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Long-Term Volatility Shapes the Stock Market's Sensitivity to News

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AWI DISCUSSION PAPER SERIES NO. 739
November 2023

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November 23, 2023

Abstract

We show that the S&P 500's instantaneous response to surprises in U.S. macroeconomic announcements depends on the level of long-term stock market volatility. When long-term volatility is high, stock returns are more sensitive to news, and there is a pronounced asymmetry in the response to good and bad news. We explain this by combining the Campbell-Shiller log-linear present value framework with a two-component volatility model for the conditional variance of cash flow news and allowing for volatility feedback. In our model, innovations to the long-term volatility component are the most important driver of discount rate news. Large announcement surprises lead to upward revisions in future required returns, which dampens/amplifies the effect of good/bad news.

Keywords: event study, long- and short-term volatility, macroeconomic announcements, stock market response, time-varying risk premia, volatility feedback effect

JEL Classification: C58, E44, G12, G14

*First version: July 2022. We would like to thank Michael Bauer, Mark Kerssenfischer, Faek Menla Ali, Anne Opschoor, Marc-Oliver Pohle, Manuel Schick, and Michael Weber, as well as seminar and conference participants at the Economic Expectations, Survey Data, and Experiments workshop in Heidelberg (July 2022), University of Heidelberg (February 2023, June 2023), University of Sussex (March 2023), International Conference for Quantitative Finance and Financial Econometrics at the Aix-Marseille School of Economics (June 2023), the Society of Financial Econometrics (SoFiE) European Summer School (June 2023), the 10th HKMetrics Workshop in Karlsruhe (July 2023), the Econometric Society European Meeting (August 2023), the Verein für Socialpolitik Annual Conference (September 2023), and the Oxford Statistics and Machine Learning in Finance Seminar (November 2023) for helpful comments and suggestions. The views expressed are those of the authors and do not necessarily reflect those of the European Central Bank or the Eurosystem. Funding by the German Federal Ministry of Education and Research (BMBF) and the Baden-Württemberg Ministry of Science as part of Germany's Excellence Strategy is gratefully acknowledged. Previously circulated as "Macroeconomic Announcements and the Volatility Feedback Effect".

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1 Introduction

Why does the sensitivity of stock markets to the release of macroeconomic news vary over time? This fundamental question has recently regained considerable attention. Gardner et al. (2022) and Elenev et al. (2023) explain the stock market's time-varying sensitivity to macroeconomic news by variation in the relative importance of cash flow versus discount rate news over the business cycle. Specifically, they highlight the importance of revisions in expectations about monetary policy for the strength of the discount rate effect. When the economy is in a good state, the central bank is expected to tighten monetary policy in response to good news, while it is not expected to change policy in response to good news in bad states. Hence, the discount rate effect of good news will weaken the positive cash flow effect in good but not in bad states of the economy. The notion that the importance of discount rate news varies over the business cycle goes back to McQueen and Roley (1993), Boyd et al. (2005), and Andersen et al. (2007). While Elenev et al. (2023) find that the output gap has the most explanatory power for explaining the time-varying sensitivity, Gardner et al. (2022) develop an FOMC sentiment index.

We propose a complementary explanation for the time-varying sensitivity of the stock market that is based on the *volatility feedback effect*: If volatility is priced, a positive volatility innovation increases expected future risks and, hence, required returns, resulting in a concurrent decline in stock prices. Depending on the current level of volatility, good news about the macroeconomy can result in a positive or negative volatility innovation and, thereby, induce a discount rate effect that reinforces or mitigates the positive cash flow effect. Because volatility varies over time, the same news can have a strong impact at one point in time, but a weak impact at other times. Thus, our explanation also focuses on discount rate news but is risk-based and not driven by expectations about monetary policy. Our main contribution is to show theoretically and empirically that volatility feedback contributes significantly to explaining the stock market's time-varying sensitivity and that the level of long-term volatility is an important predictor of the strength of the effect of macroeconomic news.

The importance of the volatility feedback effect for explaining stock price movements has been emphasized, for example, by Pindyck (1984), French et al. (1987), Campbell and Hentschel (1992), and Engle (2011). For analyzing the role of the volatility feedback effect in explaining stock returns, Campbell and Hentschel (1992) employ the Campbell-Shiller log-linear present value framework, assume that the conditional variance of cash flow news follows a GARCH-type process and highlight the *no news is good news* effect: When there is no cash flow news, expected future volatility and, hence, required returns are revised downwards and stock prices increase.

Conceptually, the volatility feedback effect rests on two pillars: (i) a positive relationship between risk and expected returns and (ii) volatility persistence. Only if volatility is persistent, volatility news will generate sufficient variation in future required returns to generate significant changes in stock prices. Hence, the appropriate modeling of the conditional variance of cash flow news is crucial. We draw on recent developments in the literature on volatility models and assume that the conditional variance of cash flow news follows a multiplicative factor multi-frequency GARCH (MF2-GARCH) process (Conrad and Engle, 2022). In this model, the conditional volatility is decomposed into a short- and a long-term component. While the short-term component captures day-to-day movements in volatility, the persistent long-term component is closely related to macroeconomic and financial conditions and behaves counter-cyclical (see Conrad and Engle, 2022). In contrast to other multiplicative GARCH models, the MF2-GARCH ensures that cash flow news is covariance stationary and multi-step ahead volatility forecasts can be easily computed. For forecast horizons of more than half a year, the forecast of the conditional volatility is predominantly determined by the forecast of the long-term component. Hence, the long-term component can be interpreted as determining the medium- and long-term volatility expectation. By combining the framework of Campbell and Hentschel (1992) with the assumption of an MF2-GARCH for the conditional variance of cash flow news, we can express news to expected returns, i.e. discount rate news, as a function of news to the short- and long-term component of volatility. Based on this model, we derive three testable predictions. First, under reasonable assumptions on model parameters, the volatility feedback effect is mainly driven by the news to long-term volatility. The intuition is that only news to the long-term component does have a sufficiently persistent effect to generate sizeable variation in discount rates. In addition, stock returns are more sensitive to news when long-term volatility is high. Second, for large pieces of good/bad news the volatility feedback effect will dampen/amplify the positive/negative cash flow effect and, hence, good and bad news have an asymmetric effect on unexpected returns. The asymmetric effect is most pronounced when long-term volatility is high. Third, in our model, the *no news is good news* effect increases with the level of long-term volatility.

Using an event-study design, we empirically evaluate our model's predictions using S&P 500 future returns and major U.S. macroeconomic announcements data over the 2001 to 2021 period. We regress high-frequency stock returns in short windows around nine macroeconomic announcements on each announcement's surprise component while controlling for the level of short- and long-term volatility as implied by the MF2-GARCH. We show that the strength of the announcement effect increases with the level of long-term volatility. We find strong evidence for an asymmetric response to good and bad news, which is again dependent on the level of long-term volatility. When long-term volatility is high, the effect of good news is dampened by the discount rate effect, while the effect of bad news is amplified. Importantly, even after controlling for the variables considered in Gardner et al. (2022) (FOMC sentiment) and Elenev et al. (2023) (output gap, interest rate expectations), the long-term component of stock market volatility remains an important predictor of the time-varying sensitivity. At first, this result might appear to conflict with Elenev et al. (2023), who conclude that periods of high volatility do not coincide with a higher news sensitivity of the stock market. Their conclusion is based on the observation that the CBOE Volatility Index (VIX) becomes insignificant when controlling for the output gap. However, we show that measures of short-term risk, such as the VIX or the conditional variance from a one-component GARCH model, also lose their explanatory power for the time-varying sensitivity when the long-term component of the MF2-GARCH is included. Hence, while we confirm Elenev et al. (2023) in that short-term volatility does not drive the sensitivity, our results strongly suggest that it is the long-term component of volatility that contributes to shaping the time-varying sensitivity and that the underlying mechanism is the volatility feedback effect. Our empirical evidence is consistent with the notion that mainly long-term risks are priced in the risk-return relationship (see, Maheu and McCurdy, 2007; Kim and Nelson, 2013). Cochrane (2011) has highlighted the importance of variation in discount rates in explaining variation in returns, and our results show that the volatility feedback effect is an important component of discount rate news.

We also contribute to the literature on the importance of macroeconomic announcements more generally (see, Guerkaynak et al., 2020; Kerssenfischer and Schmeling, 2022; Ogneva et al., 2022). While surprises in macroeconomic announcements explain roughly 19% in the variation of returns in 5-minute windows around the announcements, the explained variation increases to 23% when using long-term volatility as a driver of the time-varying sensitivity. The explained variation further increases when modeling the time-varying sensitivity as a function of long-term volatility and the output gap. Then, we can explain up to 32% of the variation in returns. Our finding that the level of long-term stock market volatility is a strong driver of the time-varying sensitivity complements recent findings on the effects of monetary policy surprises by Bauer et al. (2021). They show that the effect of monetary policy surprises on the stock market depends on the level of monetary policy uncertainty.

The remaining paper is organized as follows. Section 2 provides a review of the related literature, Section 3 presents our model and its predictions, and Section 4 the empirical analysis. Section 5 provides robustness checks, and Section 6 concludes. The proofs of Theorems 1 and 2 are presented in Appendix A, and Appendix B contains additional tables and figures.

2 Related Literature

Since McQueen and Roley (1993), a growing body of literature has focused on explaining the differences between the stock market's response to macroeconomic announcements in recessions and expansions. For example, Boyd et al. (2005) show that stock markets increase in response to lower-than-expected unemployment rates during recessions but decrease after the same news during expansions. The decomposition of unexpected returns into cash flow and discount rate news, developed by Campbell and Shiller (1988), suggests that changes in the relative importance of cash flow and discount rate news over the business cycle drive the time-varying sensitivity of returns to news. During economic expansions, the positive cash flow effect of good news is dampened by the discount rate effect due to the expectation of tighter monetary policy. In contrast, during contractions, unexpected returns are mainly driven by cash flow news (Boyd et al., 2005; Andersen et al., 2007). The more recent literature abandons the dichotomous distinction between recessions and expansions and, instead, aims at granular predictors for explaining the time-varying role of cash flow and discount rate news for the sensitivity of the stock market. Elenev et al. (2023) show that, in particular, the output gap has strong predictive power. They find that the stock market's sensitivity is the highest at the beginning of an economic expansion and almost zero towards the end of an expansion. Specifically, when the output gap is most negative, the stock market is particularly sensitive because good news about future cash flows is least offset by news about future risk-free rates. While the output gap is intended to measure the actual state of the economy, Gardner et al. (2022) argue that it is the description of the state of the economy in the FOMC statement that is most important. They develop a sentiment index based on the FOMC statement and provide evidence that the reaction to good news is more pronounced when the FOMC statement signals a negative outlook. Again, in this situation, the positive cash flow news is not offset by discount rate news because no change in monetary policy is expected. In contrast, when the FOMC statement is bullish, the cash flow effect of positive macroeconomic news is diminished by the discount rate effect. Gardner et al. (2022) argue that the effect of bad news does not vary much with the state of the economy. In good times, monetary policy is unlikely to respond to bad news by loosening monetary policy, and, in bad times, monetary policy is already expansionary or restricted by the effective lower bound (see Table A.1 in the Appendix of Gardner et al., 2022).

A complementary explanation for the time-varying sensitivity of stock returns rests on the volatility feedback effect. This effect implies that risk premium news is a key driver of discount rate news. Assuming a positive relation between risk and expected returns in combination with persistent volatility, positive volatility news increases future required returns and induces a decline of the stock price. Thus, the volatility feedback effect explains the negative correlation between news to volatility and unexpected stock returns (French et al., 1987). Campbell and Hentschel (1992) formalize this idea in a model in which changes in required returns are determined solely by changes in risk premia. They assume that the conditional variance of cash flow news follows a QGARCH and that there is a positive relation between expected returns and the conditional variance of cash flow news. If good news about future cash flows is sufficiently strong, volatility expectations and, hence, required returns will be revised upwards. Then, the discount rate effect will partly offset the positive cash flow effect. In contrast, in response to bad news of the same size, the discount rate effect reinforces the cash flow effect. Following Campbell and Hentschel (1992), several studies have provided further evidence for the importance of the volatility feedback effect. Bekaert and Wu (2001) find that volatility feedback is better suited to explain the negative correlation between returns and volatility than the leverage effect, and Bollerslev et al. (2006) provide evidence for instantaneous volatility feedback in high-frequency data. Engle (2011) links the volatility feedback effect to skewness in long-horizon returns and systemic risk.

The recent literature on modeling stock market volatility suggests that the conditional variance of stock returns is best described as consisting of a short- and long-term component (e.g. Engle and Rangel, 2008; Engle et al., 2013; Conrad and Loch, 2015; Conrad and Kleen, 2020). Engle et al. (2013) suggest the GARCH-MIDAS model, in which the long-term component is driven by macroeconomic and financial explanatory variables and behaves counter-cyclical. For example, Conrad and Loch (2015) show that long-term stock volatility is high when the term spread signals an upcoming recession and low when expected future business conditions are bright. The drawback of the GARCH-MIDAS, however, is that multi-step volatility forecasts are difficult to compute (because forecasts are needed for the explanatory variables in the long-term component) and that relevant variables may change over time. The MF2-GARCH of Conrad and Engle (2022) overcomes those shortcomings by modeling the long-term component as a function of the short-term component's volatility forecast errors. In this model, returns are stationary, and multi-step ahead volatility forecasts can be easily computed. In addition, in line with the volatility feedback effect, Conrad and Engle (2022) show that major news events, whether good or bad, lead to upward revisions in expected long-term volatility.

We also draw on the literature on modeling the risk-return relation. As emphasized by Conrad and Karanasos (2015), the appropriate modeling of the conditional variance is of crucial importance when employing GARCH-in-Mean models. Maheu and McCurdy (2007) and Kim and Nelson (2013) provide evidence that only long-term, business cycle-related volatility is priced in the risk-return relation. Campbell and Diebold (2009) show that a positive economic outlook predicts lower future volatility and lower expected future returns. The findings concerning the importance of long-term volatility in the literature on volatility modeling are consistent with evidence on the pricing of long-run risks in the asset pricing literature (see, for example, Bansal and Yaron, 2004; Adrian and Rosenberg, 2008; Campbell, 2018). Finally, Kim and Kim (2019) propose a model for returns, where expected returns are driven by market volatility. They specify market-volatility as a regime-switching process with the latent regimes driven by macroeconomic factors. Their model features volatility feedback, and risk-premium news is a function of news about macroeconomic factors.

Our paper is also closely related to the literature on the relative importance of the effects of the various macroeconomic announcements. Andersen et al. (2003, 2007) and Kilian and Vega (2011), amongst others, argue that the timeliness of macroeconomic announcements matters in explaining the strength of their effect. For example, market participants closely monitor Nonfarm Payroll Employment, which is the first published real activity measure every month. Gürkaynak and Wright (2013) explain the importance of this announcement by its informativeness for predicting the Federal Reserve's future policy actions. More generally, Gilbert et al. (2017) show that the 'intrinsic value' of an announcement consists of three components. Announcements are more valuable when they are timely, subject to few revisions, and have a nowcasting ability for GDP growth, the GDP price deflator, and the Federal Funds Target Rate.

Finally, there is literature that links the effects of macroeconomic announcements to uncertainty. For example, in Veronesi's (1999) model, good news has a weaker impact in bad times than in good times. The reason is that good news in bad times increases uncertainty about the true state of the economy, and risk-averse investors require a higher return in response. This dampens the positive cash flow effect of the good news. Kurov and Stan (2018) show empirically that macroeconomic news have weaker effects when uncertainty about monetary policy is high. The explanation is that investors update their expectations of monetary policy more in response to news when monetary policy uncertainty is high. For example, the positive effect of good news is partially offset by expectations of tighter monetary policy when monetary policy uncertainty is high, but not when it is low.

3 Volatility Feedback

In modeling the volatility feedback effect, we follow Campbell and Hentschel (1992) and combine the present value model of Campbell and Shiller (1988) with a GARCH-type model for the conditional variance of cash flow news. In this framework, the volatility feedback effect rests on two pillars. First, a positive, linear relationship between expected returns and the conditional variance of cash flow news. Second, the model for the conditional variance needs to ensure that the effects of volatility innovations are persistent enough to generate sufficient variation in discount rates (Poterba and Summers, 1986). As in Campbell and Hentschel (1992), we assume that discount rate news is solely driven by news about future risks. Although this assumption may appear to be rather strong, it will allow us to generate clear predictions about the effect of volatility feedback on the time-varying sensitivity of the stock market. In the empirical analysis in Section 4, our econometric framework will allow for risk premium news as well as risk-free rate news.

3.1 Model for stock returns

To begin, we define daily log returns as

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

where P_t and D_t are prices and dividends and p_{t+1} and d_{t+1} are log prices and log dividends. Using the Campbell and Shiller (1988) and Campbell (1991) log-linear approximation, we write unexpected returns in $t + 1$ as

$$r_{t+1} - \mathbf{E}_t[r_{t+1}] = \eta_{d,t+1} - \eta_{r,t+1}, \tag{2}$$

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

$$\begin{aligned}
\eta_{d,t+1} &= \sum_{j=0}^{\infty} \rho^j \left(\mathbf{E}_{t+1} \left[\Delta d_{t+1+j} \right] - \mathbf{E}_t \left[\Delta d_{t+1+j} \right] \right) \\
\eta_{r,t+1} &= \sum_{j=1}^{\infty} \rho^j \left(\mathbf{E}_{t+1} \left[r_{t+1+j} \right] - \mathbf{E}_t \left[r_{t+1+j} \right] \right)
\end{aligned}$$

with $\rho = 1/(1 + \exp(\overline{d - p})) < 1$. For daily return data ρ is very close to but below one. For example, Engle (2011) assumes that $\rho = 0.9998$ for daily U.S. stock market returns. Equation (2) illustrates the importance of news about required returns for explaining unexpected returns. Even in the absence of innovations to future cash flows ($\eta_{d,t+1} = 0$), there can be unexpected returns due to news about required returns. Following Campbell and Hentschel (1992), we assume that expected returns can be written as

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

where μ is a positive constant, δ is the coefficient of relative risk aversion and σ_{t+1}^2 denotes the conditional variance of cash flow news. Using equation (3), we can rewrite the news about required returns $\eta_{r,t+1}$ as

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

In our model, $\eta_{r,t+1}$ is exclusively driven by news about risk, i.e., captures the volatility feedback effect. That is, as mentioned before, we abstract from other sources (e.g., changes in expectations about future interest rates) that might induce changes in expected returns.[1]

We complete the model by making an assumption about the specification of the conditional variance of cash flow news. We assume that $\eta_{d,t}$ follows an MF2-GARCH as introduced in Conrad and Engle (2022). The MF2-GARCH ensures the stationarity of $\eta_{d,t}$, and computing multi-step ahead volatility forecasts is straightforward. In this model, cash flow news can be written as:

$$\eta_{d,t} = \sigma_t Z_t = \sqrt{h_t \tau_t} Z_t, \tag{5}$$

where τ_t and h_t are the long- and short-term components of volatility and Z_t is an innovation. We assume that the Z_t are i.i.d. with a symmetric density, $\mathbf{E}[Z_t] = 0$ and $\mathbf{E}[Z_t^2] = 1$. Further, Z_t^2 is assumed to have a non-degenerate distribution and $\kappa = \mathbf{E}[Z_t^4] < \infty$. The short-term component follows a GJR-GARCH and is given by

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

with $\alpha > 0$, $\alpha + \gamma > 0$, $\beta > 0$ and $\phi = \alpha + \gamma/2 + \beta < 1$ measuring the persistence in the short-term component. By construction, the short-term component has an expected value of one and fluctuates around the long-term component. The long-term component is defined as

$$\tau_t = \lambda_0 + \lambda_1 V_{t-1}^{(m)} + \lambda_2 \tau_{t-1}, \tag{7}$$

where $V_{t-1}^{(m)} = \frac{1}{m} \sum_{j=1}^{m} \frac{\eta_{d,t-j}^2}{h_{t-j}}$ with $\lambda_0 > 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ and $\lambda_1 + \lambda_2 < 1$. Note that we can think of $\eta_{d,t}^2$ as an unbiased proxy for the conditional variance of cash flow news. Hence, $V_{t-1}^{(m)}$ is a measure for the *local bias* of the short-term component during the previous m periods. That is, the 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. If the long-term component is constant, the MF2-GARCH reduces to the GJR-GARCH of Glosten et al. (1993). For details on the model and the estimation using quasi maximum likelihood (QML), see Conrad and Engle (2022).

3.2 Discount rate news

Next, we derive an explicit expression for the news to required returns. For simplicity in the notation but without loss of generality, we assume that $m = 1$ and $\phi < \lambda_1 + \lambda_2$. The latter condition ensures identification and implies that shocks to the long-term component have more

[1] Alternatively, we think of risk-free rate news as implicitly incorporated in the cash flow news (see Engle, 2011).

persistent effects than shocks to the short-term component. As shown in Conrad and Engle (2022), for $m = 1$ the cash flow news, $\eta_{d,t}$, are covariance stationary if $\lambda_1\phi_\kappa + \lambda_2\phi < 1$, where $\phi_\kappa = (\alpha + \gamma/2)\kappa + \beta$. News to expected returns depend on the revision of expectations about future volatility: $\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbf{E}_t[\sigma^2_{t+j+1}]$. For $j \geq 1$, this revision depends on volatility news that materializes in $t+1$. We can rewrite equation (6) as

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

where $\tilde{v}^h_{t+1} = \left[\alpha\left(Z^2_{t+1} - 1\right) + \gamma\left(\mathbf{1}_{\{Z_{t+1}<0\}}Z^2_{t+1} - \frac{1}{2}\right)\right]$. Similarly, equation (7) can be written as

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

where $\tilde{v}^\tau_{t+1} = \lambda_1\left(Z^2_{t+1} - 1\right)$. We refer to $v^h_{t+1} = h_{t+1}\tilde{v}^h_{t+1}$ and $v^\tau_{t+1} = \tau_{t+1}\tilde{v}^\tau_{t+1}$ as the innovations to the short- and long-term volatility component, respectively. By construction, v^h_{t+1} and v^τ_{t+1} are white noise.

For $j = 1$, we can write the period t to $t+1$ revision in the expected conditional variance as

$$\mathbf{E}_{t+1}[\sigma^2_{t+2}] - \mathbf{E}_t[\sigma^2_{t+2}] = (1-\phi)\tau_{t+1}\tilde{v}^\tau_{t+1} + \lambda_0 h_{t+1}\tilde{v}^h_{t+1} + \sigma^2_{t+1}\tilde{v}^\sigma_{t+1}, \tag{10}$$

where

$$\begin{aligned}\tilde{v}^\sigma_{t+1} = & \left[(\lambda_1\beta + \lambda_2\alpha)(Z^2_{t+1} - 1) + \lambda_2\gamma\left(\mathbf{1}_{\{Z_{t+1}<0\}}Z^2_{t+1} - \frac{1}{2}\right)\right] \\ & + \left[\lambda_1\left(\alpha\left(Z^4_{t+1} - \kappa\right) + \gamma\left(\mathbf{1}_{\{Z_{t+1}<0\}}Z^4_{t+1} - \frac{\kappa}{2}\right)\right)\right].\end{aligned} \tag{11}$$

We refer to $v^\sigma_{t+1} = \sigma^2_{t+1}\tilde{v}^\sigma_{t+1}$ as conditional variance news. v^σ_{t+1} is a function of the news to the short- and long-term components and, due to the correlation between $\tilde{v}^h_{t+1}$ and $\tilde{v}^\tau_{t+1}$, depends on the fourth moment of Z_t.

Theorem 1. *If σ^2_t follows an MF2-GARCH, then for $j \geq 1$, the forecast of risk in period $t+j+1$ is updated based on the new information that becomes available in period $t+1$ according to*

$$\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbf{E}_t[\sigma^2_{t+j+1}] = A^\tau_j\tau_{t+1}\tilde{v}^\tau_{t+1} + A^h_j h_{t+1}\tilde{v}^h_{t+1} + A^\sigma_j\sigma^2_{t+1}\tilde{v}^\sigma_{t+1} \tag{12}$$

with

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

The first two terms in equation (12) illustrate that volatility expectations are updated because of shocks to the short- and long-term component. In addition, expectations are updated due to conditional variance news. The following theorem shows that we can write news to expected returns as a function of the three innovations.

Theorem 2. *If returns are generated according to equations (2) and (3) and σ_t^2 follows an MF2-GARCH, then period $t+1$ news to required returns is given by*

$$\eta_{r,t+1} = A^\tau\tau_{t+1}\tilde{v}_{t+1}^\tau + A^h h_{t+1}\tilde{v}_{t+1}^h + A^\sigma\sigma_{t+1}^2\tilde{v}_{t+1}^\sigma \tag{13}$$

with

$$\begin{aligned} A^\sigma &= \delta\sum_{j=1}^{\infty}\rho^j(\lambda_1\phi_\kappa+\lambda_2\phi)^{j-1} = \delta\rho\frac{1}{1-\rho(\lambda_1\phi_\kappa+\lambda_2\phi)}, \\ A^\tau &= A^\sigma\frac{1-\phi}{1-\rho(\lambda_1+\lambda_2)}, \qquad A^h = A^\sigma\frac{\lambda_0}{1-\rho\phi}. \end{aligned}$$

Equation (13) shows how news to volatility drives discount rate news. Recall that we assumed $\phi < \lambda_1+\lambda_2$, i.e., news to long-term volatility is more persistent than news to short-term volatility. For daily data, ρ is very close to one implying that $A^\sigma < A^\tau$. Under reasonable assumptions on the parameters (see Section 3.3), we will also have that $A^h < A^\sigma$, indicating that shocks to the long-term component have the strongest effect on discount rate news. Corollary 1 in Appendix A shows how equation (13) simplifies when the long-term component is constant. In this case, our model essentially reduces to the setting considered in Campbell and Hentschel (1992).

3.3 Testable model predictions

Combining equation (2) with equations (5) and (13) leads to

$$\begin{aligned} r_{t+1} - \mathbf{E}_t[r_{t+1}] &= \eta_{d,t+1} - \eta_{r,t+1} \\ &= \sqrt{\tau_{t+1}h_{t+1}}Z_{t+1} \\ &\qquad - \left(A^\tau\tau_{t+1}\tilde{v}_{t+1}^\tau + A^h h_{t+1}\tilde{v}_{t+1}^h + A^\sigma\tau_{t+1}h_{t+1}\tilde{v}_{t+1}^\sigma\right). \end{aligned} \tag{14}$$

Since τ_{t+1} and h_{t+1} are fixed conditional on information available at time t, equation (14) shows that the excess return is a function of Z_{t+1} and the volatility innovations. Recall that those innovations are themselves functions of Z_{t+1}. In the following, we think of Z_{t+1} as the underlying macroeconomic news.

For illustrating the mechanics of the volatility feedback effect, we consider a numerical example. We set $\delta = 0.03$, and choose $\rho = 0.9998$ as in Engle (2011). The fourth moment of the innovation is restricted to $\kappa = 3$ (as for the normal distribution). The parameters in the short- and long-term component are chosen as $\alpha = 0.02$, $\gamma = 0.2$, $\beta = 0.80$, $\lambda_0 = 0.02$, $\lambda_1 = 0.05$, and $\lambda_2 = 0.93$, which are reasonable values for daily return data (see Conrad and Engle, 2022). For these parameter values, the unconditional variance of the (daily) returns is 1.05 (which corresponds to an annualized volatility of approximately 16%) and we obtain $A^\tau = 1.37$, $A^h = 0.03$, and $A^\sigma = 0.21$. These values imply that news to the long-term component has by far the strongest effect on unexpected returns.

Figure 1 shows how Z_{t+1} news affects excess returns. The upper left panel displays excess returns (green line) as a function of Z_{t+1}. We set $\tau_{t+1} = 2$ and $h_{t+1} = 1$. Because the unconditional daily variance is about one, we can think of $\tau_{t+1} = 2$ as a *high volatility regime*. The red dashed line represents cash flow news, $\eta_{d,t+1}$. The slope of this line is $\sigma_{t+1} = \sqrt{2}$, which corresponds to an annualized volatility of 22.45%. Discount rate news, $\eta_{r,t+1}$, is shown as a blue dashed line. If there is no news ($Z_{t+1} = 0$ and, hence, $\eta_{d,t+1} = 0$), expectations for future volatility and, hence, required returns are revised downwards. Consequently, news to expected returns are negative ($\eta_{r,t+1} < 0$) and the stock price increases, i.e. the excess return is positive. This is analogous to the *no news is good news* effect, as described in Campbell and Hentschel (1992).[2] The intersections of the dashed blue line with the horizontal axis indicate the level of Z_{t+1} news for which discount rate news is zero. For good/bad news above/below this level, discount rate news is positive, i.e. the good/bad Z_{t+1} news leads to upward revisions in volatility and required returns. Then, discount rate news dampens/amplifies the effect of the positive/negative dividend news and excess returns are smaller than cash flow news. In the upper right panel of Figure 1, we set $\tau_{t+1} = 0.5$ and, as before, $h_{t+1} = 1$. These values correspond to a *low volatility regime*. Decreasing the level of long-term volatility has two effects. First, in the low volatility regime, the slope of the red dashed line representing cash flow news is flatter and equals $\sqrt{0.5}$ (corresponding to an annualized volatility of 11.22%). Thus, Z_{t+1} news has a weaker cash flow effect when volatility is low. Second, lowering volatility flattens the blue dashed line showing discount rate news. For Z_{t+1} values close to zero, the discount rate curve is shifted towards zero. As a result of these two effects, excess returns (brown line) are now less responsive to news.

[2] Campbell and Hentschel (1992) plot unexpected returns as a function of cash flow news, but the mechanics are the same.

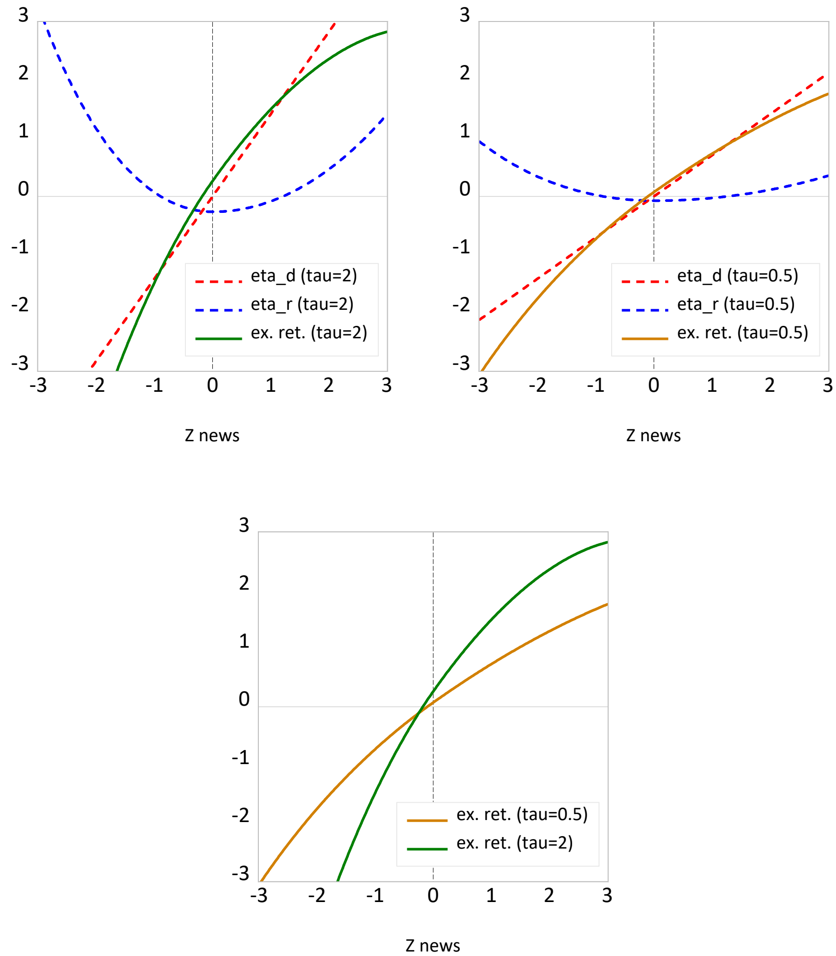

Figure 1: Excess return as a function of macroeconomic news Z_{t+1}. In the upper panels, dividend news, $\eta_{d,t+1}$, is represented by the red dashed line. The blue dashed line shows discount rate news, $\eta_{r,t+1}$. In the upper left panel, we assume a high long-term volatility with $\tau_{t+1} = 2$ and $h_{t+1} = 1$. The green line shows the excess return. In the upper right panel, we set $\tau_{t+1} = 0.5$ and $h_{t+1} = 1$. The brown line shows the excess return. In the lower panel, we compare excess returns when $\tau_{t+1} = 2$ (green line) and $\tau_{t+1} = 0.5$ (brown line).

The figure in the lower panel summarizes these effects. As before, the green line represents excess returns when $\tau_{t+1} = 2$, and the brown line shows excess returns when $\tau_{t+1} = 0.5$. Roughly speaking, the green line (high volatility regime) is above/below the brown line (low volatility regime) for positive/negative macroeconomic news. To better understand the asymmetric effect of bad and good news, assume that $A^h \approx 0$, and $A^\sigma \approx 0$. Then, after plugging in $\tilde{v}^\tau_{t+1}$, we can write unexpected returns as

$$r_{t+1} - \mathbf{E}_t[r_{t+1}] \quad = \quad \lambda_1 A^\tau \tau_{t+1} + \sqrt{\tau_{t+1} h_{t+1}} Z_{t+1} - \lambda_1 A^\tau \tau_{t+1} Z^2_{t+1}. \tag{15}$$

This representation clearly shows that the *no news is good news effect* (i.e., the first term) increases with the level of long-term volatility and that the asymmetric effect of good/bad news is more pronounced when long-term volatility is high. Based on Theorem 2 and the numerical example in Figure 1, we derive the following testable predictions regarding the effect of Z_{t+1} news:

P1 *Importance of long-term volatility:* The stock market is more sensitive to news when volatility is high and the strength of the volatility feedback effect predominantly depends on the level of long-term volatility.

P2 *Asymmetry:* Within each volatility regime, large pieces of bad news have a stronger effect than large pieces of good news. The asymmetry is more pronounced when long-term volatility is high.

P3 The *no news is good news* effect increases with the level of (long-term) volatility.

Finally, the conditional variance of unexpected returns is $\mathbf{Var}_t[r_{t+1} - \mathbf{E}_t[r_{t+1}]] = \mathbf{Var}_t[\eta_{d,t+1}] + \mathbf{Var}_t[\eta_{r,t+1}]$. In our model, the uncorrelatedness of cash flow and discount rate news follows from the assumption that the density of Z_t is symmetric. Under reasonable assumptions on model parameters, it is straightforward to show that $\mathbf{Var}_t[\eta_{r,t+1}]$ is much smaller than $\mathbf{Var}_t[\eta_{d,t+1}]$. For example, assuming the relation in equation (15), we obtain

$$\mathbf{Var}_t[r_{t+1} - \mathbf{E}_t[r_{t+1}]] = \sigma_{t+1}^2 + \lambda_1^2 (A^\tau)^2 (\kappa - 1)\tau_{t+1}^2. \tag{16}$$

With the same parameter values as before, $\mathbf{Var}_t[\eta_{r,t+1}]/\mathbf{Var}_t[\eta_{d,t+1}] = 0.02$ in the high volatility regime, and $\mathbf{Var}_t[\eta_{r,t+1}]/\mathbf{Var}_t[\eta_{d,t+1}] = 0.004$ in the low volatility regime. Based on this insight, we will use the conditional variance of unexpected returns as a proxy for $\mathbf{Var}_t[\eta_{d,t+1}]$ in the empirical analysis. Alternatively, as in Engle (2011), we can combine the assumption $r_{t+1} - \mathbf{E}_t[r_{t+1}] = \sigma_{t+1} Z_{t+1}$ with equation (3). Under this assumption, σ_{t+1}^2 is the conditional variance of unexpected returns, which are observed and can be decomposed into discount rate and cash flow news. $\eta_{r,t+1}$ is still given by equation (13), but $\eta_{d,t+1}$ is defined as the 'residual': $\eta_{d,t+1} = r_{t+1} - \mathbf{E}_t[r_{t+1}] + \eta_{r,t+1}$. Predictions P1-P3 also apply in this specification, where $\eta_{r,t+1}$ and $\eta_{d,t+1}$ are correlated.

4 Empirical Analysis

We now turn to the empirical analysis, where we will evaluate the predictions derived in the previous section. In Section 4.1, we introduce our data set of macroeconomic announcements, stock returns, volatility components, and economic control variables. In Section 4.2, we present the empirical framework. Using U.S. return data, we show that the time-varying sensitivity of the stock market depends on the level of long-term volatility and provide evidence for the importance of volatility feedback. An extension to the European stock market closes the chapter.

4.1 Data

4.1.1 Macroeconomic Announcements

We focus on pre-scheduled U.S. macroeconomic announcements that are known to have strong effects on the stock market (e.g., Andersen et al., 2007; Gilbert et al., 2017; Elenev et al., 2023): Nonfarm Payroll Employment, the Purchasing Managers' Index, Consumer Confidence, Initial Jobless Claims, Durable Goods Orders, the Consumer Price Index, Retail Sales, New Family Houses Sold, and Manufacturers New Orders. These variables belong to five categories of macroeconomic announcements, such as real activity (e.g., Nonfarm Payroll Employment) or forward-looking indicators (e.g., Purchasing Managers' Index), and each variable is published within the respective category earliest in the month. All announcements are released at 8:30 am or 10:00 am Eastern Standard Time (EST). Except for Initial Jobless Claims, which are published weekly, all indicators are published monthly. We obtained the first releases of the macroeconomic announcements and the corresponding consensus forecasts from Bloomberg and present in Table 1 the categories, the units of measurement, the frequency, and the release time. Our sample spans the period from January 2001 to December 2021. Overall, our sample includes 3083 macroeconomic announcements. Table A.1 in the Appendix shows that for all macroeconomic announcements the Bloomberg forecasts are unbiased (at the 5%-level). The coefficients of determination (R^2) of the corresponding Mincer and Zarnowitz (1969) regressions are above 80% for all variables but Durable Goods Orders.

To construct announcement surprises, we subtract the consensus forecast of professional Bloomberg forecasters from the actual release. Because forecasts can be submitted until the night before the announcement, they reflect the current knowledge of market participants. To reduce the impact of extreme surprises, we winsorize the difference between the announcement and the median forecast at the 95% level.[3] Following Balduzzi et al. (2001), we define the standardized surprise component of announcement j taking place on day t as

$$S_{j,t} = \frac{A_{j,t} - E_{j,t-1}}{sd_j}, \tag{17}$$

where $A_{j,t}$ is the realized value of announcement j, $E_{j,t-1}$ corresponds to the previous days's consensus of the Bloomberg expectations, and sd_j is the sample standard deviation of the an-

[3] In particular, extreme observations occurred for some variables during the COVID-19 pandemic.

Table 1: U.S. macroeconomic announcement data 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 (less automobiles)	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 (CPI)	250	% change	8:30 am EST	monthly
	Forward-looking				
8	Conference Board Consumer Confidence	252	Index	10:00 am EST	monthly
9	Purchasing Managers Index (PMI, ISM)	252	Index	10:00 am EST	monthly

Notes: The table reports the macroeconomic announcements used throughout the analysis, the number of observations, the unit of measurement, the release time (Eastern Standard Time) and the release frequency. Release values and median forecasts for the macroeconomic announcements are obtained from Bloomberg. The Retail Sales forecasts are available from June 2001 and for Durable Goods Orders no median forecasts are reported in 15 months of our sample.

nouncement surprise, $(A_{j,t} - E_{j,t-1})$. This standardization allows us to compare announcements measured in different units in our regression models and to interpret the regression coefficients as the effect of a one-standard-deviation surprise. Positive/negative announcement surprises can be interpreted as good/bad news. To allow for a consistent interpretation of good and bad news, we multiply Initial Jobless Claims and the Consumer Price Index with (-1).

4.1.2 Returns

To measure the stock market's reaction to macroeconomic announcements, we consider S&P 500 index futures, which are traded 23 hours a day. This allows us to analyze the impact of major announcements released at 8:30 am EST, prior the S&P 500's opening bell. The E-mini S&P 500 futures are commonly used in event studies based on high-frequency data (e.g., Gardner et al., 2022; Elenev et al., 2023). The futures data were obtained from TickData. Using the front-month contracts, we calculate log returns in k-minute windows around the announcement release times as

$$R_{t,s}[k] = 100\left(\ln(F_{t,s+k}) - \ln(F_{t,s-k})\right), \tag{18}$$

where $F_{t,s}$ refers to the last transaction (close) price of the E-mini future in minute s on day t. As mentioned before, announcements are released either at 8:30 am or 10:00 am. Because the surprise component of the announcement is almost instantaneously incorporated into prices, we set $k = 5$ minutes. Figure A.1 in the Appendix, which shows that average absolute returns are highest immediately after announcement times and decline quickly thereafter, supports this choice. As robustness checks, we set $k = 1$ and $k = 10$ minutes (see Section 5). In the following, we follow Gardner et al. (2022) and Elenev et al. (2023) and simplify the notation by dropping the index s and simply write $R_{t,s}[k] = R_t[k]$.

4.1.3 Variables explaining time-varying sensitivity

Short- and long-term volatility components

To test the three model predictions, we allow the effect of macroeconomic announcements to depend on the level of long- and short-term volatility. As discussed at the end of Section 3.3, we focus on the conditional variance of daily unexpected returns instead on the conditional variance of cash flow news. For a daily expanding window, we estimate the MF2-GARCH model using daily S&P 500 log-returns, which are calculated based on the close price of each trading day. Using daily returns up to a day $t-1$, we estimate the model parameters and compute the long- and short-term components for day t. That is, by construction, the volatility components for day t are independent of the macroeconomic news that is released on that day. The first estimation sample starts on August 15, 1969, and ends on December 29, 2000. For each day, we choose the m that minimizes the Schwarz (1978) information criterion (BIC). In the sample under consideration, the optimal m varies between 62 and 68. Figure 2 shows the estimates of the short- and long-term volatility components as well as the conditional volatility.

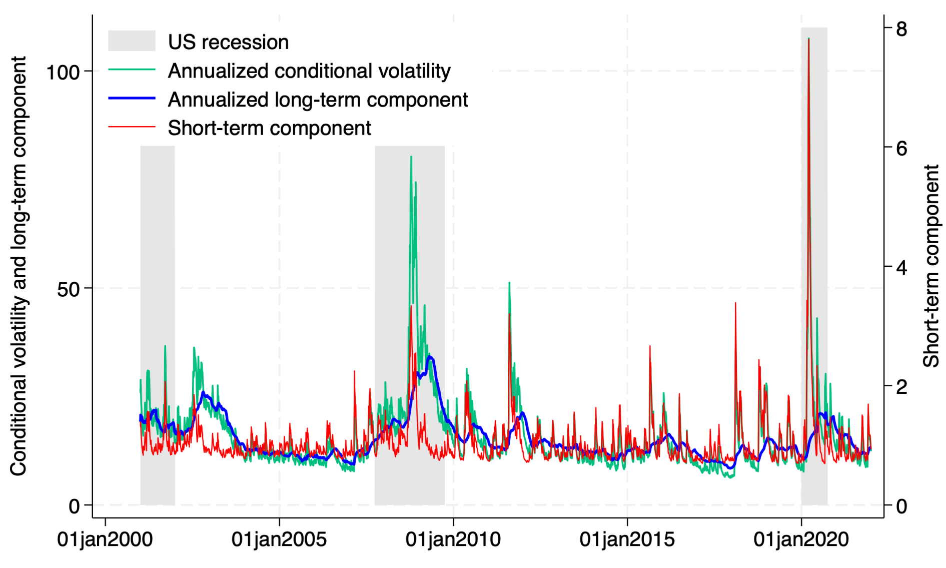

Figure 2: Plot of the annualized volatility of the MF2-GARCH for daily S&P 500 returns. The annualized conditional volatility ($\sqrt{252 \cdot \tau_t h_t}$) is shown in green and the annualized long-term volatility component ($\sqrt{252 \cdot \tau_t}$) is shown in blue. The short-term component ($\sqrt{h_t}$) is shown in red. The grey-shaded areas correspond to US recessions as inferred by the GDP-based recession indicator.

Economic variables used in previous studies

To allow for comparison with the previous literature, we use the economic variables that have been found to be the most important in explaining the time-varying return sensitivity. Those variables can be separated into three broad categories: State of the economy, stock market volatility, economic and monetary policy uncertainty.

State of the economy: Gardner et al. (2022) developed the FOMC sentiment index based on textual analysis of FOMC statements. From the author's websites, we obtained the FOMC sentiment index, which captures the FOMC's description of the labor market, output, inflation, financial conditions, and future monetary policy actions. Furthermore, we use the real-time output gap projections from the Tealbook (formerly Greenbook) of the Federal Reserve Board of Governors, which was found to be the leading explanatory variable for the time-varying sensitivity of stock returns by Elenev et al. (2023). We use the latest projection for the current quarter made by the staff of the Board of Governors of the Federal Reserve System. Because the real-time output gap measure is publicly available with a publication lag of five years, announcements after December 2017 were not included in estimations where the output gap is used as a predictor. Moreover, we follow Elenev et al. (2023) and measure the expected change in short-term interest rate expectations by the difference between the CPI-adjusted one-quarter-ahead forecast and the nowcast rate of the 3-month Treasury bill from the Survey of Professional Forecasters. As a measure of the inflation expectations of households, we use the median expected price change in the next 12 months from the Surveys of Consumers (University of Michigan).

Stock market volatility and risk appetite: We use three alternative measures of stock market risk. Short-run risk is measured by the conditional volatility from a GJR-GARCH$(1, 1)$ based on daily S&P 500 return data. The Chicago Board Options Exchange S&P 500 Volatility Index (VIX) measures volatility expectations for the next month. Finally, we use S&P 500 VIX 3-Month Futures to measure expected volatility in three months. The daily index of financial risk appetite from Bauer et al. (2023) corresponds to the common component of 14 risk-sensitive financial indicators.

Macroeconomic and monetary policy uncertainty: To proxy monetary policy uncertainty, we use the measure developed by Husted et al. (2020), tracking the frequency of newspaper articles about monetary policy uncertainty on a monthly frequency. The macroeconomic uncertainty measure from Jurado et al. (2015) is estimated from many macroeconomic time series, and it captures how predictable the economy is as a whole.

4.2 Empirical framework

In the empirical analysis, we follow Gardner et al. (2022) and Elenev et al. (2023) and utilize an event study approach. That is, we regress return changes around the release time of macroeconomic announcements on the surprise component of macroeconomic announcements while controlling for the long- and short-term components of volatility. Following Kilian and Vega (2011) and Elenev et al. (2023), we simultaneously include all data releases that occur at 8:30 am or 10:00 am in our regressions. Whenever there is no announcement for a certain indicator on day t, the corresponding surprise is set to zero. We only include k-minute windows with at least one announcement.

4.2.1 Baseline model – No time-varying sensitivity

In our baseline model, we regress high-frequency returns on all announcements:

$$R_t[k] \quad = \quad \theta_1 + \sum_{j=1}^{J} \theta_{2,j} S_{j,t} + \xi_t, \tag{19}$$

where the parameters $\theta_{2,j}$ capture the effect of a one-standard-deviation surprise of announcement j and ξ_t is the residual. By focusing on a window size of $k = 5$, we ensure that no events other than the announcements drive the price movement, i.e., we estimate the causal effect of the surprise component on returns.[4] Because the regression is based on high-frequency returns from non-consecutive k-minute windows, the serial correlation of the residuals is essentially zero. We compute robust (Eicker-Huber-White) standard errors to account for conditional heteroscedasticity. However, all results are robust to applying Newey-West standard errors.

The first column in Table 2 shows the effects of the announcement surprises on the stock market in the baseline specification. As expected, positive surprises lead to an increase in returns within five minutes after the announcement. For example, a positive one-standard-deviation surprise in the release of the Consumer Confidence indicator is expected to increase log returns by 0.132 percentage points. Nonfarm Payroll Employment has the strongest impact of all announcements, confirming its' perception as the 'king of announcements' (Andersen and Bollerslev, 1998). Overall, the surprise component of macroeconomic announcements can explain more than 18% of the return variation when $k = 5$.

[4]Recall that $R_t[k]$ refers to the k-minute return either at 8:30 or 10:00 am EST.

Table 2: Regression for baseline specification and time-varying sensitivity.

	(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)
Initial Jobless Claims	0.049***	0.049***	0.047***	0.049***	0.050***
	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)
Nonfarm Payrolls	0.212***	0.201***	0.209***	0.201***	0.200***
	(0.029)	(0.024)	(0.030)	(0.024)	(0.024)
Retail Sales	0.110***	0.095***	0.111***	0.095***	0.093***
	(0.016)	(0.014)	(0.016)	(0.014)	(0.014)
New Family Houses Sold	0.046***	0.062***	0.046***	0.062***	0.062***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.013)
Durable Goods Orders	0.073***	0.078***	0.074***	0.078***	0.077***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.016)
Manufacturers New Orders	0.046***	0.044***	0.046***	0.044***	0.044***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
Consumer Price Index	0.082***	0.061***	0.084***	0.062***	0.062***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)
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)
Constant	0.007*	0.008**	0.008*	0.008**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2826	2826	2826	2826	2826
Adjusted R^2	0.189	0.230	0.189	0.230	0.230

Notes: We set $k = 5$ minutes. Column (1) presents OLS estimates for equation (19). Columns (2) to (5) present non-linear least squares estimates as described in equation (20). In Column (2), we choose $f(\mathbf{X}_t)$ as in equation (21) with $\gamma_X'\mathbf{X}_t = \gamma_\tau\tilde{\tau}_t$. In Column (3) we focus on the short-term volatility component and set $\gamma_X'\mathbf{X}_t = \gamma_h\tilde{h}_t$. Both volatility components are added to the model in Column (4), s.t. $\gamma_X'\mathbf{X}_t = \gamma_\tau\tilde{\tau}_t + \gamma_h\tilde{h}_t$. Column (5) represents the results where we include the long- and short-term volatility components as well as the interaction of long and short-term volatility (conditional volatility) to our model ($\boldsymbol{\gamma}_X'\mathbf{X}_t = \gamma_\tau\tilde{\tau}_t + \gamma_h\tilde{h}_t + \gamma_\sigma\tilde{\tau}_t\tilde{h}_t$). $\tilde{\tau}_t$ and $\tilde{h}_t$ were obtained from an expanding window estimation and are demeaned. The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p < 0.01, **p < 0.05, *p < 0.1

4.2.2 Does volatility explain the stock market's time-varying sensitivity to news?

Our model suggests that the effect of news on the stock market predominantly depends on the level of long-term volatility (see prediction P1). We follow the approach of Swanson and Williams (2014), adopted by Elenev et al. (2023), and estimate a non-linear regression that allows for a time-varying sensitivity of the stock market that depends on specific predictor variables. We extend the baseline specification to

$$R_t[k] \quad = \quad \theta_1 + f(\mathbf{X}_t)\sum_{j=1}^{J}\theta_{2,j}S_{j,t} + \xi_t \tag{20}$$

with

$$f(\mathbf{X}_t) = 1 + \boldsymbol{\gamma}'_X \mathbf{X}_t, \tag{21}$$

where $\mathbf{X}_t$ is a vector of demeaned explanatory variables and $\boldsymbol{\gamma}_X$ is a parameter vector. The realizations of all variables in $\mathbf{X}_t$ are known *before* announcement surprises materialize. Demeaning the explanatory variables ensures the identification of γ'_X and $\theta_{2,j}$ for $j = 1, ..., J$. The coefficients $\theta_{2,j}$ are the effects of the macroeconomic announcements when all explanatory variables are at their mean, i.e., $f(\mathbf{X}_t) = 1$. Note that the model given by equations (20) and (21) imposes the restriction that the time-varying sensitivity, $f(\mathbf{X}_t)$, is the same for all macroeconomic announcements. This restriction keeps the model parsimoniously parameterized. As motivated by equation (14), we use the long- and short-term components as well as the interaction of short- and long-term volatility (i.e., the conditional variance) as explanatory variables.

In Table 2, we report the estimation results for equation (20) in Columns (2) to (5). In Column (2), we use the long-term volatility component as the predictor variable and set

$$f(\mathbf{X}_t) = 1 + \gamma_\tau \tilde{\tau}_t, \tag{22}$$

where $\tilde{\tau}_t = \sqrt{\tau_t} - \overline{\sqrt{\tau}}$. We use the (demeaned) $\sqrt{\tau_t}$ because, according to equation (5), cash flow news is macroeconomic news times the square root of conditional volatility. Thus, even in the absence of discount rate news, returns should be determined by the interaction of macroeconomic news and $\sqrt{\tau_t}$. The associated coefficient for the long-term volatility component is positive and statistically significant at the 1% level. Thus, as predicted by our model and the numerical exercise in Section 3.3, macroeconomic news have stronger effects when long-term volatility is high. Furthermore, adding the long-term component improves the model fit by more than four percentage points compared to the model in Column (1). Figure 3 illustrates the estimation results from Column (2) by plotting the marginal effects of a positive (green) and negative (red) one-standard-deviation Consumer Confidence announcement surprise. In this specification, the effect of good and bad news is symmetric and for good/bad news the estimated marginal effect is increasing/decreasing in the level of the long-term volatility component. When the long-term component is at its mean, the marginal effect of good/bad news is given by ± 0.133 (corresponding to the $\theta_{2,j}$ estimate for Consumer Confidence). Note that even for low values of the long-term component, the marginal effect of a positive/negative surprise is positive/negative.

When including only the (demeaned) short-term volatility component ($\tilde{h}_t = \sqrt{h_t} - \overline{\sqrt{h}}$, see Column (3)), or both (demeaned) volatility components jointly (see Column (4)), the short-term component is not statistically significant and does not improve the model fit. Finally, when adding the interaction of the short- and long-term volatility components in Column (5), such that $\boldsymbol{\gamma}'_X \mathbf{X}_t = \gamma_\tau \tilde{\tau}_t + \gamma_h \tilde{h}_t + \gamma_\sigma \tilde{\tau}_t \tilde{h}_t$, only the long-term component is significant. This confirms

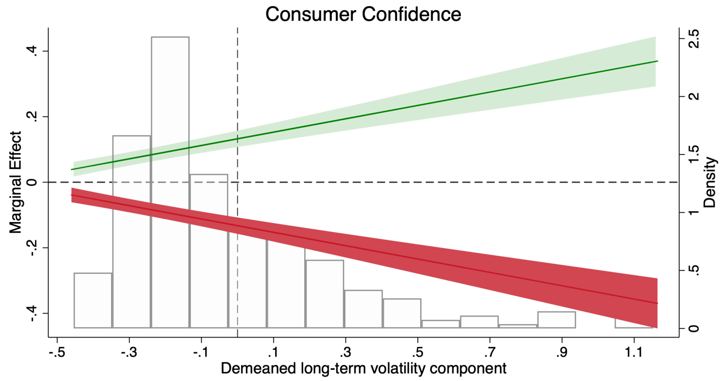

Figure 3: Marginal effect of a positive and negative one-standard deviation Consumer Confidence surprise as a function of the level of the long-term volatility component. Parameter estimates are based on Column (2) in Table 2. The green line represents good news, and the red line represents bad news. Plotted with 90%-confidence intervals. The histogram refers to the distribution of long-term volatility on days when the Consumer Confidence indicator is published.

the prediction of our model that the sensitivity of the stock market depends primarily on long-term volatility. This result also suggests that expected returns (see equation (3)) are mainly driven by long-term volatility, which is in line with the findings in Maheu and McCurdy (2007) and Kim and Nelson (2013). In the following, we will use the long-term volatility component as the only predictor of the time-varying sensitivity from the MF2-GARCH. However, the results in the subsequent sections are robust to adding the short-term component and the interaction of both volatility components as additional predictors.

4.2.3 Does long-term volatility capture more than the business cycle or economic uncertainty?

Long-term stock market volatility behaves counter-cyclical (Engle et al., 2013; Conrad and Loch, 2015; Conrad and Engle, 2022). As such, our results based on the long-term volatility component could simply be viewed as confirming previous findings of Gardner et al. (2022) and Elenev et al. (2023) using an alternative proxy of the business cycle.[5] Alternatively, the long-term volatility component could proxy for implied volatility or macroeconomic/monetary policy uncertainty. In this section, we show that neither is the case. Specifically, we show that long-term volatility still contains relevant information when controlling for those predictors.

[5] The long-term volatility component ($\sqrt{\tau}$) exhibits a correlation of -0.39 with the real-time output gap and -0.68 with FOMC sentiment. The correlation between the long-term component and the VIX is 0.73, and with the 3-Month VIX futures 0.79. The long-term component is positively correlated with macroeconomic uncertainty (0.51), and negatively correlated with monetary policy uncertainty (-0.10).

To reproduce the results from the previous literature, we first only include the predictor variables W_{t-1} by specifying $f(\mathbf{X}_t)$ as

$$f(\mathbf{X}_t) = 1 + \gamma_W W_{t-1}. \tag{23}$$

All predictor variables are known on the day before the announcement. If a variable is available at a monthly (quarterly) frequency, we use the previous month's (quarter's) release. As before, to ensure identification, the predictor variables are demeaned.

Table 3 presents in odd columns the results of estimating (20) in combination with equation (23). For the sake of clarity, we present only the estimates of the sensitivity factors γ_W but not the $\theta_{2,j}$ estimates. In line with Gardner et al. (2022) and Elenev et al. (2023), Panel A shows that the FOMC sentiment (Column (1)) and the output gap (Column (3)) have a significant effect. The negative coefficient estimates for the FOMC sentiment and the output gap imply that – due to the discount rate effect – the effect of good news gets attenuated as FOMC sentiment or the output gap increases. Interest rate (Column (5)) and inflation expectations (Column (7)) do not have a significant effect. Individually, the output gap ($R^2 = 0.291$) has considerably more explanatory power than long-term volatility ($R^2 = 0.230$, see Column (2) in Table 2).

In Panel B, we look at the effect of including alternative volatility and risk appetite measures. The GJR-GARCH volatility, the VIX, and the 3-month VIX futures all have a positive sign and are statistically significant. Still, the explanatory power of these measures is less than the explanatory power of long-term volatility (see Column (2) in Table 2). It is interesting to note that the explanatory power increases with the length of the horizon for which the volatility measures apply. The fact that a higher risk appetite reduces the effect of macroeconomic news is consistent with our model because a higher risk appetite can be interpreted as a lower risk aversion δ in equation (3). In line with Kurov and Stan (2018), Panel C shows that higher monetary policy uncertainty weakens the effect of macroeconomic announcements.

In the next step, we simultaneously include the long-term volatility component and a predictor W_{t-1} in the regression:

$$f(\mathbf{X}_t) = 1 + \gamma_\tau \tilde{\tau}_t + \gamma_W W_{t-1}. \tag{24}$$

The even columns of Table 3 show that the long-term component is always statistically significant when jointly included with a predictor variable. As in the model in equation (20), the coefficient of the long-term component is positive and improves the explanatory power of the model compared to (23). Panel A shows that besides the long-term component, the FOMC sentiment (Column (2)), the output gap (Column (4)), and also interest rate expectations (Column (6)) are now statistically significant. When including the output gap and long-term volatility jointly, we can explain approximately 31% of the variation in returns (Column (6)).

Table 3: Regression for time-varying sensitivity with additional economic predictors.

Panel A: Macroeconomic conditions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FOMC sentiment	-1.122***	-0.416*						
	(0.182)	(0.235)						
Output gap			-0.163***	-0.124***				
			(0.022)	(0.026)				
Interest rate expectations					-0.033	0.134***		
					(0.060)	(0.050)		
Inflation expectations							-0.067	0.121
							(0.094)	(0.088)
$\tilde{\tau}_t$		1.022***		0.834***		1.699***		1.599***
		(0.239)		(0.180)		(0.200)		(0.199)
Constant	0.008*	0.008**	0.008*	0.009**	0.008*	0.010**	0.007*	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2690	2690	2294	2294	2826	2826	2826	2826
Adjusted R^2	0.241	0.253	0.291	0.309	0.189	0.233	0.189	0.231

Panel B: Stock market volatility and risk appetite	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GJR-GARCH	0.326**	-0.012						
	(0.163)	(0.157)						
VIX			0.616***	-0.027				
			(0.178)	(0.244)				
3-Month VIX futures					0.035***	-0.027		
					(0.013)	(0.017)		
Risk appetite							-0.158**	-0.171***
							(0.070)	(0.065)
$\tilde{\tau}_t$		1.553***		1.566***		1.781***		1.537***
		(0.299)		(0.355)		(0.367)		(0.188)
Constant	0.009**	0.008**	0.009**	0.008**	0.006	0.005	0.007*	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Observations	2826	2826	2826	2826	1929	1929	2826	2826
Adjusted R^2	0.200	0.230	0.207	0.230	0.211	0.240	0.195	0.236

Panel C: Macroeconomic and monetary policy uncertainty	(1)	(2)	(3)	(4)
Monetary policy uncertainty	-0.004***	-0.003***		
	(0.001)	(0.001)		
Macroeconomic uncertainty			-0.634	-2.368***
			(0.423)	(0.360)
$\tilde{\tau}_t$		1.472***		1.953***
		(0.195)		(0.191)
Constant	0.008*	0.009**	0.008*	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2826	2826	2826	2826
Adjusted R^2	0.202	0.238	0.191	0.256

Notes: We set $k = 5$ minutes. Odd columns present estimates of equation (20), where we set $f(\mathbf{X}_t)$ according to (23), i.e., we only include the economic predictor. In even columns, we present estimates of equation (20) with $f(\mathbf{X}_t)$ from (24), where we include the economic predictor and the long-term volatility component. The coefficient estimates on the macroeconomic surprises are not reported in the table but are statistically significant at the 1% level. All regressions include a constant. FOMC sentiment from Columns (1) and (2) in Panel A is available from January 2001 until December 2020. Because the real-time output gap measure is obtained from green book forecasts that are not publicly available at the time of the publication of the announcements and released after five years, announcements after December 2017 were not included in the estimations from Panel A, Columns (3) and (4). VIX futures data are available from August 15, 2007 onward. For the VIX, we use the VIX on the previous trading day divided by $\sqrt{365}$. In all other columns, the estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p < 0.01, **p < 0.05, *p < 0.1.

Panel B shows that none of the alternative volatility measures is significant when jointly included with the long-term volatility component. This suggests that the long-term volatility component is the measure of financial market risk that is priced in the risk-return relation and that best captures the volatility feedback effect. Last, when combined with the long-term volatility component, both monetary policy and macroeconomic uncertainty are significant, indicating that long-term stock market volatility and macroeconomic/monetary policy uncertainty capture distinct channels affecting returns.

Overall, Table 3 provides further evidence for *prediction P1*, implying that the sensitivity of the stock market increases with the level of long-term volatility, even after controlling for other channels highlighted in the previous literature. Thus, in line with the prediction of our model, the volatility feedback effect plays a prominent role in explaining the stock market's sensitivity to news.

4.2.4 Do good and bad news have asymmetric effects?

We now test predictions P2 and P3 using two extensions of the regression model in equations (20) and (22). First, to test the prediction that good and bad news have asymmetric effects, we estimate a model with separate slope coefficients for good and bad news. We define good news as $S^+_{j,t} = \max\{0, S_{j,t}\}$ and bad news as $S^-_{j,t} = \min\{0, S_{j,t}\}$. The model is then given by

$$R_t[k] \;\; = \;\; \theta_1 + \gamma_\tau^c \dot{\tau}_t + f(\mathbf{X}_t)\left[\sum_{j=1}^{J} \theta^+_{2,j} S^+_{j,t} + \sum_{j=1}^{J} \theta^-_{2,j} S^-_{j,t}\right] + \xi_t \tag{25}$$

with $f(\mathbf{X}_t)$ as in equations (22) or (24). To capture the *no news is good news* effect, we have added the term $\gamma_\tau^c \dot{\tau}_t$ with $\dot{\tau}_t = \tau_t - \bar{\tau}$ to the regression model. Hence, even if all surprises are equal to zero, unexpected returns are allowed to depend on the level of long-term volatility.

Column (1) in Table 4 reports estimation results for equation (25) with $f(\mathbf{X}_t)$ as in equation (22). The estimate $\hat{\theta}^-_{2,j}$ is significant for all announcements, and $\hat{\theta}^+_{2,j}$ is significant for all announcements except the Consumer Price Index and Manufacturers' New Orders. Across all macroeconomic announcements, we find that $\hat{\theta}^-_{2,j}$ is bigger than $\hat{\theta}^+_{2,j}$. For five out of the nine announcements (i.e., for Initial Jobless Claims, Retail Sales, Durable Goods Orders, the Consumer Price Index, and Consumer Confidence), we can reject the null hypothesis of $\hat{\theta}^+_{2,j} = \hat{\theta}^-_{2,j}$ at the 10%-level. In combination with $\hat{\gamma}_\tau > 0$, this confirms prediction P2: bad news has stronger effects than good news, and the asymmetry is stronger for higher levels of long-term volatility. Since the estimate of γ_τ^c is positive and significant, we can also confirm prediction P3. The adjusted R^2 of equation (25) is approximately 24%.

The asymmetric effect of good and bad news is illustrated in Figure 4. For three macroeconomic announcements and two different levels of the long-term volatility component, the figure shows the model-predicted returns as a function of the size of the surprise. The blue and orange lines correspond to the model-predicted returns when long-term volatility is high (at the 90% quantile) or low (at the 10% quantile). In line with our previous results, for both good and bad news, the strength of the effect of news on returns increases with the level of long-term volatility. In addition, the figure clearly shows the asymmetric effect of good and bad news. As predicted by our model, the asymmetric effect is strong when long-term volatility is high, while the asymmetry is less pronounced when long-term volatility is low. This is because the volatility feedback effect is stronger for higher levels of long-term volatility. Finally, the figure nicely illustrates that the *no news is good news* effect indeed increases with the level of long-term volatility. Due to the strength of the discount rate effect, even small pieces of bad news can be good news for returns when long-term volatility is high.

Table 4: Testing for asymmetric effects of good and bad news (piece-wise linear specification).

	(1)		(2) **Output gap**		(3) **Risk appetite**		(4) **Macroeconomic uncertainty**	
	$S^+_{j,t}$	$S^-_{j,t}$	$S^+_{j,t}$	$S^-_{j,t}$	$S^+_{j,t}$	$S^-_{j,t}$	$S^+_{j,t}$	$S^-_{j,t}$
γ^c_τ	0.028***		0.029***		0.028***		0.029***	
	(0.010)		(0.010)		(0.009)		(0.010)	
$\tilde{\tau}_t$	1.541***		0.872***		1.523***		1.994***	
	(0.207)		(0.180)		(0.196)		(0.200)	
W_{t-1}			-0.122***		-0.156**		-2.410***	
			(0.025)		(0.064)		(0.351)	
Initial Jobless Claims	0.028***	0.065***	0.031***	0.102***	0.031***	0.065***	0.027***	0.084***
	(0.008)	(0.012)	(0.010)	(0.013)	(0.009)	(0.011)	(0.009)	(0.015)
Nonfarm Payrolls	0.200***	0.208***	0.284***	0.333***	0.198***	0.210***	0.229***	0.248***
	(0.036)	(0.033)	(0.047)	(0.040)	(0.037)	(0.030)	(0.041)	(0.036)
Retail Sales	0.073***	0.120***	0.105***	0.142***	0.075***	0.127***	0.098***	0.136***
	(0.015)	(0.022)	(0.018)	(0.024)	(0.015)	(0.020)	(0.022)	(0.023)
New Family Houses Sold	0.052***	0.075***	0.057**	0.115***	0.048***	0.073***	0.044**	0.085***
	(0.017)	(0.019)	(0.022)	(0.018)	(0.016)	(0.018)	(0.018)	(0.021)
Durable Goods Orders	0.045**	0.114***	0.046**	0.109***	0.045**	0.113***	0.050**	0.116***
	(0.020)	(0.025)	(0.022)	(0.026)	(0.019)	(0.025)	(0.020)	(0.022)
Manufacturers New Orders	0.025	0.065***	0.011	0.079***	0.029	0.066***	0.024	0.076***
	(0.023)	(0.016)	(0.024)	(0.016)	(0.023)	(0.017)	(0.024)	(0.017)
Consumer Price Index	0.027	0.093***	0.014	0.084***	0.032	0.087***	0.017	0.108***
	(0.024)	(0.024)	(0.021)	(0.025)	(0.027)	(0.023)	(0.022)	(0.025)
Consumer Confidence	0.085***	0.186***	0.090***	0.231***	0.088***	0.182***	0.083***	0.191***
	(0.018)	(0.025)	(0.022)	(0.026)	(0.016)	(0.023)	(0.019)	(0.025)
Purchasing Managers Index	0.124***	0.165***	0.133***	0.188***	0.120***	0.171***	0.141***	0.171***
	(0.024)	(0.036)	(0.027)	(0.041)	(0.024)	(0.037)	(0.022)	(0.035)
Constant	0.029***		0.037***		0.028***		0.033***	
	(0.007)		(0.007)		(0.007)		(0.007)	
Observations	2826		2294		2826		2826	
Adjusted R^2	0.237		0.321		0.243		0.266	

Notes: We set $k = 5$ minutes. Column (1) reports the results of estimating (25) using $f(\mathbf{X}_t)$ as in equation (22). In Columns (2) to (4), we extend the model from Column (1) by using $f(\mathbf{X}_t) = 1 + \gamma_\tau \tilde{\tau}_t + \gamma_W W_{t-1}$. The row labeled W_{t-1} refers to the predictor named in the table header. In the columns denoted by $S^+_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^-_{j,t}$, we report the coefficient estimates for bad news. The estimation sample spans the period from January 2001 to December 2021, except for Column (2), where we do not consider announcements after December 2017. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.

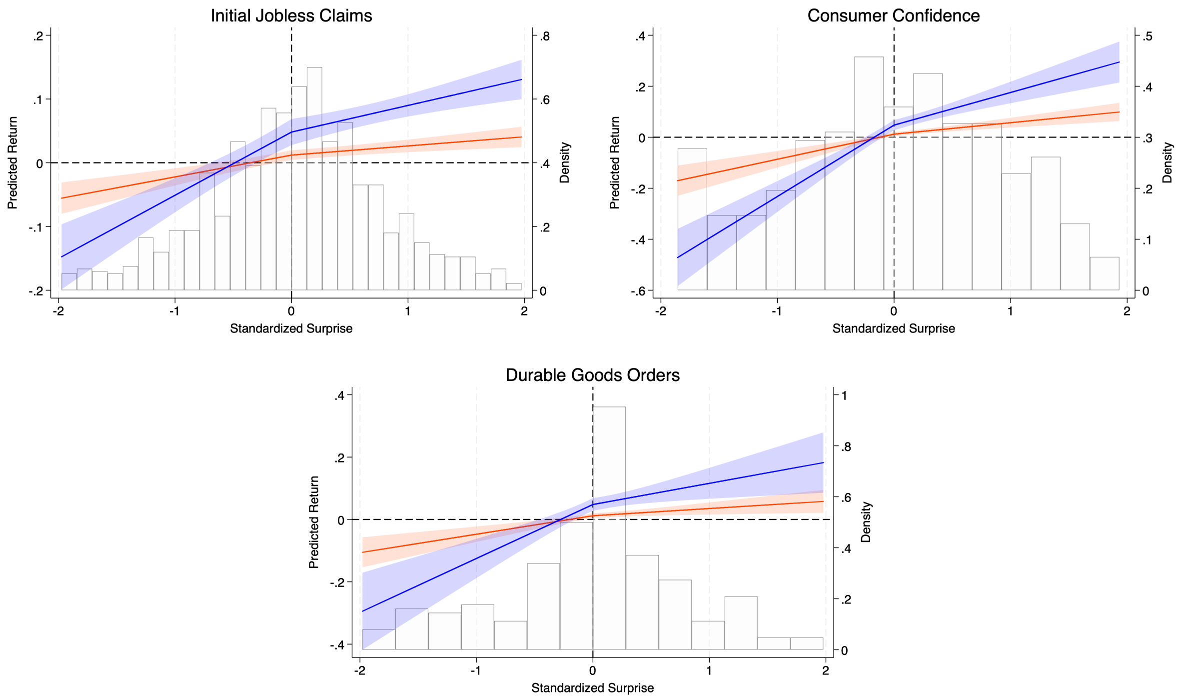

Figure 4: Return predicted by the model in Column (1) of Table 4 as a function of macroeconomic news, conditional on the long-term volatility component being either at the 10% (orange line) or 90% (blue line) quantile. To compute the quantiles, we only consider observations of long-term volatility on days when the corresponding announcements were published. For instance, when looking at the Initial Jobless Claims announcement, the 10% quantile corresponds to an annualized long-term volatility of 10.8% (e.g., September 6, 2018), and the 90% quantile corresponds to an annualized long-term volatility of 21% (e.g., January 2, 2003). For the calculation of the predicted return of an announcement, the surprises of all other announcements were set to zero. Plotted with 90%-confidence intervals. The histogram refers to the distribution of the surprises of the corresponding announcement.

To visualize the asymmetric effect of good and bad news *over time*, Figure 5 plots the absolute value of predicted returns in response to a positive and a negative two-standard deviation surprise in Consumer Confidence (again based on the estimates in Table 4, Column (1)). The time variation in predicted returns is solely driven by variation in long-term volatility. The difference between the absolute value of the predicted return after bad and good news is always positive and increases with the level of long-term volatility. Our finding of an asymmetric effect of good and bad news *conditional* on long-term volatility extends and complements the result of Elenev et al. (2023) that *unconditionally* there is no evidence for asymmetry.

Table 4 also presents estimation results for equation (25), when choosing $f(\mathbf{X}_t)$ as in equation (24). We focus on three selected W_{t-1} variables from Panels A to C in Table 3: The output gap, risk appetite, and macroeconomic uncertainty. As in Section 4.2.3, even after controlling for W_{t-1}, the long-term volatility component continues to be a significant predictor of the time-varying sensitivity, and there is evidence of asymmetric effects of good and bad news. The *no news is good news* effect is about the same size regardless of the economic predictor added to the

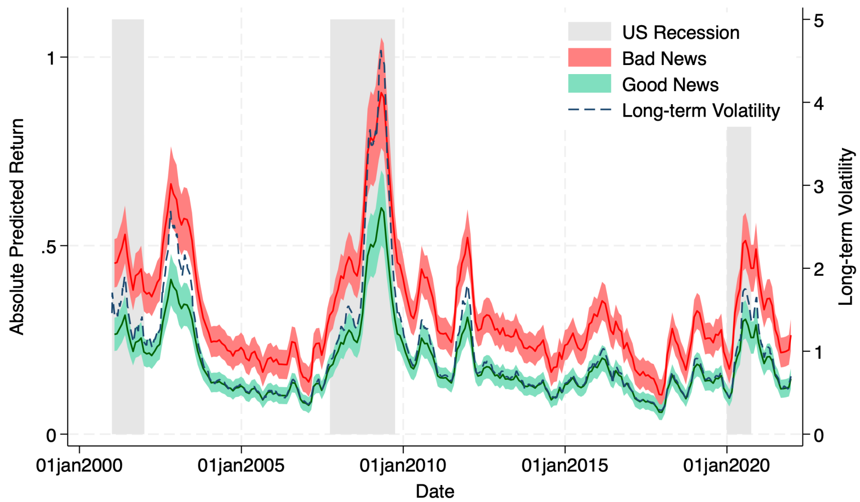

Figure 5: Absolute returns predicted by the model in Column (1) of Table 4 after a positive (good news) and negative (bad news) two-standard deviation Consumer Confidence surprise (with 68% confidence intervals). The predicted returns for bad news are multiplied by (-1) for a better comparison. The grey-shaded areas correspond to US recessions as inferred by the GDP-based recession indicator.

model. Interestingly, in all specifications, for inflation only bad news, i.e., higher than expected inflation, has a significant effect. We also estimated models that included the long-term volatility component, W_{t-1} and an interaction term in $f(\mathbf{X}_t)$. Only for the output gap the interaction with long-term volatility was significant (see Table A.2 in the Appendix). For this specification, Figure 6 illustrates how the relative position of long-term volatility and the output gap affect the predicted return following a Consumer Confidence surprise. We plot the model predicted return for different levels of long-term volatility, while holding the output gap fixed at the 90% quantile. We chose the 90% quantile for the output gap because we expect the strongest interaction between interest rate news and risk premium news when the output gap is positive and large. First, the yellow line shows the predicted return when long-term volatility is at its mean ($\tilde{\tau}_t = 0$). Clearly, good news has a less pronounced effect than bad news. As described by Elenev et al. (2023), when the output gap is strongly positive, the positive cash-flow effect of good news is partly offset by the discount rate effect due to the expectation of higher interest rates. Next, we investigate the effect of conditioning on high or low long-term volatility. The red line corresponds to a situation where long-term volatility is low (at the 10% quantile). Following good news, the predicted return is much smaller than in the previous situation because the discount rate effect is now driven by a combination of higher expected interest rates and an upward revision of future expected volatility. Hence, the interest rate news and the risk premium news operate in the same direction and reinforce each other. In contrast, when long-term volatility is high, these two channels act in opposite directions: volatility expectations are revised downwards while interest rate expectations are revised upwards. Hence, the discount rate effect is weaker, and the positive cash-flow effect of good news is less attenuated, strengthening the impact of the surprise on predicted returns (blue line).

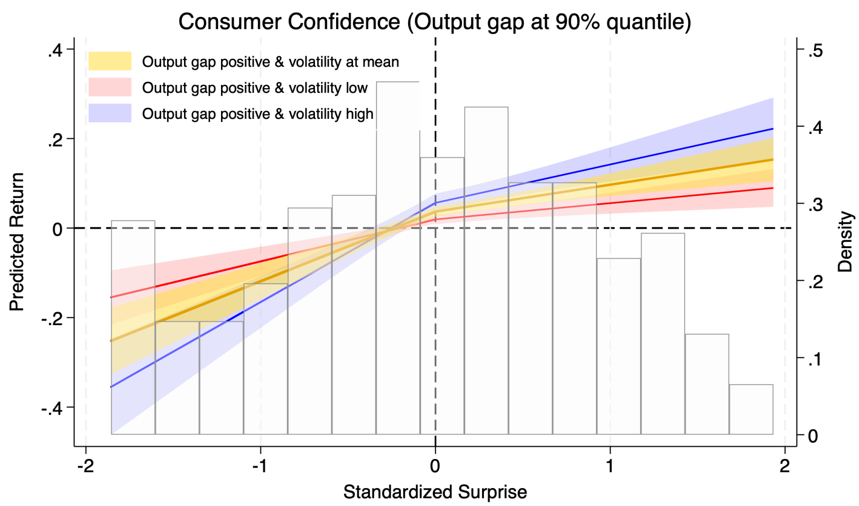

Figure 6: Return predicted by the model in Column (1) of Table A.2 as a function of Consumer Confidence news for different levels of the long-term volatility component, while the output gap is positive (fixed at the 90% quantile). The yellow line corresponds to a situation where long-term volatility is at its mean ($\tilde{\tau}_t = 0$). The blue (red) line corresponds to a situation with long-term volatility at the 90% quantile (10% quantile). Predicted returns are plotted with 90%-confidence intervals. The histogram refers to the distribution of the announcement surprise of Consumer Confidence.

Finally, as an alternative to equation (25), we consider a specification that includes surprises and squared surprises. This way of introducing non-linearity directly follows our model in equation (15) and is closely related to the regression suggested in Andersen et al. (2003) for testing the asymmetry of good and bad news. Adding the squared surprise to equation (20) and applying the sensitivity factor to both terms leads to[6]

$$R_t[k] \quad = \quad \theta_1 + \gamma_\tau^c \dot{\tau}_t + f(\mathbf{X}_t) \left[\sum_{j=1}^{J} \theta_{2,j} S_{j,t} + \sum_{j=1}^{J} \theta_{3,j} S_{j,t}^2 \right] + \xi_t. \tag{26}$$

In $f(\mathbf{X}_t)$, we include either the long-term volatility component or the long-term component in combination with the predictors from Table 4. Table 5 reports the corresponding estimation results. As in the previous specifications, long-term volatility is always a significant predictor, and in Column (1), the coefficients on the squared surprises are significant for Durable Goods, Consumer Confidence, and the Consumer Price Index. The observation that the coefficient estimates on the squared surprises are negative provides further evidence for prediction P2. Columns (2) to

[6]Equation (11) also suggests adding surprises to the power of four. However, empirically we found no improvement when including those terms. This is what one would expect if A^σ is small, as suggested by the results in Table 2, Column (5).

(4) show that the significance of the coefficients on the squared surprises varies with the predictor variables. Only for the Consumer Price Index and Consumer Confidence the coefficients on the squared terms are significant in all specifications. Compared to the piecewise linear specification, the inclusion of the squared terms might overemphasize the discount rate effect, specifically for large pieces of news. Again, the *no news is good news* effect is confirmed.

Figure 7 shows the model-predicted return as a function of the size of the news and when long-term volatility is low (orange line) or high (blue line) according to (26). In line with our prediction P2, we find evidence for asymmetry in the response to news in both situations. If long-term volatility is high, the effect of large pieces of good news is dampened, and the effect of large pieces of bad news is amplified. Furthermore, in line with our model, large pieces of good news in low volatility regimes have small effects on returns because the discount rate effect partly offsets the positive cash flow effect.

Table 5: Testing for asymmetry in the non-linear specification with squared news.

	(1)		(2) **Output gap**		(3) **Risk appetite**		(4) **Macroeconomic uncertainty**	
	$S_{j,t}$	$S_{j,t}^2$	$S_{j,t}$	$S_{j,t}^2$	$S_{j,t}$	$S_{j,t}^2$	$S_{j,t}$	$S_{j,t}^2$
γ_τ^c	0.021**		0.023**		0.022**		0.023**	
	(0.009)		(0.009)		(0.009)		(0.009)	
$\tilde{\tau}_t$	1.539***		0.872***		1.532***		1.999***	
	(0.206)		(0.182)		(0.196)		(0.204)	
W_{t-1}			-0.125***		-0.165**		-2.410***	
			(0.025)		(0.065)		(0.359)	
Initial Jobless Claims	0.048***	-0.004	0.066***	-0.013**	0.049***	-0.003	0.055***	-0.009
	(0.006)	(0.004)	(0.007)	(0.005)	(0.006)	(0.004)	(0.007)	(0.006)
Nonfarm Payrolls	0.207***	0.006	0.307***	-0.010	0.206***	0.003	0.242***	0.004
	(0.025)	(0.012)	(0.031)	(0.019)	(0.025)	(0.012)	(0.028)	(0.016)
Retail Sales	0.096***	-0.010	0.122***	-0.009	0.101***	-0.012**	0.115***	-0.009
	(0.013)	(0.006)	(0.015)	(0.008)	(0.012)	(0.006)	(0.015)	(0.008)
New Family Houses Sold	0.064***	-0.008	0.085***	-0.020***	0.061***	-0.008	0.064***	-0.013*
	(0.013)	(0.006)	(0.014)	(0.007)	(0.012)	(0.006)	(0.014)	(0.007)
Durable Goods	0.084***	-0.015*	0.081***	-0.013	0.083***	-0.015*	0.085***	-0.014
	(0.016)	(0.009)	(0.017)	(0.010)	(0.015)	(0.008)	(0.015)	(0.009)
New Orders	0.046***	-0.009	0.046***	-0.016*	0.048***	-0.009	0.051***	-0.011
	(0.013)	(0.008)	(0.013)	(0.009)	(0.013)	(0.008)	(0.014)	(0.009)
Consumer Price Index	0.056***	-0.019**	0.047***	-0.021**	0.056***	-0.016*	0.058***	-0.027***
	(0.016)	(0.009)	(0.015)	(0.010)	(0.017)	(0.009)	(0.016)	(0.010)
Consumer Confidence	0.139***	-0.026***	0.164***	-0.037***	0.137***	-0.024***	0.141***	-0.028***
	(0.016)	(0.010)	(0.017)	(0.011)	(0.014)	(0.009)	(0.016)	(0.010)
Purchasing Managers Index	0.145***	-0.010	0.159***	-0.012	0.146***	-0.014	0.156***	-0.006
	(0.021)	(0.013)	(0.024)	(0.016)	(0.022)	(0.014)	(0.021)	(0.013)
Constant	0.019***		0.025***		0.020***		0.021***	
	(0.005)		(0.006)		(0.005)		(0.005)	
Observations	2826		2294		2826		2826	
Adjusted R^2	0.237		0.320		0.243		0.265	

Notes: We set $k = 5$ minutes. The table presents the results of estimating equation (26). The row labeled W_{t-1} refers to the predictor named in the table header. In the columns denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the columns denoted by $S_{j,t}^2$, we report the coefficient estimates for the squared surprises. In Column (2), we use the output gap as an additional predictor. In Column (3), we use risk appetite, and in Column (4), we use macroeconomic uncertainty. The estimation sample in Column (2) spans the period from January 2001 to December 2017; in Columns (3) and (4), the sample is from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

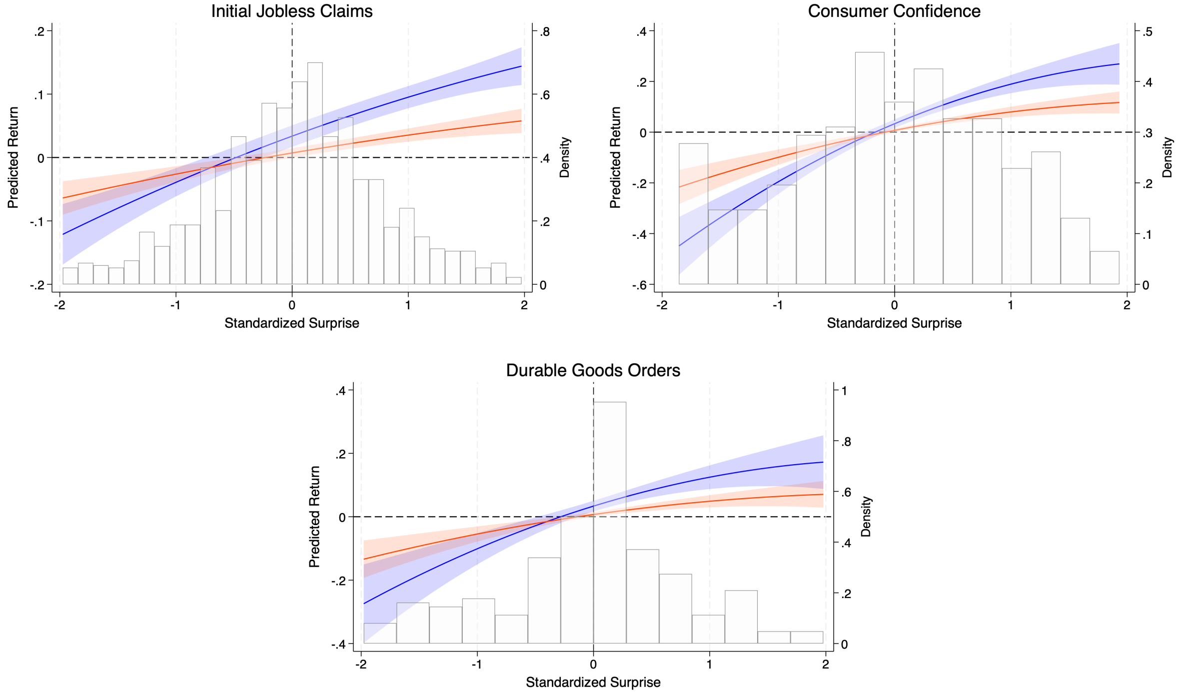

Figure 7: Return predicted by the model in Column (1) of Table 5 as a function of macroeconomic news, conditional on the long-term volatility component being either at the 10% (orange line) or 90% (blue line) quantile. For instance, when looking at the Initial Jobless Claims announcement, the 10% quantile corresponds to an annualized long-term volatility of 10.7%, and the 90% quantile corresponds to an annualized long-term volatility of 22.5%. For the calculation of the predicted return of an announcement, the surprises of all other announcements were set to zero. Plotted with 90%-confidence intervals. The histogram refers to the distribution of the announcement surprise of the corresponding announcement.

4.2.5 Extension to the European stock market

Finally, we investigate whether our findings can be extended to other stock markets. Kerssenfischer and Schmeling (2022) show that U.S. macroeconomic announcements explain a large fraction of return variation in European stock markets. Thus, we now look at European stock market data and analyze whether long-term volatility can explain the reaction of the EURO STOXX 50 to U.S. macroeconomic announcements. We repeat our analyses from Sections 4.2.2 and 4.2.4 using daily returns of the EURO STOXX 50. The EURO STOXX 50 is composed of 50 blue-chip stocks from eleven countries in the Eurozone. High-frequency return data for this index are available on TickData from 2003 onwards. Panel A of Table 6 presents estimates of equations (20) and (25) using 5-minute EURO STOXX 50 returns and the daily long-term volatility of the EURO STOXX 50. Again, we find evidence in support of predictions P1 to P3. In Panel B, we estimate the same regressions but replace the long-term component of the EURO STOXX 50 with the S&P 500's long-term volatility component. If the S&P 500's long-term volatility component is a good proxy for global long-term stock market risk, and global risk drives the time-varying response, this might further improve the model fit.[7] Indeed, Panel B confirms all previous results while the adjusted R^2's are slightly higher than in Panel A.

Table 6: Evidence for volatility feedback based on EURO STOXX 50 returns.

	Panel A: Long-term volatility component of EURO STOXX 50			***Panel B: Long-term volatility component of S&P 500***		
	(1)	(2)		(3)	(4)	
		$S_{j,t}^+$	$S_{j,t}^-$		$S_{j,t}^+$	$S_{j,t}^-$
γ_τ^c		0.032***			0.037***	
		(0.012)			(0.012)	
$\tilde{\tau}_t$	1.344***	1.277***		1.257***	1.213***	
	(0.240)	(0.229)		(0.179)	(0.195)	
Initial Jobless Claims	0.062***	0.036***	0.080***	0.063***	0.038***	0.082***
	(0.007)	(0.012)	(0.011)	(0.007)	(0.013)	(0.011)
Nonfarm Payrolls	0.266***	0.290***	0.249***	0.257***	0.285***	0.241***
	(0.037)	(0.046)	(0.058)	(0.031)	(0.047)	(0.041)
Retail Sales	0.106***	0.080***	0.138**	0.079*	0.075***	0.092
	(0.035)	(0.020)	(0.063)	(0.045)	(0.016)	(0.087)
New Family Houses Sold	0.072***	0.051***	0.104***	0.074***	0.054***	0.101***
	(0.016)	(0.019)	(0.027)	(0.016)	(0.020)	(0.024)
Durable Goods Orders	0.095***	0.034	0.137***	0.102***	0.047**	0.155***
	(0.019)	(0.030)	(0.025)	(0.014)	(0.019)	(0.024)
Manufacturers New Orders	0.032*	-0.022	0.099***	0.042**	0.004	0.087***
	(0.019)	(0.025)	(0.021)	(0.017)	(0.027)	(0.020)
Consumer Price Index	0.046**	-0.006	0.093***	0.054***	0.014	0.085***
	(0.018)	(0.025)	(0.026)	(0.020)	(0.031)	(0.026)
Consumer Confidence	0.139***	0.082***	0.213***	0.156***	0.092***	0.234***
	(0.023)	(0.032)	(0.033)	(0.020)	(0.028)	(0.032)
Purchasing Managers Index	0.177***	0.144***	0.229***	0.178***	0.155***	0.204***
	(0.028)	(0.034)	(0.048)	(0.028)	(0.034)	(0.052)
Constant	0.016***	0.044***		0.016***	0.042***	
	(0.005)	(0.008)		(0.005)	(0.009)	
Observations	1988	1988		2459	2459	
Adjusted R^2	0.206	0.221		0.213	0.226	

Notes: We set $k = 5$ minutes. In Panel A, we use the demeaned long-term volatility $\tilde{\tau}_t$ of the EURO STOXX. In Panel B, we use the demeaned long-term volatility component $\tilde{\tau}_t$ of the S&P 500 (as in the previous analysis). Columns (1) and (3) present non-linear least squares estimates as described in equation (20) using $f(\mathbf{X}_t)$ as in equation (22). Columns (2) and (4) present results of estimating (25) where we separate between good and bad news using $f(\mathbf{X}_t)$ as in equation (22). In the column denoted by $S_{j,t}^+$, we report the coefficient estimates for good news, and in the columns denoted by $S_{j,t}^-$, we report the coefficient estimates for bad news. EURO STOXX 50 data is available from TickData from July 2003 onwards. However, for the expanding window estimation of the European long-term volatility component we need a sample of at least three years for the first estimation. We use the sample from January 2007 until December 2021 in Panel A. In Panel B, the sample is from July 2003 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1

[7] The estimated long-term component from daily EURO STOXX 50 returns exhibits a correlation of 0.42 with the long-term component estimated using daily S&P 500 returns from 2007 to 2021.

5 Robustness

In this section, we confirm that our results are robust to using the long-term variance component rather than the long-term volatility component in the sensitivity factor, alternative estimation window sizes, S&P 500 index returns, a separate estimation of 8:30 am and 10:00 am EST announcements and the exclusion of announcements made on monetary policy decision days. Moreover, excluding the COVID-19 pandemic from our sample does not change the results. The corresponding tables are deferred to Appendix B.

Long-term variance vs long-term volatility

From equation (14) it follows that cash-flow news is a function of the square root of the long-term volatility component, i.e., $\sqrt{\tau_t}$, while discount rate news is a function of the long-term variance component, i.e., τ_t. While we modeled the *no news is good news* effect as a function of the long-term variance component, we always used the long-term volatility component in the sensitivity factor. Thus, we now replicate the analyses from Column (2) in Table 2, Column (1) in Table 4 and Column (1) in Table 5 using the long-term variance component ($\dot{\tau}_t = \tau_t - \bar{\tau}$). Table A.3 shows that the previous results are not affected.

Announcement window size

Previous studies of macroeconomic announcements show that the strength of the response typically declines with increasing window size k (e.g., Andersen et al., 2003). Table A.4 in the Appendix replicates Table 2 for $k = 1$ and $k = 10$ minutes. Independent of the size of the window, the long-term component has strong explanatory power (prediction P1). However, as expected, the adjusted R^2 decreases for $k = 10$. Tables A.5 and A.6 confirm the asymmetric effect of good and bad news (prediction P2) as well as prediction P3 for $k = 1$ minute windows.

Impact of scheduled monetary policy decisions

Lucca and Moench (2015) show that scheduled monetary policy decisions lead to large average excess returns in the 24 hours before the communication of the decision. This might distort our inferences if macroeconomic news is released on monetary policy decision days of the Fed or the ECB. Table A.7 shows that the estimated coefficients from Column (2) in Table 2 and Column (1) in Table 4 and Table 5 are of similar size when we exclude prescheduled FOMC and ECB monetary policy decision days.

Separate regressions for 8:30 am and 10:00 am announcements

Instead of estimating a joint model, where we pool announcements made at 8:30 am and 10:00 am EST into a single regression, we repeat our baseline analysis and estimate separate regressions for news at 8:30 am and 10:00 am EST. The results reported in Table A.8 show that the coefficient and standard error estimates are of similar size as in the pooled regression.

Futures vs. stock market index data

For announcements published at 10:00 am EST, we compare the results based on the S&P 500 E-mini futures with the results using return data for the underlying S&P 500 index. As Table A.9 shows, the size of the coefficients and the explanatory power of the estimated models are similar to the results using the E-mini futures.

Exclusion of the COVID-19 pandemic

Finally, we check whether our results are robust to excluding the COVID-19 pandemic from our sample. Table A.10 confirms that all previous results still hold.

6 Conclusions

This paper studies the importance of the volatility feedback effect for explaining the time-varying sensitivity of stock returns to macroeconomic announcements. By integrating a two-component volatility model for the conditional variance of cash flow news into a standard present value model of returns, we show that news to required returns can be decomposed into innovations to long- and short-term volatility. Following the predictions of our model, we can explain the instantaneous response of the S&P 500 to major U.S. macroeconomic announcements, confirming that volatility feedback is relevant for explaining the impact of macroeconomic news. We show that the long-term volatility component of the MF2-GARCH determines the size of the volatility feedback effect and that the stock market is most responsive to news when long-term volatility is high.

These results are complementary to recent evidence by Gardner et al. (2022) and Elenev et al. (2023). After controlling for the macroeconomic variables considered in their analyses, the long-term volatility component remains significant, and it increases the share of explained variation in unexpected returns. In particular, when jointly including the output gap and long-term volatility, we can explain the largest share of variation in returns. Our results suggest that long-term volatility is neither an alternative measure for the stance of the business cycle nor a proxy for short-term volatility, as measured by the VIX. Instead, long-term volatility contains relevant information beyond these measures about long-term financial market risks and highlights the role of the volatility feedback effect in explaining the time-varying sensitivity of stock returns to macroeconomic news. Furthermore, we confirm our models' central prediction of an asymmetric response to good and bad news that depends on the level of long-term volatility. Moreover, we show that the *no news is good news* effect, as described in Campbell and Hentschel (1992), increases with the level of long-term volatility. Because the MF2-GARCH model can be estimated using daily stock market data, our approach can be easily extended to other countries. In contrast, other predictors, such as the output gap, are not available in real-time, and are published at lower frequencies only.

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Appendix

A Proofs

Proof of Theorem 1. Based on equations (6) and (7), we obtain the following representation of the conditional variance

$$\begin{aligned}\sigma^2_{t+j+1} &= (1-\phi)\tau_{t+j} \\ &+\lambda_0\left(\alpha+\gamma\mathbf{1}_{\{r_{t+j}<0\}}\right)\frac{\eta^2_{d,t+j}}{\tau_{t+j}}+\lambda_1\left(\alpha+\gamma\mathbf{1}_{\{r_{t+j}<0\}}\right)\frac{\eta^4_{d,t+j}}{h_{t+j}\tau_{t+j}} \\ &+\lambda_2\left(\alpha+\gamma\mathbf{1}_{\{r_{t+j1}<0\}}\right)\eta^2_{d,t+j} \\ &+\lambda_0\beta h_{t+j}+\lambda_1\beta\eta^2_{d,t+j}+\lambda_2\beta h_{t+j}\tau_{t+j}. \end{aligned} \tag{A.1}$$

For $j \geq 2$, the following recursions apply:

$$\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] = (1-\phi)\mathbf{E}_{t+1}[\tau_{t+j+1}] + \lambda_0\phi\mathbf{E}_{t+1}[h_{t+j}] + (\lambda_1\phi_\kappa+\lambda_2\phi)\mathbf{E}_{t+1}[\sigma^2_{t+j}] \tag{A.2}$$

and

$$\mathbf{E}_{t}[\sigma^2_{t+j+1}] = (1-\phi)\mathbf{E}_{t}[\tau_{t+j+1}] + \lambda_0\phi\mathbf{E}_{t}[h_{t+j}] + (\lambda_1\phi_\kappa+\lambda_2\phi)\mathbf{E}_{t}[\sigma^2_{t+j}]. \tag{A.3}$$

Hence, we can write

$$\begin{aligned}\mathbf{E}_{t+1}[\sigma^2_{t+j+1}]-\mathbf{E}_{t}[\sigma^2_{t+j+1}] &= (1-\phi)(\mathbf{E}_{t+1}[\tau_{t+j+1}]-\mathbf{E}_{t}[\tau_{t+j+1}]) \\ &+\lambda_0\phi(\mathbf{E}_{t+1}[h_{t+j}]-\mathbf{E}_{t}[h_{t+j}]) \\ &(\lambda_1\phi_\kappa+\lambda_2\phi)(\mathbf{E}_{t+1}[\sigma^2_{t+j}]-\mathbf{E}_{t}[\sigma^2_{t+j}]). \end{aligned} \tag{A.4}$$

Next, we express the revisions in expectations about the short- and long-term volatility component in terms of volatility news. Using that $\phi < 1$, we can write the short-term component volatility in $t+j+1$ as

$$h_{t+j} = 1+\sum_{s=0}^{\infty}\phi^s v^h_{t+j-1-s}. \tag{A.5}$$

Similarly, because $\lambda_1+\lambda_2<1$ we can write the long-term component as

$$\tau_{t+j+1} = \frac{\lambda_0}{1-\lambda_1-\lambda_2}+\sum_{s=0}^{\infty}(\lambda_1+\lambda_2)^s v^\tau_{t+j-s}. \tag{A.6}$$

This leads to

$$\begin{aligned}
\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbf{E}_t[\sigma^2_{t+j+1}] &= (1-\phi)(\lambda_1+\lambda_2)^{j-1}v^\tau_{t+1} + \lambda_0\phi^{j-1}v^h_{t+1} \\
&\quad +(\lambda_1\phi_\kappa + \lambda_2\phi)(\mathbf{E}_{t+1}[\sigma^2_{t+j}] - \mathbf{E}_t[\sigma^2_{t+j}]) \\
&= (1-\phi)(\lambda_1+\lambda_2)^{j-1}v^\tau_{t+1} + \lambda_0\phi^{j-1}v^h_{t+1} \\
&\quad +(\lambda_1\phi_\kappa + \lambda_2\phi)\left[(1-\phi)(\lambda_1+\lambda_2)^{j-2}v^\tau_{t+1} + \lambda_0\phi^{j-2}v^h_{t+1}\right] \\
&\quad +(\lambda_1\phi_\kappa + \lambda_2\phi)^2(\mathbf{E}_{t+1}[\sigma^2_{t+j-1}] - \mathbf{E}_t[\sigma^2_{t+j-1}]) \\
&\vdots \\
&= v^\tau_{t+1}(1-\phi)[(\lambda_1+\lambda_2)^{j-1} + (\lambda_1\phi_\kappa + \lambda_2\phi)(\lambda_1+\lambda_2)^{j-2} + \dots \\
&\quad +(\lambda_1\phi_\kappa + \lambda_2\phi)^{j-2}(\lambda_1+\lambda_2)] \\
&\quad +v^h_{t+1}\lambda_0[\phi^{j-1} + (\lambda_1\phi_\kappa + \lambda_2\phi)\phi^{j-2} + \dots + (\lambda_1\phi_\kappa + \lambda_2\phi)^{j-2}\phi] \\
&\quad +(\lambda_1\phi_\kappa + \lambda_2\phi)^{j-1}(\mathbf{E}_{t+1}[\sigma^2_{t+2}] - \mathbf{E}_t[\sigma^2_{t+2}]) \\
&= v^\tau_{t+1}(1-\phi)\sum_{s=1}^{j-1}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}(\lambda_1+\lambda_2)^{j-s} \\
&\quad +v^h_{t+1}\lambda_0\sum_{s=1}^{j-1}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}\phi^{j-s} \\
&\quad +(\lambda_1\phi_\kappa + \lambda_2\phi)^{j-1}(\mathbf{E}_{t+1}[\sigma^2_{t+2}] - \mathbf{E}_t[\sigma^2_{t+2}]). \qquad \text{(A.7)}
\end{aligned}$$

We obtain equation (12) by combining equations (A.7) and (10).

□

Proof of Theorem 2. Plugging equation (12) into equation (4) and using the assumptions that $\phi < 1$, $\lambda_1 + \lambda_2 < 1$ and $\lambda_1\phi_\kappa + \lambda_2\phi < 1$ leads to equation (13).

□

Corollary 1. *The MF2-GARCH nests the one-component GJR-GARCH under the restriction* $\lambda_1 = \lambda_2 = 0$. *Then,* $\tau_t = \lambda_0$ *and the conditional variance can be written as*

$$\begin{aligned}
\sigma^2_{t+2} &= \lambda_0 h_{t+2} = \lambda_0(1-\phi) + \left(\alpha + \gamma\mathbf{1}_{\{\eta_{d,t+1}<0\}}\right)\eta^2_{d,t+1} + \lambda_0\beta h_{t+1} \\
&= \lambda_0(1-\phi) + \left(\alpha + \gamma\mathbf{1}_{\{\eta_{d,t+1}<0\}}\right)\eta^2_{d,t+1} + \beta\sigma^2_{t+1} \\
&= \lambda_0(1-\phi) + \phi\sigma^2_{t+1} + v^{GJR}_{t+1} \qquad \text{(A.8)}
\end{aligned}$$

with

$$v^{GJR}_{t+1} = \left[\alpha\left(\eta^2_{d,t+1} - \sigma^2_{t+1}\right) + \gamma\left(\mathbf{1}_{\{\eta_{d,t+1}<0\}}\eta^2_{d,t+1} - \sigma^2_{t+1}/2\right)\right].$$

For the GJR-GARCH, equation (12) reduces to

$$\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbf{E}_t[\sigma^2_{t+j+1}] \quad = \quad \phi^{j-1} v^{GJR}_{t+1}. \tag{A.9}$$

It follows that news to required returns can be rewritten as

$$\eta_{r,t+1} = A^{GJR} v^{GJR}_{t+1} \tag{A.10}$$

with

$$A^{GJR} = \delta \sum_{j=1}^{\infty} \rho^j \phi^{j-1} = \frac{\delta \rho}{1 - \rho \phi}. \tag{A.11}$$

B Additional Tables

Table A.1: Test for unbiasedness and optimality of the Bloomberg forecasts.

	Panel A: Unbiasedness	***Panel B: Mincer-Zarnowitz Regression***			
	μ	ψ_1	ψ_2	R^2	Wald
	[p-value]	(se)	(se)		[p-value]
Initial Jobless Claims	6.453	-47.812	1.136	0.944	1.969
	[0.052]	(24.199)	(0.068)		[0.140]
Nonfarm Payrolls	33.107	38.017	0.818	0.811	4.241
	[0.423]	(36.351)	(0.064)		[0.015]
Retail Sales	-0.004	-0.238	1.736	0.836	28.279
	[0.942]	(.047)	(0.098)		[0.000]
New Family Houses Sold	4.053	-1.881	1.009	0.961	0.837
	[0.280]	(6.529)	(0.011)		[0.434]
Durable Goods Orders	-0.023	-0.050	1.183	0.693	2.949
	[0.886]	(0.124)	(0.078)		[0.054]
Manufacturers New Orders	0.018	0.015	1.019	0.943	1.053
	[0.617]	(0.035)	(0.016)		[0.350]
Consumer Price Index	-0.001	-.034	1.179	0.858	16.161
	[0.962]	(0.008)	(0.032)		[0.000]
Consumer Confidence	0.306	-0.212	1.005	0.956	0.772
	[0.359]	(1.037)	(0.011)		[0.463]
Purchasing Managers Index	0.223	1.628	.974	0.881	1.776
	[0.070]	(1.413)	(0.025)		[0.171]

Notes: The table reports tests for the unbiasedness and optimality of the Bloomberg forecasts for the sample period between 2001 and 2021. In Panel A, we test for the unbiasedness of the surprises and regress the surprise $S_{j,t} = A_{j,t} - E_{j,t-1}$ on a constant ($S_{j,t} = \mu + u_{j,t}$) and test if the constant is significant ($\mathbb{H}_0 : \mu = 0$). The regression provides evidence that the forecasts made by the Bloomberg forecasters are unbiased. In Panel B, we present results of running a Mincer and Zarnowitz (1969) regression to test for the optimality of the forecasts. We regress the realization of the announcement on a constant and the Bloomberg median forecast ($A_{j,t} = \psi_1 + \psi_2 E_{j,t-1} + u_{j,t}$) using Newey-West standard errors with 3 lags. The corresponding hypothesis $\mathbb{H}_0 : \psi_1 = 0$ and $\psi_2 = 1$ is tested using a Wald test. For most macroeconomic news under consideration, we can reject the null of a systematic bias in the forecasts.

Table A.2: Testing for interaction between long-term volatility and other predictor variables.

	(1)	(2)	(3)
γ_τ^c	0.029***	0.027***	0.030***
	(0.009)	(0.009)	(.007)
$\tilde{\tau}_t$	0.982***	1.511***	1.504***
	(0.162)	(0.194)	(0.230)
Output gap	-0.131***		
	(0.024)		
Output gap $\times\ \tilde{\tau}_t$	0.215***		
	(0.056)		
Risk appetite		-0.130*	
		(0.069)	
Risk appetite $\times\ \tilde{\tau}_t$		-0.129	
		(0.160)	
Macroeconomic uncertainty			-2.451***
			(0.376)
Macroeconomic uncertainty $\times \tilde{\tau}_t$			0.262
			(1.119)
Observations	2294	2826	2826
Adjusted R^2	0.328	0.244	0.246

Notes: We set $k = 5$ minutes. The columns present results of estimating equation (25) using $f(X_t)$ as in equation (24) augmented by an interaction term. In Column (1), we use the output gap as the additional predictor. In Column (2), we use risk appetite, and in Column (3), we use macroeconomic uncertainty. The estimation sample in Column (1) spans the period from January 2001 to December 2017; in Columns (2) and (3), the sample is from January 2001 to December 2021. The coefficient estimates for the macroeconomic announcements are not shown in the table. Regressions include a constant. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.

Table A.3: Regression for baseline specification and time-varying sensitivity using the long-term variance instead of the long-term volatility.

	(1)	(2)		(3)	
		$S^+_{j,t}$	$S^-_{j,t}$	$S_{j,t}$	$S^2_{j,t}$
γ^c_τ		0.027***		0.020**	
		(0.010)		(0.009)	
$\dot{\tau}_t$	0.586***	0.593***		0.589***	
	(0.081)	(0.087)		(0.088)	
Initial Jobless Claims	0.050***	0.027***	0.066***	0.048***	-0.004
	(0.006)	(0.008)	(0.012)	(0.006)	(0.004)
Nonfarm Payrolls	0.203***	0.197***	0.212***	0.207***	0.004
	(0.024)	(0.035)	(0.032)	(0.025)	(0.012)
Retail Sales	0.096***	0.074***	0.121***	0.097***	-0.010
	(0.013)	(0.015)	(0.022)	(0.013)	(0.006)
New Family Houses Sold	0.062***	0.051***	0.075***	0.063***	-0.008
	(0.012)	(0.018)	(0.018)	(0.013)	(0.006)
Durable Goods Order	0.074***	0.041**	0.112***	0.080***	-0.015*
	(0.016)	(0.019)	(0.026)	(0.016)	(0.009)
Manufacturers New Orders	0.044***	0.024	0.065***	0.045***	-0.009
	(0.013)	(0.023)	(0.016)	(0.013)	(0.008)
Consumer Price Index	0.061***	0.027	0.093***	0.057***	-0.018**
	(0.017)	(0.023)	(0.026)	(0.016)	(0.009)
Consumer Confidence	0.130***	0.083***	0.186***	0.138***	-0.026***
	(0.015)	(0.016)	(0.026)	(0.016)	(0.009)
Purchasing Managers Index	0.143***	0.122***	0.167***	0.145***	-0.011
	(0.020)	(0.025)	(0.037)	(0.022)	(0.014)
Constant	0.008**	0.029***		0.020***	
	(0.004)	(0.007)		(0.005)	
Observations	2826	2826		2826	
Adjusted R^2	0.226	0.234		0.233	

Notes: We set $k = 5$ minutes. Column (1) reports non-linear least squares estimates as described in equation (20), where $f(\mathbf{X}_t)$ is chosen as in equation (21) with $\gamma'_X \mathbf{X}_t = \gamma_\tau \dot{\tau}_t$. Column (2) reports the results of estimating (25) using $f(\mathbf{X}_t)$ as in Column (1). In the column denoted by $S^+_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^-_{j,t}$, we report the coefficient estimates for bad news. In Column (3), we present the results of estimating equation (26) using $f(\mathbf{X}_t)$ as in Column (1). In the column denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the column denoted by $S^2_{j,t}$, we report the coefficient estimates for the squared surprises. $\dot{\tau}_t$ was obtained from an expanding window estimation and demeaned. The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table A.4: Regression for baseline specification and time-varying sensitivity using $k = 1$ and $k = 10$ minute estimation windows.

	Panel A: $k = 1$ Minutes						*Panel B: $k = 10$ Minutes*					
	(1)	(2)	(3)		(4)		(5)	(6)	(7)		(8)	
			$S^+_{j,t}$	$S^-_{j,t}$	$S_{j,t}$	$S^2_{j,t}$			$S^+_{j,t}$	$S^-_{j,t}$	$S_{j,t}$	$S^2_{j,t}$
γ^c_τ			0.016**		0.011*				0.018		0.012	
			(0.007)		(0.006)				(0.012)		(0.011)	
$\tilde{\tau}_t$		1.468***	1.486***		1.500***			1.673***	1.645***		1.638***	
		(0.184)	(0.188)		(0.188)			(0.204)	(0.211)		(0.208)	
Initial Jobless Claims	0.041***	0.040***	0.028***	0.049***	0.039***	-0.002	0.051***	0.048***	0.040***	0.054***	0.048***	-0.000
	(0.005)	(0.004)	(0.006)	(0.007)	(0.004)	(0.002)	(0.008)	(0.007)	(0.009)	(0.013)	(0.006)	(0.004)
Nonfarm Payrolls	0.176***	0.169***	0.164***	0.176***	0.174***	0.006	0.214***	0.197***	0.201***	0.200***	0.205***	0.009
	(0.024)	(0.021)	(0.032)	(0.026)	(0.021)	(0.010)	(0.032)	(0.026)	(0.037)	(0.035)	(0.026)	(0.013)
Retail Sales	0.084***	0.074***	0.058***	0.091***	0.074***	-0.008*	0.113***	0.096***	0.080***	0.114***	0.097***	-0.006
	(0.012)	(0.009)	(0.010)	(0.014)	(0.009)	(0.004)	(0.018)	(0.017)	(0.017)	(0.028)	(0.017)	(0.008)
New Family Houses Sold	0.044***	0.058***	0.044***	0.076***	0.060***	-0.006	0.051***	0.072***	0.084***	0.056**	0.071***	0.004
	(0.009)	(0.010)	(0.015)	(0.013)	(0.010)	(0.006)	(0.016)	(0.020)	(0.028)	(0.026)	(0.019)	(0.009)
Durable Goods Order	0.070***	0.072***	0.049***	0.098***	0.077***	-0.012***	0.069***	0.068***	0.042*	0.100***	0.075***	-0.014
	(0.010)	(0.010)	(0.013)	(0.014)	(0.009)	(0.004)	(0.018)	(0.019)	(0.025)	(0.027)	(0.018)	(0.009)
Manufacturers New Orders	0.031***	0.027***	0.015	0.040***	0.028***	-0.005	0.034**	0.042***	0.011	0.076***	0.045***	-0.017*
	(0.007)	(0.009)	(0.012)	(0.015)	(0.009)	(0.006)	(0.017)	(0.016)	(0.025)	(0.020)	(0.015)	(0.009)
Consumer Price Index	0.087***	0.072***	0.048**	0.093***	0.068***	-0.012	0.082***	0.062***	0.035	0.089***	0.059***	-0.016
	(0.014)	(0.014)	(0.019)	(0.019)	(0.013)	(0.008)	(0.019)	(0.018)	(0.028)	(0.023)	(0.018)	(0.010)
Consumer Confidence	0.103***	0.104***	0.064***	0.148***	0.108***	-0.020***	0.151***	0.156***	0.117***	0.202***	0.161***	-0.019*
	(0.011)	(0.009)	(0.010)	(0.015)	(0.009)	(0.005)	(0.021)	(0.016)	(0.020)	(0.028)	(0.017)	(0.010)
Purchasing Managers Index	0.090***	0.082***	0.071***	0.093***	0.082***	-0.004	0.177***	0.173***	0.142***	0.215***	0.178***	-0.016
	(0.011)	(0.012)	(0.016)	(0.018)	(0.012)	(0.007)	(0.022)	(0.022)	(0.030)	(0.037)	(0.023)	(0.015)
Constant	0.003	0.004	0.018***		0.011***		0.004	0.004	0.019**		0.012*	
	(0.003)	(0.003)	(0.005)		(0.004)		(0.005)	(0.005)	(0.008)		(0.006)	
Observations	2826	2826	2826		2826		2826	2826	2826		2826	
Adjusted R^2	0.217	0.260	0.267		0.267		0.158	0.199	0.203		0.202	

Notes: In Panel A, the estimation window is of size $k = 1$ minutes, and in Panel B, the estimation window is of size $k = 10$ minutes. Columns (1) and (5) present OLS estimates for equation (19). Columns (2) and (6) report non-linear least squares estimates as described in equation (20) with $f(\mathbf{X}_t)$ as in equation (22). Columns (3) and (7) report the results of estimating (25) using $f(\mathbf{X}_t)$ as in equation (22). In the column denoted by $S^+_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^-_{j,t}$, we report the coefficient estimates for bad news. In Columns (4) and (8), we present the results of estimating equation (26). In the column denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the column denoted by $S^2_{j,t}$, we report the coefficient estimates for the squared surprises. The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p < 0.01, **p < 0.05, *p < 0.1

Table A.5: Testing for asymmetric effects of good and bad news (piece-wise linear specification) when $k = 1$

	(1)		(2) **Output gap**		(3) **Risk appetite**		(4) **Macroeconomic uncertainty**	
	$S^+_{j,t}$	$S^-_{j,t}$	$S^+_{j,t}$	$S^-_{j,t}$	$S^+_{j,t}$	$S^-_{j,t}$	$S^+_{j,t}$	$S^-_{j,t}$
γ^c_τ	0.016**		0.016**		0.017***		0.019***	
	(0.007)		(0.007)		(0.006)		(0.007)	
$\tilde{\tau}_t$	1.486***		0.682***		1.468***		1.885***	
	(0.188)		(0.165)		(0.180)		(0.185)	
W_{t-1}			-0.164***		-0.127**		-2.181***	
			(0.025)		(0.054)		(0.324)	
Initial Jobless Claims	0.028***	0.049***	0.037***	0.079***	0.028***	0.050***	0.027***	0.067***
	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Nonfarm Payrolls	0.164***	0.176***	0.239***	0.289***	0.159***	0.180***	0.177***	0.204***
	(0.032)	(0.026)	(0.040)	(0.034)	(0.034)	(0.025)	(0.038)	(0.031)
Retail Sales	0.058***	0.091***	0.080***	0.117***	0.058***	0.095***	0.072***	0.108***
	(0.010)	(0.014)	(0.012)	(0.013)	(0.010)	(0.014)	(0.013)	(0.016)
New Family Houses Sold	0.044***	0.076***	0.041**	0.105***	0.042***	0.079***	0.032**	0.086***
	(0.015)	(0.013)	(0.018)	(0.012)	(0.015)	(0.013)	(0.016)	(0.014)
Durable Goods Orders	0.049***	0.098***	0.054***	0.094***	0.045***	0.100***	0.048***	0.098***
	(0.013)	(0.014)	(0.015)	(0.016)	(0.012)	(0.014)	(0.011)	(0.011)
Manufacturers New Orders	0.015	0.040***	0.010	0.045***	0.016	0.043***	0.016	0.050***
	(0.012)	(0.015)	(0.012)	(0.014)	(0.012)	(0.014)	(0.013)	(0.014)
Consumer Price Index	0.048**	0.093***	0.038**	0.079***	0.047**	0.091***	0.042**	0.108***
	(0.019)	(0.019)	(0.016)	(0.019)	(0.019)	(0.019)	(0.018)	(0.021)
Consumer Confidence	0.064***	0.148***	0.077***	0.175***	0.062***	0.144***	0.065***	0.156***
	(0.010)	(0.015)	(0.011)	(0.015)	(0.010)	(0.014)	(0.009)	(0.014)
Purchasing Managers Index	0.071***	0.093***	0.080***	0.109***	0.068***	0.100***	0.073***	0.100***
	(0.016)	(0.018)	(0.020)	(0.020)	(0.015)	(0.018)	(0.018)	(0.017)
Constant	0.018***		0.022***		0.019***		0.023***	
	(0.005)		(0.005)		(0.005)		(0.005)	
Observations	2826		2294		2826		2826	
Adjusted R^2	0.267		0.373		0.271		0.292	

Notes: We set $k = 1$ minutes. Column (1) reports the results of estimating (25) using $f(\mathbf{X}_t)$ as in equation (22). In Columns (2) to (4), we extend the model from Column (1) by using $f(\mathbf{X}_t)$ from equation (24). The row labeled W_{t-1} refers to the predictor named in the table header. In the columns denoted by $S^+_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^-_{j,t}$, we report the coefficient estimates for bad news. The estimation sample spans the period from January 2001 to December 2021, except for Column (2), where we do not consider announcements after December 2017. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.

Table A.6: Testing for asymmetry in the non-linear specification with squared news when $k = 1$.

	(1)		(2) **Output gap**		(3) **Risk appetite**		(4) **Macroeconomic uncertainty**	
	$S_{j,t}$	$S_{j,t}^2$	$S_{j,t}$	$S_{j,t}^2$	$S_{j,t}$	$S_{j,t}^2$	$S_{j,t}$	$S_{j,t}^2$
γ_τ^c	0.011*		0.012**		0.012**		0.013**	
	(0.006)		(0.006)		(0.006)		(0.006)	
$\tilde{\tau}_t$	1.500***		0.683***		1.497***		1.900***	
	(0.188)		(0.168)		(0.180)		(0.190)	
W_{t-1}			-0.168***		-0.121**		-2.135***	
			(0.026)		(0.056)		(0.337)	
Initial Jobless Claims	0.039***	-0.002	0.057***	-0.008***	0.040***	-0.002	0.046***	-0.007**
	(0.004)	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)	(0.004)	(0.003)
Nonfarm Payrolls	0.174***	0.006	0.264***	-0.009	0.173***	0.004	0.196***	0.005
	(0.021)	(0.010)	(0.026)	(0.017)	(0.022)	(0.010)	(0.025)	(0.014)
Retail Sales	0.074***	-0.008*	0.096***	-0.011**	0.076***	-0.009**	0.088***	-0.009
	(0.009)	(0.004)	(0.008)	(0.005)	(0.008)	(0.004)	(0.010)	(0.006)
New Family Houses Sold	0.060***	-0.006	0.072***	-0.016**	0.060***	-0.007	0.058***	-0.012*
	(0.010)	(0.006)	(0.011)	(0.007)	(0.010)	(0.006)	(0.010)	(0.006)
Durable Goods Orders	0.077***	-0.012***	0.076***	-0.010*	0.076***	-0.013***	0.075***	-0.012***
	(0.009)	(0.004)	(0.010)	(0.005)	(0.009)	(0.004)	(0.008)	(0.003)
Manufacturers New Orders	0.028***	-0.005	0.028***	-0.008	0.030***	-0.005	0.033***	-0.007
	(0.009)	(0.006)	(0.009)	(0.005)	(0.009)	(0.006)	(0.009)	(0.006)
Consumer Price Index	0.068***	-0.012	0.057***	-0.011	0.067***	-0.011	0.072***	-0.018**
	(0.013)	(0.008)	(0.012)	(0.008)	(0.013)	(0.008)	(0.013)	(0.009)
Consumer Confidence	0.108***	-0.020***	0.128***	-0.025***	0.104***	-0.019***	0.113***	-0.021***
	(0.009)	(0.005)	(0.010)	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)
Purchasing Managers Index	0.082***	-0.004	0.094***	-0.006	0.084***	-0.007	0.087***	-0.005
	(0.012)	(0.007)	(0.014)	(0.008)	(0.012)	(0.007)	(0.012)	(0.008)
Constant	0.011***		0.014***		0.012***		0.014***	
	(0.004)		(0.004)		(0.004)		(0.004)	
Observations	2826		2294		2826		2826	
Adjusted R^2	0.267		0.371		0.271		0.291	

Notes: We set $k = 1$ minutes. The Table presents the results of estimating equation (26). Column (1) reports the results of estimating (25) using $f(\mathbf{X}_t)$ as in equation (22). In Columns (2) to (4), we extend the model from Column (1) by using $f(\mathbf{X}_t)$ from equation (24). In Column (2), we use the output gap as an additional predictor. In Column (3), we use risk appetite, and in Column (4), we use macroeconomic uncertainty. The row labeled W_{t-1} refers to the predictor named in the table header. In the columns denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the columns denoted by $S_{j,t}^2$, we report the coefficient estimates for the squared surprises. The estimation sample spans the period from January 2001 to December 2021, except for Column (2), where we do not consider announcements after December 2017. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1

Table A.7: Regression for baseline specification and time-varying sensitivity when excluding monetary policy decision days of the Fed and the ECB.

	(1)	(2)	(3)		(4)	
			$S^+_{j,t}$	$S^-_{j,t}$	$S_{j,t}$	$S^2_{j,t}$
γ^c_τ			0.027**		0.021**	
			(0.011)		(0.010)	
$\tilde{\tau}_t$		1.579***	0.617***		1.595***	
		(0.203)	(0.090)		(0.213)	
Initial Jobless Claims	0.051***	0.051***	0.033***	0.065***	0.050***	-0.002
	(0.009)	(0.008)	(0.009)	(0.014)	(0.007)	(0.004)
Employees on Nonfarm Payrolls	0.212***	0.201***	0.195***	0.211***	0.206***	0.006
	(0.030)	(0.025)	(0.035)	(0.033)	(0.026)	(0.012)
Retail Sales	0.121***	0.102***	0.083***	0.122***	0.102***	-0.007
	(0.017)	(0.015)	(0.015)	(0.023)	(0.014)	(0.007)
Durable Goods Order	0.072***	0.064***	0.061***	0.066***	0.065***	-0.002
	(0.017)	(0.013)	(0.020)	(0.017)	(0.013)	(0.006)
Consumer Price Index	0.089***	0.079***	0.043**	0.111***	0.086***	-0.015*
	(0.019)	(0.017)	(0.020)	(0.028)	(0.017)	(0.009)
New Family Houses Sold	0.044***	0.046***	0.023	0.073***	0.049***	-0.013
	(0.011)	(0.018)	(0.030)	(0.018)	(0.016)	(0.010)
Manufacturers New Orders	0.047***	0.077***	0.038	0.114***	0.070***	-0.020**
	(0.015)	(0.018)	(0.025)	(0.023)	(0.017)	(0.009)
Consumer Confidence	0.130***	0.130***	0.079***	0.185***	0.136***	-0.027***
	(0.018)	(0.015)	(0.017)	(0.026)	(0.016)	(0.010)
Purchasing Managers Index	0.150***	0.143***	0.123***	0.164***	0.145***	-0.008
	(0.019)	(0.019)	(0.026)	(0.037)	(0.021)	(0.013)
Constant	0.008*	0.009**	0.029***		0.020***	
	(0.004)	(0.004)	(0.008)		(0.006)	
Observations	2470	2470	2470		2470	
Adjusted R^2	0.195	0.239	0.243		0.246	

Notes: We set $k = 5$ minutes and exclude monetary policy decision days from the estimation. Column (1) presents OLS estimates for equation (19). Column (2) reports non-linear least squares estimates as described in equation (20) using $f(\mathbf{X}_t)$ as in equation (22). Column (3) reports the results of estimating (25) using $f(\mathbf{X}_t)$ as in equation (22). In the column denoted by $S^+_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^-_{j,t}$, we report the coefficient estimates for bad news. In Column (4), we present the results of estimating equation (26) using $f(\mathbf{X}_t)$ as in equation (22). In the column denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the column denoted by $S^2_{j,t}$, we report the coefficient estimates for the squared surprises. The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1

Table A.8: Regression for time-varying sensitivity separately for 8:30 am and 10:00 am EST announcements.

			Panel A: 8:30 am EST			
	(1)	(2)	(3)		(4)	
			$S^+_{j,t}$	$S^-_{j,t}$	$S_{j,t}$	$S^2_{j,t}$
γ^c_τ			0.010		0.003	
			(0.011)		(0.010)	
$\tilde{\tau}_t$		1.483***	1.484***		1.480***	
		(0.274)	(0.282)		(0.281)	
Initial Jobless Claims	0.049***	0.050***	0.033***	0.061***	0.049***	-0.002
	(0.007)	(0.007)	(0.009)	(0.012)	(0.006)	(0.004)
Employees on Nonfarm Payrolls	0.212***	0.203***	0.207***	0.204***	0.209***	0.008
	(0.029)	(0.025)	(0.037)	(0.033)	(0.026)	(0.012)
Retail Sales	0.110***	0.096***	0.078***	0.115***	0.096***	-0.008
	(0.016)	(0.014)	(0.016)	(0.023)	(0.014)	(0.007)
Durable Goods Order	0.073***	0.079***	0.051**	0.111***	0.085***	-0.013
	(0.017)	(0.016)	(0.021)	(0.025)	(0.016)	(0.009)
Consumer Price Index	0.082***	0.062***	0.035	0.089***	0.059***	-0.016*
	(0.018)	(0.017)	(0.024)	(0.025)	(0.016)	(0.009)
Constant	0.011**	0.011**	0.025***		0.016***	
	(0.005)	(0.005)	(0.008)		(0.006)	
Observations	1857	1857	1857		1857	
Adjusted R^2	0.191	0.228	0.232		0.232	

			Panel B: 10:00 am EST			
	(1)	(2)	(3)		(4)	
			$S^+_{j,t}$	$S^-_{j,t}$	$S_{j,t}$	$S^2_{j,t}$
γ^c_τ			0.061***		0.055***	
			(0.019)		(0.017)	
$\tilde{\tau}_t$		1.601***	1.569***		1.567***	
		(0.262)	(0.275)		(0.271)	
New Family Houses Sold	0.046***	0.063***	0.043**	0.084***	0.063***	-0.011
	(0.011)	(0.012)	(0.018)	(0.021)	(0.013)	(0.007)
Manufacturers New Orders	0.046***	0.044***	0.014	0.078***	0.047***	-0.015*
	(0.013)	(0.013)	(0.025)	(0.018)	(0.013)	(0.009)
Consumer Confidence	0.133***	0.131***	0.074***	0.199***	0.140***	-0.033***
	(0.018)	(0.015)	(0.019)	(0.028)	(0.015)	(0.010)
Purchasing Managers Index	0.153***	0.143***	0.112***	0.177***	0.145***	-0.015
	(0.019)	(0.019)	(0.027)	(0.036)	(0.021)	(0.014)
Constant	0.001	0.003	0.037***		0.026***	
	(0.007)	(0.007)	(0.014)		(0.010)	
Observations	969	969	969		969	
Adjusted R^2	0.186	0.232	0.255		0.256	

Notes: We set $k = 5$ minutes and separate announcements at 8:30 and 10:00 am EST into two separate regressions. In Panel A, we present the results for including announcements scheduled for 8:30 am EST, and in Panel B, we present results for including only announcements scheduled for 10:00 am EST in the regression. Column (1) presents OLS estimates for equation (19). Column (2) reports non-linear least squares estimates as described in equation (20), where $f(\mathbf{X}_t)$ is chosen as in equation (22). Column (3) reports the results of estimating (25) using $f(\mathbf{X}_t)$ as in equation (22). In the column denoted by $S^+_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^-_{j,t}$, we report the coefficient estimates for bad news. In Column (4), we present the results of estimating equation (26) using $f(\mathbf{X}_t)$ as in equation (22). In the column denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the column denoted by $S^2_{j,t}$, we report the coefficient estimates for the squared surprises. The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table A.9: Regression for time-varying sensitivity for announcements published at 10:00 am.

	(1)	(2)	(3)		(4)	
			$S^{+}_{j,t}$	$S^{-}_{j,t}$	$S_{j,t}$	$S^{2}_{j,t}$
γ^{c}_{τ}			0.060***		0.053***	
			(0.019)		(0.017)	
$\tilde{\tau}_t$		1.620***	1.606***		1.599***	
		(0.269)	(0.282)		(0.278)	
New Family Houses Sold	0.047***	0.063***	0.044**	0.085***	0.064***	-0.011
	(0.010)	(0.012)	(0.018)	(0.020)	(0.012)	(0.007)
Manufacturers New Orders	0.045***	0.044***	0.017	0.075***	0.047***	-0.013
	(0.012)	(0.013)	(0.023)	(0.018)	(0.012)	(0.008)
Consumer Confidence	0.130***	0.129***	0.072***	0.196***	0.137***	-0.031***
	(0.018)	(0.015)	(0.021)	(0.027)	(0.016)	(0.011)
Purchasing Managers Index	0.154***	0.143***	0.111***	0.178***	0.145***	-0.016
	(0.019)	(0.019)	(0.027)	(0.034)	(0.020)	(0.013)
Constant	0.001	0.004	0.037***		0.026***	
	(0.007)	(0.007)	(0.014)		(0.010)	
Observations	967	967	967		967	
Adjusted R^2	0.192	0.240	0.263		0.263	

Notes: This Table presents results using S&P 500 returns instead of E-mini future returns, and we set $k = 5$ minutes. Column (1) presents OLS estimates for equation (19). Column (2) reports non-linear least squares estimates as described in equation (20). Column (3) reports the results of estimating (25). In the column denoted by $S^{+}_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^{-}_{j,t}$, we report the coefficient estimates for bad news. In Column (4), we present the results of estimating equation (26). In the column denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the column denoted by $S^{2}_{j,t}$, we report the coefficient estimates for the squared surprises. In all columns we use $f(\mathbf{X}_t)$ as in equation (22). The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1

Table A.10: Regression for time-varying sensitivity and testing for asymmetric effects of good and bad news when excluding the Covid-19 pandemic.

	(1)	(2)	(3)		(4)	
			$S^{+}_{j,t}$	$S^{-}_{j,t}$	$S_{j,t}$	$S^{2}_{j,t}$
γ^{c}_{τ}			0.034***		0.028***	
			(0.010)		(0.009)	
$\tilde{\tau}_t$		1.399***	1.408***		1.424***	
		(0.182)	(0.191)		(0.189)	
Initial Jobless Claims	0.059***	0.055***	0.022**	0.081***	0.051***	-0.011***
	(0.006)	(0.006)	(0.009)	(0.011)	(0.006)	(0.004)
Employees on Nonfarm Payrolls	0.258***	0.239***	0.226***	0.253***	0.237***	-0.008
	(0.027)	(0.023)	(0.038)	(0.029)	(0.024)	(0.012)
Retail Sales	0.125***	0.100***	0.093***	0.112***	0.102***	-0.001
	(0.017)	(0.015)	(0.017)	(0.023)	(0.013)	(0.008)
New Family Houses Sold	0.052***	0.067***	0.043**	0.093***	0.068***	-0.017***
	(0.012)	(0.014)	(0.018)	(0.019)	(0.013)	(0.006)
Durable Goods Order	0.077***	0.081***	0.047**	0.114***	0.083***	-0.015
	(0.017)	(0.017)	(0.021)	(0.027)	(0.017)	(0.010)
Manufacturers New Orders	0.053***	0.049***	0.023	0.077***	0.051***	-0.012
	(0.013)	(0.014)	(0.024)	(0.016)	(0.013)	(0.009)
Consumer Price Index	0.079***	0.056***	0.022	0.097***	0.059***	-0.019*
	(0.020)	(0.020)	(0.026)	(0.027)	(0.017)	(0.011)
Consumer Confidence	0.143***	0.137***	0.085***	0.190***	0.139***	-0.026***
	(0.020)	(0.016)	(0.019)	(0.025)	(0.015)	(0.009)
Purchasing Managers Index	0.166***	0.152***	0.133***	0.170***	0.151***	-0.007
	(0.020)	(0.020)	(0.026)	(0.035)	(0.021)	(0.013)
Constant	0.007*	0.008**	0.033***		0.023***	
	(0.004)	(0.004)	(0.007)		(0.005)	
Observations	2555	2555	2555		2555	
Adjusted R^2	0.242	0.287	0.298		0.297	

Notes: We set $k = 5$ minutes. Column (1) presents OLS estimates for equation (19). Column (2) reports non-linear least squares estimates as described in equation (20). Column (3) reports the results of estimating (25). In the column denoted by $S^{+}_{j,t}$, we report the coefficient estimates for good news, and in the columns denoted by $S^{-}_{j,t}$, we report the coefficient estimates for bad news. In Column (4), we present the results of estimating equation (26). In the column denoted by $S_{j,t}$, we report the coefficient estimates for the surprises, and in the column denoted by $S^{2}_{j,t}$, we report the coefficient estimates for the squared surprises. In all columns we use $f(\mathbf{X}_t)$ as in equation (22). The estimation sample spans the period from January 2001 to December 2019. Numbers in parentheses are robust standard errors (Eicker-Huber-White). Notation: ***p < 0.01, **p < 0.05, *p < 0.1

C Additional Figures

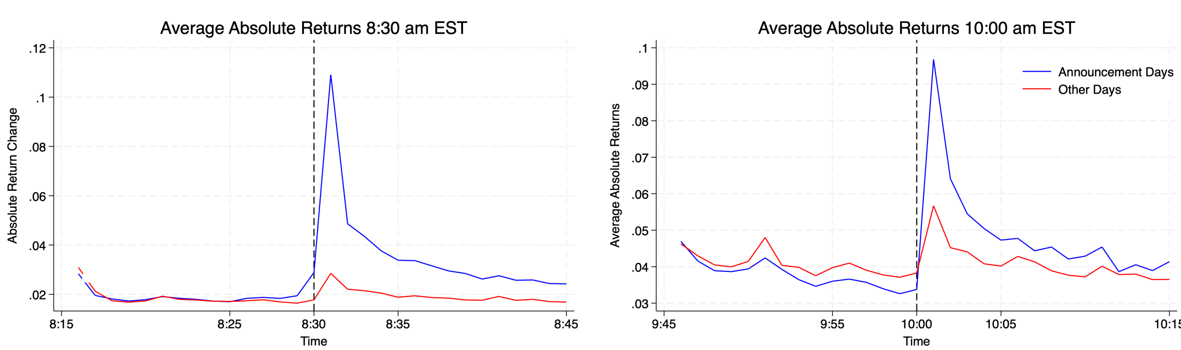

Figure A.1: Average absolute returns in 15-minute windows around the announcements at 8:30 and 10:00 am EST. The average over announcement days considered in our analysis is shown in blue, whereas the average over days not included in our analysis is shown in red.