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ABSTRACT

We examine the reaction of daily bond prices to the release of government macroeconomic news. These news releases are of interest because they are released on periodic, preannounced dates and because they cause substantial bond market volatility. The news component of volatility is not positively autocorrelated on these dates, since the news is released at a specific moment in time. We find that (1) expected returns on the short end of the bond market are significantly higher on these announcement dates, and (2) the persistence pattern of daily volatility is quite different around these days.

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Public Information and the Persistence of Bond Market Volatility

It is a well-documented fact that volatility in financial markets is correlated over time (for a review of recent work, see Bollerslev, Chou, and Kroner [1992]; for an earlier discussion see Fama [1970]). Although remarkable progress has been made in modeling this process empirically, relatively little is known about *why* financial market volatility is autocorrelated. Since volatility is equivalent to information flow in a large class of models (see Ross [1989]), one possible explanation is that public information arrives in clusters. Such autocorrelation is plausible; we know from everyday experience that publicly observable events do not occur independently over time. For example, suppose the President proposes a new tax bill to Congress on Monday. On Tuesday, the Congress may react with a counterproposal, and so forth. Thus if the news-generating process has autocorrelated volatility, we would expect financial market prices also to have autocorrelated volatility. This volatility predictability is perfectly consistent with efficient markets.

Alternatively, autocorrelated volatility could arise due to trading on private information over time, changes in tastes, liquidity trading, or some other aspect of the trading or information-gathering process itself. Some empirical evidence suggests this alternative. For example, French and Roll [1986] find that stock market volatility is lower when the market is closed, even if businesses are open. Campbell, Grossman, and Wang [1993] explain stylized facts about volume and return autocorrelation using a model with shocks to risk aversion. On the theoretical side, Brock and LeBaron [1995] show how learning can give rise to positively autocorrelated volatility even when fundamentals follow a homoskedastic random walk. Back [1992] generalizes Kyle [1985] and demonstrates that monopolistic private information trading over time may lead to volatility patterns.

It is difficult to distinguish between these alternatives, since we cannot measure information arrivals directly. Our aim, therefore, is somewhat more modest. We attempt to shed light on the sources of autocorrelated volatility in financial markets by examining the response of asset prices to the release of public information. We investigate whether inter-day volatility autocorrelation is different around a particular subset of exogenously scheduled, regular public information releases. Specifically, we investigate the response of Treasury bond prices to monthly U.S. government releases of the producer price index and employment data. The key feature of these announcements is that (unlike some news) they are not clustered in time but are released on periodic, preannounced dates. For example, unemployment statistics are generally released on the first Friday of every month.

We first document that these announcements have a contemporaneous effect on Treasury bond market daily excess return volatility. Second, we examine whether these predictable increases in the second moment of excess returns influence the expected value of the first moment of excess returns. We find some evidence of a risk premium on these announcement days.

We next explore whether shocks to bond volatility on announcement days are as persistent as shocks on non-announcement days. If announcement shocks do not persist, it would suggest that market prices quickly incorporate public information and that the trading process does not inherently generate persistent volatility in response to news. On the other hand, strong persistence of announcement shocks would suggest that some feature of the trading (or information-gathering) process itself causes volatility to be autocorrelated.

To model volatility, we develop variants of the autoregressive conditional heteroskedasticity (ARCH) framework of Engle [1982]. Engle [1982] finds that quarterly U.K. inflation has autocorrelated volatility. Since interest rates contain a component related to expected future inflation, we would naturally expect interest rates to also have autocorrelated volatility. Engle, Lilien, and Robins [1987] document this by estimating a variant of an ARCH model using monthly three and six month Treasury bill interest rates. Bollerslev, Engle, and Wooldridge [1988] use quarterly data on 20-year Treasury bonds in their multivariate linear GARCH(p,q) model and find that conditional covariances are a significant determinant of risk premia. Bollerslev, Chou, and Kroner [1992] summarize previous ARCH literature that has used interest rate data. The primary advantage of an ARCH specification in this context is that it admits time-varying risk premia. Most previous studies have focussed on this characteristic and its implications for theory on the term structure of interest rates. Bollerslev, Chou, and Kroner [1992] note that while many of the interest rate applications have used linear specifications, it is possible that nonlinear dependencies also exist. We use the GARCH(1,1) model (Bollerslev [1986]) as the starting point for our investigation of the impact of news events. The mixture model (discussed below) provides a parsimonious framework in which to incorporate potential nonlinearities.

As Bollerslev, Chou, and Kroner [1992] note, "While serial correlation in conditional second moments is clearly a property of speculative prices, a systematic search for the causes of this serial correlation has only recently begun." One explanation that they offer is the existence of serially correlated news events. Mitchell and Mulherin [1994] collect an index of news events based on headline widths on the front page of the *New York Times*, 1983-1990. They construct a daily database listing major news events with headlines that are at least three columns wide. Using this database (which the authors kindly provided us), we created a dummy variable, NEWS, which was equal to one on days on which major news events occurred and zero otherwise. This daily variable has a first-order autocorrelation coefficient of about 0.20. Thus it appears there is evidence the news-generating process is in fact positively autocorrelated at daily frequencies.

In contrast, in this study we use a source of news that is, by its very nature, not positively autocorrelated. The timing of government news releases are exogenous to financial markets. We use a dummy variable equal to one on the day that the government announces macroeconomic news; since this news is released once a month, this dummy variable is negatively autocorrelated. A key assumption we make is that the news released on announcement dates is a one-time lump of exogenous news. A possible problem with this assumption is that participants other than financial markets may also react to this news after some delay.[1]

Data

While most recent GARCH research has considered stock prices and exchange rates, which are higher frequency and thus provide more observations with which to draw inference,[2] in this study we examine daily returns on 5-, 10-, and 30-year Treasury bonds. We chose these returns because of our interest in macroeconomic announcements, which we know had a great impact on the Treasury bond market. McQueen and Roley [1993] and Ederington and Lee [1993] document that PPI and employment news surprises result in large price changes for the 10-year bond; following them, we therefore consider PPI and employment release dates.

We calculated excess returns on holding Treasury bonds over 3-month T-bills. Returns were calculated using the Federal Reserve's constant maturity interest rate series.[3] Employment announcement dates beginning in February of 1969 and PPI announcement dates beginning in February of 1971 were supplied to us by the Bureau of Labor Statistics. We were also able to identify manually PPI release dates back to February 1969;[4] our analysis begins then and extends through December 1993. Our data on 30-year Treasury bond yields begins in February 1977.

Table 1 gives summary statistics for daily excess returns. As can be seen in the first entry in the first column, excess returns on treasury bonds were essentially zero in this period. The magnitude of daily

[1] We thank Jim Poterba for suggesting this possibility. One possible scenario is that the Federal Reserve, upon observing the news, changes its policy on the subsequent day (typically, however, the Fed learns the contents of the report on the night prior to the report's release). Under this scenario, the release of news would be an autocorrelated process. To investigate this possibility, we examined whether Fed policy changes tended to occur on or subsequent to announcement dates. Specifically, we compared announcement dates to dates on which the Fed changed its target interest rate, as documented in Rudebusch [1995]. We found no evidence that Fed target changes were more likely to occur on days immediately following announcement days (using Rudebusch's sample period of 1974-9 and 1984-92). Target changes occurred on 5.3% of the days in the sample, but on only 5.0% of the post-announcement days. Thus target changes were *less likely* to occur on days following announcements than on other days. We conclude that, at least as far as Fed behavior is concerned, announcement news is not autocorrelated.

[2] Monte Carlo evidence in Hong [1987] and Lumsdaine [1995] emphasizes the need for a large amount of data in maximum likelihood estimation of models with conditional heteroskedasticity.

[3] Returns are calculated from yields by assuming a bond price equal to par at the beginning of each daily holding period (see, for example, Ibbotson and Associates [1994]). That is, we assume a hypothetical bond with a coupon equal to the yield, and we calculate an end-of-period price on this bond using the next day's yield. Total returns equal the above capital appreciation plus income accrued over the holding period, which varies from one to four days due to weekends and holidays.

[4] Using *The New York Times* and *The Wall Street Journal.*

returns was sometimes quite large, with returns for the 10-year bond as high as 4.69 percent (on October 20, 1987, the day after the stock market crash) and as low as -3.67 percent (on February 19, 1980). There is also evidence of first-order autocorrelation in excess returns. In addition, excess returns are significantly positively skewed and are significantly fat-tailed.

The upper half of Table 1 motivates our use of the ARCH class of models. The first-order autocorrelation coefficient for the absolute value of excess returns ranged from .14 to .26, and for the squared value ranged from .06 to .18. Like stock prices and foreign exchange rates, interest rates exhibit autocorrelated volatility.

The bottom half of Table 1 focuses on the announcement dates. For both the employment release and the PPI release, bond market volatility is far higher on release dates than non-release dates, measured either way. Both the excess returns and the volatility measures exhibit means that are substantially larger than the full sample. In contrast, the first-order autocorrelation coefficients of volatility following announcement days are not very different from average, rising from .16 to .18 for 10-year bond squared excess returns but falling from .26 to .25 for the analogous absolute value of excess returns.

A suggestive fact from Table 1 is that excess returns are far above average on announcement dates for both the PPI and employment. For the pooled announcement dates, excess returns are .084%, .098%, and .132% for the 5-, 10-, and 30-year bonds, on average, compared with negative excess returns for non-announcement dates. Financial market participants know beforehand that these days have high volatility. If risk is higher on these days, we would expect returns also to be higher; this is precisely what happens.[5]

We turn next to simple OLS regressions to explore the relationship of the announcement dates to both risk and return. Since the daily bond market return data used here are relatively unfamiliar, we also review some of the day-of-the-week properties. Table 2 documents the relationship between the volatility of daily excess returns, day-of-the-week effects, and the announcement dates. Again, we measure volatility in two ways, using both squared and absolute value of excess returns.

The results indicate that there are pure day-of-the-week effects for return volatility. We see that bond market volatility is generally highest on Mondays and Fridays, lowest on Wednesdays, exhibiting a U-shaped curve over the week. This contrasts somewhat with the stock market, in which return variances decline over the course of the week (French [1980]). Because we also include announcement day dummy variables, the difference between day-of-the-week volatility patterns in the two markets is not due to the macroeconomic announcements we study here, which would otherwise tend to raise bond market volatility on the applicable

[5] Interestingly, if in 1969-94 one had shorted Treasury bonds on non-announcement dates and had held Treasury bonds on announcement dates, one would have made positive excess daily returns (admittedly small and doubtless less than trading costs.

Fridays.[6] Table 2 also confirms that, controlling for day of the week effects, announcement days have significantly higher volatility than average. Across the three bonds studied, event day volatility increases by about 50% relative to Fridays, as measured by squared excess returns.

The financial press often claims that financial markets are particularly quiet on the days prior to these announcements. For example, a typical headline in the *Wall Street Journal* reads (8/5/94) "Treasurys Decline in Light Trading as Market Awaits Today's Report on Employment in July". This might be called the "calm before the storm" effect. We investigate this claim by including leads and lags of the announcement dummy in the regression. For the 10-year bond, both squared and absolute returns are lower than on average on days preceding macroeconomic announcements (12% lower for absolute, 16% lower for squared excess returns, seen by comparing the coefficients on Announcement$(t+1)$ in Table 2 to the full sample means in Table 1). The effect is statistically significant for absolute returns but not for squared returns. We conclude, therefore, that there is some evidence for the "calm before the storm" effect.[7] Volume data might cast further light on this question.

Table 2 shows that announcement dates have significantly higher volatility than average. Is this high risk accompanied by high return? Table 3 explores this issue by examining excess returns on announcement dates. The first five rows show day-of-the-week effects. Most strikingly, excess returns are consistently negative on Mondays and consistently positive on Fridays. Since Table 2 showed that both Mondays and Fridays are high volatility days, we find no obvious relation between high volatility and mean excess returns.[8]

The seventh row shows the effect of including the announcement day dummy. Holding constant day-of-the-week effects, excess returns are .045 percent higher on announcement days. This higher return is marginally significant with a t-statistic of between 1.5 and 2.5 across the three bonds we study. In contrast, the sixth and eighth rows show that the days before and after announcement dates (which we know from Table 2 do not have high volatility) do not have high return.

The fact that returns are signicantly higher on announcement dates is similar to results that might be obtained from an ARCH-M specification which allows conditional variance to affect the mean (see, for example, Engle, Lilien, and Robbins [1987]). We consider the results in Tables 2 and 3 important because they supply evidence of a time-series risk/return tradeoff without reliance on the ARCH-M specification.[9]

[6] 84% of the announcements were on Fridays, and 37% of the Fridays had announcements.

[7] The size and significance of this effect, however, appears to be dependent on the sampling period used.

[8] These day of the week patterns are stable over time. Splitting the sample in half and rerunning the preceding regressions over both time periods did not alter the significance and signs of the Monday and Friday effects.

[9] Pagan and Sabau [1987], for example, suggest that inference in the ARCH-M model will hinge critically

On the other hand, while the simple OLS specification in these tables appears appealing, there at least two reasons to consider more complex specifications. First, from an econometric standpoint, failure to account for conditional heteroskedasticity is inefficient. In addition, as the descriptive results in Table 1 suggest, the effect of announcement days on excess return volatility is of separate interest.

Main Results

Perhaps the most commonly used model of financial asset return volatility is the GARCH(1,1) model proposed by Bollerslev [1986]. Though it is not necessarily the correct specification of the return generating process, it is an important benchmark, because the same model has been estimated across a wide variety of asset classes and sampling frequencies. In addition, theoretical results are available for quasi-maximum likelihood estimators of this model (see, for example, Lumsdaine [1996]).

For these reasons, we begin by estimating a univariate GARCH(1,1) model of daily bond returns adjusted for day-of-the-week and announcement day effects. We initially accommodate these volatility effects using the procedure outlined in Andersen and Bollerslev [1994]. Dummy variables allow us to measure the (contemporaneous) impact of an announcement day on both conditional mean returns and conditional volatility. Specifically, we assume returns are of the form

$$R_t = \sum_{k=M}^{F} \mu_k I_t^k + \theta I_t^A + \phi_1 R_{t-1} + (s_t h_t)^{1/2} \xi_t \tag{1}$$

$$s_t = (1 + \delta_0 I_t^A) \prod_{k=T}^{F} (1 + \delta_k I_t^k) \tag{2}$$

where $I_t^M, \ldots, I_t^F$ are day of the week indicator dummy variables, I_t^A is the announcement indicator dummy variable, s_t is the volatility seasonal for time t, δ_0 measures the volatility effect of an announcement on day t, and ξ_t is a random variable with mean zero and unit variance, independent of s_t and h_t. That is, we estimate a (multiplicative) seasonal dummy for each day of the week as well as an announcement day volatility factor. The specification (1) allows the conditional variance to differ on announcement days, that is, the deseasonalized residual $\eta_t = (1 + \delta_0 I_t^A)^{1/2} \xi_t h_t^{1/2}$ has mean zero, with conditional variance h_t on non-announcement days and $h_t(1 + \delta_0)$ on announcement days.

We estimate an autoregressive model for the first moment because we find small but highly significant positive autocorrelation in Treasury bond returns.[10] This may be due to microstructure effects in measuring prices, or it may be due to equilibrium partial adjustment. In addition, the coefficients μ_M through μ_F

on correct specification of the conditional variance process.

[10] We also estimated a model with higher order autoregressive terms but the higher order terms were insignificant and thus are excluded.

measure day-of-the-week effects in mean returns, and θ measures changes in mean returns on announcement dates.

The benchmark GARCH(1,1) model is given the following specification of the conditional variance process h_t:

$$h_t = \omega + \alpha \xi_{t-1}^2 h_{t-1} + \beta h_{t-1} \tag{3}$$

where $\xi_t h_t^{1/2}$ is the adjusted residual, that is $\frac{\eta_t}{(1+\delta_0 I_t^A)^{1/2}}$. This is an augmented version of the residual used in Andersen and Bollerslev [1994], modified to additionally deseasonalize due to announcement effects. Alternatively, we could use $(s_t h_t)^{1/2}\xi_t$ (the first stage residual from estimation of (1)) or η_t (deseasonalizing exactly as Andersen and Bollerslev); doing so produces nearly identical results. We are principally interested in the persistence properties of the estimated conditional volatility following announcements. On one hand, if markets are efficient, we would expect information to be incorporated immediately so that announcement news would exhibit little persistence. On the other hand, if volatility is caused by some feature of the trading process itself, persistence following announcement news may be higher than on non-announcement days. Hence, we supplement our benchmark GARCH(1,1) model with alternative specifications which allow the degree of volatility persistence to vary.

Reported parameter estimates for equations (1)-(3) are obtained by quasi-maximum likelihood estimation using a normal likelihood function; starting values for conditional volatility are estimated to maximize the sample likelihood.[11]

The results are reported in Table 4 for the 5-, 10-, and 30-year bond returns. Robust standard errors, as given in Bollerslev and Wooldridge [1992], are also provided. Across all specifications of h_t, the parameter estimates in (1) and (2) are quite stable; the parameter estimates for the 5- and 10-year returns are almost identical across all specifications. The autoregressive coefficient is approximately 0.15. Expected returns are statistically significantly negative on Mondays and Thursdays (-0.037% for the 10-year bond), and positive on Fridays (0.038% for the 10-year bond). Most importantly, we confirm the earlier evidence of a risk premium on announcement days; returns on such days average 0.033%, 0.017%, and 0.026% higher for the three bonds. All three return series behave similarly, and the results over the different time periods are similar, indicating stability of the data-generating process.

Estimation of (3) reveals a statistically significant impact of the announcement; on average volatility increases by 69% on announcement days for the 10-year bond. In addition, conditional variance is highly

[11] This is because there is no one obvious choice of exogenous starting value available. Fixing the starting value at the sample estimate of the unconditional variance, as suggested in Engle and Bollerslev [1986], yielded similar results.

persistent; we cannot reject the hypothesis that the model is IGARCH(1,1) in favor of a covariance-stationary GARCH(1,1) model.

As mentioned above, we are interested in the different persistence properties on announcement days relative to non-announcement days. We use three metrics to examine the relative persistence of announcement day shocks to non-announcement day shocks. One standard measure of persistence comes from the j-step ahead forecast of conditional variance (this is noted in Andersen and Bollerslev [1994]):

$$_t h_{t+j} - \sigma^2 = (\alpha + \beta)^j (h_t - \sigma^2),$$

where $_t h_{t+j}$ is the expectation at time t of conditional volatility at time $t + j$ and σ^2 is the unconditional variance. If $\alpha + \beta < 1$ this can be used to compute a half-life, that is, the time it takes on average for conditional variance h_t to revert halfway to its unconditional value. This is computed by setting $(\alpha+\beta)^j = \frac{1}{2}$; the half-life j is thus defined as $-\frac{ln\,(2)}{ln\,(\alpha+\beta)}$. Although our estimated parameter values imply a value of $\alpha+\beta > 1$ (so that j would be negative), we can still use this measure to determine *relative* persistence. For example, $\alpha + \beta$ equals 0.996, 1.002, and 1.00 for the 5-, 10-, and 30-year bonds, respectively. Thus using this metric, we would conclude that in all three assets, there is a high degree of persistence. The implied half-life for the 5-year bond is 173 days.

Second, we consider decomposing the first notion of persistence into two pieces: α, which we call the "direct" or "immediate" effect, and β, which we call the "indirect" effect. The intuition behind this nomenclature is that a shock today can influence tomorrow's conditional volatility directly through the $\alpha\xi_{t-1}^2 h_{t-1}$ term of (3). Subsequent effects of ξ_{t-1}^2, however, will arise through lagged values of the conditional variance, that is, through the βh_{t-1} term. For example, for the 5-year bond, the direct effect of a shock on tomorrow's conditional volatility is .082; this effect decays at rate .914 subsequently.

Our third definition of persistence considers the decay of shocks to conditional volatility, in the spirit of a half-life, but useful both in the case of $\alpha + \beta < 1$ and $\alpha + \beta \geq 1$. In particular, a recursion of (3) gives

$$h_t = \omega \sum_{j=0}^{\infty} \beta^j + \alpha \sum_{j=0}^{\infty} \beta^j \varepsilon_{t-1-j}^2.$$

The total effect of a shock ε_t will be $\alpha \sum_{j=0}^{\infty} \beta^j = \frac{\alpha}{1-\beta}$. We are interested in determining the number of periods s that it takes for half of the effect of ε_t to impact h_t, that is, find the value of s such that $\beta^{s+1} = \frac{1}{2}$.[12] Thus

$$s = -\frac{\ln(2)}{\ln(\beta)} - 1. \tag{4}$$

[12] Because the decay rate is exponential, it will take $2s$ periods for three-quarters of the effect of ε_t to impact h_t.

The higher is β, the larger s will be and the longer it will take for ε_t to reach the half-impact stage. Using this metric, $s = 6.71$, 7.77, and 12.80 days, for the 5-, 10-, and 30-year bonds, respectively. Here the 30-year bond is the most persistent, due to the higher value of β (note α does not determine persistence in this metric; only the indirect effect governs the decay rate).

The obvious benefit to the latter two notions of persistence is that they allow us to differentiate between the direct effect and the indirect effect.[13] In particular, larger direct effects may correspond to smaller indirect effects and vice versa. Thus while all three assets in model (1)-(3) display similar levels of overall persistence (as measured by the first metric), the 30-year bond sample has a slower decay rate and a smaller direct impact of shocks than do the other 2 series (recall that its sample period differs from that of the 5- and 10-year bonds). We can similarly turn equation (3) around to ask what fraction of the total impact of ε_t^2 will arise within the first month following its arrival; in this case, 79% of a shock to the 30-year bond will be felt in the first month and 91-94% for the other two series.

Are announcement day volatility shocks more or less persistent than shocks on other days? To answer this question, we generalize the benchmark GARCH(1,1) model in several ways.

First, because our announcement days are anticipated, one way to explicitly model potential persistence is to include leads and lags of the announcement dummy in (2), in the spirit of column (3) in Tables 2 and 3. That is, we modify (2) in the following way:

$$(2a) \qquad s_t = \prod_{i=-1}^{2} (1 + \delta_i I_{t-i}^A) \prod_{k=T}^{F} (1 + \delta_k I_t^k).$$

Note that if we exclude $I_{t-1}^A, I_{t-2}^A, I_{t+1}^A$, (2a) becomes (2), implying no change in volatility behavior before or after announcements.

Results for this model are given in Table 5. A robust Wald test of the joint hypothesis that $\delta_{-1} = 0, \delta_1 = 0$, and $\delta_2 = 0$ is equal to 2.488, 0.951, and 0.698 for the 5-year, 10-year, and 30-year bonds, respectively. The five percent $\chi^2(3)$ critical value is 7.81, so that (2) is not rejected in favor of (2a). In addition, none of these coefficients is individually significantly different from zero. The estimates of the other coefficients in the model are very close to those obtained from estimation using (2). All three measures of persistence reproduce the results obtained with (2).[14]

[13] This is one of the many distinctions between, for example, an IGARCH(1,1) model and an I(1) process; in the latter, the rate of decay is exponentially related to the coefficient on the lagged dependent variable (and the corresponding impulse response depends on one parameter) whereas in the IGARCH(1,1) model, the impulse response will depend both on an immediate effect due to α and a rate of decay β.

[14] We also estimated a GARCH-M model. Although the newly included coefficient is significant, the values

Because the relevant δ coefficients are indistinguishable from zero, this model suggests that the announcement has no unusual effect on volatility other than on the event day. However, the key weakness of this specification is that it deals with pre- and post-announcement days deterministically. That is, while variances are allowed to differ across days, announcement shocks and non-announcement shocks affect the following day's conditional variance identically. There is no scope for differing persistence of a shock.

Thus, an alternative way to model the effects of announcements would be to allow the coefficient α in the conditional variance equation to take on a different value following announcements. That is, we now estimate the model (1) and (2) above, except that we specify the evolution of the conditional variance process as

$$h_t = \omega + [\alpha_A I_{t-1}^A + \alpha_N(1 - I_{t-1}^A)]\xi_{t-1}^2 h_{t-1} + \beta h_{t-1}. \tag{3b}$$

Note that if $\alpha_A = 0$, this implies that there is no persistence of the announcement shock, whereas if $\alpha_A = \alpha_N$, (3b) reduces to (3), which implies that shocks have the same persistence, regardless of announcement status. To compare volatility dynamics on announcement and non-announcement days, we must consider our summary measures of persistence.

For the most part, the direct impact of announcement shocks is noticeably different from that of non-announcement shocks. Table 6 shows that $\alpha_A < \alpha_N$ for the 10- and 30-year bonds. In addition, α_A is significantly different from zero for the 5- and 10-year bonds, implying that announcement shocks exhibit persistence. Conditional variance on the announcement day is 64% above the non-announcement variance h_t for the 10-year bond. It is 69% and 117% greater for the 5- and 30-year bonds, respectively. The influence of an announcement day shock to the 10-year bond on the *following day* variance (day $t+1$) is multiplied by the factor $\alpha_A(1+\delta_0)$ and is .085, compared with .082 for a non-announcement shock, roughly 4 percent higher. For the 5-year bond this difference is even more dramatic – the effect of an announcement day shock is .145 compared with .082, roughly 77% higher. For the 30-year bond, the additional effect of an announcement day shock is .061 versus .052 for a non-announcement day shock, representing a 17% increase. Interpreted another way, average volatility of the 10-year and 30-year bonds on the day following an announcement will be approximately one percentage point higher than average volatility following a non-announcement day, suggesting minimal additional persistence of announcement day shocks.

Comparing (3b) to (3), the robust t-statistic of the hypothesis that $\alpha_A = \alpha_N$ is .098, 1.364, and 1.143, failing to reject the null hypothesis that the coefficients are the same for all 3 bond rates. Thus there does

of the other coefficients did no change appreciably and we could not reject the model of (1), (2a), and (3) in favor of the GARCH-M using a likelihood ratio test. We therefore estimate regular GARCH(1,1) models as in (1) and (3) throughout the paper, as they have known asymptotic properties and do not fall under the sensitivity to misspecification noted in footnote 7.

not appear to be a distinction between the long-run impact of announcements versus non-announcements in (3b). In addition, all three persistence measures are qualitatively similar to those of (3).

In summary, Table 6 indicates that (deseasonalized) announcement day shocks are the same as non-announcement shocks, in terms of their implication for future volatility. This is surprising. If markets are able, within the space of a complete trading day, to digest fully new information, then we would expect that the size of the announcement day shock would not affect volatility in subsequent days. Yet we can reject this hypothesis (for the 5- and 10-year bonds).

So far, both of the alternatives to the benchmark model that we have considered have limited the way that announcement shocks affect conditional variance. We now allow for the possibility that the process governing the evolution of conditional variance due to announcement shocks differs from the process that describes the impact of non-announcement shocks. We do not, however, want to use a switching model (e.g., Hamilton [1989]), since that would imply that conditional volatility on announcement days depends on its previous values, ignoring effects from shocks in the intervening (non-announcement) period. Put another way, announcement day volatility changes less frequently than non-announcement day volatility (on average, only every 13th day). We would instead prefer that the model allow for differential persistence, but with conditional variance defined as the sum of announcement-related conditional variance and non-announcement related conditional variance.

This suggests a mixture model, which allows an announcement shock to feedback into future conditional variance. The model consists of (1), (2), and the following specification of the conditional variance:

$$
\begin{aligned}
(3c) \qquad h_t &= \omega + h_t^N + h_t^A \\
h_t^N &= \alpha_N(1 - I_{t-1}^A)\xi_{t-1}^2 h_{t-1} + \beta_N h_{t-1}^N \\
h_t^A &= \alpha_A I_{t-1}^A \xi_{t-1}^2 h_{t-1} + \beta_A h_{t-1}^A .
\end{aligned}
$$

Note that if $\beta_A = \beta_N$ (3c) reduces to (3b) whereas if $\alpha_N = \alpha_A$ **and** $\beta_A = \beta_N$ (3c) reduces to model (3) (the magnitude of the estimated constant term, ω, would decrease by a factor $1 - \beta_A$). Thus the models (1), (2), (3) and (1), (2), (3b) are nested in the specification (1), (2), (3c). This latter model allows for differences in both the direct and indirect effects of non-announcement shocks. It extends and is similar in spirit to the model of Lamoureux and Lastrapes [1990], which allows for deterministic shifts in the mean of the conditional variance process. In contrast, our model specifies time-dependent response parameters governing the ARCH process.

The mixture model is also related to time series models that exhibit long memory. A process exhibits long memory if shocks die out at a slower than exponential rate. Such long memory in volatility has been observed in asset return series (examples include Ding, Granger, and Engle [1993] and Bollerslev and Mikkelsen [1995]).

In terms of modelling, Baillie, Bollerslev, and Mikkelsen [1995] obtain a slow hyperbolic rate of decay for the influence of lagged squared innovations using a fractionally integrated GARCH (FIGARCH) model.

Fractional integration and mixtures are closely related. Specifically, Granger [1980] shows that a fractionally integrated ARMA process can be written as a mixture of a continuum of simpler AR(1) processes with different decay rates. Extending the analogy to the second moment, our mixture of two simple GARCH(1,1) models may capture some of the dynamics in the FIGARCH model.

Results for this model are given in Table 7. It is clear from a comparison of the likelihood ratios that (1) and (2) combined with (3c) outperforms both (1) and (2) combined with (3) and (1) and (2) combined with (3b) (it is not directly comparable to (1), (2a), (3) since the models are not nested); the values of the likelihood ratio statistic comparing models (3) and (3c) are 7.158, 49.33, and 24.10 for the 5-year, 10-year, and 30-year bonds, respectively, which exceed the $\chi^2(2)$ five percent critical value of 5.99. Even though we would expect the likelihood ratio statistic to be oversized in this context, we view these numbers as sufficiently large to reject (3) in favor of the mixture model (3c). As an additional check, we computed robust Wald statistics as in Lumsdaine [1995] for the joint null hypothesis that $\alpha_A = \alpha_N$ and $\beta_A = \beta_N$ and similarly strongly reject this hypothesis for all three series (the value of the statistic is 18.956, 31.215, and 24.148 for the 5-, 10-, and 30-year bonds, respectively). Comparing model (3b) to (3c), the values of the robust Wald statistics are 9.44, 31.21, and 23.55 for the 5-, 10-, and 30-year bonds, respectively, rejecting the null hypothesis that $\beta_A = \beta_N$ for all three series (the statistic is distributed $\chi^2(1)$ under the null hypothesis; the five percent critical value is 3.84).[15]

Returning to our measures of persistence, the value of $\alpha_A + \beta_A$ is 1.011, 1.005, and 1.003 for announcement shocks in the 5-, 10-, and 30-year bonds, respectively, suggesting a high degree of persistence, similar across the three assets. Alternatively, for non-announcement shocks, our first persistence measure yields values of 0.990, .995, and .996. Thus with this metric, announcement shocks are more persistent than non-announcement shocks; non-announcement conditional volatility follows a covariance-stationary process.

The second and third measures of persistence tell a similar story. While the direct impact is insignificantly different from zero on announcement days, for all three assets, the impact of announcement shocks persists far into the future (as seen by the indirect effect, β_A) with only half the impact arising within the

[15] We also investigated subsample stability by estimating this model over three subperiods, with breaks at 8/15/79 and 8/15/87. Although there is evidence of instability, the announcement effects and qualitative conclusions regarding persistence remain largely unchanged. While in other contexts inference is sensitive to misspecification of structural change (see, for example, Perron [1989], and Banerjee, Lumsdaine, and Stock [1992]), this does not appear to be the case with regard to the question we are investigating here. More broadly, we view this as a potentially important issue for future research but in the current context, it is beyond the scope of this paper.

first 42, 114, and 172 days, for the 5-, 10-, and 30-year bonds, respectively. In contrast, non-announcement shocks typically have a much larger direct effect (as evidenced by the much larger value of α_N relative to α_A), but their impact is short-lived, with half of the impact occurring within the first 5-10 days.[16] Put another way, in the month following an announcement shock, only 12-39% of its impact will have been felt, compared with 86-96% absorption in the month following a non-announcement shock.

The mixture model of (1), (2), and (3c) leads to quite different conclusions about announcement persistence than simpler models. If only the α parameter is allowed to vary as in (3b), we conclude that announcement shocks and non-announcement shocks are indistinguishable in terms of their persistence. Using the mixture model, on the other hand, we find that these shocks are qualitatively different. However, our results can be interpreted in two ways. One interpretation is based on the fact that we cannot reject the hypothesis that announcement shocks do not persist at all (i.e., $\alpha_A = 0$). If this is the case, then β_A is not separately identifiable from ω and the associated announcement day conditional variance is homoskedastic. Under the null hypothesis that $\alpha_A = 0$, our results agree with those of Ederington and Lee (1993, 1995) that market prices quickly incorporate the information in these macroeconomic announcements, and that volatility quickly returns to pre-announcement levels. At least for this subset of information, the null hypothesis of $\alpha_A = 0$ is consistent with the hypothesis that the trading or information-gathering process does not generate volatility on succeeding days. This interpretation suggests that in general, autocorrelated volatility is due to autocorrelated news.

If, on the other hand, the true value of α_A is nonzero, our interpretation is considerably different. A small positive α_A with β_A close to one suggests a small direct effect that is very persistent. While we could argue that potential homoskedasticity may be interpreted as infinitely persistent, we attempt to distinguish between these interpretations by estimating a constrained version of model (1), (2), and (3c), restricting $\alpha_A = \beta_A = 0$, so that conditional variance depends on and evolves according to non-announcement days only. This restricted model consists of equations (1), (2), and the following:

$$(3d) \qquad h_t = \omega + h_t^N, \qquad h_t^N = \alpha_N[1 - I_{t-1}^A]\xi_{t-1}^2 h_{t-1} + \beta_N h_{t-1}^N.$$

The results are contained in Table 8 for the 10-year bond; the value of the likelihood ratio statistic is 64, rejecting the null hypothesis of homoskedasticity on announcement days.[17] The results of Table 8 lend credibility to the second interpretation. Therefore, we conclude that announcement-day shocks are qualitatively different than shocks on non-announcement days, that is, while it may take a longer time for announcement shocks to be absorbed, they have only a small immediate impact on conditional volatility.

[16] 5.94 for the 5-year, 5.59 for the 10-year, and 10.01 for the 30-year.

[17] As noted elsewhere in this paper, the likelihood ratio statistic is likely to be oversized in this context. Relative to a $\chi^2(1)$ critical value of 5.99, however, we view the magnitude to be sufficiently high in spite of this.

Conclusions

One interpretation of this low-level, strongly persistent announcement effect is that our original assumption – that announcement news is by definition non-autocorrelated – is misleading. Under this interpretation, a big announcement day shock would raise the volatility of other (non-announcement) news shocks. So if the unemployment rate rises this month, perhaps this signals the economy is entering a recession. Thus rational agents would attach greater significance to subsequent news events, even though the next employment report will not come for another month. This "regime shift" explanation does not require that the trading process itself generates autocorrelated volatility.

A second interpretation is that announcement day volatility causes long-term changes in trading strategies. So when the unemployment rate rises, traders not only learn about the true state of the economy, they also observe the reactions of other traders and thus draw inferences about those traders' private information.

What conclusions do we draw from Table 7, our best specification for modelling the announcement day effect? First, we note that two obvious features of the data appear to be robust over all our specifications and survive into this refinement. The first feature is that conditional volatility is higher on announcement days. The second feature is that, at least at the short-end of the yield curve, there are significant positive excess returns on announcement days.

Tables 7 and 8, combined with intra-day data such as Ederington and Lee (1993,1995) give us a fairly complete picture of the life cycle of a macroeconomic announcement. Traders are frenzied in the first few minutes. After a few hours, prices stabilize. Our results suggest that the volatility effect persists for a long time thereafter. Our reading of the estimated parameters is that on subsequent days, announcement day shocks have a relatively small but long-lasting effect.

Finally, our results have direct implications for modeling conditional heteroskedasticity in asset returns. In particular, we find strong evidence that return shocks vary in their persistence in predictable ways. Ignoring this variation results in model misspecification and is likely to lead to inferior estimates of conditional volatility. This has practical considerations as well, most obviously in the area of option pricing.

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TABLE 1

Summary statistics: Treasury bond daily excess returns

XR_t is the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill. Returns are expressed in percent terms, i.e., multiplied by 100. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993.

	5-yr			10-yr			30-yr		
	XR_t	XR_t^2	$\lvert XR_t \rvert$	XR_t	XR_t^2	$\lvert XR_t \rvert$	XR_t	XR_t^2	$\lvert XR_t \rvert$
Full Sample (N = 6212 or N = 4209)									
Mean	0.005	0.116	0.225	0.005	0.235	0.323	0.010	0.552	0.516
Std Dev	0.341	0.368	0.256	0.484	0.701	0.361	0.743	1.458	0.534
Min	-2.493	0.000	0.000	-3.674	0.000	0.000	-3.946	0.000	0.000
Max	3.016	9.095	3.016	4.694	22.034	4.694	7.255	52.631	7.255
Rho	0.115	0.183	0.237	0.093	0.163	0.257	0.054	0.058	0.137
Kurtosis	8.025			6.926			4.982		
Skewness	0.379			0.369			0.310		
Employment Report Announcement Dates (N = 295 or N = 198)									
Mean	0.110	0.220	0.333	0.129	0.413	0.454	0.122	0.940	0.738
Std Dev	0.457	0.475	0.331	0.631	0.843	0.456	0.964	1.457	0.630
Rho (t to t+1)	0.139	0.184	0.176	0.101	0.203	0.254	0.067	0.116	0.120
PPI Announcement Dates (N = 293 or N = 196)									
Mean	0.065	0.155	0.273	0.081	0.344	0.407	0.154	0.824	0.694
Std Dev	0.389	0.340	0.284	0.582	0.735	0.423	0.897	1.327	0.587
Rho (t to t+1)	0.128	0.143	0.165	0.092	0.140	0.264	0.137	0.112	0.205
Announcement Dates (N = 552 or N = 374)									
Mean	0.084	0.183	0.301	0.098	0.363	0.426	0.132	0.862	0.712
Std Dev	0.420	0.396	0.304	0.595	0.737	0.426	0.920	1.347	0.598
Rho (t to t+1)	0.123	0.181	0.179	0.082	0.179	0.248	0.077	0.124	0.153
Non-announcement Dates (N = 5660 or N = 3835)									
Mean	-0.003	0.110	0.218	-0.004	0.222	0.312	-0.002	0.521	0.497
Std Dev	0.331	0.365	0.250	0.471	0.697	0.353	0.722	1.465	0.524
Rho (t to t+1)	0.115	0.182	0.244	0.095	0.160	0.258	0.052	0.052	0.134

TABLE 2

Treasury bond return volatility by day of week and event day

Mean values of the volatility of the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill. Returns are expressed in percent terms, i.e., multiplied by 100. Announcement is a dummy variable which equals one on the PPI and employment report announcement dates. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993. Robust standard errors are given in parentheses.

	5-yr	10-yr	30-yr
Panel A: Absolute value of excess returns			
Monday	0.248	0.352	0.561
	(0.010)	(0.014)	(0.027)
Tuesday	0.210	0.301	0.490
	(0.007)	(0.010)	(0.019)
Wednesday	0.190	0.278	0.449
	(0.006)	(0.009)	(0.016)
Thursday	0.218	0.321	0.516
	(0.008)	(0.011)	(0.021)
Friday	0.251	0.348	0.518
	(0.008)	(0.011)	(0.019)
Announcement(t+1)	-0.028	-0.040	-0.067
	(0.011)	(0.016)	(0.030)
Announcement	0.064	0.092	0.199
	(0.014)	(0.019)	(0.034)
Announcement(t-1)	-0.008	-0.014	-0.015
	(0.014)	(0.019)	(0.037)
Panel B: Squared excess returns			
Monday	0.151	0.289	0.696
	(0.016)	(0.027)	(0.072)
Tuesday	0.108	0.221	0.549
	(0.011)	(0.024)	(0.072)
Wednesday	0.076	0.168	0.418
	(0.006)	(0.016)	(0.039)
Thursday	0.102	0.217	0.522
	(0.009)	(0.018)	(0.047)
Friday	0.135	0.255	0.500
	(0.012)	(0.020)	(0.038)
Announcement(t+1)	-0.023	-0.037	-0.112
	(0.015)	(0.029)	(0.062)
Announcement	0.060	0.124	0.367
	(0.018)	(0.032)	(0.073)
Announcement(t-1)	-0.008	-0.021	-0.052
	(0.022)	(0.042)	(0.097)

TABLE 3

Treasury bond daily excess returns by day of week and event day

Mean values of the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill. Returns are expressed in percent terms, i.e., multiplied by 100. Announcement is a dummy variable which equals one on the PPI and employment report announcement dates. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993. Robust standard errors are given in parentheses.

	5-yr	10-yr	30-yr
Monday	-0.042	-0.059	-0.075
	(0.013)	(0.018)	(0.036)
Tuesday	0.010	0.018	0.048
	(0.009)	(0.013)	(0.025)
Wednesday	0.001	-0.007	-0.015
	(0.008)	(0.012)	(0.022)
Thursday	-0.031	-0.030	-0.006
	(0.010)	(0.015)	(0.030)
Friday	0.060	0.069	0.069
	(0.011)	(0.016)	(0.028)
Announcement(t+1)	-0.005	-0.010	-0.036
	(0.014)	(0.021)	(0.041)
Announcement	0.045	0.051	0.077
	(0.019)	(0.027)	(0.052)
Announcement(t-1)	0.017	0.027	0.010
	(0.018)	(0.025)	(0.050)

TABLE 4

Benchmark deseasonalized AR(1)-GARCH(1,1) model of Treasury bond daily excess returns

Maximum likelihood estimates of the model

(1) $R_t = \sum_{k=M}^{F} \mu_k I_t^k + \theta I_t^A + \phi_1 R_{t-1} + (s_t h_t)^{1/2} \xi_t,$

(2) $s_t = (1 + \delta_0 I_t^A) \prod_{k=T}^{F} (1 + \delta_k I_t^k),$

(3) $h_t = \omega + \alpha \xi_{t-1}^2 h_{t-1} + \beta h_{t-1},$

where R_t is the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill, I_t^k are day-of-the-week indicator variables, and I_t^A is an indicator variable equal to one on employment or PPI announcement days. Returns are expressed in percent terms, i.e., multiplied by 100. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993. Robust standard errors are given in parentheses.

	First moment parameters				Second moment parameters		
	5-yr	10-yr	30-yr		5-yr	10-yr	30-yr
ϕ_1	0.135	0.146	0.067	ω (x10^{-4})	9.082	7.796	11.665
	(0.014)	(0.015)	(0.016)		(1.628)	(1.476)	(3.438)
μ_M	-0.031	-0.037	-0.045	α	0.082	0.080	0.049
	(0.007)	(0.010)	(0.021)		(0.016)	(0.014)	(0.010)
μ_T	0.001	0.000	0.019	β	0.914	0.922	0.951
	(0.007)	(0.008)	(0.019)		(0.015)	(0.013)	(0.009)
μ_W	0.003	-0.006	0.002	δ_0	0.684	0.693	1.232
	(0.006)	(0.008)	(0.017)		(0.137)	(0.139)	(0.169)
μ_R	-0.032	-0.037	-0.024	δ_T	-0.166	-0.204	-0.058
	(0.007)	(0.009)	(0.018)		(0.085)	(0.085)	(0.113)
μ_F	0.033	0.038	0.037	δ_W	-0.362	-0.320	-0.275
	(0.008)	(0.011)	(0.019)		(0.052)	(0.074)	(0.077)
θ	0.033	0.017	0.026	δ_R	-0.214	-0.206	-0.174
	(0.016)	(0.017)	(0.042)		(0.071)	(0.078)	(0.069)
log L	4985.266	2919.139	-160.091	δ_F	0.015	-0.046	-0.208
					(0.078)	(0.144)	(0.068)

TABLE 5
GARCH(1,1) with additional announcement-related volatility seasonals

Maximum likelihood estimates of the model

(1) $R_t = \sum_{k=M}^{F} \mu_k I_t^k + \theta I_t^A + \phi_1 R_{t-1} + (s_t h_t)^{1/2} \xi_t,$

(2a) $s_t = \prod_{i=-1}^{2} (1 + \delta_i I_{t-i}^A) \prod_{k=T}^{F} (1 + \delta_k I_t^k),$

(3) $h_t = \omega + \alpha \xi_{t-1}^2 h_{t-1} + \beta h_{t-1},$

where R_t is the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill, I_t^k are day-of-the-week indicator variables, and I_t^A is an indicator variable equal to one on employment or PPI announcement days. Returns are expressed in percent terms, i.e., multiplied by 100. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993. Robust standard errors are given in parentheses.

	First moment parameters				Second moment parameters		
	5-yr	10-yr	30-yr		5-yr	10-yr	30-yr
ϕ_1	0.134	0.147	0.066	ω (x10^{-4})	8.915	7.625	11.028
	(0.015)	(0.015)	(0.015)		(1.624)	(1.382)	(2.448)
μ_M	-0.031	-0.038	-0.047	α	0.083	0.080	0.049
	(0.007)	(0.010)	(0.020)		(0.016)	(0.014)	(0.007)
μ_T	0.002	0.000	0.022	β	0.912	0.922	0.952
	(0.006)	(0.008)	(0.018)		(0.016)	(0.012)	(0.005)
μ_W	0.004	-0.006	0.002	δ_0	0.704	0.697	1.235
	(0.006)	(0.008)	(0.016)		(0.151)	(0.137)	(0.216)
μ_R	-0.032	-0.037	-0.025	δ_T	-0.181	-0.194	-0.098
	(0.007)	(0.009)	(0.018)		(0.079)	(0.066)	(0.129)
μ_F	0.033	0.038	0.037	δ_W	-0.331	-0.304	-0.253
	(0.008)	(0.011)	(0.019)		(0.063)	(0.060)	(0.089)
θ	0.031	0.017	0.026	δ_R	-0.156	-0.186	-0.139
	(0.015)	(0.017)	(0.038)		(0.087)	(0.070)	(0.117)
				δ_F	0.042	-0.029	-0.185
					(0.104)	(0.082)	(0.100)
				δ_{-1}	-0.116	-0.002	-0.028
					(0.095)	(0.128)	(0.282)
				δ_1	0.140	0.114	0.128
					(0.156)	(0.117)	(0.192)
log L	4991.489	2920.712	-156.752	δ_2	0.129	0.002	0.180
					(0.157)	(0.129)	(0.340)

TABLE 6

GARCH(1,1) with differing α parameter

Maximum likelihood estimates of the model

(1) $R_t = \sum_{k=M}^{F} \mu_k I_t^k + \theta I_t^A + \phi_1 R_{t-1} + (s_t h_t)^{1/2} \xi_t$,

(2) $s_t = (1+\delta_0 I_t^A) \prod_{k=T}^{F} (1+\delta_k I_t^k)$,

(3b) $h_t = \omega + \left(\alpha_A I_{t-1}^A + \alpha_N \left[1 - I_{t-1}^A\right]\right) \xi_{t-1}^2 h_{t-1} + \beta h_{t-1}$,

where R_t is the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill, I_t^k are day-of-the-week indicator variables, and I_t^A is an indicator variable equal to one on employment or PPI announcement days. Returns are expressed in percent terms, i.e., multiplied by 100. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993. Robust standard errors are given in parentheses.

	First moment parameters				Second moment parameters		
	5-yr	10-yr	30-yr		5-yr	10-yr	30-yr
ϕ_1	0.135	0.146	0.067	ω (x10^{-4})	9.082	7.685	12.350
	(0.015)	(0.016)	(0.016)		(1.647)	(1.438)	(3.614)
μ_M	-0.031	-0.037	-0.045	α_N	0.082	0.082	0.052
	(0.007)	(0.010)	(0.021)		(0.016)	(0.016)	(0.011)
μ_T	0.001	0.000	0.019	α_A	0.086	0.052	0.028
	(0.007)	(0.008)	(0.019)		(0.043)	(0.019)	(0.017)
μ_W	0.003	-0.006	0.002	β	0.913	0.923	0.951
	(0.006)	(0.008)	(0.017)		(0.015)	(0.013)	(0.009)
μ_R	-0.032	-0.037	0.024	δ_0	0.691	0.640	1.173
	(0.007)	(0.009)	(0.018)		(0.166)	(0.156)	(0.200)
μ_F	0.033	0.038	0.037	δ_T	-0.167	-0.203	-0.058
	(0.008)	(0.011)	(0.020)		(0.080)	(0.069)	(0.111)
θ	0.033	0.018	0.029	δ_W	-0.362	-0.323	-0.278
	(0.017)	(0.017)	(0.041)		(0.055)	(0.062)	(0.078)
				δ_R	-0.214	-0.208	-0.177
					(0.069)	(0.060)	(0.077)
log L	4985.290	2920.841	-158.770	δ_F	0.016	-0.048	-0.209
					(0.129)	(0.072)	(0.072)

TABLE 7

Mixture of announcement and non-announcement GARCH(1,1) models

Maximum likelihood estimates of the model

(1) $R_t = \sum_{k=M}^{F} \mu_k I_t^k + \theta I_t^A + \phi_1 R_{t-1} + (s_t h_t)^{1/2} \xi_t,$

(2) $s_t = (1+\delta_0 I_t^A)\prod_{k=T}^{F}(1+\delta_k I_t^k),$

(3c) $h_t = \omega + h_t^N + h_t^A, \;\; h_t^N = \alpha_N\left[1 - I_{t-1}^A\right]\xi_{t-1}^2 h_{t-1} + \beta_N h_{t-1}^N, \;\; h_t^A = \alpha_A I_{t-1}^A \xi_{t-1}^2 h_{t-1} + \beta_A h_{t-1}^A,$

where R_t is the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill, I_t^k are day-of-the-week indicator variables, and I_t^A is an indicator variable equal to one on employment or PPI announcement days. Returns are expressed in percent terms, i.e., multiplied by 100. For 5 and 10 year securities, the sample extends from February 1, 1969 to December 31, 1993; the sample for the 30-year extends from February 16, 1977 to December 31, 1993. Robust standard errors are given in parentheses.

	First moment parameters				Second moment parameters		
	5-yr	10-yr	30-yr		5-yr	10-yr	30-yr
ϕ_1	0.136	0.147	0.066	ω (x10^{-4})	88.08	70.11	189.68
	(0.013)	(0.015)	(0.016)		(12.43)	(13.15)	(55.27)
μ_M	-0.030	-0.035	-0.043	α_N	0.085	0.095	0.057
	(0.007)	(0.010)	(0.021)		(0.013)	(0.017)	(0.012)
μ_T	0.000	-0.001	0.018	α_A	0.027	0.011	0.007
	(0.004)	(0.008)	(0.019)		(0.027)	(0.007)	(0.004)
μ_W	0.003	-0.006	0.002	β_N	0.905	0.900	0.939
	(0.004)	(0.008)	(0.017)		(0.015)	(0.017)	(0.012)
μ_R	-0.033	-0.037	-0.023	β_A	0.984	0.994	0.996
	(0.005)	(0.009)	(0.018)		(0.016)	(0.003)	(0.002)
μ_F	0.032	0.037	0.036	δ_0	0.644	0.567	1.078
	(0.006)	(0.010)	(0.020)		(0.102)	(0.128)	(0.186)
θ	0.032	0.023	0.030	δ_T	-0.149	-0.200	-0.054
	(0.010)	(0.017)	(0.040)		(0.084)	(0.070)	(0.112)
				δ_W	-0.366	-0.325	-0.274
					(0.050)	(0.057)	(0.079)
				δ_R	-0.219	-0.209	-0.178
					(0.069)	(0.060)	(0.077)
log L	4988.840	2943.805	-148.040	δ_F	0.006	-0.053	-0.202
					(0.090)	(0.076)	(0.071)

TABLE 8

Mixture model with no persistence of announcement-day shocks

Maximum likelihood estimates of the model

(1) $R_t = \sum_{k=M}^{F} \mu_k I_t^k + \theta I_t^A + \phi_1 R_{t-1} + (s_t h_t)^{1/2} \xi_t,$

(2) $s_t = (1 + \delta_0 I_t^A) \prod_{k=T}^{F} (1 + \delta_k I_t^k),$

(3d) $h_t = \omega + h_t^N, \; h_t^N = \alpha_N [1 - I_{t-1}^A] \xi_{t-1}^2 h_{t-1} + \beta_N h_{t-1}^N,$

where R_t is the daily log excess return of the relevant constant maturity Treasury security over the three month Treasury bill, I_t^k are day-of-the-week indicator variables, and I_t^A is an indicator variable equal to one on employment or PPI announcement days. Returns are for the 10-year bond and are expressed in percent terms, i.e., multiplied by 100. The sample extends from February 1, 1969 to December 31, 1993. Robust standard errors are given in parentheses.

	First moment parameters		Second moment parameters
ϕ_1	0.144 (0.015)	ω	0.304 (0.109)
μ_M	-0.037 (0.010)	α_N	0.081 (0.014)
μ_T	0.000 (0.008)	β_N	0.928 (0.011)
μ_W	-0.006 (0.008)	δ_0	0.640 (0.138)
μ_R	-0.037 (0.009)	δ_T	-0.198 (0.069)
μ_F	0.038 (0.011)	δ_W	-0.328 (0.057)
θ	0.021 (0.018)	δ_R	-0.217 (0.059)
log L	2911.576	δ_F	-0.047 (0.075)