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Economic Policy Uncertainty and Forecast Bias in the Survey of Professional Forecasters

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Abstract

This paper analyzes the properties of forecast bias in the Survey of Professional Forecasters in relation to economic policy uncertainty. Employing the quarterly forecast bias of 14 key macroeconomic variables and 12 measures of policy uncertainty from 1985 to 2020, we demonstrate that most real activity variables have significant negative responses to economic policy uncertainty. On the other hand, there is a substantial degree of sluggishness in the corresponding forecasts, generating long-lasting forecast bias. In other words, our results show that inattentive forecasters cause SPF forecast bias using both static and dynamic frameworks.

Keywords: Survey of Professional Forecasters; Forecast Bias; Economic Policy Uncertainty; Cross-Section Dependence

JEL Classification: C52; E32; E60

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1 Introduction

In their seminal work, Mincer and Zarnowitz (1969) suggest practical guidelines to assess the accuracy and efficiency of economic forecasts. Romer and Romer (2000) find that both the private sector's and the Federal Reserve's forecasts of inflation are unbiased, which is partially supported by Sims (2002) for the Fed's forecasters. More recent studies, however, often document the existence of persistent systematic bias in key macroeconomic forecasts, which is at odds with earlier assessments.

Capistrán (2008) shows that the Fed's inflation forecasts tend to have systematic underprediction bias during the pre-Volcker era, followed by over-prediction during the post-Volcker era. Elliott et al. (2008) report similar evidence from private sector forecast survey data for output growth. Batchelor (2007) points out the international evidence of such systematic bias in the real GDP and inflation forecasts in the private sectors of the G7 economies. In addition, Engelberg et al. (2009) claim that point prediction of real GDP and inflation rate may have systematically favorable bias in the Survey of Professional Forecasters data, and Capistrán and Timmermann (2009) show that inflation forecasts of the same survey data have a systematic bias, which can be explained using an asymmetric loss function.

Why forecasters tend to make persistent forecast errors is the subject of many papers in macroeconomic analysis. Several studies explain it with irrationality in the markets, specifically professional forecasters' forecasting behavior, such as herding, anchoring, and conservatism. For example, Bernhardt et al. (2006) study professional financial analysts and develop a test for herding in their forecasts. Rülke et al. (2016) use international data set and show anti-herding in business cycle forecasters. Clements (2018) focuses on typical herding tests and apply them to SPF data for inflation and output growth rate, which does not show herding behavior.

Some studies connect forecast bias to information rigidity which discuss information frictions to explain macroeconomic dynamics in two categories. First is sticky information, where collecting and processing information is costly, so agents do not update their information set continually. See, for example, Mankiw and Reis (2002); Mankiw et al. (2003); Coibion and Gorodnichenko (2012), Kiley (2007). Second is noisy information; it is an economic theory that claims people have a limited capacity to process information. See, among others, Woodford (2001); Sims (2003), Sims (2010), Mackowiak and Wiederholt (2009), Matějka (2015).

Furthermore, some studies suggest different views about the loss function. For instance, Capistrán (2008) reports asymmetry in the loss function of the Fed's inflation forecast considering the change of Chair of the Federal Reserve. He claims that if the central bank is cautious regarding inflation, it means inflation beyond the target rate is more costly than inflation below the target, so forecasters adjust their forecasts based on this view and create a negative bias (systematic over-prediction). This difference in the cost is called asymmetric loss, which explains the rationality and unbiasedness of forecasts. Similarly, Elliott et al. (2008) demonstrate private sector forecast bias for output growth and use flexible families of loss functions to test forecast rationality. Their results provide evidence that asymmetric loss functions explain a lower rate of rejection of rationality in the macroeconomic forecast of output growth. Capistrán and Timmermann (2009) show inflation forecasts of private sector data have a systematic bias and could explain it using the asymmetric loss function. See among others, Patton and Timmermann (2007), Lahiri and Liu (2009), Clements (2010), Komunjer and Owyang (2012), Patton (2020).

Motivated by their work, this paper proposes a different explanation for the persistent forecast bias in relation to EPU. First, we confirm the existence of persistent forecast bias for many macroeconomic variables by utilizing the median unbiased estimator, half-life, and Mincer-Zarnowitz test. Then, noting close correlations between forecast bias variables and measures of economic policy uncertainty (EPU), we seek the source of bias in relation to policy-generated uncertainty by investigating the contemporaneous and dynamic relationships between them. For this purpose, we employ the policy uncertainty indices that are constructed using newspapers developed by Baker et al. (2016), so they are fairly exogenous to forecast biases.

Our results show a significant degree of cross-section correlations between EPU indices and forecast bias variables but with a positive sign, implying an enhanced optimism in the forecasters in response to economic policy uncertainty shocks. Instead of explaining these seemingly puzzling responses, we decompose the forecast bias into the data and the forecast. This approach shows that real activity variables respond overall negatively to EPU shocks, whereas there is a surprising amount of inertia in forecast responses. Our findings in the dynamic section are consistent with these results, which imply that forecasters' responses to economic policy shocks were relatively sluggish and negligible, which explains the persistent bias. Employing 12 categorical economic policy uncertainty indices with an array of forecasts of 14 macroeconomic variables, we also report other interesting results, such as bias in the financial market variables to the monetary policy shock.

The remainder of this paper is organized as follows. Section 2 presents data descriptions and verifies the existence of forecast bias using preliminary statistical analysis. Section 3 reports static mechanisms via cross-section properties of bias variables with measures of economic policy uncertainty. Then we utilize the decomposition of forecast bias and present our major findings of the paper. Section 4 provides alternative approaches based on dynamic analysis, and then we report some other interesting results. Section 5 concludes.

2 Empirical Properties of the Forecast Bias

2.1 Data Description

We employ the Survey of Professional Forecasters (SPF) data from the Philadelphia FED. To measure the bias for an array of key macroeconomic variables, we obtained median point forecasts of the variable that are forecasters' projections from the one quarter back (backcasts, t - 1) and up to four quarters (t + 4) ahead forecasts. Note that forecasters are asked to provide their projections of the past and current values (nowcasts) as well as future values.¹ We also acquired the corresponding realized data of these forecast variables from the Federal Reserve Economic Data (FRED) in order to construct the forecast bias as described below.

We pay special attention to the forecast bias of the real GDP (RGDP, billion dollars), unemployment rate (Urate, %), and GDP deflator (PGDP, index), which are two real variables and one nominal variable. In addition, we also utilize forecasts of other important macroeconomic variables, such as corporate profits after tax (CoPr, billion dollars), industrial production (InPd, index), housing starts (Hsng, millions), real consumption, the real federal government expenditures, real state and local government expenditures, real residential investment, real non-residential investment, Treasury bill yield, and share of Real Net Exports of RGDP. See Table A1 in the Appendix for detailed information.

As we briefly discussed in the introduction, the forecast bias seems to be closely related to economic policy uncertainty. We obtained an array of policy uncertainty indices from the Economic Policy Uncertainty website, including monetary policy uncertainty, fiscal policy uncertainty, and regulation uncertainty.² Observations are monthly, ranging from January 1985 to September 2020. We transformed the monthly frequency data to quarterly frequency by taking the average to match with the frequency of the SPF bias. See Table A2 for detailed information in the Appendix.

2.2 Defining the Forecast Bias

We first define the j-quarter ahead growth rate of the variable x_t from the forecasts formulated at time t.

$$\gamma_{j,t}^{SPF} = x_{t+j}^{SPF} - x_{t-1}^{SPF}, \tag{1}$$

¹Recall that, at time t, one period behind data (x_{t-1}) are subject to revision, and the current data (x_t) are not yet available.

²https://www.policyuncertainty.com/

where x_{t+j}^{SPF} denotes the *j*-quarter ahead log SPF forecast unless it is a percent variable such as unemployment rate or Treasury bill yields or share of real net export of RGDP. Note that (1) is a long-differenced series as in Mark (1995). The corresponding realized *j*-quarter ahead growth rate is defined as follows.

$$\gamma_{j,t} = x_{t+j} - x_{t-1} \tag{2}$$

The j-quarter ahead forecast bias for x_t is defined as follows.

$$b_{j,t}^x = \gamma_{j,t}^{SPF} - \gamma_{j,t} \tag{3}$$

For example, $b_{5,t}^x$ denotes a 5-quarter ahead (long-horizon) growth rate forecast bias of a key macroeconomic variable x_t . In addition, we also report the short-horizon forecast bias (j = 1), which is a two-period ahead (annualized) growth rate forecast. In what follows, we discuss the contemporaneous properties of forecast bias of an array of key macroeconomic variables and their relationship with economic policy uncertainty.

2.3 Persistence of Forecast Bias

We first note highly persistent dynamics of forecast bias in the SPF for all macroeconomic variables, which is consistent with the findings of Capistrán (2008) and Elliott et al. (2008), among others. See Figure 1 for the long-horizon (5-quarter) forecast bias of the three key macroeconomic variables of interest: real GDP growth, unemployment rate changes, and GDP deflator inflation.

Real GDP growth forecast bias exhibits predominantly persistent negative values in the earlier sample period prior to 2000, while mostly positive bias observed during the post-2000 period. See Elliott et al. (2008) and Kim and Zhang (2022) for similar observations and discussion.

Since we define the bias as the forecast growth minus realized growth, negative bias

implies that private sector forecasters were pessimistic in formulating their expectation of real GDP growth, whereas positive bias suggests optimism in the forecast. Furthermore, persistent bias dynamics means that private sector forecasters are reluctant to change their sentiments even when they repeatedly observe their systemic errors.

Forecast bias in the unemployment rate changes resembles a mirror image of bias in the real GDP growth forecast. Since the unemployment rate commonly exhibits countercyclical dynamics, these findings jointly imply overall pessimism in the forecast bias during the pre-2000 sample period, while the sentiment in the SPF forecast bias switched to a more optimistic pattern. The short-run forecast bias shows qualitatively similar but somewhat less persistent patterns.

Note also predominantly positive inflation bias during the pre-2000 sample period, which implies that forecasters tend to over-predict inflation in the future. Capistrán (2008) claims such findings are consistent with rational forecasts with an asymmetric loss function. During the post-2000 period, we observe persistent inflation forecast bias with long swings. See Figure A1 in the appendix for 11 other forecast bias dynamics.

Figure 1 around here

A way to show the existence of forecast bias is by using Mincer-Zarnowitz Regression (Mincer and Zarnowitz (1969)).

$$\gamma_{j,t} = \alpha + \beta \gamma_{j,t}^{SPF} + \varepsilon_{j,t},\tag{4}$$

where $\gamma_{j,t}$ denotes the realized j-quarter ahead growth rate and $\gamma_{j,t}^{SPF}$ is corresponding SPF forecast. They defined the weak test of rationality as the joint test of $\alpha = 0$ and $\beta = 1$. Table (3) reports the results for both long- and short-horizon forecast data. The tests reject the null for 12 out of 14 macroeconomic variables, verifying the forecast bias.

Tables 1 around here

We next statistically test the stationary of the SPF forecast bias via the augmented Dickey-Fuller (ADF) test via the following self-exciting process with an intercept. Let b_t denotes a generic notation for the forecast bias in (3).

$$b_t = c + \alpha b_{t-1} + \sum_{j=1}^k \beta_j \Delta b_{t-j} + \varepsilon_t, \qquad (5)$$

where α denotes the persistence parameter. Results are reported in Tables 1 and 2 for 14 long- and short-horizon forecast biases, respectively. The ADF test rejects all forecast bias at the 10% significance level, meaning that the forecast bias obeys a stationary process.

The persistence of the bias can be formally measured by the α estimate or the half-life of the impulse-response function based on (5). It is well known that the ordinary least squares (LS) estimate $\hat{\alpha}_{LSE}$ is (downward) biased in the presence of deterministic terms, such as an intercept and/or time trend.³ See Andrews (1993), Andrews and Chen (1994), and Hansen (1999) for median unbiased estimators and Kendall (1954), Shaman and Stine (1988), So and Shin (1999) for mean unbiased estimators.

Tables 1 and 2 report the median unbiased estimate $\hat{\alpha}_{MU}$ in addition to bias-corrected 95% confidence interval that is constructed as follows.

Following Hansen (1999), we define the following grid-t statistic at each of M grid points $\alpha_j \in [\alpha_1, \alpha_2, \cdots, \alpha_M]$ around the neighborhood of the least square point estimate $\hat{\alpha}_{LSE}$.

$$t_T(\alpha_j) = \frac{\hat{\alpha}_{LS} - \alpha_j}{se(\hat{\alpha}_{LS})},\tag{6}$$

where $se(\hat{\alpha}_{LS})$ denotes the least squares standard error of $\hat{\alpha}_{LS}$. We then generate pseudo samples of the same sample size T for each grid point α_j . Implementing LS estimations for B bootstrap iterations at each of M grid points of α_j , we obtain the (p quantile) grid-t

 $^{{}^{3}\}hat{\alpha}_{LS}$ is downward biased for AR(1) processes, although it may not necessarily be true for higher order AR(p) processes.

bootstrap quantile function estimates, $\hat{q}_{T,p}^*(\alpha_j) = \hat{q}_{T,p}^*(\alpha_j, \varphi(\alpha_j))$, where φ denotes nuisance parameters such as β 's that are functions of α_j . Note that each function is evaluated at each grid point α_j rather than at the point estimate.⁴ We smooth the estimated quantile functions using kernel regression.⁵

The median unbiased estimator is then defined as follows.

$$\hat{\alpha}_{MU} = \alpha_j \in R, \text{ s.t. } t_T(\alpha_j) = \tilde{q}_{T.50\%}^*(\alpha_j), \tag{7}$$

while its associated bias-corrected 95% grid-t confidence interval $[\hat{\alpha}_{MU,L}, \hat{\alpha}_{MU,U}]$ is determined as follows.

$$\hat{\alpha}_{MU,L} = \alpha_j \in R \text{ s.t. } t_T(\alpha_j) = \tilde{q}^*_{T,97.5\%}(\alpha_j),$$

$$\hat{\alpha}_{MU,U} = \alpha_j \in R \text{ s.t. } t_T(\alpha_j) = \tilde{q}^*_{T,2.5\%}(\alpha_j)$$
(8)

Corresponding half-life estimates are obtained by the conventional method using the formula $\ln(1/2)/\ln(\hat{\alpha})$, divided by 4 to annualize the half-life in years.⁶

Table 1 clearly shows that the long-horizon forecast bias in the SPF obeys highly persistent processes. Although the ADF test rejects the null of a unit root at the 5% level for all long-horizon biases, the median unbiased estimates suggest that these bias variables follow a near unit root process, where the 95% confidence bands often extend to unity. We obtained compact confidence bands only for 4 out of 14 SPF forecast biases.

The short-horizon biases in Table 2 exhibit similar properties but much less persistent dynamics. For all short-horizon biases, we obtained compact 95% confidence bands with all

⁴The estimators reduce to the Tibshirani and Efron (1993) bootstrap-t estimators if they are evaluated at the point estimate $\hat{\alpha}_{LS}$, which are the biased LS estimate.

⁵Following Hansen (1999), we used the Epanechinikov kernel $K(u) = 3(1 - u^2)/4I(|u| \le 1)$, where $I(\cdot)$ is an indicator function. The bandwidth parameter was chosen by least squares leave-one-out cross-validation.

⁶We implicitly assume that the deviation from the equilibrium monotonically decays. We may use the impulse-response function analysis to obtain half-life estimates allowing for non-monotonic convergence, although the order of the length of half-life estimates is mainly preserved. Since we are interested in persistence properties, we employ this simpler approach.

upper-bound half-life estimates below 1.5 years. The half-life point estimates range from 0.216 to 0.646 years.

Additionally, we note a substantial degree cross-section dependence across these 14 SPF forecast bias variables over time. To measure and report this property, we employ the following cross-section dependence test statistic proposed by Pesaran (2021).

$$CD = \left(\frac{2T}{N(N-1)}\right)^{1/2} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{i,j}\right) \to^{d} \mathcal{N}(0,1),$$
(9)

where $\hat{\rho}_{i,j}$, i, j = 1, ...N is the pair-wise correlation coefficients from the residuals $(\hat{\varepsilon}_t)$ of the ADF regression (5) for each SPF bias variable. The test rejects the null of cross-section independence at the 1% significance level for both the long- and short-horizon forecast bias variables. We also report the average correlation $\hat{\rho}$ of each bias variable with respect to the other bias variables. In addition, we also report the average of $\hat{\rho}$.

The average pair-wise correlation coefficients are mostly substantial, ranging from -0.312 for bias in the unemployment rate change to 0.405 for bias in the real GDP growth. It should be noted that these correlation coefficients are positive, except for the bias in unemployment rate forecast. Note also that unemployment rate is a counter-cyclical variable, while others follow pro-cyclical dynamics. In other words, these correlation properties in the SPF forecast bias are consistent with business cycle dynamics. The short-horizon biases also exhibit similar cross-section proprieties.

Tables 2 and 3 around here

Figure 2 reports more detailed cross-section dependence properties in the long-horizon SPF forecast bias. Real GDP growth bias shares substantial positive correlations with other biases such as industrial production, consumption, and non-residential investment growth. Unemployment rate bias has mostly negative correlations with others, except the net exports bias. The correlation coefficients of inflation bias are overall weak compared to those of other biases, although correlations are overall positive with procyclical variables. Short-run bias correlation properties are qualitatively similar; see Figure 2.

Figure 2 around here

3 Static Analysis

3.1 Cross-Section Properties with Economic Policy Uncertainty

This sub-section presents the comovement dynamics of the SPF forecast bias with an array of measures of economic policy uncertainty (EPU). As can be seen in Figure 3, the biases in the real GDP forecast and the inverse (-) of the unemployment rate forecast exhibit a clear resemblance with the EPU index. The comovement between the inflation forecast bias and the EPU index doesn't seem obvious.

We closely examine these observations by looking at the overall trend dynamics in the second panel. For this purpose, we extracted the trend components of the three forecast biases as well as the EPU index by employing the Hodrick-Prescott (HP) filter.⁷ Results clearly show a strong comovement of the EPU and the RGDP and unemployment rate forecast bias, while the inflation trend often moves in the opposite direction with the EPU.

Figure 3 around here

Motivated by these comovement dynamics, we investigate the statistical properties of economic policy uncertainty as a potential cause that results in forecast bias in the SPF.

 $^{^{7}}$ We used 1600 for the smoothing parameter for quarterly frequency data as suggested by Hodricd and Prescott (1997).

We first study the persistence properties of 12 economic policy uncertainty indices to see whether they match the dynamics of forecast bias.

The ADF test rejects the null of nonstationarity for most EPU indices at the 10% level. The median unbiased estimates show highly persistent dynamics similar to forecast bias. Unlike the forecast bias, however, all 95% confidence intervals of the $\hat{\alpha}_{MU}$ estimates are compact, with the exception of the trade policy uncertainty index.

We observe a substantial degree of cross-section dependence across these EPU indices. The overall EPU index and most other specific policy uncertainty indices are closely correlated with each other. Pesaran's CD statistics (9) rejects the null of cross-section independence at the 1% level. The average correlation coefficients range from 0.124 for the sovereign debt uncertainty index to 0.679 for the overall EPU index. The average value of $\hat{\rho}$ is 0.478, which is greater than 0.152 for the SPF forecast bias in Table 2.

Table 4 around here

The heat map in Figure 4 reports a more detailed cross-section correlation analysis among the EPU indices. The overall EPU index shares substantial positive correlations with key economic policy uncertainty indices such as the monetary policy uncertainty index (MntU) and fiscal policy uncertainty index (FscU). The national security uncertainty index (NScU) and regulation uncertainty index (RgI) also exhibit strong positive correlations with the EPU.

The trade policy uncertainty index (TrdU) shows a moderately positive correlation with the EPU, although it shares much weaker correlations with other policy uncertainty indices. The currency crisis uncertainty index (CrsU) also exhibits similar patterns to TrdU.

Since disaggregate level economic policy uncertainty indices show substantial degree positive correlations with the overall EPU, we study the effects of economic policy uncertainty on the SPF forecast bias mainly focusing on the effects of EPU. In what follows, we revisit the impact of these disaggregate level indices on SPF bias of specific variables.

Figure 4 around here

Figure 5 reports cross-section correlations of the total EPU index and individual forecast bias variables. Correlations are overall positive with the bias in procyclical variables. A negative correlation with unemployment rate forecast bias can be similarly understood because unemployment rate obeys counter-cyclical dynamics. Weak correlations with inflation forecast bias may be understood in the context of money neutrality.

Recall that the SPF bias is defined as in (3) so that a positive forecast bias reflects an optimistic forecast that exceeds its eventual realized value. This casts an interesting question of why economic policy uncertainty is positively correlated with more optimistic forecast bias. In what follows, we attempt to explain how to understand this puzzling phenomenon.

Figure 5 around here

3.2 Decomposition of Forecast Bias and EPU

The top panel of Figure 6 reports the cross-correlations of the EPU and the two components of long-horizon SPF forecast bias, that is, the SPF forecast and corresponding realized macroeconomic data.

It should be noted that we often observe potentially incorrect correlations of SPF forecast for macroeconomic variables. Furthermore, correlations between SPF forecast tends to be much weaker than those of corresponding realized macroeconomic variables, implying inattentive revision of the information set of the SPF forecasters.

For example, the correlation of the real GDP forecast was about 0.8, while it was about -2.7 for its corresponding realized value. As will be shown in the next section, economic policy uncertainty tends to generate substantial negative responses to economic growth. Given such prior knowledge, the correlation of GDP forecast not only has a wrong sign but

is also much weaker than its realized counterpart. We observed similar results for most other real variables, such as unemployment rate, industrial production, consumption, and investment. We also note that virtually negligible correlations were found for many forecasts, such as industrial production inflation, T-bills, and net exports.

The low panel of Figure 6 provides correlations between the EPU and the short-horizon SPF forecasts and their associated realized values. Unlike the long-horizon forecasts, we observe those correlations of short-run forecasts mostly share the same, possibly correct signs with their corresponding realized values, although the magnitude of the correlations is still overall lower, which implies that revisions of forecasters' predictions in response to a higher degree of policy uncertainty tends to occur slowly and can be highly inaccurate when forecasters make long-horizon predictions.

It should be noted that the correlations of most short-horizon forecasts assume opposite signs for the correlations of their long-horizon predictions. More specifically, forecasters tend to recognize the negative impacts of economic policy uncertainty and incorporate it in the formulation of their macroeconomic forecasts shortly. However, they are likely to end their pessimistic forecasts fairly quickly because their long-horizon (5-quarter) forecasts reflect recoveries from such economic loss as can be seen as positive correlations of the long-horizon forecasts with EPU.

Figure 6 around here

Recall $\gamma_{j,t}^{SPF} - \gamma_{j,t}$ in (3) for the definition of the SPF forecast bias. Since the correlations of EPU and $\gamma_{5,t}^{SPF}$ are in general different from those of $\gamma_{5,t}$, and because the latter tends to dominate the former in most cases, we may infer close correlations of the SPF bias with the EPU are mainly driven by the responses of the macroeconomic variables, given the inertial responses of the forecasters when they face a higher degree of economic policy uncertainty.

Tables 5 and 6 report the ADF statistics and the median unbiased estimates of the persistence parameter for the macroeconomic data and corresponding SPF forecasts. Note

that the long-horizon data (Table 5) are likely to be characterized as a highly persistent near unit root process, which greatly resembles the properties of the SPF bias reported in Table 1. The long-horizon forecasts also exhibit persistent dynamics, although less persistent than the data. Short-horizon forecasts and the macroeconomic data share similar persistence that are much weaker than the cases of long-horizon forecasts and the data, which match the persistence shown in Table 2 for short-horizon bias.

Tables 5 and 6 around here

Our cross-correlation analysis reveals that the dynamics of forecast bias in the SPF are closely correlated with economic policy uncertainty. Furthermore, we showed that close correlations between the EPU and the bias are mainly driven by the correlations between the EPU and the realized macroeconomic data. We report strong evidence of inertia in revising the long-horizon forecasts when the forecasters update their information set with a higher degree of economic policy uncertainty.

In the next section, we extend our analysis to dynamic investigation using the vector autoregressive framework.

4 Dynamic Analysis

This section investigates the effects of economic policy uncertainty on the SPF bias variables via the following recursively identified vector autoregressive (VAR) model. Abstracting from deterministic terms, consider the following VAR(p) model.

$$y_t = \sum_{j=1}^q A_j y_{t-j} + A_0^{-1} u_t, \tag{10}$$

where

 $y_t = [EPU_t \ z_t^x]',$

is a 2×1 vector of variables of interest. EPU_t is one of the economic uncertainty indices while z_t denotes either the realized bias $b_{j,t}^x$ in the SPF forecast of a variable x_t , or one of its components of the bias, $\gamma_{j,t}^{SPF}$ or $\gamma_{j,t}$. A_0^{-1} denotes the usual lower-triangular Cholesky factor that governs the contemporaneous relationship between the variables in x_t . u_t is a vector of orthonormal structural shocks, that is, $Eu_tu'_t = I$, where I is an identity matrix. Following Nodari (2014), Baker et al. (2016) and Chuliá et al. (2017) EPU_t is placed before z_t^x meaning that economic policy uncertainty affects the median forecasters' information, while the reverse does not hold within a quarter.

We are particularly interested in the *j*-period ahead orthogonalized impulse response function (IRF) of z_t^x to the one unit structural shock to EPU_t that occurs at time *t* as follows.

$$IRF_{j} = E(z_{t+j}^{x}|u_{EPU,t} = 1, \Omega_{t-1}) - E(z_{t+j}^{x}|\Omega_{t-1}),$$
(11)

where $E(.|\Omega_{t-1})$ is the adaptive conditional expectation operator given the information set Ω_{t-1} at time t-1, that is, $\Omega_j \supseteq \Omega_{j-1}, \forall j$. $u_{EPU,t}$ is the shock to EPU_t at time t. The level responses of the macroeconomic variable are obtained via cumulative summation as follows.

$$\eta(j) = \sum_{s=1}^{j} IRF_s \tag{12}$$

4.1 Dynamic Responses of the Key SPF Bias to EPU Shocks

Figure 7 shows the dynamic responses of the three key macroeconomic variables of interest to the overall economic policy uncertainty shock. First column in this figure shows bias dynamics; the second one belongs to realized data dynamic and the last column displays forecast responses toward the shock. As can be seen in the top panel, the economic policy uncertainty shock creates positive responses of the bias in the real GDP growth forecast, meaning that the EPU shock generates positive forecast bias, $b_{j,t}^x = \gamma_{j,t}^{SPF} - \gamma_{j,t} > 0$.

Such positive bias should not be interpreted as optimism in GDP forecasts because both

the data and the forecast respond negatively, but the quantitative response of the data is greater than that of the forecast, resulting in increases in the bias. The initial response of the forecast to the shock is close to zero, reaching its maximum response at -0.185 and converging to zero later.⁸ On the other hand, the first response of data to the shock is at -1.587, then drops and reaches the maximum at -1.973, and afterward goes up and fades. Therefore, we observe that both initial and maximum data responses are over ten times greater than the forecast's, meaning a substantial degree of inertia of the forecast responses compared with those of the data.

The middle panel of the figure reports the unemployment rate responses to the overall EPU shock. Dynamic responses of unemployment rate bias and data exhibit mirror images of RGDP responses. The bias responds to the shock deeply and negatively, starting at - 1.019, falling to -1.349, then increasing before it dies out. On the other hand, data responses are positive, with the first response close to 1, which goes up and falls later. Similar to RGDP, the Urate forecast responses to the shock are weak. Based on these two variables, we could observe the impact of overall EPU shock on the RGDP and Urate is strong and has adverse effects on the economy; however, forecaster reactions to the shock tend to be weak and insignificant.

Inflation responses to the overall EPU shock are in the bottom panel. All three figures show near zero reactions at first, following a hump shape IRF later, which is positive for the bias, negative for the data, and mixed for the forecast. Compared to previous panels, inflation responses are quantitatively small, with a wide confidence interval for both data and forecast. Again, EPU shocks cause negative economic impacts, that is, deflation here and weak and mixed responses on the forecast side. The sign and size differences between realized data and forecast responses show the forecasters' inattention toward overall EPU shock in these three macroeconomic variables.

Figure 7 around here

⁸Maximum response is the largest absolute value between all responses of a variable.

4.2 Dynamics of the Key SPF Bias to Policy Uncertainty Shocks

This subsection presents candle stick charts that show dynamic responses of real GDP, unemployment rate, and inflation toward the shock in all 12 measures of policy uncertainty indices. This reports evidence in favor of our results presented in the previous section, which implies the inattention behavior of professional forecasters.

Figure 8 presents all the initial and maximum responses with their corresponding confidence intervals for real GDP. The blue-centered sticks show initial responses and their confidence interval, while the red-centered sticks display the maximum responses. The top panel of this figure shows the RGDP bias responses, which are mostly positive. The middle panel displays the corresponding realized data candlesticks. All initial responses are negative and quantitatively large except for trade and currency uncertainties. On the other hand, the bottom panel shows forecast responses which are comparatively small and fluctuating around zero with their range between -0.129 to 0.108.

Figure 8 around here

The candle stick figures of the unemployment rate also follow similar dynamics to those of the RGDP bias with opposite signs. Mostly the bias responses are negative, realized data responses are positive and quantitatively large, and forecast ones are small and volatile.

Figures 9 around here

Figure 10 presents inflation rate dynamics. As can be seen, bias, realized data, and forecast responses are mostly small and around zero. The inflation rate is a nominal variable which could explain why its' responses are smaller than previous real variables.

Figures 10 around here

Based on these dynamics, realized data and forecast data responses differ in quantity and sign. As the forecast responses are mostly smaller than the data ones, we confirm that biases are affected by the realized data rather than forecast ones. Moreover, it shows forecasters do not quickly respond to the shocks, which creates bias. These results hold for all other macro variables dynamics toward policy uncertainty shocks. ⁹

4.3 Other Interesting Responses

This subsection reports additional empirical findings that shed further insights into the literature. For this purpose, we report selected dynamic responses of monetary, financial regulation, and trade policy uncertainty indices.

We start with discussing the monetary policy uncertainty shock effect on three key macroeconomics. Figure 11 plots the dynamic responses of real GDP, unemployment rate, and inflation rate to the shock. The first column displays bias responses which are significant and positive for real GDP and inflation and negative for unemployment rate. The second column shows data responses that are significant and persistent for real GDP and unemployment rate.¹⁰ In contrast, the inflation rate response is insignificant and short-lived. These findings are in line with the report of Husted et al. (2020) that shows the negative economic effect of a positive shock to monetary policy uncertainty. However, the shock in monetary policy uncertainty generates insignificant and weak responses for all three forecasts of macro variables in the third column, demonstrating the forecast response's inertia relative to data one. In other words, monetary policy shock affects the business cycle dynamics in the economy, but forecasters are not updating their responses quickly, which creates forecast bias.

Figure 11 around here

⁹Appendix includes tables showing initial and maximum responses and IRF figures for all fourteen macrovariables.

¹⁰This result holds for other real activity variables like consumption and state and local expenditures.

The financial regulation policy uncertainty index captures important financial-related events like the Great Recession. Figure 12 presents the impulse response functions of real GDP, unemployment rate, and industrial production. As seen in the second column, FRgU shock generates a persistent negative effect on these three real economy variables.¹¹ Nodari (2014) also reports persistent negative reactions of unemployment rate and industrial production to financial regulation uncertainty shock. However, the last column shows that forecasters' responses to the shock tend to be much smaller in comparison with those of the data.

Figure 12 around here

Trade uncertainty shock effects are weak and close to zero for almost all fourteen macro variables. Figure 13 shows real GDP, corporate profits, and share of real net exports of RGDP responses. There are wide confidence intervals for all three variables in all the panels, suggestive of insignificant trade policy uncertainty shock. This implies a relatively weak role of trade policy uncertainty in determining the U.S. real activity although it may generate substantial policy uncertainty through foreign affairs.

Figure 13 around here

5 Concluding Remarks

The existence of persistent forecast bias in private-sector forecasters motivates many discussions among economists. Why do forecasters make persistent forecast bias? Many researchers have proposed alternative explanations regarding this seemingly puzzling phenomenon, although no consensus seems to be settled in the current literature.

 $^{^{11}}$ The adverse impact of FRgU on real economy variables holds for consumption, state and local government expenditures, and nonresidential investment.

Inspired by the work of Capistrán (2008) and Elliott et al. (2008), we seek the source of the private-sector forecast bias by studying the static and the dynamic interactions between economic policy uncertainty and different forecast biases in the Survey of Professional Forecasters.

First, we use the Mincer-Zarnowitz parametric test and show the existence of forecast bias. Second, using median unbiased estimators and half-life, we confirm the forecast biases are highly persistent in the long-horizon SFP forecasts for the key macroeconomic variables. Then, employing static and dynamic mechanisms, we demonstrate that forecasters' inattention is the source of bias in relation to economic policy uncertainty measures. Specifically, this paper takes an alternative view of the source of forecast bias by decomposing the bias into the data and the forecast.

Starting with static analysis, we observe a strong comovement between real GDP and unemployment rate biases with the EPU index. Our results demonstrate a significant degree of cross-section correlation between the EPU index and forecast bias variables which are overall positive with the bias in procyclical variables. This surprising behavior motivates us to decompose forecast bias into the realized and forecast data. The finding shows that close correlations between the EPU and biases are mainly driven by the correlation between the EPU and the realized data. In contrast, long-horizon forecasts show strong evidence of inertia when forecasters update their information sets with a higher degree of economic policy uncertainty.

Turning to the dynamic mechanism, we use a vector autoregression (VAR) model to identify the effect of uncertainty shock on the forecasters' responses. Our results show that policy uncertainty shocks generate positive responses to the bias, which means optimism in the forecasters, so we focus on the dynamics of the realized data and forecast. The findings report that policy uncertainty shocks negatively affect the economy, as real GDP falls and unemployment rises and generates deflation. However, forecasters do not adjust their responses fast enough, and forecast responses are weak, mixed, and insignificant. These dynamics confirm our findings in the static part, which implies that realized data is directing the forecast bias rather than the forecast data. In other words, forecasters' sluggishness to the shock creates bias.

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Table 1. Mincer-Zarnowitz Test Results					
	Long-Run	Short-Run			
Real GDP	0.16	3.91^{\ddagger}			
Unemployment Rate	5.32^{\ddagger}	7.65^{\ddagger}			
Corporate Profits	0.00	4.24^{\dagger}			
Housing	12.47^{\ddagger}	3.22^{\dagger}			
Industrial Prod	7.63^{\ddagger}	3.04^{*}			
Nominal GDP	3.56^{\dagger}	1.14			
GDP Deflator	48.68^{\ddagger}	15.63^{\ddagger}			
Real Consumption	3.89^{\dagger}	4.77^{\ddagger}			
Real Gov't Spending	5.63^{\ddagger}	0.95			
Nonresidential Inv't	22.19^{\ddagger}	10.89^{\ddagger}			
Residential Inv't	3.82^{\dagger}	3.5^{\dagger}			
Real S&L Gov't	80.45^{\ddagger}	50.68^{\ddagger}			
Treasury Bill	25.92^{\ddagger}	22.7^{\ddagger}			
Real Net Exports	5.01^{\ddagger}	3.28^\dagger			

Note: Table reports F-statistics results. Null hypothesis is $\alpha = 0$ and $\beta = 1$ jointly, which is equivalent to there is no bias in the forecast. [‡], [†] and ^{*} denote a rejection at the 1%, 5% and 10% significance level.

	ADF	$\hat{\alpha}_{MU}$	95% CI	HL	95% CI	$\hat{ ho}$		
Real GDP	-3.697^{\ddagger}	0.888	[0.805, 1.004]	1.462	$[0.799, \infty)$	0.405		
Unemployment Rate	-4.031^{\ddagger}	0.912	[0.834, 1.011]	1.884	$[0.955, \infty)$	-0.312		
Corporate Profits	-5.711^{\ddagger}	0.740	[0.628, 0.859]	0.577	[0.373, 1.137]	0.282		
Housing	-2.905^{\dagger}	0.935	[0.863, 1.016]	2.586	$[1.175, \infty)$	0.313		
Industrial Prod	-5.708^{\ddagger}	0.911	[0.833, 1.011]	1.854	$[0.949, \infty)$	0.365		
Nominal GDP	-4.084^{\ddagger}	0.882	[0.794, 0.982]	1.376	[0.753, 9.310]	0.421		
GDP Deflator	-3.603^{\ddagger}	0.919	$[0.846 \ 1.010]$	2.057	$[1.037, \infty)$	0.180		
Real Consumption	-3.504^{\ddagger}	0.923	[0.849, 1.013]	2.163	$[1.057, \infty)$	0.351		
Real Gov't Spending	-3.662^{\ddagger}	0.798	[0.690, 0.908]	0.770	[0.468, 1.793]	0.039		
Nonresidential Inv't	-5.438^{\ddagger}	0.895	[0.814, 1.006]	1.565	$[0.842, \infty)$	0.316		
Residential Inv't	-3.358^{\dagger}	0.966	[0.905, 1.020]	4.977	$[1.739, \infty)$	0.286		
Real S&L Gov't	-3.455^{\ddagger}	0.937	[0.870, 1.013]	2.683	$[1.242, \infty)$	0.185		
Treasury Bill	-4.766^{\ddagger}	0.898	[0.816, 1.008]	1.612	$[0.854, \infty)$	0.204		
Real Net Exports	-3.478^{\ddagger}	0.845	[0.745, 0.951]	1.030	[0.589, 3.447]	0.023		
CD Statistics: 17.608^{\ddagger}								
Average $\hat{\rho}$: 0.158								

Table 2. Persistence of Long-Run SPF Bias

Note: Long-run SPF bias denotes the bias in the 5-quarter ahead growth rate (long-differencing) forecast of a variable, that is, SPF forecast minus its corresponding realized data. ADF denotes the augmented Dickey-Fuller statistics. Asymptotic p-values in parentheses are calculated by authors. $\hat{\alpha}_{MU}$ denotes the median unbiased estimate of the persistence parameter from AR(1) specification using Hansen's (1999) method. 95% CI is the median unbiased confidence band. $\hat{\rho}$ refers the average correlation coefficient of each index with the rest of the indices after whitening via the ADF regression. CD statitics is the cross-section dependence test statistics proposed by Pesaran (2021). [‡], [†] and ^{*} denote a rejection at the 1%, 5% and 10% significance level.

	ADE	â	0507 CI	UT	0507 CI	â		
	ADF	α_{MU}	95% CI	ПL	95% CI	ρ		
Real GDP	-3.478^{\ddagger}	0.566	[0.427, 0.708]	0.304	[0.204, 0.502]	0.399		
Unemployment Rate	-5.797^{\ddagger}	0.618	[0.484, 0.755]	0.36	[0.239, 0.617]	-0.179		
Corporate Profits	-6.588^{\ddagger}	0.448	[0.301, 0.600]	0.216	[0.144, 0.339]	0.265		
Housing	-3.812^{\ddagger}	0.658	[0.526, 0.789]	0.414	[0.270, 0.730]	0.280		
Industrial Prod	-5.068^{\ddagger}	0.765	[0.652, 0.880]	0.646	[0.405, 1.359]	0.288		
Nominal GDP	-4.495^{\ddagger}	0.552	[0.412, 0.696]	0.291	[0.195, 0.479]	0.392		
GDP Deflator	-3.124^{\dagger}	0.696	[0.571, 0.823]	0.478	[0.310, 0.888]	0.085		
Real Consumption	-2.918^{\dagger}	0.608	[0.474, 0.746]	0.348	[0.232, 0.592]	0.288		
Real Gov't Spending	-3.972^{\ddagger}	0.461	[0.310, 0.612]	0.224	[0.148, 0.353]	0.093		
Nonresidential Inv't	-5.192^{\ddagger}	0.626	[0.494, 0.760]	0.370	[0.245, 0.633]	0.240		
Residential Inv't	-2.721^{*}	0.753	[0.640, 0.870]	0.612	[0.388, 1.248]	0.273		
Real S&L Gov't	-3.031^{\dagger}	0.676	[0.550, 0.805]	0.443	[0.290, 0.799]	0.210		
Treasury Bill	-4.500^{\ddagger}	0.530	[0.386, 0.668]	0.273	[0.182, 0.430]	0.219		
Real Net Exports	-3.689^{\ddagger}	0.550	[0.406, 0.697]	0.290	[0.192, 0.481]	0.123		
CD Statistics: 16.717^{\ddagger}								
Average $\hat{\rho}$: 0.152								

Table 3. Persistence of Short-Run SPF Bias

Note: Short-run SPF bias denotes the 2-quarter ahead growth rate (long-differencing) forecast of a variable, that is, SPF forecast minus its corresponding realized data. ADF denotes the augmented Dickey-Fuller statistics. Asymptotic p-values in parentheses are calculated by authors. $\hat{\alpha}_{MU}$ denotes the median unbiased estimate of the persistence parameter from AR(1) specification using Hansen's (1999) method. 95% CI is the median unbiased confidence band. $\hat{\rho}$ refers the average correlation coefficient of each index with the rest of the indices after whitening via the ADF regression. CD statitics is the cross-section dependence test statistics proposed by Pesaran (2021). Asymptotic p-value is in the parenthesis.[‡], [†] and ^{*} denote a rejection at the 1%, 5% and 10% significance level.

EPU	ADF	$\hat{\alpha}_{MU}$	95% CI	HL	95% CI	$\hat{ ho}$		
Overall EPU	-3.701^{\ddagger}	0.606	[0.470, 0.739]	0.346	[0.229, 0.573]	0.679		
Monetary	-8.190^{\ddagger}	0.373	[0.215, 0.521]	0.176	[0.113, 0.266]	0.577		
Fiscal	-3.639^{\ddagger}	0.597	[0.458, 0.730]	0.336	[0.222, 0.550]	0.646		
Tax	-3.658^{\ddagger}	0.613	[0.475, 0.744]	0.354	[0.233, 0.585]	0.633		
Gov't Spending	-3.038^{\dagger}	0.508	[0.357, 0.645]	0.256	[0.168, 0.395]	0.594		
Health Care	-2.276	0.711	[0.588, 0.833]	0.508	[0.326, 0.947]	0.540		
Nat'l Security	-3.175^{\dagger}	0.619	[0.483, 0.749]	0.361	[0.238, 0.599]	0.559		
Entitlement	-2.655^{*}	0.552	[0.408, 0.692]	0.291	[0.193, 0.471]	0.590		
Regulation	-3.604^{\ddagger}	0.649	[0.516, 0.780]	0.401	[0.262, 0.698]	0.583		
Finanial Reg	-3.269^{\dagger}	0.647	[0.510, 0.773]	0.398	[0.257, 0.674]	0.473		
Trade	-1.560	0.913	[0.813, 1.020]	1.907	$[0.838, \infty)$	0.255		
Crisis	-6.003^{\ddagger}	0.598	[0.451, 0.719]	0.337	[0.217, 0.524]	0.124		
CD Statistics: 44.749^{\ddagger}								
Average $\hat{\rho}$: 0.478								

Table 4. Persistence of Economic Policy Uncertainty Indices

Note: ADF denotes the augmented Dickey-Fuller statistics. Asymptotic p-values in parentheses are calculated by authors. $\hat{\alpha}_{MU}$ denotes the median unbiased estimate of the persistence parameter from AR(1) specification using Hansen's (1999) method. 95% CI is the median unbiased confidence band. $\hat{\rho}$ refers the average correlation coefficient of each index with the rest of the indices after whitening via the ADF regression. CD statitics is the cross-section dependence test statistics proposed by Pesaran (2021). Asymptotic p-value is in the parenthesis. [‡], [†] and ^{*} denote a rejection at the 1%, 5% and 10% significance level.

	Data			Forecast			
	ADF	$\hat{\alpha}_{MU}$	95% CI	ADF	$\hat{\alpha}_{MU}$	95% CI	
Real GDP	-4.323^{\ddagger}	0.922	[0.853, 1.009]	-4.247^{\ddagger}	0.797	[0.698, 0.902]	
Unemployment Rate	-3.506^{\ddagger}	0.962	[0.904, 1.018]	-3.970^{\ddagger}	0.851	[0.761, 0.947]	
Corporate Profits	-5.207^{\ddagger}	0.782	[0.677, 0.893]	-4.847^{\ddagger}	0.729	[0.615, 0.849]	
Housing	-3.255^{\dagger}	0.908	[0.827, 1.011]	-3.057^{\dagger}	0.888	[0.803, 1.003]	
Industrial Prod	-3.314^{\dagger}	0.937	[0.868, 1.015]	-5.359^{\ddagger}	0.758	[0.651, 0.867]	
Nominal GDP	-4.025^{\ddagger}	0.931	[0.871, 1.006]	-3.413^{\dagger}	0.869	[0.803, 0.947]	
GDP Deflator	-3.555^{\ddagger}	0.962	[0.913, 1.009]	-3.150^{\dagger}	0.952	[0.911, 1.004]	
Real Consumption	-3.967^{\ddagger}	0.949	[0.889, 1.012]	-4.031^{\ddagger}	0.808	[0.710, 0.912]	
Real Gov't Spending	-3.310^{\dagger}	0.923	[0.850, 1.012]	-2.477	0.794	[0.695, 0.892]	
Nonresidential Inv't	-5.085^{\ddagger}	0.943	[0.879, 1.015]	-3.934^{\ddagger}	0.895	[0.812, 1.005]	
Residential Inv't	-2.613^{*}	0.988	[0.930, 1.022]	-2.533	0.930	[0.858, 1.014]	
Real S&L Gov't	-2.828^{*}	0.969	[0.916, 1.014]	-2.64^{*}	0.953	[0.892, 1.014]	
Treasury Bill	-5.945^{\ddagger}	0.947	[0.881, 1.017]	-4.712^{\ddagger}	0.732	[0.613, 0.852]	
Real Net Exports	-3.187^{\dagger}	0.903	[0.822, 1.009]	-3.030^{\dagger}	0.874	[0.786, 0.974]	
CD Statistics:	13.300^{\ddagger}			10.871^{\ddagger}			
Average $\hat{\rho}$:		0.12	21	0.099			

Table 5. Persistence of Long-Run SPF Forecast and Data

Note: Long-run SPF bias denotes the 5-quarter ahead growth rate (long-differencing) of the variable, that is, the realized data subtracted by corresponding SPF forecast. ADF denotes the augmented Dickey-Fuller statistics. Asymptotic p-values in parentheses are calculated by authors. $\hat{\alpha}_{MU}$ denotes the median unbiased estimate of the persistence parameter from AR(1) specification using Hansen's (1999) method. 95% CI is the median unbiased confidence band. $\hat{\rho}$ refers the average correlation coefficient of each index with the rest of the indices after whitening via the ADF regression. CD statistics is the cross-section dependence test statistics proposed by Pesaran (2021). Asymptotic p-value is in the parenthesis.[‡], [†] and ^{*} denote a rejection at the 1%, 5% and 10% significance level.

	Data				Forecast		
	ADF	$\hat{\alpha}_{MU}$	95% CI	ADF	$\hat{\alpha}_{MU}$	95% CI	
Real GDP	-3.475^{\ddagger}	0.775	[0.665, 0.889]	-4.752^{\ddagger}	0.730	[0.612, 0.850]	
Unemployment Rate	-2.989^{\dagger}	0.889	[0.803, 1.004]	-3.933^{\ddagger}	0.813	[0.713, 0.920]	
Corporate Profits	-6.286^{\ddagger}	0.476	[0.333, 0.625]	-6.850^{\ddagger}	0.497	[0.349, 0.646]	
Housing	-3.090^{\dagger}	0.661	[0.530, 0.794]	-4.806^{\ddagger}	0.725	[0.605, 0.846]	
Industrial Prod	-3.850^{\ddagger}	0.840	[0.743, 0.943]	-6.718^{\ddagger}	0.647	[0.518, 0.780]	
Nominal GDP	-4.007^{\ddagger}	0.806	[0.701, 0.913]	-3.816^{\ddagger}	0.787	[0.684, 0.897]	
GDP Deflator	-2.228	0.857	[0.766, 0.953]	-2.656^{*}	0.932	[0.871, 1.007]	
Real Consumption	-2.875^{\dagger}	0.779	[0.672, 0.890]	-3.768^{\ddagger}	0.684	[0.559, 0.806]	
Real Gov't Spending	-3.042^{\dagger}	0.659	[0.530, 0.788]	-2.592^{\dagger}	0.534	[0.392, 0.676]	
Nonresidential Inv't	-4.917^{\ddagger}	0.848	[0.753, 0.949]	-4.099^{\ddagger}	0.865	[0.775, 0.963]	
Residential Inv't	-2.378	0.890	[0.804, 1.005]	-2.875	0.887	[0.802, 1.003]	
Real S&L Gov't	-2.437	0.806	[0.704, 0.913]	-1.955	0.925	[0.859, 1.008]	
Treasury Bill	-3.439^{\ddagger}	0.814	[0.720, 0.913]	-5.442^{\ddagger}	0.673	[0.550, 0.798]	
Real Net Exports	-2.681^{*}	0.645	[0.512, 0.780]	-3.119^{\dagger}	0.764	[0.653, 0.882]	
CD Statistics:	15.787^{\ddagger}			16.695^{\ddagger}			
Average $\hat{\rho}$:	0.143			0.152			

Table 6. Persistence of Short-Run SPF Forecast and Data

Note: Short-run SPF bias denotes the 2-quarter ahead growth rate (long-differencing) of the variable, that is, the realized data subtracted by corresponding SPF forecast. ADF denotes the augmented Dickey-Fuller statistics. Asymptotic p-values in parentheses are calculated by authors. $\hat{\alpha}_{MU}$ denotes the median unbiased estimate of the persistence parameter from AR(1) specification using Hansen's (1999) method. 95% CI is the median unbiased confidence band. $\hat{\rho}$ refers the average correlation coefficient of each index with the rest of the indices after whitening via the ADF regression. CD statitics is the cross-section dependence test statistics proposed by Pesaran (2021). Asymptotic p-value is in the parenthesis. [‡], [†] and ^{*} denote a rejection at the 1%, 5% and 10% significance level.



Note: Top panel shows Long-run SPF bias. It denotes the 5-quarter ahead growth rate (long-differencing) of the variables, that is, the realized data subtract from corresponding SPF forecast. Bottom panel presents short-run SPF forecast bias which is 2-quarter ahead.



Figure 2. Bias Heat Map

Note: Pair-wise cross section correlation coefficients from the residuals of the ADF regression for each SPF bias variables. Top panel reports long-run and bottom one presents short-run forecast bias correlation properties.



Figure 3. Long-Horizon Bias and EPU

Note: Comovement dynamics of the SPF forecast bias of real GDP, inverse of (-) unemployment rate and inflation rate with overall economic policy uncertainty measure (EPU). Top panel demonstrates comovements and bottom one shows them after employing the Hodrick-Prescott (HP) filter and extracting trend components.
EPU	1	0.86	0.862	0.83	0.755	0.626	0.735	0.71	0.75	0.609	0.308	0.11		
MntU	0.86		0.634	0.601	0.576	0.5	0.651	0.575	0.612	0.611	0.221	0.087		0.9
FscU	0.862	0.634	1	0.983	0.87	0.692	0.641	0.734	0.653	0.45	0.16	0.075	-	0.8
TxU	0.83	0.601	0.983		0.821	0.7	0.626	0.722	0.653	0.426	0.172	0.059	-	0.7
GvSU	0.755	0.576	0.87	0.821		0.677	0.572	0.75	0.553	0.413	0.066	0.082	-	0.6
HItU	0.626	0.5	0.692	0.7	0.677		0.494	0.818	0.539	0.313	0.146	-0.021	-	0.5
NScU	0.735	0.651	0.641	0.626	0.572	0.494		0.554	0.625	0.57	0.314	-0.068	_	0.4
EntU	0.71	0.575	0.734	0.722	0.75	0.818	0.554		0.61	0.456	0.131	0.018	_	0.3
RgU	0.75	0.612	0.653	0.653	0.553	0.539	0.625	0.61		0.651	0.348	-0.001		0.2
FRgU	0.609	0.611	0.45	0.426	0.413	0.313	0.57	0.456	0.651	1	0.11	0.063		0.2
TrdU	0.308	0.221	0.16	0.172	0.066	0.146	0.314	0.131	0.348	0.11	1	0.085	-	0.1
CrsU	0.11	0.087	0.075	0.059	0.082	-0.021	-0.068	0.018	-0.001	0.063	0.085	1	-	0
•	EPU N	MntU F	UJecu	TXU C	NEN	HINU N	scu r	EntU	ROU F	RgU -	rrdu (Uenc		

Figure 4. Economic Policy Uncertainty Indices Heat Map

Note: Pair-wise cross section correlation coefficients from the residuals of the ADF regression for each measure of economic policy uncertainty.



Note: Cross section correlation coefficients from the residuals of the ADF regression for overall economic policy uncertainty (EPU) and each long-run forecast bias variables.



Figure 6. Decomposition of Bias and EPU

Note: Cross section correlation coefficients from the residuals of the ADF regression for overall economic policy uncertainty (EPU) and each SPF forecasts (blue) and corresponding realized macroeconomic data (orange). Top panel reports long-run and bottom one presents short-run correlation properties.



Figure 7. Dynamic of RGDP, Urate and Inflation to EPU Shocks

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. Top panel reports the IRF estimate (solid) of the real GDP bias, data and forecast, respectively, along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle panel shows dynamic responses unemployment rate and bottom one displays inflation rate dynamics to the economic policy uncertainty shock.



Figure 8. Initial and Maximum Responses of Real GDP to EPU Shocks

Note: The blue-centered sticks show initial responses and their confidence interval while the red-centered sticks display the maximum responses of the IRF. Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation policy uncertainty shock along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions. Three panels reports real GDP bias, data and forecast, respectively.



Figure 9. Initial and Maximum Responses of Unemployment rate to EPU Shocks Urate Bias Response

Note: The blue-centered sticks show initial responses and their confidence interval while the red-centered sticks display the maximum responses of the IRF. Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation policy uncertainty shock along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions. Three panels reports uncertainty uncertainty and forecast, respectively.



Figure 10. Initial and Maximum Responses of Inflation to EPU Shocks

Note: The blue-centered sticks show initial responses and their confidence interval while the red-centered sticks display the maximum responses of the IRF. Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation policy uncertainty shock along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions. Three panels reports inflation rate bias, data and forecast, respectively.



Figure 11. Dynamic of Monetary Policy Uncertainty Shocks

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation monetary policy uncertainty shock. Top panel reports the IRF estimate (solid) of the real GDP bias, data and forecast, respectively, along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle panel shows dynamic responses of unemployment rate and bottom one displays inflation rate dynamics.



Figure 12. Dynamic of Financial Regulation Policy Uncertainty Shocks

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation financial regulation policy uncertainty shock. Top panel reports the IRF estimate (solid) of the real GDP bias, data and forecast, respectively, along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle panel shows dynamic responses of unemployment rate and bottom one displays inflation rate dynamics.



Figure 13. Dynamic of Trade Policy Uncertainty Shocks

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation trade policy uncertainty shock. Top panel reports the IRF estimate (solid) of the real GDP bias, data and forecast, respectively, along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle panel shows dynamic responses of unemployment rate and bottom one displays inflation rate dynamics.

Appendix

Abbreviation	Full Name	Unit
RGDP	Real Gross Domestic Product	Growth Rate (\$Bil.)
Urt	Unemployment Rate	Percent Change $(\%)$
CoPr	Corporate Profits after tax	Growth Rate (\$Bil.)
Hsng	Housing starts	Growth Rate (Mil.)
InPd	Index of Industrial Production	Growth Rate (Index)
NGDP	Nominal Gross Domestic Product	Growth Rate (\$Bil.)
Infl	Inflation rate	Percent Change $(\%)$
Cnsm	Real Personal Cons Expenditures	Growth Rate (\$Bil.)
FedE	Real Fed Gov't Cons and Invt	Growth Rate (\$Bil.)
NRsI	Real Non-residential Fixed Invt	Growth Rate (\$Bil.)
RsI	Real Residential Fixed Investment	Growth Rate (\$Bil.)
S&LE	Real State and Local Gov't Cons and Invt	Growth Rate (\$Bil.)
Tbil	3-month Treasury Bill Rate	Percent Change $(\%)$
NEx	share of Real Net Exports of RGDP	Percent Change (%)

Table A1. SPF Macroeconomic Variables

Note: The unit of the level variables appear in the parenthesis. We log-difference each of the quantity variables while percent point changes are used for the percent variables.

Abbreviation	Categories of Policy Uncertainty	Selective Keywords
EPU	Overall Economic Policy	uncertainty, economy, Fed
MntU	Monetary Policy	federal reserve, fed funds rate
FscU	Fiscal Policy	taxes, government spending
TxU	Tax Policy	taxes, taxation
GvSU	Government Spending Other Spending	federal budget, military spending
HltU	Healthcare	Medicaid, health insurance
NScU	National Security	war, police action
EntU	Entitlement Programs	entitlements, social security
RgU	Overall Regulation	union rights, minimum wage
FRgU	Financial Regulation	banking supervision, dodd-frank
TrdU	Trade Policy	import tariffs, wto
CrsU	Sovereign Debt & Currency Crises	currency crash, currency devaluation

Table A2. Economic Policy Uncertainty Indices

Note: All data are obtained from policyuncertainty.com and we transformed monthly frequency data into quarterly data by taking the period average values. Visit the website for more detailed descriptions of the keywords.

	Mean	Std Dev	Skewness	Kurtosis	JB	Min	Max	Median
RGDP	0.081	2.018	3.483	32.416	5406.812^{\ddagger}	-3.840	11.553	-0.035
Urt	-0.051	1.189	-8.434	89.551	46006.110^{\ddagger}	-9.480	1.033	0.233
CoPr	-0.076	15.515	-0.371	14.517	788.080^{\ddagger}	-73.724	67.398	-0.170
Hsng	5.088	19.162	0.238	4.513	14.882^{\ddagger}	-24.818	77.434	2.710
InPd	1.362	4.316	1.359	13.567	704.386^{\ddagger}	-6.726	19.722	1.074
NGDP	0.470	2.160	3.432	32.023	5262.504^{\ddagger}	-3.551	12.878	0.239
Infl	0.401	0.858	0.165	3.109	0.716	-1.859	2.549	0.409
Cnsm	-0.372	1.954	4.6	48.188	12582.190^{\ddagger}	-3.651	12.832	-0.526
FedE	-0.551	3.204	0.011	3.115	0.081	-7.652	7.438	-0.601
NRsI	2.716	5.352	0.199	5.781	46.698^{\ddagger}	-6.442	22.305	1.283
RsI	0.215	11.802	-0.214	3.579	3.066	-18.691	34.54	-2.453
S&LE	-1.413	2.051	0.21	2.825	1.222	-5.793	3.876	-1.437
Tbil	0.659	1.254	0.649	4.17	18.064^{\ddagger}	-2.577	4.085	0.428
NEx	0.001	0.005	-0.062	3.799	3.869	-0.013	0.016	0.003

Table A3. Summary of Statistics of Long-Run SPF Bias

Note: $^{\ddagger},\,^{\dagger}$ and * denote a rejection at the 1%, 5% and 10% significance level.

Table A4.	Summary	of	Statistics	of	Long-Run	SPF	Data
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	Mean	Std Dev	Skewness	Kurtosis	JB	Min	Max	Median
RGDP	3.150	2.197	-4.018	38.594	7878.111 [‡]	-9.097	6.390	3.541
Urt	-0.040	1.392	8.029	85.610	41903.916^{\ddagger}	-1.533	9.200	-0.433
CoPr	7.526	16.105	0.448	14.279	757.502^{\ddagger}	-62.356	75.220	6.207
Hsng	-0.959	19.710	-0.085	3.862	4.568	-79.188	38.373	1.980
InPd	2.228	4.649	-1.606	15.831	1035.062^{\ddagger}	-17.876	9.448	3.281
NGDP	5.824	2.609	-4.013	39.039	8065.523^{\ddagger}	-7.855	10.863	6.163
Infl	2.674	0.968	-0.204	2.858	1.103	0.539	5.114	2.546
Cnsm	3.435	2.167	-4.416	48.756	12848.907^{\ddagger}	-9.890	6.925	3.731
FedE	1.812	4.590	-0.022	2.783	0.290	-8.406	12.291	1.546
NRsI	3.013	6.955	-0.400	5.771	49.218^{\ddagger}	-21.068	13.864	5.152
RsI	2.540	14.094	0.683	4.382	22.348^{\ddagger}	-44.384	20.002	6.920
S&LE	3.423	2.687	-0.330	3.190	2.793	-3.428	8.359	3.386
Tbil	-0.294	1.520	-0.519	3.644	8.829^{\dagger}	-4.299	2.680	-0.053
NEx	-0.001	0.006	-0.150	4.575	15.211^{\ddagger}	-0.014	0.017	-0.002

Note: $^{\ddagger},\,^{\dagger}$ and * denote a rejection at the 1%, 5% and 10% significance level.

	Mean	Std Dev	Skewness	Kurtosis	JB	Min	Max	Median
RGDP	3.231	0.817	-0.788	7.157	116.927^{\ddagger}	-0.490	5.027	3.313
Urt	-0.091	0.477	0.111	6.950	92.626^{\ddagger}	-1.000	2.050	-0.200
CoPr	7.450	4.262	0.595	4.357	19.261^{\ddagger}	-0.659	23.648	6.536
Hsng	4.128	13.120	0.780	4.917	36.147^{\ddagger}	-16.705	49.248	1.471
InPd	3.590	1.400	0.497	8.230	167.670^{\ddagger}	-2.175	6.814	3.843
NGDP	6.294	1.356	-1.032	8.969	235.985^{\ddagger}	0.933	11.103	6.048
Infl	3.075	1.089	-0.398	5.774	49.288^{\ddagger}	1.395	6.278	2.749
Cnsm	3.063	0.712	-1.277	6.393	106.700^{\ddagger}	0.189	4.587	3.107
FedE	1.262	2.668	0.295	6.917	92.834^{\ddagger}	-4.143	13.134	1.193
NRsI	5.729	3.475	-1.039	9.464	272.749^{\ddagger}	-8.802	11.891	6.354
RsI	2.755	5.486	0.513	5.963	58.174^{\ddagger}	-10.310	15.805	1.679
S&LE	2.009	0.936	-0.315	3.044	2.366	-0.880	3.572	2.193
Tbil	0.365	0.596	-0.544	4.174	15.165^{\ddagger}	-1.250	1.820	0.300
NEx	0.001	0.003	-0.063	3.459	1.343	-0.006	0.013	0.000

Table A5. Summary of Statistics of Long-Run SPF Forecast

Note: $^{\ddagger},\,^{\dagger}$ and * denote a rejection at the 1%, 5% and 10% significance level.

Shock	Initial Response	se		Maximum Resp	oonse	
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	6.057	-4.414	1.499	6.057	-4.414	2.003
	[1.924, 10.349]	[-8.687, -0.400]	[0.515, 2.371]	[1.924, 10.349]	[-8.687, -0.400]	[0.959, 3.070]
MntU	3.101	-1.946	1.123	3.101	-1.946	1.126
	[1.410, 5.075]	[-3.822, -0.527]	[0.504, 1.677]	[1.410, 5.075]	[-3.822, -0.527]	[0.398, 1.815]
FscU	3.291	-2.423	0.758	3.291	-2.423	1.668
	[0.340, 6.369]	[-5.567, 0.460]	[0.009, 1.495]	[0.340, 6.369]	[-5.567, 0.460]	[0.887, 2.413]
TxU	3.769	-2.894	0.765	3.769	-2.894	1.805
	[0.714, 6.943]	[-6.050, 0.040]	[-0.048, 1.562]	[0.714, 6.943]	[-6.050, 0.040]	[1.022, 2.571]
GvSU	1.240	-0.820	0.371	-1.376	2.249	0.819
	[-0.429, 3.162]	[-2.688, 0.799]	[-0.084, 0.805]	[-2.980, 0.546]	[0.038, 3.808]	[0.277, 1.311]
HltU	2.472	-1.703	0.703	2.472	3.099	1.067
	[-0.123, 5.105]	[-4.236, 0.793]	[0.113, 1.292]	[-0.123, 5.105]	[0.659, 5.465]	[0.467, 1.587]
NScU	2.617	-1.698	1.022	2.617	3.512	1.807
	[0.371, 5.282]	[-4.149, 0.474]	[0.330, 1.704]	[0.371, 5.282]	[0.540, 6.206]	[1.056, 2.423]
EntU	0.772	-0.145	0.595	-2.177	3.221	1.074
	[-1.040, 2.706]	[-2.058, 1.719]	[0.103, 1.084]	[-4.447, -0.007]	[1.015, 5.394]	[0.494, 1.624]
RgU	4.198	-3.755	0.320	4.198	-3.755	1.644
	[0.795, 7.788]	[-7.192, -0.571]	[-0.518, 1.237]	[0.795, 7.788]	[-7.192, -0.571]	[0.734, 2.486]
FRgU	1.499	-1.359	0.076	2.452	-2.124	0.623
	[-0.134, 3.353]	[-3.133, 0.291]	[-0.342, 0.484]	[0.204, 4.372]	[-4.119, -0.047]	[0.143, 1.085]
TrdU	0.108	-0.025	0.109	-1.256	1.075	-0.254
	[-2.019, 2.112]	[-1.901, 2.043]	[-0.304, 0.517]	[-3.462, 1.200]	[-1.269, 3.106]	[-0.821, 0.308]
CrsU	0.815	-0.763	0.030	0.815	-0.763	0.075
	[0.458, 1.582]	[-1.652, -0.398]	[-0.086, 0.145]	[0.458, 1.582]	[-1.652, -0.398]	[-0.183, 0.279]

Table A6. Corporate Profits Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the corporate profits bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Respons	e		Maximum Resp	ponse	
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	2.429	-2.299	0.536	-4.570	7.590	4.348
	[-1.429, 5.640]	[-5.705, 1.635]	[-1.378, 2.599]	[-8.609, 0.015]	[1.843, 11.914]	[1.195, 6.967]
MntU	0.839	-1.250	-0.148	1.510	-2.103	0.323
	[-0.794, 2.325]	[-2.941, 0.386]	[-1.379, 1.094]	[-0.804, 3.847]	[-4.476, 0.367]	[-1.410, 1.748]
FscU	0.412	-0.669	0.262	-3.802	6.477	3.504
	[-2.086, 2.625]	[-2.951, 1.669]	[-1.303, 1.659]	[-6.930, -0.498]	[2.220, 9.663]	[1.177, 5.473]
TxU	0.563	-1.173	-0.039	-4.065	6.464	3.279
	[-2.029, 2.778]	[-3.424, 1.388]	[-1.683, 1.430]	[-7.318, -0.583]	[2.207, 9.777]	[0.913, 5.392]
GvSU	0.665	-0.197	0.642	-1.855	3.727	2.042
	[-0.914, 2.253]	[-1.773, 1.203]	[-0.343, 1.518]	[-3.581, 0.578]	[0.980, 5.559]	[0.523, 3.517]
HltU	0.824	-0.182	1.185	-3.567	5.858	2.957
	[-1.296, 2.719]	[-2.043, 2.097]	[-0.067, 2.378]	[-6.379, -0.587]	[2.897, 8.307]	[1.152, 4.476]
NScU	2.246	-1.829	0.550	2.528	-1.829	0.925
	[0.461, 3.924]	[-3.750, -0.021]	[-0.730, 1.731]	[-0.132, 5.218]	[-3.750, -0.021]	[-0.807, 2.637]
EntU	0.765	-0.525	0.296	-6.104	7.871	1.742
	[-1.470, 2.620]	[-2.240, 1.675]	[-0.779, 1.280]	[-8.648, -3.296]	[4.947, 9.993]	[0.050, 3.224]
RgU	5.901	-4.534	2.479	6.641	-4.534	7.537
	[2.585, 8.455]	[-7.301, -1.014]	[0.509, 4.440]	[2.898, 9.782]	[-7.301, -1.014]	[5.028, 9.904]
FRgU	2.507	-1.394	1.229	3.352	-1.431	3.476
	[1.108, 3.691]	[-2.823, 0.107]	[0.405, 2.062]	[1.226, 5.381]	[-3.274, 0.608]	[1.966, 4.685]
TrdU	-0.194	0.442	0.149	-1.842	1.436	0.746
	[-2.145, 1.416]	[-1.389, 2.395]	[-0.707, 1.125]	[-4.184, 0.579]	[-1.189, 4.024]	[-0.518, 2.116]
CrsU	-0.999	1.437	0.337	-0.999	2.018	1.182
	[-1.345, -0.632]	[1.004, 1.954]	[0.023, 0.711]	[-1.345, -0.632]	[1.227, 2.775]	[0.692, 1.673]

Table A7. Housing Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the housing bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Respons	e		Maximum Resp	oonse	
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	1.944	-2.053	-0.184	3.028	-3.366	-0.446
	[0.665, 3.025]	[-3.108, -0.822]	[-0.471, 0.087]	[1.453, 4.412]	[-4.810, -1.751]	[-0.817, -0.035]
MntU	0.722	-0.770	-0.032	1.760	-1.709	0.191
	[0.355, 1.112]	[-1.122, -0.439]	[-0.210, 0.115]	[1.092, 2.515]	[-2.405, -1.052]	[-0.026, 0.410]
FscU	1.225	-1.180	-0.007	2.009	-2.043	0.266
	[0.550, 1.891]	[-1.847, -0.493]	[-0.216, 0.191]	[1.018, 2.918]	[-3.020, -1.099]	[0.012, 0.528]
TxU	1.385	-1.291	0.029	2.186	-2.184	0.300
	[0.636, 2.087]	[-1.986, -0.573]	[-0.202, 0.243]	[1.159, 3.044]	[-3.155, -1.218]	[0.034, 0.563]
GvSU	0.717	-0.737	-0.026	0.957	-1.018	0.158
	[0.290, 1.136]	[-1.125, -0.343]	[-0.148, 0.094]	[0.347, 1.630]	[-1.681, -0.456]	[-0.005, 0.349]
HltU	1.186	-1.093	-0.002	1.636	-1.795	-0.265
	[0.559, 1.761]	[-1.644, -0.470]	[-0.156, 0.156]	[0.821, 2.325]	[-2.529, -0.940]	[-0.483, -0.044]
NScU	0.658	-0.761	-0.110	1.795	-1.689	0.130
	[0.188, 1.102]	[-1.145, -0.339]	[-0.331, 0.098]	[0.863, 2.541]	[-2.452, -0.832]	[-0.134, 0.383]
EntU	0.744	-0.753	-0.071	1.275	-1.235	0.281
	[0.120, 1.299]	[-1.277, -0.145]	[-0.198, 0.055]	[0.496, 2.007]	[-1.949, -0.377]	[0.096, 0.463]
RgU	1.527	-1.724	-0.239	2.530	-2.741	-0.290
	[0.533, 2.335]	[-2.461, -0.789]	[-0.474, -0.001]	[1.311, 3.549]	[-3.905, -1.412]	[-0.621, 0.040]
FRgU	0.639	-0.791	-0.188	1.533	-1.663	-0.188
	[0.244, 1.013]	[-1.122, -0.415]	[-0.316, -0.068]	[0.997, 2.003]	[-2.147, -1.062]	[-0.316, -0.068]
TrdU	-0.334	0.110	-0.117	-0.444	0.110	-0.207
	[-0.687, 0.004]	[-0.231, 0.457]	[-0.242, -0.007]	[-0.935, 0.074]	[-0.231, 0.457]	[-0.395, -0.042]
CrsU	-0.200	0.097	-0.060	-0.325	0.218	0.115
	[-0.273, -0.080]	[-0.066, 0.171]	[-0.109, -0.033]	[-0.455, -0.116]	[-0.080, 0.421]	[0.045, 0.174]

Table A8. Industrial Production Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the industrial production bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Respons	e		Maximum Resp	ponse	
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	1.470	-1.718	-0.262	1.524	-1.782	-0.348
	[0.404, 2.329]	[-2.573, -0.717]	[-0.425, -0.090]	[0.793, 2.156]	[-2.433, -1.086]	[-0.524, -0.158]
MntU	0.451	-0.574	-0.113	0.606	-0.738	-0.152
	[0.201, 0.705]	[-0.833, -0.335]	[-0.214, -0.013]	[0.310, 0.921]	[-1.001, -0.457]	[-0.262, -0.029]
FscU	0.746	-0.962	-0.232	0.828	-0.962	-0.232
	[0.196, 1.244]	[-1.440, -0.417]	[-0.340, -0.118]	[0.381, 1.256]	[-1.440, -0.417]	[-0.340, -0.118]
TxU	0.813	-1.009	-0.208	0.872	-1.009	-0.208
	[0.221, 1.331]	[-1.517, -0.417]	[-0.315, -0.088]	[0.396, 1.318]	[-1.517, -0.417]	[-0.315, -0.088]
GvSU	0.356	-0.497	-0.149	0.356	-0.497	-0.159
	[0.035, 0.660]	[-0.790, -0.209]	[-0.219, -0.080]	[0.035, 0.660]	[-0.790, -0.209]	[-0.244, -0.071]
HltU	0.769	-0.839	-0.079	0.896	-0.960	-0.159
	[0.281, 1.212]	[-1.267, -0.372]	[-0.142, -0.015]	[0.536, 1.250]	[-1.303, -0.601]	[-0.252, -0.061]
NScU	0.431	-0.556	-0.116	0.701	-0.755	-0.116
	[0.156, 0.705]	[-0.839, -0.308]	[-0.235, -0.016]	[0.355, 1.068]	[-1.130, -0.387]	[-0.235, -0.016]
EntU	0.620	-0.734	-0.119	0.820	-0.812	-0.119
	[0.164, 1.050]	[-1.159, -0.278]	[-0.179, -0.049]	[0.471, 1.154]	[-1.126, -0.465]	[-0.179, -0.049]
RgU	1.180	-1.405	-0.239	1.180	-1.405	-0.296
	[0.416, 1.798]	[-2.013, -0.676]	[-0.366, -0.119]	[0.416, 1.798]	[-2.013, -0.676]	[-0.453, -0.113]
FRgU	0.496	-0.632	-0.134	0.559	-0.668	-0.182
	[0.248, 0.724]	[-0.865, -0.408]	[-0.209, -0.063]	[0.354, 0.795]	[-0.919, -0.445]	[-0.262, -0.095]
TrdU	-0.289	0.222	-0.069	0.461	-0.525	-0.069
	[-0.537, -0.026]	[-0.031, 0.473]	[-0.131, -0.011]	[0.192, 0.671]	[-0.794, -0.206]	[-0.131, -0.011]
CrsU	-0.086	0.061	-0.037	-0.140	0.113	-0.062
	[-0.126, 0.038]	[-0.048, 0.113]	[-0.054, -0.017]	[-0.202, -0.015]	[-0.025, 0.188]	[-0.094, -0.029]

Table A9. Real Personal Cons Expenditures Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the real personal consumption expenditure bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Respon	se		Maximum Resp	ponse	
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	0.888	-0.987	0.161	0.888	-2.001	-0.401
	[0.293, 1.595]	[-1.626, -0.396]	[-0.209, 0.509]	[0.293, 1.595]	[-2.929, -1.100]	[-0.936, 0.108]
MntU	0.356	-0.433	0.126	-0.709	-0.433	0.126
	[-0.043, 0.748]	[-0.789, -0.084]	[-0.120, 0.348]	[-1.194, -0.314]	[-0.789, -0.084]	[-0.120, 0.348]
FscU	0.726	-1.207	-0.237	0.836	-1.744	-0.237
	[0.277, 1.238]	[-1.637, -0.809]	[-0.491, 0.052]	[0.237, 1.352]	[-2.368, -1.068]	[-0.491, 0.052]
TxU	0.612	-1.072	-0.182	0.775	-1.624	-0.182
	[0.166, 1.142]	[-1.526, -0.672]	[-0.432, 0.099]	[0.210, 1.252]	[-2.259, -0.956]	[-0.432, 0.099]
GvSU	0.565	-0.954	-0.280	0.603	-1.348	-0.418
	[0.235, 0.924]	[-1.265, -0.678]	[-0.433, -0.103]	[0.236, 0.948]	[-1.733, -0.819]	[-0.694, -0.161]
HltU	0.542	-1.081	-0.413	1.023	-1.126	-0.413
	[0.148, 0.961]	[-1.423, -0.764]	[-0.649, -0.160]	[0.574, 1.389]	[-1.625, -0.521]	[-0.649, -0.160]
NScU	0.396	-0.257	0.389	-0.453	-0.378	0.389
	[-0.021, 0.816]	[-0.715, 0.126]	[0.080, 0.669]	[-1.014, -0.009]	[-0.983, 0.208]	[0.080, 0.669]
EntU	0.586	-0.931	-0.279	0.836	-1.032	-0.279
	[0.254, 0.942]	[-1.246, -0.628]	[-0.459, -0.077]	[0.386, 1.226]	[-1.489, -0.527]	[-0.459, -0.077]
RgU	-0.071	-0.488	-0.391	1.357	-1.615	-0.391
	[-0.662, 0.520]	[-1.038, 0.025]	[-0.740, -0.040]	[0.661, 1.941]	[-2.300, -0.762]	[-0.740, -0.040]
FRgU	-0.051	-0.154	-0.048	-0.294	-0.335	0.289
	[-0.342, 0.233]	[-0.389, 0.100]	[-0.233, 0.126]	[-0.659, 0.052]	[-0.715, 0.121]	[0.039, 0.482]
TrdU	-0.067	0.299	0.165	-0.322	0.300	-0.196
	[-0.385, 0.225]	[0.037, 0.578]	[-0.053, 0.362]	[-0.724, 0.040]	[-0.034, 0.630]	[-0.467, 0.066]
CrsU	0.094	-0.163	-0.088	0.368	-0.293	-0.088
	[-0.038, 0.173]	[-0.294, -0.076]	[-0.243, -0.033]	[0.177, 0.511]	[-0.468, -0.113]	[-0.243, -0.033]

Table A10. Real Fed Gov't Cons and Invt Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the real federal government consumption and investment bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Response			Maximum Response		
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	2.698	-2.306	0.175	3.989	-4.536	-0.949
	[1.918, 3.435]	[-2.946, -1.542]	[-0.225, 0.654]	[2.569, 5.365]	[-5.963, -3.046]	[-1.923, 0.040]
MntU	1.354	-1.011	0.192	2.910	-2.693	0.192
	[0.998, 1.735]	[-1.399, -0.692]	[-0.076, 0.461]	[2.079, 3.763]	[-3.709, -1.722]	[-0.076, 0.461]
FscU	1.679	-1.340	0.191	2.550	-2.556	-0.219
	[1.110, 2.246]	[-1.847, -0.786]	[-0.159, 0.590]	[1.545, 3.522]	[-3.590, -1.408]	[-0.938, 0.492]
TxU	1.884	-1.510	0.226	2.789	-2.767	0.226
	[1.310, 2.429]	[-2.014, -0.910]	[-0.159, 0.676]	[1.714, 3.734]	[-3.982, -1.396]	[-0.159, 0.676]
GvSU	0.889	-0.627	0.159	1.154	-1.147	0.159
	[0.508, 1.285]	[-1.027, -0.259]	[-0.045, 0.372]	[0.575, 1.849]	[-1.995, -0.458]	[-0.045, 0.372]
HltU	1.189	-0.953	0.077	1.419	-1.428	0.502
	[0.593, 1.680]	[-1.449, -0.436]	[-0.198, 0.338]	[0.596, 2.201]	[-2.218, -0.594]	[-0.052, 1.027]
NScU	1.409	-0.914	0.319	2.819	-2.800	0.319
	[0.863, 2.039]	[-1.430, -0.447]	[-0.080, 0.691]	[1.802, 3.792]	[-3.857, -1.513]	[-0.080, 0.691]
EntU	0.823	-0.636	0.076	1.201	-0.997	0.697
	[0.310, 1.279]	[-1.073, -0.176]	[-0.176, 0.328]	[0.484, 1.909]	[-1.676, -0.266]	[0.120, 1.188]
RgU	1.241	-1.393	-0.362	2.368	-2.950	-0.729
	[0.494, 1.936]	[-2.016, -0.683]	[-0.775, 0.102]	[1.172, 3.591]	[-4.425, -1.196]	[-1.548, 0.196]
FRgU	0.608	-0.853	-0.407	1.602	-2.397	-0.864
	[0.263, 0.947]	[-1.166, -0.574]	[-0.613, -0.195]	[0.855, 2.136]	[-3.073, -1.426]	[-1.260, -0.449]
TrdU	0.247	-0.064	0.306	0.247	-0.264	0.322
	[-0.131, 0.611]	[-0.402, 0.270]	[0.111, 0.514]	[-0.131, 0.611]	[-1.166, 0.763]	[0.012, 0.676]
CrsU	-0.048	-0.093	-0.039	-0.221	0.254	0.308
	[-0.134, 0.103]	[-0.277, -0.017]	[-0.109, 0.023]	[-0.399, 0.026]	[-0.145, 0.589]	[0.109, 0.455]

Table A11. Real Non-residential Fixed Invt Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the real non-residential fixed investment bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Response			Maximum Response		
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	2.181	-2.018	-0.100	-5.291	10.344	3.318
	[0.470, 3.774]	[-3.454, -0.315]	[-0.846, 0.660]	[-7.559, -2.033]	[5.989, 13.563]	$[1.778, \! 4.663]$
MntU	0.840	-0.901	-0.150	1.060	2.531	0.798
	[0.162, 1.560]	[-1.546, -0.233]	[-0.558, 0.246]	[-0.132, 2.215]	[0.367, 4.129]	[-0.041, 1.698]
FscU	1.373	-1.181	0.061	-3.411	6.785	2.681
	[0.285, 2.427]	[-2.071, -0.214]	[-0.504, 0.608]	[-5.357, -1.007]	[3.908, 9.010]	[1.580, 3.728]
TxU	1.527	-1.285	0.101	-3.419	6.766	2.689
	[0.402, 2.563]	[-2.240, -0.303]	[-0.484, 0.654]	[-5.542, -1.025]	[3.772, 9.018]	[1.531, 3.705]
GvSU	1.042	-0.881	0.085	-1.820	3.966	1.725
	[0.413, 1.643]	[-1.413, -0.330]	[-0.240, 0.397]	[-2.944, -0.233]	[2.070, 5.206]	[1.001, 2.404]
HltU	1.409	-1.330	0.076	-2.390	4.562	1.899
	[0.560, 2.165]	[-2.124, -0.462]	[-0.335, 0.533]	[-4.001, -0.474]	[2.253, 6.474]	[1.064, 2.668]
NScU	0.962	-0.792	0.125	-2.411	3.510	0.810
	[0.179, 1.868]	[-1.587, -0.150]	[-0.346, 0.583]	[-4.158, -0.136]	[0.932, 5.595]	[-0.211, 1.776]
EntU	0.707	-0.584	0.086	-4.779	7.323	1.984
	[-0.199, 1.559]	[-1.373, 0.255]	[-0.248, 0.400]	[-6.285, -2.868]	[5.019, 9.044]	[1.244, 2.679]
RgU	2.409	-1.795	0.349	3.187	6.181	2.960
	[1.127, 3.616]	[-2.890, -0.618]	[-0.237, 0.953]	[1.352, 4.773]	[2.967, 8.940]	[1.682, 4.035]
FRgU	0.422	-0.431	-0.223	0.635	2.060	1.098
	[-0.173, 0.980]	[-0.939, 0.111]	[-0.490, 0.084]	[-0.345, 1.581]	[0.407, 3.482]	[0.433, 1.687]
TrdU	0.322	-0.291	0.097	-0.860	0.816	0.482
	[-0.277, 1.025]	[-0.904, 0.238]	[-0.159, 0.395]	[-2.257, 0.614]	[-1.100, 2.679]	[0.063, 0.949]
CrsU	-0.282	0.310	0.079	-0.561	0.781	0.617
	[-0.526, -0.099]	[0.122, 0.548]	[-0.008, 0.189]	[-0.960, -0.224]	[0.186, 1.391]	[0.350, 0.884]

Table A12. Real Residential Fixed Investment Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the real residential fixed investment bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Response			Maximum Response		
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	0.426	-0.511	-0.095	1.432	-2.002	-0.532
	[0.084, 0.703]	[-0.805, -0.211]	[-0.195, -0.002]	[0.911, 1.868]	[-2.473, -1.369]	[-0.678, -0.325]
MntU	0.205	-0.257	-0.014	0.583	-0.811	-0.123
	[0.054, 0.354]	[-0.415, -0.103]	[-0.078, 0.044]	[0.295, 0.861]	[-1.112, -0.473]	[-0.212, -0.020]
FscU	0.308	-0.370	-0.107	0.966	-1.337	-0.424
	[0.095, 0.510]	[-0.572, -0.172]	[-0.187, -0.033]	[0.604, 1.287]	[-1.688, -0.907]	[-0.537, -0.280]
TxU	0.346	-0.422	-0.124	1.015	-1.408	-0.457
	[0.138, 0.557]	[-0.631, -0.226]	[-0.199, -0.048]	[0.649, 1.349]	[-1.750, -0.960]	[-0.573, -0.299]
GvSU	0.130	-0.175	-0.063	0.456	-0.670	-0.225
	[-0.006, 0.249]	[-0.296, -0.046]	[-0.112, -0.024]	[0.186, 0.676]	[-0.906, -0.348]	[-0.303, -0.124]
HltU	0.339	-0.402	-0.087	1.082	-1.360	-0.352
	[0.162, 0.497]	[-0.562, -0.227]	[-0.143, -0.040]	[0.826, 1.327]	[-1.627, -1.042]	[-0.441, -0.238]
NScU	-0.042	-0.113	-0.145	0.684	-1.098	-0.324
	[-0.228, 0.143]	[-0.322, 0.067]	[-0.220, -0.076]	[0.283, 1.025]	[-1.442, -0.624]	[-0.444, -0.165]
EntU	0.291	-0.380	-0.115	0.764	-0.961	-0.270
	[0.122, 0.431]	[-0.530, -0.224]	[-0.170, -0.068]	[0.480, 1.000]	[-1.221, -0.631]	[-0.356, -0.169]
RgU	0.431	-0.522	-0.109	1.687	-2.153	-0.496
	[0.179, 0.662]	[-0.754, -0.266]	[-0.186, -0.024]	[1.247, 2.047]	[-2.559, -1.630]	[-0.627, -0.303]
FRgU	0.198	-0.225	-0.029	0.727	-1.044	-0.301
	[0.090, 0.310]	[-0.331, -0.121]	[-0.081, 0.019]	[0.466, 0.925]	[-1.273, -0.720]	[-0.367, -0.191]
TrdU	0.012	0.004	0.029	0.157	-0.186	0.045
	[-0.097, 0.146]	[-0.125, 0.114]	[-0.010, 0.077]	[-0.076, 0.402]	[-0.495, 0.114]	[-0.043, 0.151]
CrsU	-0.063	0.106	0.035	-0.114	0.138	0.035
	[-0.096, 0.056]	[-0.020, 0.142]	[0.019, 0.048]	[-0.172, 0.018]	[-0.012, 0.195]	[0.019, 0.048]

Table A13. Real State and Local Gov't Cons and Invt Responses: Initian and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the real state and local government consumption bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Response			Maximum Response		
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	0.368	-0.322	-0.114	0.854	-0.905	-0.259
	[0.205, 0.527]	[-0.461, -0.202]	[-0.242, -0.007]	[0.549, 1.194]	[-1.220, -0.599]	[-0.405, -0.096]
MntU	0.270	-0.231	-0.008	0.649	-0.705	-0.132
	[0.166, 0.368]	[-0.321, -0.153]	[-0.083, 0.059]	[0.460, 0.832]	[-0.903, -0.499]	[-0.231, -0.021]
FscU	0.278	-0.190	-0.054	0.557	-0.478	-0.103
	[0.154, 0.415]	[-0.304, -0.096]	[-0.150, 0.026]	[0.331, 0.797]	[-0.727, -0.260]	[-0.211, 0.016]
TxU	0.325	-0.215	-0.041	0.615	-0.505	-0.091
	[0.188, 0.475]	[-0.342, -0.117]	[-0.138, 0.042]	[0.380, 0.873]	[-0.752, -0.267]	[-0.215, 0.025]
GvSU	0.125	-0.085	-0.043	0.277	-0.245	-0.095
	[0.039, 0.221]	[-0.165, -0.023]	[-0.109, 0.013]	[0.158, 0.427]	[-0.414, -0.107]	[-0.161, -0.015]
HltU	0.187	-0.019	0.060	0.307	0.248	0.101
	[0.081, 0.292]	[-0.117, 0.071]	[-0.041, 0.148]	[0.159, 0.465]	[0.064, 0.409]	[0.034, 0.174]
NScU	0.236	-0.152	0.007	0.566	-0.567	-0.094
	[0.108, 0.356]	[-0.266, -0.040]	[-0.098, 0.095]	[0.372, 0.762]	[-0.820, -0.316]	[-0.212, 0.020]
EntU	0.130	-0.064	-0.022	0.276	-0.199	-0.051
	[0.023, 0.229]	[-0.154, 0.005]	[-0.100, 0.049]	[0.136, 0.431]	[-0.354, -0.068]	[-0.139, 0.043]
RgU	0.110	-0.152	-0.191	0.545	-0.499	-0.191
	[-0.027, 0.253]	[-0.267, -0.038]	[-0.299, -0.089]	[0.291, 0.795]	[-0.831, -0.167]	[-0.299, -0.089]
FRgU	0.042	-0.028	-0.082	0.347	-0.320	-0.082
	[-0.027, 0.112]	[-0.093, 0.028]	[-0.135, -0.038]	[0.217, 0.482]	[-0.500, -0.116]	[-0.135, -0.038]
TrdU	0.006	-0.066	-0.022	-0.029	-0.108	-0.042
	[-0.087, 0.090]	[-0.136, -0.001]	[-0.095, 0.041]	[-0.186, 0.154]	[-0.236, 0.008]	[-0.139, 0.040]
CrsU	-0.046	0.005	-0.027	-0.072	0.071	0.042
	[-0.066, 0.017]	[-0.104, 0.031]	[-0.049, -0.015]	[-0.113, 0.007]	[-0.056, 0.134]	[0.017, 0.067]

Table A14. 3-month Treasury Bill Rate Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the 3-month treasury bill rate bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.

Shock	Initial Response			Maximum Response		
	Bias	Data	Forecast	Bias	Data	Forecast
EPU	0.001	-0.001	0.000	0.001	-0.001	0.000
	[-0.001, 0.002]	[-0.002, 0.000]	[-0.001, 0.001]	[-0.001, 0.002]	[-0.002, 0.000]	[-0.001, 0.001]
MntU	0.000	0.000	0.000	-0.001	0.001	0.000
	[0.000, 0.001]	[-0.001, 0.000]	[0.000, 0.000]	[-0.002, 0.000]	[0.000, 0.002]	[0.000, 0.000]
FscU	0.000	-0.001	0.000	0.000	-0.001	0.000
	[-0.001, 0.001]	[-0.001, 0.000]	[-0.001, 0.000]	[-0.001, 0.001]	[-0.001, 0.000]	[0.000, 0.001]
TxU	0.000	-0.001	0.000	0.000	-0.001	0.000
	[0.000, 0.001]	[-0.002, 0.000]	[-0.001, 0.000]	[0.000, 0.001]	[-0.002, 0.000]	[-0.001, 0.000]
GvSU	0.000	0.000	0.000	0.000	0.001	0.000
	[-0.001, 0.000]	[-0.001, 0.000]	[0.000, 0.000]	[-0.001, 0.000]	[0.000, 0.001]	[0.000, 0.001]
HltU	0.000	0.000	0.000	0.000	-0.001	-0.001
	[-0.001, 0.000]	[-0.001, 0.000]	[-0.001, 0.000]	[-0.001, 0.000]	[-0.002, 0.000]	[-0.001, 0.000]
NScU	0.000	-0.001	0.000	0.000	-0.001	-0.001
	[0.000, 0.001]	[-0.001, 0.000]	[-0.001, 0.000]	[-0.001, 0.000]	[-0.001, 0.000]	[-0.001, 0.000]
EntU	0.000	-0.001	0.000	0.001	-0.002	-0.001
	[0.000, 0.001]	[-0.001, 0.000]	[0.000, 0.000]	[0.000, 0.002]	[-0.003, -0.001]	[-0.001, 0.000]
RgU	0.001	-0.001	0.000	0.001	-0.001	-0.001
	[0.000, 0.001]	[-0.002, 0.000]	[0.000, 0.001]	[0.000, 0.001]	[-0.002, 0.000]	[-0.001, 0.000]
FRgU	0.000	0.000	0.000	-0.001	0.001	0.000
	[0.000, 0.001]	[-0.001, 0.000]	[0.000, 0.000]	[-0.001, 0.000]	[0.000, 0.001]	[0.000, 0.000]
TrdU	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.001]	[0.000, 0.000]	[-0.001, 0.000]	[0.000, 0.001]	[-0.001, 0.000]
CrsU	0.000	0.000	0.000	0.001	-0.001	0.000
	[0.000, 0.001]	[-0.001, 0.000]	[0.000, 0.000]	[0.001, 0.001]	[-0.001, 0.000]	[0.000, 0.001]

Table A15. Share of Real Net Exports of RGDP Responses: Initial and Maximum

Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t \ z_t^x]'$ to a 1 standard deviation economic policy uncertainty shock. This table reports the initial and maximum response of IRF estimate of the share of real net exports of real GDP bias, data and forecast, respectively, along with its one standard deviation confidence band that were obtained from 500 bootstrap simulations with empirical distributions.



Figure A1. Forecast Bias in the SPF: Long-horizon

Note: Long-run SPF bias. It denotes the 5-quarter ahead growth rate (long-differencing) of the variables, that is, the realized data subtract from corresponding SPF forecast.



Figure A2. Forecast Bias in the SPF: Short-horizon

Note: Short-run SPF bias. It denotes the 2-quarter ahead growth rate (long-differencing) of the variables, that is, the realized data subtract from corresponding SPF forecast.



Figure A3. Dynamic of RGDP to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the real GDP bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A4. Dynamic of Urate to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Unemployment rate bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A5. Dynamic of Corporate Profits to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Corporate Profits bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A6. Dynamic of Housing Starts to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Housing Starts bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A7. Dynamic of Industrial Production to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Industrial Production bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A8. Dynamic of NGDP to Policy Uncertainty Shocks


Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the NGDP bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A9. Dynamic of Inflation rate to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Inflation rate bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A10. Dynamic of Real Personal Cons Expenditures to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Real Personal Cons Expenditures bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.





Years

FRgU~FedE Bias

MntU~FedE Bias









Years

TxU~FedE Data

10

TxU~FedE Bias

1.5

0.

-0.5-

-1+

0

-0.1-

0.57

-0.5

-1.5+ 0

-0.3

10

10







Years



Years

















0.9-

0.6-

0.3-

0

-0.3

-0.6

-0.9

-1.2-

0.4

0.2-

0

-0.2-

-0.4

-0.6

-0.8-



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Real Federal Government Consumption and Investment bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A12. Dynamic of Real Non-residential Fixed Invt to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Real Non-residential Fixed Investment bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A13. Dynamic of Real Residential Fixed Investment to Policy Uncertainty Shocks

10

10

10

10

10

8 10

8

-4

- 6

2.

-2

10-



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Real Residential Fixed Investment bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A14. Dynamic of Real State and Local Govt Cons and Invt to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the Real State and Local Government Consumption and Investment bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A15. Dynamic of 3-month Treasury Bill Rate to Policy Uncertainty Shocks



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the 3-month Treasury Bill bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.



Figure A16. Dynamic of share of Real Net Exports of RGDP to Policy Uncertainty Shocks

Years

Years

Years

Years

Years

Years

10

10

10

0.002

0.0015

0.001

0.0005

-0.0005

-0.001 -0.0015-

0.0008

0.0004

-0.0004

-0.0008-

0.0015

0.001

0.0005

-0.0005

-0.001

-0.0015--0.002-

0.001

0.0005

-0.0005

-0.001

-0.0015

-0.002

-0.0025-

0.0015

0.001

0.0005

-<mark>0.</mark>0005

-0.001

0.0006

-0.0006

-0.0012

-0.0018

-0.0024



Note: Impulse-response function (IRF) estimates from $y_t = [EPU_t z_t^x]'$ to a 1 standard deviation policy uncertainty shock. Top three rows report the IRF estimate (solid) of the share of Real Net Exports of RGDP bias along with its one standard deviation confidence band (dashed) that were obtained from 500 bootstrap simulations with empirical distributions. Middle three rows show data dynamic responses and bottom three rows display forecast dynamics to the different policy uncertainty shocks.