Uncertainty and Macro Expectation

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Abstract

This letter examines how uncertainty affects information rigidity in the formation of macroeconomic expectations. Matching data from the Survey of Professional Forecasters (SPF) alongside various uncertainty metrics, we find that heightened uncertainty diminishes information rigidity. This reduction occurs because agents allocate more resources to interpreting aggregate shocks rather than idiosyncratic ones, which lessens their underreaction to aggregate information.

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1 Introduction

Information and rationality critically shape macroeconomic expectations and influence forecast adjustments. Under the Full Information Rational Expectation (FIRE) hypothesis, forecast errors are expected to be unpredictable, yet deviations from FIRE have been extensively debated. Coibion and Gorodnichenko (2015) offer a framework to assess forecast rationality, revealing information rigidity in consensus forecasts of macroeconomic indicators. Bordalo, Gennaioli, Ma, and Shleifer (2020) further elucidate macroeconomic expectations by exploring individual overreactions and consensus underreactions, integrating these observations within a dispersed information learning model that employs diagnostic expectations. Kucinskas and Peters (2022) advances this area of study by introducing a novel framework to assess under- and overreaction in expectation formation. His analysis reveals that forecasts typically underreact to aggregate shocks and overreact to idiosyncratic ones. Importantly, he demonstrates that the individual-level overreaction is predominantly driven by an excessive emphasis on idiosyncratic shocks, which contribute to over 80% of the effect, while a corresponding underreaction to aggregate shocks, weighted less than 20%, similarly distorts the forecasts.

This letter primarily investigates the impact of uncertainty on information rigidity in expectation formation. Existing theoretical models, such as those discussed by (Gorodnichenko, 2008), suggest that increased uncertainty about aggregate shocks prompts economic agents to allocate more resources to understanding the current macroeconomic environment. In other words, as the uncertainty in the economic environment increases, the cost of underreacting to aggregate shocks rises. This compels agents to dedicate more resources to understanding current macroeconomic conditions, resulting in a more responsive approach to aggregate information and a reduction in information rigidity. The empirical results of this paper substantiate the hypothesis that uncertainty mitigates information rigidity through two key observations: First, we provide direct evidence that uncertainty weakens information rigidity. Building on the framework of Kucinskas and Peters (2022), we distinguish information shocks into aggregate shocks and idiosyncratic shocks, and study the impact of uncertainty on individuals' expectation formation for each type. Our findings reveal a significant reduction in underreaction to aggregate shocks with increased uncertainty, whereas overreaction to idiosyncratic shocks remains relatively unchanged. Second, our empirical results corroborate the mechanism suggested by Gorodnichenko (2008). Specifically, the observed reduction in information rigidity is attributed to agents reallocating more resources towards understanding aggregate shocks instead of idiosyncratic shocks under conditions of heightened uncertainty.

This letter distinguishes itself from other studies on time-varying or state-dependent factors by focusing on how uncertainty specifically influences information rigidity and its mechanisms. For example, Minami (2024) examines how representativeness strength varies in time using a diagnostic expectations framework premised on irrational expectations. While these findings correspond with our observations regarding the idiosyncratic components, our analysis prioritizes the aggregate component to examine information rigidity rather than representativeness. Furthermore, An, Liu, and Wu (2021) document a significant decline in information rigidity following pandemic events. Our study confirms this trend using tailored uncertainty measures, but more importantly, we provide evidence that amidst heightened uncertainty, agents allocate significantly more weight to processing information from aggregate shocks.

2 Empirical Results

2.1 Data and Measure

We collected forecast data from the Survey of Professional Forecasters (SPF), managed by the Federal Reserve Bank of Philadelphia. The SPF assembles quarterly forecasts on a range of macroeconomic variables from professional forecasters. Our analysis focuses on a one-year-ahead forecast horizon. Diverges from studies that examine a single variable, we select five representative macroeconomic indicators: real GDP, nominal GDP, the unemployment rate (covering the period from 1968Q4 to 2023Q4), real nonresidential investment, and real residential investment (from 1981Q3 to 2023Q4). [1] Data on actual macroeconomic outcomes are obtained from the Philadelphia Fed's Real-Time Data Set for Macroeconomists. This dataset provides real-time observations of various economic indicators, allowing accurate comparisons between forecasted values and actual outcomes. [2] We employ several distinct indices to measure uncertainty. The first three indices, developed by Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021), capture financial, macro, and real uncertainty, respectively. The second, the Economic Policy Uncertainty (EPU)

[1]The SPF database is taken from https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters.

[2]The actual outcomes are taken from https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/real-time-data-set-for-macroeconomists.

index by Baker, Bloom, and Davis (2016), is derived from text analysis. Data for all indices are sourced from the authors' publicly available repositories. [3]

Next, to assess the impact of uncertainty on expectation formation, we adopt the framework established by Kucinskas and Peters (2022) and perform the following three CG-type regressions: [4]

$$\begin{aligned} e_{t+1} &= \alpha + \beta_{consensus} \cdot r_t + u_t \\ e_{i,t+1} &= \alpha + \beta_{individual} \cdot r_{i,t} + u_{i,t} \\ e_{i,t+1} - e_{t+1} &= \alpha + \beta_{idiosyncratic} \cdot \left(r_{i,t} - r_t\right) + u_{i,t} \end{aligned} \tag{1}$$

where $e_{i,t+1} = x_{t+1} - \mathbb{F}_{i,t}[x_{t+1}]$ denotes individual forecast error, and $r_{i,t} = \mathbb{F}_{i,t}[x_{t+1}] - \mathbb{F}_{i,t-1}[x_{t+1}]$ stands for individual forecast revisions. Consequently, e_{t+1} and r_t denote forecast error and revisions at the consensus level, respectively.

The first regression estimates information rigidity using consensus-level forecasts, where a positive $\beta_{consensus}$ indicates underreaction at the consensus level due to information rigidity. The second regression applies the same approach to individual-level forecasts, with a negative $\beta_{individual}$ suggesting overreaction at the individual level. The third regression further decomposes $\beta_{individual}$ into its aggregate and idiosyncratic components; here, a negative $\beta_{idiosyncratic}$ stems from overreaction to idiosyncratic shocks.

According to the method proposed by Kucinskas and Peters (2022), the weights assigned to aggregate and idiosyncratic shocks can be determined from the coefficients of three CG-type regressions: [5]

$$weight = \frac{\beta_{individual} - \beta_{consensus}}{\beta_{idiosyncratic} - \beta_{consensus}} \tag{2}$$

where *weight* implies how much individual CG coefficient puts on idiosyncratic shocks.

2.2 Impact of uncertainty on information rigidity

This letter focuses on how uncertainty affects information rigidity. Figure 1 shows the estimated coefficients from three different CG regressions for samples before and after the

[3] Financial, macro, and real uncertainty can be obtained from https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes, and the Economic Policy Uncertainty (EPU) index is from http://www.policyuncertainty.com/categorical_epu.html.

[4] This approach was first proposed by Coibion and Gorodnichenko (2015) and has since been widely used to quantify the length of information rigidity in the literature.

[5] The *weight* can be easily obtained by solving $\beta_{individual} = (1 - weight) \cdot \beta_{consensus} + weight \cdot \beta_{idiosyncratic}$.

year 2000, highlighting the changes in weights assigned to idiosyncratic shocks. Before 2000, our estimates align with previous studies, showing that individual forecasters tend to overreact to news, while consensus forecasters underreact (Bordalo, Gennaioli, Ma, and Shleifer, 2020). Furthermore, forecasters underreact to aggregate shocks but overreact to idiosyncratic shocks (Kucinskas and Peters, 2022). Across all variables, $\beta_{consensus}$ exhibits a significant decline, indicating a reduced underreaction to aggregate shocks, which suggests an alleviation of information rigidity. Although $\beta_{idiosyncratic}$ also declines, this decrease is considerably less pronounced. Notably, the significant reduction in the weights assigned to idiosyncratic shocks indicates a strategic shift in agents' resource allocation, with a decreased focus on idiosyncratic shocks and an increased emphasis on aggregate shocks.

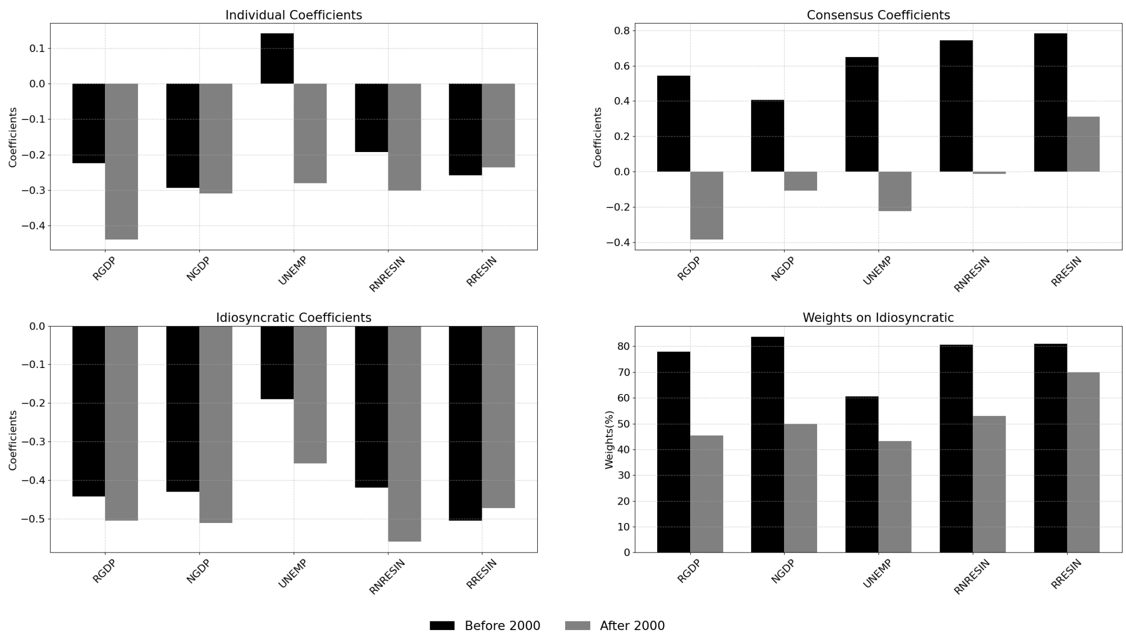

Figure 1. Coefficients and Weights Change Before and After 2000

For a more formal test, we incorporate measures of uncertainty, obtained through various methodologies, along with their interaction terms with forecast revisions, into the three types of CG regressions previously mentioned:

$$\begin{aligned}
e_{t+1} &= \alpha + \beta_1 r_t + \beta_2 Unc_t + \beta_3 r_t \times Unc_t + u_t \\
e_{i,t+1} &= \alpha + \beta_1 r_{i,t} + \beta_2 Unc_t + \beta_3 r_{i,t} \times Unc_t + u_{i,t} \\
e_{i,t+1} - e_{t+1} &= \alpha + \beta_1 \left(r_{i,t} - r_t\right) + \beta_2 Unc_t + \beta_3 \left(r_{i,t} - r_t\right) \times Unc_t + u_{i,t}
\end{aligned} \tag{3}$$

Table 1. Coefficients for the Interaction between Uncertainty and Revisions

Individual Level	financial	macro	real	policy
Real GDP	-1.979***	-1.789***	-2.112***	-0.208***
	(0.629)	(0.297)	(0.308)	(0.022)
Nominal GDP	-2.084***	-0.814***	-0.451	-0.138***
	(0.572)	(0.256)	(0.275)	(0.028)
Unemployment Rate	-4.583***	-3.278***	-3.749***	-0.352***
	(0.582)	(0.260)	(0.188)	(0.019)
Real Nonresidential Investment	-0.988	-2.716***	-3.622***	-0.303***
	(0.842)	(0.475)	(0.363)	(0.023)
Real Residential Investment	-1.417	-2.104***	-3.926***	-0.290***
	(0.879)	(0.643)	(0.558)	(0.034)
Consensus Level	**financial**	**macro**	**real**	**policy**
Real GDP	-7.257*	-5.375***	-5.621***	-0.456***
	(4.166)	(1.771)	(1.700)	(0.161)
Nominal GDP	-10.753***	-3.838**	-3.805**	-0.594***
	(3.961)	(1.809)	(1.667)	(0.158)
Unemployment Rate	-7.675**	-5.289***	-6.127***	-0.567***
	(3.655)	(1.570)	(1.413)	(0.145)
Real Nonresidential Investment	-6.087	-7.520***	-8.312***	-0.751***
	(5.650)	(2.483)	(2.234)	(0.172)
Real Residential Investment	-7.783	-7.333**	-11.014***	-0.909***
	(5.619)	(3.299)	(2.699)	(0.230)
Idiosyncratic Level	**financial**	**macro**	**real**	**policy**
Real GDP	-0.886	-0.417	-0.634	-0.082*
	(0.846)	(0.467)	(0.620)	(0.049)
Nominal GDP	-0.968	-0.369	-0.465	-0.043
	(0.803)	(0.416)	(0.494)	(0.039)
Unemployment Rate	-3.446***	-1.965***	-1.941***	-0.223***
	(1.189)	(0.733)	(0.574)	(0.052)
Real Nonresidential Investment	-1.536	-0.424	-0.784	-0.096*
	(1.036)	(0.912)	(0.866)	(0.055)
Real Residential Investment	-0.295	-0.425	-0.535	-0.066
	(1.007)	(0.828)	(1.099)	(0.061)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For consensus time series regressions, standard errors are calculated using the Newey-West method with an automatic bandwidth selection procedure as described by Newey and West (1994). For individual-level panel regressions, standard errors are clustered by both individual and time.

where the interaction term captures the nonlinear and uncertainty-dependent information rigidity. A significantly negative β_3 indicates that as uncertainty increases, the tendency for underreaction reduces and for overreaction amplifies.

Table 2. Time Series Regressions of *weight* and Δ*weight* on Uncertainty.

weight	financial	macro	real	policy
Real GDP	-0.885**	-1.005**	-1.655***	-0.086**
	(0.442)	(0.408)	(0.460)	(0.040)
Nominal GDP	-0.629	-0.984**	-1.739***	-0.087**
	(0.449)	(0.390)	(0.401)	(0.038)
Unemployment Rate	-0.545	-0.729*	-1.326***	-0.076**
	(0.418)	(0.390)	(0.452)	(0.036)
Real Nonresidential Investment	-0.332**	-0.345***	-0.572***	-0.040***
	(0.140)	(0.116)	(0.086)	(0.011)
Real Residential Investment	-0.573**	-0.415*	-0.567**	-0.050***
	(0.224)	(0.213)	(0.255)	(0.019)
Δ*weight*	financial	macro	real	policy
Real GDP	-0.066**	-0.097***	-0.096***	-0.009**
	(0.030)	(0.027)	(0.036)	(0.004)
Nominal GDP	-0.071***	-0.124***	-0.142***	-0.017***
	(0.024)	(0.022)	(0.029)	(0.003)
Unemployment Rate	-0.065**	-0.121***	-0.093**	-0.013***
	(0.032)	(0.032)	(0.041)	(0.004)
Real Nonresidential Investment	-0.080***	-0.086***	-0.084***	-0.014***
	(0.023)	(0.023)	(0.0028)	(0.003)
Real Residential Investment	-0.027	-0.067**	-0.063*	-0.007**
	(0.039)	(0.026)	(0.038)	(0.004)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are calculated using the Newey-West method with an automatic bandwidth selection procedure as described by Newey and West (1994).

Table 1 reports the empirical results. At the consensus level, the interaction between various uncertainty measures and revisions consistently yields significantly negative coefficients across all variables. This suggests that agents more effectively update information stemming from aggregate shocks, consequently reducing information rigidity. Notably, such significant effects are absent at the idiosyncratic level, aligning with findings reported in Figure 1. At the individual level, although the interactions yield negative and significant coefficient estimates, these should not be interpreted merely as the additive result of a significantly negative consensus-level coefficient and an insignificant idiosyncratic-level coefficient. The influence of weights on idiosyncratic (or aggregate) shocks must also be considered. [6]

Our final specification investigates how uncertainty changes agents' behavior in allocating resources to information stemming from aggregate and idiosyncratic shocks. We estimate three CG-type regressions using a rolling window of 20 years to compute both the *weight* and Δ*weight*, based on the coefficients from each window. As previously discussed, *weight* reflects the proportion of resources agents allocate to processing idiosyncratic information. A decrease in *weight* suggests a shift in resource allocation towards handling aggregate information, and vice versa. Subsequently, we conduct time series regressions to analyze the relationship between *weight*, Δ*weight*, and uncertainty.

Table 2 reports the coefficients for *weight* and Δ*weight*. While some results show that financial uncertainty as an independent variable is insignificant, other coefficients are significantly negative at least at the 10% level. This supports our main conclusion: uncertainty prompts agents to increase the emphasis they place on processing information from aggregate shocks rather than idiosyncratic shocks. To ensure the robustness of our findings, we adjust the forecast horizons from one year to one to three quarters. The results remain robust across these variations.

3 Conclusion

This letter contributes to the literature by investigating the mechanisms through which uncertainty diminishes information rigidity during expectation formation. By matching survey forecasts with various uncertainty measures, we observe a notable reduction in information rigidity post-2000. Formal tests indicate that during periods of high uncertainty, agents pay more attention to information from aggregate shocks over idiosyncratic shocks, facilitating more efficient information updating and a consequent decrease in information rigidity. Our findings introduce a fresh perspective on the study of information rigidity, highlighting the significance of resource allocation decisions by forecasters. Specifically, in uncertain environments, forecasters divert resources away from processing idiosyncratic information towards a deeper understanding of prevailing macroeconomic conditions. This strategic reallocation mitigates information rigidity and underscores the critical role of understanding how uncertainty impacts the formation of expectations.

[6] $\Delta\beta_{individual} \neq \Delta\beta_{consensus} + \Delta\beta_{idiosyncratic}$ since $\Delta weight \neq 0$.

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