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Macroeconomic Announcements and the Volatility Feedback Effect

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The views expressed are those of the authors and do not reflect those of the Central Bank of Ireland or the Eurosystem.

Motivation

Empirical observation:

1. Stock markets respond to macroeconomic announcements
2. Response to the same macroeconomic news varies over time

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What explains the time-varying sensitivity of stock markets to macroeconomic announcements?

- Early literature: stock market responds more strongly during recessions than during expansions (McQueen and Roley, 1993; Boyd et al., 2005; Andersen et al., 2007)
- Recent evidence: intensity of discount rate effect varies over time due to expected monetary policy response ⇒ relevant predictors for explaining the time-varying sensitivity
  - FOMC sentiment index: 'state of the economy as described by the FOMC statement' (Gardner et al., 2021)
  - output gap and interest rate expectations, but not the VIX (Elenev et al., 2022)

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$\Rightarrow$ **How much does the volatility feedback effect contribute to explaining the time-varying sensitivity of the stock market to news?**

Our paper in a nutshell

Volatility feedback effect (Campbell and Hentschel, 1992): If volatility is priced, a positive volatility innovation leads to upward revisions of future required returns and a concurrent decline in the stock price

$$\text{macroeconomic news} \Rightarrow \text{volatility news}$$

Our paper in a nutshell

Volatility feedback effect (Campbell and Hentschel, 1992): If volatility is priced, a positive volatility innovation leads to upward revisions of future required returns and a concurrent decline in the stock price

$$\text{macroeconomic news} \Rightarrow \text{volatility news}$$

- **What volatility measure?** Combine standard present value model with a novel two-component volatility model for the conditional variance of cash-flow news
  - multiplicative factor multi-frequency GARCH (MF2-GARCH) consisting of a short- and long-term volatility component (Conrad and Engle, 2022)
  - discount rate news can be written as a function of shocks to volatility components
- **Testable predictions:**
  - long-term volatility predominantly determines the size of the volatility feedback effect
  - asymmetric response to good and bad news is most pronounced when long-term volatility is high
- **Empirical results:** Confirm model predictions with S&P 500 and U.S. macroeconomic announcements

Literature

Volatility feedback

- negative relation between the unpredictable component of stock market volatility and unexpected returns (French et al., 1987)
- Campbell and Hentschel (1992) combine a present value model with GARCH-type model for conditional variance of dividend news
  - 'no news is good news': in the absence of dividend news, future required returns are revised downwards, and stock prices increase today
  - asymmetric effect of good and bad news: large bad news has a stronger effect than large good news
- Bollerslev et al. (2006) provide evidence for instantaneous volatility feedback in high-frequency data

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Risk-return relationship

- business cycle-related market volatility is priced (Maheu and McCurdy, 2007; Kim and Nelson, 2013)

We define log returns as

$$r_{t+1} = \ln(P_{t+1} + D_{t+1}) - \ln(P_t) = p_{t+1} - p_t + \ln(1 + \exp(d_{t+1} - p_{t+1})), \quad (1)$$

where p_{t+1} and d_{t+1} are log prices and dividends. Following Campbell and Shiller (1988), we write unexpected returns as

$$r_{t+1} - \mathrm{E}_t[r_{t+1}] = \eta_{d,t+1} - \eta_{r,t+1}, \quad (2)$$

where $\eta_{d,t+1}$ and $\eta_{r,t+1}$ are news about future expected cash flows and required returns:

$$\eta_{d,t+1} = \sum_{j=0}^{\infty} \rho^j \left(\mathrm{E}_{t+1}\left[\Delta d_{t+1+j}\right] - \mathrm{E}_t\left[\Delta d_{t+1+j}\right]\right)$$

$$\eta_{r,t+1} = \sum_{j=1}^{\infty} \rho^j \left(\mathrm{E}_{t+1}\left[r_{t+1+j}\right] - \mathrm{E}_t\left[r_{t+1+j}\right]\right)$$

with $\rho = 1/(1 + \exp(\overline{d - p}))$. Even if dividends are perfectly predictable, there will be surprises in returns through changes in required returns.

Following Campbell and Hentschel (1992), we assume that expected returns can be expressed as

$$\mathrm{E}_t[r_{t+1}] = \mu + \delta\sigma^2_{t+1}, \tag{3}$$

where δ is the coefficient of relative risk aversion and σ^2_{t+1} is the conditional variance of cash-flow news.

Using equation (3), we can rewrite $\eta_{r,t+1}$ being exclusively driven by news about future volatility

$$\eta_{r,t+1} = \delta \sum_{j=1}^{\infty} \rho^j \left(\mathrm{E}_{t+1}[\sigma^2_{t+j+1}] - \mathrm{E}_t[\sigma^2_{t+j+1}] \right). \tag{4}$$

Volatility Feedback Effect

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How to model σ_t^2 ?

- volatility innovations must have persistent effects to generate sufficient variation in discount rates $\Rightarrow$ volatility component models: Spline-GARCH (Engle and Rangel, 2008), GARCH-MIDAS (Engle et al., 2013; Conrad and Loch, 2015), MF2-GARCH (Conrad and Engle, 2022)
- need a model that allows to compute multi-step ahead forecasts $\Rightarrow$ MF2-GARCH is dynamically complete

Volatility Feedback Effect

Assume that σ_t^2 follows a multiplicative factor multi-frequency GARCH (Conrad and Engle, 2022)

$$\eta_{d,t+1} = \sigma_{t+1} Z_{t+1} = \sqrt{h_{t+1}\tau_{t+1}} Z_{t+1}, \quad Z_t \overset{iid}{\sim} (0,1); \;\; \kappa = \mathrm{E}[Z_t^4] < \infty \tag{5}$$

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Short-term component h_t follows a GJR-GARCH(1,1)

$$h_t = (1-\phi) + \left(\alpha + \gamma \mathbf{1}_{\{\eta_{d,t-1}<0\}}\right) \frac{\eta_{d,t-1}^2}{\tau_{t-1}} + \beta h_{t-1}, \tag{6}$$

with $\alpha > 0$, $\alpha + \gamma > 0$, $\beta > 0$ and $\phi = \alpha + \gamma/2 + \beta < 1$.

Long-term component τ_t

$$\tau_t = \lambda_0 + \lambda_1 \frac{1}{m} \sum_{j=1}^{m} \frac{\eta_{d,t-j}^2}{h_{t-j}} + \lambda_2 \tau_{t-1} \tag{7}$$

with $\lambda_0 > 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ and $\lambda_1 + \lambda_2 < 1$. Long-term component scales the volatility forecast, σ_t^2, up/down if the short-term component has under-/overestimated volatility in the recent past.

▸ Motivation for MF2-GARCH

In the following, we assume that $m = 1$ and $\phi < \lambda_1 + \lambda_2 < 1$ (identification). Cash flow news, $\eta_{d,t+1}$, are covariance stationary if $\lambda_1 \phi_\kappa + \lambda_2 \phi < 1$, where $\phi_\kappa = (\alpha + \gamma/2)\kappa + \beta$.

We can rewrite equations (6) and (7) as

$$h_{t+2} = (1 - \phi) + \phi h_{t+1} + h_{t+1} \tilde{v}^h_{t+1} \quad (8)$$

$$\tau_{t+2} = \lambda_0 + (\lambda_1 + \lambda_2)\tau_{t+1} + \tau_{t+1} \tilde{v}^\tau_{t+1} \quad (9)$$

with white noise innovations defined as

$$\tilde{v}^h_{t+1} = \left[\alpha \left(Z^2_{t+1} - 1\right) + \gamma \left(\mathbf{1}_{\{Z_{t+1}<0\}} Z^2_{t+1} - \frac{1}{2}\right)\right] \quad (10)$$

$$\tilde{v}^\tau_{t+1} = \lambda_1 \left(Z^2_{t+1} - 1\right). \quad (11)$$

Result 1: Discount rate news

$$\begin{aligned}\eta_{r,t+1} &= \delta \sum_{j=1}^{\infty} \rho^j \left(\mathrm{E}_{t+1}[\sigma^2_{t+j+1}] - \mathrm{E}_t[\sigma^2_{t+j+1}] \right) \\ &= \left(A^\tau \tau_{t+1} \tilde{v}^\tau_{t+1} + A^h h_{t+1} \tilde{v}^h_{t+1} \right) \\ &\quad + A^{\sigma,\kappa} \tau_{t+1} h_{t+1} \left((\lambda_1 + \lambda_2) \tilde{v}^h_{t+1} + \phi \tilde{v}^\tau_{t+1} \right) \\ &\quad + A^{\sigma,\kappa} \tau_{t+1} h_{t+1} \left(\tilde{v}^\tau_{t+1} \tilde{v}^h_{t+1} - \mathrm{E}_t[\tilde{v}^\tau_{t+1} \tilde{v}^h_{t+1}] \right) \end{aligned} \tag{12}$$

where A^τ, A^h and $A^{\sigma,\kappa}$ are positive constants that depend on the persistence of the volatility components.

Under reasonable assumptions on the model parameters: $A^h < A^{\sigma,\kappa} << A^\tau$.

Intuition: Shocks to the long-term component have persistent effects and, thus, drive discount rate news.

Volatility Feedback Effect

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Volatility Feedback Effect

Combining cash flow and discount rate news yields

Result 2: Unexpected returns

$$
\begin{aligned}
r_{t+1} - \mathrm{E}_t[r_{t+1}] &= \eta_{d,t+1} - \eta_{r,t+1} \\
&= \sqrt{\tau_{t+1} h_{t+1}} Z_{t+1} - \left(A^{\tau} \tau_{t+1} \tilde{v}^{\tau}_{t+1} + A^{h} h_{t+1} \tilde{v}^{h}_{t+1} + A^{\sigma,\kappa} \tau_{t+1} h_{t+1} (\tilde{v}^{\sigma}_{t+1} + \tilde{v}^{\kappa}_{t+1}) \right)
\end{aligned} \tag{13}
$$

- $\tilde{v}^{\sigma}_{t+1}$ = news to conditional volatility
- $\tilde{v}^{\kappa}_{t+1}$ = fourth moment news

▸ Definition of $\tilde{v}^{\sigma}_{t+1}$ and $\tilde{v}^{\kappa}_{t+1}$

Numerical Example: Model parameters are chosen such that $\mathbf{E}[\sigma^2_{t+1}] = 1$. We assume $\tau_{t+1} = 2$ and $h_{t+1} = 1$.

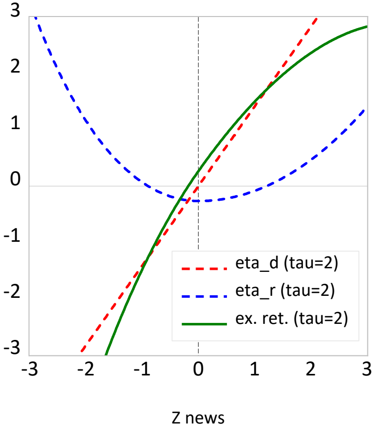

Figure 1: Excess return as a function of Z_{t+1} news.

Cash-flow news: $\eta_{d,t+1} = \sqrt{\tau_{t+1} h_{t+1}} Z_{t+1}$
Discount rate news: $\eta_{r,t+1}$
Excess returns: $r_{t+1} - \mathbf{E}_t[r_{t+1}] = \eta_{d,t+1} - \eta_{r,t+1}$

Volatility Feedback Effect

Numerical Example: Same parameter values as before. $\tau_{t+1} = \mathbf{0.5}$ and $h_{t+1} = 1$

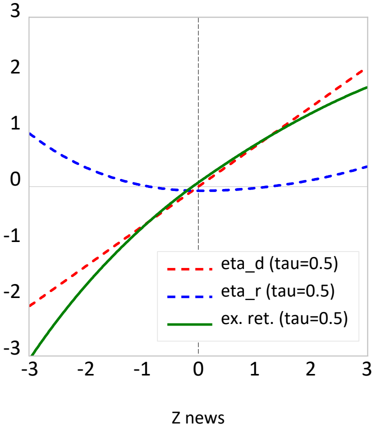

Figure 2: Excess return as a function of Z_{t+1} news.

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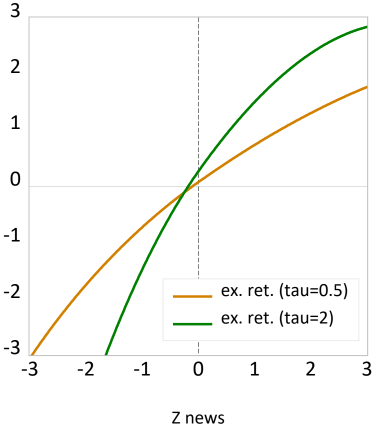

Figure 3: Excess return as a function of Z_{t+1} news where $\tau_{t+1} = 2$ *(high volatility regime)* and $\tau_{t+1} = 0.5$ *(low volatility regime)*.

We derive the following **model predictions**:

- P1 *Importance of long-term volatility:* The size of the volatility feedback effect predominantly depends on long-term volatility.
- P2 The 'no news is good news' effect increases with the level of long-term volatility.
- P3 *Asymmetry:* Within each volatility regime, large pieces of bad news have a stronger effect than large pieces of good news.

Data

Returns:

- event study: Log-return change of the E-mini S&P 500 futures from k-minutes before to k-minutes after each announcement

$$R_t[k] = 100\left(\ln(P_{t+k}) - \ln(P_{t-k})\right)$$

- volatility components: estimate MF2-GARCH based on an expanding window of daily S&P 500 data from 1984 onwards where m is chosen every day according to the BIC

▸ Absolute Return Changes

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Announcements:

- we focus on nine US macroeconomic announcements that are highly informative about the state of the economy and published early in the month (Andersen et al., 2003; Gilbert et al., 2017; Elenev et al., 2022)
- standardized surprises are computed as

$$S_{j,t} = \frac{A_{j,t} - E_{j,t}}{sd_j}$$

where $A_{j,t}$ is the announcement, $E_{j,t}$ the median of the Bloomberg expectations and sd_j is the sample standard deviation of $A_{j,t} - E_{j,t}$

▸ Announcements ▸ Release Calendar

Empirical Results: Importance of long-term volatility

Baseline regression: Instantaneous effect of announcement $S_{j,t}$ on S&P 500 return

$$R_t[k] \quad = \quad \beta_1 + \sum_{j=1}^{J} \beta_{2,j} S_{j,t} + \xi_t \tag{14}$$

Following Elenev et al. (2022), we extend the baseline regression to capture a time-varying sensitivity

$$R_t[k] \quad = \quad \beta_1 + (1 + \gamma_\tau \tilde{\tau}_t + \gamma_h \tilde{h}_t + \gamma_\sigma \tilde{\tau}_t \tilde{h}_t) \sum_{j=1}^{J} \beta_{2,j} S_{j,t} + \xi_t, \tag{15}$$

where, for example, $\tilde{\tau}_t = \sqrt{\tau_t} - \overline{\sqrt{\tau}}$ is demeaned long-term volatility.

Empirical Results: Importance of long-term volatility

Table 1: Baseline Regression Models.

	(1)	(2)	(3)	(4)
$\tilde{\tau}_t$		1.537***		1.519***
		(0.196)		(0.190)
$\tilde{h}_t$			0.106	0.029
			(0.221)	(0.199)
$\tilde{\tau}_t \tilde{h}_t$				0.383
				(0.536)
Initial Jobless Claims	0.049***	0.049***	0.047***	0.050***
	(0.007)	(0.006)	(0.008)	(0.006)
Nonfarm Payrolls	0.212***	0.201***	0.209***	0.200***
	(0.029)	(0.024)	(0.030)	(0.024)
Retail Sales	0.110***	0.095***	0.111***	0.093***
	(0.016)	(0.014)	(0.016)	(0.014)
New Family Houses Sold	0.046***	0.062***	0.046***	0.062***
	(0.011)	(0.012)	(0.011)	(0.013)
Durable Goods Orders	0.073***	0.078***	0.074***	0.077***
	(0.017)	(0.016)	(0.017)	(0.016)
New Orders	0.046***	0.044***	0.046***	0.044***
	(0.013)	(0.014)	(0.013)	(0.013)
CPI	0.082***	0.061***	0.084***	0.062***
	(0.018)	(0.017)	(0.018)	(0.017)
Consumer Confidence	0.132***	0.133***	0.133***	0.132***
	(0.018)	(0.015)	(0.018)	(0.015)
PMI	0.152***	0.143***	0.150***	0.141***
	(0.019)	(0.020)	(0.020)	(0.020)
Observations (Adj. R^2)	2826 (0.189)	2826 (0.230)	2826 (0.189)	2826 (0.230)

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

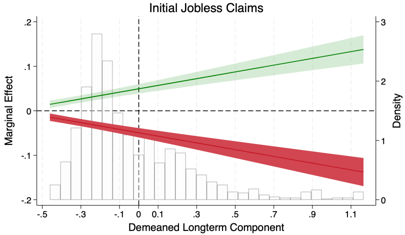

Figure 4: Marginal effect of good and bad macroeconomic news for different levels of the long-run volatility component from Column (2) in Table 1. 90%-confidence intervals.

▸ Robustness (1 minute window)

Empirical Results: Comparison with other Predictor Variables

To compare our results with Elenev et al. (2022) and Gardner et al. (2021), we include further predictors W_{t-1} in our regression model

$$R_t[k] \quad = \quad \beta_1 + (1 + \gamma_\tau \tilde{\tau}_t + \gamma_W W_{t-1}) \sum_{j=1}^{J} \beta_{2,j} S_{j,t} + \xi_t. \tag{16}$$

Table 2: Time-varying Sensitivity Regression Extended with Alternative Predictors.

	GJR-GARCH		Realtime Output Gap FED Greenbook		Interest Rate Expectations SPF (3M Treasury bill)		VIX^2		FOMC Sentiment Gardner et al. (2021)	
W_{t-1}	0.326**	-0.012	-0.163***	-0.124***	-0.033	0.133***	0.136***	-0.010	-1.122***	-0.415*
	(0.163)	(0.157)	(0.022)	(0.026)	(0.061)	(0.049)	(0.052)	(0.061)	(0.182)	(0.235)
$\tilde{\tau}_t$		1.553***		0.834***		1.692***		1.569***		1.022***
		(0.299)		(0.180)		(0.199)		(0.285)		(0.235)
Observations	2826	2826	2294	2294	2826	2826	2826	2826	2690	2690
Adjusted R^2	0.200	0.230	0.291	0.309	0.189	0.233	0.201	0.230	0.241	0.253

Five minutes estimation window. Robust standard errors in parentheses. Notation: ***p < 0.01, **p < 0.05, *p < 0.1

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Prediction 1: Importance of long-term volatility ✅

▸ Time series plot ▸ Futher predictors

Empirical Results: Testing for Volatility Feedback

i) separate sensitivity factors for good and bad news

$$R_t[k] \quad = \quad \beta_1 + \gamma_\tau^c \dot{\tau}_t + (1 + \gamma_\tau^+ \tilde{\tau}_t) \sum_{j=1}^{J} \beta_{2,j}^+ S_{j,t}^+ + (1 + \gamma_\tau^- \tilde{\tau}_t) \sum_{j=1}^{J} \beta_{2,j}^- S_{j,t}^- + \xi_t \tag{17}$$

with $\dot{\tau}_t = \tau_t - \bar{\tau}$, $S_{j,t}^+ = \mathbf{max}\{0, S_{j,t}\}$ and $S_{j,t}^- = \mathbf{min}\{0, S_{j,t}\}$.

ii) including squared terms

$$R_t[k] \quad = \quad \beta_1 + \gamma_\tau^c \dot{\tau}_t + (1 + \gamma_\tau \tilde{\tau}_t) \sum_{j=1}^{J} \beta_{2,j} S_{j,t} + \sum_{j=1}^{J} \beta_{3,j} S_{j,t}^2 + \xi_t \tag{18}$$

Empirical Results: Separate Sensitivity Factors for Good and Bad news

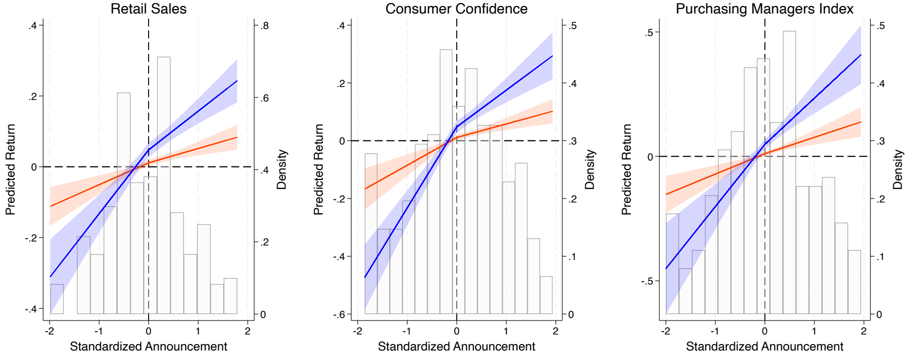
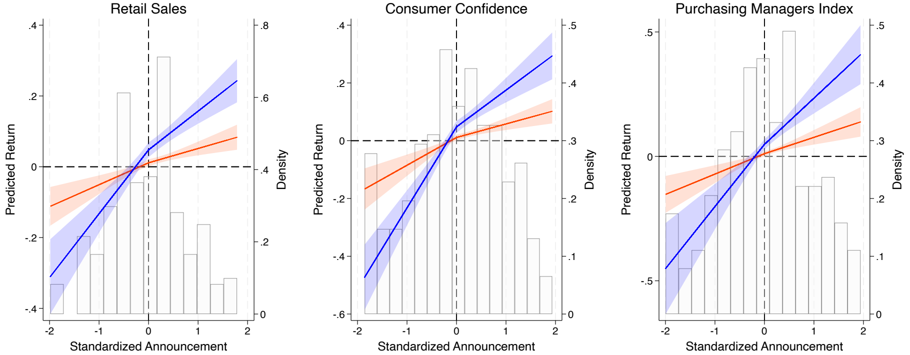


Figure 5: Predicted effect of macroeconomic news separated for good and bad news for different levels of the long-term volatility component where the red line corresponds to the 10% quantile and the blue line corresponds to the 90% quantile of the long-term component. Plotted with 90%-confidence intervals.

Empirical Results: Separate Sensitivity Factors for Good and Bad news



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Prediction 2: The 'no news is good news' effect increases with the level of long-term volatility ✅

Empirical Results: Including Squared Terms

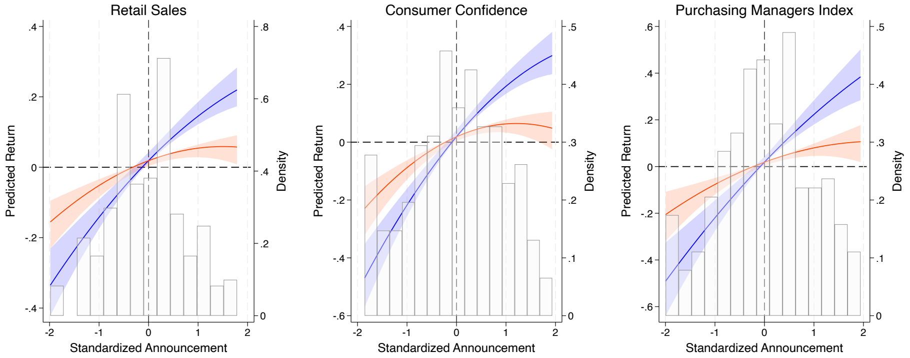

Figure 6: Predicted effect of macroeconomic news for different levels of the long-term volatility component where the red line corresponds to the 10% quantile and the blue line corresponds to the 90% quantile of the distribution of long-term component. Plotted with 90%-confidence intervals.

Empirical Results: Including Squared Terms

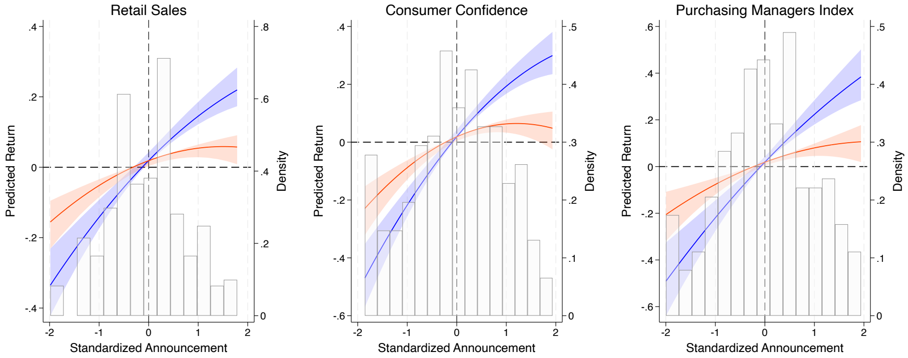

Figure 6: Predicted effect of macroeconomic news for different levels of the long-term volatility component where the red line corresponds to the 10% quantile and the blue line corresponds to the 90% quantile of the distribution of long-term component. Plotted with 90%-confidence intervals.

Prediction 3: Asymmetry - Within each volatility regime, large pieces of bad news have a stronger effect than large pieces of good news. ✅

Robustness Checks

Empirical findings are robust to

- ▸ R1 changing the window size around announcements (1 and 10 minutes)
- ▸ R2 separate regressions for 8:30 and 10:00 am EST
- ▸ R3 using S&P 500 returns for 10:00 am EST announcements
- ▸ R4 using Euro Stoxx 50 returns
- ▸ R5 excluding FOMC and ECB meeting days to account for pre-FOMC announcement drift
- ▸ R6 coding small surprises as zero surprises

Conclusions

Volatility feedback contributes to explaining the instantaneous response of the S&P 500 to major U.S. macroeconomic announcements

- long-term volatility component has explanatory power for the sensitivity of returns to news
- long-term volatility component remains relevant when controlling for variables considered important for the time-varying sensitivity of returns in Gardner et al. (2021) and Elenev et al. (2022)
- asymmetric response to good and bad news is most pronounced in high-volatility regimes
- response to negative news differs between low and high volatility regimes (cannot be explained by the theory of Gardner et al. (2021))
- approach can be easily extended to other countries (more difficult for other proxies)

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Volatility Feedback Effect: Motivation for MF2-GARCH

- one-component GARCH models assume that τ_t is constant
- standard misspecification tests check for predictability in $\eta^2_{d,t}/h_t$
- Conrad and Engle (2022) show that there is predictability in the (non-overlapping) $\frac{1}{m}\sum_{j=1}^{m}\eta^2_{d,t-j}/h_{t-j}$
  - $V^{(m)}_{t-1}$ as rolling window measure of the local bias of the GARCH component
- long-term component is exploiting this predictability
- model is dynamically complete
- returns are stationary: unconditional variance depends on κ
- implemented in the Volatility Lab (https://vlab.stern.nyu.edu)

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Volatility Feedback Effect: Motivation for MF2-GARCH

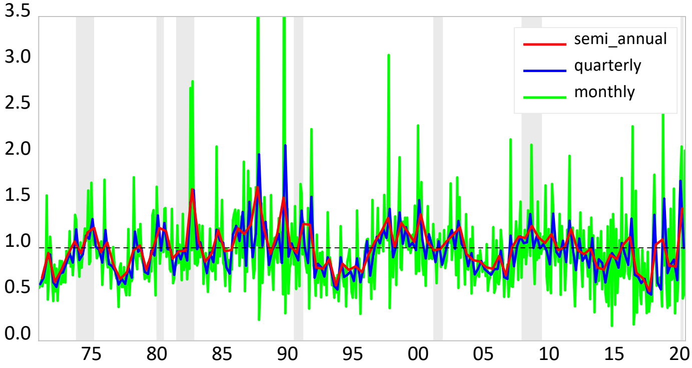

Figure 7: A GJR-GARCH(1,1) is estimated for the S&P 500 using daily return data for the January 1971 to June 2020 period. The figure shows the average volatility forecast errors at a semi-annual (red line), quarterly (blue line), and monthly (green line) frequency. Grey shaded areas represent NBER recession periods. Source: Conrad and Engle (2022).

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Volatility Feedback Effect

If σ_t^2 follows an MF2-GARCH, then for $j \geq 1$ forecasts of risks in period $t+j+1$ are updated based on the new information that becomes available in period $t+1$ according to

$$\mathbb{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbb{E}_t[\sigma^2_{t+j+1}] \quad = \quad A_j^\tau v_{t+1}^\tau + A_j^h v_{t+1}^h + A_j^{\sigma,\kappa}(v_{t+1}^\sigma + v_{t+1}^\kappa) \tag{19}$$

$$\text{with} \qquad A_j^\tau = (1-\phi)\sum_{s=1}^{j}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}(\lambda_1+\lambda_2)^{j-s},$$

$$A_j^h = \lambda_0 \sum_{s=1}^{j}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}\phi^{j-s}, \qquad A_j^{\sigma,\kappa} = (\lambda_1\phi_\kappa + \lambda_2\phi)^{j-1},$$

and

$$v_{t+1}^\sigma \quad = \quad \sigma^2_{t+1}\left[(\lambda_1\beta + \lambda_2\alpha)(Z^2_{t+1}-1) + \lambda_2\gamma(\mathbf{1}_{\{\eta_{d,t+1}<0\}}Z^2_{t+1} - 1/2))\right] \tag{20}$$

$$v_{t+1}^\kappa \quad = \quad \sigma^2_{t+1}\left[\lambda_1\left(\alpha\left(Z^4_{t+1}-\kappa\right) + \gamma\left(\mathbf{1}_{\{\eta_{d,t+1}<0\}}Z^4_{t+1} - \frac{\kappa}{2}\right)\right)\right]. \tag{21}$$

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Data: Announcements

Table 3: U.S. macroeconomic announcement data the for January 2001 to December 2021 period

		Observations	Unit	Release Time	Frequency
	Real activity				
1	Initial Jobless Claims	1095	Level	8:30 am EST	weekly
2	Nonfarm Payroll Employment (NPE)	251	Change	8:30 am EST	monthly
3	Retail Sales	244	% change	8:30 am EST	monthly
	Consumption				
4	New Family Houses Sold	252	Change	10:00 am EST	monthly
	Investment				
5	Durable Goods Orders	236	% change	8:30 am EST	monthly
6	Manufacturers New Orders	251	% change	10:00 am EST	monthly
	Prices				
7	Consumer Price Index	250	% change	8:30 am EST	monthly
	Forward-looking				
8	CB Consumer Confidence	252	Index	10:00 am EST	monthly
9	Purchasing Managers Index (PMI)	252	Index	10:00 am EST	monthly

To allow a consistent interpretation, we multiply jobless claims and the CPI with (-1).

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Data: Macroeconomic Announcement Calendar

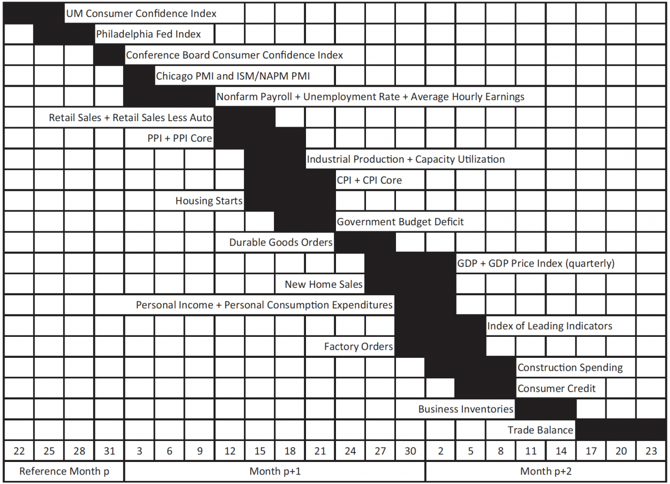

Figure 8: Macroeconomic announcement calendar (Gilbert et al., 2017)

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Empirical Results: Volatility components

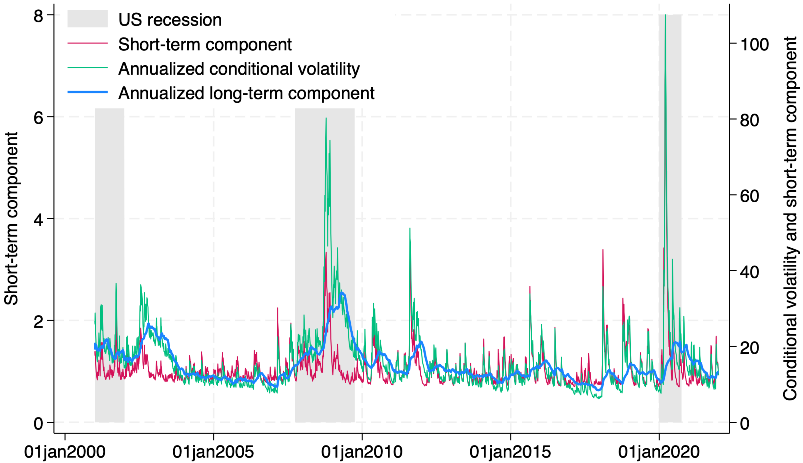

Figure 9: Plot of the one-step-ahead annualized volatility forecasts of the MF2-GARCH (expanding window).

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Empirical Results

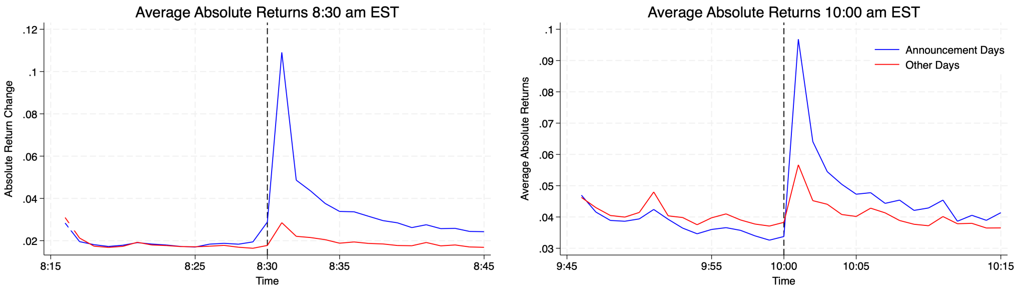

Figure 10: Average Absolute Returns in 15-minute windows around the announcements at 8:30 and 10:00 am EST.

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Empirical Results: Baseline Regression (One-Minute)

Table 4: Baseline Regression.

	(1)	(2)	(3)	(4)	(5)
$\tilde{\tau}_t$		1.537***		1.534***	1.519***
		(0.196)		(0.198)	(0.190)
$\tilde{h}_t$			0.106	0.033	0.029
			(0.221)	(0.203)	(0.199)
$\tilde{\tau}_t\tilde{h}_t$					0.383
					(0.536)
Nonfarm Payrolls	0.212***	0.201***	0.209***	0.201***	0.200***
	(0.029)	(0.024)	(0.030)	(0.024)	(0.024)
CPI	0.082***	0.061***	0.084***	0.062***	0.062***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)
Retail Sales	0.110***	0.095***	0.111***	0.095***	0.093***
	(0.016)	(0.014)	(0.016)	(0.014)	(0.014)
Durable Goods Orders	0.073***	0.078***	0.074***	0.078***	0.077***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.016)
Initial Jobless Claims	0.049***	0.049***	0.047***	0.049***	0.050***
	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)
Manufacturers New Orders	0.046***	0.044***	0.046***	0.044***	0.044***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
New Family Houses Sold	0.046***	0.062***	0.046***	0.062***	0.062***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.013)
Consumer Confidence	0.132***	0.133***	0.133***	0.133***	0.132***
	(0.018)	(0.015)	(0.018)	(0.015)	(0.015)
Purchasing Managers Index	0.152***	0.143***	0.150***	0.143***	0.141***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
Observations (Adjusted R^2)	2826 (0.189)	2826 (0.230)	2826 (0.189)	2826 (0.230)	2826 (0.230)

One minute estimation window. Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Empirical Results: Good and Bad News

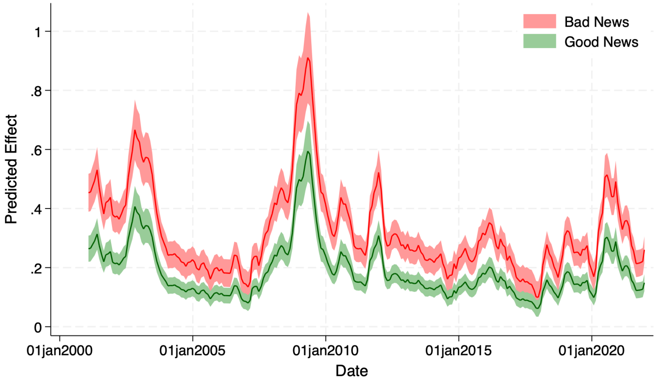

Figure 11: Predicted Effect of a positive and negative two-standard-deviation announcement surprise in Consumer Confidence over time with 68% confidence intervals.

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Empirical Results: Comparison with other explanations

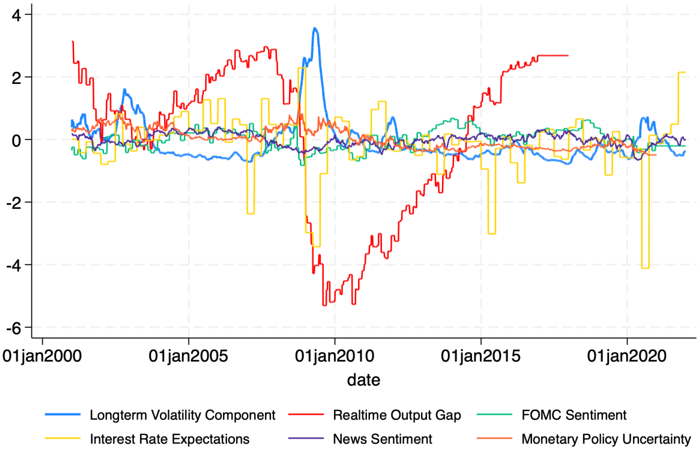

Figure 12: Alternative business cycle measures: CPI-adjusted interest rate expectations based on the Survey of Professional Forecasters, real-time output gap (Greenbook forecasts), and FOMC from Gardner et al. (2021).

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Empirical Results: Comparison with other explanations

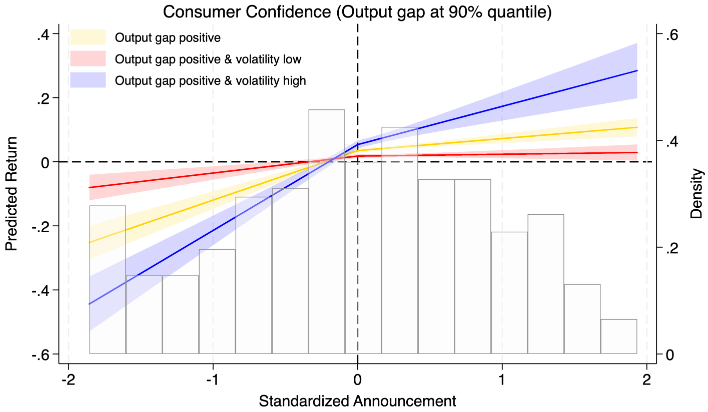

Figure 13: Interaction of output gap and long-term volatility for Consumer Confidence.

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Empirical Results: Comparison with other explanations

Table 5: Time-varying Sensitivity Regression Extended with Alternative Predictors.

	News-Sentiment		Business Conditions		Monetary Policy Uncerainty				Output Gap and Interest Rate Exp.		Risk Appetite	
	Shapiro et al. (2022)		Aruoba et al. (2009)		Bauer et al. (2021)		Husted et al. (2020)				Bauer et al. (2023)	
$W_{1,t-1}$	-1.292***	-0.110	0.038**	0.047***	1.145***	0.798***	-0.004***	-0.004***	-0.169***	-0.129***	-0.158*	-0.171***
	(0.373)	(0.412)	(0.018)	(0.017)	(0.188)	(0.204)	(0.001)	(0.001)	(0.022)	(0.026)	(0.069)	(-0.065)
$W_{2,t-1}$									0.081*	0.174***		
									(0.049)	(0.050)		
$\tilde{\tau}_t$		1.501***		1.543***		0.960***		1.512***		0.984***		1.537***
		(0.262)		(0.191)		(0.170)		(0.199)		(0.171)		(0.188)
Observations	2826	2826	2826	2826	2690	2690	2826	2826	2294	2294	2826	2826
Adjusted R^2	0.202	0.230	0.193	0.236	0.247	0.262	0.200	0.239	0.293	0.316	0.195	0.236

Five minutes estimation window. Robust standard errors in parentheses. Notation: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

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Robustness Checks: separate regressions for 8:30 and 10:00 am EST

Table 6: Separating between 8:30 am and 10:00 am EST

		(1)	(2)	(3)	(4)	(5)
8:30 am EST	Constant	0.005	0.011**	0.011**	0.011**	0.011**
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	$\tilde{\tau}_t$		1.483***		1.485***	1.454***
			(0.274)		(0.274)	(0.258)
	$\tilde{h}_t$			0.048	-0.017	-0.022
				(0.270)	(0.250)	(0.242)
	$\tilde{\tau}_t \tilde{h}_t$					0.514
						(0.679)
	Observations	1857	1857	1857	1857	1857
	Adjusted R^2	0.000	0.228	0.191	0.228	0.228
8:30 am EST	Constant	0.009	0.003	0.001	0.003	0.003
		(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
	$\tilde{\tau}_t$		1.601***		1.591***	1.590***
			(0.262)		(0.268)	(0.266)
	$\tilde{h}_t$			0.222	0.134	0.133
				(0.349)	(0.314)	(0.315)
	$\tilde{\tau}_t \tilde{h}_t$					0.131
						(0.812)
	Observations	969	969	969	969	969
	Adjusted R^2	0.000	0.232	0.188	0.232	0.231

All Announcements are significant on the 0.1% level.

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Robustness Checks: S&P 500 returns for 10:00 EST announcements

Table 7: Estimation results for the non-linear model using the S&P500 at 10:00 am with five-minute returns

	(1)	(2)	(3)	(4)
Constant	0.004	0.002	0.004	0.004
	(0.007)	(0.007)	(0.007)	(0.007)
$\tilde{\tau}_t$	1.620 ***		1.612 ***	1.612 ***
	(0.269)		(0.274)	(0.270)
$\tilde{h}_t$		0.206	0.118	0.120
		(0.343)	(0.306)	(0.311)
$\tilde{\tau}_t \tilde{h}_t$				-0.140
				(0.952)
Manufacturers New Orders	0.044 ***	0.045 ***	0.043 ***	0.044 ***
	(0.013)	(0.012)	(0.013)	(0.013)
New Family Houses Sold	0.063 ***	0.047 ***	0.064 ***	0.063 ***
	(0.012)	(0.011)	(0.012)	(0.012)
Consumer Confidence	0.129 ***	0.131 ***	0.129 ***	0.129 ***
	(0.015)	(0.019)	(0.015)	(0.015)
Purchasing Managers Index	0.143 ***	0.149 ***	0.140 ***	0.141 ***
	(0.019)	(0.018)	(0.018)	(0.019)
Observations	967	967	967	967
Adjusted R^2	0.240	0.194	0.240	0.239

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Robustness Checks: Euro Stoxx 50 Returns

Table 8: Regression of return changes of the Euro Stoxx 50 (50 blue-chip stocks from 11 Eurozone countries, 07:2003-12:2021)

	Panel A: Long-term volatility component of Euro Stoxx 50				*Panel B: Long-term volatility component of S&P 500*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{\tau}_t$	1.344***		1.395***	1.415***	1.257***		1.265***	1.277***
	(0.240)		(0.239)	(0.229)	(0.179)		(0.181)	(0.177)
$\tilde{h}_t$		0.097	0.137	0.175		-0.023	-0.082	-0.083
		(0.201)	(0.236)	(0.217)		(0.164)	(0.136)	(0.138)
$\tilde{\tau}_t \tilde{h}_t$			-0.771					-0.206
			(0.867)					(0.593)
Initial Jobless Claims	0.062***	0.061***	0.059***	0.060***	0.063***	0.060***	0.064***	0.064***
	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Nonfarm Payrolls	0.266***	0.252***	0.254***	0.260***	0.257***	0.259***	0.260***	0.260***
	(0.037)	(0.040)	(0.037)	(0.037)	(0.031)	(0.033)	(0.030)	(0.031)
Retail Sales	0.106***	0.093**	0.099**	0.099**	0.079*	0.094***	0.079*	0.083**
	(0.035)	(0.046)	(0.041)	(0.043)	(0.045)	(0.035)	(0.044)	(0.040)
New Family Houses Sold	0.072***	0.067***	0.075***	0.074***	0.074***	0.051***	0.074***	0.074***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.012)	(0.015)	(0.015)
Durable Goods Orders	0.095***	0.112***	0.095***	0.098***	0.102***	0.089***	0.100***	0.101***
	(0.019)	(0.022)	(0.018)	(0.018)	(0.014)	(0.017)	(0.014)	(0.015)
Manufacturers New Orders	0.032*	0.043**	0.029	0.031*	0.042**	0.041***	0.042**	0.042**
	(0.019)	(0.017)	(0.018)	(0.018)	(0.017)	(0.015)	(0.017)	(0.017)
Consumer Price Index	0.046**	0.072***	0.050***	0.049**	0.054***	0.064***	0.051***	0.051**
	(0.018)	(0.022)	(0.019)	(0.019)	(0.020)	(0.018)	(0.020)	(0.020)
Consumer Confidence	0.139***	0.138***	0.140***	0.140***	0.156***	0.141***	0.156***	0.156***
	(0.023)	(0.023)	(0.022)	(0.023)	(0.020)	(0.023)	(0.020)	(0.021)
Purchasing Managers Index	0.177***	0.192***	0.171***	0.174***	0.178***	0.176***	0.180***	0.182***
	(0.028)	(0.030)	(0.028)	(0.029)	(0.028)	(0.024)	(0.028)	(0.029)
Constant	0.016***	0.017***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	1988	1988	1988	1988	2459	2459	2459	2459
Adjusted R^2	0.206	0.183	0.208	0.208	0.213	0.183	0.213	0.213

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Robustness Checks: excluding FOMC and ECB meeting days

FOMC press conference days are associated with large average excess returns (Lucca and Moench, 2015)

Table 9: Excluding FOMC and ECB meeting press conference days.

	(1)	(2)	(3)	(4)	(5)
$\tilde{\tau}_t$		1.579***		1.575***	1.563***
		(0.203)		(0.206)	(0.197)
$\tilde{h}_t$			0.127	0.055	0.049
			(0.253)	(0.238)	(0.237)
$\tilde{\tau}_t\ \tilde{h}_t$					0.308
					(0.585)
Initial Jobless Claims	0.051***	0.051***	0.049***	0.050***	0.051***
	(0.009)	(0.008)	(0.010)	(0.008)	(0.008)
Employees on Nonfarm Payrolls	0.212***	0.201***	0.208***	0.200***	0.200***
	(0.030)	(0.025)	(0.030)	(0.024)	(0.024)
Retail Sales	0.121***	0.102***	0.122***	0.103***	0.100***
	(0.017)	(0.015)	(0.017)	(0.015)	(0.015)
Durable Goods Order	0.072***	0.064***	0.044***	0.064***	0.064***
	(0.017)	(0.013)	(0.011)	(0.013)	(0.013)
Consumer Price Index	0.089***	0.079***	0.074***	0.079***	0.079***
	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
New Family Houses Sold	0.044***	0.046***	0.047***	0.046***	0.046***
	(0.011)	(0.018)	(0.015)	(0.018)	(0.017)
Manufacturers New Orders	0.047***	0.077***	0.092***	0.078***	0.078***
	(0.015)	(0.018)	(0.019)	(0.018)	(0.017)
Consumer Confidence	0.130***	0.130***	0.131***	0.130***	0.130***
	(0.018)	(0.015)	(0.019)	(0.015)	(0.015)
Purchasing Managers Index	0.150***	0.143***	0.147***	0.142***	0.140***
	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
Constant	0.008*	0.009**	0.009**	0.009**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2470	2470	2470	2470	2470
Adjusted R^2	0.195	0.239	0.195	0.239	0.239

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Robustness Checks: coding small surprises as zero surprises

Table 10: Time-varying sensitivity of stock returns estimated as in equation (15) with small surprises as zero surprises.

	(1)	(2)	(3)	(4)
Constant	0.008 **	0.008 *	0.008 **	0.009 **
	(0.004)	(0.004)	(0.004)	(0.004)
$\tilde{\tau}_t$	1.528 ***		1.526 ***	1.510 ***
	(0.196)		(0.198)	(0.190)
$\tilde{h}_t$		0.105	0.032	0.027
		(0.221)	(0.203)	(0.199)
$\tilde{\tau}_t \tilde{h}_t$				0.391
				(0.535)
Initial Jobless Claims	0.050 ***	0.048 ***	0.049 ***	0.050 ***
	(0.006)	(0.008)	(0.006)	(0.006)
Nonfarm Payrolls	0.201 ***	0.209 ***	0.201 ***	0.200 ***
	(0.025)	(0.030)	(0.024)	(0.024)
Retail Sales	0.095 ***	0.111 ***	0.096 ***	0.093 ***
	(0.014)	(0.016)	(0.014)	(0.014)
New Family Houses Sold	0.061 ***	0.046 ***	0.061 ***	0.062 ***
	(0.012)	(0.011)	(0.012)	(0.013)
Durable Goods Orders	0.078 ***	0.074 ***	0.079 ***	0.077 ***
	(0.016)	(0.017)	(0.016)	(0.016)
Manufacturers New Orders	0.044 ***	0.046 ***	0.044 ***	0.044 ***
	(0.014)	(0.013)	(0.014)	(0.013)
Consumer Price Index	0.062 ***	0.085 ***	0.062 ***	0.062 ***
	(0.017)	(0.018)	(0.017)	(0.017)
Consumer Confidence	0.132 ***	0.133 ***	0.133 ***	0.132 ***
	(0.015)	(0.018)	(0.015)	(0.015)
Purchasing Managers Index	0.143 ***	0.150 ***	0.143 ***	0.141 ***
	(0.020)	(0.020)	(0.020)	(0.020)
Observations	2826	2826	2826	2826
Adjusted R^2	0.229	0.189	0.229	0.229

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