Journal of Forecasting

WILEY

RESEARCH ARTICLE OPEN ACCESS

Identifying Drivers of Deviations From Rational Expectations: Using a New Irrational Index for Inflation Forecasts

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Received: 11 January 2026 | **Revised:** 11 January 2026 | **Accepted:** 11 February 2026

Keywords: deviations | inflation | rational expectations | rationality test

ABSTRACT

Most studies on inflation forecasts have studied behavioral biases, informational frictions, or external shocks in isolation, without considering how these factors jointly drive deviations from rational expectations. We therefore adopt an integrated framework that simultaneously estimates the behavioral, informational, and external determinants of deviations from rationality. To measure the deviations, we develop a novel irrationality index—following Rossi and Sekhposyan's (2016) Fluctuation Rationality Test—to measure experts' time-varying deviations from rationality in US year-ahead inflation forecasts between 2010 and 2022. We then estimate the impact of different behavioral, informational, and external drivers on deviations from rationality using panel models. Our results indicate that external information shocks, interest rate expectations, as well as geopolitical risk all significantly drive the deviations from rationality. These findings highlight the value of a unified approach to expectation formation, moving beyond the isolated analyses that are common to the literature.

JEL Classification: E31, E37

1 | Introduction

Understanding how experts form expectations holds significant importance in macroeconomics due to its influence on policy decisions and market behavior. Rational expectation theory (Muth 1961) is built on the assumption that experts produce unbiased forecasts using all available information and without systematic errors. However, experts form expectations in highly unstable ways, often shifting due to behavioral biases or external factors (Maćkowiak et al. 2023). A key challenge has been explaining why deviations from rationality still persist, even when agents have full access to information.

A large body of literature has looked into behavioral reasons, informational problems, and external shocks as reasons for these deviations in rationality by experts. These studies have measured each of these deviations separately, analyzing only one aspect. For example, Kahneman and Tversky (1979) and Barberis and Thaler (2003) develop a behavioral perspective, which indicates that cognitive biases such as overconfidence, anchoring, and herding can distort forecast accuracy. Another line explains the deviations from rationality as a consequence of informational frictions. Sims' (2003) rational inattention framework argues that experts face cognitive constraints in processing huge amounts of information. Recent empirical studies, including Coibion and Gorodnichenko (2012, 2015), provide evidence of inattentive forecasting behavior and highlight that most agents' deviations are sizable and consistent with moderate attention to macroeconomic data.[1] Macroeconomic shocks and structural changes also impact forecast deviations (Ascari et al. 2023). These shocks can include cost-push disturbances such as energy price spikes (Coibion and Gorodnichenko 2015); monetary policy shocks—especially when central bank communication is ambiguous or lacks credibility (see Romer and Romer 2004; Gürkaynak et al. 2005)—or fiscal shocks (Bloom 2009). The literature also highlights the role of institutional characteristics in shaping experts' expectations. Experts are often influenced by political and organizational decisions (Sanders and Manrodt 2003). Fildes and Goodwin (2007) empirically confirm that institutional forecasts often deviate due to organizational constraints.

While these approaches highlight important mechanisms, they usually treat each channel in isolation without considering how these multiple factors may simultaneously interact to drive deviations from rational expectations. Dovern and Weisser (2011) attempt to move beyond this single-explanation approach, demonstrating that inflation forecasts systematically violate the assumptions of rational expectations. In their definition, this violation means that forecast errors are not white noise but exhibit bias, autocorrelation, and heterogeneity across the expert forecasters. By decomposing forecast errors, Dovern and Weisser (2011) demonstrate that deviations cannot be explained solely by macrolevel shocks but also stem from persistent individual-level factors. However, Dovern and Weisser's (2011) decomposition measures bias and efficiency as time-invariant parameters and estimates them separately. Their results remain static because they do not model the dynamic processes of bias or efficiency, nor do they empirically identify the specific behavioral mechanisms behind forecast deviations, or how these evolve over time or differ systematically across individuals.

Building on this literature, and using a similar dataset as Dovern and Weisser (2011), we focus on monthly year-ahead forecasts of US inflation in the period of January 2010 to April 2022 from the Consensus Economics survey to evaluate the evolution of deviations from rationality and its drivers.

Our study makes two main contributions. First, we introduce a novel Irrationality Index that aggregates how each expert deviates from the rational expectations assumptions over time. We use the Fluctuation Rationality (FR) test developed by Rossi and Sekhposyan's (2016) to construct this Irrationality index. The null hypothesis of this test is that forecast errors are rational, implying unbiasedness and no systematic pattern in the forecast errors. The FR Test applies rolling-window regressions to detect time-specific deviations in forecast rationality and compares forecast errors against realized outcomes. We compute the irrationality index as the difference between the time-varying FR test statistical test and the critical value. A negative value of the Index indicates a rejection of rational forecaster behavior, while a positive value indicates consistency with rational expectations assumptions.

The Irrationality Index for each expert allows us to then explain jointly the behavioral and informational drivers of each expert's deviations from rationality. Because we can trace how deviations differ across experts and time, we use a fixed-effects panel model to explain deviations from rationality by different drivers—behavioral reasons, informational problems, and external shocks—as explanatory variables. Using panel models allows us to move away from the traditional approach of estimating each phenomenon separately. Instead, it provides an integrated framework to identify how multiple behavioral and informational drivers interact and shape deviations from rational expectations.

Our main findings show that deviations from rational expectations are important and occur regularly across experts. However, these deviations are not random, but mostly driven by behavioral reasons, informational problems, and external shocks. For example, long-term interest rate expectations are also associated with greater deviations from rationality. This could indicate overconfidence or misjudgment in interpreting monetary policy signals. In addition, external information shocks increase deviations from rationality; experts may overreact to new data or struggle to distinguish relevant information. These results are consistent with evidence from Bordalo et al. (2020) and Afrouzi et al. (2021). Geopolitical risk is a key determinant of irrationality across all model specifications, indicating that rising global risk significantly weakens experts' forecasting rationality.

To ensure robustness of our results, we additionally conduct three complementary checks. We include a dynamic Arellano–Bond GMM panel model to account for the persistence of irrationality and address endogeneity concerns, a Common Correlated Effects Mean Group (CCEMG) estimator to control for unobserved global shocks and cross-sectional dependence across experts (Pesaran 2006), and conditional fixed-effects logit models to treat irrationality as a binary outcome. We confirm that geopolitical risk and interest rate expectations increase deviations from rationality as found in the fixed-effects specification.

The remainder of the paper is structured as follows. Section 2 describes the dataset and derives the baseline metrics to measure the deviations of rationality across experts. Section 3 first derives the Irrationality Index and then examines the drivers of irrationality. Section 4 presents the main robustness checks. Finally, Section 5 concludes.

2 | Data

We use Consensus Economics (CE) forecasts data to investigate how experts form their macroeconomic expectations. This survey provides inflation, GDP, and interest rate forecasts from a wide range of professional economists (investment firms, banks, and research organizations) across more than 100 countries (Cimadomo et al. 2016). These forecasts are then published early in the second week of the same month, reflecting real-time expert expectations under current market and policy conditions.

Unlike other surveys, experts' forecasts in CE do not suffer a bias, as often happens for official government official projections (Ottaviani and Sorensen 2006; D'Agostino and Ehrmann 2014). CE data are public, which should help to prevent the herding behavior (Trueman 1994) as experts should not show discrepancies between the survey and their private recommendation to their clients. Overall, the CE survey data broadly reflects the spectrum of expectations of market experts.[2].

We focus on monthly year-ahead US inflation forecasts between January 2010 and April 2022. Given the data availability across time, we retained only those experts who submitted forecasts in at least 70% of the months in the sample period. The final dataset

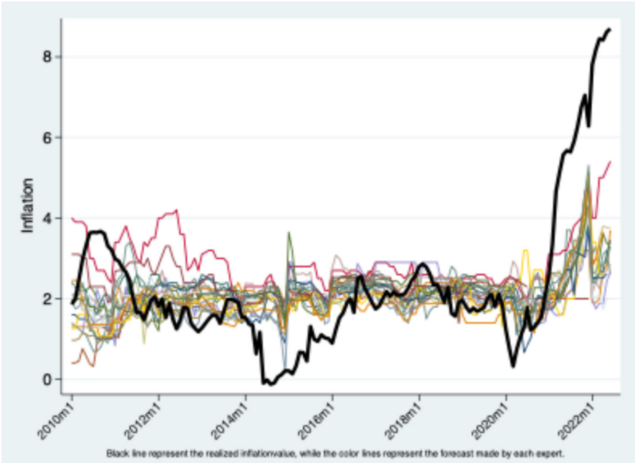


FIGURE 1 | Realized and forecast inflation.

results in a panel of 19 experts. Figure 1 shows the comparison between realized inflation and the inflation forecast 1 year-ahead made by all experts at each moment of time.

Figure 1 suggests that experts tend to systematically under- or overestimate year-ahead inflation, often deviating from the realized values. This graph motivates the construction of several behavioral and informational metrics—bias, herding, response to external shocks, overconfidence, and dispersion—to systematically analyze the dispersion among experts and the deviations from rationality. These metrics are computed at the individual level and shown in Figure 2, enabling us to track expert-specific behavioral patterns over time.

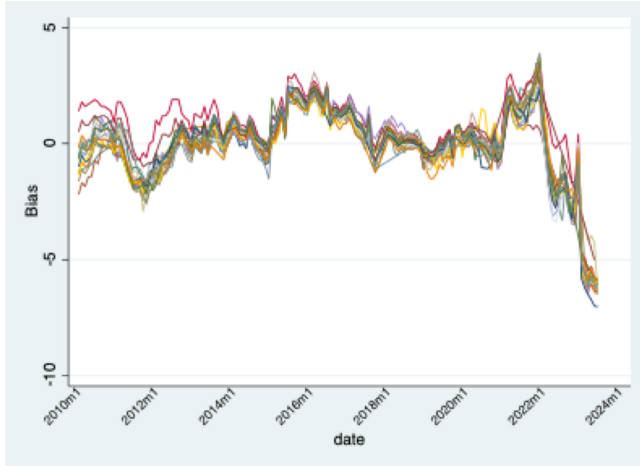
Firstly, forecast bias is calculated as the difference between forecast and realized inflation values, averaged across experts in each period. A positive bias indicates overestimation, while a negative value indicates underestimation. In Figure 2a, we observe that although bias fluctuates modestly over time and is consistent with the concept of adaptive learning (Coibion et al. 2019), where experts update their inflation forecast in response to past forecast errors rather than remaining passive. This persistent pattern is consistent with Coibion and Gorodnichenko (2012) and Andrade and Le Bihan (2013), who also find biases in experts' year-ahead US inflation forecasts, including anchoring on past inflation rates and underreacting to new information.

Secondly, herding behavior captures experts' tendency to align closely with peers experts rather than independently processing information. As in Lamont (2002) and Ehrbeck and Waldmann (1996), we measure herding by the absolute deviation of each expert forecast from the mean forecast as shown in (1), in which $F_{i,t}$ is the forecast by expert i at time t, and N_t is the number of experts reporting forecasts in a period:

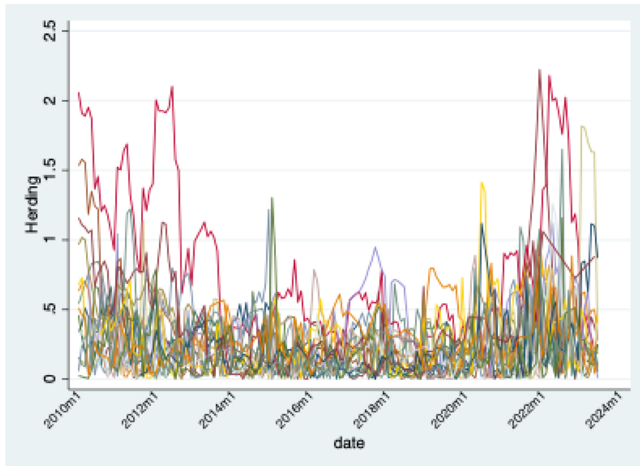
$$H_{i,t} = \frac{1}{N_{i,t}} \left| F_{i,t} - \overline{F_t} \right| \tag{1}$$

Lower values of the herding index implies that experts are aligning their forecast more closely with peers rather than relying on independent assessments, whereas higher values reflect less herding behavior. Until around 2021, most inflation forecasters

(a) Bias



(b) Herding



(c) Shock of external information

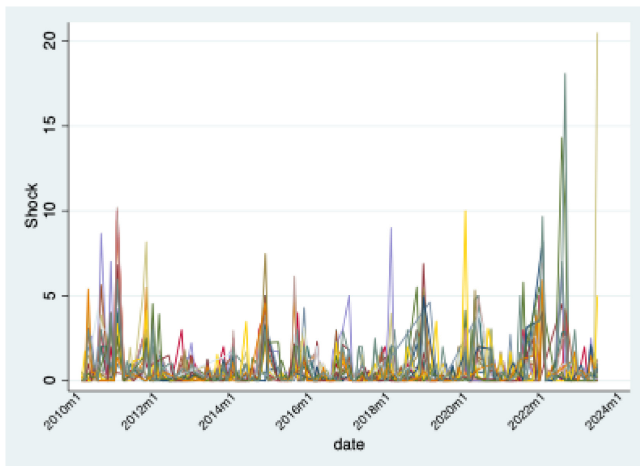
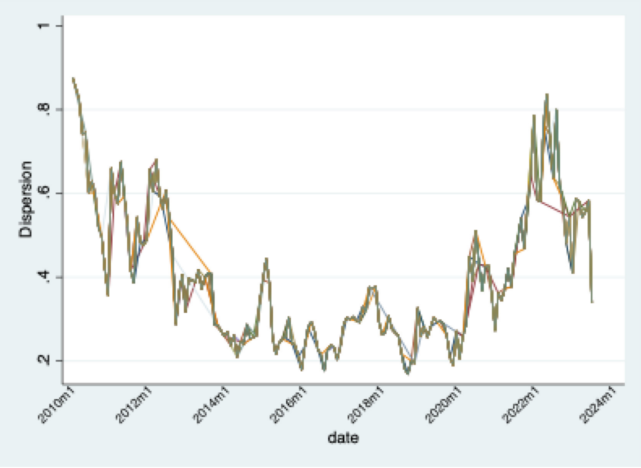


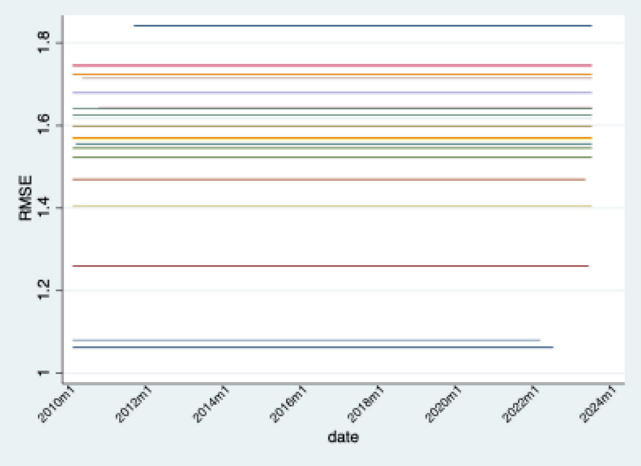
FIGURE 2 | Behavioral and informational metrics of year-ahead inflation forecasts at expert level.

were clustered around 2% to 3%, showing high herding behavior. This can also be observed in Figure 2b with values between 0.2 and 0.5 where experts align with the consensus. Spikes in the herding index (which indicates more disagreement between exeprts) are especially visible during periods of uncertainty and geopolitical conflicts, for example, during COVID-19 and the Russia–Ukraine war, where the herding index exceeds 2. These

(d) Dispersion



(e) RMSE



(f) Skewness

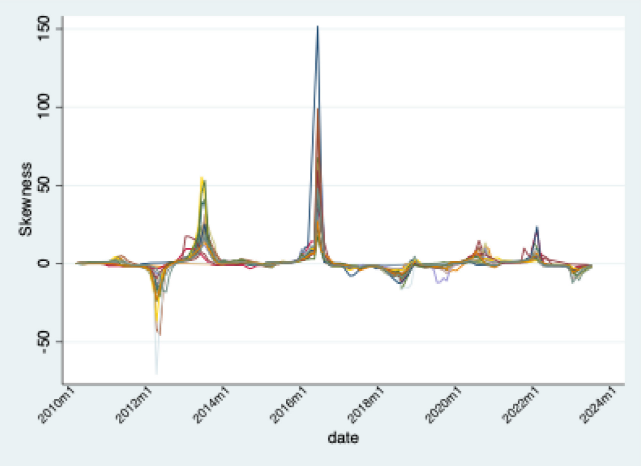


FIGURE 2 | (Continued)

spikes occur when inflation diverges from prior patterns and experts break from the mean. These results match with previous research by Glick and Kouchekinia (2021) who find higher inflation forecast disagreement between experts in the United States since 2021. Kahneman and Tversky (1979) and Barberis and Thaler (2003) show that individuals become overconfident, anchor their predictions based on past values, or follow their peers rather than processing information on their own. These mechanisms explain why we often observe persistent forecast bias and herding behavior on Figure 2a,b.

Thirdly, there are informational constraints that make experts stray away from rationality. Sims (2003) and Woodford (2012) argue that forecasters face cognitive limits in processing information so they may react only to new data or with delay. We measure this with an external information shocks index (in (2) and in Figure 2c). This metric shows how deviations from rational expectations can arise by external shocks, which complicate the interpretation of macroeconomic signals and increase deviations from rational behavior, as demonstrated in Bekaert et al. (2013), Kang et al. (2014), and Baker et al. (2016).

In order to measure information shocks, Davies and Lahiri (1995) propose to measure it as the difference between an expert's forecast revision and the average revision across all other experts at each period of time. Formally, the shock is calculated as:

$$S_{i,t} = \left(F_{i,t} - F_{i,t-1}\right) - \frac{1}{N_t}\sum_{j=1}^{N_t}\left(F_{j,t} - F_{j,t-1}\right) \quad (2)$$

A value close to zero indicates that the expert is not affected by shocks of external information, while large positive values indicate that the expert overreacts to new information. In Figure 2c, we can see that between 2012 and 2014 the shock of external information remains tightly clustered around zero, reflecting anchored inflation expectations. Nevertheless, there are several points—early 2012, during the COVID-19, and again in 2022–2023 with postpandemic inflation, the Russia–Ukraine war and energy price shocks—when the index increases sharply. These match with the periods in Figure 1 when realized inflation either diverged from or surged beyond prepandemic norms, especially after 2021 when inflation increased but experts stayed clustered.

Fourthly, we include a dispersion index that captures the heterogeneity of experts at each point in the time In (3), $F_{i,t}$ is the forecast of expert i at moment t, and F_t the mean across all experts (N_t).

$$D_{i,t} = \sqrt{\frac{1}{N_t}\left(F_{i,t} - \overline{F}_t\right)^2} \quad (3)$$

The dispersion index captures the degree of heterogeneity among experts. Low dispersion values show tightly clustered forecasts reflecting consensus or potential herding, whereas high values signal greater dispersion and heightened uncertainty (Mankiw et al. 2003; Carroll 2003). Results on Figure 2d follow a similar pattern as for the herding metrics. There is less dispersion from 2010 to around 2016, reaching a trough near 0.2. Starting in 2020, dispersion increases sharply, peaking close to 0.8 during 2022. This period matches with the post-COVID inflation surge, supply-chain disruptions, and the Russia–Ukraine war, all of which introduced considerable uncertainty into inflation dynamics (as seen in Figure 1). The rising dispersion therefore signals greater disagreement among experts precisely when inflation became harder to predict.

Finally, we also compute some standard statistics of forecasting performance. On Figure 2e we show the metrics for RMSE to summarize each expert's average forecasting accuracy. Experts with lower values are more accurate than those with higher RMSE values. Since this measure averages over time, the metrics on Figure 2e show the long-run forecasting accuracy rather than time variation.

We also calculate the skewness of forecast errors, computed over a 24-month rolling window and 0.05 as significance level for each institution. A positive skewness indicates underestimation of inflation (errors skewed to the right), while negative skewness means overestimation. This approach aligns with Adrian et al. (2020), who model time-varying macroeconomic risk by estimating the asymmetry in the conditional distribution of forecast outcomes (real GDP growth, unemployment, and inflation). They find that these distributions are often skewed and that this skewness contains valuable information about risks and economic uncertainty. In our context, applying skewness to forecast errors provides a simple way to capture how individual experts perceive inflation risks. In Figure 2f, experts show persistent positive skew between 2016 and 2017.

Taken together, these patterns illustrate that deviations from rationality are not driven by a unique explanation. Rather, different theoretical explanations seem to interact and explain the deviations. For example, under conditions of stability, forecasts are tightly clustered and revisions are smooth, but in periods of uncertainty (COVID-19, Ukraine–Russia war), herding, delayed information processing, and asymmetric risk perceptions seem to reinforce one another. This interaction is consistent with models of sticky expectations (Mankiw and Reis 2002), rational inattention (Sims 2003), and adaptive learning (Coibion et al. 2019), in which forecasters update gradually, rely on past anchors, and interpret new information through heterogeneous perspectives.

3 | Identifying the Drivers of Irrationality

Most studies typically focus on measuring why experts deviate from rationality by analyzing one source in isolation without considering how these multiple factors may simultaneously interact. Dovern and Weisser (2011) attempt to move beyond this single explanation. The authors decompose inflation forecast errors to assess the accuracy, bias, and weak efficiency of macroeconomic forecasts. Their decomposition allows the separation of macrolevel shocks from individual-specific components, but the framework remains estimating the effect of each source in isolation. They did not empirically identify the specific behavioral or informational drivers of forecast deviations nor does it capture how the deviations from rationality evolve over time or differ across individuals.

Building on this literature, and based on the descriptive statistics just shown, our hypothesis is that behavioral reasons, informational problems, and external shocks at the same time influence deviations from rational expectations. Cognitive biases and herding are expected to produce autocorrelated errors, whereas limited attention and processing constraints may generate persistent heterogeneity across forecasters. Macroeconomic shocks and high uncertainty are likely to amplify these deviations, especially during periods of policy changes or global risk (Coibion and Gorodnichenko 2012, 2015; Caldara and Iacoviello 2018).

To address these limitations, we introduce two key methodological innovations. First, we construct a time-varying, expert-level irrationality index that captures when and how experts deviate from rational expectations. Second, we then relate this index to jointly identify how different drivers—bias, herding, dispersion, overconfidence, political risk, economic uncertainty, and so forth—impact deviations from rationality. We use fixed-effects panel regressions, which allow us to control for unobserved heterogeneity across experts and time. This approach allows us to move from the traditional approach of estimating separate regressions to, instead, provide an integrated framework to identify how multiple behavioral and informational drivers interact and shape deviations from rational expectations.

3.1 | The New Irrationality Index

The concept of rationality is fundamental in economic theory, particularly in the area of expectations formation and forecasts. The concept of rationality implies three key conditions: unbiasedness, efficiency and errors do not follow any systematic pattern over time (Muth 1961; Fama 1970). These conditions ensure that deviations from actual outcomes are random and reflect noise rather than systematic distortions. However, as the literature has shown, forecasts often fail to meet these criteria. Behavioral biases (Kahneman and Tversky 1979; Barberis and Thaler 2003), informational frictions (Sims 2003; Woodford 2012), and external shocks (Coibion and Gorodnichenko 2015; Gürkaynak et al. 2005) are the three main explanations of drivers of deviation from rationality. The statistics shown in Figure 2 confirm that our data sample also exhibit these deviations from rationality.

We construct a novel Irrationality Index that allows us to identify when experts are deviating from rational expectations assumptions. This index is based on the Fluctuation Rationality (FR) Test developed by Rossi and Sekhposyan (2016) and the null hypothesis is that forecast errors are rational, implying unbiasedness and forecast errors do not follow any systematic pattern. The FR Test applies rolling-window regressions to detect time-specific deviations in forecast rationality; it compares forecast errors against realized outcomes using a Wald statistic corrected for heteroskedasticity and serial correlation (Newey–West adjustment).

Formally, the FR Test builds upon the econometric framework originally proposed by West and McCracken (1998):

$$v_{t+h}\left(\hat{\gamma}_t, R\right) = \hat{g}_t'.\theta + \eta_{t+h}, \qquad t = R, \ \ldots \tag{4}$$

where $\hat{g}_t' \equiv g_t\left(\hat{\gamma}_t, R\right)$ is an $(lx1)$ vector function of period t. θ is an $lx1$ parameter vector, and $v_{t+h}\left(\hat{\gamma}_t, R\right)$ is the forecast error defines as the difference between forecast and realized value.

In this equation, the forecast error $v_{t+h}\left(\hat{\gamma}_t, R\right)$ (defined as the difference between forecasted and actual values) is explained by the vector function $\hat{g}_t' \equiv g_t\left(\hat{\gamma}_t, R\right)$, which is an $(lx1)$ vector function of period t. The parameter vector θ captures deviations from

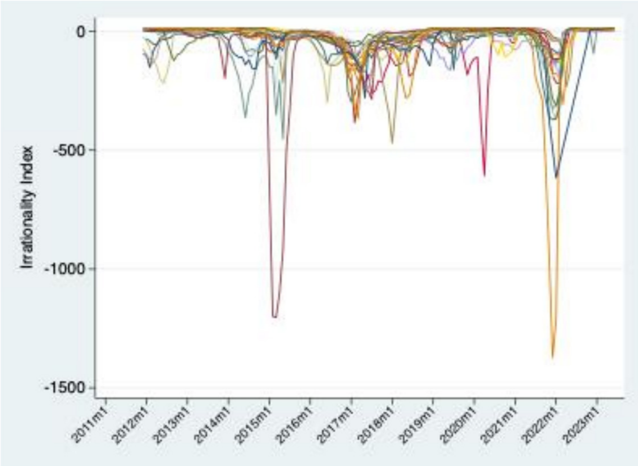


FIGURE 3 | Irrationality index by expert.

TABLE 1 | Descriptive statistics of irrationality index by expert.

Experts	Mean	Standard deviation	Min.	Max.
A	−[1]24.09	33	−151.2	12.86
B	−26.18	62.7	−383.93	13
C	−24.2	51.61	−295.49	13.06
D	−67.53	198.75	−1371.77	13.02
E	−52.02	80.48	−452.86	13.92
F	−43.88	90.33	−606.46	12.91
G	−24.49	42.04	−180.88	9.94
H	−40.6	77.12	−369.72	13.08
I	−18.21	33.53	−116.63	12.82
J	−22.99	60.42	−324.73	13.03
K	−36.61	70.25	−370.72	13.07
L	−43.93	76.31	−468.83	13.06
M	−18.68	43.78	−241.45	12.98
N	−24.98	45.64	−166.31	13.07
O	−25.13	48.65	−242.38	13.02
P	−46.48	84.22	−615.9	12.71
Q	−68.14	208.93	−1203.87	13.07
R	−23.29	57.15	−311.03	13.04
S	−20.24	56.41	−306.34	14.9

rationality. Under the null hypothesis of rational forecasts, these parameters equal zero:

$$H_0 : \theta = \theta_0 \; vs. H_A : \theta \neq \theta_0 \;\; where \; \theta_0 = 0 \tag{5}$$

The Wald statistic computed is

$$w_P = P\left(\hat{\theta}_P - \theta_0\right)' \hat{V}^{-1}_{\theta,P}\left(\hat{\theta}_P - \theta_0\right) \tag{6}$$

where $\hat{\theta}_P$ represents the estimated parameters, and $\hat{V}^{-1}_{\theta,P}$ is the variance–covariance matrix robustly corrected for heteroskedasticity and autocorrelation (Newey–West adjustments). A rejection of the null hypothesis occurs when the maximum observed value of the Wald statistic series exceeds the critical threshold, indicating systematic deviations from rationality.

Summarizing, the Fluctuation Rationality Test covers the following cases:

1. Forecast unbiasedness tests, where $\hat{g}_t = 1$;
2. Forecast efficiency, where $\hat{g}_t = y_{t+h|t}$;
3. Forecast rationality (Mincer and Zarnowitz 1969), where $\hat{g}_t = \left[1 \; y_{t+h|t}\right]$;
4. Forecast encompassing tests, where $\hat{g}_t$ is the forecast of the encompassed model;
5. Serial uncorrelation tests, where $\hat{g}_t = v_t\left(\hat{\gamma}_{t-h}, R\right)$.

We compute the FR Test at individual expert level using a 12-month rolling window and significance level of 0.05. The Irrationality Index is then constructed as the difference between the FR test statistic and its critical value. A negative value of the Index indicates a rejection of rational behavior, while a positive value signals consistency with rational expectations.

Figure 3 presents the Irrationlaity Index for each expert over time, while Table 1 shows some summary statistics.[3] In general, most of the values in the index reject the hypothesis of rational behavior. Between mid-2021 and early 2022, there are peaks of irrationality which align with the post-COVID-19 period. In Figure 1 we saw how realized inflation rapidly increased, while experts' forecasts remained anchored at lower levels, generally around 2% to 3%. During this time, experts underestimated the inflationary consequences of reopening the economy. Figure 2 supports this interpretation by showing an increase in dispersion, bias, and an elevated herding behavior during this time, as experts clustered around the mean forecast rather than responding independently to new signals.

Another episode of deviations from rationality appears at the beginning of 2015. Figure 1 clearly shows that many experts' inflation forecasts were significantly higher than the realized values. The realized inflation was close to or below 1% in early 2015, while some experts exceeded 3% or even 4%. This difference highlights a systematic overestimation of inflation that could possibly be driven by expectations of monetary policy normalization or just misinterpretation of macro signals. Figure 2 reinforces this interpretation with elevated levels of bias and herding in 2015, suggesting that forecasters failed to adjust adequately.

Similar patterns reappear during later crises. In 2020, COVID-19, and in early 2022 (postpandemic reopening and the Russia–Ukraine war), Figure 2 again shows sharp spikes in dispersion, herding, and shocks, aligning with deep drops in the irrationality index. These episodes confirm that deviations from rational assumptions are recurrent and heterogeneous across experts, with some adapting faster to new conditions, while others misinterpret signals.

3.2 | Analysis of Drivers of Irationality

After identifying periods of deviations from rational expectations, we now explore the underlying mechanisms driving these deviations. The literature generally points to three drivers: behavioral biases, informational frictions, and external shocks. Moreover, as already demonstrated on Figure 2 and in Dovern and Weisser (2011), deviations from rationality are not driven by an unique explanation. Rather, several theoretical explanations seem to interact and explain these deviations.

We therefore include in our empirical model a set of variables that align with these drivers. Forecast bias, herding, overconfidence, and forecast dispersion capture behavioral mechanisms. External information shocks are proxied by the metric in (2), but also using the Geopolitical Risk Index (Caldara and Iacovello 2022), economic policy uncertainty (Baker et al. 2016), and expert's macro expectations such GDP growth and interest rates collected from Consensu Economic dataset. On Appendix A we report diagnostic tests—including a full correlation matrix and VIFs—to confirm that multicollinearity and overfitting are not driving our results.

We use a fixed-effects model to control for unobserved, time-invariant heterogeneity across experts, capturing within-expert variation over time rather than differences across them.[4] Due to potential heteroscedasticity and autocorrelation in the panel, we cluster standard errors by experts.

The results on Table 2 demonstrate that deviations from forecast rationality are not random, instead, they are influenced primarily by shock of external information, global political risk, and interest rate forecast. Other drivers, such as bias, herding, and GDP expectations, are not significant in our estimation.

The external information shocks have a significant and negative effect (−2.31) implying that greater responsiveness to new information is associated with higher deviations from rationality. This finding suggests that experts may overreact to new data or misinterpret signals. It is also consistent with recent literature of systematic overreaction in expert forecasts (Bordalo et al. 2020; Afrouzi et al. 2021). Similarly, the Geopolitical Risk Index has a significant negative effect (−16.82), which indicates that periods of high uncertainty increase deviations from rational expectations, likely due to increased ambiguity and complexity in interpreting macroeconomic signals. Additionally, the 12-month interest rate forecast is negatively associated with the index (−37.91), suggesting that long-horizon monetary policy expectations may introduce distortions, either through overconfidence or misjudgment, thus reducing forecast rationality.

The other variables do not have a significant impact on deviations from rationality. Nevertheless, the results show interesting insights. For instance, the negative coefficient on forecast bias (−12.49) implies that greater forecast bias is associated with more negative values of the irrationality index. Similarly, the large negative coefficient on forecast dispersion (−117.27) suggests that higher disagreement among experts coincides with more deviations from rational expectations. This could indicate that dispersion, rather than reflecting diversity of independent thought, may sometimes signal confusion or lack of consensus in interpreting economic signals. The herding index, on the other hand, shows a positive coefficient (20.41), which would imply that more herding is associated with more positive index values.

TABLE 2 | Drivers of irrationality on inflation expectations.

	Fixed-effects
Bias	−12.49
	(7.54)
Herding index	20.41
	(20.78)
Shock of external information	−2.31***
	(1.42)
Forecast dispersion	−117.27
	(71.22)
Overconfidence	0.43
	(0.26)
Economic Political Uncertainty index	0.03
	(0.04)
Global political risk	−16.82***
	(4.81)
% Change of expected current-year GDP	−0.67
	(1.75)
% Change of expected year-ahead GDP	−8.10
	(5.13)
Interest rate 12-month forecast	−37.91**
	(17.46)
Interest rate 3-month forecast	32.14
	(19.64)
Constant	75.31*
	(42.28)
Observations	1496
R-within	0.12
R-between	0.11
R^2	0.12
No. of experts	19
F-test	19.27***

Note: Clustered standard errors in parentheses.
Source: Consensus Economic Forecasts and authors' estimations.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

The coefficient on skewness of forecast errors is positive, meaning greater asymmetry in forecast errors is weakly associated with more rational forecasts, though this effect is small (0.43) and not significant.

Likewise, the Economic Policy Uncertainty Index appears to be positively associated with the Irrationality Index, implying slightly more rational forecasts under higher policy uncertainty. This result is in line with most of the literature on the effects of uncertainty (Bekaert et al. 2013; Kang et al. 2014; and Baker et al. 2016), which posit that experts become more cautious in the revisions of their forecasts when faced with uncertainty on economic policies.

For the macroeconomic controls, the expected change in current-year GDP and year-ahead GDP both have negative signs, indicating that more optimistic growth forecasts correlate with more irrational forecasts. Meanwhile, the forecast for short-term interest rates is positive, suggesting that expectations of near-term policy tightening may improve rationality, though the result is not significant.

In sum, this integrated approach shows that deviations from rational expectations are not explained by a single channel but by the combined influence of shocks of external information, global political risk, and interest rate expectations, while alternative explanations related to behavioral bias are less relevant.

4 | Robustness Checks

To validate the empirical findings, we include some robustness checks using three complementary econometric approaches. Firstly, we use a dynamic Arellano–Bond GMM model to account for the temporal persistence of deviations from rationality and address potential endogeneity through lagged instruments (Arellano and Bond 1991; Roodman 2009).[5] specification additionally accounts for temporal dependence and potential endogeneity.

Secondly, we apply the CCEMG estimator to control for unobserved common factors that may influence experts simultaneously over time. In addition, CCEMG allows for heterogeneous slope coefficients across individuals and corrects for cross-sectional dependence, providing more robust estimates in the presence of unobserved global shocks or correlated errors (Pesaran 2006).

Finally, as it may be hard to interpret deviations from rationality in absolute terms, one can consider any significant deviation from rationality by an expert as a period of irrational behavior. We thus classify all months with a negative irrationality index as 0, and all other "rational" months as a one. To model the probability of irrationality, we estimate conditional fixed-effects logit models (Greene 2012) that account for within-expert variation in binary outcomes.

Column (a) of Table 3 presents the results for the three complementary regressions. First, the dynamic GMM model confirms the persistence of irrationality over time, as indicated by the highly significant lag coefficient.[6] This finding complements the panel FE estimates by showing that deviations from rationality today tend to carry over into subsequent periods. While the baseline FE model captures the structural drivers of irrationality after controlling for unobserved heterogeneity, the dynamic GMM.

We then show the CCEMG estimates. As for the panel results, the significance of geopolitical risk and long-term interest rate expectations underlines the role of external shocks. This finding aligns with earlier studies showing that geopolitical events and policy signals shape forecast behavior (Caldara and Iacoviello 2018; Baker et al. 2016). The behavioral elements driving experts' deviations from rationality are not important at all.

Finally the conditional fixed-effects logit model further supports the significant impact of geopolitical risk and interest expectations as both significantly increase the likelihood of deviations from rationality. In contrast to previous results, short-term interest rate expectations are positively and significantly associated with rationality. This distinction suggests that while long-horizon monetary policy expectations may raise overreaction, shorter term expectations can anchor forecasts more effectively, which is consistent with Bordalo et al. (2020) as they find an overreaction to distant signals.

Across all three approaches, behavioral variables such as herding, dispersion, and policy uncertainty remain statistically insignificant, as in the panel FE model. These results confirm that these factors play only a secondary role relative to external shocks and interest rate expectations.

5 | Conclusion

This study contributes to understanding the deviations from rationality in expert forecasts by developing a novel "irrationality index" based on Rossi and Sekhposyan's (2016) Fluctuation Rationality Test. Unlike previous literature, which tends either to analyze isolated dimensions of forecast deviations—such as behavioral biases (Kahneman and Tversky 1979), informational frictions (Sims 2003; Woodford 2012)—or to interpret forecast deviations as random (Blanchard and Watson 1982; Orphanides and Williams 2004), our index integrates temporal fluctuations and expert-level heterogeneity into a unified empirical framework.

The two key contributions are the irrationality index and the identification of the drivers of it. First, the index allows us to identify periods of heightened deviations from rational expectations across experts and time. Second, this study advances by jointly identifying the drivers of deviation from rationality: bias, herding behavior, forecast dispersion, uncertainty, global political risk, and macro expectations.

Our results show that deviations from rationality are certainly not random but instead are influenced by different factors. Yet, among these factors, it is interest rate expectations, external information, and, in particular, geopolitical risk that are important. This result reinforces the idea that uncertainty complicates the interpretation of macroeconomic signals. Similarly, long-term interest rate expectations are associated with increased deviations from rational expectations. Experts may misinterpret or overreact to monetary policy outlooks news (Gennaioli et al. 2015; Angeletos and Lian 2018). Furthermore, the persistence of deviations over time, supported by GMM results, indicates that experts may have learning lags or cognitive inertia.

TABLE 3 | Robustness checks.

	Dynamic GGM	CCEMG	Logit model
Lag of irrationality	0.87***		
	(0.15)		
Bias	−54.46	−9.95*	−0.49***
	(113.55)	(5.62)	(0.09)
Herding index	60.78	−2.55	0.23
	(264.35)	(15.91)	(0.31)
Shock of external information	0.90	−2.85	0.11
	(18.17)	(2.78)	(0.06)
Forecast dispersion	−225.37	−77.73	0.59
	(612.87)	(51.89)	(0.64)
Overconfidence	−7.11	0.78	0.01*
	(10.03)	(0.40)	(0.01)
Economic Political Uncertainty index	19.43	−0.02	0.00*
	(67.73)	(0.04)	(0.00)
Global political risk	−43.19	−15.04***	−0.63***
	(208.73)	(4.30)	(0.13)
% Change of expected current-year GDP	50.71	3.11	0.03
	(76.20)	(3.21)	(0.04)
% Change of expected year-ahead GDP	−170.96	−5.06	−0.09
	(372.62)	(8.16)	(0.09)
Interest rate 12-month forecast	−1962.11	−38.74***	−2.35***
	(7468.21)	(12.10)	(0.23)
Interest rate 3-month forecast	0.87***	30.60*	2.29***
	(0.15)	(16.31)	(0.25)
Constant	−54.46		
	(113.55)		
Observations	1496	1496	1496
R-within		0.64	
R-between		0.60	
R^2		0.61	
No of experts	19	19	19
F-test	149687***		475.5***
AR(1) *p*	0.108		
AR(2) *p*	0.766		
Hansen *p*	0.287		
Sargan *p*	1.19e-05		
Instruments	19		

Source: Consensus Economic Forecasts and authors' estimations.
Note: Logit estimation. Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Other variables, such as forecast bias, dispersion, and information shocks, also contribute to irrational behavior, though their significance varies. For instance, high dispersion—often interpreted as diversity of opinion—may sometimes signal confusion rather than disagreement, while herding behavior, surprisingly, does not increase deviations in our models. This could reflect strategic alignment rather than mimicry (Trueman 1994).

These findings have direct policy implications. For example, central banks and economic institutions must consider that experts may be systematically deviating from rationality, especially during high-risk or uncertain periods such as the post-COVID-19 recovery or geopolitical crises. Transparent, consistent, and forward-looking communication can help to reduce these informational problems, avoid overreactions to external shocks, and realign expectations. In addition, monitoring the irrationality index can support early detection of expectation misalignments and inform more responsive policy design.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] See Maćkowiak et al. 2023, for a more detailed rational inattention literature review.

[2] Despite the methodological advantages of the Consensus Economics (CE) dataset, some authors have pointed out limitations in the way forecasts are aggregated. For example, Crowe (2010) demonstrates that Consensus Economics forecasts tend to overreact to the prior and underutilize new information. This inefficiency is not due to individual errors, it is due to the information aggregation process itself.

[3] This index follows a similar interpretative logic to other composite indicators widely used in macroeconomic research—such as the Economic Policy Uncertainty Index (Baker et al. 2016), the Geopolitical Risk Index (Caldara and Iacoviello 2022), the Financial Stress Index (e.g., Federal Reserve Bank of Kansas City), the VIX Volatility Index, the Michigan Consumer Sentiment Index, the Index of Leading Economic Indicators (The Conference Board), and the Financial Conditions Index (FCI)—where the emphasis is placed on tracking the direction and relative magnitude of changes over time, rather than providing a direct economic meaning or absolute thresholds. These indices are primarily designed to facilitate comparative analysis across time periods, countries, or agents, without requiring a fixed benchmark for interpretation.

[4] A Hausman test rejects the null hypothesis of no systematic difference between a fixed and random effects model ($\chi^2 = 27.4$).

[5] We conduct standard diagnostic checks for the GMM specifications. These include tests such as AR(1) and AR(2) and over-identification, Hansen and Sargan tests. All models pass the AR(2) requirement (p-values > 0.1), and most demonstrate acceptable Hansen p-values (above 0.25), indicating no major concerns regarding instrument validity or overfitting. Moreover, to mitigate potential endogeneity between forecast irrationality and behavioral indicators—such as bias, herding, and forecast dispersion—we instrument endogenous regressors with their own lagged levels (lags 2 to 4). As instruments, we also include predetermined external variables, such as the Economic Policy Uncertainty (EPU) Index and Global Political Risk (GPR) Index.

[6] We conduct standard disgnostic tests for the GMM model. The AR(1) and AR(2) tests do not reject the absence of second-order serial correlation, and the Hansen test supports the validity of the instruments ($p = 0.287$). The Sargan test, however, is significant, suggesting some degree of instrument proliferation, a common issue in GMM applications that we attempt by restricting lag value.

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Appendix A

Model Diagnostics

To ensure the robustness of our regression specifications and address potential multicollinearity concerns, we conducted two key diagnostic checks: a correlation matrix between all explanatory variables and variance inflation factors (VIF). Table A1 shows the correlation matrices for the full set of explanatory variables demonstrating no correlations exceeding 0.8, supporting the conclusion that the included controls measure distinct dimensions of irrational forecasting behavior. Second, on Table A2, we compute VIFs for each country using pooled OLS models. While the short- and long-term interest rate forecasts exhibited higher VIFs (Germany: up to 35), all other regressors—such as bias, herding, forecast dispersion, RMSE, skewness, and risk indicators—had VIFs below standard thresholds (VIF < 5), suggesting no severe multicollinearity among behavioral or macroeconomic variables. These results confirm that the model does not suffer from specification problems due to multicollinearity or overfitting.

TABLE A1 | Correlation matrix by country correlations.

		Bias	Herding index	Shock of external information	Forecast dispersion	Forecast RMSE	Skewness on errors	Economic Political Uncertainty index	Global political risk	% Change of expected current-year GDP	% Change of expected year-ahead GDP	Interest rate 12-month forecast	Interest rate 3-month forecast
The United States	Bias	1.00	−0.09	−0.02	−0.40	−0.05	0.28	−0.16	−0.20	0.27	0.54	−0.58	−0.72
	Herding index	−0.09	1.00	0.11	0.39	0.08	−0.03	0.07	0.08	0.01	−0.01	0.05	0.08
	Shock of external information	−0.02	0.11	1.00	0.19	0.02	0.01	0.08	0.03	0.01	−0.01	0.03	0.04
	Forecast dispersion	−0.40	0.39	0.19	1.00	0.08	−0.11	0.19	0.17	0.05	−0.07	0.10	0.17
	Forecast RMSE	−0.05	0.08	0.02	0.08	1.00	−0.07	0.12	0.04	−0.01	0.02	0.10	0.12
	Skewness on errors	0.28	−0.03	0.01	−0.11	−0.07	1.00	−0.04	−0.15	−0.05	0.12	−0.26	−0.27
	Economic Political Uncertainty index	−0.16	0.07	0.08	0.19	0.12	−0.04	1.00	−0.14	−0.51	0.05	0.01	0.11
	Global political risk	−0.20	0.08	0.03	0.17	0.04	−0.15	−0.14	1.00	0.18	−0.27	0.43	0.33
	% Change of expected current-year GDP	0.27	0.01	0.01	0.05	−0.01	−0.05	−0.51	0.18	1.00	0.04	0.04	−0.02
	% Change of expected year-ahead GDP	0.54	−0.01	−0.01	−0.07	0.02	0.12	0.05	−0.27	0.04	1.00	−0.62	−0.66
	Interest rate 12-month forecast	−0.58	0.05	0.03	0.10	0.10	−0.26	0.01	0.43	0.04	−0.62	1.00	0.94
	Interest rate 3-month forecast	−0.72	0.08	0.04	0.17	0.12	−0.27	0.11	0.33	−0.02	−0.66	0.94	1.00

TABLE A2 | VIF results.

	The United States
Interest rate 12-month forecast	18
Interest rate 3-month forecast	12.95
Forecast dispersion	4.01
Bias	1.95
Economic Political Uncertainty index	1.88
Herding index	1.83
% Change of expected current-year GDP	1.71
% Change of expected year-ahead GDP	1.42
Global political risk	1.23
Shock of external information	1.14
Skewness on errors	1.06
Forecast RMSE	1.05