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**Who Believes in Fiscal Stimulus? Forecaster
Heterogeneity and the Transmission of
Fiscal News**

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Who Believes in Fiscal Stimulus? Forecaster Heterogeneity and the Transmission of Fiscal News

Elahe Boskabadi*, Hyeongwoo Kim[†], Peng Shao[‡], and Shuwei Zhang[§]

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Abstract

This paper studies heterogeneity in how forecasters translate fiscal stimulus news into longer-term output expectations. Using individual-level data from the Survey of Professional Forecasters, we classify forecasters according to their relative positions in the distributions of federal government spending and real GDP forecasts. A state-space model with drifting coefficients estimates the time-varying pass-through from near-term spending forecast revisions to longer-term GDP forecast revisions. We find pronounced cross-sectional asymmetry early in the sample: lower-tail forecasters exhibit substantially weaker pass-through than upper-tail forecasters, reflecting more pessimistic responses to fiscal news. Over time, lower-tail pass-through rises markedly and converges toward the relatively stable response of optimists, narrowing the initial disagreement over the transmission of fiscal news.

Keywords: Forecast Revisions; Survey of Professional Forecasters; Heterogeneous Beliefs; Kalman Filter; Kalman Smoother

JEL Classification: C32; D84; E62; E37

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1 Introduction

The profession has long debated the effectiveness of fiscal policy in stimulating real economic activity. See [Morelli \(2026\)](#) and [Ramey \(2019\)](#) for recent comprehensive surveys of this literature. In addition to this broader debate, a growing literature has examined nonlinear fiscal policy effects using state-dependent stochastic models that distinguish between different phases of the business cycle, such as recessions and expansions. See, among others, [Albertini et al. \(2021\)](#), [Bernardini et al. \(2020\)](#), [Fazzari et al. \(2015\)](#), [Auerbach and Gorodnichenko \(2012\)](#), and [Mittnik and Semmler \(2012\)](#), which find that fiscal stimulus has stronger effects on economic activity when economic slack is high, whereas [Ramey and Zubairy \(2018\)](#) and [Owyang et al. \(2013\)](#) find no evidence of such state dependence in historical U.S. data.¹

More recently, [Cappelletti \(2026\)](#), [Ben Zeev et al. \(2023\)](#), and [Barnichon et al. \(2022\)](#), among others, have examined whether the effects of government spending shocks differ depending on whether the shocks are positive or negative, with mixed evidence. [Cappelletti \(2026\)](#) finds stronger fiscal stimulus effects following positive shocks, whereas [Barnichon et al. \(2022\)](#) finds the opposite. [Ben Zeev et al. \(2023\)](#) find no clear evidence of asymmetry in fiscal multipliers.

Unlike the existing literature, which has primarily focused on asymmetries in the macroeconomic effects of fiscal shocks, we ask whether the pass-through from government spending news to output expectations differs across the distribution of professional forecasters and whether this relationship evolves over time. To identify government spending news shocks, we employ identification approaches similar to those used in [Cappelletti \(2026\)](#), [Adam et al. \(2025\)](#), [Cascaldi-Garcia \(2025\)](#), and [Bordalo et al. \(2020\)](#), building on the influential seminal framework of [Coibion and Gorodnichenko \(2015\)](#) and [Forni and Gambetti \(2016\)](#). We then extend this approach to examine how individually perceived government spending news shocks affect professional forecasters' longer-term output expectations.

More specifically, we use individual-level data from the Survey of Professional Forecasters (SPF) and classify forecasters according to their positions in the cross-sectional distributions of their level forecasts for real GDP and federal government spending. Focusing on the lower- and upper-tail groups, we construct group-specific series of forecast revisions for real GDP and real federal government spending. We then estimate a time-varying relationship between the two revision series.

¹[Caggiano et al. \(2015\)](#) report a statistically significant difference only during deep recessions. [Jo and Zubairy \(2025\)](#) find larger fiscal multipliers during recessions characterized by low inflation or weak demand than during supply-driven recession.

Our main findings are as follows. Early in the sample, the lower-tail group—referred to as pessimists because they tend to forecast lower government spending—exhibits a substantially smaller pass-through coefficient than the upper-tail group, referred to as optimists because they tend to forecast higher spending. In response to new information about government spending, pessimistic forecasters revise their GDP expectations relatively little, whereas optimists exhibit a much stronger positive response. Over time, however, the pass-through coefficient for the pessimistic group rises considerably, while that for the optimistic group remains relatively stable. As a result, the initial gap between the two groups gradually narrows. Overall, this pattern points to substantial heterogeneity in forecasters’ beliefs at the beginning of the sample, followed by asymmetric learning dynamics across the forecaster distribution.

Taken together, these findings introduce a new dimension of asymmetry in the fiscal news literature by exploiting SPF microdata to examine heterogeneity in forecasters’ beliefs about the effectiveness of fiscal stimulus across the forecaster distribution and its evolution over time. We show that this cross-sectional heterogeneity is initially substantial, with large differences in responses to fiscal news across forecasters, but gradually narrows over time.

Our findings contribute to the literature on the sentiment channel of fiscal stimulus (see, among others, [Bellifemine et al. 2026](#); [L’Huillier et al. 2024](#); [Georgarakos and Kenny 2022](#); [Angeletos and Lian 2022](#); [Bachmann and Sims 2012](#); [Beaudry and Portier 2007](#); [Beaudry and Portier 2006](#)). Whereas existing studies typically focus on aggregate sentiment, implicitly assuming homogeneous belief formation, we examine how agents incorporate new information about fiscal stimulus into their expectations of future economic activity and how this process evolves over time.

Our analysis highlights pervasive cross-sectional heterogeneity in the transmission of fiscal news to macroeconomic expectations. We find that this transmission is initially highly asymmetric across the forecaster distribution: lower-tail skeptics exhibit substantially weaker pass-through than upper-tail optimists. This asymmetry diminishes over time, consistent with asymmetric learning dynamics.

The remainder of the paper proceeds as follows. Section 2 describes the SPF data and the construction of the forecaster groups, and then presents the empirical model. Section 3 presents the main evidence on cross-sectional asymmetry and convergence. Section 4 concludes.

2 The Empirics

2.1 Individual-Level Forecast Data

Our analysis uses individual-level forecasts from the Survey of Professional Forecasters (SPF), maintained by the Federal Reserve Bank of Philadelphia. The data are quarterly and span from 1968Q4 to 2026Q1. The cross-section is unbalanced, reflecting the entry and exit of SPF participants as well as missing observations for particular variables.

The first survey that includes forecasts of real federal government expenditures begins in 1981Q3. For the earlier period, 1968Q4 to 1981Q2, we obtain nominal defense spending forecasts from Thomas Stark at the Federal Reserve Bank of Philadelphia and use the median forecast of the GDP deflator to convert nominal defense spending forecasts (**DEFENSE**) into real spending forecasts (**PGDP**). Following [Ramey \(2011\)](#), we combine the resulting real defense spending forecasts with forecasts of real federal government expenditures.²

We combine two types of information. First, level forecasts of real GDP (**RGDP**) and real federal government spending (**RFEDGOV**) are used to characterize each forecaster's relative position in the cross-sectional distribution. Second, revisions to forecasts of real GDP (y_t) and real federal government spending (g_t) from $t-1$ to t are used to estimate the time-varying relationship between fiscal news and output expectations.

Specifically, let $r_{i,t}^y$ denote forecaster i 's revision to the forecast of y_{t+h} , and let $r_{i,t}^g$ denote the corresponding revision to the forecast of g_{t+1} , defined as follows:

$$r_{i,t}^y = \frac{\mathcal{F}_i(y_{t+h}|\Omega_{i,t}) - \mathcal{F}_i(y_{t+h}|\Omega_{i,t-1})}{\mathcal{F}_i(y_{t+h}|\Omega_{i,t-1})}, \quad r_{i,t}^g = \frac{\mathcal{F}_i(g_t|\Omega_{i,t}) - \mathcal{F}_i(g_t|\Omega_{i,t-1})}{\mathcal{F}_i(g_t|\Omega_{i,t-1})}, \quad (1)$$

where $\Omega_{i,t}$ denotes forecaster i 's information set at time t , and $h > 1$ indicates that we focus on revisions to longer-horizon output forecasts in response to new information about government spending at $t + 1$. Specifically, $r_{i,t}^y$ denotes the percentage revision from the 4-quarter-ahead ($h = 3$) forecast at time $t - 1$ to the forecast for the same quarter at time t , which is 3 quarters ahead, whereas $r_{i,t}^g$ is the percentage revision from the 1-quarter-ahead forecast at time $t - 1$ to the nowcast at time t .^{3,4}

²There were ten changes in the base year of the National Income and Product Accounts (NIPA) over our full sample period. Because SPF forecasts do not incorporate these changes, they can generate outliers when the base year is revised. We therefore rescaled all relevant forecast data to a common 2017 base year.

³The SPF data provide six forecast horizons, ranging from backcasts (e.g., **RGDP1**) and nowcasts (e.g., **RGDP2**) to forecasts up to four quarters ahead (e.g., **RGDP6**).

⁴Individual-level SPF survey data are unavailable for 1969Q1–1969Q3 and 1970Q1, but are

2.2 Identifying and Assigning Lower- and Upper-Tail Groups

For each quarter, we construct lower- and upper-tail groups based on the empirical distributions of the level forecasts. Let $Q_{p,t}^g$ and $Q_{p,t}^y$ denote the p^{th} cross-sectional percentiles of the forecasts for real federal government spending (g_t) and real GDP (y_t), respectively. We assign a forecaster to group $\mathcal{G}_t(a, b)$ if their forecast lies within the percentile band $[Q_{a,t}, Q_{b,t}]$ for either government spending or GDP, according to one of the following three assignment rules:

$$\mathbf{1}\{i \in \mathcal{G}_t(a, b)\} = \begin{cases} \mathbf{1}\{Q_{a,t}^g \leq \mathcal{F}_i(g_t|\Omega_{i,t}) \leq Q_{b,t}^g\}, (\text{G rule}) \\ \mathbf{1}\{Q_{a,t}^y \leq \mathcal{F}_i(y_t|\Omega_{i,t}) \leq Q_{b,t}^y\}, (\text{Y rule}) \\ \mathbf{1}\{Q_{a,t}^g \leq \mathcal{F}_i(g_t|\Omega_{i,t}) \leq Q_{b,t}^g\} \vee \mathbf{1}\{Q_{a,t}^y \leq \mathcal{F}_i(y_t|\Omega_{i,t}) \leq Q_{b,t}^y\}, (\text{OR rule}) \end{cases} \quad (2)$$

The three cases correspond to group assignments based on the forecast of g_t , the forecast of y_t , and the union of the two groups, respectively. For the last rule (the OR rule), we exclude forecasters who fall within both bands.⁵

Note that group membership is determined by level forecasts rather than by the ranks of forecast revisions. Thus, the groups capture forecasters' positions in the distribution of expectations, while the subsequent empirical analysis examines how forecasters in these groups revise their beliefs in response to new information.

Although the SPF identifiers (i) are designed to track individual forecasters over time, there are known issues with identifier reassignment, particularly during the ASA/NBER period (1968Q4–1990Q1). To mitigate potential measurement error arising from such reassignment, we construct the following group-specific revision series after identifying the members of $\mathcal{G}_t(a, b)$.⁶

$$\bar{r}_t^y(a, b) = \text{mean}_{i \in \mathcal{G}_t(a, b)} r_{i,t}^y, \quad \bar{r}_t^g(a, b) = \text{mean}_{i \in \mathcal{G}_t(a, b)} r_{i,t}^g \quad (3)$$

available continuously from 1970Q3 onward. Accordingly, our revision data begin in 1970Q3.

⁵This OR rule results in some forecasters belonging to both the optimistic and pessimistic groups. However, only 6.5% of observations belong to both groups, and excluding these overlapping forecasters yields very similar results.

⁶The SPF confidential identifiers (i) are designed to track individual forecasters over time. However, the Philadelphia Fed notes several caveats regarding their interpretation, including potential reassignment of identifiers during the historical ASA/NBER period, before the Philadelphia Fed took over in 1990Q2, and changes in identification when a forecaster changes affiliation. To the extent that such ID changes introduce idiosyncratic measurement error into forecaster-level revision series, aggregating revisions within groups may attenuate their effects, provided that these errors are not systematically related to forecasters' group membership or revisions and that ID changes occur infrequently.

These revision series are purged of macroeconomic shocks other than fiscal news shocks by taking the residuals from regressions on five latent common factors ($\hat{\mathbf{F}}_t$) from the **FRED-QD**, denoted by $\tilde{r}_t^y(a, b)$ and $\tilde{r}_t^g(a, b)$.⁷ That is,

$$\tilde{r}_t^y(a, b) = \bar{r}_t^y(a, b) - \hat{r}_t^y(a, b), \quad (4)$$

where $\hat{r}_t^y(a, b)$ denotes the fitted value from this regression. The corresponding residual $\tilde{r}_t^g(a, b)$ is obtained analogously. See, among others, [Cappelletti \(2026\)](#), [Cascaldi-Garcia \(2025\)](#), [Miranda-Agrippino and Ricco \(2023\)](#), and [Caggiano et al. \(2015\)](#) for related discussions.

For notational simplicity, we denote the Pessimist group as the lower-tail group $\mathcal{G}_t(0, 0.15)$ and the Optimist group as the upper-tail group $\mathcal{G}_t(0.85, 1)$. These two groups retain roughly 30% of the full set of observations in each quarter, with the former tending to generate lower forecasts and the latter higher forecasts. The cross-sectional median group, $\mathcal{G}_t(0.425, 0.575)$, serves as a benchmark. In what follows, our estimates show that the Pessimist group tends to anticipate weaker fiscal stimulus effects, whereas the Optimist group tends to hold more favorable views about the effectiveness of fiscal policy.

2.3 Fiscal News Shock Pass-Through to Output Prospects

For each forecaster group, we estimate

$$\tilde{r}_t^y(a, b) = \alpha_t + \beta_t \tilde{r}_t^g(a, b) + e_t, \quad (5)$$

where the intercept and slope follow independent random walks,

$$\theta_t = \theta_{t-1} + \eta_t, \quad \theta_t = \begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix}, \quad \eta_t \sim \mathcal{N}(0, Q), \quad (6)$$

where

$$Q = \text{diag}\{k_{Q_\alpha}^2 V_0[1, 1], k_{Q_\beta}^2 V_0[2, 2]\}, \quad k_{Q_\alpha} = 0.05, k_{Q_\beta} = 0.12, \quad (7)$$

and V_0 is the full-sample OLS training covariance of $(\hat{\alpha}, \hat{\beta})$. The coefficient k_{Q_β} is the signal-to-noise ratio governing how fast β_t may move relative to OLS coefficient uncertainty.⁸

⁷We select $k = 5$ latent factors based on the $IC_{p2}(k)$ criterion of [Bai and Ng \(2002\)](#), with a maximum of eight factors considered.

⁸See the Appendix for an explanation of the estimation procedures for k_{Q_α} and k_{Q_β} .

To accommodate highly leptokurtic observation errors, we allow the errors to be serially correlated and heavy-tailed:

$$e_t = \rho e_{t-1} + u_t, \quad u_t \sim t_\nu(0, s_u^2), \quad (8)$$

where $\nu = 5$.⁹ The Student- t specification allows isolated extreme observations to receive less weight without imposing a stochastic-volatility process. The AR(1) component controls remaining serial correlation and allows the state-space model to produce approximately white noise innovations for the Kalman recursions.

The coefficient of primary interest is β_t . It measures the contemporaneous pass-through from a revision in expected government spending in the near future to a revision in longer-term expected GDP for a given region of the forecaster distribution. The model is estimated by representing the Student- t disturbance as a Gaussian scale mixture and applying an augmented Kalman filter and Kalman smoother conditional on the latent scale weights, allowing smoothed estimates of β_t and conditional state intervals. See the Appendix for detailed explanations of the estimation procedures and robustness/sensitiveness checks (Table A2).

It should be noted that the time-varying specification presented here allows us to investigate whether different groups across the forecaster distribution respond differently when revising their output forecasts in response to new fiscal information, and whether these group-specific sensitivities evolve over time through learning and subsequently converge. Our findings and interpretation are presented in the following section.

3 Time-Varying Asymmetry across Forecasters

Figure 1 plots the estimated time-varying slopes (β_t) in (5) for the lower (Pessimist) and upper (Optimist) tails of the forecaster distribution, $[0, 0.15]$ and $[0.85, 1]$, respectively, along with their 90% confidence bands.¹⁰ The median benchmark is shown by the dotted line. Panels (a) and (b) report the Kalman smoother and filter estimates, respectively, with group assignments based on the OR rule in (2), excluding overlapping forecasters. The filter uses information available up to each period and thus captures learning dynamics, whereas the smoother uses the full sample and provides more precise retrospective estimates. Panels (c)

⁹We calibrate $\nu = 5$ as the smallest integer greater than 2 for which neither the Jarque–Bera test nor the ARCH test with four lags rejects the null hypothesis at the 10% significance level for the innovations. We obtain very similar results for $\nu \in \{3, 5, 8, 15\}$.

¹⁰That is, $\hat{\beta}_{t|T} \pm 1.645\sqrt{P_{t|T}[2, 2]}$ for the smoother and $\hat{\beta}_{t|t} \pm 1.645\sqrt{P_{t|t}[2, 2]}$ for the filter.

and (d) report the corresponding estimation results using alternative group assignment rules based on g_t and y_t , respectively.

Figure 1(a) shows a marked increase in the response of the lower-tail group, particularly following the onset of the Great Moderation in the mid-1980s, while the upper-tail response remains relatively stable. At the beginning of the sample, the estimated pass-through coefficient is approximately 0.038 for the lower tail and 0.133 for the upper tail, with a median coefficient of 0.069. By the end of the sample, the lower-tail coefficient rises to approximately 0.087, a 129% increase, while the upper-tail coefficient increases only modestly to 0.144, an 8% increase. The median coefficient rises to 0.112, a 62% increase.

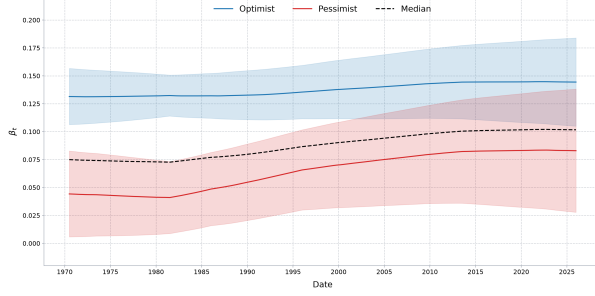
This asymmetry arises from the cross-sectional distribution of forecasters rather than from the sign of fiscal shocks emphasized in the existing literature. Although forecasters receive the same information about expected government spending, their anticipated output responses differ substantially, particularly at the beginning of the sample. Over time, this gap narrows, suggesting greater convergence in how forecasters interpret fiscal information. We obtain similar results when groups are assigned using alternative rules, with the results being particularly strong when the assignments are based on the government spending forecast distribution.

Figure 1(b) provides additional evidence of this convergence. The pessimist group has substantially wider confidence bands at the beginning of the sample, indicating greater uncertainty about the effectiveness of fiscal stimulus. This difference in uncertainty diminishes over time as the confidence bands for the two groups become more balanced.

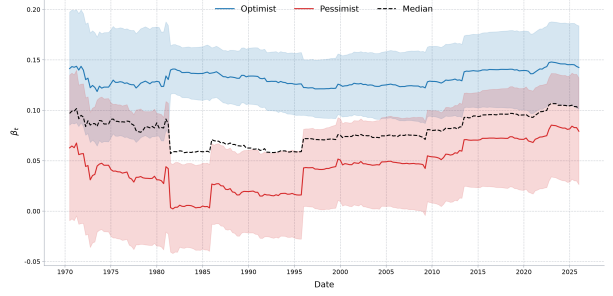
Figure 2 examines the corresponding time-varying group variances and their rolling-window averages. Early in the sample, the pessimist group exhibits substantially greater variance than the optimist group. Both variances decline over time, with a particularly pronounced decline for the pessimist group beginning around the onset of the Great Moderation. The variances also spike sharply during the COVID-19 pandemic, reflecting the substantial increase in uncertainty during that period.

Taken together, the rising lower-tail pass-through and declining cross-sectional variance suggest that forecasters have become more similar in how they map fiscal information into expectations of aggregate economic activity. This pattern is consistent with faster learning among pessimistic forecasters, although other explanations include greater agreement about the macroeconomic transmission mechanism, changes in the information environment, and changes in the composition of the SPF panel. Since our evidence cannot distinguish among these mechanisms, we interpret them as possible explanations rather than identified causal

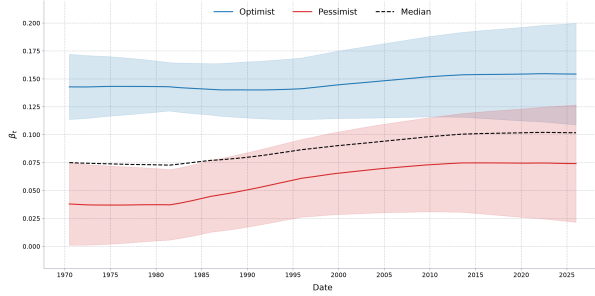
Figure 1: Fiscal News Shock Pass-Through to Output Forecasts



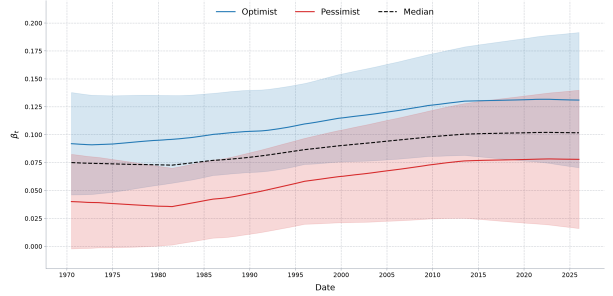
(a) Kalman Smoother Estimation: OR Rule



(b) Kalman Filter Estimation: OR Rule



(c) $\mathbf{1}\{Q_{a,t}^g \leq \mathcal{F}_i(g_t|\Omega_{i,t}) \leq Q_{b,t}^g\}$



(d) $\mathbf{1}\{Q_{a,t}^y \leq \mathcal{F}_i(y_t|\Omega_{i,t}) \leq Q_{b,t}^y\}$

Note: The Pessimist and Optimist groups are defined as the lower tail, $\mathcal{G}_t(0, 0.15)$, and upper tail, $\mathcal{G}_t(0.85, 1)$, respectively, under each of the three group assignment rules in (2). When the OR rule is used, overlapping forecasters are excluded. We construct the revision series using group means to alleviate potential measurement error and then purge them of other macroeconomic effects using five latent macroeconomic factors from FRED-QD. We estimate the time-varying coefficient β_t in (5) using the Kalman smoother and filter, with the corresponding results under the OR rule reported in panels (a) and (b), respectively. The Kalman smoother estimates based on the distributions of government spending forecasts and real GDP forecasts are reported in panels (c) and (d), respectively. The estimates for the Optimist and Pessimist groups are accompanied by 90% confidence bands.

channels.

4 Conclusion

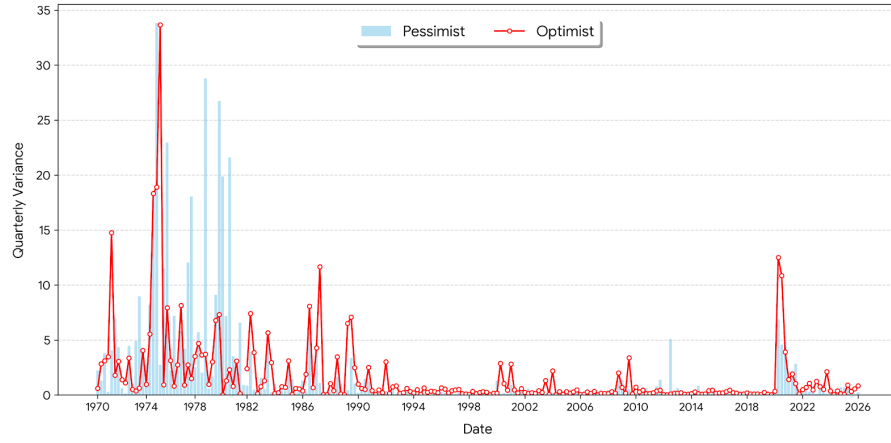
This paper documents a new form of asymmetry in the transmission of fiscal news. Using individual-level forecasts from the Survey of Professional Forecasters, we show that the relationship between revisions in expected government spending and revisions in expected GDP differs systematically across the forecaster distribution.

Early in the sample, lower-tail forecasters exhibit substantially weaker pass-through from spending revisions to GDP revisions than upper-tail forecasters. In this sense, the lower-tail group processes fiscal information more passively, whereas the upper-tail group responds more strongly. This asymmetry is not constant, however. Over time, lower-tail pass-through rises substantially, while the upper-tail response remains comparatively stable. The initially divergent responses therefore become increasingly similar.

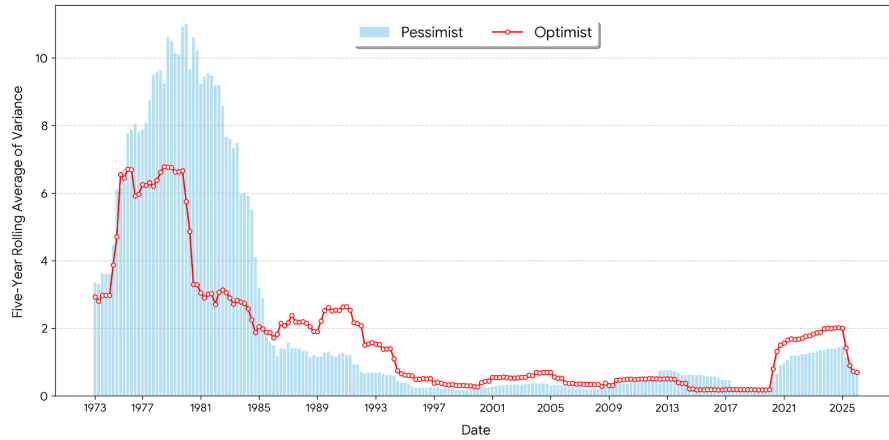
Our results contribute to the literature on fiscal news and expectations by shifting attention from asymmetry in the effects of shocks to asymmetry in the *interpretation of information*. Fiscal news may be common across forecasters, but its translation into output expectations is heterogeneous, reflecting differences in beliefs that can generate heterogeneous sentiment effects of fiscal stimulus. In particular, the initially weaker response among pessimistic forecasters suggests that the sentiment channel may transmit fiscal news less strongly for some forecasters than for others. As these differences diminish over time, the sentiment response to fiscal news becomes more homogeneous across forecasters, potentially making the expectations channel of fiscal stimulus more uniform.

An important next step is to investigate the sources of this convergence. Future work could examine whether it is related to changes in the composition of the SPF panel, learning from fiscal episodes, evolving beliefs about fiscal multipliers, monetary–fiscal interactions, or changes in the information available to professional forecasters. These questions may help explain not only why forecasters disagree, but also why disagreement in the interpretation of fiscal news, and hence in the sentiment response to fiscal stimulus, diminishes over time.

Figure 2: Disagreement within Each Tail of the GDP Revision Distribution



(a) Quarterly Variance



(b) Rolling-Window Average of Group Variance

Note: Variance is computed across members of each tail within a survey quarter and measures disagreement about the news. No standardization is applied. The five-year rolling window requires a minimum of 12 observations.

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Appendix

A Data Description

A.1 Data

The sample is the $T = 223$ survey quarters from 1970Q3, the first quarter with revisions, to 2026Q1. Each of the three series (pessimist, optimist and median) is observed in $n = 221$ of them; revisions are missing in 1974Q3–1974Q4.

The level forecasts in (2) are the forecasts of real GDP three quarters after the survey quarter and of real federal government spending one quarter after it. $Q_{p,t}^y$ and $Q_{p,t}^g$ are computed in each survey over the forecasters who report both forecasts. With the N forecasts sorted from lowest to highest, $Q_{p,t}^y$ sits at position $1 + p(N - 1)$, and likewise $Q_{p,t}^g$; when this position falls between two forecasts, the percentile lies between them in the same proportion (Hyndman and Fan 1996).

For example, with $N = 10$ and $p = 0.15$ the position is 2.35, so the percentile is the second-lowest forecast plus 35% of the gap to the third-lowest. The revisions in (1) are in percent, with $h = 3$; each compares the forecasts of the same quarter from consecutive surveys: real GDP in quarter $t + 3$ and real federal government spending in quarter t . The median benchmark is the middle group, $\mathcal{G}_t(0.425, 0.575)$, formed using (2) in the same manner as the tail groups. The means in (3) are calculated over forecasters who also provided forecasts for the same quarters in survey $t - 1$.

A.2 Purging Revisions of Other Shocks Using Latent Factors

Latent factors $\hat{\mathbf{F}}_t$ is estimated from the August 2026 vintage of FRED-QD (McCracken and Ng 2021) over the sample period 1960Q1–2026Q1, 265 quarters. Of its 245 quarterly series, 125 are marked for factor estimation: the disaggregated series that Stock and Watson (2012) use to estimate factors. Top-level aggregates such as real GDP, total industrial production and total payroll employment are not among them.

Each series is made stationary by the transformation following McCracken and Ng (2016); for these series it is the level, the first difference, or the first or second difference of the log. The 104 series observed in at least 90% of the quarters after transformation are kept.

Observations more than ten interquartile ranges from the median of their series are treated as missing (McCracken and Ng 2016); this rule removes 31 observations. Each series

is standardized by the mean and standard deviation of its available observations. Missing observations are imputed iteratively as in [Stock and Watson \(2002\)](#): starting from zero, each missing observation is replaced by its fitted value from the first m principal components, until the largest change in an imputed value is below 10^{-6} .

We select 5 latent factors via the IC_{p2} criterion of [Bai and Ng \(2002\)](#) with a maximum eight factors. The panel is then imputed again with five factors, and $\hat{\mathbf{F}}_t$ is its first five principal components, normalized so that $\sum_t \hat{\mathbf{F}}_t \hat{\mathbf{F}}_t' / 265$ is the identity matrix.

The regressions behind (4) are OLS regressions of $\tilde{r}_t^y(a, b)$ and of $\tilde{r}_t^g(a, b)$ on a constant and the factors of the calendar quarter before the survey quarter, $\hat{\mathbf{F}}_{t-1}$, over the n observed quarters.

B Description of the Estimation Methods

B.1 State-Space Form

Each group is estimated separately; from here on, $\tilde{r}_t^y$ and $\tilde{r}_t^g$ denote the purged series $\tilde{r}_t^y(a, b)$ and $\tilde{r}_t^g(a, b)$ of the group being estimated. The Kalman filter and smoother are applied to (5), (6) and (8) with the state vector $\xi_t = (\theta_t', e_t)'$, which adds the AR(1) error e_t to the coefficients θ_t , so (5) has no separate measurement error. In the Gaussian scale mixture that represents u_t in (8), $u_t \mid w_t \sim \mathcal{N}(0, s_u^2/w_t)$ with $w_t \sim \text{Gamma}(\nu/2, \nu/2)$, shape and rate $\nu/2$, so that $E w_t = 1$; given $w = (w_1, \dots, w_T)$, the system is linear and Gaussian.

We calibrate $\nu = 5$ in (8) such that, for all three series, the Jarque–Bera test and the ARCH test with four lags do not reject at the 10% level on the innovations; $\nu = 5$ is the smallest integer above 2 that does so. The Ljung–Box test with eight lags does not reject for the two tails and rejects for the median series (Table A1). The innovations are the standardized one-step-ahead prediction errors of the Kalman filter in step (i) of the final iteration (Section B.4).

B.2 Covariance of the Random Walk

Q is set by (7) before the iteration. V_0 in (7) is the OLS covariance matrix of $(\hat{\alpha}, \hat{\beta})$ in the regression of $\tilde{r}_t^y$ on a constant and $\tilde{r}_t^g$ over the n observed quarters. It is computed with the OLS residual variance $\hat{s}^2 = \sum_t (\tilde{r}_t^y - \hat{\alpha} - \hat{\beta} \tilde{r}_t^g)^2 / (n - 2)$. The first-stage regressions include a constant, so both purged series have mean zero, $\hat{\alpha} = 0$ and V_0 is diagonal. Table A1 reports Q .

Origin of $k_{Q_\beta} = 0.12$ and $k_{Q_\alpha} = 0.05$. We regress the revision of the median level forecast of real GDP, taken across all forecasters in each survey, on the revision of the median level forecast of real federal government spending, both unpurged, over the survey quarters 1969Q1–2026Q1, with a random-walk slope and a constant intercept, and estimate the standard deviation of the slope innovation by the median-unbiased estimator of [Stock and Watson \(1998\)](#). The estimate, 0.0115 per quarter, is 0.12 times the OLS standard error of the slope over 1969Q1–1978Q4, the first 40 quarters of this regression, 0.095. Backing out k_{Q_β} from the median level forecasts guards against overfitting: the multiplier is set outside the three group series, so it is not tuned to the noise in them.

The same estimator applied to the intercept, with the slope held constant, gives $k_{Q_\alpha} = 0$, with 90% confidence interval $[0, 0.46]$. The estimate of zero says that drift in the intercept is too small to detect. Setting $k_{Q_\alpha} = 0$ would turn the random-walk intercept in (6) into a constant; we keep the random-walk intercept and set $k_{Q_\alpha} = 0.05$, inside the interval. With $k_{Q_\alpha} = 0$, the slope paths of Figure 1(a) move by less than 0.001.

Table A1: Parameters and Diagnostics of Kalman Estimations

	Pessimist $\mathcal{G}_t(0, 0.15)$	Optimist $\mathcal{G}_t(0.85, 1)$	Median $\mathcal{G}_t(0.425, 0.575)$
$Q[1, 1]$	1.74×10^{-5}	1.26×10^{-5}	1.19×10^{-5}
$Q[2, 2]$	6.95×10^{-6}	4.19×10^{-6}	4.98×10^{-6}
$\hat{\rho}$	−0.062	0.069	0.048
$\hat{s}_u^2$	0.676	0.575	0.508
Ljung–Box, 8 lags: p -value	0.27	0.64	0.02
Jarque–Bera: p -value	0.33	0.16	0.20
ARCH, 4 lags: p -value	0.25	0.31	0.28

Notes: Q from (7) and Section B.2; $\hat{\rho}$ and $\hat{s}_u^2$ from Section B.4. The last three rows refer to the innovations (Section B.1).

B.3 Initial State

The initial state in 1970Q3, with $(\hat{\alpha}, \hat{\beta})$ and V_0 from Section B.2, is distributed as

$$\xi_1 = \begin{pmatrix} \alpha_1 \\ \beta_1 \\ e_1 \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} \hat{\alpha} \\ \hat{\beta} \\ 0 \end{pmatrix}, \begin{pmatrix} 4V_0 & 0 \\ 0 & s_u^2/(1 - \rho^2) \end{pmatrix} \right). \quad (\text{a1})$$

B.4 Iteration

Given ν , Q , $(\hat{\alpha}, \hat{\beta})$ and V_0 , the iteration estimates ρ , s_u^2 and the weights w . It starts from $w_t = 1$ for all t , $\rho = 0.336$ for every series and $s_u^2 = \hat{s}^2(1 - \rho^2)$, so that e_t starts with variance $\hat{s}^2$. The starting value of ρ does not matter: from $\rho = 0, 0.2, 0.5$ and 0.8 , the iteration reaches the same $\hat{\rho}$ to within 10^{-8} and the same slope path to within 10^{-7} . Each iteration repeats four steps.

- (i) Apply the Kalman filter and the Kalman smoother over the T quarters, with the current (ρ, s_u^2, w) . The initial-state distribution (a1) uses the current (ρ, s_u^2) . In a missing quarter the filter performs the prediction step only.
- (ii) From the smoothed means of the error states, $\hat{e}_t \equiv \hat{e}_{t|T}$, form $\hat{u}_1 = \hat{e}_1 \sqrt{1 - \rho^2}$ and $\hat{u}_t = \hat{e}_t - \rho \hat{e}_{t-1}$ for $t \geq 2$.
- (iii) Update, in this order,

$$w_t = \frac{\nu + 1}{\nu + \hat{u}_t^2 / s_u^2}, \quad s_u^2 = \frac{1}{n} \sum_t w_t \hat{u}_t^2, \quad \rho = \frac{\sum_{t \geq 2} w_t \hat{e}_t \hat{e}_{t-1}}{\sum_{t \geq 2} w_t \hat{e}_{t-1}^2}.$$

The weights use the s_u^2 of step (i) and are updated at the observed quarters; at the missing quarters they equal one. The sums run over the observed quarters, and $\hat{e}_{t-1}$ enters for every such t , including one that follows a missing quarter. ρ is restricted to $[-0.98, 0.98]$.

- (iv) Stop when the largest absolute change in $\hat{\beta}_{t|T}$ across the T quarters between consecutive iterations is below 10^{-8} ; otherwise return to (i). Every estimation converges in fewer than 200 iterations, the maximum allowed.

B.5 Quasi-Maximum Likelihood Estimates of k_{Q_α} and k_{Q_β}

In the QML version of Figure 1, k_{Q_α} and k_{Q_β} in (7) are estimated for each series from the Gaussian likelihood of (5), (6), and (8) over the observed quarters from 1970Q3,

$$\ell = -\frac{1}{2} \sum_t \left(\log(2\pi S_t) + \frac{v_t^2}{S_t} \right), \quad (\text{a2})$$

where v_t is the one-step-ahead prediction error of the Kalman filter for $\tilde{r}_t^y$ and S_t is its variance. The filter uses Q from (7), with V_0 of Section B.2, the variance s_u^2/w_t for u_t , and

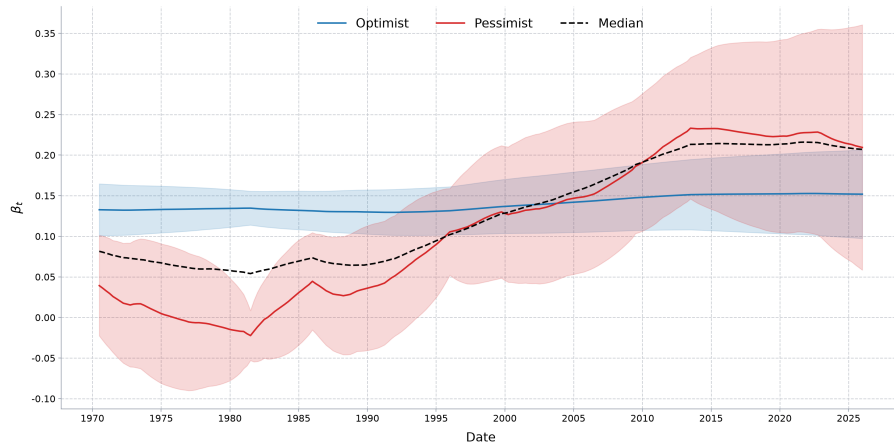
the initial state (a1) at the current ρ and s_u^2 ; in a missing quarter it performs the prediction step only. Both k 's are bounded below by 10^{-4} . The estimation has two stages.

Starting values. With $w_t = 1$ for all t , (a2) is maximized over k_{Q_α} , k_{Q_β} , ρ and s_u^2 , subject to $|\rho| < 0.98$ and $s_u^2 > 0$; it is a quasi-likelihood because u_t in (8) is Student- t . The maximization is run from nine starting points, the pairs $k_{Q_\alpha} \in \{0.01, 0.05, 0.25\}$ and $k_{Q_\beta} \in \{0.05, 0.12, 0.5\}$, each with $\rho = 0$ and $s_u^2 = 0.6 \hat{s}^2$. From each, the Nelder–Mead method and then a quasi-Newton method (BFGS) search over the four parameters, and the highest of the nine maxima is kept. Only the two k 's are carried forward.

Estimates. Two steps alternate until the k 's change by less than 10^{-5} . First, with Q at the current k 's, the iteration of Section B.4 with $\nu = 5$ runs to convergence. Then, with the ρ , s_u^2 and weights w_t of its final iteration held fixed, (a2) is maximized over k_{Q_α} and k_{Q_β} by the Nelder–Mead method, from four starting points: the current k 's, (0.05, 0.12), (0.01, 0.5) and (0.25, 0.05). The estimates are $k_{Q_\beta} = 0.56, 10^{-4}$ and 0.45 and $k_{Q_\alpha} = 0.46, 10^{-4}$ and 10^{-4} for the pessimist, optimist and median series; with both k 's at the lower bound, the optimist slope is constant. The bands of the QML version treat the k 's as known.

Figure A1 reports the evolution of β_t using the quasi-maximum likelihood estimator, where k_{Q_α} and k_{Q_β} are also estimated at each revision. The evolution of β_t for pessimists exhibits a similar upward trend over time, whereas that for optimists remains relatively stable, suggesting a convergence in forecasters' beliefs toward the end of the sample period.

Figure A1: QML Estimations of Fiscal News Shock Pass-Through



B.6 Figures

Figures 1(a) and 1(b) plot the smoothed slope $\hat{\beta}_{t|T}$ and the filtered slope $\hat{\beta}_{t|t}$ from step (i) of the final iteration, and the bands of footnote 6 use $P_{t|T}[2, 2]$ and $P_{t|t}[2, 2]$ from the same step. Both panels use the purged series, the initial state (a1), Q , and the ρ , s_u^2 and weights w_t of the final iteration, all estimated on the full sample, so the filtered slope in quarter t depends on later data through these quantities. The bands treat these quantities and ν as known.

C Sensitivity Checks

Each check changes the specification as described below and repeats every step for the three series. For each check and series, Table A2 reports two numbers: the estimated slope $\hat{\beta}_{t|T}$ in 1970Q3 and in 2026Q1, the first and last points of the lines drawn in Figure 1(a).

- A. *Disturbance distribution.* $\nu = 3, 8$ and 15 (footnote 5); and a Gaussian disturbance u_t , with $w_t = 1$ for all t .
- B. *Error dynamics.* An i.i.d. error ($\rho = 0$); and $\rho = 0$ with the lagged dependent variable $\tilde{r}_{t-1}^y$ added to (5), with a constant coefficient that the filter estimates along with α_t and β_t , and V_0 from the OLS regression that includes $\tilde{r}_{t-1}^y$. The lag is missing in 1970Q3 and 1975Q1, which leaves 219 observed quarters. The estimated coefficients on the lag are -0.057 , 0.037 and 0.035 for the pessimist, optimist and median series.
- C. *Initial state.* The covariance of the coefficients in (a1) set to V_0 and to $16V_0$.
- D. *Factor control.* The unpurged series, $\tilde{r}_t^y(a, b)$ and $\tilde{r}_t^g(a, b)$; and one, two, four and eight factors, the panel imputed with the same number of factors.

Table A2: Sensitivity of Figure 1: $\hat{\beta}_{t|T}$ in 1970Q3 and 2026Q1

	Pessimist		Optimist		Median	
	1970Q3	2026Q1	1970Q3	2026Q1	1970Q3	2026Q1
Figure 1(a)	0.041	0.079	0.133	0.142	0.075	0.102
<i>A. Disturbance distribution</i>						
$\nu = 3$	0.037	0.069	0.135	0.142	0.071	0.095
$\nu = 8$	0.042	0.085	0.133	0.144	0.079	0.107
$\nu = 15$	0.044	0.090	0.134	0.147	0.083	0.113
Gaussian u_t ($w_t \equiv 1$)	0.053	0.104	0.138	0.152	0.092	0.123
<i>B. Error dynamics</i>						
i.i.d. error ($\rho = 0$)	0.040	0.078	0.134	0.144	0.075	0.102
Lagged dependent variable, $\rho = 0$	0.043	0.082	0.132	0.142	0.074	0.101
<i>C. Initial state</i>						
Initial covariance V_0	0.053	0.086	0.137	0.144	0.086	0.107
Initial covariance $16V_0$	0.031	0.073	0.131	0.142	0.069	0.099
<i>D. Factor control</i>						
Unpurged series	0.031	0.099	0.124	0.148	0.067	0.113
One factor	0.043	0.104	0.129	0.146	0.079	0.114
Two factors	0.049	0.105	0.133	0.152	0.082	0.120
Four factors	0.046	0.084	0.134	0.145	0.076	0.103
Eight factors	0.042	0.068	0.132	0.139	0.076	0.097

Notes: Section C defines the rows; all other choices are those of Figure 1.