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Forecaster Heterogeneity and the Transmission of Fiscal News

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Forecaster Heterogeneity and the Transmission of Fiscal News

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

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Abstract

This paper examines heterogeneity in how forecasters translate fiscal stimulus news into longer-term output expectations. Using individual-level Survey of Professional Forecasters data, we classify forecasters by their relative positions in federal spending and real GDP forecast distributions. A state-space model with drifting coefficients estimates the time-varying pass-through from near-term spending forecast revisions to longer-term GDP revisions. We find pronounced initial asymmetry: 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 stable response of optimists, narrowing initial disagreement.

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 effectiveness of fiscal policy in stimulating economic activity remains debated (see Morelli (2026) and Ramey (2019) for recent surveys). A growing literature examines state-dependent fiscal multipliers, with mixed evidence on whether stimulus effects are stronger during recessions (see, among others, Albertini et al. 2021; Bernardini et al. 2020; Auerbach and Gorodnichenko 2012; Ramey and Zubairy 2018; Jo and Zubairy 2025). Recent studies also investigate sign-dependent fiscal effects, finding stronger responses to either positive or negative spending shocks, or no clear evidence of asymmetry (Cappelletti 2026; Barnichon et al. 2022; Ben Zeev et al. 2023).

We examine a distinct dimension of asymmetry: whether the pass-through from government spending news to output expectations varies across professional forecasters and over time. Building on Coibion and Gorodnichenko (2015) and Forni and Gambetti (2016), we adopt approaches similar to those in Cappelletti (2026), Adam et al. (2025), Cascaldi-Garcia (2025), and Bordalo et al. (2020), extending them to study heterogeneous responses to spending news. Using individual-level Survey of Professional Forecasters (SPF) data, we classify forecasters by their positions in the cross-sectional distributions of real GDP and government spending forecasts. We then construct group-specific forecast revisions to estimate time-varying pass-through coefficients.

We find substantial initial asymmetry. Pessimists, who forecast lower government spending, exhibit considerably smaller pass-through from spending news to GDP expectations than optimists, who forecast higher spending. Over time, however, pessimists' pass-through increases substantially, while optimists' response remains relatively stable, narrowing the initial gap. These findings point to substantial initial belief heterogeneity and subsequent asymmetric learning across forecasters.

Our findings contribute to the literature on fiscal news and 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). Whereas existing studies primarily focus on aggregate sentiment, we document how the transmission of fiscal news to macroeconomic expectations varies across forecasters and evolves over time, with initially pronounced differences that gradually diminish.

The remainder of the paper proceeds as follows. Section 2 describes the data and empirical strategy. Section 3 presents the main findings, and Section 4 concludes.

2 The Empirics

2.1 Individual-Level Forecasts and Revisions

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 $2026Q1$.[1] The cross-section is unbalanced, reflecting the entry and exit of SPF participants as well as missing observations for particular variables.

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 $r^y_{i,t}$ and $r^g_{i,t}$ denote forecaster i's percentage revisions to forecasts of y_{t+3} and g_t, respectively:

$$r^y_{i,t} = \frac{\mathcal{F}_i(y_{t+3}|\Omega_{i,t}) - \mathcal{F}_i(y_{t+3}|\Omega_{i,t-1})}{\mathcal{F}_i(y_{t+3}|\Omega_{i,t-1})}, \qquad r^g_{i,t} = \frac{\mathcal{F}_i(g_t|\Omega_{i,t}) - \mathcal{F}_i(g_t|\Omega_{i,t-1})}{\mathcal{F}_i(g_t|\Omega_{i,t-1})}, \tag{1}$$

where $\Omega_{i,t}$ denotes forecaster i's information set at time t. Thus, $r^y_{i,t}$ measures the revision to the 4-quarter-ahead forecast made at $t-1$ for the same target quarter, which is 3 quarters ahead at t, while $r^g_{i,t}$ measures the revision from the 1-quarter-ahead forecast at $t-1$ to the nowcast at t. See Section A.1 of the Online Appendix for details.

2.2 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 $Q^g_{p,t}$ and $Q^y_{p,t}$ denote the p^{th} cross-sectional percentiles of the *forecasts* for real federal government spending (g) and real GDP (y), respectively. We assign forecaster i to group $\mathcal{G}_t(a,b)$ if his or her forecast for either government spending or GDP falls within the percentile band $[Q_{a,t}, Q_{b,t}]$, according to one of the following three assignment

[1] Real federal government expenditure forecasts begin in $1981Q3$. For $1968Q4$–$1981Q2$, we obtain nominal defense spending forecasts from Thomas Stark (Federal Reserve Bank of Philadelphia) and deflate them using median GDP deflator forecasts (`PGDP`). Following Ramey (2011), we combine these real defense spending forecasts with real federal government expenditure forecasts. See Section A.1 of the Online Appendix for further details.

rules:

$$\mathbf{1}\{i \in \mathcal{G}_t(a,b)\} = \begin{cases} \mathbf{1}\{Q^g_{a,t} \leq \mathcal{F}_i(g_{t+1}|\Omega_{i,t}) \leq Q^g_{b,t}\}, \text{(G rule)} \\ \mathbf{1}\{Q^y_{a,t} \leq \mathcal{F}_i(y_{t+3}|\Omega_{i,t}) \leq Q^y_{b,t}\}, \text{(Y rule)} \\ \mathbf{1}\{Q^g_{a,t} \leq \mathcal{F}_i(g_{t+1}|\Omega_{i,t}) \leq Q^g_{b,t}\} \vee \mathbf{1}\{Q^y_{a,t} \leq \mathcal{F}_i(y_{t+3}|\Omega_{i,t}) \leq Q^y_{b,t}\}, \text{(OR rule)} \end{cases} \tag{2}$$

Under the OR rule, some forecasters may belong to both the optimistic and pessimistic groups. We exclude these overlapping observations. However, retaining them yields very similar results, as they account for only 4.6% of the sample.

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 SPF identifiers (i) are intended to track individual forecasters over time, identifier reassignment is a known issue, particularly during the ASA/NBER period ($1968Q4$–$1990Q1$).[2] To mitigate potential measurement error arising from such reassignment, we construct the following group-specific revision series after identifying the members of $\mathcal{G}_t(a,b)$.

$$\bar{r}^y_t(a,b) = \text{mean}_{i \in \mathcal{G}_t(a,b)}\, r^y_{i,t}, \qquad \bar{r}^g_t(a,b) = \text{mean}_{i \in \mathcal{G}_t(a,b)}\, r^g_{i,t} \tag{3}$$

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 $\tilde{r}^y_t(a,b)$ and $\tilde{r}^g_t(a,b)$.[3] That is,

$$\tilde{r}^y_t(a,b) = \bar{r}^y_t(a,b) - \hat{r}^y_t(a,b), \tag{4}$$

where $\hat{r}^y_t(a,b)$ denotes the fitted value from this regression. The corresponding residual $\tilde{r}^g_t(a,b)$ 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 $\mathcal{G}_t(0.85, 1)$. Under the OR rule, these two groups retain about 49% of the full set of observations. The former tend to generate lower

[2] See Section A.1 of the Online Appendix for a detailed explanation.

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

forecasts, whereas the latter tend to generate 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

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

where the intercept and slope follow independent random walks,

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

where

$$Q = \operatorname{diag}\{k_{Q_\alpha}^2 V_0[1,1],\ k_{Q_\beta}^2 V_0[2,2]\}, \qquad k_{Q_\alpha} = 0.05,\ k_{Q_\beta} = 0.12, \tag{7}$$

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.[4]

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

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

where $\nu = 5$.[5] 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

[4] See Section B of the Online Appendix for an explanation of the estimation procedures for k_{Q_α} and k_{Q_β}.

[5] We 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 $\nu \in \{3, 5, 8, 15\}$.

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 Section C.1 of the Online Appendix for detailed explanations of the robustness checks.

The time-varying specification presented here allows us to examine whether forecasters across the distribution differ in how they revise their output forecasts in response to new fiscal information and whether these group-specific sensitivities evolve through learning and eventually converge. Our findings and interpretation are presented in the next 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, with 90% confidence bands.[6] The median benchmark is shown by the dotted line. Panels (a) and (b) report Kalman smoother and filter estimates, respectively, using the OR rule in (2) and excluding overlapping forecasters. The filter uses information available up to each period and captures learning dynamics, whereas the smoother uses the full sample to provide more precise retrospective estimates. Panels (c) and (d) report smoother estimates using alternative group assignments based on g_t and y_t, respectively.

Figure 1(a) shows a marked increase in the lower-tail response, particularly after the onset of the Great Moderation, while the upper-tail response remains relatively stable.[7] Initially, the estimated pass-through coefficients are approximately 0.044 and 0.131 for the lower and upper tails, respectively, compared with 0.075 for the median. By the end of the sample, they rise to 0.083 (88% increase), 0.144 (10% increase), and 0.102 (36% increase), respectively. Thus, the initial gap between pessimists and optimists narrows substantially over time.[8]

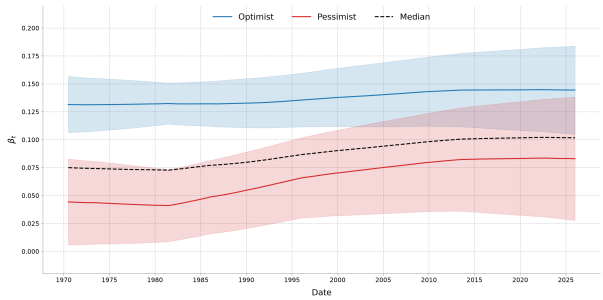
This asymmetry reflects differences in forecasters' expectations rather than the sign of fiscal shocks emphasized in the existing literature. Although forecasters receive the same

[6] The bands are $\hat{\beta}_{t|T} \pm 1.645\sqrt{P_{t|T}[2,2]}$ for the smoother and $\hat{\beta}_{t|t} \pm 1.645\sqrt{P_{t|t}[2,2]}$ for the filter.

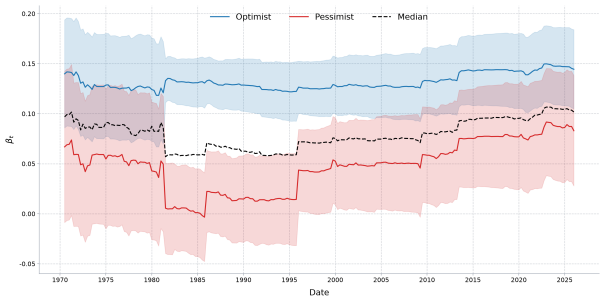
[7] We re-estimated the model using the $1981Q3$–$2026Q1$ sample, excluding the earlier period during which the forecasts pertained to defense spending. The results are similar to our baseline findings and are reported in Section C.2 of the Online Appendix, along with additional diagnostics and sensitivity analyses.

[8] We re-estimated Equation (5) using the purged measure of government spending revisions as the explanatory variable, while retaining the unpurged revisions of real GDP forecasts as the dependent variable. The results, reported in Section A.2 of the Online Appendix, are similar to those shown in Figure 1(a), although the confidence bands are wider.

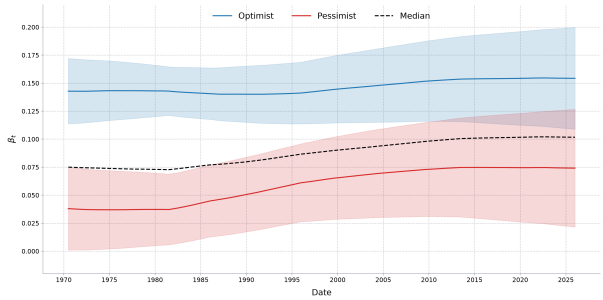
Figure 1: Fiscal News Shock Pass-Through to Output Forecasts



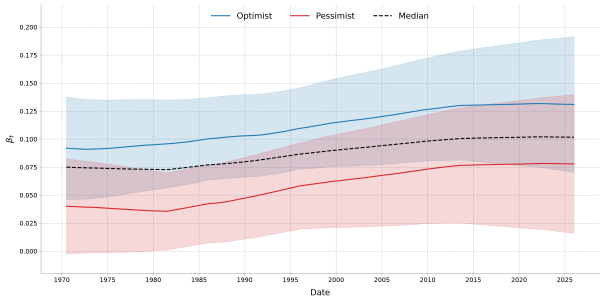
(a) Kalman Smoother Estimation: OR Rule



(b) Kalman Filter Estimation: OR Rule



(c) $\mathbf{1}\{Q^g_{a,t} \leq \mathcal{F}_i(g_{t+1}|\Omega_{i,t}) \leq Q^g_{b,t}\}$



(d) $\mathbf{1}\{Q^y_{a,t} \leq \mathcal{F}_i(y_{t+3}|\Omega_{i,t}) \leq Q^y_{b,t}\}$

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. The estimates for the Optimist and Pessimist groups are accompanied by 90% confidence bands.

spending news, their anticipated output responses initially differ substantially but gradually converge. Similar patterns emerge under alternative group assignment rules, particularly when groups are defined using the government spending forecast distribution.

Figure 1(b) further shows that pessimists initially have substantially wider confidence bands than optimists, indicating greater estimation uncertainty about the pass-through coefficient. This difference diminishes over time as the confidence bands become more balanced.

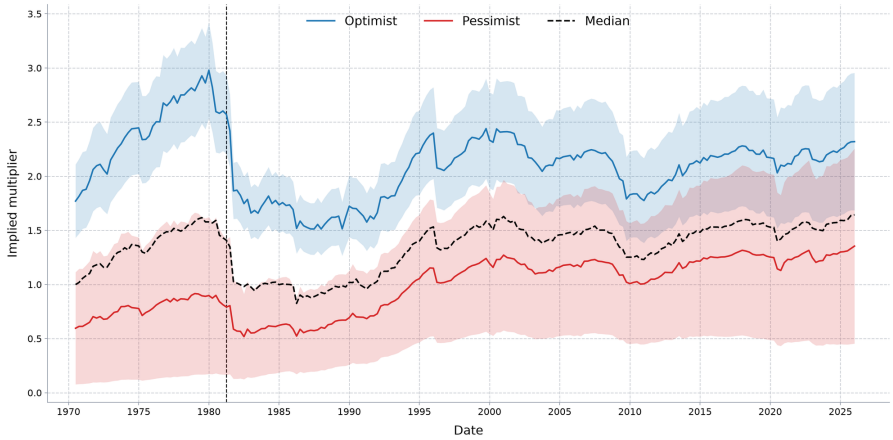
We also report the implied fiscal multipliers using the forecast data.[9] Specifically, $\beta_t = (\Delta y/y)/(\Delta g/g)$, where y and g denote the survey $t-1$ forecasts appearing in the denominators of (1), namely, $\mathcal{F}_i(y_{t+3}|\Omega_{i,t-1})$ and $\mathcal{F}_i(g_t|\Omega_{i,t-1})$, respectively. The implied multiplier, $\Delta y/\Delta g$, is given by $\beta_t\,(y/g)^{\mathsf{med}}_{j,t}$, where β_t is taken from Figure 1(a) and $(y/g)^{\mathsf{med}}_{j,t}$ denotes the median ratio for each of the two forecaster groups (j = optimists and pessimists) in survey $t-1$, calculated using forecasters who report both variables.

[9]We thank an anonymous referee for this helpful suggestion.

As shown in Figure 2, the implied fiscal multipliers also exhibit clear asymmetry, reflecting forecasters' expectations about the effectiveness of fiscal stimulus. Similar to Figure 1(a), the lower-tail multiplier increases steadily, whereas the upper-tail multiplier remains consistently higher and relatively stable. Consequently, the initial gap between pessimists and optimists narrows over time, indicating convergence in their anticipated output responses to the same spending news.

Note also the sharp declines around $1981Q2$ (marked by the vertical dashed line), when $\mathcal{F}_i(g_t|\Omega_{i,t-1})$ switches from the defense spending forecast to the federal government spending forecast, of which defense spending is a subcomponent. This change in the definition of government spending generates a level shift, resulting in a decrease in $(y/g)^{\text{med}}_{j,t}$.[10]

Figure 2: Implied Fiscal Multipliers $\hat{\beta}_{t|T}(\frac{y}{g})^{\text{med}}_{j,t}$



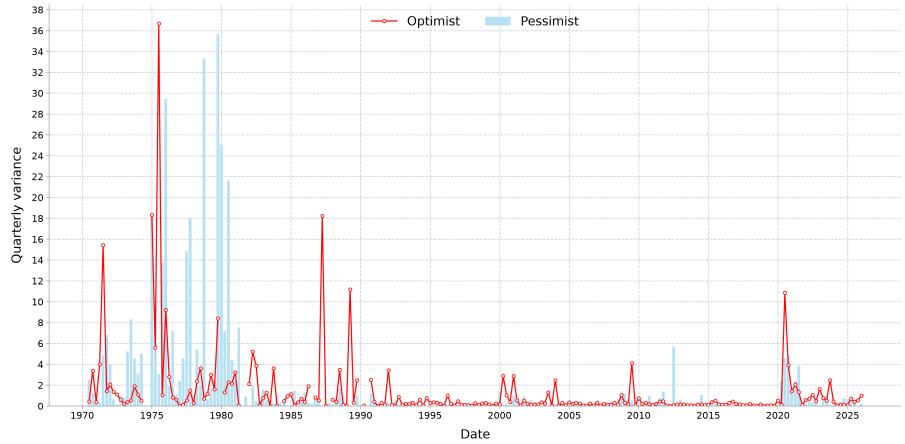
Note: The Pessimist and Optimist groups are defined similarly under the OR rule in (2), excluding overlapping forecasters. Shaded areas indicate 90% confidence bands. The vertical dashed line marks $1981Q2$.

Figure 3 presents time-varying group variances, calculated across members of each tail within each survey quarter to measure disagreement about the news, along with their five-year rolling averages. Pessimists initially exhibit greater cross-sectional variance than optimists, but both decline over time, with a particularly pronounced decline among pessimists following the onset of the Great Moderation. Both variances spike during the COVID-19 pandemic, reflecting heightened uncertainty.

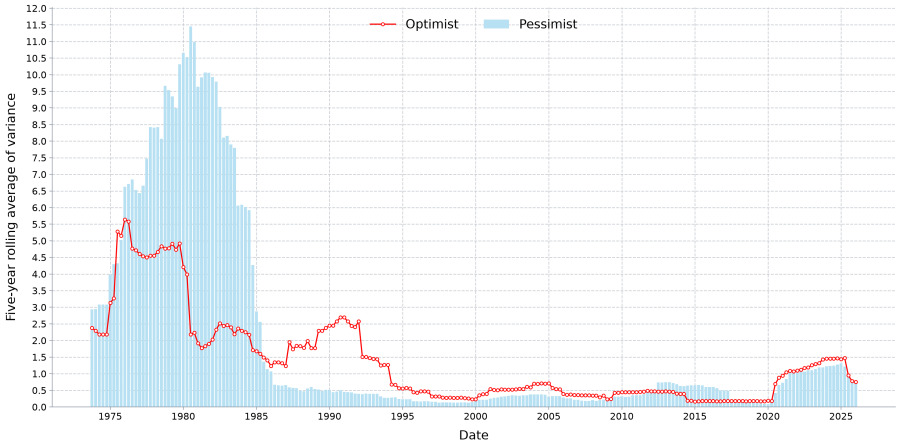
Rising lower-tail pass-through alongside declining variance suggests greater convergence in how forecasters translate fiscal news into output expectations. This pattern is consistent

[10] As explained in footnote 1 and the Online Appendix, the government spending forecast refers to defense spending through the $1981Q2$ survey, after which it switches to federal government spending.

Figure 3: Disagreement within Each Tail of the GDP Revision Distribution



(a) Quarterly Variance



(b) Rolling-Window Average of Group Variance

with faster learning among pessimists, but may also reflect greater agreement about the transmission mechanism, changes in the information environment, or shifts in SPF panel composition. Since our evidence cannot distinguish these mechanisms, we view them as potential rather than identified causal explanations.

4 Conclusion

This paper documents a new form of asymmetry in the transmission of fiscal news. Using individual-level Survey of Professional Forecasters data, we show that the relationship between revisions in expected government spending and GDP varies 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. However, lower-tail pass-through rises considerably over time, while the upper-tail response remains relatively stable, leading to increasingly similar responses across groups.

Our findings contribute to the fiscal news literature by shifting attention from asymmetry in the effects of shocks to asymmetry in the *interpretation of information*. Although forecasters receive common fiscal news, their translation of that information into output expectations differs, generating heterogeneous sentiment effects of fiscal stimulus. The subsequent convergence in these responses suggests that the expectations channel of fiscal stimulus becomes more homogeneous across forecasters over time.

An important direction for future research is to identify the sources of this convergence, including changes in SPF panel composition, learning from fiscal episodes, evolving beliefs about fiscal multipliers, monetary–fiscal interactions, and changes in the information available to forecasters. Understanding these mechanisms may help explain why disagreement in interpreting fiscal news diminishes over time.

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Online Appendix for "Forecaster Heterogeneity and the Transmission of Fiscal News"

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A Data Description

A.1 Data

Our analysis uses individual-level forecasts from the Survey of Professional Forecasters (SPF), maintained by the Federal Reserve Bank of Philadelphia. The quarterly data span $1968Q4$–$2026Q1$. The SPF provides six forecast horizons, ranging from backcasts (e.g., `RGDP1`) and nowcasts (e.g., `RGDP2`) to forecasts up to four quarters ahead (e.g., `RGDP6`).

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 (`PGDP`) to convert nominal defense spending forecasts (`DEFENSE`) into real spending forecasts. Following Ramey (2011), we combine the resulting real defense spending forecasts with forecasts of real federal government expenditures.

Individual-level SPF survey data are unavailable for $1969Q1$–$1969Q3$ and $1970Q1$, but are available continuously from $1970Q3$ onward. Accordingly, our revision data begin in $1970Q3$. The resulting sample consists of $T = 223$ survey quarters, from $1970Q3$ through

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2026$Q1$. Each of the three series (pessimists, optimists, and median) is observed in $n = 221$ quarters, with revisions also missing in 1974$Q3$–1974$Q4$.

Over the full sample period, the National Income and Product Accounts (NIPA) underwent ten base-year revisions. Because SPF forecasts do not account for these changes, they can generate outliers in the forecast data. We therefore rescaled all relevant forecasts to a common 2017 base year.

The level forecasts in (2) correspond to real GDP three quarters after the survey quarter and real federal government spending one quarter after it. We compute $Q^y_{p,t}$ and $Q^g_{p,t}$ in each survey using only forecasters who report forecasts for both variables. Let the N forecasts be sorted in ascending order. The pth percentile is located at position $1 + p(N - 1)$, with linear interpolation between adjacent forecasts when this position is noninteger (Hyndman and Fan 1996).

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

The confidential SPF identifiers (i) are designed to track individual forecasters over time. However, the Philadelphia Fed notes several caveats regarding their interpretation. These include potential identifier reassignment during the historical ASA/NBER period, before the Philadelphia Fed assumed responsibility for the survey in 1990$Q2$, and changes in identifiers when forecasters switch affiliations. To the extent that such changes introduce idiosyncratic measurement error into forecaster-level revision series, group-level aggregation may attenuate their effects, provided that the errors are not systematically related to group membership or revisions and that identifier changes are infrequent.

A.2 Purging Revisions of Other Shocks Using Latent Factors

The latent factors $\hat{\mathbf{F}}_t$ are estimated from the August 2026 vintage of FRED-QD (McCracken and Ng 2021) over the sample period 1960$Q1$–2026$Q1$, 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.

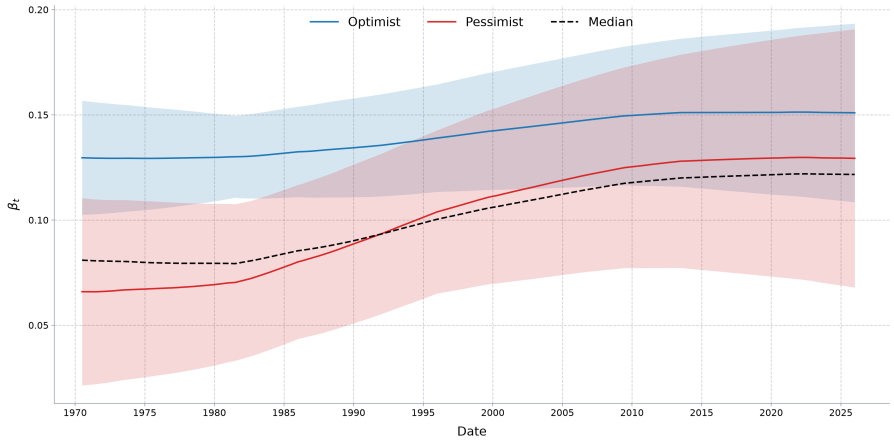
Observations more than ten interquartile ranges from the median of their series are treated as missing (McCracken and Ng 2016); this rule removes 31 observations. Each series is standardized by the mean and standard deviation of its available observations. Missing observations are imputed iteratively 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 five 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 $\bar{r}_t^y(a,b)$ and of $\bar{r}_t^g(a,b)$ on a constant and the factors of the calendar quarter before the survey quarter, $\hat{\mathbf{F}}_{t-1}$, over the n observed quarters.

In addition to Figure 1(a) in the main text, Figure A1 reports the estimation results for Equation (5), using the *unpurged* GDP revision, $\bar{r}_t^y(a,b)$, as the dependent variable and the *purged* spending revision, $\tilde{r}_t^g(a,b)$, as the regressor. V_0 is obtained from an OLS regression of $\bar{r}_t^y(a,b)$ on a constant and $\tilde{r}_t^g(a,b)$. All other specifications are as in Figure 1(a). The Ljung–Box, Jarque–Bera, and ARCH tests fail to reject their respective null hypotheses at the 10% level for all three groups.[1]

Figure A1: Fiscal News Shock Pass-Through with Only Fiscal Revisions Purged



[1]We thank an anonymous referee for this suggestion.

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 $w = (w_1, \ldots, w_T)$, the system is linear and Gaussian.

We calibrate $\nu = 5$ in (8) such that, for all three series. Neither the Jarque–Bera test nor the ARCH test with four lags rejects the null 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 0.095, the OLS standard error of the slope over 1969Q1–1978Q4 (first 40 quarters of this regression). 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 indicates 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 $\mathcal{G}_t(0.425, 0.575)$
$Q[1,1]$	1.83×10^{-5}	1.13×10^{-5}	1.19×10^{-5}
$Q[2,2]$	7.61×10^{-6}	3.89×10^{-6}	4.97×10^{-6}
$\hat{\rho}$	-0.038	0.160	0.050
$\hat{s}_u^2$	0.690	0.492	0.506
Ljung–Box, 8 lags: p-value	0.42	0.69	0.02
Jarque–Bera: p-value	0.33	0.12	0.20
ARCH, 4 lags: p-value	0.28	0.21	0.27

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

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

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^{-7} and the same slope path to within 10^{-7}. Each iteration consists of 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,

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

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 those that follow 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 $1970Q3$,

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

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.

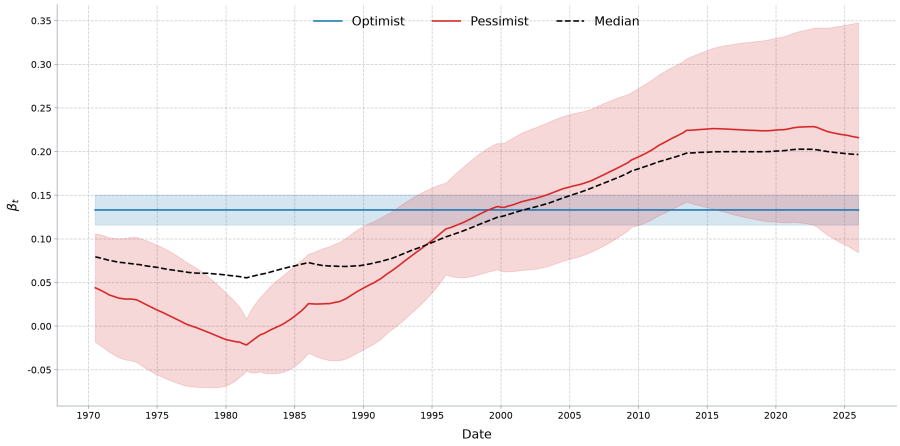
Starting values. With $w_t = 1$ for all t, (a2) is maximized over k_{Q_α}, k_{Q_β}, ρ and s_u^2, subject to $|\rho| < 0.98$ and $s_u^2 > 0$; it is a quasi-likelihood because u_t in (8) is Student-t. The maximization is run from nine starting points, the pairs $k_{Q_\alpha} \in \{0.01, 0.05, 0.25\}$ and $k_{Q_\beta} \in \{0.05, 0.12, 0.5\}$, each with $\rho = 0$ and $s_u^2 = 0.6\,\hat{s}^2$. From each, a Nelder–Mead search followed by a quasi-Newton (BFGS) search is run 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 $k_{Q_\alpha} = 0.33$, 0.08 and 10^{-4} for the pessimist, optimist and median series; with k_{Q_β} at the lower bound, the optimist slope is constant. The bands of the QML version treat the k's as known.

Figure A2 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 an upward trend similar to that in Figure 1(a), whereas that for optimists remains relatively stable, suggesting a convergence in forecasters' beliefs toward the end of the sample period.

Figure A2: QML Estimations of Fiscal News Shock Pass-Through



C Robustness Checks

C.1 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 $\tilde{r}^y_{t-1}$ 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 $\tilde{r}^y_{t-1}$. The lag is missing in 1970Q3 and 1975Q1, which leaves 219 observed quarters. The estimated coefficients on the lag are −0.041, 0.109 and 0.036 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, $\bar{r}^y_t(a,b)$ and $\bar{r}^g_t(a,b)$; and one, two, four and eight factors, the panel imputed with the same number of factors.

Table A2: Sensitivity $\hat{\beta}_{t|T}$ (1970Q3 and 2026Q1)

	Pessimist		Optimist		Median	
	1970Q3	2026Q1	1970Q3	2026Q1	1970Q3	2026Q1
Figure 1(a)	0.044	0.083	0.131	0.144	0.075	0.102
A. Disturbance distribution						
$\nu = 3$	0.035	0.068	0.132	0.144	0.071	0.095
$\nu = 8$	0.047	0.090	0.132	0.146	0.079	0.107
$\nu = 15$	0.049	0.096	0.133	0.149	0.083	0.113
Gaussian u_t ($w_t \equiv 1$)	0.057	0.116	0.138	0.155	0.092	0.123
B. Error dynamics						
i.i.d. error ($\rho = 0$)	0.044	0.083	0.132	0.146	0.075	0.102
Lagged dependent variable, $\rho = 0$	0.048	0.086	0.131	0.144	0.074	0.101
C. Initial state						
Initial covariance V_0	0.057	0.091	0.135	0.146	0.086	0.107
Initial covariance $16V_0$	0.032	0.075	0.129	0.144	0.069	0.099
D. Factor control						
Unpurged series	0.046	0.113	0.126	0.152	0.067	0.113
One factor	0.061	0.122	0.130	0.150	0.079	0.114
Two factors	0.060	0.118	0.133	0.156	0.082	0.120
Four factors	0.049	0.088	0.132	0.146	0.076	0.103
Eight factors	0.046	0.074	0.131	0.142	0.076	0.097

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

C.2 Alternative Sample Period: 1981Q3–2026Q1

The first stage, V_0, the initial state, and the filter use the 1981Q3–2026Q1 sample. No earlier revisions are included, except for the 1981Q2 revision, which enters as the 1981Q3 lag in the lagged-dependent-variable row of Table A4. The values of k_{Q_α} and k_{Q_β} are based on the full sample. The factors are estimated over 1960Q1–2026Q1 (see Section A.2).

Figure A3: Fiscal News Shock Pass-Through (1981Q3-2026Q1)

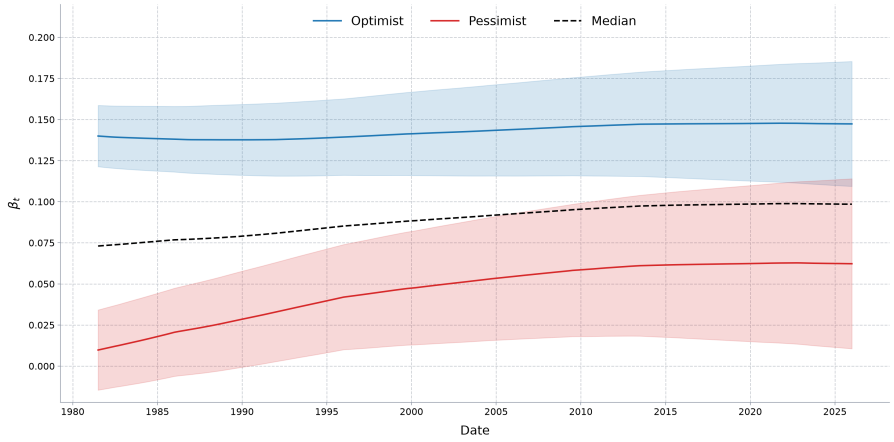


Table A3: Parameters and Diagnostics of Kalman Estimations (1981Q3-2026Q1)

	Pessimist	Optimist	Median
$Q[1,1]$	1.94×10^{-5}	1.20×10^{-5}	1.24×10^{-5}
$Q[2,2]$	7.00×10^{-6}	3.56×10^{-6}	4.46×10^{-6}
$\hat{\rho}$	0.042	0.150	0.090
$\hat{s}_u^2$	0.531	0.445	0.413
Ljung–Box, 8 lags: p-value	0.38	0.13	0.03
Jarque–Bera: p-value	0.37	0.18	0.26
ARCH, 4 lags: p-value	0.51	0.14	0.57

Table A4: Sensitivity $\hat{\beta}_{t|T}$ (1981$Q3$ and 2026$Q1$)

	Pessimist		Optimist		Median	
	1981Q3	2026Q1	1981Q3	2026Q1	1981Q3	2026Q1
Figure A3	0.010	0.062	0.140	0.147	0.073	0.098
A. Disturbance distribution						
$\nu = 3$	0.000	0.046	0.140	0.145	0.070	0.093
$\nu = 8$	0.018	0.075	0.140	0.150	0.076	0.104
$\nu = 15$	0.027	0.087	0.142	0.153	0.080	0.111
Gaussian u_t ($w_t \equiv 1$)	0.048	0.115	0.145	0.159	0.088	0.122
B. Error dynamics						
i.i.d. error ($\rho = 0$)	0.008	0.060	0.137	0.146	0.072	0.098
Lagged dependent variable, $\rho = 0$	0.008	0.060	0.135	0.144	0.070	0.096
C. Initial state						
Initial covariance V_0	0.024	0.074	0.141	0.149	0.079	0.102
Initial covariance $16V_0$	0.004	0.058	0.140	0.147	0.071	0.097
D. Factor control						
Unpurged series	0.004	0.091	0.138	0.159	0.067	0.116
One factor	0.004	0.088	0.139	0.155	0.068	0.112
Two factors	0.006	0.093	0.141	0.160	0.072	0.118
Four factors	0.011	0.063	0.142	0.149	0.074	0.100
Eight factors	0.006	0.047	0.138	0.142	0.072	0.092

D Forecasting

Table A5 reports the forecasting performance of the pessimist and optimist groups. Forecast error is defined as the group's mean level forecast minus the first-published value, expressed as a percentage of the first-published value, for real GDP in $t + 3$ (`RGDP5`) and real federal government spending in $t + 1$ (`RFEDGOV3`). First-published values are obtained from the Philadelphia Fed's real-time data set.

Mean squared prediction error (MSPE) is the average of squared forecast errors across survey quarters. A survey quarter is excluded if its target value is first published in a subsequent base year. This excludes 40 quarters for GDP and 18 quarters for spending, leaving 180 quarters (1970Q3–2025Q2) and 160 quarters (1981Q3–2025Q4), respectively. Spending forecast errors begin in 1981Q3 because earlier spending forecasts pertain to defense spending.

The test of equal MSPE over the full sample uses autocorrelation-robust standard errors with eight lags. The pessimist-minus-optimist MSPE difference is 0.27 for GDP (p value

0.85) and −2.32 for spending (p value 0.09). Prob. (% of quarters) denotes the percentage of survey quarters in which the pessimist group's forecast errors are smaller than those of the optimist group.

Table A5: Mean Squared Prediction Errors by Group and Period

	MSPE			
Survey quarters	Pessimist	Optimist	Median	Prob. (% of quarters)
Real GDP in $t+3$				
1970Q3–1979	7.7	10.1	6.8	50
1980–1989	10.8	6.2	7.5	31
1990–1999	4.3	3.0	3.3	21
2000–2009	2.1	4.6	3.2	88
2010–2019	6.2	8.7	7.3	81
2020–2025Q2	9.2	4.2	5.5	33
Full sample	6.7	6.4	5.7	52
Real federal government spending in $t+1$				
1981Q3–1989	16.1	21.3	14.2	59
1990–1999	5.7	7.3	4.3	53
2000–2009	4.9	3.7	3.4	50
2010–2019	2.0	6.3	3.2	67
2020–2025	8.1	9.8	8.1	50
Full sample	7.1	9.4	6.3	56

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