ARTICLE IN PRESS

Journal of Econometrics xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Econometrics

journal homepage: www.elsevier.com/locate/jeconom

Long-term volatility shapes the stock market's sensitivity to news☆

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ARTICLE INFO

JEL classification:
C58
E44
G12
G14

Keywords:
Event study
Long- and short-term volatility
Macroeconomic announcements
Time-varying risk premia
Volatility feedback effect

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 dampen/amplify the effect of good/bad news.

1. Introduction

Why does the sensitivity of stock markets to the release of macroeconomic news vary over time? This paper offers an explanation based on the *volatility feedback effect*: If volatility is priced, positive/negative volatility innovations increase/decrease future required returns, thereby affecting the current stock price via the discount rate effect. We suggest a model of stock returns in which macroeconomic news not only affects expectations about future cash flows but – via the volatility feedback effect – also future required returns. In our model, the relative importance of cash flow versus discount rate news varies over time and crucially depends on the level of *long-term volatility*. The main prediction of our model is that long-term volatility has explanatory power for the time-varying sensitivity of the stock market to macroeconomic news, and specifically, explains variation in the asymmetric response to good and bad news.

The importance of volatility feedback for explaining stock price movements has been emphasized, for example, by Pindyck (1984), French et al. (1987), and Campbell and Hentschel (1992). Those papers focus on providing evidence for the existence of a positive risk-return relation or on explaining empirical properties of stock returns. For example, French et al. (1987) provide indirect evidence for a positive risk-return relation by showing a negative contemporaneous correlation between volatility innovations and

☆ This article is part of a Special issue entitled: 'Mixed Frequency Data' published in Journal of Econometrics.

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https://doi.org/10.1016/j.jeconom.2025.106148
Received 23 May 2024; Received in revised form 6 November 2025; Accepted 10 November 2025

unexpected stock returns. The negative correlation is induced by volatility feedback.[1] Campbell and Hentschel (1992) highlight that volatility feedback can explain why stock returns are negatively skewed. Bollerslev et al. (2006) provide evidence for instantaneous volatility feedback in high-frequency data and Engle (2011) links volatility feedback to skewness in long-horizon returns and systemic risk. More recently, Kim and Kim (2019) demonstrate that accounting for volatility feedback is essential for detecting the predictive ability of macroeconomic factors for future expected returns.

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. Following Campbell and Hentschel (1992), we assume that the conditional variance of cash flow news follows a GARCH-type process and that expected returns positively depend on the conditional variance of cash flow news. We draw on recent developments in the literature on volatility models showing that volatility is best modelled as consisting of multiplicative components (e.g., Engle and Rangel, 2008; Engle et al., 2013; Conrad and Loch, 2015). Following this literature, we assume that the conditional variance of cash flow news follows a multiplicative factor multi-frequency GARCH (MF2-GARCH) process (Conrad and Engle, 2025). 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, behaves counter-cyclical, and is a proxy for medium-term volatility expectations (see Conrad and Engle, 2025).[2]

Within this framework, we express news to expected returns, i.e., discount rate news, as a function of news to the short- and long-term component of volatility. We derive three testable predictions. First, stock returns are more sensitive to news when (long-term) volatility is high. Second, under reasonable assumptions on model parameters, the volatility feedback effect is mainly driven by news to long-term volatility. The intuition is that only news to long-term volatility has a sufficiently persistent effect to generate sizeable variation in discount rates. For large pieces of good/bad news the volatility feedback effect dampens/amplifies the positive/negative cash flow effect and, hence, good and bad news have an asymmetric effect on unexpected returns. The asymmetry is most pronounced when long-term volatility is high. Notably, the volatility feedback mechanism implies that bad news has a more substantial effect when long-term volatility is high than when it is low. Third, our model predicts that stock prices increase when there is no cash flow news. This is because expected future volatility and, hence, required returns are revised downwards. Campbell and Hentschel (1992) referred to this effect as *no news is good news*. In our model, the *no news is good news* effect increases with the level of long-term volatility.

The prominent role of long-term volatility in our model is consistent with Maheu and McCurdy (2007) and Kim and Nelson (2013), who provide empirical evidence that only long-term, business cycle-related volatility is priced in the risk-return relationship. We enhance their findings both theoretically and empirically by investigating the role of long-term volatility in explaining asymmetry and time variation in the *high-frequency response* of the stock market to surprises in macroeconomic announcements.

Our explanation for the time-varying sensitivity of stock returns complements a recent strand of literature that has highlighted an alternative mechanism for explaining variation in the relative importance of cash flow versus discount rate news. Gardner et al. (2022) and Elenev et al. (2024) argue that the effect of good news depends on the state of the economy and expectations about future monetary policy. 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 and is due to monetary policy anticipation effects goes back to McQueen and Roley (1993), Boyd et al. (2005), and Andersen et al. (2007).

Another model that rationalizes the time-varying sensitivity by a time-varying risk premium has been provided by Veronesi (1999). In contrast to our model, the model of Veronesi (1999) predicts that bad news has a stronger impact in good times than in bad times. The reason is that bad news in good times increases uncertainty about the true state of the economy, and risk-averse investors require a higher return in response, which amplifies the negative cash flow effect of bad news.

To test whether volatility feedback explains the time-varying sensitivity, we follow the event study approach of Elenev et al. (2024) and estimate the causal effect of major U.S. macroeconomic announcements on E-mini S&P 500 futures returns 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 allowing the impact of the surprises to depend on the level of volatility. First, we show that long-term volatility has strong predictive power for the time-varying sensitivity. Second, we find evidence for an asymmetric response to good and bad news, which is again dependent on the level of long-term volatility. Third, there is heterogeneity across announcements. While the strength of the effect of news regarding various measures of economic activity depends on the level of long-term volatility, the effect of inflation news does not. Our interpretation is that – as predicted by our model – news about economic activity leads to revisions in expectations about future cash flows but also to revisions in expectations about future risks. The size of both revisions depends on the level of long-term volatility. When long-term volatility is high, the positive cash flow effect of a large piece of good news is severely dampened by the discount rate effect, while the effect of a large piece of bad news is severely amplified. On the other hand, news about inflation affects stock prices mainly by changing expectations about future

[1] While volatility feedback implies that there is a causal effect from volatility to returns, the so-called leverage-effect describes a causal effect from returns to volatility. Although both effects can explain the negative correlation between volatility and returns, Bekaert and Wu (2001) find the volatility feedback effect to be more relevant empirically.

[2] In the MF2-GARCH, the modelling of the long-term component is inspired by the class of mixed data sampling models pioneered by Ghysels et al. (2004) and Ghysels et al. (2006).

monetary policy. This effect does not depend on the level of long-term volatility. Importantly, we find that a large piece of bad news about economic activity has the strongest effect when the economy is in a bad state (i.e., when long-term volatility is high). This effect is consistent with volatility feedback but cannot be rationalized by expectations about future monetary policy or the model of Veronesi (1999). We also provide evidence for the *no news is good news* effect and its dependence on the level of long-term volatility.

Importantly, our findings are robust to controlling for various measures of the state of the economy and monetary policy uncertainty. For example, we control for the output gap, which had strong explanatory power for explaining the time-varying sensitivity in Elenev et al. (2024), as well as the FOMC sentiment index developed in Gardner et al. (2022). Interestingly, including those variables leads to some new insights regarding the time-varying effects of inflation news. For example, the adverse effect of higher-than-expected inflation is more substantial when the output gap is more positive and weaker when monetary policy uncertainty is higher. The latter finding complements recent evidence from Bauer et al. (2021) showing that monetary policy surprises have weaker effects on asset prices when monetary policy uncertainty is high.

Last, we contribute to the literature on the importance of macroeconomic announcements more generally (see, Guerkaynak et al., 2020; Boehm and Kroner, 2025). While surprises in macroeconomic announcements explain roughly 19% of the variation in returns in 10-minute windows around the announcements, the explained variation increases to 23% when including long-term volatility as a driver of the time-varying sensitivity. When combining long-term volatility with measures of macroeconomic and monetary policy uncertainty, we can explain up to 31% of the variation in returns.

Related Literature. In addition to the work referenced above, our paper builds on and relates to a number of further contributions. First, we draw on the literature on modelling the risk-return relation. As emphasized by Ghysels et al. (2005) and Ghysels et al. (2014) the appropriate modelling of the conditional variance is of crucial importance. Specifically, Ghysels et al. (2005) highlight the importance of persistence in the conditional variance process for capturing variation in expected returns. In addition, they find that a one-component asymmetric GARCH model in which the conditional variance is mainly driven by negative shocks is not suited for capturing the risk-return relationship. Instead, consistent with the evidence in Chen and Ghysels (2011), good and bad news have a symmetric effect on long-term volatility in the MF2-GARCH. Second, our finding concerning the importance of long-term volatility in explaining time variation in the risk premium is consistent with evidence on the pricing of long-run risks in the asset pricing literature (see, for example, Adrian and Rosenberg, 2008). Third, our paper is linked to work that emphasizes uncertainty as a determinant of the strength of the effect of news. For example, Conrad et al. (2002) and Andersen et al. (2003) provide evidence supporting the prediction of the model by Veronesi (1999). Kurov and Stan (2018) show that macroeconomic news has weaker effects when monetary policy uncertainty is high because then investors update expectations of monetary policy more strongly. Finally, our paper is related to the literature on the relative importance of the effects of different types of macroeconomic announcements, which can be explained, for example, by timeliness and informativeness about future monetary policy (see Andersen et al., 2003, 2007; Gilbert et al., 2017).

Roadmap. The remaining paper is organized as follows. Section 2 presents our model and testable predictions, Section 3 the estimation strategy, and Section 4 the empirical analysis. Section 5 provides robustness checks, and Section 6 concludes. Details on the derivation of the theoretical results presented in Section 2, the estimation of the MF2-GARCH model, and additional tables and figures can be found in the Appendix. Sections B to F of the Appendix are provided as an online Supplementary Appendix.

2. Volatility feedback

In modelling 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. 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, we test those predictions in a general empirical framework accounting for risk-free rate news.

2.1. 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. The latter is defined as

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

with $\rho = 1/(1+\exp(\overline{d-p})) < 1$. For daily return data, ρ is very close to but below one. Eq. (2) illustrates that 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

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

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

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

Thus, $\eta_{r,t+1}$ is exclusively driven by news about risk, capturing the volatility feedback effect.[3] We complete the model by making an assumption about the specification of the conditional variance of cash flow news. Conrad and Engle (2025) propose the MF2-GARCH for modelling (unexpected) returns. Instead, we assume that $\eta_{d,t}$ follows an MF2-GARCH process. Under this assumption, 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 assumption that cash flow news follows a conditionally heteroscedastic process is supported, for example, by recent evidence in Cenesizoglu and Ibrushi (2022). The short-term component follows a GJR-GARCH and is given by

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

with $\alpha > 0$, $\alpha + \gamma > 0$, $\beta > 0$ and $\phi = \alpha + \gamma/2 + \beta < 1$ measuring the persistence of 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

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

with $\lambda_0 > 0$, $\lambda_1 > 0$, $\lambda_2 > 0$, and $\lambda_1 + \lambda_2 < 1$. As discussed in Conrad and Engle (2025), we can think of $\frac{1}{m}\sum_{j=1}^{m} \eta^2_{d,t-j}/h_{t-j}$ as a measure for the *local bias* of the short-term component. The long-term component increases/decreases when 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).

2.2. Discount rate news

To clarify what distinguishes our approach from Conrad and Engle (2025), we would like to reemphasize that they assume the conditional variance of unexpected returns to follow an MF2-GARCH and expected returns to be constant, i.e., they do not consider a risk-return relation. Instead, in the spirit of Campbell and Hentschel (1992), we assume that the conditional variance of cash flow news follows an MF2-GARCH. Combining this assumption with Eq. (3) allows us to 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 persistent effects than shocks to the short-term component. It follows from Theorem 1 in Conrad and Engle (2025) that for $m = 1$ the cash flow news, $\eta_{d,t}$, are covariance stationary if $\lambda_1\phi_\kappa + \lambda_2\phi < 1$, where $\phi_\kappa = (\alpha + \gamma/2)\kappa + \beta$. Further, it is straightforward to compute multi-step ahead forecasts of the volatility of cash flow news.

Under these assumptions, we can write news to required returns in period $t+1$ as the sum of three terms (see Appendix A). The first and second term depend on news to the long- and short-term component. The third term arises due to the correlation between the short- and long-term component.[4] We refer to this news term as conditional variance news. Formally, we can decompose news to required returns as

$$\eta_{r,t+1} = A^\tau \tau_{t+1}\tilde{v}^\tau_{t+1} + A^h h_{t+1}\tilde{v}^h_{t+1} + A^\sigma \sigma^2_{t+1}\tilde{v}^\sigma_{t+1}, \tag{8}$$

where $v^\tau_{t+1} = \tau_{t+1}\tilde{v}^\tau_{t+1}$ and $v^h_{t+1} = h_{t+1}\tilde{v}^h_{t+1}$ represent news to the long- and short-term volatility components, $v^\sigma_{t+1} = \sigma^2_{t+1}\tilde{v}^\sigma_{t+1}$ is conditional variance news, and A^τ, A^h, and A^σ are positive constants (see Eqs. (A.13)–(A.15) in Appendix A).[5] In the following, we

[3] As mentioned before, our model abstracts from other sources (e.g., changes in expectations about future interest rates) that might induce changes in expected returns. Alternatively, we think of risk-free rate news as implicitly incorporated in the cash flow news (see Engle, 2011).

[4] The correlation is generated by the feedback between the two components (see Section 3.1. in Conrad and Engle, 2025).

[5] In Appendix B.1 we show how Eq. (8) simplifies when the long-term component is constant. In this case, our model essentially reduces to the setting considered in Campbell and Hentschel (1992).

think of Z_{t+1} as the underlying macroeconomic news and discuss how Z_{t+1} affects discount rate news via the three terms. First, news to the long-term component can be written as

$$v^{\tau}_{t+1} = \tau_{t+1}\tilde{v}^{\tau}_{t+1} = \tau_{t+1}\lambda_1\left(Z^2_{t+1}-1\right). \tag{9}$$

That is, required returns are updated upwards/downwards if risk, as measured by the squared news, Z^2_{t+1}, is higher/lower than $\mathbf{E}[Z^2_{t+1}]=1$. The updating is the stronger the higher the level of long-term volatility. Second, we can write news to the short-term component as

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

The $(\mathbf{1}_{\{Z_{t+1}<0\}}Z^2_{t+1}-\frac{1}{2})$ term arises due to the asymmetry in the short-term component. In Eq. (10), the strength of the updating depends on the level of the short-term component. Third, conditional variance news is given by

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

Eq. (11) implies that investors also care about tail risks, i.e., require higher returns when Z^4_{t+1} is bigger than $\mathbf{E}[Z^4_{t+1}]=\kappa$.

For the relative contributions of the three news terms to discount rate news, the constants A^{τ}, A^{h}, and A^{σ} are crucial. Under reasonable assumptions on the parameters (including the assumption that $\phi<\lambda_1+\lambda_2$) and using that ρ is very close to one for daily data, it follows that A^{τ} is much bigger than A^{σ} and A^{h} (see the numerical example at the beginning of Section 2.3). As a consequence, shocks to the long-term component have the strongest effect on discount rate news. This is due to the persistence in the long-term component: Only shocks to long-term volatility generate sizable variation in future required returns.[6] Because there is no asymmetry in the long-term component, discount rate news load (almost) equally on positive and negative Z_{t+1} news. This property of our model is in line with Ghysels et al. (2005) who argue that models for the risk-return relationship should allow volatility to update in response to positive and negative news.

Finally, following Maheu and McCurdy (2007) and Kim and Nelson (2013), we consider a version of the model in which expected returns depend on long-term volatility only. If $\eta_{d,t+1}$ follows an MF2-GARCH with $m=1$ and expected returns are given by $\mathbf{E}_t[r_{t+1}]=\mu+\delta\tau_{t+1}$, news to required returns can be obtained by plugging equation (A.10) into Eq. (4) and are given by

$$\eta_{r,t+1} = \bar{A}^{\tau}\tau_{t+1}\tilde{v}^{\tau}_{t+1}, \tag{12}$$

with $\bar{A}^{\tau}=\delta\rho/(1-\rho(\lambda_1+\lambda_2))$. Thus, although the conditional variance of cash-flow news has two components, news to required returns depends on news to long-term volatility only.

2.3. Testable model predictions

Combining Eq. (2) with Eqs. (5) and (8) leads to

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

In the following, we illustrate the effect of volatility feedback using 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 $\alpha=0.02$, $\gamma=0.1$, $\beta=0.80$, $\lambda_0=0.02$, $\lambda_1=0.06$, and $\lambda_2=0.92$, which are reasonable values for daily return data (see Conrad and Engle, 2025). For these parameter values, the unconditional variance of the (daily) cash flow news is 1.06 (which corresponds to an annualized volatility of approximately 16%). Finally, we obtain $A^{\tau}=1.39$, $A^{h}=0.03$, and $A^{\sigma}=0.22$.

Fig. 1 shows unexpected returns as a function of Z_{t+1} news. We assume that the short-term component is at its unconditional expectation, i.e., $h_{t+1}=1$. The green line represents unexpected returns when $\tau_{t+1}=2$, and the orange line shows unexpected returns when $\tau_{t+1}=0.5$. Because $\mathbf{E}[\tau_t]=1$, we can think of $\tau_{t+1}=2$ as a *high volatility regime* and of $\tau_{t+1}=0.5$ as a *low volatility regime*. Without discount rate news, unexpected returns would equal cash flow news, $\eta_{d,t+1}=\sqrt{\tau_{t+1}h_{t+1}}Z_{t+1}$, and the curves would be linear. However, the discount rate news introduces non-linearity. Because cash flow news dominate, the green and orange lines are upward sloping, i.e., positive/negative Z_{t+1} news translates into positive/negative unexpected returns. The slope is steeper when long-term volatility is high ($\tau_{t+1}=2$). Due to the discount rate effect, the positive/negative cash flow effect of positive/negative Z_{t+1} news is dampened/amplified if Z_{t+1} is sufficiently large.[7] Thus, volatility feedback generates an asymmetric response to good and bad news, which becomes stronger at higher levels of long-term volatility. To better understand the asymmetric effect of bad

[6] We provide a numerical illustration of this mechanism in Appendix B.2.

[7] For a detailed discussion of the interaction between cash flow and discount rate news, see Appendix B.3.

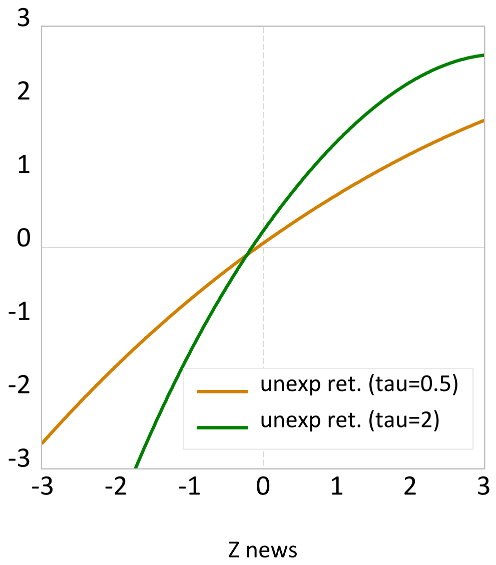

Fig. 1. The figure plots unexpected returns as a function of macroeconomic news Z_{t+1}. We assume that $h_{t+1} = 1$ and compare unexpected returns when $\tau_{t+1} = 2$ (green line) and $\tau_{t+1} = 0.5$ (orange line). Model parameters are given by $\delta = 0.03$, $\rho = 0.9998$, $\kappa = 3$, $\alpha = 0.02$, $\gamma = 0.1$, $\beta = 0.80$, $\lambda_0 = 0.02$, $\lambda_1 = 0.06$, and $\lambda_2 = 0.92$.

and good news, assume that expected returns depend on long-term volatility only. Then, using Eq. (12) and after plugging in $\tilde{v}^{\tau}_{t+1}$, we can write unexpected returns as

$$r_{t+1} - \mathbf{E}_t[r_{t+1}] = \underbrace{\lambda_1 \bar{A}^{\tau} \tau_{t+1}}_{\text{no news is good news}} + \underbrace{\sqrt{\tau_{t+1} h_{t+1}} Z_{t+1}}_{\text{cash flow news}} - \underbrace{\lambda_1 \bar{A}^{\tau} \tau_{t+1} Z^2_{t+1}}_{\text{asymmetry}}. \tag{14}$$

This representation clearly shows that the asymmetric effect of good/bad news is more pronounced when long-term volatility is high. Third, when $Z_{t+1} = 0$, expected returns are revised downward and unexpected returns are positive. The size of this *no news is good news* effect depends on the level of long-term volatility.

Based on these observations, we derive the following testable predictions regarding the effect of Z_{t+1} news:

P1 *Time-varying sensitivity:* Due to the dominance of the cash flow effect, the stock market is more sensitive to news when (long-term) volatility is high.

P2 *Asymmetry and importance of long-term volatility:* The strength of the volatility feedback effect predominantly depends on the level of long-term volatility. 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 *No news is good news:* The size of the *no news is good news* effect predominantly depends on the level of long-term volatility.

Finally, for the specification in Eq. (14), the conditional variance of unexpected returns is $\mathbf{Var}_t[r_{t+1} - \mathbf{E}_t[r_{t+1}]] = \mathbf{Var}_t[\eta_{d,t+1}] + \mathbf{Var}_t[\eta_{r,t+1}]$. 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 $\mathbf{Var}_t[\eta_{d,t+1}]$. This is because most daily news events "move returns beyond the information on risk" (Engle, 2011, p.459). Based on this insight, we will estimate an MF2-GARCH-in-mean for the daily stock market returns and use the short- and long-term components of the conditional variance of unexpected returns as a proxy for the components of $\mathbf{Var}_t[\eta_{d,t+1}]$ in the empirical analysis. This approach is in line with Engle (2011), who combines the assumption $r_{t+1} - \mathbf{E}_t[r_{t+1}] = \sigma_{t+1} Z_{t+1}$ with Eq. (3). For details on the quasi-maximum likelihood estimation (QMLE) of the MF2-GARCH-in-mean see Appendix C.

3. Estimation strategy

We utilize an event study approach to test the predictions derived in Section 2.3. While Z_t represents generic macroeconomic news in the theoretical model, in the empirical analysis we focus on the effects of the standardized surprises, $S_{j,t}$, of $j = 1, \ldots, J$ macroeconomic announcements. Intuitively, this means that we split up Z_t in different types of macroeconomic news (e.g., Nonfarm Payroll Employment or Consumer Confidence). To estimate announcement-specific effects, we regress stock market returns in a tight window around the release time of the announcements on the surprises in different types of macroeconomic news. By focusing on tight announcement windows, we ensure that no events other than the announcements drive returns, i.e., we estimate the causal effect of the surprises on returns. We denote the return in a k-minute window around the release time of an announcement on day

t by $R_t[k]$. The announcement and return data are described in detail in Sections 4.1.1 and 4.1.2. To ensure comparability with the previous literature, our empirical analysis proceeds in several steps, which are described in the following.

Baseline model: The baseline model estimates announcement-specific effects but does not allow for a time-varying sensitivity or asymmetric effects of good and bad news. We regress high-frequency returns on all announcements that take place at the same release time:

$$R_t[k] = \theta_1 + \sum_{j=1}^{J} \theta_{2,j} S_{j,t} + \xi_t, \tag{15}$$

where the parameters $\theta_{2,j}$ capture the effect of a one-standard-deviation surprise in announcement j and ξ_t is the error term. Estimation results for the baseline model are presented in Section 4.2.1.

Time-varying sensitivity (Testing *prediction P1*): Next, we extend Eq. (15) by estimating a non-linear regression that allows for a time-varying sensitivity of stock market returns that depends on specific predictor variables. We follow the approach of Swanson and Williams (2014), adopted by Elenev et al. (2024), and specify the model as

$$R_t[k] = \theta_1 + f(\mathbf{X}_t) \sum_{j=1}^{J} \theta_{2,j} S_{j,t} + \xi_t, \tag{16}$$

where

$$f(\mathbf{X}_t) = 1 + \boldsymbol{\gamma}'_X \mathbf{X}_t \tag{17}$$

represents the time-varying sensitivity. In general, $\mathbf{X}_t$ 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 $\boldsymbol{\gamma}_X$ and $\theta_{2,j}$ for $j = 1, \dots, J$. The coefficients $\theta_{2,j}$ are the effects of the macroeconomic announcements when all explanatory variables are at their mean, i.e., $f(\mathbf{X}_t) = 1$. As motivated by Eq. (13), we use the conditional volatility, the long-term volatility, and the short-term component as explanatory variables. For example, when long-term volatility is the only predictor, the sensitivity factor can be written as

$$f(\mathbf{X}_t) = 1 + \gamma_\tau \tilde{\tau}_t, \tag{18}$$

where $\tilde{\tau}_t = \sqrt{\tau_t} - \overline{\sqrt{\tau}}$ is the demeaned long-term volatility. In Eq. (18), the hypothesis of a time-varying sensitivity corresponds to testing $H_0 : \gamma_\tau = 0$. Section 4.2.2 presents the corresponding empirical evidence.

The model given by Eqs. (16) and (17) imposes the restriction that the time-varying sensitivity, $f(\mathbf{X}_t)$, is the same for all macroeconomic announcements. We relax this assumption by introducing $g = 1, \dots, G$ announcement groups denoted by A_g and allow for announcement-group specific sensitivities. Based on the findings from Section 4.2.2, we will assume that the sensitivity factor depends only on long-term volatility. That is, we replace Eqs. (16) and (17) with

$$R_t[k] = \theta_1 + \sum_{g=1}^{G} f_g(\mathbf{X}_t) \sum_{j \in A_g} \theta_{2,j} S_{j,t} + \xi_t, \tag{19}$$

where

$$f_g(\mathbf{X}_t) = 1 + \gamma_{g,\tau} \tilde{\tau}_t \tag{20}$$

is the sensitivity factor of group A_g. For empirical evidence on group-specific sensitivity factors, see Section 4.2.3.

Asymmetry and *no news is good news* (Testing *predictions P2* and *P3*): Both extensions of the baseline model constrain the effect of good and bad news to be the same and, hence, do not yet allow us to test *predictions P2* and *P3*. To allow good and bad news to have asymmetric effects, we consider two alternative specifications. For brevity, we present the specifications with group-specific sensitivities, but in the empirical application, we also consider specifications with homogeneous sensitivities for all types of announcements. 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 first specification is a piece-wise linear model with separate slope coefficients for good and bad news:

$$R_t[k] = \theta_1 + \theta_{1,\tau} \dot{\tau}_t + \sum_{g=1}^{G} f_g(\mathbf{X}_t) \left[\sum_{j \in A_g} \theta^+_{2,j} S^+_{j,t} + \sum_{j \in A_g} \theta^-_{2,j} S^-_{j,t} \right] + \xi_t, \tag{21}$$

where $f_g(\mathbf{X}_t)$ is the group-specific sensitivity factor from Eq. (20). To capture the *no news is good news* effect, we include the term $\theta_{1,\tau} \dot{\tau}_t$, where $\dot{\tau}_t = \tau_t - \bar{\tau}$ is the demeaned long-term variance. Hence, even if all surprises are equal to zero, unexpected returns are allowed to depend on the level of long-term volatility. Good and bad news have asymmetric effects, if the hypothesis $H_0 : \theta^+_{2,j} = \theta^-_{2,j}$ can be rejected.

The second specification introduces non-linearity by including surprises and squared surprises. This specification directly follows Eq. (14) and is closely related to the regression suggested in Andersen et al. (2003) for testing the asymmetry of good and bad news.

Table 1
U.S. macroeconomic announcement data for January 2001 to December 2021 period.

	Announcements/Groups	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
	Investment & Consumption				
4	New Family Houses Sold	252	Change	10:00 am EST	Monthly
5	Durable Goods Orders	236	% change	8:30 am EST	Monthly
6	Manufacturers New Orders	251	% change	10:00 am EST	Monthly
	Forward-looking				
7	Conference Board Consumer Confidence	252	Index	10:00 am EST	Monthly
8	Purchasing Managers Index (PMI, ISM)	252	Index	10:00 am EST	Monthly
	Prices				
9	Consumer Price Index (CPI)	250	% change	8:30 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 onward, and for Durable Goods Orders, no median forecasts are reported in 15 months of our sample.

Adding the squared surprise to Eq. (19) and applying the sensitivity factor to both terms leads to[8]

$$R_t[k] = \theta_1 + \theta_{1,\tau}\dot{\tau}_t + \sum_{g=1}^{G} f_g(\mathbf{X}_t)\left[\sum_{j\in A_g}\theta_{2,j}S_{j,t} + \sum_{j\in A_g}\theta_{3,j}S_{j,t}^2\right] + \xi_t \tag{22}$$

with $f_g(\mathbf{X}_t)$ as before. We can check for asymmetry by testing the hypothesis $H_0 : \theta_{3,j} = 0$.

Last, in Section 4.2.5, we will include several control variables in the sensitivity factor in Eq. (20) that have been proposed as alternative predictors in the previous literature. Including those predictors allows us to test volatility feedback against other economic mechanisms that can explain the time-varying sensitivity.

Apart from the baseline model, which is estimated by ordinary least squares, all specifications are estimated by non-linear least squares. To account for conditional heteroscedasticity and serial correlation in the error term, we rely on Newey–West standard errors.

4. Empirical analysis

We introduce the data set of U.S. macroeconomic announcements, stock return data, and economic control variables in Section 4.1 and empirically test *predictions P1-P3* in Section 4.2.[9]

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., 2024): 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. Following Andersen et al. (2003), we classify the nine announcements into $G = 4$ groups: *Real Activity*, *Investment & Consumption*, *Forward-looking*, and *Prices*. Within those groups the selected announcements are the ones that are most timely, i.e., published the earliest in the month (see Gilbert et al., 2017).[10] Table 1 presents the announcements, units of measurement, publication frequency, release time, and the announcement-groups. All indicators are published monthly, except for Initial Jobless Claims, which are published weekly. Announcements are released at 8:30 am or 10:00 am Eastern Standard Time (EST). We obtained the first releases of the macroeconomic announcements and the corresponding consensus forecasts from Bloomberg. The sample spans the period from January 2001 to December 2021 and includes 3083 macroeconomic announcements.

Because professional Bloomberg forecasters can submit their forecasts until the night before the announcement, their forecasts reflect the current knowledge of market participants.[11] To construct announcement surprises, we subtract the consensus forecasts

[8] Eq. (11) also suggests adding surprises to the power of four. However, empirically, we found no improvement when including those terms. This is consistent with the notion that only long-term risks are priced.

[9] On the first page of the Supplementary Appendix, we provide a link to the replication package with the code to reproduce the paper's results and further details on the data.

[10] The Producer Price Index is published before the Consumer Price Index but available to us only for a shorter sample. We use the Producer Price Index for robustness analyses.

[11] Table A.1 in Appendix D shows that we cannot reject the hypothesis of unbiasedness of the consensus (i.e., median) forecasts for all macroeconomic announcements at the 5% level. The coefficients of determination of the corresponding (Mincer and Zarnowitz, 1969) regressions are above 80% for all variables but Durable Goods Orders.

from the actual releases. To reduce the impact of extreme surprises, we winsorize the difference between the announcement and the consensus forecast at the 95% level.[12] Following Balduzzi et al. (2001), we define the standardized surprise component of announcement j taking place on day t as

$$S_{j,t} = \frac{A_{j,t} - E_{j,t-1}}{sd_j}, \tag{23}$$

where $A_{j,t}$ is the realized value of announcement j, $E_{j,t-1}$ corresponds to the previous day's consensus of the Bloomberg expectations, and sd_j is the sample standard deviation of the announcement surprise, $(A_{j,t} - E_{j,t-1})$. This standardization allows us to compare announcements measured in different units and to interpret the regression coefficients as the effect of a one-standard-deviation surprise. To allow for a consistent interpretation of positive and negative announcement surprises as good and bad news, we multiply Initial Jobless Claims and the Consumer Price Index by (-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 h a day. This allows us to analyse the impact of major announcements released at 8:30 am EST, prior to 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., 2024). 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

$$R_{t,s}[k] = 100\left(\ln\left(F_{t,s+\frac{k}{2}}\right) - \ln\left(F_{t,s-\frac{k}{2}}\right)\right), \tag{24}$$

where, for example, $F_{t,s+k/2}$ refers to the last transaction (close) price of the E-mini future in minute $s + k/2$ 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 $k = 10$ min. Figure A.3 in Appendix E, which shows that average absolute returns are highest immediately after announcement times and decline quickly thereafter, supports this choice. As robustness checks, we consider $k = 2$ and $k = 20$ min (see Section 5). To be consistent with the notation introduced in Section 3, we simplify the notation by dropping the index s and write $R_{t,s}[k] = R_t[k]$ in the following.

4.1.3. Variables explaining the 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 well as on the overall conditional volatility. As discussed at the end of Section 2.3, we focus on the conditional variance of daily unexpected returns instead of the conditional variance of cash flow news. Based on the close price of each trading day, we compute daily S&P 500 log-returns. For a daily expanding window and using daily returns up to a day $t-1$, we estimate an MF2-GARCH-in-mean model (see Appendix C). The first estimation sample starts on July 10, 1970, and ends on December 29, 2000. For each estimation window, we choose the m that minimizes the Bayesian information criterion (BIC). In the expanding estimation windows, the optimal m varies between 62 and 68. The long- and short-term components for the first day following the estimation window are then computed using the estimated model parameters and daily returns up to the last day of the estimation window. That is, by construction, the volatility components for day t are independent of the macroeconomic news that is released on that day. Fig. 2 shows the rolling window estimates of the short- and long-term volatility components as well as the conditional volatility. Table A.2 presents the median as well as the lower and upper quartiles of the parameter estimates from the expanding window estimation. For example, the median estimate of δ corresponds to a coefficient of relative risk aversion of 3.2.

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 important in explaining the time-varying return sensitivity. Those variables can be separated into three broad categories: state of the economy, economic and monetary policy uncertainty, and stock market volatility.

State of the economy: We distinguish between low-frequency (i.e., monthly or quarterly) and daily predictor variables. The low frequency variables are the monthly FOMC sentiment index of Gardner et al. (2022), which is available on their website, the quarterly real-time output gap estimates from the U.S. Bureau of Economic Analysis, the expected change in the short-term interest rate as measured by the difference between the CPI-adjusted one-quarter-ahead forecast and the nowcast of the 3-month Treasury bill from the Survey of Professional Forecasters, and inflation (i.e., the year-over-year log change in the GDP deflator). The daily explanatory variables are the term spread as measured by the difference between the daily 10-year Treasury constant maturity and the 3-month Treasury constant maturity (obtained from FRED), and the credit spread, calculated as the difference between Moody's bond indices AAA corporate bond yield and the 10-year government yield (obtained from Bloomberg). In addition, we use the daily realized volatility of the Eurodollar futures (3-month continuous contract obtained from Refinitiv Eikon) as a proxy for economic growth uncertainty and interest rate risk. The realized volatility is computed as the square root of an exponentially weighted moving average of lagged squared daily returns, with the smoothing parameter set to 0.97.

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

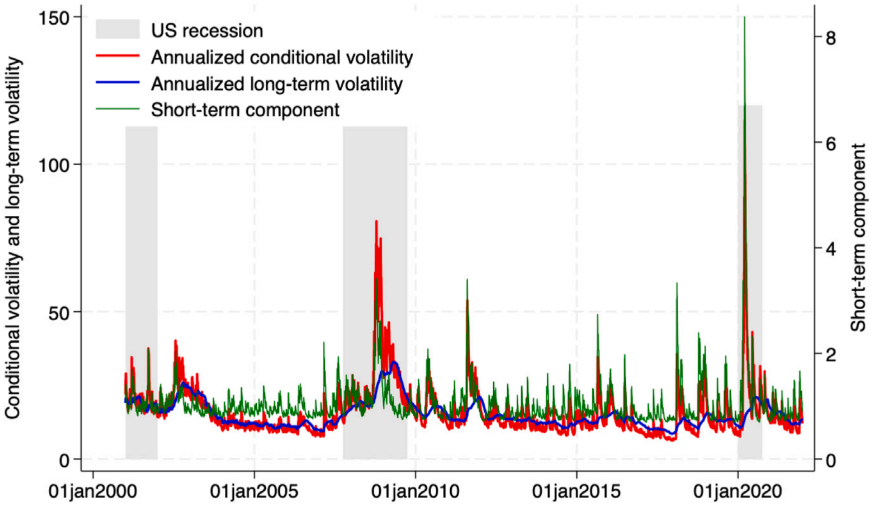

Fig. 2. Plot of the estimated annualized volatility of the MF2-GARCH-in-mean for daily S&P 500 returns. The annualized conditional volatility ($\sqrt{252 \cdot \tau_t h_t}$) is shown in red, and the annualized long-term volatility component ($\sqrt{252 \cdot \tau_t}$) is shown in blue (left axis). The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

Macroeconomic and monetary policy uncertainty: To capture macroeconomic uncertainty, we use the monthly macro uncertainty index of Jurado et al. (2015), which measures how predictable the economy is. We employ several measures as proxies for monetary policy uncertainty. First, we use the measure developed by Husted et al. (2020), which tracks the frequency of newspaper articles about monetary policy uncertainty on a monthly frequency. Second, as daily proxies for monetary policy uncertainty, we use the Merrill Lynch Option Volatility Index (MOVE, obtained from Bloomberg), the CBOE 10-year U.S. Treasury Note Volatility Index (TYVIX, obtained from Bloomberg), and the realized volatility of 10-year Treasury futures (obtained from Refinitiv Eikon). The realized volatility of 10-year Treasury futures is constructed using the same methodology as for the realized volatility of the Eurodollar futures.

Stock market volatility and risk appetite: We use the conditional volatility of a GJR-GARCH(1,1) based on daily S&P 500 return data as a proxy for short-term risks and the Chicago Board Options Exchange S&P 500 Volatility Index (VIX) to capture volatility expectations for the next month. Daily changes in financial risk appetite are measured by the index from Bauer et al. (2023), which corresponds to the common component of 14 risk-sensitive financial indicators.

Table A.3 in Appendix D displays the pairwise correlations of the conditional volatility, σ_t, the long-term volatility, $\sqrt{\tau_t}$, and the short-term component, $\sqrt{h_t}$, with the economic predictor variables. Panel A shows the correlations with the daily variables and Panel B correlations with monthly/quarterly predictor variables. While the conditional volatility is most strongly related to the VIX index, long-term volatility is closely associated with the TYVIX, the realized volatility of the 10-year Treasury futures, and the MOVE (see Panel A). As expected, long-term volatility behaves counter-cyclical (i.e., exhibits a negative correlation with the real-time output gap and FOMC sentiment) and is positively related to the monthly measure of macroeconomic uncertainty. While the long-term volatility is strongly correlated with the daily measures of monetary policy uncertainty (i.e., the MOVE and TYVIX), it is essentially uncorrelated with the monthly measure of monetary policy uncertainty (see Panel B).

4.2. *Empirical results*

In the following subsections, we present empirical results from applying the specifications introduced in Section 3 to the data. Following Kilian and Vega (2011) and Elenev et al. (2024), we simultaneously include all data releases that occur at 8:30 am or 10:00 am in the 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*

We start by presenting the results for the baseline model. The first column in Table 2 shows the effects of the announcement surprises on stock market returns, as measured by the $\theta_{2,j}$ coefficients, when estimating the model in Eq. (15). As expected, positive surprises lead to a significant increase in returns within the 10-minute window around the announcements. The parameter estimates reflect a mixture of the cash flow and the discount rate effects induced by the surprises. The relative importance of the two effects is likely to be announcement-specific. For example, Nonfarm Payroll Employment has the strongest impact of all announcements, confirming its perception as the 'king of announcements' (Andersen and Bollerslev, 1998). A positive one-standard-deviation surprise in the release of Nonfarm Payroll Employment is expected to increase log returns by 0.212 percentage points. For this announcement, the positive $\theta_{2,j}$ estimate is likely driven by the cash flow effect of better-than-expected economic activity. On the other hand, the

Table 2
Regression results for baseline specification and extensions with time-varying sensitivity.

	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\sigma}_t$		0.451**			0.048	0.349
		(0.219)			(0.233)	(0.567)
$\tilde{\tau}_t$			1.699***		1.638***	1.299**
			(0.239)		(0.419)	(0.625)
$\tilde{h}_t$				0.129		−0.321
				(0.265)		(0.674)
Initial Jobless Claims	0.049***	0.042***	0.047***	0.047***	0.046***	0.047***
	(0.007)	(0.010)	(0.006)	(0.008)	(0.006)	(0.006)
Nonfarm Payrolls	0.212***	0.193***	0.190***	0.208***	0.190***	0.191***
	(0.029)	(0.031)	(0.024)	(0.029)	(0.024)	(0.023)
Retail Sales	0.110***	0.103***	0.090***	0.111***	0.090***	0.089***
	(0.016)	(0.017)	(0.013)	(0.016)	(0.013)	(0.014)
New Family Houses Sold	0.046***	0.053***	0.059***	0.046***	0.059***	0.059***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
Durable Goods Orders	0.073***	0.080***	0.075***	0.074***	0.075***	0.074***
	(0.017)	(0.017)	(0.015)	(0.017)	(0.015)	(0.015)
Manufacturers New Orders	0.046***	0.046***	0.042***	0.046***	0.042***	0.042***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Consumer Confidence	0.132***	0.134***	0.125***	0.133***	0.126***	0.126***
	(0.018)	(0.018)	(0.014)	(0.018)	(0.014)	(0.014)
Purchasing Managers Index	0.152***	0.136***	0.136***	0.150***	0.135***	0.134***
	(0.019)	(0.023)	(0.019)	(0.020)	(0.019)	(0.018)
Consumer Price Index	0.082***	0.084***	0.058***	0.085***	0.059***	0.059***
	(0.018)	(0.019)	(0.016)	(0.018)	(0.016)	(0.016)
Constant	0.007*	0.009**	0.008**	0.008**	0.008**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2826	2826	2826	2826	2826	2826
Adjusted R^2	0.189	0.205	0.230	0.190	0.229	0.229

Notes: We set $k = 10$ min. Column (1) presents OLS estimates for Eq. (15). Columns (2) to (6) present non-linear least squares estimates of Eqs. (16) and (17). In Column (2), we set $\gamma'_X \mathbf{X}_t = \gamma_\sigma \tilde{\sigma}_t$, in Column (3) we set $\gamma'_X \mathbf{X}_t = \gamma_\tau \tilde{\tau}_t$, and in Column (4) we set $\gamma'_X \mathbf{X}_t = \gamma_h \tilde{h}_t$. Column (5) specifies $\gamma'_X \mathbf{X}_t = \gamma_\tau \tilde{\tau}_t + \gamma_h \tilde{\sigma}_t$ and Column (6) sets $\boldsymbol{\gamma}'_X \mathbf{X}_t = \gamma_\sigma \tilde{\sigma}_t + \gamma_\tau \tilde{\tau}_t + \gamma_h \tilde{h}_t$. The estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are Newey–West standard errors. Notation: ***p < 0.01, **p < 0.05, *p < 0.1.

positive $\theta_{2,j}$ estimate for inflation is likely driven by revisions in expectations about future monetary policy: Higher-than-expected inflation (i.e., a negative surprise) leads to an upward revision in interest rate expectations and, hence, a decline in the stock price via the discount rate effect. Overall, the surprise component of macroeconomic announcements can explain almost 19% of the variation in returns in the 10-minute window.

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

Prediction P1 suggests that the effect of news on the stock market depends on the level of (long-term) volatility. We test this prediction by estimating the model given by Eqs. (16) and (17). Recall that this specification constrains the effect of good and bad news to be the same. Again, the $\theta_{2,j}$ estimates from this model reflect a mixture of the cash flow and discount rate effects of the macroeconomic news. Because the cash flow effect will dominate for most variables, we expect the estimates of the sensitivity coefficients in Eq. (17) to be positive. That is, in accordance with *prediction P1*, we expect the strength of the effect of macroeconomic news to increase with the level of volatility.

In Columns (2) to (6) of Table 2, we report estimation results for different choices of $\mathbf{X}_t$. In Column (2), we set $f(\mathbf{X}_t) = 1 + \gamma_\sigma \tilde{\sigma}_t$, where $\tilde{\sigma}_t = \sqrt{\sigma_t} - \sqrt{\sigma}$. The estimate of γ_σ is positive and significant at the 5% level. Thus, as expected, macroeconomic news have stronger effects when the conditional volatility is high. In Column (3), we focus on long-term volatility and set $f(\mathbf{X}_t)$ as in Eq. (18). The estimate of 1.699, which is significant at the 1% level, in combination with an adjusted R^2 in Column (3) that is almost three percentage points higher than in Column (2), shows that long-term volatility has strong explanatory power for the time-varying sensitivity. When including only the (demeaned) short-term volatility component, $\tilde{h}_t = \sqrt{h_t} - \sqrt{h}$, in Column (4), the associated parameter estimate is not statistically significant. Thus, Columns (2)-(4) suggest that long-term volatility does best in capturing the time-varying sensitivity. This is also confirmed in Column (5), where the conditional volatility and long-term volatility are jointly included, and in Column (6), which includes all three measures. In both columns, only γ_τ is statistically significant.

Fig. 3 illustrates the estimation results from Column (3) 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 long-term volatility. When long-term volatility is at its mean, the marginal effect of good/bad news is given by ± 0.125 (corresponding to the $\theta_{2,j}$ estimate for Consumer Confidence). Most importantly, the figure shows that there is sizable variation in the effect of a one-standard-deviation Consumer Confidence announcement surprise: When long-term volatility is at its 10% quantile (corresponding to an annualized volatility of 10.9%) the effect is only 0.069, but it increases to 0.2 when long-term volatility is at its 90% quantile (corresponding

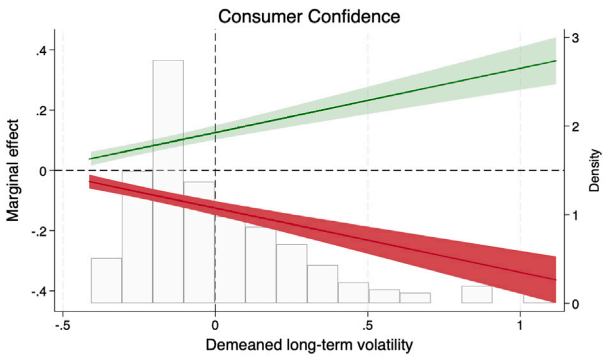

Fig. 3. Marginal effect of a positive and negative one-standard deviation Consumer Confidence surprise as a function of the level of long-term volatility. Parameter estimates are based on Column (3) in Table 2. The green line represents good news, and the red line represents bad news. The mean of the annualized long-term volatility in our sample is 15.17%. The marginal effects are plotted with 90%-confidence intervals. The histogram shows the distribution of long-term volatility on days of Consumer Confidence releases.

to an annualized volatility of 20.6%). Last, note that even for very low values of long-term volatility, the marginal effect of a positive/negative surprise is positive/negative.

In summary, Table 2 confirms *prediction P1* that the stock market's sensitivity to news depends on the level of volatility. Specifically, long-term volatility is more informative about the time-varying sensitivity than either the conditional variance or short-term volatility. This finding can be rationalized by the empirical observation that the long-term component serves as an accurate proxy for the current volatility regime, while the conditional volatility is a rather noisy proxy due to the influence of the short-term component (see Conrad and Engle, 2025). The importance of long-term volatility is also consistent with Maheu and McCurdy (2007) and Kim and Nelson (2013), who have shown that the long-term volatility component, which carries business cycle related information, primarily drives expected returns. Based on these insights, we will use long-term volatility as the only predictor of the time-varying sensitivity in the subsequent analyses.[13]

4.2.3. Is the time-varying sensitivity announcement specific?

Thus far, we have assumed that the time-varying sensitivity is the same across all macroeconomic announcements. We now relax this assumption in two steps. First, we allow for group-specific sensitivities as specified in Eqs. (19)–(20). We use the $G = 4$ groups as defined in Table 1.

Column (1) of Table 3 shows that the group-specific sensitivity coefficients $\gamma_{g,\tau}$ are estimated to be significantly positive for all groups except *Prices*. Although the sensitivity is the largest for announcements from the category *Investment & Consumption* and slightly lower for *Real Activity* and *Forward-looking* announcements, there are no significant differences in the $\gamma_{g,\tau}$ estimates of those three groups. This result suggests that the effect of surprise announcements in those three groups depends on the size of revisions in expectations about future cash flows and future risks, and that those revisions are sensitive to the current level of long-term volatility. On the other hand, inflation surprises, which mainly affect stock returns by leading to revisions in expectations about future interest rates, are not sensitive to long-term volatility. The estimates of the $\theta_{2,j}$ coefficients are close to those in Column (3) of Table 2.

Second, Column (2) of Table 3 reports estimates for a version of Eq. (19) that allows for announcement-specific $\gamma_{j,\tau}$ coefficients in the sensitivity factor. That is, we treat each announcement as a group. Column (2) shows that within the first three groups, the sensitivity is the highest for the announcements that are released the earliest. For example, within the *Real Activity* group, the estimate of $\gamma_{j,\tau}$ for Initial Jobless Claims, which is released before Nonfarm Payroll Employment, is 2.909, while the corresponding estimate for Nonfarm Payroll Employment is 1.575. As before, the effect of inflation surprises does not depend on the level of long-term volatility.

Because the results regarding *Prices* in Table 3 are based on Consumer Price Index inflation surprises only, we have reestimated Columns (1) and (2) and included surprises in the Producer Price Index as an additional announcement in the *Prices* group. Table A.4 in Appendix D shows that our results remain unaffected. As for Consumer Price Index surprises, the $\theta_{2,j}$ coefficient estimate for Producer Price Index surprises is significantly positive. However, neither the group-specific *Prices* sensitivity coefficient nor the individual sensitivity coefficients for the two inflation surprises are significant. Because the series of Producer Price Index surprises is available to us only from June 2004 onwards, our focus in the main text remains on Consumer Price Index inflation, which is available from January 2001.

[13] When adding the conditional volatility or the short-term component as predictors they almost always turn out to be insignificant.

Table 3
Heterogeneity in the time-varying sensitivity to news across announcements.

	(1)		(2)		(3)	
	group-specific		announcement-specific		interaction terms	
	$\gamma_{g,\tau}$	$\theta_{2,j}$	$\gamma_{j,\tau}$	$\theta_{2,j}$	$\theta_{2,j}$	$\theta^{\tau}_{2,j}$
Real Activity	1.741***					
	(0.376)					
Initial Jobless Claims		0.047***	2.909***	0.039***	0.039***	0.115***
		(0.007)	(0.761)	(0.006)	(0.006)	(0.023)
Nonfarm Payrolls		0.189***	1.575***	0.194***	0.194***	0.309***
		(0.025)	(0.483)	(0.027)	(0.027)	(0.080)
Retail Sales		0.090***	1.475**	0.095***	0.095***	0.142***
		(0.014)	(0.635)	(0.015)	(0.015)	(0.051)
Investment & Consumption	2.570***					
	(0.468)					
New Family Houses Sold		0.056***	2.969***	0.055***	0.054***	0.159***
		(0.012)	(0.922)	(0.011)	(0.011)	(0.054)
Durable Goods Orders		0.065***	2.437***	0.066***	0.066***	0.158***
		(0.014)	(0.677)	(0.013)	(0.013)	(0.054)
Manufacturers New Orders		0.036***	1.738	0.041***	0.041***	0.073
		(0.012)	(1.144)	(0.011)	(0.011)	(0.050)
Forward-looking	1.664***					
	(0.343)					
Consumer Confidence		0.126***	2.433***	0.112***	0.113***	0.270***
		(0.015)	(0.430)	(0.014)	(0.014)	(0.044)
Purchasing Managers Index		0.136***	1.038**	0.148***	0.148***	0.150**
		(0.018)	(0.486)	(0.018)	(0.018)	(0.073)
Prices	−0.262					
	(0.682)					
Consumer Price Index		0.080***	−0.266	0.080***	0.080***	−0.026
		(0.018)	(0.682)	(0.018)	(0.018)	(0.055)
Observations	2826		2826		2826	
Adjusted R^2	0.232		0.233		0.234	

Notes: We set $k = 10$ min. Column (1) reports the results for group-specific sensitivities as in Eqs. (19)–(20), Column (2) for announcement-specific sensitivities, and Column (3) for estimating equation (25). The estimation sample spans the period from January 2001 to December 2021. All regressions include a constant. Numbers in parentheses are Newey–West standard errors. Notation: ***p < 0.01, **p < 0.05, *p < 0.1.

As a robustness check, the last column of Table 3 presents results from estimating announcement-specific sensitivities via a specification that has been employed in Gardner et al. (2022). Instead of estimating the non-linear regression model, we rely on interaction terms:

$$R_t[k] = \theta_1 + \sum_{j=1}^{J} \theta_{2,j} S_{j,t} + \sum_{j=1}^{J} \theta^{\tau}_{2,j} S_{j,t}\tilde{\tau}_t + \theta_\tau \tilde{\tau}_t + \xi_t. \tag{25}$$

In this specification, the $\theta^{\tau}_{2,j}$ coefficients capture the time-varying sensitivity. Column (3) confirms our findings from Column (2) using a different estimation strategy. Overall, the results from Table 3 provide further evidence for *prediction P1* that the S&P 500's response to macroeconomic news depends on the level of long-term volatility, except for inflation news.

4.2.4. Is there an asymmetric effect of good and bad news? Does it depend on long-term volatility?

We now test *predictions P2* and *P3*. For this, we rely on the specifications introduced in Eqs. (21) and (22). Column (1) of Table 4 reports estimation results for the piece-wise linear model while imposing the restriction that the *same* sensitivity factor applies to all announcements. The estimate of $\hat{\theta}^-_{2,j}$ is significant for all announcements, and the estimate of $\hat{\theta}^+_{2,j}$ 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 a positive and highly significant estimate of γ_τ, this confirms *prediction P2*: Bad news has stronger effects than good news, and the asymmetry is stronger for higher levels of long-term volatility. In addition, since the estimate of $\theta_{1,\tau}$ is positive and significant, we also confirm *prediction P3*. The adjusted R^2 in Column (1) is approximately 24%. If we extend Column (1) from Table 2 by distinguishing between good and bad news (detailed estimation results not shown), we only get a marginal improvement in the adjusted R^2 to 0.195. Thus, allowing the asymmetry to depend on the level of long-term volatility increases the adjusted R^2 by approximately four percentage points.

Column (2) shows the corresponding results when allowing for group-specific sensitivities. As in Section 4.2.3, we find that the sensitivity parameter $\gamma_{g,\tau}$ is the highest for the *Investment & Consumption* group and insignificant for *Prices*. As in Column (1), for all announcements the effect of bad news is stronger than for good news. Interestingly, although the time-varying sensitivity is

Table 4
Testing for asymmetric effects of good and bad news.

	Panel A: Piece-wise linear specification						*Panel B: Squared news*					
	(1)			(2)			(3)			(4)		
	γ_τ	$\theta^+_{2,j}$	$\theta^-_{2,j}$	$\gamma_{g,\tau}$	$\theta^+_{2,j}$	$\theta^-_{2,j}$	γ_τ	$\theta_{2,j}$	$\theta_{3,j}$	$\gamma_{g,\tau}$	$\theta_{2,j}$	$\theta_{3,j}$
$\tilde{\tau}_t$	1.706***						1.721***					
	(0.255)						(0.256)					
Real Activity				1.771***						1.732***		
				(0.386)						(0.380)		
Initial Jobless Claims		0.026***	0.062***		0.027***	0.060***		0.059***	−0.018***		0.059***	−0.017**
		(0.008)	(0.012)		(0.008)	(0.012)		(0.010)	(0.007)		(0.010)	(0.007)
Nonfarm Payrolls		0.188***	0.197***		0.188***	0.194***		0.195***	0.004		0.195***	0.005
		(0.034)	(0.032)		(0.036)	(0.032)		(0.025)	(0.012)		(0.026)	(0.012)
Retail Sales		0.069***	0.114***		0.070***	0.111***		0.118***	−0.029***		0.118***	−0.028***
		(0.014)	(0.022)		(0.015)	(0.022)		(0.020)	(0.011)		(0.021)	(0.011)
Investment & Consumption				2.432***						2.557***		
				(0.474)						(0.465)		
New Family Houses Sold		0.049***	0.071***		0.051***	0.064***		0.079***	−0.021*		0.074***	−0.019*
		(0.016)	(0.018)		(0.016)	(0.018)		(0.018)	(0.011)		(0.018)	(0.011)
Durable Goods Orders		0.043**	0.109***		0.040**	0.098***		0.079***	−0.015*		0.071***	−0.013*
		(0.020)	(0.024)		(0.018)	(0.021)		(0.015)	(0.009)		(0.013)	(0.007)
Manufacturers New Orders		0.023	0.062***		0.023	0.052***		0.043***	−0.010		0.037***	−0.008
		(0.021)	(0.016)		(0.021)	(0.014)		(0.013)	(0.008)		(0.011)	(0.007)
Forward-looking				1.582***						1.587***		
				(0.375)						(0.375)		
Consumer Confidence		0.080***	0.176***		0.083***	0.178***		0.131***	−0.026***		0.134***	−0.026***
		(0.018)	(0.024)		(0.018)	(0.025)		(0.015)	(0.009)		(0.015)	(0.010)
Purchasing Managers Index		0.117***	0.156***		0.121***	0.158***		0.137***	−0.011		0.140***	−0.011
		(0.023)	(0.033)		(0.023)	(0.031)		(0.020)	(0.012)		(0.019)	(0.012)
Prices				−0.179						−0.126		
				(0.790)						(0.841)		
Consumer Price Index		0.025	0.088***		0.058**	0.097***		0.052***	−0.019**		0.074***	−0.011
		(0.023)	(0.022)		(0.023)	(0.027)		(0.015)	(0.009)		(0.018)	(0.011)
No news is good news	$\theta_{1,\tau}$			$\theta_{1,\tau}$			$\theta_{1,\tau}$			$\theta_{1,\tau}$		
$\dot{\tau}_t$	0.031***			0.029***			0.028***			0.027***		
	(0.011)			(0.011)			(0.010)			(0.010)		
Observations	2826			2826			2826			2826		
Adjusted R^2	0.237			0.239			0.241			0.242		

Notes: We set $k = 10$ min. Column (1) reports the results of estimating (21) while imposing the sensitivity to be the same across announcements. In Column (2), we report results of estimating (21) using $f_g(\mathbf{X}_t)$ as in Eq. (20). In the columns denoted by $\theta^+_{2,j}$, we report the coefficient estimates for good news, and in the columns denoted by $\theta^-_{2,j}$, we report the coefficient estimates for bad news. In Column (3), we report results of estimating equation (22). In Column (4), we report results of estimating (22) where we include squared terms only for good news of Retail Sales, Initial Jobless Claims, and New Family Houses Sold. In the column denoted by $\theta_{2,j}$, we report the coefficient estimates for the surprises, and in the column denoted by $\theta_{3,j}$, we report the coefficient estimates for the squared surprises. The estimation sample spans the period from January 2001 to December 2021. All regressions include a constant. Numbers in parentheses are Newey–West standard errors. Notation: ***p < 0.01, **p < 0.05, *p < 0.1.

insignificant for CPI inflation, the corresponding estimates of $\theta^+_{2,j}$ and $\theta^-_{2,j}$ are both significant when allowing for a group-specific sensitivity.

Next, we focus on the specification with squared news terms (see Eq. (22)). Columns (3) and (4) present the corresponding estimation results when either imposing the same sensitivity factor for all announcements or allowing for group-specific sensitivities. The estimates of γ_τ and $\gamma_{g,\tau}$ in Columns (3) and (4) are similar to those in Columns (1) and (2). The coefficients on the squared surprises are significant for six (Column (3)) and five (Column (4)) out of the nine announcements, which provides further evidence for *prediction P2*.[14] Again, the significantly positive estimate of $\theta_{1,\tau}$ confirms the *no news is good news* effect. The fit of the models in Columns (3) and (4) is slightly higher than the fit of the corresponding piece-wise linear specification.

The asymmetric effect of good and bad news is illustrated in Fig. 4. For this, we rely on the group-specific estimates from Column (4) of Table 4.[15] For four macroeconomic announcements and two different levels of the long-term volatility component, Fig. 4 shows the model-predicted returns as a function of the size of the announcement 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). As implied by *prediction P1*, the impact of both good and bad news on returns is much stronger when long-term volatility is high. Further, in line with *prediction P2*, the figure clearly shows the asymmetric effect of good and bad news. As predicted by our model, the

[14] For Initial Jobless Claims, Retail Sales, and New Family Houses Sold, it turned out that the squared term was only supported for good news (and, hence, is omitted for bad news). For those announcements, either discount rate news is only driven by positive surprises or the specification with squared surprises overemphasizes the effect of negative surprises and, hence, is not supported by the data.

[15] Figure A.4 in Appendix E shows the corresponding plot for Column (2) of Table 4.

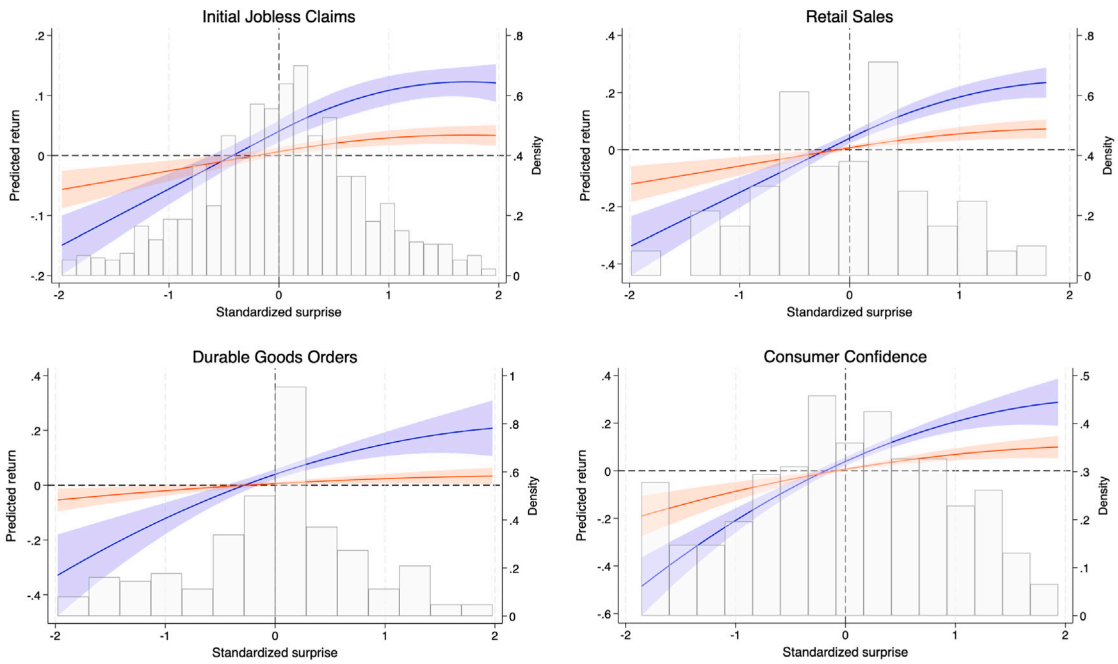

Fig. 4. Returns predicted by the model in Column (4) of Table 4 as a function of macroeconomic news, conditional on the long-term volatility component being either at the 10% (orange line) or 90% (blue line) quantile. To compute the quantiles, we only consider observations of long-term volatility on 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 10.9% (e.g., September 6, 2018), and the 90% quantile corresponds to an annualized long-term volatility of 20.9% (e.g., May 17, 2001). 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.

asymmetry is strong when long-term volatility is high, while it 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. It is important to note that this confirms our model's prediction that a large piece of bad news has a stronger effect in bad times (τ_t high) than in good times (τ_t low). This feature cannot be explained by interest rate news: While monetary policy will not respond to bad news in good times, policy might become more expansionary in response to bad news in bad times. However, this would imply that the negative cash flow news is partly offset by the discount news of the expansionary policy. Our estimates are not consistent with this explanation. Likewise, our result contrasts with the prediction of the model by Veronesi (1999) that bad news has a more substantial effect in good times. Finally, the figure 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. Overall, the figure shows that negative news have much stronger effects than positive news.

To visualize the asymmetric effect of good and bad news *over time*, Fig. 5 plots the absolute value of predicted returns in response to a positive/negative two-standard deviation surprise in Consumer Confidence over time (again based on the estimates in Table 4, Column (4)). 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.

4.2.5. Controlling for other predictors of the time-varying sensitivity

In this section, we control for other variables, which the previous literature identified as predictors of the time-varying sensitivity. Importantly, those variables were not meant to capture volatility feedback. Instead, the time-varying sensitivity has been explained by variables capturing the state of the economy, monetary policy uncertainty, and financial risks. Specifically, variables that proxy for the state of the economy are helpful in anticipating whether a certain news leads to revisions in expectations about future monetary policy (see Gardner et al., 2022; Elenev et al., 2024). In the following, we address the concern that our previous results are simply driven by the correlation of long-term volatility with those variables. Our results will confirm that the volatility feedback mechanism remains relevant for explaining the time-varying sensitivity even after controlling for other mechanisms.

Table 5 presents the corresponding estimation results. Based on the findings in Section 4.2.3, we consider regressions with group-specific sensitivity factors. In addition to the long-term component, we include K predictor variables in the sensitivity factor. To keep the specification parsimonious, we only distinguish between two groups: We combine all announcements from the groups

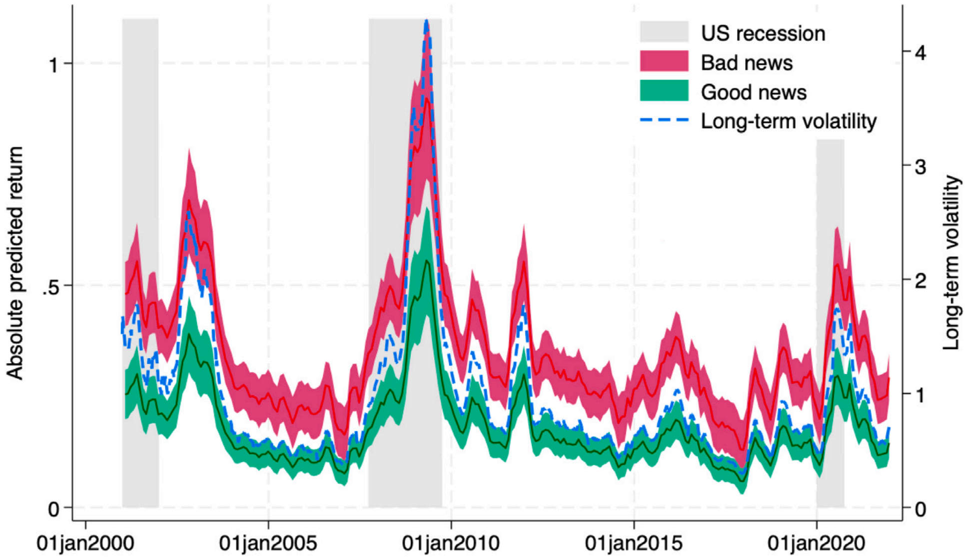

Fig. 5. Absolute returns predicted by the model in Column (4) of Table 4 after a positive (good news) and negative (bad news) two-standard deviation Consumer Confidence surprise (with 68% confidence intervals). The predicted returns for bad news are multiplied by (-1) for a better comparison. The grey-shaded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

Real Activity, *Investment & Consumption*, and *Forward-looking* into a single group, which we refer to as *Activity*, and treat *Prices* as a separate group. We specify the group-specific sensitivity factors as

$$f_g(\mathbf{X}_t) = 1 + \gamma_{g,\tau}\tilde{\tau}_t + \sum_{k=1}^{K}\gamma_{g,k}W_{k,t-1}, \tag{26}$$

where the $W_{k,t-1}$, $k = 1, \ldots, K$, are the other predictor variables. Recall that τ_t is a function of information available on day $t-1$. By including $W_{k,t-1}$, we ensure that all variables are known on the day before the announcement. For daily predictor variables, we employ the observation from the day before the announcement. For monthly (quarterly) predictor variables, we use the previous month's (quarter's) release. We demean and standardize the K predictor variables.

Table 5 presents the estimates of $\gamma_{g,\tau}$ and $\gamma_{g,k}$, $k = 1, \ldots, K$, for the *Activity* and *Prices* groups. The estimates of the remaining parameters can be found in Table A.6. Column (1) shows results when imposing symmetry of good and bad news and Columns (2) and (3) present results for the two specifications that allow for asymmetry (see Section 4.2.4). In Panels A and B, the predictor variables are intended to capture macroeconomic conditions. To keep the number of predictor variables in one regression manageable, we ran separate regressions for monthly/quarterly (Panel A) and daily (Panel B) variables. The predictor variables included in Panel C capture macroeconomic and monetary policy uncertainty and those in Panel D stock market volatility and risk appetite.

Our most important finding from Table 5 is that in all panels and all three columns, the sensitivity coefficient of long-term volatility for announcements in the *Activity* group is estimated to be positive and significant at the 5% level. That is, whatever predictor variable we control for, the predictive power of long-term volatility remains intact. In other words, long-term volatility contains relevant information that is beyond what is covered by the other predictors. Again, in line with our previous findings, in all but one specification, the effect of inflation news does not depend on long-term volatility. In all panels, Columns (2) and (3) also confirm that the *no news is good news* effect depends on the level of long-term volatility.

Beyond confirming the robustness of our previous results, Table 5 allows for some new insights. In line with the findings in Elenev et al. (2024), the estimated sensitivity coefficient of the output gap is negative and significant for announcements in the *Activity* group in Panel A. As discussed in Elenev et al. (2024), the negative sign of the sensitivity coefficient can be rationalized as follows: If the economy is in a good state (as measured by a positive output gap), the positive cash flow effect of good *Activity* news is partly offset by the expectation of tighter monetary policy in the future. For inflation surprises, we find that the sensitivity coefficient of the output gap is significantly positive (at the 10% level). That is, for high values of the output gap, negative inflation surprises (i.e., higher-than-expected inflation) are followed by strongly negative returns. This is a new result and can be explained by monetary policy anticipation effects: The response of monetary policy to higher-than-expected inflation is expected to be stronger the more positive the output gap. In contrast to Gardner et al. (2022), we do not find a significant effect of the FOMC index when including the index jointly with the other predictors in Panel A. Interestingly, for *Activity* surprises, the sensitivity coefficient of interest rate expectations is significantly positive. The positive sign of the sensitivity coefficient can be rationalized by the mechanism described in Veronesi (1999). When market participants expect higher interest rates due to the perception that the economy is in a good state, the negative cash flow effect of bad *Activity* news is reinforced by an increase in uncertainty about the state of the economy and, hence, an increase in required returns.

Figure A.5 in Appendix E visualizes model-predicted returns based on the estimates of Column (2) of Table 5 for surprises in Consumer Confidence (left) and Consumer Price Index inflation (right). In the panels in the top two rows of the figure, predicted returns are plotted as a function of the size of the surprise and for different levels of the output gap and interest rate expectations while all other predictor variables from Panel A are assumed to be at their means.[16] The figure confirms the previous interpretations and highlights the asymmetry in the response to good and bad news. For example, the upper right panel shows that the positive effect of lower-than-expected inflation is much weaker than the negative effect of higher-than-expected inflation when the output gap is at the 90% quantile.

In Panel B, the term spread is a highly relevant predictor for the size of the effect of surprises in *Activity* announcements. The positive sensitivity coefficient is again in line with the model of Veronesi (1999): When the term spread is positive, i.e., when the economy is (expected to be) in a good state, the negative cash flow effect of bad *Activity* news is reinforced by the discount rate effect due to an increase in uncertainty about the true state of the economy (see the left panel in the third row of Figure A.5). In Column (2) of Panel B, the sensitivity of inflation news with respect to long-term volatility is estimated to be negative and significant at the 10% level. While the negative sign of the sensitivity coefficient is not in line with volatility feedback, it is consistent with the notion that monetary policy will react less strongly to the news of higher-than-expected inflation if long-term financial risks are high. This is, because in such a situation, the central bank is expected to adopt a "wait and see" approach. However, since the sensitivity coefficient is only marginally significant in one out of three specifications, we do not want to overemphasize this interpretation.

Because the MOVE index and the TYVIX have a correlation of 0.951 (see Table A.3), we estimate two regressions in Panel C. The regressions either combine the MOVE or the TYVIX with all other measures of macroeconomic and monetary policy uncertainty. In addition, the second regression is for a shorter sample because the TYVIX is only available until May 2020. Panel C shows that the effect of better-than-expected *Activity* is weaker the higher either macroeconomic or monthly monetary policy uncertainty (see also Kurov and Stan, 2018). In contrast, the effect of *Activity* surprises increases with the level of the MOVE. This might indicate that the MOVE, which has a correlation of 0.676 with long-term volatility, not only captures monetary policy uncertainty but also (long-term) financial market risks. As a result, the sign of the sensitivity coefficient is the same as for long-term volatility. Thus, the effects of uncertainty and long-term financial risks work oppositely: While increased uncertainty decreases the market's sensitivity to *Activity* news, greater long-term volatility enhances that sensitivity. Regarding inflation surprises, the sensitivity coefficient of monthly monetary policy uncertainty is significantly negative (in the regression that includes the MOVE and the longer sample). That is, when uncertainty about future monetary policy is high, the negative effect of higher-than-expected inflation is attenuated (see the right panel in the fourth row of Figure A.5). This result squares with Bauer et al. (2021), who find that the effect of a monetary policy surprise is weaker when uncertainty about monetary policy is high. For high-frequency measures of monetary policy uncertainty (MOVE and realized volatility of Treasury futures), we see no such effects.[17] Finally, Panel D shows that the sensitivity with respect to *Activity* news decreases with higher risk appetite. This is in line with the notion that investors "reach-for-yield" when risk appetite is high (see Bauer et al., 2023): The market is "complacent" and, hence, less sensitive to bad and good news when risk appetite increased on the previous day.[18]

In Table A.5 in Appendix D, we reestimate Table 5 but include only a single predictor variable in the sensitivity factor, i.e., each line of the table presents the estimates from a separate regression. When considering the predictor variables in isolation, we recover some of the results from the previous literature. For example, when only including the FOMC index, we estimate a significantly negative sensitivity coefficient for *Activity* news as in Gardner et al. (2022). On the other hand, the credit spread, the TYVIX, and the realized volatility of 10y-Treasury futures have significantly positive sensitivity coefficients for *Activity* news. As shown by Table 5, the significance of the respective sensitivity coefficients disappears when those variables are included jointly and in combination with long-term volatility.

5. Robustness

Last, we conduct several robustness checks. The corresponding tables are presented in Appendix F.

Long-term variance vs. long-term volatility: From Eq. (13), it follows that cash flow news is a function of long-term volatility, i.e., $\sqrt{\tau_t}$, while discount rate news is a function of the long-term variance, i.e., τ_t. While we modelled the *no news is good news* effect as a function of the long-term variance, we always used the long-term volatility in the sensitivity factor. Table A.7 shows that the previous results are not affected when replicating the analyses from Column (3) in Table 2, Column (1) in Table 3, and Columns (2) and (4) in Table 4 while replacing $\tilde{\tau}_t$ by $\dot{\tau}_t = \tau_t - \bar{\tau}$.

Announcement window size: Table A.8 replicates the main results of Tables 3 and 4 for windows around the announcements of $k = 2$ and $k = 20$ min. Independent of the size of the window, the long-term component has strong explanatory power for *Activity* announcements. However, as expected, the adjusted R^2 decreases for $k = 20$.

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[16] Predicted returns are only shown for predictor variables for which the estimate of $\gamma_{g,k}$ is significant.

[17] We also considered the realized volatility of Treasury futures with maturities of two and five years. Again, they did not turn out to be significant.

[18] As mentioned before, the risk appetite index of Bauer et al. (2023) is based on 14 variables. Among those variables are the MOVE, the TYVIX, and the VIX. As Table A.3 shows, the correlation between the VIX, which is also included in Panel C, and the risk appetite index is only −0.154.

Table 5
Explaining the time-varying sensitivity with additional economic predictors.

	Panel A: Macroeconomic conditions (low-frequency)					
	Symmetry		*Asymmetry: Piece-wise linear*		*Asymmetry: Squared news*	
	(1)		(2)		(3)	
	Activity	*Prices*	*Activity*	*Prices*	*Activity*	*Prices*
$\tilde{\tau}_t$	1.181***	0.642	1.179***	0.730	1.244***	0.869
	(0.319)	(0.951)	(0.319)	(1.063)	(0.315)	(1.291)
FOMC sentiment	−0.101	0.197	−0.093	0.241	−0.088	0.202
	(0.086)	(0.265)	(0.085)	(0.235)	(0.084)	(0.218)
Output gap	−0.252**	0.508*	−0.265***	0.334*	−0.250**	0.300*
	(0.100)	(0.261)	(0.102)	(0.194)	(0.101)	(0.164)
Interest rate expectations	0.288***	0.161	0.286***	0.199	0.306***	0.260
	(0.066)	(0.246)	(0.067)	(0.214)	(0.070)	(0.220)
Inflation	−0.084	−0.445	−0.055	−0.563	−0.063	−0.644
	(0.108)	(0.360)	(0.106)	(0.380)	(0.102)	(0.415)
No news is good news			$\theta_{1,\tau}$		$\theta_{1,\tau}$	
$\dot{\tau}_t$			0.028***		0.028***	
			(0.010)		(0.009)	
Observations	2690		2690		2690	
Adjusted R^2	0.273		0.280		0.284	
	Panel B: Macroeconomic conditions (high-frequency)					
	(1)		(2)		(3)	
	Activity	*Prices*	*Activity*	*Prices*	*Activity*	*Prices*
$\tilde{\tau}_t$	0.880**	−1.196	0.914**	−1.325*	0.907**	−1.315
	(0.366)	(0.761)	(0.376)	(0.799)	(0.374)	(0.803)
Term spread	0.365***	−0.149	0.392***	−0.180	0.386***	−0.168
	(0.082)	(0.187)	(0.081)	(0.184)	(0.079)	(0.186)
Credit spread	0.178	0.210	0.129	0.286	0.127	0.258
	(0.113)	(0.296)	(0.113)	(0.294)	(0.111)	(0.299)
RV Eurodollar futures	0.079	0.331	0.076	0.268	0.085	0.286
	(0.064)	(0.248)	(0.063)	(0.248)	(0.063)	(0.255)
No news is good news			$\theta_{1,\tau}$		$\theta_{1,\tau}$	
$\dot{\tau}_t$			0.031***		0.029***	
			(0.010)		(0.010)	
Observations	2826		2826		2826	
Adjusted R^2	0.259		0.267		0.269	
	Panel C: Macroeconomic and monetary policy uncertainty					
	(1)		(2)		(3)	
	Activity	*Prices*	*Activity*	*Prices*	*Activity*	*Prices*
$\tilde{\tau}_t$	1.464***	−2.278	1.455***	−0.856	1.453***	−0.604
	(0.284)	(1.481)	(0.283)	(1.440)	(0.286)	(1.500)
Monetary policy uncertainty	−0.155***	−0.484*	−0.164***	−0.577**	−0.163***	−0.611**
	(0.054)	(0.266)	(0.055)	(0.243)	(0.054)	(0.242)
Macroeconomic uncertainty	−0.270***	0.333	−0.273***	0.103	−0.271***	0.034
	(0.057)	(0.314)	(0.055)	(0.303)	(0.057)	(0.309)
MOVE-Index	0.241**	0.796	0.264**	0.757	0.289**	0.743
	(0.116)	(0.596)	(0.114)	(0.502)	(0.115)	(0.483)
RV 10-year Treasury futures	0.016	−0.298	−0.013	−0.531	−0.026	−0.505
	(0.108)	(0.565)	(0.112)	(0.504)	(0.114)	(0.486)
No news is good news			$\theta_{1,\tau}$		$\theta_{1,\tau}$	
$\dot{\tau}_t$			0.034***		0.032***	
			(0.010)		(0.010)	
Observations	2826		2826		2826	
Adjusted R^2	0.278		0.288		0.291	
	(1)		(2)		(3)	
	Activity	*Prices*	*Activity*	*Prices*	*Activity*	*Prices*
$\tilde{\tau}_t$	1.538***	−3.496	1.592***	−3.225	1.579***	−2.743
	(0.329)	(2.145)	(0.343)	(2.257)	(0.359)	(2.349)
Monetary policy uncertainty	−0.162**	−0.434	−0.184***	−0.522	−0.182***	−0.623*

(*continued on next page*)

Table 5 (*continued*).

	(0.066)	(0.317)	(0.069)	(0.355)	(0.068)	(0.372)
Macroeconomic uncertainty	−0.276***	0.139	−0.286***	0.041	−0.289**	−0.072
	(0.076)	(0.518)	(0.076)	(0.535)	(0.079)	(0.550)
TYVIX	0.168	0.143	0.154	0.374	0.165	0.486
	(0.156)	(0.553)	(0.150)	(0.596)	(0.154)	(0.654)
RV 10-year Treasury futures	0.026	0.821	0.017	0.505	0.028	0.344
	(0.188)	(1.044)	(0.186)	(1.097)	(0.187)	(1.162)
No news is good news			$\theta_{1,\tau}$		$\theta_{1,\tau}$	
$\dot{\tau}_t$			0.030***		0.027**	
			(0.011)		(0.011)	
Observations	2338		2338		2338	
Adjusted R^2	0.299		0.309		0.308	
	Panel D: Stock market volatility and risk appetite					
	(1)		(2)		(3)	
	Activity	*Prices*	*Activity*	*Prices*	*Activity*	*Prices*
$\tilde{\tau}_t$	1.992***	−2.096	2.057***	−2.336	2.030***	−2.384
	(0.375)	(1.339)	(0.388)	(1.647)	(0.397)	(1.818)
GJR-GARCH	0.106	1.252*	0.114	1.099	0.091	1.070
	(0.173)	(0.674)	(0.171)	(0.686)	(0.176)	(0.717)
VIX	−0.182	−0.564	−0.227	−0.285	−0.186	−0.237
	(0.193)	(0.724)	(0.192)	(0.753)	(0.197)	(0.827)
Risk appetite	−0.209***	−0.509	−0.203***	−0.515	−0.201***	−0.542
	(0.076)	(0.436)	(0.074)	(0.384)	(0.074)	(0.423)
No news is good news			$\theta_{1,\tau}$		$\theta_{1,\tau}$	
$\dot{\tau}_t$			0.029***		0.027***	
			(0.010)		(0.010)	
Observations	2826		2826		2826	
Adjusted R^2	0.244		0.251		0.254	

Notes: We set $k = 10$ min. We distinguish between two groups, *Activity* and *Price* announcements, and present the coefficient estimates of $\gamma_{g,\tau}$ and $\gamma_{g,k}$ for all k predictor variables in two separate columns corresponding to each group. Columns (1) present estimates of Eq. (19) with $f(\mathbf{X}_t)$ from (26), where we include all economic predictors and the long-term volatility component jointly. In Column (2), we extend the specification from Column (1) by separating between good and bad news, as in Eq. (21) with $f(\mathbf{X}_t)$ as before. In Column (3), we report results of estimating equation (22). We include squared terms only for good news of Retail Sales, Initial Jobless Claims, and New Family Houses Sold. For the VIX/MOVE/TYVIX, we use the VIX/MOVE/TYVIX on the previous trading day divided by $\sqrt{365}$. All economic predictors are standardized by dividing each by its standard deviation. To mitigate the influence of extreme observations, we winsorize the TYVIX and Eurodollar futures returns at the 99th percentile (top 1%). The coefficient estimates on the macroeconomic surprises are not reported in the table. The estimates of the remaining parameters can be found in Table A.6. All regressions include a constant. FOMC sentiment in Panel A is available from January 2001 until December 2020. The TYVIX is available from January 2003 to May 15, 2020. In Panels B, C, and D, the estimation sample spans the period from January 2001 to December 2021. Numbers in parentheses are Newey–West standard errors. Notation: ***p < 0.01, **p < 0.05, *p < 0.1.

Excluding announcement days with scheduled monetary policy decisions: Lucca and Moench (2015) show that scheduled monetary policy decisions lead to large average excess returns in the 24 h 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.9 shows that the estimated coefficients from Column (3) in Table 2, Column (1) in Table 3, and Columns (2) and (4) in Table 4 are of similar size when we exclude pre-scheduled 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 into a single regression, we estimate separate regressions for news at 8:30 am and 10:00 am. The results reported in Table A.10 show that the coefficient estimates are of similar size as in the pooled regression.

Futures vs. stock market index data: For announcements published at 10:00 am, 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.11 shows, the size of the coefficients and the explanatory power of the estimated models are comparable 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.12 confirms our results' robustness.

Extension to the European stock market: In Appendix F.2, we extend our analyses to the EURO STOXX 50. For all announcements but CPI inflation, the response of the EURO STOXX 50 to U.S. announcements increases with the level of the S&P 500's long-term volatility component.

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 multiplicative 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. This long-term volatility dependence holds for all macroeconomic announcements, except inflation news. Moreover, we show that the *no news is good news* effect increases with the level of long-term volatility.

These results are complementary to recent evidence by Gardner et al. (2022) and Elenev et al. (2024). 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. Our results suggest that long-term volatility is neither an alternative measure for the stance of the business cycle nor a proxy for monetary policy uncertainty. Instead, long-term volatility contains relevant information about long-term financial market risks that are priced in the risk-return relation. Overall, we find that volatility feedback is an important mechanism for explaining the time-varying sensitivity of stock returns to macroeconomic news.

Funding

This work was supported by the German Federal Ministry of Education and Research (BMBF) and the Baden-Württemberg Ministry of Science as part of Germany's Excellence Strategy [grant number: ExU 10.2.31].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are grateful to the Co-Editor, Viktor Todorov, the Associate Editor, and two anonymous referees for comments, which greatly improved our paper. We would like to thank Torben Andersen, Michael Bauer, Maximilian Boeck, Rob Engle, Eric Ghysels, Mark Kerssenfischer, Faek Menla Ali, Anne Opschoor, Marc-Oliver Pohle, Lara Schadwinkel, Manuel Schick, Carsten Trenkler, and Michael Weber, as well as the participants of the CIREQ-CMP Econometrics Conference in Honor of Eric Ghysels (May 2024), 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.

Appendix A. Derivation of discount rate news

Assuming that $\eta_{d,t+1}$ follows an MF2-GARCH with $m = 1$, this section provides a derivation of Eq. (11). Recall that 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 Eq. (6) as

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

where $\tilde{v}^h_{t+1} = \left[\alpha\left(Z^2_{t+1} - 1\right) + \gamma\left(\mathbf{1}_{\{Z_{t+1}<0\}}Z^2_{t+1} - \frac{1}{2}\right)\right]$ (see Eq. (10)). Note that for deriving $\tilde{v}^h_{t+1}$, we use that $\mathbf{E}[Z_{t+1}] = 0$, $\mathbf{E}[Z^2_{t+1}] = 1$ and that the density of Z_{t+1} is symmetric. Similarly, Eq. (7) can be written as

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

where $\tilde{v}^\tau_{t+1} = \lambda_1\left(Z^2_{t+1} - 1\right)$ (see Eq. (9)). By construction, v^h_{t+1} and v^τ_{t+1} are white noise.

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

$$\mathbf{E}_{t+1}[\sigma^2_{t+2}] - \mathbf{E}_t[\sigma^2_{t+2}] \quad = \quad (1-\phi)\tau_{t+1}\tilde{v}^\tau_{t+1} + \lambda_0 h_{t+1}\tilde{v}^h_{t+1} + \sigma^2_{t+1}\tilde{v}^\sigma_{t+1}, \tag{A.3}$$

where

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

We refer to $v^\sigma_{t+1} = \sigma^2_{t+1}\tilde{v}^\sigma_{t+1}$ as conditional variance news (see Eq. (11)). 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.

Second, based on Eqs. (6) and (7), the conditional variance can be written as

$$\begin{aligned}\sigma^2_{t+j+1} \;=\; & (1-\phi)\tau_{t+j} \\ & + \lambda_0\left(\alpha + \gamma\mathbf{1}_{\{r_{t+j}<0\}}\right)\frac{\eta^2_{d,t+j}}{\tau_{t+j}} + \lambda_1\left(\alpha + \gamma\mathbf{1}_{\{r_{t+j}<0\}}\right)\frac{\eta^4_{d,t+j}}{h_{t+j}\tau_{t+j}} \\ & + \lambda_2\left(\alpha + \gamma\mathbf{1}_{\{r_{t+j1}<0\}}\right)\eta^2_{d,t+j} + \lambda_0\beta h_{t+j} + \lambda_1\beta\eta^2_{d,t+j} + \lambda_2\beta h_{t+j}\tau_{t+j}.\end{aligned} \tag{A.5}$$

Thus, for $j \geq 2$, the following recursions apply:

$$\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] = (1-\phi)\mathbf{E}_{t+1}[\tau_{t+j+1}] + \lambda_0\phi\mathbf{E}_{t+1}[h_{t+j}] + (\lambda_1\phi_\kappa + \lambda_2\phi)\mathbf{E}_{t+1}[\sigma^2_{t+j}] \tag{A.6}$$

$$\mathbf{E}_{t}[\sigma^2_{t+j+1}] = (1-\phi)\mathbf{E}_{t}[\tau_{t+j+1}] + \lambda_0\phi\mathbf{E}_{t}[h_{t+j}] + (\lambda_1\phi_\kappa + \lambda_2\phi)\mathbf{E}_{t}[\sigma^2_{t+j}]. \tag{A.7}$$

Hence, we can write

$$\begin{aligned}\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbf{E}_t[\sigma^2_{t+j+1}] &= (1-\phi)(\mathbf{E}_{t+1}[\tau_{t+j+1}] - \mathbf{E}_t[\tau_{t+j+1}]) \\ &\quad + \lambda_0\phi(\mathbf{E}_{t+1}[h_{t+j}] - \mathbf{E}_t[h_{t+j}]) \\ &\quad + (\lambda_1\phi_\kappa + \lambda_2\phi)(\mathbf{E}_{t+1}[\sigma^2_{t+j}] - \mathbf{E}_t[\sigma^2_{t+j}]).\end{aligned} \tag{A.8}$$

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

$$h_{t+j} = 1 + \sum_{s=0}^{\infty} \phi^s v^h_{t+j-1-s}. \tag{A.9}$$

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

$$\tau_{t+j+1} = \frac{\lambda_0}{1-\lambda_1-\lambda_2} + \sum_{s=0}^{\infty}(\lambda_1+\lambda_2)^s v^\tau_{t+j-s}. \tag{A.10}$$

This leads to

$$\begin{aligned}\mathbf{E}_{t+1}[\sigma^2_{t+j+1}] - \mathbf{E}_t[\sigma^2_{t+j+1}] &= (1-\phi)(\lambda_1+\lambda_2)^{j-1}v^\tau_{t+1} + \lambda_0\phi^{j-1}v^h_{t+1} \\ &\quad + (\lambda_1\phi_\kappa + \lambda_2\phi)(\mathbf{E}_{t+1}[\sigma^2_{t+j}] - \mathbf{E}_t[\sigma^2_{t+j}]) \\ &= (1-\phi)(\lambda_1+\lambda_2)^{j-1}v^\tau_{t+1} + \lambda_0\phi^{j-1}v^h_{t+1} \\ &\quad + (\lambda_1\phi_\kappa + \lambda_2\phi)\left[(1-\phi)(\lambda_1+\lambda_2)^{j-2}v^\tau_{t+1} + \lambda_0\phi^{j-2}v^h_{t+1}\right] \\ &\quad + (\lambda_1\phi_\kappa + \lambda_2\phi)^2(\mathbf{E}_{t+1}[\sigma^2_{t+j-1}] - \mathbf{E}_t[\sigma^2_{t+j-1}]) \\ &= \dots \\ &= v^\tau_{t+1}(1-\phi)\sum_{s=1}^{j-1}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}(\lambda_1+\lambda_2)^{j-s} \\ &\quad + v^h_{t+1}\lambda_0\sum_{s=1}^{j-1}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}\phi^{j-s} \\ &\quad + (\lambda_1\phi_\kappa + \lambda_2\phi)^{j-1}(\mathbf{E}_{t+1}[\sigma^2_{t+2}] - \mathbf{E}_t[\sigma^2_{t+2}]).\end{aligned} \tag{A.11}$$

By combining Eqs. (A.11) and (A.3), we obtain the following result: 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

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

with

$$A^\tau_j = (1-\phi)\sum_{s=1}^{j}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}(\lambda_1+\lambda_2)^{j-s},$$

$$A^h_j = \lambda_0\sum_{s=1}^{j}(\lambda_1\phi_\kappa + \lambda_2\phi)^{s-1}\phi^{j-s}, \qquad A^\sigma_j = (\lambda_1\phi_\kappa + \lambda_2\phi)^{j-1}.$$

Finally, by plugging equation (A.12) into Eq. (4) and using the assumptions that $\phi < 1$, $\lambda_1 + \lambda_2 < 1$, and $\lambda_1\phi_\kappa + \lambda_2\phi < 1$, we obtain Eq. (8). The constants A^σ, A^τ, and A^h are

$$A^\sigma = \delta\sum_{j=1}^{\infty}\rho^j(\lambda_1\phi_\kappa + \lambda_2\phi)^{j-1} = \delta\rho\frac{1}{1-\rho(\lambda_1\phi_\kappa + \lambda_2\phi)}, \tag{A.13}$$

$$A^\tau = A^\sigma\frac{1-\phi}{1-\rho(\lambda_1+\lambda_2)}, \tag{A.14}$$

$$A^h = A^\sigma\frac{\lambda_0}{1-\rho\phi}. \tag{A.15}$$

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeconom.2025.106148.

References

Adrian, Tobias, Rosenberg, Joshua, 2008. Stock returns and volatility: Pricing the short-run and long-run components of market risk. J. Financ. 63 (6), 2997–3030.
Andersen, Torben G., Bollerslev, Tim, 1998. Deutsche mark-dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. J. Financ. 53 (1), 219–265.
Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., Vega, Clara, 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. Am. Econ. Rev. 93 (1), 38–62.
Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., Vega, Clara, 2007. Real-time price discovery in global stock, bond and foreign exchange markets. J. Int. Econ. 73 (2), 251–277.
Balduzzi, Pierluigi, Elton, Edwin J., Green, T. Clifton, 2001. Economic news and bond prices: Evidence from the U.S. treasury market. J. Financ. Quant. Anal. 36 (4), 523–543.
Bauer, Michael D., Bernanke, Ben S., Milstein, Eric, 2023. Risk appetite and the risk-taking channel of monetary policy. J. Econ. Perspect. 37 (1), 77–100.
Bauer, Michael D., Lakdawala, Aeimit, Mueller, Philippe, 2021. Market-based monetary policy uncertainty. Econ. J. 132 (644), 1290–1308.
Bekaert, Geert, Wu, Guojun, 2001. Asymmetric volatility and risk in equity markets. Rev. Financ. Stud. 13 (1), 1–42.
Boehm, Christoph E., Kroner, Niklas T., 2025. The U.S., economic news, and the global financial cycle. Rev. Econ. Stud. (Forthcoming).
Bollerslev, Tim, Litvinova, Julia, Tauchen, George, 2006. Leverage and volatility feedback effects in high-frequency data. J. Financ. Econ. 4 (3), 353–384.
Boyd, John H., Hu, Jian, Jagannathan, Ravi, 2005. The stock market's reaction to unemployment news: Why bad news is usually good for stocks. J. Financ. 60 (2), 649–672.
Campbell, John Y., 1991. A variance decomposition for stock returns. Econ. J. 101 (405), 157–179.
Campbell, John Y., Hentschel, Ludger, 1992. No news is good news: An asymmetric model of changing volatility in stock returns. J. Financ. Econ. 31 (3), 281–318.
Campbell, John Y., Shiller, Robert J., 1988. Stock prices, earnings, and expected dividends. J. Financ. 43 (3), 661–676.
Cenesizoglu, Tolga, Ibrushi, Denada, 2022. Time variation in cash flows and discount rates.
Chen, Xilong, Ghysels, Eric, 2011. News—Good or bad—and its impact on volatility predictions over multiple horizons. Rev. Financ. Stud. 24 (1), 46–81.
Conrad, Jennifer, Cornell, Bradford, Landsman, Wayne R., 2002. When is bad news really bad news? J. Financ. 57 (6), 2507–2532.
Conrad, Christian, Engle, Robert F., 2025. Modelling volatility cycles: The MF2-GARCH model. J. Appl. Econometrics 40 (4), 438–454.
Conrad, Christian, Loch, Karin, 2015. Anticipating long-term stock market volatility. J. Appl. Econometrics 30 (7), 1090–1114.
Elenev, Vadim, Law, Tzuo-Hann, Song, Dongho, Yaron, Amir, 2024. Fearing the fed. How wall street reads main street. J. Financ. Econ. 153, 103790.
Engle, Robert F., 2011. Long-term skewness and systemic risk. J. Financ. Econ. 9 (3), 437–468.
Engle, Robert F., Ghysels, Eric, Sohn, Bumjean, 2013. Stock market volatility and macroeconomic fundamentals. Rev. Econ. Stat. 95 (3), 776–797.
Engle, Robert F., Rangel, Jose Gonzalo, 2008. The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. Rev. Financ. Stud. 21 (3), 1187–1222.
French, Kenneth R., William Schwert, G., Stambaugh, Robert F., 1987. Expected stock returns and volatility. J. Financ. Econ. 19 (1), 3–29.
Gardner, Ben, Scotti, Chiara, Vega, Clara, 2022. Words speak as loudly as actions: Central bank communication and the response of equity prices to macroeconomic announcements. J. Econometrics 231 (2), 387–409.
Ghysels, Eric, Guérin, Pierre, Marcellino, Massimiliano, 2014. Regime switches in the risk–return trade-off. J. Empir. Financ. 28, 118–138.
Ghysels, Eric, Santa-Clara, Pedro, Valkanov, Rossen, 2004. The MIDAS touch: Mixed data sampling regression models. Working Paper, UNC and UCLA.
Ghysels, Eric, Santa-Clara, Pedro, Valkanov, Rossen, 2005. There is a risk-return trade-off after all. J. Financ. Econ. 76 (3), 509–548.
Ghysels, Eric, Santa-Clara, Pedro, Valkanov, Rossen, 2006. Predicting volatility: Getting the most out of return data sampled at different frequencies. J. Econometrics 131 (1), 59–95.
Gilbert, Thomas, Scotti, Chiara, Strasser, Georg, Vega, Clara, 2017. Is the intrinsic value of a macroeconomic news announcement related to its asset price impact? J. Monet. Econ. 92, 78–95.
Glosten, Lawrence R., Jagannathan, Ravi, Runkle, David E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. J. Financ. 48 (5), 1779–1801.
Guerkaynak, Refet S., Kisacikoglu, Burcin, Wright, Jonathan H., 2020. Missing events in event studies: Identifying the effects of partially measured news surprises. Am. Econ. Rev. 110 (12), 3871–3912.
Husted, Lucas, Rogers, John, Sun, Bo, 2020. Monetary policy uncertainty. J. Monet. Econ. 115, 20–36.
Jurado, Kyle, Ludvigson, Sydney C., Ng, Serena, 2015. Measuring uncertainty. Am. Econ. Rev. 105 (3), 1177–1216.
Kilian, Lutz, Vega, Clara, 2011. Do energy prices respond to U.S. macroeconomic news? A test of the hypothesis of predetermined energy prices. Rev. Econ. Stat. 93 (2), 660–671.
Kim, Chang-Jin, Kim, Yunmi, 2019. A unified framework jointly explaining business conditions, stock returns, volatility and volatility feedback news effects. Stud. Nonlinear Dyn. Econom. 23 (2), 20160151.
Kim, Yunmi, Nelson, Charles R., 2013. Pricing stock market volatility: Does it matter whether the volatility is related to the business cycle? J. Financ. Econ. 12 (2), 307–328.
Kurov, Alexander, Stan, Raluca, 2018. Monetary policy uncertainty and the market reaction to macroeconomic news. J. Bank. Financ. 86, 127–142.
Lucca, David O., Moench, Emanuel, 2015. The pre-FOMC announcement drift. J. Financ. 70 (1), 329–371.
Maheu, John M., McCurdy, Thomas H., 2007. Components of market risk and return. J. Financ. Econ. 5 (4), 560–590.
McQueen, Grant, Roley, Vance V., 1993. Stock prices, news, and business conditions. Rev. Financ. Stud. 6 (3), 683–707.
Mincer, Jacob, Zarnowitz, Victor, 1969. The evaluation of economic forecasts. In: Economic Forecasts and Expectations: Analysis of Forecasting Behavior and Performance. National Bureau of Economic Research, pp. 3–46.
Pindyck, Robert S., 1984. Risk, inflation, and the stock market. Am. Econ. Rev. 74 (3), 335–351.
Swanson, Eric T., Williams, John C., 2014. Measuring the effect of the zero lower bound on medium- and longer-term interest rates. Am. Econ. Rev. 104 (10), 3154–3185.
Veronesi, Pietro, 1999. Stock market overreaction to bad news in good times: A rational expectations equilibrium model. Rev. Financ. Stud. 12 (5), 975–1007.