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The Macroeconomic News Cycle and Uncertainty Resolution

Arjun Chatrath
University of Portland, chatrath@up.edu

Rohan Christie-David

William T. Moore

Arjun Chatrath
University of Portland

Rohan Christie-David
University of Louisville

William T. Moore
University of South Carolina

The Macroeconomic News Cycle and Uncertainty Resolution*

We examine the behavior of return volatility and trading at 5-minute intervals in the treasury bond futures market in the context of the monthly macroeconomic news cycle. We advance and confirm the hypothesis that volatility and trading activity are higher in the first half of the month. The data indicate that these patterns arise from at least two sources: (1) a higher level of uncertainty regarding the value of news in announcements in the first half of the month, and (2) improvement in efficiency of macroeconomic forecasts from the first to the second half of the month.

Introduction

We examine return volatility and trading activity at 5-minute intervals in the treasury futures market to investigate the linkage between macroeconomic news announcements and these important series. We advance and test hypotheses that volatility and trading activity are higher in the first half of the month. The hypothesized patterns are expected to be due to higher levels of trader uncertainty in the first half of the month, as well as improvements in forecast efficiency exhibited during the month. These patterns are confirmed—both series are notably higher in the first half of the month, and the data support the linkage with higher levels of trader uncertainty in the first half. Moreover, we find that volatility and trading activity are explained significantly by improvements in forecasting efficiency.

Recent findings suggest that increased levels of re-

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turn volatility and trading activity in treasury markets may correspond to the timing of macroeconomic news releases. Ederington and Lee (1993) associate higher volatility in interest rate futures shortly after market opening and toward the end of the trading week with the release of macroeconomic news.[1] Jones, Lamont, and Lumsdaine (1998) investigate treasury bond data at daily intervals and report shocks in volatility following releases of the employment report and the producer price index (PPI). Li and Engle (1998) analyze daily treasury bond futures data and find that scheduled news announcements have a strong influence on volatility in the short run. Fleming and Remolona (1999) report that volume and volatility in the treasury bond market surge upon the release of scheduled news announcements, and the surge persists apparently due to disagreement among investors over what the news means. The adjustment process triggered by news is extended by investors' private information. More recently, Bollerslev, Cai, and Song (2000) examine treasury futures data at 5-minute intervals and identify spikes in volatility at 7:30 and 9:00 a.m. (CST), corresponding to regularly scheduled news releases.

Our argument, that volatility and trades are higher in the first half of the month, while relying on the linkage between news announcements and return variance, is underpinned by two key features of the news release cycle. Announcements issued in the first half of the month, particularly in the first week, provide the first new information on different sectors of the economy. For instance, the employment report is issued on the first Friday of each month and provides statistics for the prior month. In addition, news releases in the first half of the month provide inputs used in computing statistics released in later announcements. For example, the Federal Reserve Board uses inputs from the employment report to compute the manufacturing portion of industrial production (see, e.g., Rogers 1998).

These two features of the cycle play a central role in the formulation of our two noncompeting hypotheses: (1) elevated levels of volatility and trades in the first half of the month are the result of higher levels of trader uncertainty (or lower levels of trader consensus) regarding the value of news in the announcements in the first half of the month, and (2) these patterns result from improved efficiency in forecasting news in announcements in the second half of the month.

Our findings show that volatility and trading activity are more pronounced in the first half of the month, following the release of announcements, compared with the second half. The evidence we find is consistent with the results in Green (2004) that find that prices are more sensitive to trading activity during periods of enhanced liquidity, particularly in the first half of the month.

1. See also Balduzzi, Elton, and Green (2001).

Research Design

Futures Data

We examine treasury bond futures traded on the Chicago Board of Trade (CBT) from July 1994 through June 1999.[2] The sampling interval is 5 minutes for a total of 101,211 observations. To establish patterns in prices and returns, researchers use daily or longer frequency data (e.g., Jones et al. 1998). However, to discern changing patterns within a trading day, and to make detailed inferences about the effects of news releases, short-interval observations are needed.

The treasury bond futures market presents some important advantages for this analysis. We avoid a potential information-related gaming problem associated with the use of equity-related instruments. For instance, the literature notes that gaming activity could accompany earnings and dividend news (e.g., Chambers and Penman 1984). Scheduling of monthly macroeconomic news releases tends to follow a recurring sequence, and the timing pattern is independent of the content of the announcement. For example, the Bureau of Labor Statistics releases the employment report on the first Friday of each month and the PPI sometime in the second week of the month, which precedes the release of the consumer price index (CPI) by a few days (see, e.g., Rogers 1998). Becausef the timing of the releases is fixed, uncertainty about the scheduling of news releases is eliminated.

Another advantage of CBT futures data is that prices rapidly adjust to unanticipated information (e.g., Ederington and Lee 1995), thus we are able to identify announcement effects with precision. Moreover, the CBT reports treasury bond futures prices on a transaction basis, rather than using dealer quotes. A disadvantage of futures data arises from the effects of contract expiration, and we confront this in two ways. First, we roll the expiring contract into the next-to-nearby contract 2 trading days before the start of the expiration month to ensure that the most liquid contracts are used. Second, we report tests in the preliminary stages of our analysis of the effects of expiration.

Monthly News Releases

We analyze the 19 announcements described in the appendix. It is well documented that most of the responses to news in financial markets are caused by the unexpected component of news (e.g., McQueen and Roley 1993; Balduzzi et al. 2001; and Green 2004). In keeping with these studies, survey data provided by Money Market Services (MMS) are used to measure surprises in the announcements. The MMS surveys about 40 academicians and practitioners and reports the median forecast of each announcement as the expected

2. The data are obtained from the Futures Industry Institute.

value. The MMS surveys have been shown to be generally unbiased (Almeida, Goodhart, and Payne 1998).

The 19 announcements, released by federal agencies and the National Association of Purchasing Managers (NAPM), can be grouped into four release times (all in CST): 7:30, 8:15, and 9:00 a.m. and 1:00 p.m. Studies find the first set of releases at 7:30 a.m. to have the largest effects, especially the employment report (Ederington and Lee 1993). Monthly news releases are selected because major news is released through these announcements, and weekly releases may suffer from confounding day-of-the-week effects (Ederington and Lee 1993).

Return Volatility and Trading Activity

Return volatility may be viewed as consisting of three components: (1) the immediate average response of prices to the surprise of the announcement, (2) deviations of the immediate response from the average response, and (3) volatility that follows the immediate response reflecting reactions of prices to trading. The third component represents private-information effects. Our measures of volatility and trades are intended to purge the average effects of the surprises in economic announcements, thus the first component is removed. We measure volatility of the unanticipated return in each 5-minute interval t according to[3]

$$\hat{\sigma}_t = \sqrt{\pi/2}\,|\hat{\varepsilon}_t|, \tag{1}$$

where $\hat{\varepsilon}_t$ is the residual from a parsimonious model of returns described below. We compute returns as $r_t = \ln(P_t^c/P_{t-1}^c)$, where P_t^c is the closing price over a 5-minute interval t, and P_{t-1}^c is the closing price of the immediately preceding interval. For each day's opening 5-minute interval, we use $r_t = (P_t^c/P_t^0)$, where P_t^0 is the opening price for that interval.

For each 5-minute interval in which a scheduled macroeconomic announcement occurs (i.e., the 5-minute intervals 7:30–7:34, 8:15–8:19, 9:00–9:04, and 10:00–10:04 a.m.), $\hat{\varepsilon}_t$ is the residual from the regression

$$r_t = a + \sum_{l=1}^{L} \eta_j r_{t-1} + \sum_{i=1}^{K} \lambda_{1,i} S_{i,t} + \sum_{i=1}^{K} \lambda_{2,i} |S_{i,t}| + \varepsilon_t, \tag{2a}$$

where r_t is the return for interval t, a is the intercept, and $S_{i,t}$ is the surprise

3. A standard result of normality is $E(|x|) = \sigma\sqrt{2/\pi}$.

component of the ith announcement.[4] For each of the other 5-minute intervals, the estimate is the demeaned return, or the residual from the regression

$$r_t = a + \sum_{l=1}^{L} \eta_j r_{t-l} + \varepsilon_t. \tag{2b}$$

Thus, $\hat{\varepsilon}_t$ in equation (1) is the consolidated time series of residuals from equations (2a) and (2b). The surprise element of the ith announcement at time t ($S_{i,t}$ in eq. [2a]) is

$$S_{i,t} = \left(\frac{A_{i,t} - F_{i,t-\Delta}}{\sigma_{A_{i,t}} - F_{i,t-\Delta}} \right), \tag{3}$$

the difference between the announced value ($A_{i,t}$) at time t and the forecast value ($F_{i,t-\Delta}$) from the MMS for announcement i at some time $t - \Delta$, scaled by the standard deviation of their differences. In equation (3), Δ denotes the number of days before the announcement date on which the final forecast is made. For example, Δ is 4–7 days for CPI announcements and 6–8 days for nonfarm payroll reports. This setup follows that in Balduzzi et al. (2001). Inclusion of surprises ($S_{i,t}$) is standard in tests for announcement effects in prices. The absolute values for surprises ($|S_{i,t}|$) are included to capture possible nonlinearities in price responses to the surprises. The lag length in equations (2a) and (2b) is selected at $l = 6$, which may be generous, based on serial correlation estimates from the time series of 5-minute returns.

Our measure of trading activity is similarly motivated and is based on the number of transactions over a 5-minute interval. Trading activity is a supplemental measure of volatility (Jones, Kaul, and Lipson 1994). Along the same lines, Ane and Geman (2000) find that the number of trades cumulated over an interval is better than trading volume in explaining the distribution of stock returns. Further, Green (2004) notes that trade size has little influence on trade impact.[5]

Trades are given by

$$\hat{\tau}_t = \psi_t + \hat{\upsilon}_t, \tag{4}$$

where the right-hand side estimates are obtained using regressions, as in the

4. Very similar results are obtained when we estimate separate regressions for announcement days and nonannouncement days to obtain a consolidated ε_t series employed in eq. [1]. Specifically, in our alternate set of computations, for the 5-minute interval 7:30–7:34 a.m., we estimate eq. [2a] for days that witnessed a 7:30 announcement and eq. [2b] for all other days. Similarly, two sets of regressions were estimated for each of the intervals 8:15–8:19, 9:00–9:04, and 10:00–10:04 a.m. The other 5-minute intervals were used in regression eq. [2b]. The results are almost identical across the two methods.

5. We note that inferring the number of trades from the number of tick changes will likely induce a downward bias in the trade numbers, since only trades that are accompanied by tick changes are recorded.

case of formulating the volatility measure. For each announcement interval (7:30–7:34, 8:15–8:19 a.m., etc.), the estimates are from the regression

$$T_t = \psi + \sum_{i=1}^{K} \lambda_{l,i} S_{i,t} + \sum_{i=1}^{K} \lambda_{2,i} |S_{i,t}| + \upsilon_t, \tag{5a}$$

where T_t is the cumulative number of ticks between open and close of the 5-minute interval t, ψ is the intercept, and υ_t is the regression error. For each of the other intervals, the estimates are from the regression

$$T_t = \psi + \upsilon_t, \tag{5b}$$

so that trades are simply the number of ticks for these intervals. In equation (5a), the absolute surprise element is introduced to capture the information effect in trades, and the surprise element captures possible asymmetries in the trading patterns corresponding to positive and negative surprises.[6]

Assessing the Role of Information

Volatility and the Number of Trades

A preliminary look at the data indicates striking evidence of calendar patterns in volatility and the number of trades. In figure 1, we depict the two series for the full sample and for a subsample with announcements removed (nonannouncement sample).

For the full sample, both series drop noticeably around midmonth. In contrast, neither of the corresponding figures for the nonannouncement sample exhibit such breaks, and the patterns of series in both the full sample and the nonannouncement sample are similar after midmonth. It appears that the scheduled announcements elevate volatility and trading activity noticeably in the first half of the month.

In figures 2 and 3, volatility and trades are further decomposed by time of day. Because most of the announcements are made earlier in the day, we display these variables for only the first few hours of the trading day. The results in figure 2 for volatility over the full sample (panel a) indicate that the largest calendar disparities occur in the first hour of trading. In particular, the plot for 7:30–8:29 shows elevated levels of volatility until midmonth and a decline thereafter until near the end of the month. For nonannouncement days (panel b), the calendar effects are not discernible. Moreover, for nonannouncement days, differences in volatility across time of day are reduced.

In figure 3, we find that the pattern for trades is again most evident for the first hour of trading for the full sample (panel a). As in the case of volatility,

6. The $\lambda_{1,j}$ coefficients are generally insignificant, indicating little asymmetry in trade responses to new information. As a diagnostic to insure we have succeeded in purging the average public announcement effects, we include lagged surprise components up to 1 hour following announcements in returns eq. [2a] as well as trades eq. [5a]. In all cases, the lagged effects are insignificant.

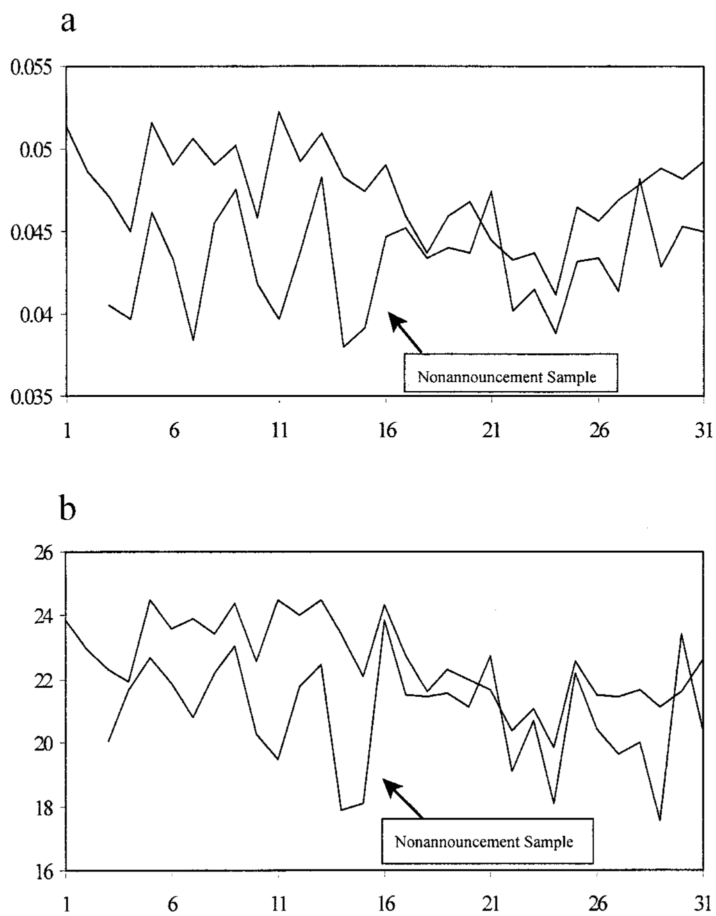

FIG. 1.—Mean volatility by day of month (*a*) and number of trades by day of month (*b*) for the full sample and the sample filtered for macroeconomic news announcements (no-announcement sample).

these patterns are less discernible once the information days are removed from the sample (panel b).

In table 1, we report mean volatility (panel A) and number of trades (panel B) for the full day, for the first 10-minute interval, and for hourly intervals thereon, for the first and second halves of the month. We note pronounced differences in volatility and trading activity for the full sample for the full day and for several time intervals across the two halves of the month. Moreover, the differences are not symmetric across times of day. The largest differences occur over the first hour and 10 minutes, and the differences then decline fairly smoothly over the day. For instance, mean differences in vol-

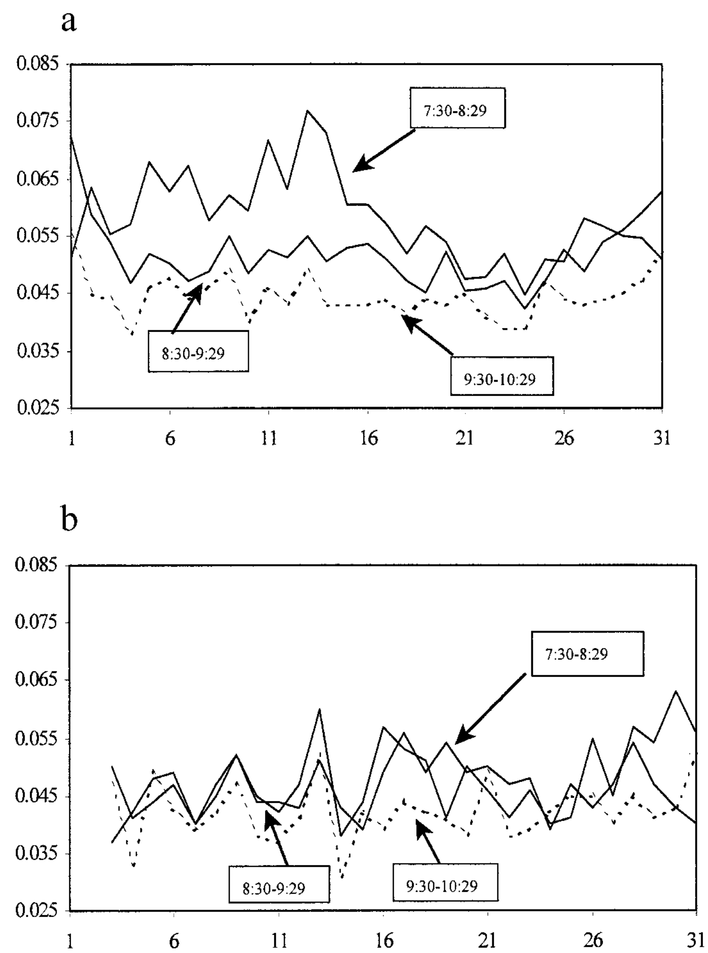

FIG. 2.—Mean volatility by day of month for select time periods for the full sample (*a*) and the sample filtered for macroeconomic news announcements (*b*).

atility in the first through the fifteenth of the month versus the sixteenth through the thirty-first are significant at the 0.01 level in the first six intervals examined. However, the differences between the two halves of the month are much more pronounced in the early intervals (e.g., 7:30–8:29 a.m.) than in the later intervals (e.g., from 11:30 a.m. to 12:29 p.m.).

We report in table 1 average volatility and trading activity for days that did not witness one of the 19 announcements (nonannouncement days). Comparing these results with the results for the full sample, we see that the announcement control explains much of the difference in average volatility and average trading activity across the first and second halves of the month. We

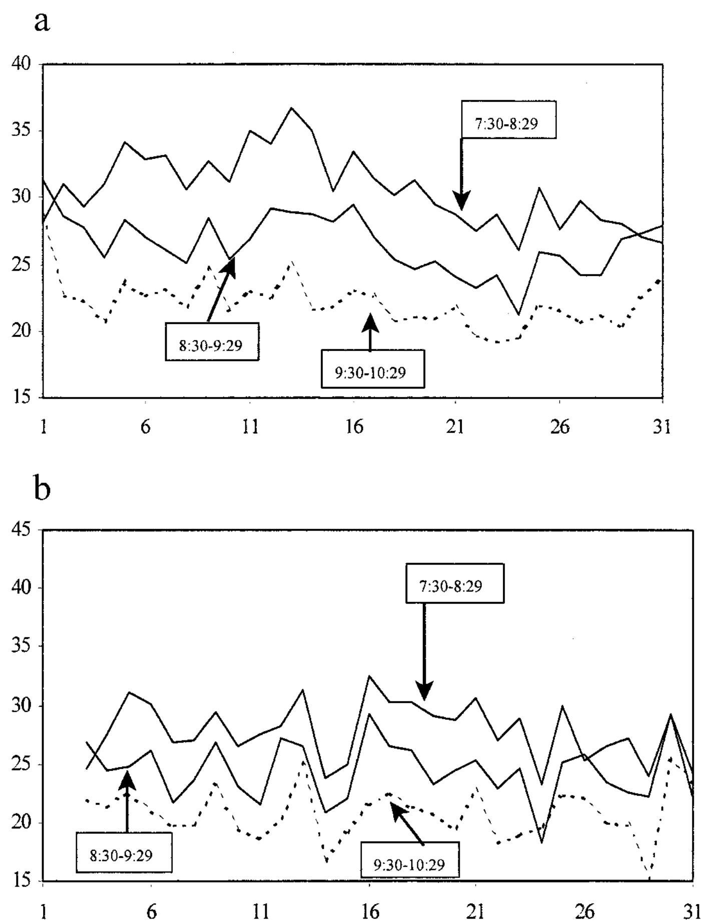

FIG. 3.—Mean number of trades by day of month for select time periods for the full sample (*a*) and the sample filtered for macroeconomic news announcements (*b*).

note differences in the nonannouncement sample across the two halves of the month for only one interval for volatility and for three intervals for trades.

Table 1 also reports the figures for the sample (nonexpiration) that excludes the futures expiration months (March, June, September, and December). Days prior to delivery tend to witness greater activity arising from contract settlement,[7] and futures volatility should be expected to rise as one approaches delivery (Samuelson 1965). The results in table 1 suggest that some of the intramonth effect is an expiration effect.

7. For treasury bond futures, the first delivery day is the first business day of the delivery month, and the last possible delivery day is the business day prior to the last 7 days of the delivery month.

TABLE 1 Intramonthly Patterns in Volatility and Trades

Time	Full Sample: First through the Fifteenth	Full Sample: Sixteenth through the Thirty-First	Full Sample: Difference	Nonexpiry Months: First through the Fifteenth	Nonexpiry Months: Sixteenth through the Thirty-First	Nonexpiry Months: Difference	Nonannouncement Days: First through the Fifteenth	Nonannouncement Days: Sixteenth through the Thirty-First	Nonannouncement Days: Difference
A. Volatility:									
Full day	.0483	.0452	.0031**	.0487	.0460	.0027[a]	.0432	.0434	−.0001
7:20–7:29	.0684	.0606	.0078**	.0696	.0610	.0086**	.0693	.0613	.0080*
7:30–8:29	.0626	.0531	.0095**	.0618	.0548	.0070**	.0448	.0477	−.0029
8:30–9:29	.0522	.0497	.0024**	.0522	.0510	.0021**	.0458	.0484	−.0026
9:30–10:29	.0450	.0434	.0017**	.0440	.0438	.0002	.0418	.0420	−.0002
10:30–11:29	.0407	.0369	.0037**	.0406	.0379	.0027**	.0368	.0352	.0016
11:30–12:29	.0397	.0382	.0015**	.0398	.0391	.0007	.0378	.0367	.0011
12:30–1:29	.0448	.0438	.0010	.0452	.0445	.0007	.0442	.0421	.0020
1:30–2:00	.0516	.0527	−.0012	.0514	.0528	−.0014	.0508	.0524	−.0016
B. Trades:									
Full day	23.653	21.883	1.770**	23.771	22.634	1.137**	21.674	20.993	.681**
7:20–7:29	39.532	35.852	3.572**	40.167	37.329	2.838**	36.645	34.876	1.769*
7:30–8:29	32.811	29.489	3.322**	32.828	30.918	1.910**	27.990	27.847	.143
8:30–9:29	27.930	25.458	2.471**	27.583	26.198	1.385**	24.421	24.229	.122
9:30–10:29	23.148	21.238	1.766**	23.094	22.164	.931**	20.767	20.603	.163
10:30–11:29	17.306	15.730	1.577**	17.259	16.413	.846**	15.659	14.959	.699
11:30–12:29	17.090	15.884	1.207**	17.195	16.681	.514**	16.097	15.012	1.085**
12:30–1:29	18.903	18.177	.726**	19.454	19.021	.433*	19.054	17.691	1.405**
1:30–2:00	27.822	27.500	.322	27.692	28.175	−.483	27.502	26.709	.793

NOTE.—The sample period is May 7, 1994, to June 30, 1999. Volatility for the 5-minute interval is given by $\hat{\sigma}_t = \sqrt{\pi/2}\,|\hat{\varepsilon}_t|$. For each 5-minute announcement interval, $\hat{\varepsilon}_t$ is the residual from the regression $r_t = a + \sum_{l=1}^{L} \eta_j r_{t-l} + \sum_{i=1}^{K} \lambda_{1,i} S_{i,t} \sum_{i=1}^{K} \lambda_{2,i} |S_{i,t}| + \varepsilon_t$, where r_t is the return at t and $S_{i,t}$ is the surprise component of the ith announcement. For the other 5-minute intervals of the trading day, $\hat{\varepsilon}_t$ is from the regression $r_t = a + \sum_{l=1}^{L} \eta_j r_{t-1} + \varepsilon_t$. The ε_t is the consolidated series of residuals from the two regressions. Trades are given by $\hat{\tau}_t = \psi_t + \hat{\upsilon}_t$, where the right-hand side estimates are obtained for each announcement interval from the regression $T_t = \psi + \sum_{i=1}^{K} \lambda_{1,i} S_{i,t} + \sum_{i=1}^{K} \lambda_{2,i} |S_{i,t}| + \upsilon_t$, where T_t is the cumulative number of ticks between open and close of the 5-minute interval t, ψ is the intercept, and υ_t is the regression residual. For the nonannouncement interval, the estimates are from the regression $T_t = \psi + \upsilon_t$.

* Significant at the 5% level.

** Significant at the 1% level.

More formal analysis of the patterns suggested in figures 1–3 and table 1 is conducted by estimating regression models alternately for volatility and trading activity. The first model represents a simple test of differences in levels for the first and second halves of the month and is given by

$$y_t = \beta_0 + \beta_1 D_t^{1-15} + \varepsilon_t, \tag{6}$$

where D_t^{1-15} takes the value of one if the day falls between the first and the fifteenth, and y_t represents volatility in the 5-minute interval t or, alternately, trading activity.

The second model accounts for whether the interval is during a day witnessing a scheduled macroeconomic announcement and is given by

$$y_t = \beta_0 + \beta_1 D_t^I + \varepsilon_t, \tag{7}$$

where D_t^I takes the value of one, if one or more of the 19 announcements occurred on that day, and zero otherwise. Our third model accounts for possible interactions between D_t^{1-15} and D_t^I and takes the form

$$y_t = \beta_0 + \beta_1 D_t^{1-15} + \beta_2 D_t^{1-15} D_t^I + \beta_3 D_t^I + \varepsilon_t. \tag{8}$$

Regression equations (6)–(8) are estimated for 5-minute volatility and trades pooled across various time intervals for the trading day. The results are reported in table 2, panels A (volatility) and B (trades). Because the sample sizes are very large (over 100,000 for the full day), the null hypothesis that a particular coefficient is zero may be rejected using classical inference, even if the posterior odds are even (Lindley 1957). A sample-size adjustment may be made by comparing the classical t-statistic with a cutoff value (t*) at which the posterior odds ratio equals one. Thus, if the reported t-statistic exceeds t*, odds are against the null hypothesis, and it would be rejected in a Bayesian framework. Connolly (1989) shows that the appropriate cutoff (t*), given even prior odds, is

$$t^* = (s - \varkappa)^{0.5}(s^{1/s} - 1)^{0.5}, \tag{9}$$

where s denotes sample size and $\varkappa$ represents the number of parameters estimated including the intercept. In table 3, as well as all remaining regression results reported in the article, we include t* and the respective t-statistics.

The results from regression equation (6) show that for the full day and for the intervals ranging from 7:20 to 9:29 a.m., and in the 10:30–11:29 a.m. interval in table 3, panel A, volatility is higher (as noted by the sample-size-adjusted significance of the β_1 coefficient estimate) in the first half of the month. Furthermore, trades in the first half of the month appear to be significantly higher in all intervals examined, except the last interval (1:30–2:00 p.m.). Results from the second regression (eq. [7]) show that volatility is elevated on announcement days for the full day and for the intervals beginning at 7:30 a.m. to the interval ending at 12:29 p.m. The evidence for trades (panel B) is very similar.

The results from the third regression model (eq. [8]), intended to capture

TABLE 2 Regression Estimation of the Role of Macroeconomic Announcements in the Intramonth Effect in Volatility and the Number of Trades

	$y_t = \beta_0 + \beta_1 D_t^{1-15} + \varepsilon_t$			$y_t = \beta_0 + \beta_1 D_t^{1} + \varepsilon_t$			$y_t = \beta_0 + \beta_1 D_t^{1-15} + \beta_2 D_t^{1-15} + \beta_3 D_t^{1} + \varepsilon_t$				
	β_0	β_1	R^2_{adj}	β_0	β_1	R^2_{adj}	β_0	β_1	β_2	β_3	R^2_{adj}
A. Volatility:											
Full day	.046**	.003**	.001	.043**	.007**	.004	.043**	−.000	.005**	.004**	.005
	(195.00)[a]	(9.38)[a]		(180.20)[a]	(19.68)		(136.90)[a]	(−.28)	(6.87)[a]	(8.58)[a]	
7:20–7:29	.006**	.008**	.004	.065**	−.000	.000	.061**	.008*	.000	−.002	.003
	(35.14)[a]	(3.17)[a]		(37.96)[a]	(−.01)		(27.99)[a]	(2.31)	(.06)	(−.54)	
7:30–8:29	.053**	.010**	.004	.046**	.022**	.022	.048**	−.003	.019**	.011**	.029
	(63.34)[a]	(7.97)[a]		(54.36)[a]	(18.37)[a]		(42.03)[a]	(−1.69)	(8.19)[a]	(6.37)[a]	
8:30–9:29	.050**	.002**	.001	.047**	.007**	.004	.048**	−.002	.008**	.003*	.005
	(77.13)[a]	(3.27)[a]		(71.38)[a]	(7.66)[a]		(54.89)[a]	(−1.91)	(4.51)[a]	(2.16)	
9:30–10:29	.043**	.002**	.001	.042**	.004**	.002	.042**	−.000	.003	.003**	.003
	(85.78)[a]	(2.61)		(80.71)[a]	(6.03)[a]		(60.66)[a]	(−.17)	(1.88)	(2.85)	
10:30–11:29	.037**	.004**	.002	.036**	.005**	.005	.035**	.001	.003*	.004**	.007
	(82.20)[a]	(5.86)[a]		(77.85)[a]	(8.52)[a]		(57.30)[a]	(1.72)	(2.37)	(4.02)[a]	
11:30–12:29	.038**	.002**	.001	.037**	.003**	.002	.037**	.001	−.000	.003**	.002
	(84.55)[a]	(2.57)		(77.90)[a]	(5.01)[a]		(59.30)[a]	(1.11)	(−.05)	(3.42)[a]	
12:30–1:29	.044**	.001	.000	.043**	.002**	.001	.042**	.002	−.002	.004**	.001
	(79.68)[a]	(1.31)		(74.04)	(3.12)		(55.87)[a]	(1.73)	(−1.59)	(3.23)	
1:30–2:00	.053**	−.001	.000	.052**	.001	.000	.052**	−.002	.001	.001	.000
	(62.34)[a]	(−.96)[a]		(57.92)[a]	(.63)		(45.15)[a]	(−.90)	(.25)	(.40)	

B. Trades:											
Full day	21.883**	1.770**	.004	21.283**	2.783**	.009	20.993**	.681**	1.412**	1.909**	.012
	(341.8)[a]	(19.43)[a]		(321.3)[a]	(30.58)[a]		(240.60)[a]	(2.98)	(7.74)[a]	(14.94)[a]	
7:20–7:29	35.960**	3.572**	.020	35.583**	4.489**	.031	34.878**	1.769*	2.166*	2.850**	.044
	(102.0)[a]	(7.11)[a]		(103.2)[a]	(8.98)[a]		(78.85)[a]	(2.53)	(2.14)	(3.98)[a]	
7:30–8:29	29.489**	3.322**	.011	27.909**	6.174**	.037	27.847**	.144	4.872**	3.506**	.049
	(161.0)[a]	(12.74)[a]		(150.1)[a]	(23.97)[a]		(113.10)[a]	(.38)	(9.47)[a]	(9.74)[a]	
8:30–9:29	25.458**	2.471**	.008	24.352**	4.461**	.025	24.299**	.122	3.622**	2.475**	.034
	(158.1)	(10.78)[a]		(148.3)[a]	(19.61)[a]		(111.50)[a]	(.37)	(7.95)[a]	(7.77)[a]	
9:30–10:29	21.382**	1.766**	.005	20.675**	3.028**	.013	20.603**	.163	2.476**	1.662**	.019
	(143.3)[a]	(8.31)[a]		(135.3)[a]	(14.30)[a]		(101.40)[a]	(.53)	(5.83)[a]	(5.60)[a]	
10:30–11:29	15.730**	1.576**	.005	15.265**	2.384**	.013	14.959**	.699	1.218**	1.645**	.017
	(129.3)[a]	(9.10)[a]		(122.4)[a]	(13.79)[a]		(90.15)[a]	(1.95)	(3.51)[a]	(6.79)[a]	
11:30–12:29	15.884**	1.207**	.003	15.453**	1.876**	.007	15.012**	1.085**	−.274	1.858**	.009
	(124.7)[a]	(6.66)[a]		(115.0)[a]	(10.33)[a]		(86.11)[a]	(3.97)[a]	(−.74)	(7.30)[a]	
12:30–1:29	18.177**	.726**	.001	18.222**	.574**	.001	17.649**	1.405**	−1.366**	1.125**	.002
	(128.9)[a]	(3.73)[a]		(122.3)[a]	(2.85)		(91.23)[a]	(4.64)[a]	(−3.35)[a]	(3.98)[a]	
1:30–2:00	27.500**	.322	.000	27.033**	1.145**	.001	26.709**	.792	−1.176	1.650**	.001
	(111.1)[a]	(.92)		(103.5)[a]	(3.24)[a]		(78.66)[a]	(1.49)	(−1.64)	(3.40)**	

NOTE.—Three regressions are estimated separately for 5-minute volatility and trades, as defined in table 1. The first regression takes the form $y_t = \beta_0 D_t^{l-15} + \varepsilon_t$, where D_t^{l-15} is a (0, 1) dummy variable that takes the value of one if the day falls between the first and the fifteenth of the month. The second regression takes the form $y_t = \beta_0 D_t^{I} + \varepsilon_t$, where D_t^{I} takes the value of one if the day witnessed a scheduled macroeconomic announcement.A third regression accounts for the interaction between D_t^{1-15} and D_t^{I} and takes the form $y_t = \beta_0 + \beta_1 D_t^{1-15} + \beta_2 D_t^{1-15} D_t^{I} + \beta_3 D_t^{I} + \varepsilon_t$.

[a] Posterior odds are against the null hypothesis based on the size-adjusted t-statistic $t^* = (s - \varkappa)^{0.5}(s^{1/s} - 1)^{0.5}$, where s = sample size and $\varkappa$ = number of parameters estimated, including the intercept.

* Significant at the 5% level.

** Significant at the 1% level.

TABLE 3 **Fourier Flexible Form Estimates of Announcements**

Early (First Half)			Late (Second Half)		
A. Volatility:					
$\lambda(E)_{-1}$	.001	(.01)	$\lambda(L)_{-1}$	−.119*	(−3.65)[a]
$\lambda(E)_0$	1.284**	(48.48)[a]	$\lambda(L)_0$	.838**	(26.05)[a]
$\lambda(E)_1$	.474**	(17.88)[a]	$\lambda(L)_1$	.197**	(6.12)[a]
$\lambda(E)_2$	.321**	(12.12)[a]	$\lambda(L)_2$	.121**	(3.74)[a]
$\lambda(E)_3$	.207**	(7.80)[a]	$\lambda(L)_3$	.063**	(1.90)
$\lambda(E)_4$	.222**	(8.30)[a]	$\lambda(L)_4$	−.013	(−.40)
$\lambda(E)_5$	.159**	(5.96)[a]	$\lambda(L)_5$	.044	(1.36)
$\lambda(E)_6$	.153**	(5.72)[a]	$\lambda(L)_6$	−.013	(−.40)
$\lambda(E)_7$	.145**	(5.41)[a]	$\lambda(L)_7$	.066*	(2.03)
$\lambda(E)_8$	.158**	(5.89)[a]	$\lambda(L)_8$	.080*	(2.49)
$\lambda(E)_9$	.114**	(4.37)[a]	$\lambda(L)_9$	.056	(1.78)
$\lambda(E)_{10}$	.051**	(1.96)	$\lambda(L)_{10}$	.017	(.52)
$\lambda(E)_{11}$	.093**	(3.52)[a]	$\lambda(L)_{11}$	−.028	(−.86)
$\lambda(E)_{12}$	.088**	(3.38)[a]	$\lambda(L)_{12}$	−.033	(−1.04)

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 0(10.78)^{\mathrm{a},**}$$

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 1, \ldots, 6(11.10)^{\mathrm{a},**}$$

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 7, 8, 9(3.24)^{\mathrm{a},**}$$

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 10, 11, 12(4.56)^{\mathrm{a},**}$$

Early (First Half)			Late (Second Half)		
B. Trades:					
$\lambda(E)_{-1}$	7.976**	(11.82)[a]	$\lambda(L)_{-1}$	5.211**	(6.37)[a]
$\lambda(E)_0$	15.121**	(22.37)[a]	$\lambda(L)_0$	7.113**	(8.68)[a]
$\lambda(E)_1$	12.299**	(18.32)[a]	$\lambda(L)_1$	6.815**	(8.36)[a]
$\lambda(E)_2$	10.318**	(15.39)[a]	$\lambda(L)_2$	4.984**	(6.12)[a]
$\lambda(E)_3$	10.168**	(14.81)[a]	$\lambda(L)_3$	3.962*	(4.17)[a]
$\lambda(E)_4$	9.062**	(13.34)[a]	$\lambda(L)_4$	3.330**	(4.08)[a]
$\lambda(E)_5$	8.874**	(13.09)[a]	$\lambda(L)_5$	2.244**	(2.71)
$\lambda(E)_6$	8.774**	(12.95)[a]	$\lambda(L)_6$	2.116**	(2.57)
$\lambda(E)_7$	6.858**	(10.11)[a]	$\lambda(L)_7$	2.495**	(3.06)
$\lambda(E)_8$	7.151**	(10.65)[a]	$\lambda(L)_8$	1.038	(1.27)
$\lambda(E)_9$	7.239**	(10.79)[a]	$\lambda(L)_9$	1.654*	(2.03)
$\lambda(E)_{10}$	5.761**	(8.60)	$\lambda(L)_{10}$	1.462	(1.80)
$\lambda(E)_{11}$	5.736**	(8.56)[a]	$\lambda(L)_{11}$	1.568	(1.93)
$\lambda(E)_{12}$	−4.480	(−1.62)	$\lambda(L)_{12}$	3.992	(1.73)

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 0(6.92)^{\mathrm{a},**}$$

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 1, \ldots, 6(13.90)^{\mathrm{a},**}$$

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 7, 8, 9(8.64)^{\mathrm{a},**}$$

$$\sum \lambda(E)_m = \sum \lambda(L)_m \quad m = 10, 11, 12(-0.12)$$

NOTE.—The estimates for volatility are from $\hat{\sigma}_t = c + \sum_{m=-1}^{M} \lambda_m^E I_{m,t+m}^E + \sum_{m=-1}^{M} \lambda_m^L I_{m,t+m}^L + \delta_{0,1}(n/N_1) + \delta_{0,2}(n^2/N_2) + \sum_{p=1}^{6} [\delta_{c,p} \cos(2\pi p/N)n + \delta_{s,p} \sin(2\pi p/N)n] + \delta_x X_t + \varepsilon_{t,n}$, employing surprise-filtered volatility as the dependent variable. Similarly, we employ surprise-filtered trades. The coefficients in panel A are $\times 10$. Two sets of dummies are created to represent announcements in the first half of the month and the second half of the month. The $\lambda()_m$ coefficients are for the dummy variables representing 14 5-minute intervals, $m = -1, 0, 1, \ldots, 12$, following an announcement. Variables E and L denote early (first through the fifteenth) and late (sixteenth through the thirty-first) announcements, respectively. For instance, $\lambda(E)_0$ and $\lambda(E)_1$ represent the coefficient on the dummy for the interval corresponding to the first 5 minutes and the next 5 minutes following the announcements in the first half of the month. The figures in parentheses are t-statistics.

[a] Posterior odds are against the null hypothesis based on the size-adjusted t-statistic.

* Significant at the 5% level.

** Significant at the 1% level.

the overlap or commonality in information and calendar effects, show that controlling for information explains almost all of the intramonth effects. The coefficient estimate for D_t^{1-15} (calendar dummy) is insignificant for all periods for volatility and significant for only one interval (12:30–1:29 p.m.) for trades. A cursory comparison of the estimated coefficients for D_t^{1-15} in equations (6) and (8) indicates that most of what appear to be calendar effects are in fact macroeconomic announcement effects.[8] We note that the results in tables 1 and 2 aggregate the second and third components of volatility described earlier. Our next set of tests attempts to disaggregate these components. We also perform corresponding tests for trades.

Flexible Fourier Form Model

In this section, we explicitly model the intraday patterns to identify meaningful dynamics in volatility and trades (Andersen and Bollerslev 1997, 1998). This allows us to test for differences in the impacts of announcements at different times following the releases.

To model volatility and trades, we employ a Fourier Flexible Form (FFF) model adapted from Gallant (1981) and similar to that in Andersen and Bollerslev (1998) and Bollerslev et al. (2000). The model for volatility is

$$\hat{\sigma}_t = c + \sum_{m=-1}^{M} \lambda_m^E I_{m,t+m}^E + \sum_{m=-1}^{M} \lambda_m^L I_{m,t+m}^L + \delta_{0,1} \frac{n}{N_1} + \delta_{0,2} \frac{n^2}{N_2} + \sum_{p=1}^{6} \left(\delta_{c,p} \cos \frac{2\pi p}{N} n + \delta_{s,p} \sin \frac{2\pi p}{N} n \right) + \delta_x X_t + \varepsilon_{t,n}. \tag{10}$$

In equation (10), I_{t+m} is the announcement dummy for interval $t+m$, taking the value of one if interval t witnessed a scheduled announcement and zero otherwise; N represents the number of 5-minute intervals in a trading day; and n represents the interval time ($n = 1, 2, \ldots, N$). The superscripts E and L represent early (first through the fifteenth) and late (sixteenth through the thirty-first) announcements, respectively. We chose a response length of $M = 12$, given the evidence that most of the response of treasury instruments to macroeconomic announcements is exhausted within 1 hour. The dummy variable X takes the value one if the interval falls within an expiration month and zero otherwise, p is the "tuning parameter," and $N_1 = (N+1)/2$ and $N_2 = (N+1)(N+2)/6$ are normalizing constants. Other than the expiration and announcement coefficients, equation (10) may be thought of as a semi-

8. A fourth regression (not reported) indicates that virtually all of the remaining calendar effects for volatility and trading activity are accounted for by the expiration-month effect.

nonparametric specification that allows for fairly exhaustive controls for time-of-day cycles in volatility.[9]

We also employ the above specification of the FFF model to examine the response of trading by replacing the dependent variable in equation (10) with τ_t, the surprise-adjusted number of ticks accumulated over 5-minute intervals. We find, with some experimentation, that the intraday cyclical patterns in this measure are more perceptibly annihilated using a higher order of parameter p ($p = 9$) and higher-order polynomials on n ($n = 3$). Figure 4 offers a comparison of the demeaned measures of volatility (panel a) and trades (panel b) alongside the residuals from the FFF model (without the information dummies). For both volatility and trades, the FFF specification appears to remove most of the strong patterns evident in the demeaned series.

The results from the FFF estimations of volatility and trades are reported in table 3. Our volatility estimate for the deviation of the immediate response from average is the coefficient estimate $\lambda()_0$. This component is expected to be larger, the harder it is to interpret the news in the announcements, and given our preceding explanations, we expect this component of volatility to be larger in the first half of the month. Our findings confirm our priors. The estimate $\lambda(E)_0$ is larger than $\lambda(L)_0$, and their difference is significant on a sample-size-adjusted basis.

Volatility that reflects the reaction of prices to trading is represented by $\lambda()_m$ ($m = 1, 2, \ldots, N$). These coefficients provide an estimate of the extent of private-information effects. Our arguments suggest that private-information effects will be more evident in the first half of the month. The results in table 3 show the $\lambda(E)_m$ for volatility to be significant, employing sample-size-adjusted p-values, for 45 minutes beyond the initial 5-minute interval. However, the corresponding $\lambda(L)_m$ coefficients are not significant, using the same metric, beyond 10 minutes of the initial interval. Thus, in addition to differences in their immediate responses, there are noticeable differences in the persistence of volatility across the two halves of the month. This is borne out by the rejection of the null hypothesis that the cumulative responses for the first 60 minutes beyond the initial interval are equal.

The results for the number of trades also indicate large differences in the initial response and lagged response to the announcements across the two halves of the month. The estimate $\lambda(E)_0$ is more than twice as large as $\lambda(L)_0$, and the difference is significant. In addition, the $\lambda(E)_m$ ($m = 1, 2, \ldots, N$) coefficients tend to be significant for at least 45 minutes beyond the initial interval, whereas the corresponding $\lambda(L)_m$ coefficients are significant for less than half that time.

9. A separate estimation of eq. [10] that is more comparable to that in Andersen and Bollerslev (1998) and Bollerslev et al. (2000) was conducted, employing an alternate measure of volatility and, more important, imposing a decay structure to the dynamic response function of volatility to macroeconomic announcements. These results, available from the authors, are not materially different from those presented here.

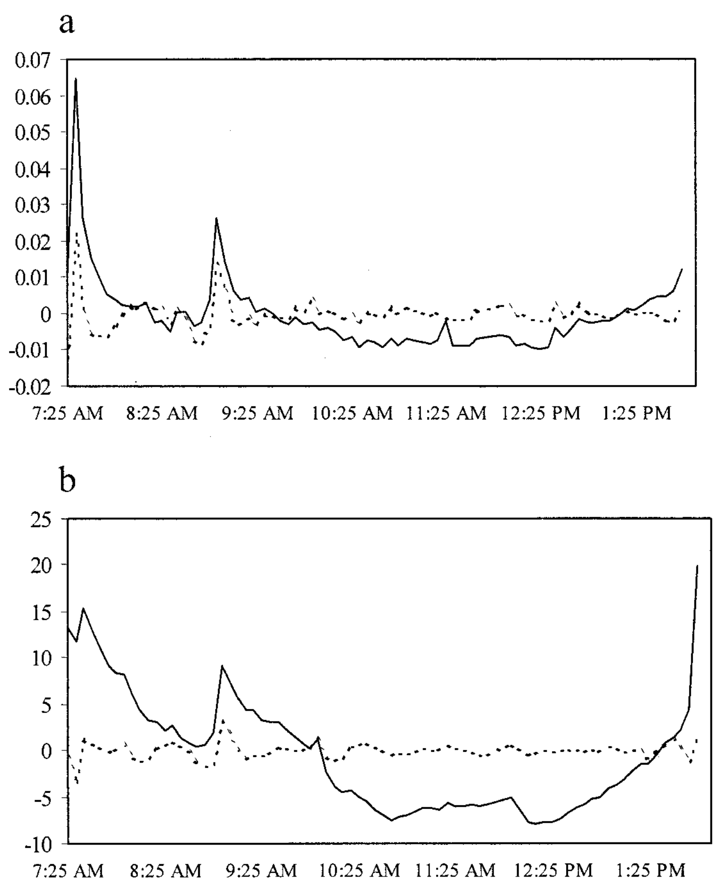

FIG. 4.—Intraday demeaned (*solid line*) and FFF-filtered (*dashed line*) patterns in volatility (*a*) and trades (*b*) over 5-minute intervals.

The results also show that the coefficient pertaining to trades in the 5-minute interval prior to the announcement (λ_{-1}) is positive and significant for both halves of the month. But, there appears to be no elevation in volatility in the corresponding interval for both halves. In fact, volatility in the second half of the month appears to be less than normal ($\lambda(L)_{-1}$). This evidence is generally consistent with elevation of uninformed trading prior to the announcements.

Our Findings Compared with Those from the Treasury Bond Market

Green (2004) applies a model to treasury bond transaction data similar to that used by Madhavan, Richardson, and Roomans (1997) for stock transactions. Green's purpose is to clarify the relation between information asymmetry and the informational role of trading. He finds evidence that prices are more sensitive to trading following announcements. We find similar evidence for volatility and trading activity, particularly in the first half of the month. Note the significance of the $\lambda(E)$ coefficients for volatility and trades in table 3.

Our evidence also is consistent with the contention that prices are more sensitive to orders (trades) during periods of enhanced liquidity. Note the elevated levels of volatility following news releases coupled with an increase in trading activity in the first half in table 3. Green (2004) finds similar evidence in contrast to findings in Fleming (2001) and Brandt and Kavajecz (2003).

Information Surprises and Forecast Uncertainty

Surprise Coefficients

In this section, we examine the relationship between volatility (trades) and macroeconomic announcements, by assessing the influence of the surprise component of a particular announcement. While the surprise measure is defined as before (eq. [3]), our volatility measure, given our objective, is not purged of the surprise elements. Volatility is obtained from equation (1) and by applying an autoregressive filter (eq. [2b]) over the entire sample. Trades are simply the unfiltered number of ticks accumulated over 5-minute intervals.

Using the same form as equation (3), we denote surprise elements of announcements other than i, but concurrent with i, as $S_{ik,t}$. To test the hypothesized links, we estimate the following equation for each announcement in standardized form:[10]

$$y_{i,t} = \beta_0 + \beta_1|S_{i,t}| + \sum_{k=2}^{K} \beta_{ik}|S_{ik,t}| + \varepsilon_{i,t}, \tag{11}$$

where $y_{i,t}$ is the volatility, or alternatively, the number of trades in the 5-minute interval following the ith announcement. We use absolute values of the surprise coefficients in equation (11) because the sign is unimportant.

The absolute magnitudes of the coefficient estimates imply the economic influence of surprises on the two series, and the adjusted R^2 (from now on R^2) from the regressions (eq. [11]) helps us determine whether the linkages are stronger in the first half of the month, as we hypothesize.[11] In table 4, we report standardized estimates of β_1 in equation (11) for volatility and the

10. To allow comparison across different announcements, we subtract the mean and divide by the standard deviation of all variables in eq. [11], thus the intercept term β_0 vanishes in the estimated model.

11. It is notable that if uncertainty is greater in the first half of the month, these tests are likely to be biased toward rejecting the hypothesis that the announcements in the first half of the month are more important to traders. For instance, a 1 standard deviation shock in the surprise element should have a larger effect on the market when the consensus is high (or uncertainty is low), as compared to a 1 standard deviation shock when the consensus is low (or uncertainty is high).

TABLE 4 Surprise Coefficients for Volatility and the Number of Trades in 5-Minute Intervals

			Volatility			Trades		
Day	Announcement	Time	Coefficient		R^2_{adj}	Coefficient		R^2_{adj}
A. First half:								
2	NAPM	9:00	.538**	(4.78)[a]	.292	.471**	(4.50)[a]	.220
3	Leading indicators	7:30	.029	(.22)	.313	.046	(.03)	.029
4	New home sales	9:00	.406**	(3.33)[a]	.165	.407**	(3.33)[a]	.166
4	Construction spending	9:00	.085	(.79)	.360	−.028	(−.25)	.309
5	Factory orders	9:00	.216	(1.65)	.047	.117	(.87)	.014
5	Hourly earnings	7:30	.253*	(1.97)[a]	.101	−.051	(−.35)	.030
5	Unemployment rate	7:30	−.021	(−.13)	.020	−.050	(−.13)	.001
5	Nonfarm payrolls	7:30	.218*	(2.00)[a]	.092	.006	(.04)	.001
12	PPI	7:30	.176	(1.71)	.012	.075	(.10)	.015
13	Retail sales	7:30	.131	(.94)	.002	.161	(1.16)	.010
B. Second half:								
16	Business inventories	7:30	−.066	(−.42)	.004	−.538	(−.15)	.000
16	CPI	7:30	.302	(1.85)	.085	.427**	(2.75)[a]	.097
16	Capacity utilization	8:15	.464**	(2.91)[a]	.119	.332	(1.91)	.035
16	Industrial production	8:15	−.113	(−.68)	.008	−.011	(−.07)	.019
18	Housing starts	7:30	.325**	(2.54)[a]	.108	.170	(1.27)	.029
22	Treasury budget	1:00	−.088	(−.66)	.008	−.219	(−1.69)	.034
25	Durable goods orders	7:30	.190	(1.45)	.031	.159	(1.26)	.025
28	GDP	7:30	.328**	(2.50)[a]	.108	.456**	(3.70)[a]	.183

NOTE.—We estimate models of volatility and number of trades, alternately, using surprise as the explanatory variable. Surprise is the standardized absolute difference between the actual and forecast values. The coefficients are standardized regression coefficients. For example, a 1-standard-deviation change in the NAPM announcement surprise is associated with a .538 standard deviation change in volatility. The figures in parantheses are *t*-statistics. We omit consumer credit announcements that had a 2:00 p.m. release time for much of the sample period.

[a] Posterior odds are against the null hypothesis.

* Significant at the 5% level.

** Significant at the 1% level.

number of trades. In panel A are the results for the first half of the month, and in panel B are results for the last half.

The R^2 values are on average higher in the first half of the month; the mean R^2 for the 10 announcements is 0.140 for volatility and 0.080 for trades (panel A). For the second half, the mean R^2 value is 0.059 for volatility and 0.053 for trades. All significant coefficient estimates in table 4 are positive. Note also that the largest coefficients for both volatility and trades are those for NAPM and new home sales in the first half. In the second half, surprises in capacity utilization, gross domestic product (GDP), and housing starts have the greatest effect on volatility, and CPI and GDP surprises have the greatest effect on trades.

Uncertainty Coefficients

Our hypothesized link between the announcements and volatility (and trades) arises from variations in traders' beliefs, that is, forecast uncertainty. We adapt the approach taken by Zarnowitz and Lambros (1987). However, one point of departure is that we are interested in the effect of uncertainty among traders, rather than forecasters, on the forecast figures. We take the approach that, if there is no trader uncertainty about a forecast (consensus) figure, there should be no reaction in price or trading activity on the mere fulfillment of that forecast. Responses to the announcements will reflect two factors: (1) differences in statistics between the forecasted figure and the actual forecast and (2) trader uncertainty regarding the value of a particular indicator. We are more interested in factor 2. To control for the effects of factor 1, we examine only zero-surprise announcements. In this instance, the diffuseness of the consensus figure is least. While we expect volatility and trading to ensue following zero-surprise announcements, we also expect to find both outcomes to be larger in the first half of the month.

To control for intraday effects, we examine the reactions to the 7:30 a.m. announcements alone. Moreover, because our objective here is to examine the reaction to zero-surprise announcements, days that have nonzero unexpected components are dropped from the sample. The nonannouncement sample is retained to serve as a control. The regression for the 5-minute interval that immediately follows a zero-surprise announcement takes the form

$$y_t = \beta_0 + \beta_1 D_t^z + \varepsilon_t, \tag{12}$$

where y_t is volatility (alternatively, trades) for the 5-minute interval following the zero-surprise announcement, and D_t^z equals one if we witness a zero-surprise announcement in interval t, and D_t^z equals zero if there is no announcement. A positive sign for β_1 confirms elevated uncertainty surrounding the announcements, and we expect β_1 to be greater in the first half than in the second half of the month. Similar regressions are estimated for four other 5-minute intervals surrounding the announcements (7:20–7:24, 7:25–7:29, 7:35–7:39, and 7:40–7:44 a.m.).

TABLE 5 Uncertainty Coefficients for Zero-Surprise Announcements

	First-Half Coefficient (1)		R^2_{adj} (2)	Second-Half Coefficient (3)		R^2_{adj} (4)	Relative Coefficient (5)		R^2_{adj} (6)
A. Volatility:									
7:20–7:24	.018	(1.82)	.000	.003	(.37)	.000	.012	(1.72)	.006
7:25–7:29	.005	(.42)	.000	−.019	(−1.48)	.002	.020	(1.55)	.003
7:30–7:34	.157**	(6.89)[a]	.077	.041	(1.57)	.003	.113**	(3.21)[a]	.057
7:35–7:39	.104**	(7.91)	.101	.056*	(2.27)	.020	.049**	(2.55)[a]	.048
7:40–7:44	.049**	(5.57)[a]	.052	.014	(1.12)	.002	.037**	(2.97)[a]	.095
B. Trades:									
7:20–7:24	3.609**	(3.01)[a]	.014	.322	(.17)	.000	2.941*	(2.14)	.022
7:25–7:29	9.242**	(6.09)[a]	.071	6.300**	(2.82)[a]	.012	3.659**	(2.76)[a]	.025
7:30–7:34	22.195**	(8.93)[a]	.123	15.122**	(4.92)[a]	.037	7.768**	(4.16)[a]	.077
7:35–7:39	13.642**	(7.44)[a]	.092	9.929**	(4.16)[a]	.028	6.110**	(2.59)[a]	.049
7:40–7:44	10.745**	(6.11)[a]	.063	7.411**	(3.55)[a]	.033	4.439*	(2.14)	.030

NOTE.—For the first two sets of results, the model estimated is $y_t = \beta_0 + \beta_1 D_t^Z + \varepsilon_t$, where y_t represents volatility or number of trades in interval t, and D_t^Z equals one if at the open of period t (7:30 a.m.) we observe a zero-surprise announcement, and zero otherwise. A zero-surprise announcement is one for which the consensus forecast and actual value are the same. The sample excludes announcement days with non-zero-surprise elements. The third set of results is from the regression $y_t = \beta_0 + \beta_1 D_t^{1-15} + \varepsilon_t$, where D_t^{1-15} equals one if the zero-surprise announcement is in the first half of the month, and zero otherwise. The parentheses are t-statistics.

[a] Posterior odds are against the null hypothesis.

* Significant at the 5% level.

** Significant at the 1% level.

In table 5, we report estimation results for equation (12) for the first half of the month and for the second half. The β_1 estimates for both series are larger in the first half. For example, for volatility in the 7:30–7:34 a.m. interval, the coefficient estimate for the first half is more than three times as large as the coefficient estimate in the second half. Furthermore, the coefficient estimates in the first half are significant for volatility for intervals after 7:30 a.m. but insignificant in the second half. For trades, the coefficients are uniformly larger in the first half.

A third model allows a formal test of whether the zero-surprise announcements have greater influence in the first half of the month:

$$y_t = \beta_0 + \beta_1 D_t^{1-15} + \varepsilon_t, \tag{13}$$

where D_t^{1-15} equals one if the zero-surprise announcement occurs in the first half, and y_t is as defined in equation (12). Here, only announcement days are considered. The results are in columns 5–6 of table 5. The estimated β_1 coefficient in equation (13) is significant in three of five intervals for volatility as well as for trades. Thus, the elevated levels of volatility and trading activity earlier in the month correspond to higher levels of forecast uncertainty in the first half.

Forecast Unbiasedness and Efficiency

We also determine whether forecast efficiency follows a monthly pattern that mirrors the patterns in volatility and trades that we document in this study.

To conserve space, we summarize our methods and results that relate to these tests.[12]

Let $A_{i,t}$ represent the realized value of a particular economic indicator i (say the CPI) in interval t. Formula $F_{i,t-\Delta}$ denotes the median forecast of A_t at time $t - \Delta$. Assuming rational forecasts (Muth 1961), the following model parameters should be $\beta_0 = 0$, $\beta_1 = 1$, and

$$A_{i,t} = \beta_0 + \beta_1 F_{i,t-\Delta} + \varepsilon_t. \tag{14}$$

We estimate equation (14) for the two halves of the month. For the test of efficiency, the figures of most interest are the χ^2 statistics (that test the joint hypothesis $\beta_0 = 0$, $\beta_1 = 1$) and the changes in R^2 across the two halves. As a group, the forecasts in the first half of the month appear to be relatively inefficient. The average R^2 in the first half is 0.5185, while in the second half it is 0.6970. The χ^2 statistics reject the null hypothesis in four cases in the first half and in three cases in the second half. Thus, the forecasts are not consistently rational in the sense of Muth (1961).

If the forecasts are inefficient, it may be possible to improve the forecasting accuracy of $A_{i,t}$ by combining equation (14) with forecasts from an autoregressive model (e.g., Lupoletti and Webb 1986; Aggarwal, Mohanty, and Song 1995). Given the preceding line of reasoning on forecasting efficiency, we estimate the following regression.

$$A_{i,t} = \beta_0 + \beta_1 F_{i,t-\Delta} + \beta_2 F^{AR}_{i,t-\Delta} + \beta_3 F^{P}_{i,t-\Delta} + \varepsilon_{\mathrm{t}}, \tag{15}$$

where $F^{AR}_{i,t-\Delta}$ is the forecast of $A_{i,t}$ from an autoregressive model of lag $= 3$, and $F^{P}_{i,t} - \Delta$ is the forecast of $A_{i,t}$ from

$$F^{P}_{i,t-\Delta} = \beta_0 + \sum_{k=1}^{k-1} \beta_k A_{k,t-\Delta-\Phi} + \varepsilon_{t-\Delta}, \tag{16}$$

where $A_{k,t-\Delta-\Phi}(k = 1, 2, \ldots, k-1)$ represents the kth announcement occurring prior to $t - \Delta$, at time $t - \Delta - \Phi$. Since we are interested in efficiency patterns across the halves of the month, $A_{k,t-\Delta-\Phi}$ is restricted to the half month (first through the fifteenth or sixteenth through the thirty-first) prior to announcement time $t - \Delta$.

We estimate equation (15) using ordinary least squares. The results from these tests show the average R^2 in the first half is 0.5933, while in the second, it is 0.7000. The χ^2 statistic, testing the joint significance of $F^{AR}_{i,t-\Delta}$ and $F^{P}_{i,t-\Delta}$, indicates joint significance for eight of the 11 announcements in the first half, while joint significance is found for only two of the eight announcements in the second half. The combined evidence from equations (14) and (15) suggests that improvements in forecast efficiency from the first to the second half of the month are manifest.

12. Detailed descriptions of the methods employed and complete results of these tests are available from the authors on request.

Summary and Conclusion

We examine return volatility and trading activity in the treasury futures market to investigate the linkage between macroeconomic news announcements and these two important series. Additionally, we advance and test two noncompeting hypotheses on the role of macroeconomic announcements in the noted intramonth patterns: (1) the elevated levels of volatility and trades earlier in the month are the result of higher levels of trader uncertainty (or lower levels of trader consensus) regarding news in the announcements in the first half of the month, and (2) these patterns are the result of improved forecasting efficiency in the second half of the month.

Volatility and trades are found to be higher in the first half of the month, as hypothesized. Moreover, the largest disparities occur in the first hour or so of the trading day; that is, differences in the first and second halves are not symmetric across times of day. We find that controlling for information explains almost all of the intramonth pattern. Consistent with Green (2004) for the treasury bond market, we report evidence that futures prices are more sensitive to trades following announcements and during periods of enhanced liquidity.

Finally, we report evidence that levels of trader uncertainty are higher (consensus is lower) in the first half of the month. Moreover, we find that forecast efficiency improves from the first to the second half of the month, consistent with the linkage we hypothesize.

Appendix

TABLE A1 Announcement Days and Times for 19 Macroeconomic News Releases Announced Monthly, May 1994 through May 1999

		Announcement Days			Announcement
	Time	Earliest	Latest	Mean	Lag
A. Announcements in the first half of the month:					
NAPM	9:00	First	Fourth	Second	1
Leading indicators	7:30	29[a]	20	3	2
New home sales	9:00	28[a]	24	4	2
Construction spending	9:00	1	16	4	2
Factory orders	9:00	30[a]	15	5	2
Hourly earnings	7:30	1	19	5	1
Unemployment rate	7:30	1	19	5	1
Nonfarm payrolls	7:30	1	19	5	1
Consumer credit	2:00 p.m.	5	11	7	2
PPI	7:30	9	31	12	1
Retail sales	7:30	11	30	13	1
B. Announcements in the second half of the month:					
Business inventories	7:30	12	28	15	2

TABLE A1 (*Continued*)

	Time	Announcement Days			Announcement Lag
		Earliest	Latest	Mean	
CPI	7:30	12	28	16	1
Capacity utilization	8:15	14	24	16	1
Industrial production	8:15	14	24	16	1
Housing starts	7:30	16	28	18	1
Treasury budget	1:00 p.m.	18	30	22	1
Durable goods orders	7:30	5	30	25	1
GDP	7:30	23	31	28	3

NOTE.—Announcement lag refers to the month to which the information pertains. For instance, a lag of one would imply that the information pertains to the month prior ($m-1$).

[a] Contains announcements that typically occur in the first half of month m but in a few instances occurred in the last few days of the second half of month $m-1$. These are treated, for the computation of the mean, as occurring on the first day of month m.

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