INTRADAY VOLATILITY IN INTEREST-RATE AND FOREIGN-EXCHANGE MARKETS: ARCH, ANNOUNCEMENT, AND SEASONALITY EFFECTS

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We explore the determinants of intraday volatility in interest-rate and foreign-exchange markets, focusing on the importance and interaction of three types of information in predicting intraday volatility: (a) knowledge of recent past volatilities (i.e., ARCH or Autoregressive Conditional Heteroskedasticity effects); (b) prior knowledge of when major scheduled macroeconomic announcements, such as the employment report or Producer Price Index, will be released; and (c) knowledge of seasonality patterns. We find that all three information sets have significant incremental predictive power, but macroeconomic announcements are the

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most important determinants of periods of very high intraday volatility (particularly in the interest-rate markets). We show that because the three information sets are not independent, it is necessary to simultaneously consider all three to accurately measure intraday volatility patterns. For instance, we find that most of the previously documented time-of-day and day-of-the-week volatility patterns in these markets are due to the tendency for macroeconomic announcements to occur on particular days and at particular times. Indeed, the familiar U-shape completely disappears in the foreign-exchange market. We also find that estimates of ARCH effects are considerably altered when we account for announcement effects and return periodicity; specifically, estimates of volatility persistence are sharply reduced. Separately, our results show that high volatility persists longer after shocks due to unscheduled announcements than after equivalent shocks due to scheduled announcements, indicating that market participants digest information much more quickly if they are prepared to receive it. However, contrary to results from equity markets, we find no evidence of a meaningful difference in volatility persistence after positive or negative price shocks. Jrl Fut Mark 21: 517–552, 2001

INTRODUCTION

In recent years, considerable progress has been achieved in modeling and predicting financial market volatility. A majority of these models, ARCH–GARCH (i.e., Autoregressive Conditional Heteroskedastic and Generalized Autoregressive Conditional Heteroskedastic) models in particular, forecast future volatility on the basis of recent past volatilities. However, market participants have other important information sources with predictive ability. First, it is well known that volatility increases around information releases, and the timing of many important releases (hereafter termed *scheduled releases*) is known in advance. For instance, the market normally knows when earnings reports will be released (Brown, Clinch, & Foster, 1992), and the release dates for macroeconomic statistics, such as the money supply, employment report, or Consumer Price Index, are known up to a year in advance. Second, numerous studies have found evidence of time-of-day and day-of-the-week volatility patterns, and these seasonality patterns should be known to market participants.

This article explores the determinants of intraday volatility in interest-rate and foreign-exchange futures markets with particular attention to the importance and interaction of three types of information in predicting volatility: (a) knowledge of recent past volatilities, (b) knowledge of the timing of upcoming news releases, and (c) knowledge of seasonality patterns. Numerous studies, such as those reviewed in Bollerslev, Chou, and Kroner (1992) and Andersen and Bollerslev (1998), have found that recent past volatilities have predictive ability in interest-rate and foreign-exchange markets, whereas day-of-the-week volatility patterns, time-of-day volatility patterns, or both have been documented in foreign-exchange markets by Harvey and Huang (1991), Baille and Bollerslev (1991), and Andersen and Bollerslev (1998) and in interest-rate markets by Webb and Smith (1994), Chang and Schacter (1991), Jones, Lamont, and Lumsdaine (1998), and Fleming and Remolona (1999). Ederington and Lee (1993, 1995), Goodhart, Hall, Henry, and Pesaran (1993), Becker, Finnerty and Kopecky (1993), Webb (1994), Jones et al. (1998), Balduzzi, Elton, and Green (1997), Fleming and Remolona, and Andersen and Bollerslev showed that scheduled macroeconomic announcements lead to sharply higher interest-rate volatility, exchange-rate volatility, or both, and Ederington and Lee (1996) showed that the implied volatility calculated from option prices increases prior to scheduled announcements and drops immediately after their release.

One issue considered in this article is the relative predictive power of these three information sets. Although most studies have focused on the information in past volatilities, our evidence indicates that in forecasting intraday periods of very high volatility, knowledge of the timing of upcoming macroeconomic news releases is more important, particularly in interest-rate markets. Of course, the different information sets are likely to be complementary rather than exclusive. Although knowledge of the timing of upcoming news releases may allow market participants to predict high volatility at the time of the release, ARCH models predict likely volatility in its aftermath. We expect and find that predictive ability is improved considerably by the incorporation of all three information sets.

A related issue is the interaction between these three sets of volatility determinants and the resulting modeling bias if one set is considered in isolation, as in ARCH–GARCH models. For instance, like Ederington and Lee (1993), Fleming and Remolona (1999), and Andersen and Bollerslev (1998), we find that much of the time-of-day and day-of-the-week volatility pattern in these markets is due to announcement effects. More importantly, we find that estimates of intraday ARCH model parameters are considerably altered when seasonal patterns and announcement effects are incorporated into the model. Although the source of ARCH effects remains unknown, one common hypothesis, that of Engle, Ito, and Lin (1990) and Bollerslev et al. (1992), is that they arise because information itself is bunched, coming to the market in heat waves or meteor showers. We find no evidence that important announcements are bunched but find that estimates of intraday volatility persistence are considerably altered once announcement effects are taken into account.

Other important findings regarding intraday volatility include the following. First, the GARCH(1,1) model does not model volatility persistence at high frequencies very well, in that it tends to underestimate the impact of the most recent and very distant shocks and overestimate the impacts of shocks with intermediate lags. Second, when one controls for announcement effects, the commonly observed U-shaped time-of-day volatility pattern disappears in the foreign-exchange markets and is greatly reduced in the interest-rate markets. Third, after one controls for macroeconomic announcements, volatility in all three markets is lowest on Monday (contrary to the predictions of some microstructure theories) and highest on Tuesday or Friday. Fourth, consistent with other studies, the monthly employment report has the greatest impact in both interest-rate and foreign-exchange markets. Other important announcements include the producer price index, the consumer price index, durable goods orders, retail sales, construction spending, and the foreign-trade figures. Announcements that have very little impact on either interest or foreign-exchange rates include the index of leading indicators, inventories, personal income, federal budget figures, and the weekly money-supply/bank-reserve figures. Fifth, contrary to the finding of Balduzzi et al. (1997) that many macroeconomic announcements impact long-term but not short-term interest rates, we find a similar impact on both. Sixth, in the interest-rate markets volatility returns to virtually normal levels within 30 to 40 min after the release of new macroeconomic statistics (considerably faster than suggested by other recent studies), but volatility remains high much longer in the foreign-exchange market. Seventh, when we compare scheduled announcements (i.e., announcements whose release date is known in advance) and unscheduled announcements with the same initial price shock, high volatility persists much longer after unscheduled announcements. Eighth, contrary to findings for the equity markets,[1] there appears to be little difference in volatility persistence after positive and negative price shocks.

The article most closely related to ours is that of Andersen and Bollerslev (1998), who also used three information sets to forecast intraday exchange-rate volatility. However, there are important differences

[1] French, Schwert, and Stambaugh (1987); Engle and Ng (1993); and Braun, Nelson, and Sunier (1995).

between our two studies. First, although their study is restricted to the Deutschmark–dollar exchange-rate market, we examine both this market and two interest-rate markets. Second, Andersen and Bollerslev used 12 months of data on 5-min returns covering a full 24-hr day, whereas we employ 47 months of data on 10-min returns across the 6-hr and 40-min U.S. trading day (plus the overnight return). Third, they used a two-stage procedure in which the data were first adjusted for daily ARCH effects before intraday announcement and time-of-day patterns were analyzed. In contrast, we estimate a simultaneous model incorporating all three information sets. This allows us to explore how announcements, seasonality patterns, and ARCH effects are related. Specifically, we show that most time-of-day and day-of-the-week effects are due to announcements and that ARCH effects appear quite different once we control for announcements. Fourth, our model allows us to test how volatility persistence patterns following a price shock depend on characteristics of the shock. For instance, we hypothesize that because market participants are prepared to receive and analyze the information in scheduled announcements, the market will incorporate this information into prices more quickly than equivalent information in an unscheduled announcement. Our findings confirm this hypothesis.

In the following section, we describe our data set. In the second section, we develop our model of intraday return volatility by first developing and estimating separate submodels for each of the three information sets. This allows us to compare our simultaneous model developed in the third section with the more usual intraday volatility models. After the simultaneous model is estimated in the third section, the incremental information provided by each information set is measured. The issues of scheduled-versus-unscheduled announcements and positive-versus-negative shocks are explored in the fourth section, and results are summarized in the last section.

DATA

These issues are explored with 10-min interval return data from 7/3/89 through 5/28/93 for two interest-rate markets, one long and one short, and one foreign-exchange market. Specifically, we utilize data for the Chicago Board of Trade's Treasury-bond (T-bond) futures contract, the 90-day Eurodollar or London Interbank Offering Rate (LIBOR) contract traded on the International Monetary Market (IMM) at the Chicago Mercantile Exchange, and the Dollar–Deutschmark exchange-rate contract, also traded on the IMM. The Eurodollar (or LIBOR) futures is the most heavily traded short-term interest-rate futures contract in the world, whereas the T-bond contract is the most heavily traded long-term interest-rate contract. We generally use prices for the nearby contract switching to the second nearby contract when its trading volume exceeds that of the nearby contract.[2] Although we use futures to observe prices timed to the second, because the time to the expiration of our futures contracts is very short, our results should be generalizable to spot rates. The 16 scheduled macroeconomic announcements (or announcement pairs) that we consider are those analyzed in Ederington and Lee (1993) and are listed in the Appendix. We also examine the impact of the weekly money-supply figures.

For each market, we calculate log returns, $R_t = \ln(P_t/P_{t-1})$, for each 10-min interval from the opening of the markets at 7:20 a.m. Central Time (CT) through the closing at approximately 2:00 p.m. Because many announcements are released at 7:30 a.m. (CT; see the Appendix), or 10-min after the opening at 7:20, the use of 10-min intervals allows us to separate the opening and these announcements.[3]

Because the futures prices are quoted in different units and volatility differs, to facilitate interpretation of the results and comparisons across the three markets, we standardize returns in each market to a (0,1) basis.[4] To maintain a continuous series, we include the overnight or close-to-open returns. Because these overnight returns are much more volatile than the average 10-min return, they are standardized to a (0,1) basis separately.

[2]This normally occurs roughly 10 days before expiration of the Deutschmark contract, 20 days before expiration of the T-bond contract, and 40 days before expiration of the Eurodollar contract. Of course, we always use the same contract to calculate returns. For instance, if we switch contracts on 10/1, the opening price is observed on both contracts that day. The opening price on the nearby contract is used to calculate the overnight return, and the opening price on the second nearby is used to calculate the return over the opening period.

[3]In calculating the 10-min returns, we use the price in effect at the 10-min mark. For instance, if the time-and-sales data show a trade at 100 at 10:19:56 and a price of 100.1 at 10:20:01, we use the 10:19:56 price of 100 even though the price of 100.1 was observed a couple of seconds closer to 10:20. Only trades associated with price changes are reported for futures markets, so it is quite possible that one or more trades at 100 occurred after 10:19:56. The median time between price changes ranges from 6 s in the T-bond market to 12 s in the Deutschmark market, so most of our returns are based on trades within a few seconds of the 10-min marks.

[4]As shown later, this means that if the coefficient of the dummy variable for announcement X is 1.0 in one market and 1.5 in another, volatility in the first market is double normal volatility when X is announced and 250% of normal volatility in the second. Because the unstandardized mean is approximately zero in each market, the only meaningful impact is on the standard deviation. Prior to standardization, the standard deviations are as follows: Eurodollars, .0001200; T-bonds, .0007583; and Deutschmarks, .0009242. The coefficients estimated later may be converted to raw return levels with these factors.

DETERMINANTS OF INTRADAY VOLATILITY

Because of bid-ask bounce, there is a slight tendency (particularly in the Eurodollar market) for a positive (negative) return in one 10-min interval to be followed by a negative (positive) return in the next interval. To capture this and measure the return innovation, we estimate[5]

$$R_t = \xi_0 + \xi_1 R_{t-1} + e_t \tag{1}$$

Assuming that the log return innovation, e_t, is normally distributed with mean zero and a time-varying variance v_t,we model v_t as a linear function of three information sets:

$$\begin{aligned} v_t = \alpha_0 &+ \sum_{i=1}^{6} \alpha_i e_{t-i}^2 + \alpha_7 e_{\text{hour}}^2 + \alpha_8 e_{\text{day}}^2 + \alpha_9 e_{\text{week}}^2 \\ &+ \sum_{j=1}^{16} \beta_j A_{jt} + \sum_{k=1}^{19} \theta_k S_{kt} + u_t \end{aligned} \tag{2}$$

where, as explained more fully later, the lagged e^2 terms represent ARCH effects, A_{jt} represents scheduled macroeconomic announcements, and S_{kt} captures time-of-day and day-of-the week volatility patterns. To motivate the specification in Equation 2, compare our variance model with the usual models that incorporate only one of the three information sets, and explore the relative importance of the three information sets, in this section we first develop and estimate three separate submodels before incorporating all three into Equation 2 in the third section.

ARCH Effects

In Table I, we report estimates of two ARCH-type models of the variance, v_t, of the return innovation, e_t: the GARCH(1,1) model, $v_t = \eta + \xi e_{t-1}^2 + \lambda v_{t-1} + w_{t-1}$, and the expanded ARCH model,

$$v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e_{t-i}^2 + \alpha_7 e_{\text{hour}}^2 + \alpha_8 e_{\text{day}}^2 + \alpha_9 e_{\text{week}}^2 \tag{3}$$

[5]Although Equation 1 is always estimated simultaneously with our models of the variance v_t to conserve space and focus on the issue at hand, we do not report its parameter estimates in the tables. Depending on the information sets included in the estimation, estimates of ξ_1 range from $-.12$ to $-.20$ in the Eurodollar estimation, from $-.03$ to $-.06$ in the T-bond regression, and from $-.03$ to $-.05$ in the Deutschmark regression. However, the explanatory or predictive power, as measured by the adjusted R^2, is very low, below 2% in the Eurodollar regressions and below 0.3% in the other markets. Dropping this equation has virtually no impact on the results. The form of Equation 1 was chosen to eliminate any correlation due to bid–ask bounce.

TABLE I

General Autoregressive Conditional Heteroskedastic and Expanded Autoregressive Conditional Heteroskedastic Intraday Volatility Models

Panel A: GARCH(1,1) Model Estimates

	Eurodollar	*Treasury Bonds*	*Deutschmark*
η	.1809**	.1325**	.0667**
	(.0011)	(.0014)	(.0011)
ξ	.2925**	.2058**	.1768**
	(.0020)	(.0029)	(.0021)
λ	.5939**	.6938**	.7522**
	(.0018)	(.0030)	(.0025)

Panel B: Comparison of Expanded ARCH Coefficient Estimates With Implied GARCH Coefficients

	Eurodollar		*Treasury Bonds*		*Deutschmark*	
	ARCH	*GARCH*	*ARCH*	*GARCH*	*ARCH*	*GARCH*
e^2_{t-1}	.3664	.2925	.2274	.2058	.2172	.1768
e^2_{t-2}	.0878	.1737	.0834	.1428	.0973	.1330
e^2_{t-3}	.1231	.1031	.0996	.0991	.0770	.1000
e^2_{t-4}	.0000	.0613	.0510	.0687	.0399	.0753
e^2_{t-5}	.0240	.0364	.0654	.0477	.0273	.0566
e^2_{t-6}	.0258	.0216	.0427	.0331	.0192	.0426
e^2_{hour}	.0105	.0051	.0069	.0111	.0101	.0176
e^2_{day}	.00153	.00005	.00215	.00029	.00450	.00081
e^2_{week}	.00033	<.00001	.00050	<.00001	.00087	<.00001

Note: Panel A reports estimates of the GARCH(1,1) model, $v_t = \eta + \xi e^2_{t-1} + \lambda v_{t-1} + w_{t-1}$ where e_t is the return innovation in 10-min interval t from the relation $R_t = \xi_0 + \xi_1 R_{t-1} + e_t$. Estimated standard errors are shown in parentheses. One and two asterisks designate estimates significantly different from zero at the .01 and .001 levels, respectively. Panel B reports estimates of the expanded ARCH model: $v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e^2_{t-i} + \alpha_7 e^2_{\text{hour}} + \alpha_8 e^2_{\text{day}} + \alpha_9 e^2_{\text{week}}$, where $e^2_{\text{hour}} = \sum_{i=7}^{12} e^2_{t-i}$, $e^2_{\text{day}} = \sum_{i=13}^{41} e^2_{t-i}$, and $e^2_{\text{week}} = \sum_{i=42}^{205} e^2_{t-i}$. For comparison, we also report implied coefficients for the same terms based on the GARCH(1,1) models from Panel A, restated as $v_t = \eta' + \xi e^2_{t-1} + \lambda\xi e^2_{t-2} + \lambda^2 \xi e^2_{t-3} + \cdots + \lambda^{i-1}\xi e^2_{t-1} + \cdots + z_{t-1}$. Averages of the implied GARCH coefficients are reported for the terms e^2_{hour}, e^2_{day}, and e^2_{week}.

where e^2_{t-i} represents the squared-return innovation in the 10-min interval $t-i$, e^2_{hour} is the sum of the squared-return innovations over the penultimate hour prior to t (i.e., $e^2_{\text{hour}} = \sum_{i=7}^{12} e^2_{t-i}$), e^2_{day} is the sum of e^2 over the day prior to interval t excluding the 2-hr immediately before t (i.e., $e^2_{\text{day}} = \sum_{i=13}^{41} e^2_{t-i}$), and e^2_{week} is the sum over the last week excluding the last day (i.e., $e^2_{\text{week}} = \sum_{i=42}^{205} e^2_{t-i}$).[6] We use summary measures for the

[6] e^2_{hour}, e^2_{day}, and e^2_{week} are measured as sums rather than averages so that their coefficients will be comparable with those of the e^2_{t-i} terms. The lag length was made purposefully long (1 week) to capture any long memory effects, even if minor.

periods more than an hour before t to keep the model manageable yet maintain a fairly flexible lag structure.

Results for each market are reported in Panel A of Table I. Although there is evidence of strong intraday ARCH effects, we, like Ding, Granger, and Engle (1993) and Baille, Bollerslev, and Mikkelsen (1996), find that in an intraday context, a GARCH(1,1) model implies that after a shock, volatility returns to virtually normal levels too quickly in all three markets. If v represents the unconditional variance, the j-step-ahead conditional variance according to the GARCH(1,1) model is $E_t = v + (\xi + \lambda)^j[v_t - v]$. In the two interest-rate markets, $(\xi + \lambda)^{41} < .01$, implying that over 99% of a shock is dissipated within 1 day. Yet, when we estimate GARCH models for our markets using daily data (the results are not reported), we find evidence that high volatility tends to continue for a few days.

To better capture both short-term and long-term effects of a volatility shock, we estimate the expanded ARCH model shown in Equation 3, which allows a much more flexible decay function than the GARCH(1,1) model. Maximum-likelihood estimation results are shown in the columns labeled *Separate* in Panel A of Table II. As shown there, intraday ARCH effects are quite strong in all three markets. With the single exception of e^2_{t-4} in the Eurodollar market, all six e^2_{t-i}, as well as e^2_{hour}, e^2_{day}, and e^2_{week}, are easily significant at the .01 level in all three markets. (To avoid the possibility of negative estimated variances, our ARCH estimation program restricts the estimated coefficients to nonnegative values, so the .000 coefficient for e^2_{t-4} in the Eurodollar equation indicates that the log-likelihood-maximizing coefficient is nonpositive.) In the Deutschmark estimation, the coefficients of the lagged innovations decline monotonically. In the two interest-rate markets, the decline is close to, but not perfectly, monotonic. Although the coefficients of e^2_{day}, and e^2_{week} are small because they are sums, these variables are much larger and more variable than the 10-min e^2_{t-i}'s, so their impact on v_t is considerable. Both terms are significant at the .0001 level in all three markets, implying that (contrary to the implication of the GARCH model) a shock today does impact volatility tomorrow and beyond.

With successive substitution, the GARCH model can be rewritten as

$$v_t = \eta' + \xi e^2_{t-1} + \lambda\xi e^2_{t-2} + \lambda^2\xi e^2_{t-3} + \cdots + \lambda^{i-1}\xi e^2_{t-i} + \cdots + z_{t-1}$$

illustrating that the coefficients of past shocks decay in exponential fashion. For $\lambda < 1$ and long lags i, the implied coefficient of e^2_{t-i}, $\lambda^{i-1}\xi$, can

TABLE II
Parameter Estimates for Intraday Volatility Models

Variables	*Eurodollars* Separate	*Eurodollars* Combined	*Treasury Bonds* Separate	*Treasury Bonds* Combined	*Deutschmarks* Separate	*Deutschmarks* Combined
			Panel A: ARCH Variables (e^2)			
Constant (α_0)	.3706* (.0029)	.1250* (.0078)	.3353* (.0033)	.0282* (.0080)	.2219* (.0041)	.0000
e^2_{t-1}	.3664* (.0026)	.1461* (.0039)	.2274* (.0036)	.1434* (.0044)	.2172* (.0034)	.1789* (.0031)
e^2_{t-2}	.0878* (.0015)	.0492* (.0032)	.0834* (.0030)	.0714* (.0035)	.0973* (.0035)	.0860* (.0035)
e^2_{t-3}	.1231* (.0017)	.0251* (.0027)	.0996* (.0023)	.0345* (.0033)	.0770* (.0030)	.0594* (.0032)
e^2_{t-4}	.000	.0101* (.0022)	.0510* (.0017)	.0235* (.0027)	.0399* (.0023)	.0559* (.0022)
e^2_{t-5}	.0240* (.0009)	.0187* (.0015)	.0654* (.0011)	.0533* (.0013)	.0273* (.0021)	.0374* (.0024)
e^2_{t-6}	.0258* (.0011)	.0185* (.0019)	.0427* (.0019)	.0215* (.0022)	.0192* (.0013)	.0282* (.0014)
e^2_{hour}	.0105* (.0003)	.0077* (.0005)	.0069* (.0005)	.0110* (.0006)	.0101* (.0006)	.0152* (.0007)
e^2_{day}	.0015* (.0001)	.0028* (.0001)	.0021* (.0001)	.0034* (.0002)	.0045* (.0001)	.0033* (.0001)
e^2_{week}	.00033* (.00002)	.00049* (.00003)	.00050* (.00003)	.00087* (.00005)	.00087* (.00003)	.00044* (.00003)
			Panel B: Seasonality Variables (S_k)			
Constant (α_0)	.4270* (.0072)	.1250* (.0079)	.4658* (.0059)	.0282* (.0080)	.3952* (.0097)	.0000
OPEN	1.0251* (.0503)	.9348* (.0537)	.8915* (.0482)	.7707* (.0447)	.2045* (.0224)	.3472* (.0166)
7:30–7:40	8.9941* (.1159)	1.726* (.0123)	5.8239* (.1248)	.5739* (.0459)	2.8636* (.0685)	.3234* (.0182)
7:40–7:50	.9576* (.0281)	.3388* (.0195)	.6519* (.0394)	.3020* (.0279)	.5625* (.0286)	.3719* (.0181)
7:50–8:00	.3912* (.0215)	.0829* (.0262)	.3946* (.0284)	.0745* (.0259)	.4312* (.0230)	.1267* (.0183)
8:00–9:00	.2026* (.0078)	.0772* (.0078)	.2265* (.0106)	.0685* (.0094)	.4261* (.0116)	.2714* (.0075)
9:00–10:00	.2577* (.0077)	.0342* (0074)	.1951* (.0082)	.0480* (.0078)	.7182* (.0137)	.4082* (.0094)
10:00–11:00	.1565* (.0070)	.1187* (.0071)	.0281* (.0075)	.0010 (.0074)	.5327* (.0137)	.3861* (.0085)

TABLE II
(Continued)

	Eurodollars		*Treasury Bonds*		*Deutschmarks*	
Variables	*Separate*	*Combined*	*Separate*	*Combined*	*Separate*	*Combined*
			Panel B: Seasonality Variables (S_k)			
11:00–12:00	.0237* (.0076)	.0101 (.0075)	EX	EX	.3927* (.0106)	.1743* (.0085)
12:00–1:00	EX	EX	.1579* (.0085)	.0827* (.0088)	.1139* (.0082)	.0468* (.0063)
1:00–1:30	.0927* (.0102)	.0355* (.0106)	.3701* (.0134)	.2297* (.0147)	.0192 (.0099)	.0101 (.0043)
1:30–1:40	.1497* (.0172)	.1046* (.0173)	.3748* (.0259)	.2053* (.0250)	.0764* (.0097)	EX
1:40–1:50	.2032* (.0210)	.1257* (.0182)	.5235* (.0369)	.4141* (.0317)	EX	.0231 (.0102)
CLOSE	.4789* (.0287)	.3581* (.0290)	.8251* (.0408)	.5258* (.0362)	.1105* (.0117)	.1031* (.0128)
OVERNIGHT	.1630* (.0196)	.2111* (.0194)	.2358* (.0164)	.2142* (.0154)	.2513* (.0315)	.4309* (.0284)
THURS-OVER	.0000	.0000	.0000	.0000	.0000	.0000
WEEKEND	1.5685* (.0475)	.4731* (.0452)	.7543* (.0841)	.1801 (.0749)	1.1009* (.1240)	.8609* (.1152)
Monday	EX	EX	EX	EX	EX	EX
Tuesday	.1625* (.0068)	.1202* (.0066)	.1405* (.0087)	.1022* (.0085)	.1990* (.0073)	.0313* (.0051)
Wednesday	.1081* (.0070)	.0877* (.0069)	.1275* (.0084)	.0733* (.0082)	.0592* (.0079)	.0174* (.0059)
Thursday	.1115* (.0064)	.0764* (.0065)	.1663* (.0069)	.0944* (.0072)	.1429* (.0076)	.0037 (.0062)
Friday	.3109* (.0081)	.1342* (.0066)	.4114* (.0093)	.1802* (.0088)	.3963* (.0074)	.0038 (.0062)
			Panel C: Scheduled Announcement Dummies (A_j)			
Constant (α_0)	.784* (.001)	.125* (.008)	.854* (.002)	.028* (.008)	.993* (.002)	.000
Consumer Price Index	12.532* (2.726)	12.198* (2.637)	17.511* (4.383)	17.324* (4.284)	2.829 (1.107)	2.840* (1.049)
Durable goods	8.367* (.925)	6.713* (.933)	6.687* (.815)	6.219* (.778)	8.268* (1.188)	7.973* (1.199)
Employment	102.252* (24.831)	100.565* (24.833)	52.480* (14.216)	52.056* (14.232)	21.413* (5.470)	21.263* (5.436)
Gross National (or Domestic) Product	3.589* (.955)	1.668 (.915)	3.682* (.540)	2.814* (.516)	2.982* (.773)	3.195* (.773)

(Continued)

TABLE II
(Continued)

	Eurodollars		*Treasury Bonds*		*Deutschmarks*	
Variables	*Separate*	*Combined*	*Separate*	*Combined*	*Separate*	*Combined*
	Panel C: Scheduled Announcement Dummies (A_j)					
Housing starts	4.570* (1.384)	2.624 (1.278)	4.582* (1.235)	3.719* (1.096)	1.316* (.474)	1.168* (.437)
Leading indicators	.942* (.383)	.000	.935 (.425)	.591 (.413)	.662 (.423)	.793 (.398)
Trade deficit	1.977* (.412)	.000	2.964* (.773)	2.324* (.819)	9.379* (1.866)	9.157* (1.898)
Producer Price Index	13.699* (2.894)	12.618* (2.955)	21.686* (4.326)	21.529* (4.362)	2.756* (.849)	2.556* (.721)
Retail sales	13.048* (2.909)	11.428* (2.907)	8.059* (2.877)	7.690* (2.865)	6.878* (.884)	7.101* (.895)
Industrial prod.–capacity util.	2.453* (.640)	2.283* (.589)	2.479* (.626)	1.531* (.632)	1.358* (.282)	.626* (.242)
Business inventories	.281 (.161)	.333* (.122)	.214 (.192)	.030 (.142)	.494 (.261)	.476 (.283)
Construction spending–NAPM survey	6.120* (1.229)	6.222* (1.219)	3.782* (.944)	3.848* (.943)	2.821* (.702)	2.771* (.721)
Factory inventories	1.112* (.375)	1.050* (.327)	.878* (.238)	.465 (.252)	2.072* (.376)	.344 (.285)
Home sales	.751 (.381)	.980* (.377)	1.131 (.573)	1.227 (.537)	1.036* (.275)	1.148* (.282)
Personal income	.421 (.274)	.747* (.253)	.754 (.340)	.968* (.346)	.615 (.304)	.460 (.292)
Federal budget	.000	.127 (.105)	.000	.000	.000	.000

Note: Estimated parameters are reported for variations of the equation

$$v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e_{t-i}^2 + \alpha_7 e_{\text{hour}}^2 + \alpha_8 e_{\text{day}}^2 + \alpha_9 e_{\text{week}}^2 + \sum_{j=1}^{16} \beta_j A_{jt} + \sum_{k=1}^{19} \theta_k S_{kt} + u_t$$

where v_t is the variance of the return innovation, e_t, from $R_t = \xi_0 + \xi_1 R_{t-1} + e_t$, $e_{\text{hour}}^2 = \sum_{i=7}^{12} e_{t-i}^2$, $e_{\text{day}}^2 = \sum_{i=13}^{41} e_{t-i}^2$, and $e_{\text{week}}^2 = \sum_{i=42}^{205} e_{t-i}^2$; A_{jt} are announcement dummies where $A_{jt} = 1$ if announcement j is released in 10-min interval t and zero otherwise; and S_{kt} are zero-one dummies designating the time of day and day of the week. Coefficients for the ARCH, seasonality, and announcement variables are reported in Panels A, B, and C, respectively. In the first column for each market, the results for a model that includes only that information set are reported. Parameter estimates for the model including all three information sets are shown in the second column. The models are estimated with maximum-likelihood and 10-min return data from 7/3/89 through 5/28/93. Standard errors are shown in parentheses. Asterisks denote significance at the .01 level in one-tailed tests. EX denotes an excluded dummy variable, and a value of .000 indicates an estimate at the lower bound (zero).

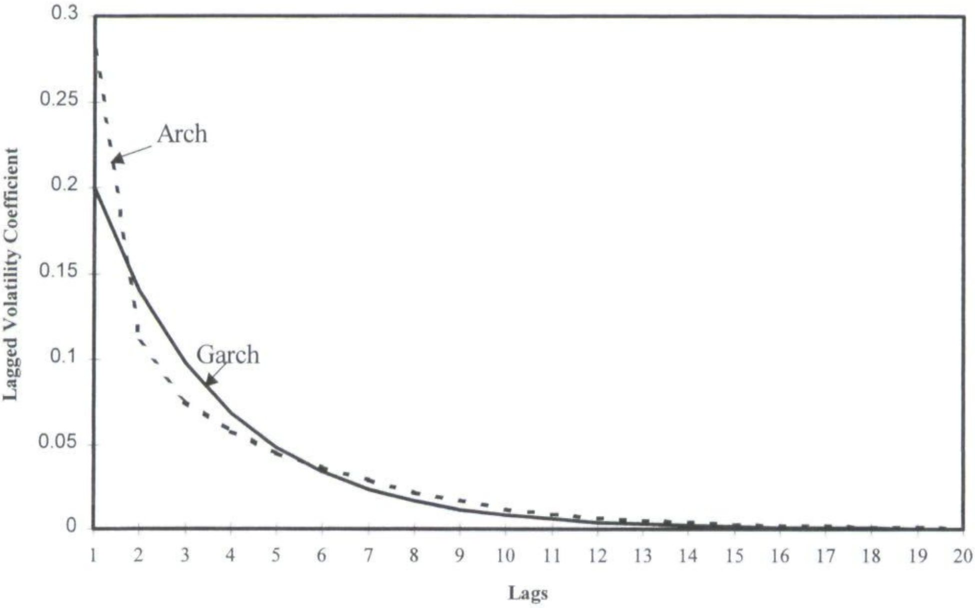

FIGURE 1
Comparison of ARCH coefficients with those implied by a GARCH(1,1) model. The implied coefficients for a GARCH model, where $v_t = .2e_{t-1}^2 + .7v_{t-1}$ (the approximate average for the three markets in our estimations), are represented by the solid line. The dashed line illustrates a smoothed average of the ARCH coefficients across our three markets.

be quite small. For instance, in the Eurodollar market the implied coefficient for a shock that occurred 2-hr earlier is $.5939^{11}(.2925) = .000948$. For comparison, these implied GARCH coefficients (where the average coefficients are reported for e^2_{hour}, e^2_{day}, and e^2_{week}) are shown alongside their ARCH counterparts in Panel B of Table I. As shown there and illustrated in Figure 1 for Eurodollars, in comparison with the expanded ARCH model, in all three markets an intraday GARCH(1,1) model tends to underestimate the influence of the most recent and more distant return innovations and tends to overestimate the influence of shocks at the intermediate lags. On the basis of the log likelihoods in Panel A of Table III, the GARCH model's implied hypothesis that the coefficients decline exponentially as the lags lengthen is rejected at the .01 level in all three markets.[7]

[7]As shown in Panel A of Table III, the log likelihood of the expanded ARCH model consistently exceeds that of the GARCH(1,1) model. As shown previously, the 3-parameter GARCH(1,1)model may be viewed as approximately (but not completely) nested within our less restrictive 10-parameter ARCH model. The test is based on this nesting presumption.

TABLE III

Tests of the Information Provided by ARCH, Seasonal, and Announcement Variables

Information Sets Included	*Eurodollars*	*Treasury Bonds*	*Deutschmarks*
Panel A: Log-Likelihood Statistics			
ARCH (e^2)	−53868.5	−54860.8	−53410.5
GARCH(1,1) model	−54075.4	−54973.5	−53720.3
Seasonals (S)	−52104.4	−54192.9	−55463.8
Announcements (A)	−52879.5	−54479.5	−56011.0
Both current and lagged announcements	−52368.4	−54210.3	−55655.6
ARCH and announcements (e^2, A)	−50007.5	−51975.5	−51945.9
ARCH and seasonals (e^2, S)	−49461.3	−52007.7	−51587.3
Announcements and seasonals (A, S)	−51516.5	−53624.9	−55119.1
All (e^2, A, S)	−48818.9	−51409.2	−51174.9
None (α_0 only)	−56867.7	−57095.2	−57111.1
Panel B: Likelihood Ratio Tests of Incremental Information			
ARCH (e^2)	5395.2*	4431.4*	7888.4*
Seasonals (S)	2377.2*	1132.6*	1542.0*
Announcements (A)	1284.8*	1197.0*	824.8*

Note: Log-likelihood statistics are presented for variations of the equation

$$v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e_{t-i}^2 + \alpha_7 e_{\text{hour}}^2 + \alpha_8 e_{\text{day}}^2 + \alpha_9 e_{\text{week}}^2 + \sum_{j=1}^{16} \beta_j A_{jt} + \sum_{k=1}^{19} \theta_k S_{kt} + u_t$$

where v_t is the variance of the return innovation, e_t, from $R_t = \xi_0 + \xi_1 R_{t-1} + e_t$, $e_{\text{hour}}^2 = \sum_{i=7}^{12} e_{t-h}^2$, $e_{\text{day}}^2 = \sum_{i=13}^{41} e_{t-h}^2$ and $e_{\text{week}}^2 = \sum_{i=42}^{205} e_{t-i}^2$; A_{jt}'s are announcement dummies where $A_{jt} = 1$ if announcement j is released in 10-min interval t and $A_{jt} = 0$ otherwise; and the S_{kt}'s are zero-one seasonal dummies designating the day of the week and time of day. A GARCH(1,1) model is also estimated. The models are estimated with 10-min interval return data from 7/3/89 through 5/28/93. In Panel A, log-likelihood statistics are presented for estimations with different combinations of the e^2, A, and S variables. Results of log-likelihood tests for each information set are shown in Panel B, excluding the other two information sets. Asterisks denote significance at the .0001 level.

Seasonality

Seasonality patterns are represented by the submodel

$$v_t = \alpha_0 + \sum_{k=1}^{19} \theta_k S_{kt} + w_t \tag{4}$$

where S_{kt} represents the 15 time-of-day zero-one dummy variables and 4 day-of-the-week dummies listed in Panel B of Table II. For instance, OPEN equals 1 for the 10-min interval from 7:20 a.m. CT (the open) through 7:30. Likewise the 7:30–7:40 dummy variable equals 1 for the 7:30–7:40 interval and zero otherwise. To keep the model manageable, combined variables are defined for the midday periods. For example, the 8:00–9:00 variable equals 1 for all six 10-min intervals between 8:00 a.m. (CT) and 9:00 a.m. However, we define separate dummies for the 10-min intervals just after the open and just before the close. Similarly, zero-one dummy variables are defined to designate the day of the week. To avoid negative variance forecasts, our estimation procedure does not allow negative coefficients, so we exclude dummies for the day (Monday in all markets) and time when volatility is lowest on average.

OVERNIGHT_t equals 1 in the close-to-open interval. Because these overnight returns are standardized separately, its coefficient is not on the same scale as those of 10-min interval dummies. Two additional dummies are defined to designate particular close-to-open intervals. WEEKEND_t equals 1 for the Friday-close-to-Monday-open interval and zero otherwise. A positive coefficient for WEEKEND (which we expect) would indicate that the Friday-close-to-Monday-open return tends to be more volatile than the normal weekday close-to-open return. THUR-OVER equals 1 for the Thursday-close-to-Friday-open interval. If the weekly money-supply announcements, which are released after the markets close on Thursday, impact the market, THUR-OVER should have a positive coefficient.

Maximum-likelihood estimates of Equation 4 are reported in the columns labeled *Separate* in Panel B of Table II. As seen there, the data in all three markets exhibit strong time-of-day and day-of-the-week patterns. For instance, the estimated variance between 7:30 and 7:40 on Friday is $\alpha_0 + \theta_{7:30-7:40} + \theta_{\text{Fri}} = .4270 + 8.9941 + .3109 = 9.732$, or over nine times the unconditional or average variance. In all three markets, volatility is lowest on Monday and highest on Friday. Moreover, in all three volatility is highest in the 7:30–7:40 a.m. CT interval, but, as we discuss later, this is largely due to the fact that major macroeconomic announcements are often announced at this time. Aside from the 7:30–7:40 period, the interest-rate markets, but not the Dollar–Deutschmark market, display a U (or reverse J) volatility pattern, in that volatility is highest at the open, falls through midday, and rises to a secondary peak at the close. These time-of-day patterns are analyzed more thoroughly after we control for announcement-induced volatility in the third section.

The log likelihoods for this model, which are reported in Row 3 of Table III, underscore the fact that the seasonality information set is highly significant in all three markets. Indeed, when the information sets are considered separately, its log likelihood is the highest of the three

(ARCH, seasonals, and announcements) in the interest-rate markets and ranks second in the Deutschmark market.

Scheduled Announcements

The impact of scheduled announcements on volatility[8] is captured by the submodel

$$v_t = \alpha_0 + \sum_{j=1}^{16} \beta_j A_{j,t} + u_t \tag{5}$$

Announcement dummy variables are defined for each of the 16 announcements (or announcement pairs if released simultaneously) listed in Panel C of Table II. $A_{jt} = 1$ if announcement j is released in 10-min interval t, and $A_{jt} = 0$ otherwise. We employ zero-one dummies, rather than the figures released, because all market participants know prior to t that a particular announcement will be released then, not what the announcement will be. Because all are monthly announcements, each A_{jt} equals 1 for about 47 of our 40,508 observations.[9] Estimated volatility in intervals without a scheduled announcement is represented by α_0, whereas volatility in periods when announcement j is released is measured by $\alpha_0 + \beta_j$.

Estimates of Equation 5 are reported in the columns labeled *Separate* in Panel C of Table II. Like the other two information sets, the announcement information set is highly significant in explaining volatility. With the sole exception of the dummy variable designating release of the federal budget statistics,[10] all coefficients β_j in Panel C of Table II are positive in all three markets, indicating higher than normal volatility immediately after their release. Most are significant at the .01 level.

Although consistent with the results in Ederington and Lee (1993, 1995), Fleming and Remolona (1999), Balduzzi et al. (1997), and Andersen and Bollerslev (1998), the impact of the employment report on

[8]Although the expected impact on the variance is positive, because the timing, but not the content (bullish or bearish), is known ahead of time, the expected impact on the mean return is zero. If some announcements tend to be bullish more often than bearish, efficient markets implies that this should be impounded in preannouncement prices, so positive and negative surprises should balance. For this reason, announcement dummies are included in the variance equations but not in Equation 1.

[9]The number of observations varies slightly from market to market because they were closed different days during the Chicago flood. Observations total 40,467 for T-bonds, 40,508 for Deutschmarks, and 40,549 for Eurodollars.

[10]Given the results in Ederington and Lee (1993), the fact that this dummy has the wrong sign is surprising. Perhaps the Treasury Department, which releases this statistic, is less consistent and prompt than the Bureau of Labor Statistics and Department of Commerce, which release the others so that the figures do not appear promptly at 2:00. However, we find no evidence that volatility is significantly higher in the second or third interval following the scheduled release time.

volatility is still impressive. In the Eurodollar market, the estimated normal variance of returns during the 10-min interval immediately following the release of the employment report (102.252 + 0.784 = 103.036) is over 100 times larger than the normal 10-min return variance (approximately 1.0) and over 130 times larger than the normal nonannouncement interval variance (0.784).[11] In the T-bond market, it is over 50 times the normal variance, and in the Deutschmark market, it is over 20 times the normal variance. Other announcements with a big impact on volatility are the PPI, CPI, retail sales, and durable goods orders in the interest-rate markets and U.S. trade-deficit figures in the Dollar–Deutschmark market.

Although our results for longer term interest rates correspond fairly closely to the findings in Balduzzi et al. (1997), our results for 90-day Eurodollar futures differ fairly sharply from their findings for 90-day Treasury-bills (T-bills). Although we find that 12 announcements significantly (.01 level) impact 90-day Eurodollar rates, they found that only 3 (employment, durable goods orders, and trade figures) significantly impacted 90-day T-bill rates. Since Eurodollars and T-bills are widely viewed as very close substitutes, these different findings are surprising.

Although our dummy variables capture only volatility in the 10-min interval following the announcement, it is quite possible that volatility remains high considerably longer. To test whether the announcement information set has predictive ability for later periods yet keep the model manageable, we proceed as follows. First, we construct an index of the predicted excess volatility in the first 10-min interval based on the estimated coefficient, $\hat{\beta}_j$, in the first column for each market in Panel C of Table II (i.e., $I_t = \sum_{j=1}^{16} \hat{\beta}_j A_{jt}$). For instance, in the Eurodollar market, $I_t = 12.532A_{\text{CPI},t} + 8.367A_{\text{Durable Goods Orders},t} + 102.252A_{\text{employment},t} + \cdots + .000A_{\text{federal budget},t}$. We then estimate the model

$$v_t = \alpha_0 + \delta_0 I_t + \delta_1 I_{t-1} + \delta_2 I_{t-2} + \delta_3 I_{t-3} + \delta_4 I_{t-4} + \delta_5 I_{t-5} + \delta_6 I_{t-6} \tag{6}$$

By construction, the coefficient of I_t is approximately 1.0. Log likelihoods for estimates of Equation 6 are shown in Table III in the row labeled *Both Current and Lagged Announcements*.

[11]Several readers have expressed incredulity at the size of the employment announcement coefficient and have expressed the opinion that it may reflect a data error or single huge outlier. We have checked, and it does not. Readers are reminded that the dependent variable is the variance, not the standard deviation as in Ederington and Lee (1993, 1995). The implied coefficient for the standard deviation (the square root of that in Table II) is in line with previous studies.

In the Eurodollar market, the coefficients of the lagged terms are I_{t-1}, 0.175; I_{t-2}, 0.042; I_{t-3}, 0.013; I_{t-4}, 0.009; I_{t-5}, 0.007; and I_{t-6}, 0.008, implying that excess volatility (defined as volatility in excess of the nonannouncement period volatility) in the second 10-min interval averages 17.5% of the first 10-min interval's excess volatility and that excess volatility in the third 10-min period averages 4.2% of the excess volatility in the first 10-min period. All six lagged I_{t-i}'s are significant at the .01 level. Virtually the same results are obtained for the T-bond market, except that the longer lags are not all significant.[12]

Because in both interest-rate markets the estimated coefficients for I_{t-4}, I_{t-5}, and I_{t-6} are all less than .01, the implication in both is that volatility returns to virtually normal levels within 40-min of the release. This is a considerably more rapid return to normal volatility levels than that estimated by Ederington and Lee (1993) and Fleming and Remolona (1999). In contrast, in the Dollar–Deutschmark market volatility remains high considerably longer, perhaps because this contract is less heavily traded. In order, the lagged coefficients are I_{t-1}, 0.230; I_{t-2}, 0.130; I_{t-3}, 0.085; I_{t-4}, 0.057; I_{t-5}, 0.061; and I_{t-6}, 0.083. All are significant at the .01 level.

Relative Predictive Power

We employ two measures of the relative information regarding future volatility provided by the three information sets. The first consists of the log likelihoods reported in the first five rows of Table III. By this measure, time-of-day and day-of-the-week patterns are most important in the two interest-rate markets, whereas recent past volatilities (or ARCH effects) provide the most information in the exchange-rate market.

For our second measure, we employ Pagan and Schwert's (1990) procedure of regressing the squared-return innovation, e_t^2, for each 10-min interval on $\hat{v}_t$, where $\hat{v}_t$ is the conditional variance implied by the estimation (i.e., Equations 2, 3, 4, 5, or 6). The resulting R^2 provides a measure of the model's in-sample predictive ability. Because the number of independent variables varies considerably between models, we report an adjusted R^2, which is constructed as if the e_t^2 were being regressed directly on the independent variables instead of $\hat{v}_t$; that is, $\bar{R}^2 = R^2 - [(k-1)/(n-k)](1-R^2)$, where n is the number of observations and k is the number of independent variables in the original

[12] In the T-bond market, the estimated coefficients for I_{t-1} through I_{t-6} are in order .133, .0536, .030, .007, .005, and .008.

TABLE IV

Regression Tests of the Predictive Ability of Intraday Volatility Models

Information Sets Included	*Eurodollars*	*Treasury Bonds*	*Deutschmarks*
ARCH (e^2)	.0059	.0062	.0420
GARCH(1,1)	.0051	.0061	.0394
Seasonals (S)	.0261	.0394	.0137
Announcements (A)	.1680	.1945	.0435
Current and lagged announcements	.1684	.1964	.0472
ARCH and announcements (e^2, A)	.1553	.1837	.0473
ARCH and seasonals (e^2, S)	.0260	.0360	.0510
Announcements and seasonals (A, S)	.1685	.1972	.0832
All three information sets (e^2, A, S)	.1634	.1894	.0844

Note: We report adjusted R^2 statistics from the regression of e_t^2 on $\hat{v}_t$, where e_t is the return innovation from $R_t = \xi_0 + \xi_1 R_{t-1} + e_t$, R_t is the log return in interval t, and $\hat{v}_t$, is the variance of e_t forecast by variations of Equation 2 (also by a GARCH model). $\bar{R}^2 = R^2 - [(k-1)/(n-\mathrm{k})](1-R^2)$, where R^2 is the original R^2, n = the number of observations, and k = the number of variables in the original model. The regression is estimated on an in-sample basis with 10-min interval return data from 7/3/89 through 5/28/93.

equation. Because the dependent variable in this regression is the squared-return innovation, this measure puts more weight on a model's ability to predict very high volatility periods than the log-likelihood measure.

The $\bar{R}^2$ measures for our different models are reported in the first five rows of Table IV. Applying this measure, we see that the announcement information set clearly dominates in terms of volatility predictability in the two interest-rate markets. Indeed, in both interest-rate markets the adjusted R^2 of the announcement set exceeds 16%, whereas the adjusted R^2 for the seasonality information set never exceeds 4%, and the adjusted R^2 of the ARCH and GARCH models never exceeds 1%. The information set that has received the most attention in the literature ranks last in terms of volatility predictability, at least by this measure, in these two markets. In the Dollar–Deutschmark market, the adjusted R^2 for both the ARCH and announcement information sets is around 4%, with the announcement R^2 being slightly higher.

Note that the 10-min forecast horizon in Tables III and IV tends to favor the ARCH information set. Because both announcement times and seasonal patterns are known well in advance, the measures of predictability for these two information sets at longer forecast horizons would be identical to those shown in Tables III and IV. However, because it relies on data from the most recent 10-min interval, the predictive power of the intraday ARCH model would deteriorate as the forecast horizon is lengthened.

A GENERAL MODEL OF INTRADAY VOLATILITY

Next, we combine the three information sets into the general model of intraday volatility presented in Equation 2. The resulting parameter estimates from the log likelihood estimation of Equation 2 are shown in the columns labeled *Combined* in Table II. The log likelihood is reported in the penultimate row in Panel A of Table III (labeled *All*), and the adjusted R^2 from the regression of the squared-return innovation, e_t^2, on $\hat{v}$ from Equation 2 is reported in the last row of Table IV.[13]

Incremental Information

To test the incremental information provided by an individual information set, Equations 1 and 2 are re-estimated, forcing the coefficients for that information set to zero (e.g., setting $\beta_j = 0$ for all j). The resulting log likelihoods are reported in Rows 6, 7, and 8 in Panel A of Table III, whereas likelihood ratio tests of the null hypotheses that an information set provides no incremental information are shown in Panel B. As shown in Panel B, all three sets of determinants are incrementally significant at the .0001 level. As measured in terms of incremental log likelihoods, the ARCH information set, that is, knowledge of recent past volatilities, is most important incrementally in all three markets, whereas (as discussed earlier) the seasonal set had higher log likelihoods on a nonincremental basis in the two interest-rate markets. As explained later, this difference is probably due to the fact that much of the time-of-day patterns and day-of-the-week patterns are due to announcement patterns. Once these announcement patterns are controlled for, the information supplied by the seasonals is considerably less.

We also measure the incremental information provided by each information set by the improvement in the adjusted R^2 from the regression of the squared-return innovation in a 10-min interval, e_t^2, on the predicted volatility for the interval, $\hat{v}_t$. In other words, estimates of $\hat{v}_t$ are obtained by the estimation of Equation 2 both with and without a given information set, and the improvement in the adjusted R^2 from the

[13]Because Equations 3, 4, and 5 are nested within Equation 2, the log likelihood for Equation 2 must be at least as high as the others' by definition. Although the R^2 of an OLS equation cannot fall as additional variables are added, this is not the case with the R^2's in Table III. All the adjusted R^2's in Table III are for the simple regression of e_t^2 on $\hat{v}_t$, where $\hat{v}_t$ is estimated with maximum likelihood and different variables. Also note that the R^2's are adjusted for the difference in the number of variables.

Pagan–Schwert regression is measured. As shown in Table IV, by this measure the announcement information set is clearly the most important in the two interest-rate markets. The reason the ARCH information set ranks highest in terms of incremental log likelihood whereas the announcement set dominates in terms of incremental adjusted R^2 is that the latter measure attaches a higher weight to predicting the very high volatility periods. Although the 10-min intervals with the highest volatilities are almost all associated with one of our announcements, the intervals with announcements constitute only a small minority of all the intervals in our data set.

Scheduled Announcements

As reported in Panel C of Table II, of the three information sets the estimated coefficients of the major announcement variables, such as the employment report, are little altered when the other two information sets are included. Again, we find extremely high volatility during the intervals when the employment report, PPI, or CPI is released, particularly in the interest-rate markets. However, the coefficients of some of the minor announcements, such as gross domestic product and housing starts, are reduced somewhat. Apparently, these announcements tend to occur during times when volatility tends to be relatively high anyway, so when we control for time-of-day and day-of-the-week patterns, their coefficients are reduced.

Seasonality

As shown in Panel B of Table II, many of the time-of-day and day-of-the-week coefficients are substantially altered once we control for announcement effects. Most dramatically, when the announcement dummies are included, the coefficient of the 7:30–7:40 a.m. CT dummy is sharply reduced, an expected result because the employment report, CPI, PPI, and others are released at 7:30.[14] In addition, the 7:40–7:50 and 7:50–8:00 coefficients are reduced somewhat because the high post-announcement volatility is captured by the ARCH terms. Friday's coefficient is also reduced, although it remains the most volatile day in the interest-rate markets. To further test whether scheduled announcements

[14]Similar results were obtained by Ederington and Lee (1993), Anderson and Bollerslev (1998), Balduzzi et al. (1997), and Fleming and Remolona (1999).

are responsible for the large 7:30–7:40 and Friday coefficients observed when only seasonal patterns are considered, we calculate an index of the volatility due to the macroeconomic announcements, $I_t = \sum_{j=1}^{16} \hat{\beta}_j A_{jt}$, where the $\hat{\beta}_j$ is the estimated coefficient from the estimation of Equation 2. We then regress this index of implied volatilities I_t on the seasonal dummies, S_{kt}. In this regression, the coefficients of both the 7:30–7:40 and Friday dummies are large and highly significant in all three markets, confirming that announcements are indeed responsible for their large coefficients in the submodel estimations.[15] Because no other seasonal dummy variables are significant in this estimation, it appears that no other seasonal patterns can be explained as proxying for announcement effects.

The implied time-of-day volatility patterns before and after controlling for ARCH and announcement effects are shown in Figure 2 for the Eurodollar market. The line labeled *Seasonals Only* is an estimate

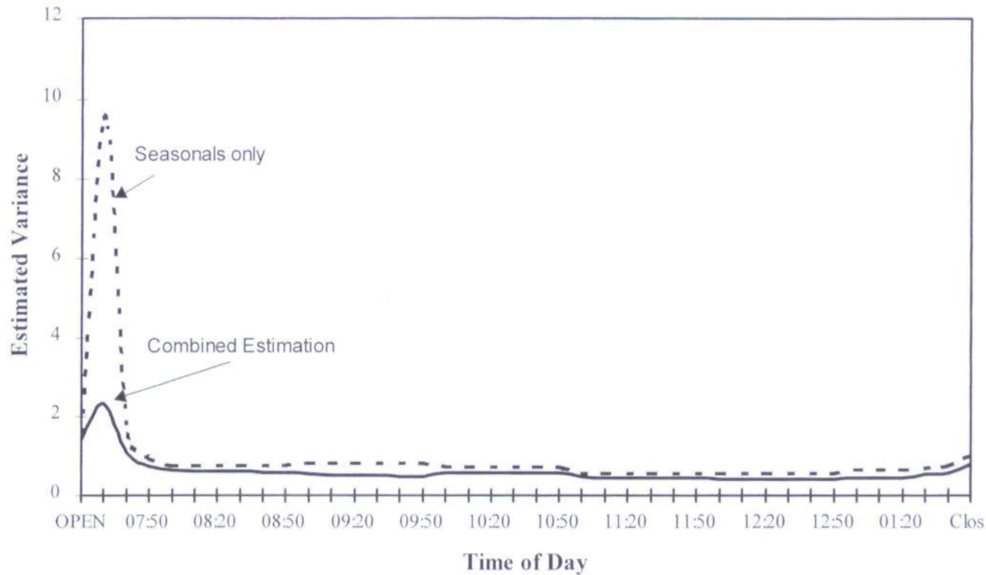

FIGURE 2
Time-of-day Eurodollar volatility patterns. The dashed line reports the estimated conditional volatilities in the Eurodollar market based on seasonal dummies only. The solid line reports the conditional volatilities on a day with no announcements after we controlled for announcement and ARCH effects.

[15]To test whether announcement volatilities display a time-of-day and day-of-the-week pattern, the index of announcement-induced volatilities is regressed on the seasonality dummies, the reverse of the hypothesized causation.

of the time-of-day implied volatility based on the time-of-day dummies in the set S_k, excluding the ARCH and announcement variables; that is, $\hat{v}_{sT} = \hat{\alpha} + \sum_{k=1}^{12} \hat{\theta}_k S_{kT}$, where T is the time of day, $\hat{\theta}_k$ is the estimated coe-fficient from the estimation of Equation 4, and $\hat{\alpha} = \hat{\alpha}_0 + .2(\hat{\theta}_{\text{Tues}} + \hat{\theta}_{\text{Wed}} + \hat{\theta}_{\text{Thur}} + \hat{\theta}_{\text{Fri}})$. The line labeled *Combined* is an index, $\hat{v}_{cT}$, of implied time-of-day volatilities on days without any scheduled announcements based on the ARCH and seasonality coefficients from the estimation of Equation 2. Specifically,

$$\hat{v}_{cT} = \hat{\alpha} + \sum_{i=1}^{6} \hat{\alpha}_i \hat{v}_{T-i} + \hat{\alpha}_7 \hat{v}_{\text{hour}} + \hat{\alpha}_8 \hat{v}_{\text{day}} + \hat{\alpha}_9 \hat{v}_{\text{week}} + \sum_{k=1}^{12} \hat{\theta}_k S_{kT} \quad (7)$$

where the estimated coefficients are from the estimation of Equation 2.[16] Because $\hat{v}_{sT}$ measures volatility patterns on all days, whereas $\hat{v}_{cT}$ measures volatility on days without scheduled announcements, $\hat{v}_{cT}$ generally lies below $\hat{v}_{sT}$. Our concern is with relative patterns, and clearly the time-of-day pattern is much flatter once we remove announcements. Nonetheless, in the Eurodollar market but in not the other two, estimated volatility during the 7:30–7:40 period remains somewhat higher than normal even after announcement effects are controlled for. This is possibly due to the fact that although we control for all important monthly announcements (and GDP, for which preliminary, revised, and final figures are released in successive months), we do not consider statistics, such as indexes of import prices, which are only released quarterly or annually. The remaining 7:30–7:40 excess volatility in this market could reflect these other announcements.

As reported in Table II and illustrated for Eurodollars in Figure 2, once we control for announcement (and ARCH) effects, volatility in the two interest-rate markets displays the traditional U or reversed J pattern, being highest at the open, relatively high at the close, and relatively flat and low over most of the trading day. This matches the pattern observed in interest-rate markets by Ederington and Lee (1993), Webb and Smith (1994), Balduzzi et al. (1997), and Fleming and Remolona (1999). However, as shown in Table II, once we control for announcements, we do not observe a U pattern in the Dollar–Deutschmark market, where volatility is relatively flat at the open and close and slightly higher

[16]Note that we account for the fact that in an ARCH model, volatility at, for example, 9:00 depends on volatilities at 8:50, 8:40, and before by including estimated normal volatilities for those periods on the right-hand side of the equation. We did this by first substituting the overall average of e_{t-i}^2 for all $\hat{v}_{t-i}$ on the right-hand side of the equation. We then re-estimated Equation 7, substituted the resulting estimates for $\hat{v}_{cT}$ on the right-hand side, and re-estimated. We iterated in this fashion until estimates of all $\hat{v}_{cT}$ changed by less than .001.

between 9:00 and 11:00 CT. Because the trading mechanism is the same in all three futures markets, it appears that the U pattern in the interest-rate markets cannot be attributed to this factor. Although all three securities are traded in Europe and Japan, as well as the United States, the exchange rate is more of a true 24-hr market and should be affected more by non-U.S. news. Possibly the high volatility at the open in the interest-rate markets arises because traders are digesting the implications of the overnight news, which has not been fully reflected in the less liquid foreign markets, and the high volatility at the close arises because traders want to settle their positions before the most active market closes.

As shown by the WEEKEND variable's positive coefficient, returns over the Friday-close-to-Monday-open interval are considerably more volatile than over the normal weekday close-to-open interval. Interestingly, as shown by the coefficient of the THUR-OVER variable, volatility over the period from the close of trading on Thursday to the Friday open, the period when the Fed's money-supply and bank-reserve figures are released, is no higher than for other overnight returns in any of the three markets.[17] It appears that the market viewed these releases as unimportant during our 1989–1993 period. This contrasts somewhat with the findings of Balduzzi et al. (1997), who found some reaction to the release of the M2 figures in the T-bill and T-bond markets. In the Eurodollar market, we observe slightly higher than normal volatility during "Fed Time", that is, 10:00 to 11:00 CT, when most Fed trading occurs, but this pattern does not hold in the T-bond futures market.

Before we control for scheduled announcements, volatility is highest on Friday and lowest on Monday in all three markets. Once we control for the impact of scheduled macroeconomic announcements, Monday remains the lowest volatility day. This finding is inconsistent with the view that volatility is highest after nontrading periods but consistent with the frequent contention that Monday is normally a slow news day. It also conflicts with the finding of Jones et al. (1998), who reported that volatility in the T-bond markets is highest on Monday, but they apparently included the weekend in the Monday return. Most of the high volatility on Friday seems due to the tendency for major macroeconomic announcements to be released on Fridays. After we control for these announcements, Friday is still the most volatile day in the T-bond markets, but Tuesday is more

[17]Recall that to avoid the possibility of negative implied variances, the estimation program does not allow estimation of negative coefficients, so the estimated coefficient of .000 for this variable indicates that the unconstrained coefficient would be nonpositive.

volatile in the Dollar–Deutschmark market, and Friday and Tuesday are approximately equally volatile in the Eurodollar market.

ARCH Effects

As shown in Panel A of Table II, the estimated volatility persistence pattern following a shock is altered considerably when we add announcements and seasonal patterns to the equation. In particular, the estimated ARCH coefficient for e^2_{t-1} is considerably less. For instance, in the Eurodollar market, the coefficient of e^2_{t-1} is reduced from .366 to .146, whereas less dramatic but still sizable reductions are observed in the other two markets. The coefficients of e^2_{t-2} and e^2_{t-3} are also reduced in all three markets.[18]

To illustrate the difference in volatility patterns, in Figure 3 we chart volatility patterns in the Eurodollar market following a 1-standard-deviation shock. Specifically, we chart $\hat{v}_t = \alpha'_0 + \sum_{i=1}^{6} \hat{\alpha}_i e^2_{t-i} + \hat{\alpha}_7 e^2_{\text{hour}} + \hat{\alpha}_8 e^2_{\text{day}} + \hat{\alpha}_9 e^2_{\text{week}}$, where prior to 10-min period 10, all e^2 are assumed equal to 1.0, and in Period 10, $e^2_t = 4.0$ (a 1-standard-deviation shock).[19] The dotted line in Figure 3 shows the estimated v_t's for latter periods based on the estimated α coefficients in the first column in Table II (Panel A), and the solid line shows the implied pattern based on the coefficients in the second column (i.e., after controlling for announcement and seasonality effects). Clearly, our model (Equation 2), which incorporates announcement and seasonality information, implies a return to normal volatility levels much more quickly than the simple ARCH model (Equation 3), where this information is ignored.

A natural question is whether this change in the estimated ARCH coefficients arises because we control for announcement effects, seasonality effects, or both. Goodhart et al. (1993) argued that unbiased GARCH model coefficients can only be obtained by controlling for major news announcements, whereas Andersen and Bollerslev (1997) argued that an accurate estimation of intraday GARCH models requires controlling for seasonal patterns. Our evidence supports both positions. Like us,

[18]A similar change in the estimated coefficients is observed when announcement and seasonality variables are added to an intraday GARCH(1,1) model.

[19]For instance, for an ARCH-only line, for $t = 1, \ldots, 10$, $\hat{v}_t = .2138 + .3664(1) + .0878(1) + .1231(1) + 0(1) + .0240(1) + .0258(1) + .0105(1) + .0015(1) + .00033(1)$. In Period 11, $\hat{v}_t = .2138 + .3664(4) + .0878(1) + .1231(1) + 0(1) + .0240(1) + .0258(1) + .0105(1) + .0015(1) + .00033(1)$. In Period 12, $\hat{v}_t = .2138 + .3664(2.10) + .0878(4) + .1231(1) + 0(1) + .0240(1) + .0258(1) + .0105(1) + .0015(1) + .00033(1)$. We continue substituting the implied $\hat{v}_{t-j}$ for the e^2_{t-j} in the equation. For these simulations, we set $\alpha'_0 = .2138$ so that the steady state value of v_t is 1.0.

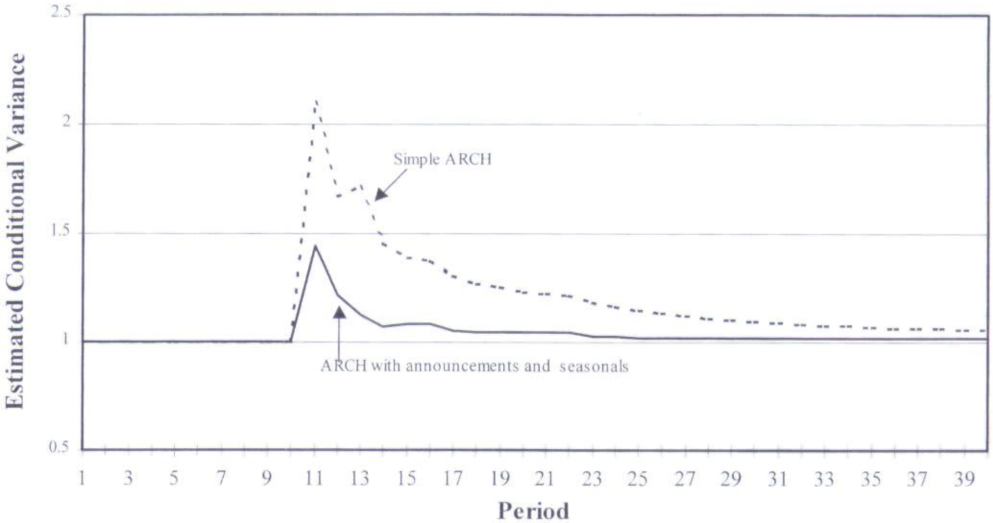

FIGURE 3

Comparison of Eurodollar conditional volatility patterns following a price shock for ARCH models with and without seasonal and announcement variables. The conditional volatility and squared-return innovations prior to Period 10 are assumed equal to 1.0. In Period 10, the squared-return innovation is assumed equal to 4.0, and in periods after 10, the squared-return innovation is assumed equal to the conditional variance. The dashed line reports the estimated implied volatility pattern in the Eurodollar market according to an ARCH model that excludes season and announcement dummies, whereas the solid line shows the implied pattern when these variables are incorporated into the model.

Goodhart et al. observed sharp declines in the estimated coefficients of an intraday GARCH model after they controlled for (only) two news announcements, the release of U.S. trade figures and a rise in U.K. interest rates, in a single-month sample of intraday data for the Dollar–Sterling exchange market. They argued that omitting these news effects biased GARCH parameter estimates "upward" because "if the true explanation for the increase in the variance is missing, this will tend to be explained by finding serial correlation" (p. 2). Andersen and Bollerslev found that GARCH coefficients are altered when one controls for time-of-day patterns and argued that accurate estimates can only be obtained by doing so. However, unlike Goodhart et al., they did not argue that the bias takes a particular sign (positive or negative).

Our much more extensive evidence supports both positions. When we completely exclude the announcement dummies, in the Eurodollar estimations the coefficient of e_{t-1}^2 declines from .3664 when the seasonal dummies are not included, to .1879 when they are. When we estimate an expanded ARCH model excluding the seasonal dummies, the coefficient of e_{t-1}^2 declines from .3664 when the announcement variables are not included, to .1497 when they are. When all three information sets are included, the coefficient is .1461. Similar declines are observed for the other ARCH variables and in the other two markets. In summary, controlling for either scheduled announcements or time-of-day patterns sharply lowers estimates of how long volatility remains high after a price shock.

VOLATILITY PERSISTENCE FOLLOWING DIFFERENT PRICE SHOCKS

Attention is now turned to questions concerning volatility patterns following different types of price shocks. First, does the volatility pattern differ after scheduled and unscheduled announcements or, more precisely, after price shocks due to scheduled announcements and those not due to scheduled announcements? Second, does the pattern differ after positive and negative shocks? Although the latter issue has been previously tested, these studies have not controlled for scheduled announcements and seasonality patterns. The first issue has not been tested previously.

To focus on these questions involving the ARCH coefficients and keep the estimations manageable, instead of re-estimating all 35 announcement and seasonality coefficients each time, we follow a two-stage procedure in which the announcement and seasonal coefficients are estimated in the first stage and the outlined questions are tested in the second stage. Specifically, we first estimate Equation 2 and then calculate an index of the volatility implied by the scheduled announcement and seasonal dummies: $I_t = \sum_{j=1}^{16} \hat{\beta}_j A_{jt} + \sum_{k=1}^{19} \hat{\theta}_k S_{kt}$. The conditional variance, v_t, is then expressed as a function of this term (whose coefficient is approximately 1 by construction) and respecified ARCH terms.

Scheduled Versus Unscheduled Announcements

Although the specification in Equation 2 forces the volatility pattern to be the same after price shocks due to scheduled announcements and identical shocks not due to scheduled announcements, the pattern following scheduled and unscheduled announcements could well be different. As Engle et al. (1990) put it, it is normally assumed that the explanation for ARCH effects "lies either in the arrival process for news or in the market dynamics in response to news" (p. 525). With respect to market dynamics, volatility may return to normal more rapidly after scheduled announcements because market participants are prepared for the release and, therefore, work out its implications for market prices more quickly than after unscheduled announcements for which they are unprepared. With respect to the news arrival pattern, although scheduled macroeconomic announcements are relatively complete and self-contained, a major unscheduled release may well be followed by subsequent releases on the same subject. For example, the unexpected resignation of a Federal Reserve Board member might well be followed by leaks and speculations regarding a possible replacement. Again, the implication is that volatility may return to normal more quickly after scheduled announcements. In agreement with these hypotheses, on the basis of the implied standard deviation from options markets, Ederington and Lee (1996) found evidence that the market expects higher than normal volatility to persist longer after unscheduled announcements than after scheduled announcements. We test whether actual volatility behaves the way the market expects.

Because all unscheduled announcements cannot be identified, we cannot directly test scheduled announcements versus unscheduled announcements.[20] However, we can test whether the volatility pattern is different after scheduled announcements than after identical shocks not associated with scheduled announcements. If all meaningful price changes reflect some information flow, this is equivalent to a test of scheduled announcements versus unscheduled announcements.

To test for a difference in volatility patterns, we first define a dummy variable $D_t = 1$ if a scheduled announcement was made in period t, and $D_t = 0$ otherwise. Likewise, $D_{\text{hour}} = 1$ if a scheduled announcement occurred in the previous hour, and $D_{\text{day}} = 1$ if a scheduled announcement occurred the previous day. We then estimate

$$\begin{aligned} v_t = \alpha_0 &+ \sum_{i=1}^{6} \alpha_i e_{t-i}^2 (1 - D_{t-i}) + \alpha_7 e_{\text{hour}}^2 (1 - D_{\text{hour}}) + \alpha_8 e_{\text{day}}^2 (1 - D_{\text{day}}) \\ &+ \alpha_9 e_{\text{week}}^2 + \sum_{i=1}^{6} \lambda_i e_{t-i}^2 (D_{t-i}) + \lambda_7 e_{\text{hour}}^2 (D_{\text{hour}}) \\ &+ \lambda_8 e_{\text{day}}^2 (D_{\text{day}}) + \beta I_t + u_t \end{aligned} \tag{8}$$

[20]Likewise, we cannot be certain that all unscheduled shocks are in fact unscheduled. The is particularly the case in the Deutschmark market because we observe only U.S. scheduled announcements, not the German announcements. However, because our observations are for 10-min intervals, these could comprise no more than 2% of the unscheduled periods.

TABLE V

Volatility Patterns Following Scheduled and Unscheduled Announcements

	Eurodollar Market		*Treasury-Bond Market*		*Deutschmark Market*	
Period	α (*Unscheduled*)	λ (*Scheduled*)	α (*Unscheduled*)	λ (*Scheduled*)	α (*Unscheduled*)	λ (*Scheduled*)
$t-1$	.1388 (.0032)	.2041[d] (.0189)	.1380 (.0045)	.1842[d] (.0182)	.1764 (.0031)	.2512[d] (.0210)
$t-2$	.0476 (.0034)	.0443 (.0055)	.0697 (.0040)	.0707 (.0058)	.0883 (.0036)	.0744 (.0116)
$t-3$	.0352 (.0029)	.0035[d] (.0030)	.0416 (.0036)	.0151[d] (.0047)	.0593 (.0032)	.0577 (.0093)
$t-4$	.0096 (.0026)	.0085 (.0037)	.0276 (.0032)	.0142[d] (.0039)	.0571 (.0022)	.0286[d] (.0076)
$t-5$	.0296 (.0016)	.0051[d] (.0016)	.0625 (.0014)	.0000[d]	.0391 (.0026)	.0233[d] (.0055)
$t-6$	.0261 (.0024)	.0000[d]	.0310 (.0023)	.0024[d] (.0021)	.0317 (.0015)	.0146[d] (.0049)
Previous hour	.0136 (.0006)	.0024[d] (.0004)	.0170 (.0007)	.0037[d] (.0006)	.0164 (.0008)	.0100[d] (.0011)
Previous day	.0028 (.0002)	.0024 (.0001)	.0035 (.0002)	.0028 (.0002)	.0042 (.0002)	.0026 (.0001)
Log likelihood	−48757.2		−51324.3		−51152.4	
Likelihood ratio	123.4*		169.8*		45.0*	

Note: Maximum-likelihood estimates of the parameters α and λ are reported for the equation

$$v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e_{t-i}^2 (1 - D_{t-i}) + \alpha_7 e_{\text{hour}}^2 (1 - D_{\text{hour}}) + \alpha_8 e_{\text{day}}^2 (1 - D_{\text{day}}) + \alpha_9 e_{\text{week}}^2$$
$$+ \sum_{i=1}^{6} \lambda_i e_{t-i}^2 (D_{t-i}) + \lambda_7 e_{\text{hour}}^2 (D_{\text{hour}}) + \lambda_8 e_{\text{day}}^2 (D_{\text{day}}) + \beta I_t + u_t$$

where v_t is the variance of the return innovation, e_t, from $R_t = \xi_0 + \xi_1 R_{t-1} + e_t$, $e_{\text{hour}}^2 = \sum_{i=7}^{12} e_{t-i}^2$, $e_{\text{day}}^2 = \sum_{i=13}^{41} e_{t-i}^2$, and $e_{\text{week}}^2 = \sum_{i=42}^{205} e_{t-i}^2$; $D_t = 1$ if an announcement is released in period t and $D = 0$ otherwise; and I_t is an index of implied volatility in period t calculated from the announcement and seasonal dummies with the estimated coefficients in Table I. Standard errors are shown in parentheses. A d superscript on the λ coefficient indicates that it is significantly different from the α coefficient at the .01 level. Asterisks on the likelihood ratios indicate rejection at the .01 level of the null hypothesis of equality between all eight λ and α coefficients.

Note that the λ and α measure the ARCH coefficients after periods with and without scheduled announcements, respectively. Our hypothesis that volatility returns to normal more quickly after scheduled announcements implies $\alpha_i > \lambda_i$ for the longer lags. As explained previously $\hat{\beta} \approx 1$ by construction. Results are presented in Table V.

As shown by the likelihood ratio statistics in the last row of the table, the ARCH coefficients are significantly different for scheduled and

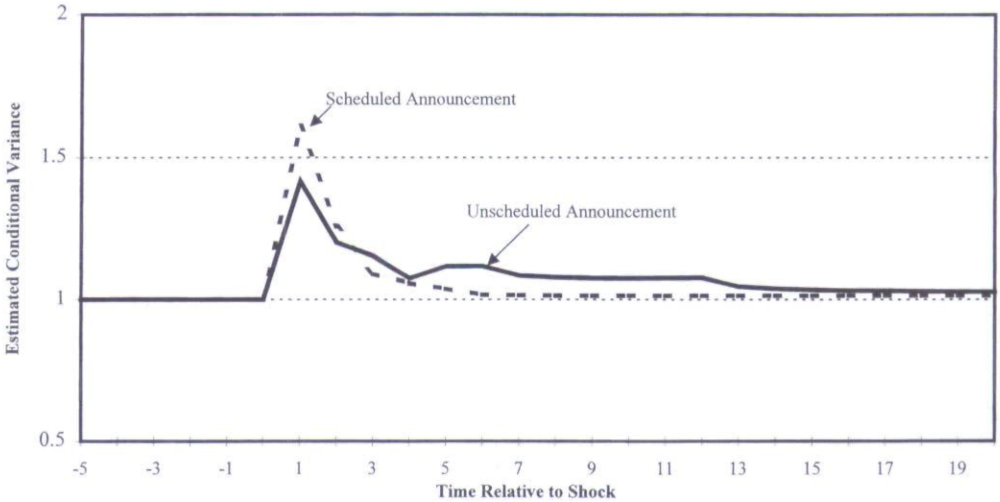

FIGURE 4

The conditional volatility patterns following scheduled and unscheduled announcements in the Eurodollar market. The conditional volatilites and squared-return innovations prior to the 10-min period 0 are assumed equal to 1.0. In Period 0, the squared-return innovation is assumed equal to 4.0, and in periods after 0, the squared-return innovation is assumed equal to the conditional variance. The dashed line shows the implied pattern in the Eurodollar market if the return innovation at time 0 is due to a scheduled announcement, and the solid line shows the implied pattern if the innovation is not due to a scheduled announcement.

unscheduled announcements.[21] Moreover, roughly the same coefficient patterns are observed in all three markets: (a) λ_1 is significantly greater (.01 level) than α_1, and (b) $\alpha_i > \lambda_i$ for all $i > 2$ (and, in most cases, the difference is significant at the .01 level). The implication is that in the first 10 to 20 min after a scheduled announcement, volatility is higher than after an unscheduled announcement with an identical price impact, but it then falls quickly to near normal levels, whereas volatility remains high considerably longer after unscheduled announcements. This is illustrated in Figure 4, where we chart the implied volatility patterns levels after a 1-standard-deviation price shock due to a scheduled announcement and after a 1-standard-deviation shock not due to a scheduled announcement for the Eurodollar market based on the estimates in Table V. This means the initial shock or price adjustment is the same for both announcements. Clearly, high volatility persists much longer after an unscheduled shock.

[21]The likelihood ratio is based on the log likelihood for this estimation and the estimation forcing the α and λ coefficients to be equal, the estimation labeled *All* in Table III. For instance, for Eurodollars the likelihood ratio is $2(48818.9 - 48757.2) = 123.4$. This is distributed as a chi-square with 8 degrees of freedom.

We presented two hypotheses for why volatility should return to normal more quickly after scheduled announcements than after unscheduled announcements: (a) because the market is prepared for the announcement, it works out its implications more quickly, and (b) the information in unscheduled announcements dribbles out over a longer period of time. Although the finding that $\alpha_i > \lambda_i$ for all $i > 2$ is consistent with either, the finding that λ_1 is significantly greater than α_1 is only consistent with the former. If the information is more spread out in unscheduled announcements, we should observe higher volatility after unscheduled announcements in period $t + 1$ as well. The fact that volatility is in fact higher in period $t + 1$ for scheduled announcements implies that the market was anticipating the announcement and works out its implications quickly. For scheduled announcements, the implications of new information are apparently worked out fairly quickly, with much of the digestion occurring in the second 10-min interval. For unscheduled announcements, there is an initial reaction, but then the implications seem to be worked out more gradually.

Positive Versus Negative Shocks

Numerous studies, including French et al. (1987), Engle and Ng (1993), and Braun et al. (1995), have found evidence that in equity markets high volatility persists longer after negative price shocks than after positive price shocks. The most frequent explanation for this phenomenon in equity markets is that, because the market value of the firm's equity is reduced, negative shocks increase financial leverage, which in turn leads to higher volatility, whereas positive shocks decrease leverage. Obviously, this explanation does not apply to interest-rate and foreign-exchange markets. In addition, most studies documenting this asymmetry examine daily or longer returns. Because Braun et al. (1995) challenged the leverage explanation, it is interesting to determine if the same pattern is observed in interest and exchange markets on an intraday basis.

Although an EGARCH (or Exponential GARCH) model is normally used to test for differences between positive and negative shocks, it is not appropriate here because it is difficult in such a model to disentangle announcement and seasonality effects from the effects of recent past volatilities.[22] To test for a difference in volatility after positive and

[22]When both seasonality and announcement dummies and a function of the lagged variance appear on the right-hand side of the equation, the announcement and seasonality dummies no longer measure volatility in that period only because previous dummies are incorporated into the lagged variance.

TABLE VI

Volatility Patterns Following Positive and Negative Shocks

	Eurodollar Market		Treasury-Bond Market		Deutschmark Market	
Period	α (*Positive*)	λ (*Negative*)	α (*Positive*)	λ (*Negative*)	α (*Positive*)	λ (*Negative*)
$t-1$	.1535 (.0038)	.1386 (.0049)	.1386 (.0057)	.1496 (.0057)	.1821 (.0046)	.1767 (.0038)
$t-2$	.0227 (.0037)	.0695[d] (.0040)	.0559 (.0044)	.0836[d] (.0044)	.0871 (.0045)	.0848 (.0048)
$t-3$	.0294 (.0036)	.0095 (.0029)	.0425 (.0045)	.0292 (.0040)	.0596 (.0038)	.0601 (.0044)
$t-4$	.0095 (.0029)	.0090 (.0030)	.0169 (.0035)	.0310[d] (.0036)	.0544 (.0040)	.0578 (.0022)
$t-5$	.0091 (.0021)	.0366[d] (.0019)	.0188 (.0033)	.0769[d] (.0014)	.0295 (.0032)	.0468[d] (.0034)
$t-6$	.0098 (.0023)	.0258[d] (.0027)	.0366 (.0037)	.0144[d] (.0023)	.0153 (.0032)	.0384[d] (.0019)
Log likelihood	−48795.5		−51375.5		−51168.4	
Likelihood ratio	46.8*		67.4*		13.0	

Note: Maximum-likelihood estimates of the parameters α and λ are reported for the equation

$$v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e_{t-i}^2 (1 - P_{t-i}) + \sum_{i=1}^{6} \lambda_i e_{t-i}^2 (P_{t-i}) + \alpha_7 e_{\text{hour}}^2 + \alpha_8 e_{\text{day}}^2 + \alpha_9 e_{\text{week}}^2 + \beta I_t + u_t$$

where v_t is the variance of the return innovation, e_t, from $R_t = \xi_0 + \xi_1 R_{t-1} + e_t$, $e_{\text{hour}}^2 = \sum_{i=7}^{12} e_{t-i}^2$, $e_{\text{day}}^2 = \sum_{i=13}^{41} e_{t-i}^2$, and $e_{\text{week}}^2 = \sum_{i=42}^{205} e_{t-i}^2$; $P_t = 1$ if the price shock in period t is negative and $P_t = 0$ if positive; and I_t is an index of implied volatility in period t as calculated from the announcement and seasonal dummies with the estimated coefficients in Table I. Standard errors are shown in parentheses. A d superscript on the λ coefficient indicates that it is significantly different from the α coefficient at the .01 level. An asterisk on the likelihood ratio indicates a significant rejection at the .01 level of the null hypothesis of equality between the α and λ coefficients.

negative shocks while controlling for announcement and seasonality effects, we estimate the equation

$$v_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i e_{t-i}^2 (1 - P_{t-i}) + \sum_{i=1}^{6} \lambda_i e_{t-i}^2 (P_{t-i}) + \alpha_7 e_{\text{hour}}^2 + \alpha_8 e_{\text{day}}^2 + \alpha_9 e_{\text{week}}^2 + \beta I_t + u_t \tag{9}$$

where $P_t = 1$ if $e_t < 0$ and $P_t = 0$ if $e_t > 0$ and I_t is the Index defined earlier. Results are shown in Table VI. Although the difference in the log likelihoods is significant at the .01 level in the two interest-rate equations, the likelihood ratios are relatively small, and there is no clear pattern; that is, in some cases $\alpha_i > \lambda_i$, whereas in others the reverse is true. In the Dollar–Deutschmark estimation, the likelihood ratio is only significant at the .05 level. In summary, there appears to be no meaningful difference in volatility persistence after positive and negative shocks in these markets.

CONCLUSIONS

In summary, we find that in interest-rate and foreign-exchange markets, all three information sets (knowledge of recent past volatilities, knowledge of the timing of future macroeconomic releases, and knowledge of normal time-of-day and day-of-the-week patterns) are important determinants of intraday volatility. However, knowing when the important macroeconomic figures will be released is most important in forecasting high volatility periods.

Contrary to the findings of Balduzzi et al. (1997), we find that most macroeconomic announcements have very similar impacts on volatility in both the short-term and long-term interest-rate markets; that is, the most (least) important announcements in one market are also the most (least) important in the other. Also, in contrast to other recent studies, our results indicate that in the interest-rate markets, volatility returns to virtually normal levels within 30 to 40 min after the release of new macroeconomic statistics, emphasizing the high efficiency of these markets in incorporating new information into prices. However, volatility remains high much longer in the foreign-exchange markets.

Our evidence indicates that the timing of important macroeconomic releases is responsible for most but not all of the observed time-of-day and day-of-the-week volatility patterns. After announcement effects are controlled for, a much more subdued but still significant U-shaped time-of-day volatility pattern is observed in the interest-rate futures markets but not in the Dollar–Deutschmark futures market, where volatility is slightly higher in midmorning than at the open or close. Also, after macroeconomic announcements are controlled for, volatility in all three markets is lowest on Monday and highest on Tuesday, Friday, or both.

We find that to obtain accurate estimates of volatility persistence patterns in interest-rate and foreign-exchange markets, it is important to account for major economic announcements and seasonality patterns.

APPENDIX

Macroeconomic Announcements

Release Time[a]	Title of Report	Reporting Agency	*Number of Announcements by Day of the Week* M	T	W	Th	F
7:30 a.m.	Consumer price index	Bureau of Labor Statistics	0	12	11	11	12
7:30 a.m.	Durable goods orders	Bureau of the Census	0	13	19	6	9
7:30 a.m.	Employment	Bureau of Labor Statistics	0	0	0	1	46
7:30 a.m.	Gross national product[b]	Bureau of Economic Analysis	0	7	14	13	12
7:30 a.m.	Housing starts	Bureau of the Census	0	18	17	7	4
7:30 a.m.	Leading indicators	Bureau of Economic Analysis	1	16	10	2	15
7:30 a.m.	Merchandise trade	Bureau of the Census	0	7	8	17	15
7:30 a.m.	Deficit	Bureau of Labor Statistics	0	2	4	12	28
7:30 a.m.	Producer price index	Bureau of the Census	0	12	7	15	13
8:15 a.m.	Retail sales	Federal Reserve Board	2	12	9	3	20
9:00 a.m.	Industrial production/ capacity utilization	Federal Reserve Board Bureau of the Census	10	3	12	7	14
9:00 a.m.	Business inventories	Bureau of the Census	19	8	6	7	7
9:00 a.m.	Construction spending	Bureau of the Census	1	9	11	14	10
9:00 a.m.	Factory inventories/ NAPM survey	National Association of Purchasing Managers Bureau of the Census	8	14	11	6	4
9:00 a.m.	New single-family home sales	Bureau of Economic Analysis	12	0	8	12	14
1:00 p.m.	Personal income Federal budget	Department of the Treasury	13	7	6	7	14

[a]All times are Central Time.

[b]Gross Domestic Product (GDP) has been released instead of Gross National Product (GNP) since January 1992. No distinction between GDP and GNP was made in our analysis.

Estimated ARCH effects are considerable weaker once one controls for announcement effects and seasonality patterns. We also find that a GARCH(1,1) model does not model high-frequency volatility persistence patterns very well, in that it tends to underestimate the impact of the most recent and very distant shocks and overestimate the impacts of shocks with lags in between. Comparing scheduled announcements and unscheduled announcements with identical initial price shocks, in all three markets we find that high volatility persists much longer after unscheduled announcements, a pattern we attribute to the fact that market participants are prepared to analyze the information in scheduled but not unscheduled announcements. However, there appears to be little difference in volatility persistence after positive and negative price shocks.

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