_{t,\tau} = \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N]$$

$$= \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} h_{t,\tau-1} + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} h_{t,\tau-1} + \beta_N h_{t,\tau-1}^N] \text{ where}$$

$$h_{t,\tau}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A, \quad h_{t,\tau}^N = (\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N .$$

In the equations above,  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day  $t-1$ ;  $I_{t-1,B} = 0$ , otherwise.  $I_{t,A}$  is the dummy variable for announcement on day  $t$ ,  $I_{t,N} = 1 - I_{t,A}$ . Notice that if not for the small percentage (14%) of announcement days out of the whole sample and that (32%) of the big-announcement days out of the announcement days, the impact on  $h^A$  (ha in the graph) would be higher.

**Graph 4. Impulse response for shocks from announcement days**



Note: this graph depicts the time profile of one-unit increase of  $|\varepsilon_t|$  from announcement days on the  $\tau$ -step volatility forecast, where (-) indicates a negative shock while (+) indicates a positive shock. The 1-step forecast equation could be expressed as the following:

$$h_{t,1}|_{I_{t,A}=1} \equiv h_{t+1}|_{I_{t,A}=1} = \omega + h_{t,1}^A|_{I_{t,A}=1} + h_{t,1}^N|_{I_{t,A}=1} \quad \text{where}$$

$$h_{t,1}^A|_{I_{t,A}=1} \equiv h_{t+1}^A|_{I_{t,A}=1} = (\alpha_A + \gamma_A I_t^- + \varphi I_{t,B}|_{I_{t,A}=1}) \varepsilon_t^2 + \beta_A h_{t,\tau-1}^A \quad \text{and} \quad h_{t,1}^N|_{I_{t,A}=1} \equiv h_{t+1}^N|_{I_{t,A}=1} = \beta_N h_{t,\tau-1}^N$$

In our sample,  $P(I_{t,B}|_{I_{t,A}=1}) = 0.322$

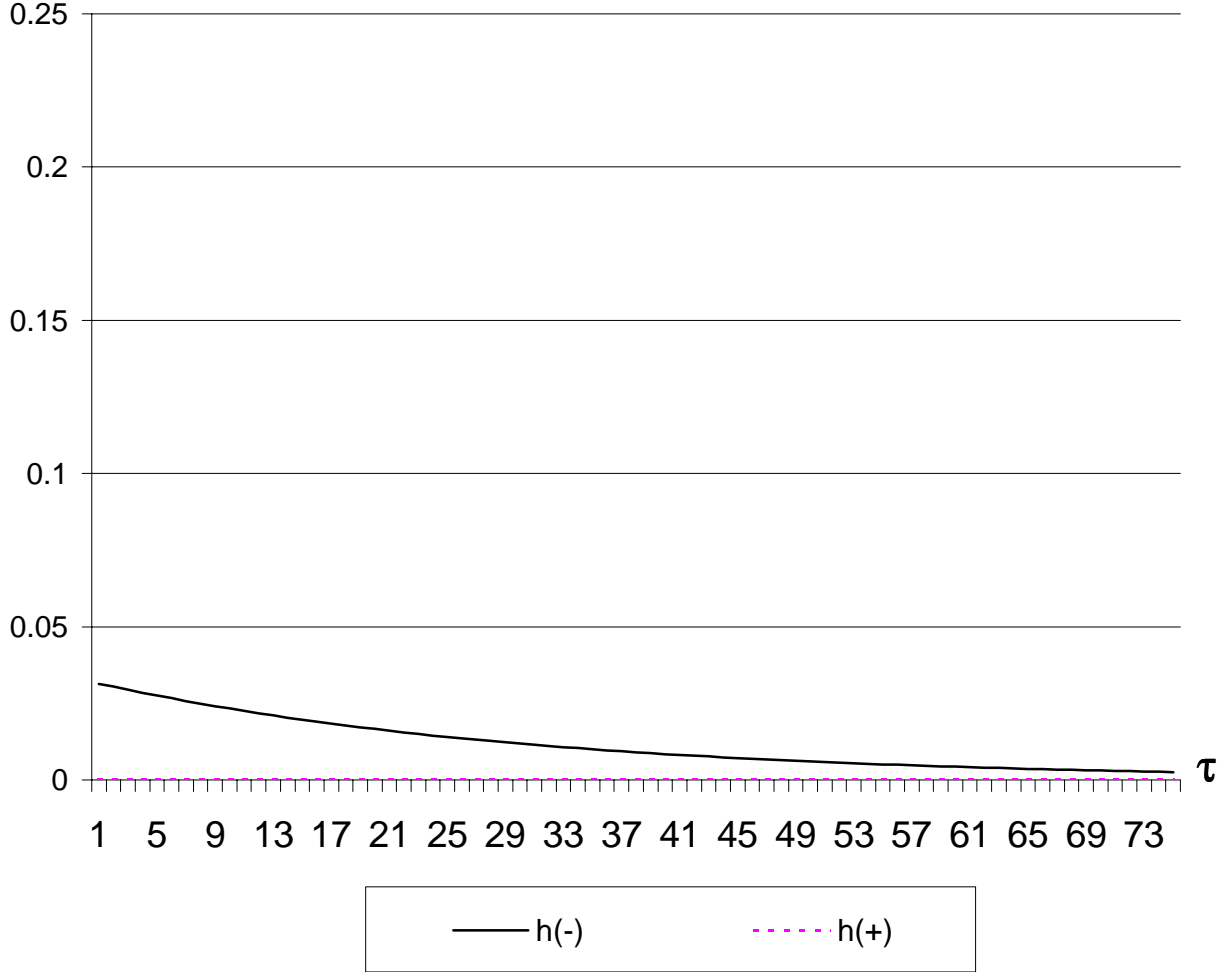
For  $\tau > 1$ , then the forecast equation could be expressed as the following:

$$h_{t,\tau} = \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi)I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N)I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N] \\ = \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi)I_{t+\tau-1,A} h_{t,\tau-1} + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N)I_{t+\tau-1,N} h_{t,\tau-1} + \beta_N h_{t,\tau-1}^N] \quad , \quad \text{where}$$

$$h_{t,\tau}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi)I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A \quad , \quad h_{t,\tau}^N = (\alpha_N + 0.5\gamma_N)I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N \quad .$$

In the equations above,  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t-1,B} = 1$ , if the announcement brings big shock on day  $t-1$ ;  $I_{t-1,B} = 0$ , otherwise.  $I_{t,A}$  is the dummy variable for announcement on day  $t$ ,  $I_{t,N} = 1 - I_{t,A}$ . The percentage of  $I_{t+\tau-1,A} = 1$  is 14% out of our sample.

**Graph 5. Impulse response for shocks from non-announcement days**



Note: this graph depicts the impulse response of one-unit of  $|\varepsilon_t|$  from non-announcement days on the  $\tau$ -step volatility forecast ( $h$ ). Where  $h(-)$  indicates impulse response from a negative shock while  $h(+)$  indicates that from a positive shock. The one-step forecast equation could be expressed as the following:

$$h_{t,1} \Big|_{I_{t,N}=1} \equiv h_{t+1} \Big|_{I_{t,N}=1} = \omega + h_{t,1}^A \Big|_{I_{t,N}=1} + h_{t,1}^N \Big|_{I_{t,N}=1} \quad \text{where}$$

$$h_{t,1}^A \Big|_{I_{t,N}=1} \equiv h_{t+1}^A \Big|_{I_{t,N}=1} = \beta_A h_t^A \quad \text{and} \quad h_{t,1}^N \Big|_{I_{t,N}=1} \equiv h_{t+1}^N \Big|_{I_{t,N}=1} = (\alpha_N + \gamma_N I_t^-) \varepsilon_t^2 + \beta_N h_t^N$$

For  $\tau > 1$ , then the forecast equation could be expressed as the following:

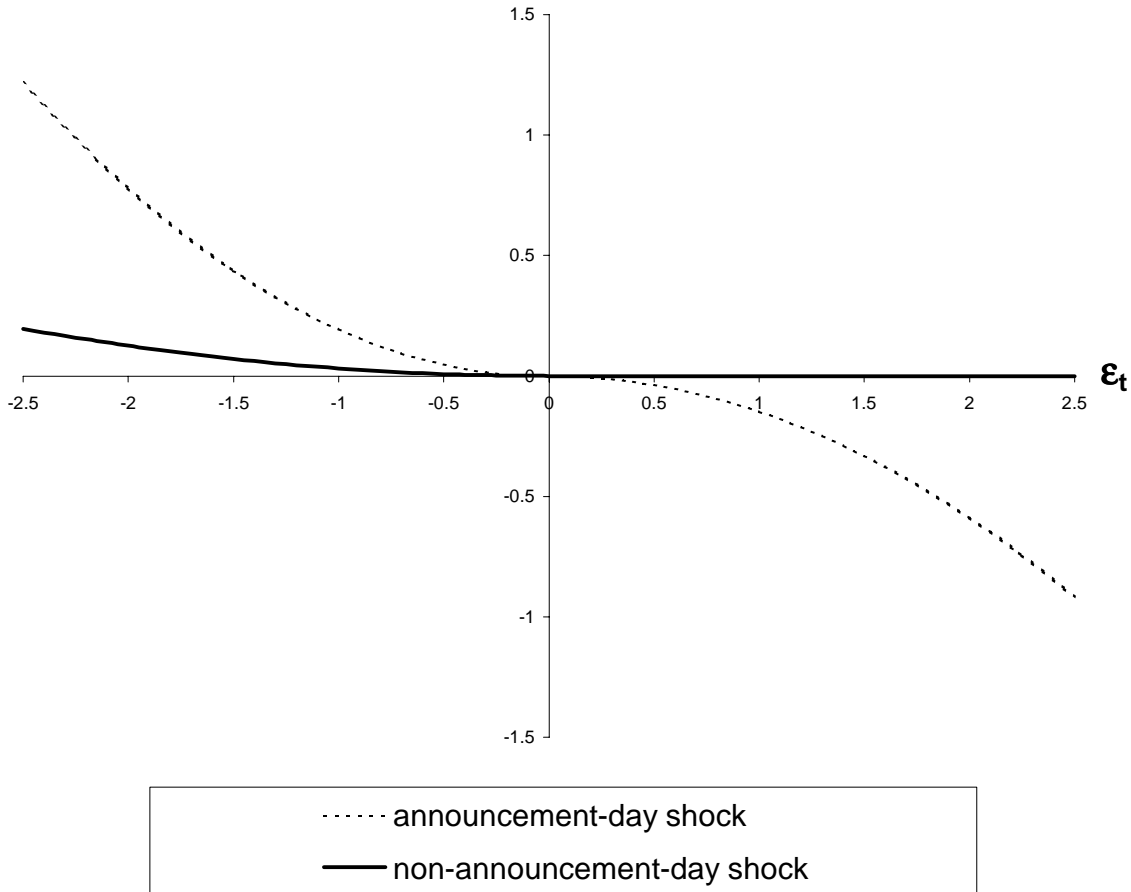
$$h_{t,\tau} = \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N]$$

$$= \bar{\omega} + [(\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} h_{t,\tau-1} + \beta_A h_{t,\tau-1}^A] + [(\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} h_{t,\tau-1} + \beta_N h_{t,\tau-1}^N], \text{ where}$$

$$h_{t,\tau}^A = (\alpha_A + 0.5\gamma_A + 0.322\varphi) I_{t+\tau-1,A} E_t \varepsilon_{t+\tau-1}^2 + \beta_A h_{t,\tau-1}^A, \quad h_{t,\tau}^N = (\alpha_N + 0.5\gamma_N) I_{t+\tau-1,N} E_t \varepsilon_{t+\tau-1}^2 + \beta_N h_{t,\tau-1}^N.$$

In the equations above,  $I_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$ ;  $I_{t-1}^- = 0$ , otherwise.  $I_{t,N}$  is the dummy variable for non-announcement on day  $t$ ,  $I_{t,N} = 1 - I_{t,A}$ . The percentage of  $I_{t+\tau-1,N} = 1$  is 86% out of our sample. Since  $\alpha_N = 0$  for our sample, we find the impulse response for  $h(+)$  on the x axis.

## Graph 6. News impact curve



Note: this graph depicts news impact on the one-step forecast, the estimates with close-close return data for the sample period of Nov. 9, 1988 to Dec. 31, 1996 are used here.

The one-step forecast from an announcement-day is:

$$h_{t-1,1} \Big|_{I_{t-1,A}=1} \equiv h_t \Big|_{I_{t-1,A}=1} = \omega + h_t^A \Big|_{I_{t-1,A}=1} + h_t^N \Big|_{I_{t-1,A}=1} = (\alpha_A + \gamma_A I_{t-1}^- + \phi I_{t-1,B}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A + \beta_N h_{t-1}^N,$$

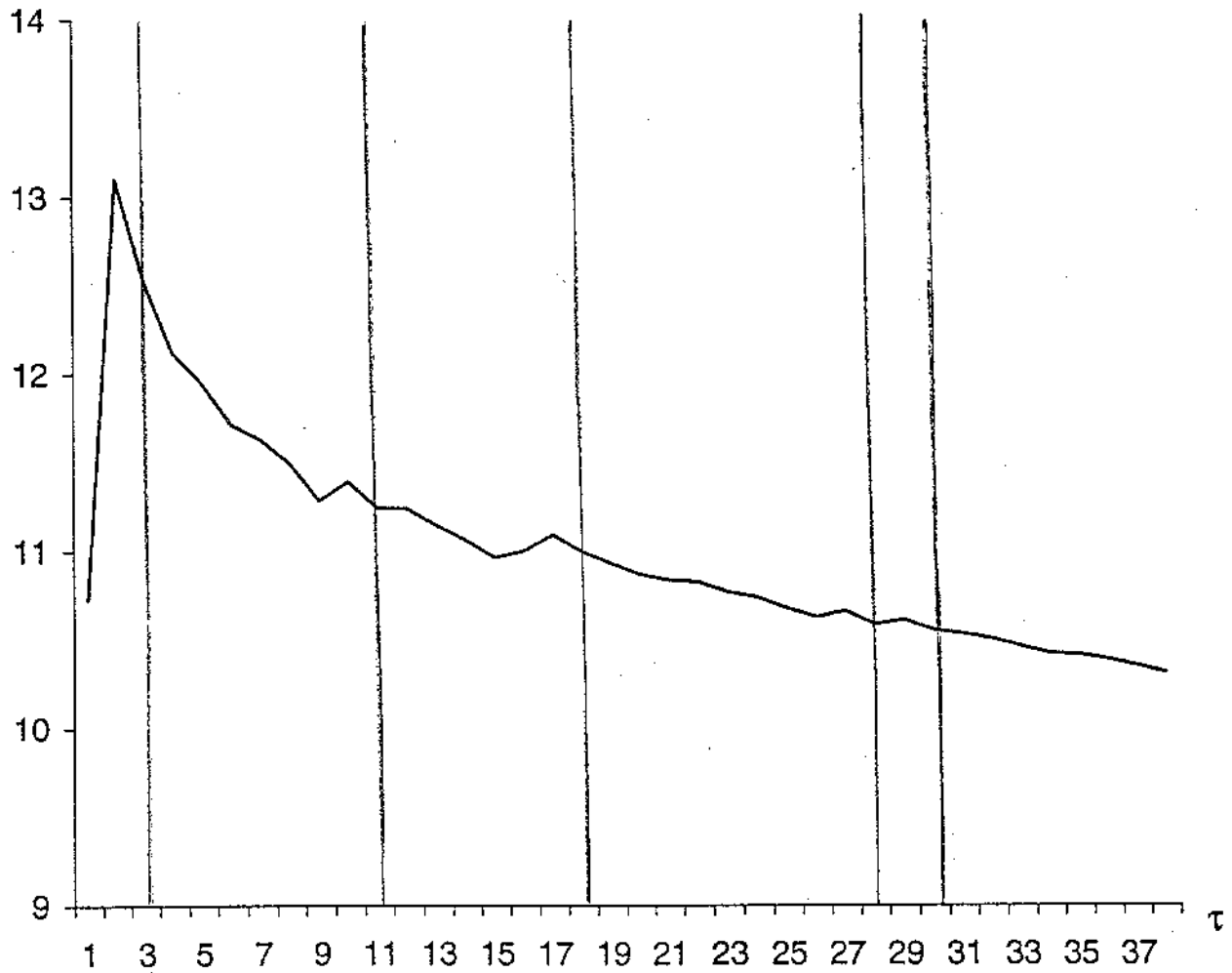
where  $h_t^A \Big|_{I_{t-1,A}=1} = (\alpha_A + \gamma_A I_{t-1}^- + \phi I_{t-1,B}) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A$  ,  $h_t^N \Big|_{I_{t-1,A}=1} = \beta_N h_{t-1}^N$

The one-step forecast from a non-announcement-day is:

$$h_{t-1,1} \Big|_{I_{t-1,N}=1} \equiv h_t \Big|_{I_{t-1,N}=1} = \omega + h_t^A \Big|_{I_{t-1,N}=1} + h_t^N \Big|_{I_{t-1,N}=1} = (\alpha_N + \gamma_N I_{t-1}^-) \varepsilon_{t-1}^2 + \beta_A h_{t-1}^A + \beta_N h_{t-1}^N,$$

where  $h_t^A \Big|_{I_{t-1,N}=1} = \beta_A h_{t-1}^A$  ,  $h_t^N \Big|_{I_{t-1,N}=1} = (\alpha_N + \gamma_N I_{t-1}^-) \varepsilon_{t-1}^2 + \beta_N h_{t-1}^N$

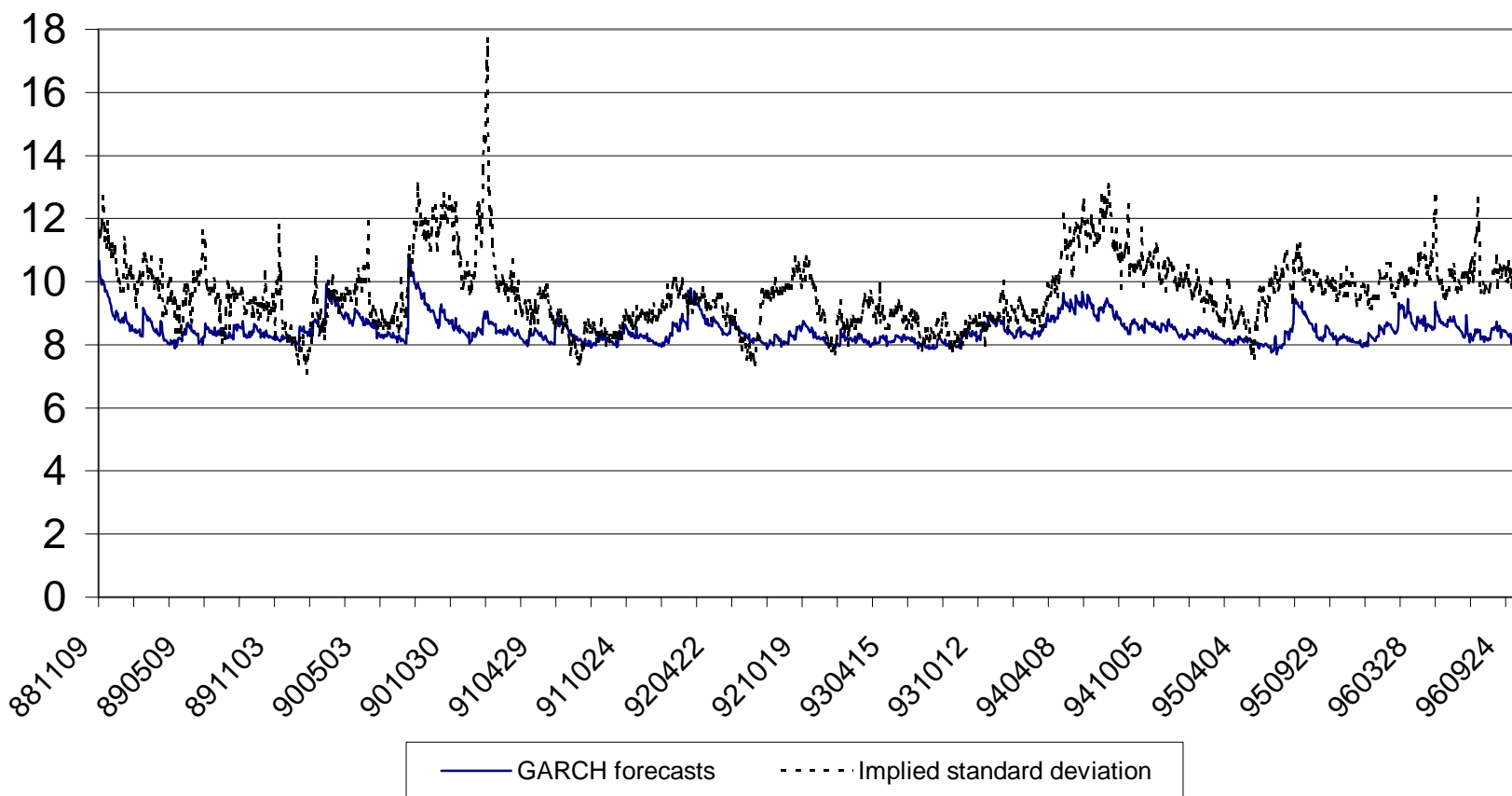
**Graph 7. Term structure of volatility forecast**



Note: this graph displays the term structure of the annualized forecasted standard deviation on a typical day. The day shown here is Nov. 9, 1988. Vertical lines indicates future announcement-days.

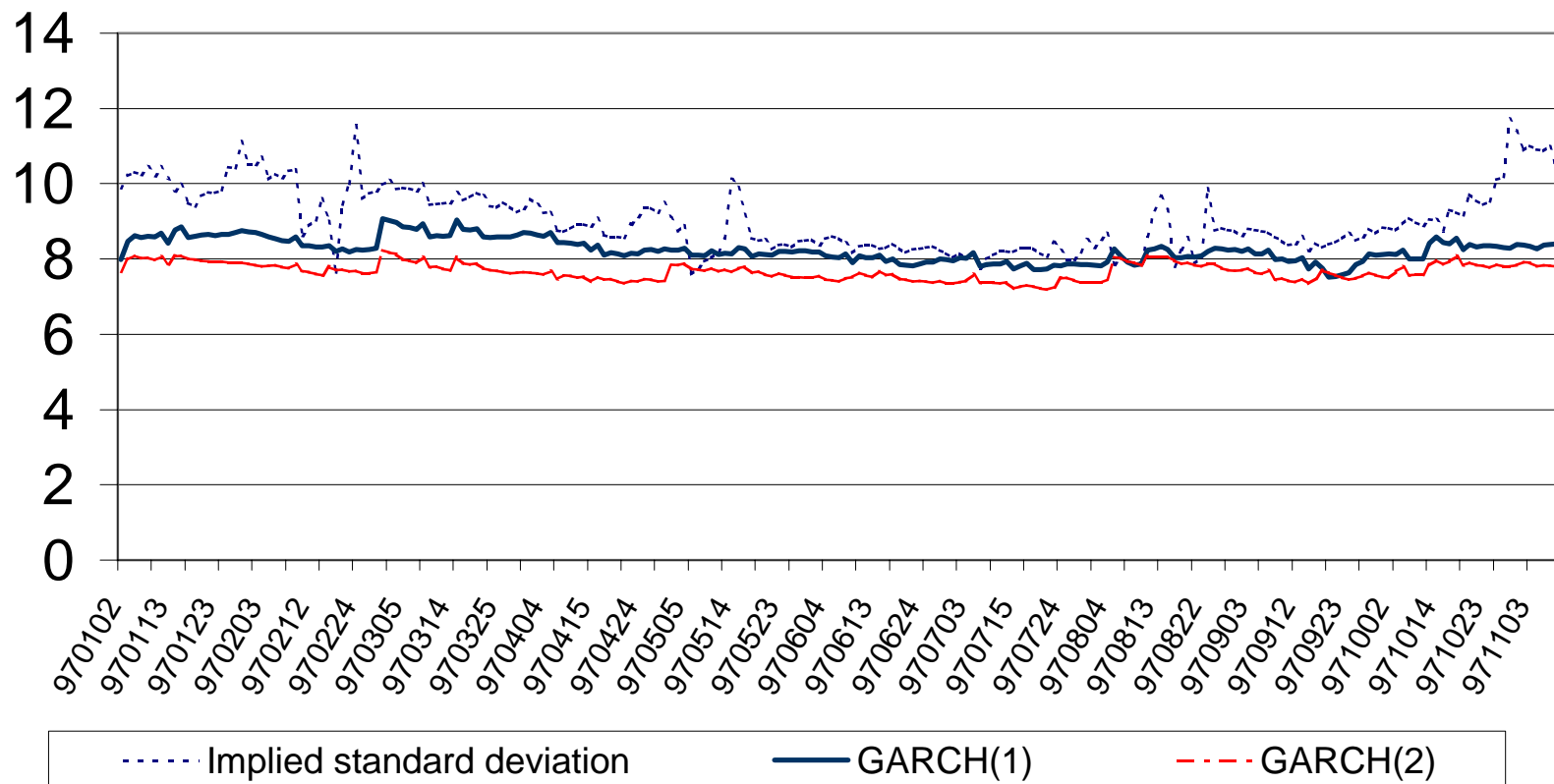
The term structure is constructed as  $\sqrt{\frac{252}{k} \sum_{r=1}^k H_{t,r}}$ .

### Graph 8. in-sample GARCH forecasts and implied volatility



Note: implied deviation denotes the annualized square root of implied volatility, and GARCH forecasts are the annualized square root of the mathematical mean of one-step to 38-step (trading-day based) forecasted volatility from the model.

## Graph 9: out-of-sample GARCH forecasts and implied volatility



Note: implied deviation denotes the annualized square root of implied volatility, and GARCH(1) and GARCH(2) are the annualized square root of the mathematical mean of one-step to 38-step (trading-day based) forecasted volatility from the models with and without asymmetric effect, respectively.