THREE ESSAYS IN BEHAVIORAL MACROECONOMICS

Nayeon Kang

Submitted to the faculty of the Graduate School in partial

fulfillment of the requirements

for the degree

Doctor of Philosophy

in the Department of Economics,

Indiana University

May 2025

Accepted by the Graduate Faculty, Indiana University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Doctoral Committee

Christian Matthes, Ph.D., Chair

Rupal Kamdar, Ph.D.

Daniela Puzzello, Ph.D.

Todd B. Walker. Ph.D.

May 1, 2025

Acknowledgments

First and foremost, I am deeply grateful to my advisor and committee chair, Christian Matthes, for his steadfast encouragement and for continuously pushing me toward my goals. Whenever I felt lost, he was like a compass—providing new direction and clarity. As a mentor, he gave exactly the guidance I needed at each stage of my growth, and I cannot thank him enough for walking this path with me.

I would also like to express my sincere thanks to my dissertation committee members, Rupal Kamdar, Daniela Puzzello, and Todd B. Walker. All three are outstanding economists and inspiring mentors to whom I am deeply indebted. This dissertation would not have been possible without their generous support, insightful feedback, and guidance throughout the process.

Over the past six years, I've had the good fortune of meeting wonderful fellow graduate students, faculty, and staff at Bloomington. I would like to thank Elizabeth Bolyard, Ryan Byun, Hyeyun Cho, Ellie Cothren, Paulette Davidson, Hee Soo Kim, Nastassia Krukava, Eungik Lee, Nayoung Lee, Laura Liu, Vladimir Menshikov, Byung Goog Park, Brandie Roberts, Christina Robertson, Seongbo Sim, Anthony Vecchia, Nadine Williams, Qian Wu, Po-Shyan Wu, and Huiqi Zhuang. I feel truly lucky to have crossed paths with them—they brought joy, energy, and resilience to this otherwise difficult chapter.

I am also grateful to Jinill Kim, my mentor and master's advisor, who guided me to the starting line of this journey and whose mentorship has been invaluable. I also thank Donghoon Yoo, a professor at Korea University, for his insightful academic guidance and warm encouragement.

Lastly, I am endlessly thankful for the love and support of my family. Words cannot express how much their warmth has meant to me. My nephew, Sun-oh, born just six months ago, brought laughter and light into the most difficult moments of this journey. And above all, I am profoundly grateful to Sergii Drobot—for believing in me even when I doubted myself, and for always being by my side with love and support.

Nayeon Kang

THREE ESSAYS IN BEHAVIORAL MACROECONOMICS

Economic agents make decisions and form forecasts about the future based on their perceptions. However, as human beings, we are subject to psychological and cognitive limitations, which can lead to suboptimal or biased choices. This dissertation investigates how such human traits shape expectations and decision-making and whether they help explain empirical patterns observed in economic data.

The first chapter studies the effect of the Federal Reserve's communication on short-term inflation forecasts. Using micro-level survey data, I show that after the Fed adopted an explicit inflation target in 2012, individuals (1) became more confident in their beliefs with lower subjective uncertainty, and (2) less prone to overreacting to new information, aligning more closely with rational expectations. I develop a parsimonious inflation expectations model featuring smooth diagnostic expectations. The findings suggest that transparent monetary communication not only anchors long-run inflation expectations but also enhances the rationality of short-run forecasting behavior.

The second chapter applies a rational inattention model to the pre-Great Moderation era, a period marked by high macroeconomic volatility. I find that during such volatile times, households and firms respond more swiftly in their consumption and pricing decisions. A DSGE model with rational inattention generates sluggish responses to monetary, technology, and firm-specific shocks—even in the absence of Calvo pricing or habit formation. This suggests that slow adjustment dynamics in the data may reflect cognitive constraints rather than structural rigidities.

The third chapter, co-authored with Sergii Drobot, examines how political partisanship shapes individuals' forecasting behavior. To assess the impact of electoral outcomes on expectations, we conducted two waves of surveys, with the second wave administered on the morning of November 6, 2024—immediately after the U.S. presidential election. We find that: (1) Democratic-affiliated households revise their forecasts more pessimistically, while Republican-affiliated households revise theirs more optimistically, particularly lowering their unemployment forecasts; (2) Republican households exhibit greater confidence, indicating reduced subjective uncertainty; and (3) despite the public nature of the news—Trump's victory—forecast disagreement narrows among Republicans but widens among Democrats.

Christian Matthes, Ph.D., Chair

Rupal Kamdar, Ph.D.

Daniela Puzzello, Ph.D.

Todd B. Walker. Ph.D.

Contents

Chapter 1

The Fed Explicitly Speaks: Numerical Inflation Targeting and Smooth Diagnostic Expectations

1.1 Introduction

> *"Explicit inflation targeting is characterized by the announcement of an official target for the inflation rate and by an acknowledgment that low inflation is a priority for monetary policy."* (Goodfriend, 2004)
> *"Should the FOMC then take the next step and announce this number to the public? Some have argued that such an announcement would be unnecessary because the Fed's implicit inflation objective is already well understood by the market. I am skeptical.... To reassure those worried about possible loss of short-run flexibility, my proposal is that the FOMC announce its value for the OLIR (optimal long-run inflation rate) to the public."* (Bernanke, 2004)

Echoing the collective wisdom of numerous economists, the Federal Reserve first publicly announced its long-term inflation target of 2% in 2012. Since then, much of the literature has focused on the anchoring effect of this communication. However, disclosing the long-term inflation target does more than merely anchor long-horizon expectations; it also affects short-term inflation forecasts. Specifically, forecasters experience lower subjective uncertainty, as reflected in the shrinking second moment of their predictive densities, and their point forecasts—representing the first moment of these densities—become less overreactive to new information.

This paper explains the shifts in both moments through a parsimonious inflation expectations model. A key driver behind these behavioral changes is the reduction in uncertainty in forecasters' information sets, stemming from the transparent communication of long-term inflation goals. By publicizing the 2% target, the Federal Reserve provides transparent information about trend inflation, thereby reducing conditional uncertainty regarding the trend component of inflation given the available information. This, in turn, influences short-term inflation forecasts, as agents incorporate both trend and cyclical components in their predictions, bringing their expectations more in line with rational expectations.

This research sheds light on subjective uncertainty, a critical but often overlooked aspect of expectations formation. Subjective uncertainty refers to an individual's perception of the level of unpredictability or lack of certainty when making forecasts. It reflects personal beliefs, perceptions, or incomplete information, rather than objective measurement. While previous research has primarily examined how far point forecasts (i.e., the first moment) of short-run inflation deviate from long-term goals, less attention has been paid to this uncertainty. An well-anchored stable point forecast does not necessarily imply low uncertainty around the forecast. For instance, a forecaster may predict inflation near 2% while also considering high risks of both deflation and inflation, indicating a lack of confidence in the forecast. When subjective uncertainty is high, economic agents are less confident in their beliefs, leading them to place greater weight on extreme possible future outcomes, even in response to small shocks and noisy signals.

Kumar et al. (2015) highlight the importance of such confidence by proposing five distinct definitions of anchored expectations to evaluate whether the inflation expectations of New Zealand firms' managers were well-anchored. These criteria include: 1) average beliefs closely aligned with the target, 2) limited dispersion of beliefs across agents, 3) *agents' confidence in their beliefs,* 4) minimal forecast revisions, particularly for variables with longer forecast horizons, and 5) limited co-movement between long-term and short-term expectations. The third criterion is particularly relevant to subjective uncertainty, which serves as a measure of forecasters' confidence in their point forecasts. Specifically, it reflects the forecasters' belief that inflation will stabilize within a specific range in the future. If this range is not sufficiently constrained—implying a forecaster lacks confidence in his own belief—then even small disturbances could lead to deviations from the anchored point forecast, resulting in de-anchoring. Despite the importance of this factor, it has received relatively little attention in the expectations formation literature. I address how explicit quantitative communication enhances individuals' confidence and reduces subjective uncertainty, thereby indirectly contributing to another dimension of anchoring.

This research makes two key contributions. First, unlike prior studies focused on aggregate-level long-term forecasts, this paper examines how the Federal Reserve's policy shift affects individual inflation forecasts, especially short-term expectations formation. While aggregate forecasts have garnered substantial attention, individual forecasts responding to monetary policy changes remain underexplored. This paper suggests that transparent communication, which reduces uncertainty in the information set, influences not only the conditional mean of an individual's subjective forecast distribution but also its conditional variance, thereby impacting both moments jointly. Consequently, this study documents how transparent and accountable policy disclosures by monetary authorities can alter individuals' forecasting behaviors.

Second, I propose a parsimonious model to explain three empirical findings observed in survey data, specifically for four-quarter-ahead inflation forecasts: 1) a reduction in overreaction to news since 2012, 2) increased confidence in beliefs, and 3) decreased disagreement among forecasters, arising from enhanced rationality. This model, in which forecasters share all parameters but differ only in receiving heterogeneous signals, successfully replicates forecast patterns observed in actual data, delivering clear and interpretable insights.

This study builds on three strands of research to explore how policy communications influence individual forecasts. Foremost, I develop an expectations formation model, rooted in diagnostic expectations (Bordalo et al., 2018; Bordalo et al., 2019; Bordalo et al., 2020) and smooth diagnostic expectations (Bianchi, Ilut and Saijo, 2024), to explain the overreaction of point forecasts to news and the shifts in subjective uncertainty. Diagnostic expectations (DE), which are based on Kahneman and Tversky (1972)'s representativeness heuristic, have been instrumental in advancing our understanding of individual expectations formation. When new information arrives, as measured with respect to a reference distribution based on past data, memory selectively recalls more vividly past events that are more associated with, or representative of, that current news. Extending this framework by incorporating changes in uncertainty surrounding current and past beliefs, Bianchi, Ilut and Saijo (2024) emphasize that new information not only updates the point estimate but also changes the conditional uncertainty surrounding the forecasted variable. In the standard DE model by Bordalo, Gennaioli and Shleifer (2018), the reference distribution is centered on the conditional mean of the true density at the past point when it was generated. However, its variance matches that of the true density based on current information. Alternatively, Bianchi, Ilut and Saijo (2024) condition their model on only reference information, thus the reference distribution captures the uncertainty from the time when expectations were first formed, rather than reflecting the current level of uncertainty. They call this approach "smooth diagnostic expectations". A key feature of Smooth Diagnostic Expectations (Smooth DE) is that as current uncertainty declines relative to past uncertainty, expectations distortion lessens. This aligns with the Federal Reserve's explicit messaging on long-term inflation goals, which has reduced both subjective uncertainty and expectations distortion. DE has been applied to financial markets (Adam and Nagel, 2023; Bordalo et al., 2021; Maxted, 2023) and a small open economy business cycle model (Na and Yoo, 2024). It has also been extended by L'Huillier, Singh and Yoo (2023), who incorporate the New Keynesian framework and demonstrate that the DE model outperforms the rational expectations model in a medium-scale DSGE setting. Bianchi, Ilut and Saijo (2023) integrate distant memory into their model, showing that the interaction between actions and DE repeatedly triggers boom-bust cycles in response to a single initial shock.

Secondly, this paper closely relates to public communication strategies. Eusepi and Preston (2010) and D'Acunto et al. (2020) demonstrate that communication is more effective in shaping expectations when it emphasizes policy goals and targets rather than the specific tools used to achieve those goals. This approach is particularly impactful for less sophisticated demographic groups. They conclude that target-based communication enhances policy effectiveness and helps build public trust in central banks, which is crucial for the success of their policies. Similarly, Coibion, Gorodnichenko and Kumar (2018) find that firm managers respond more strongly to information about the central bank's inflation target compared to other forms of information. Their experiments reveal that firms make the most significant adjustments to their forecasts when provided with information about the central bank's inflation target or recent inflation figures, indicating that firms place greater confidence in signals regarding these targets. Coibion, Gorodnichenko and Weber (2022) further demonstrate that households revise their inflation forecasts more significantly in response to FOMC statements and inflation targets delivered by the Fed compared to USA Today news articles. Despite similar information being conveyed, the stronger response to FOMC statements suggests that respondents may discount some information presented in newspapers. Experimental evidence supports the notion that households' and firms' information sets are significantly influenced by clear guidance from monetary authorities on policy directions. Given these findings, it is reasonable to assume that long-term inflation targets serve as strong signals to professionals, who tend to pay closer attention to the Federal Reserve's public speeches and data releases. Recent studies by Coibion et al. (2024) and Kostyshyna and Petersen (2024) demonstrate that heightened uncertainty negatively impacts household spending in experimental settings[1]. Distinctively, I focus on both the first and second moments of the predictive density using extensive survey data.

Finally, to measure individual forecaster's subjective uncertainty, I rely on Ganics, Rossi and Sekhposyan (2024). Direct measures of expectations, such as point forecasts, are typically gathered as fixed-horizon projections in the survey data. The Survey of Professional Forecasters (SPF) also conduct fixed-horizon point forecasts surveys. However, the SPF collects density forecasts in a "fixed-event" format, making it difficult to comprehensively observe and understand both the fixed-horizon point forecast and the uncertainty surrounding it. Density forecasts in the SPF are provided for fixed events, with panelists predicting inflation and output growth for the current and following calendar years, meaning the forecast horizon changes each quarter. Since I focus on four-quarter-ahead inflation forecasts, the fixed-event nature of the SPF density forecasts limits their direct applicability. Ganics, Rossi and Sekhposyan (2024) address this issue by proposing a method to reshape fixed-event uncertainty into fixed-horizon uncertainty. To accomplish this, they suggest combining current-year and next-year forecast densities through a convex combination. Using the probability integral transform (PIT) criterion, they estimate the weights required for this combination, resulting in a correctly calibrated predictive distribution. While Ganics, Rossi and Sekhposyan (2024) focus on aggregate-level uncertainty, I extend this methodology to measure individual-level uncertainty. Several researchers have explored expectations uncertainty. Binder (2017) and Krüger and Pavlova (2024) introduce a new measure of uncertainty in probabilistic survey

[1] Coibion et al. (2024) reveal that high uncertainty about economic growth reduces household spending, and Kostyshyna and Petersen (2024) show that uncertainty surrounding inflation similarly has a negative effect on spending.

on expectations at the individual response level. Abel et al. (2016) find no consistent relationship between forecast uncertainty and the dispersion of individual respondents' point forecasts using ECB-SPF data. Other studies, such as Grishchenko, Mouabbi and Renne (2019), use dynamic latent factor models to jointly estimate inflation uncertainty and point forecasts.

The remainder of this paper is structured as follows. Section 1.2 provides an overview of the survey data and inflation realizations, the key macroeconomic variable of interest. Section 1.3 presents empirical findings on how individual expectation behavior changed before and after 2012. Sections 1.4 and 1.5 lay the theoretical foundations of DE and Smooth DE, and discuss the structural framework of this research. Section 1.6 analyzes the estimation results and, through simulation, assesses how well the Smooth DE model which incorporates the Federal Reserve's long term inflation target announcement replicates the observed data. Section 1.7 demonstrates that the key findings of this paper are robust regardless of the estimated fundamental parameters.

1.2 Data

This study investigates professional forecasts using the Survey of Professional Forecasters (SPF), which is conducted in the middle month of each quarter. For instance, in the first quarter, questionnaires are distributed to panelists by the end of January, and responses are collected between the second and third weeks of February. The Philadelphia Fed took over the administration of the survey from the ASA/NBER in the second quarter of 1990, making the 1990Q2 survey the first one administered by the Philadelphia Fed.

To ensure data consistency and reliability, I exclude the period prior to 1990Q2 due to evidence suggesting that the same identification numbers may have been assigned to different forecasters.

For example, some individuals participated, then abruptly dropped out for several periods, and later re-entered, suggesting potential inconsistencies in the assignment of identifiers. Unfortunately, due to the lack of hard-copy historical records from the early surveys, the Philadelphia Fed could not investigate these cases further[2]. Given my focus on individual forecasters' expectations, I exclude these problematic periods from the analysis.

I use point forecasts to measure the conditional mean—the first moment—of the predictive distribution and density forecasts to capture the conditional variance—the second moment—of the predictive distribution. For point forecasts, the SPF questionnaire collects projections for both the quarterly and annual levels of the chain-weighted GDP price index (PGDP). Figure A-1 presents the exact question asked. Survey participants provide PGDP projections in levels, and I use their responses from the first column (PGDP1) and the fifth column (PGDP5) to construct each forecaster's four-quarter-ahead inflation forecast.

$$\pi^i_{t+4,t} = 100 \times \left(\frac{PGDP5^i_t}{PGDP1^i_t} - 1 \right). \tag{1.2.1}$$

Although the Federal Reserve's Statement on Longer-Run Goals and Monetary Policy Strategy specifies a 2% inflation target based on the Personal Consumption Expenditures (PCE) measure, I do not use the PCE measure for four-quarter-ahead inflation forecasts. This is primarily because the PCE inflation survey only began in 2007, which would significantly reduce the available data. Additionally, the SPF survey does not ask for distributional forecasts, limiting its usefulness in measuring forecast uncertainty.

The SPF compiles respondents' probabilistic assessments of changes in the GDP price index,

[2] See "4. Forecasts of Individual Participants" in Survey of Professional Forecasters Documentation from the Philadelphia Fed.

asking them to provide a probability distribution for forecasted outcomes. Figure A-2 shows the exact question posed, and Section 1.3.2 details the construction of a density forecast for inflation over a four-quarter horizon.

Not only short-term inflation forecasts but also long-term inflation forecasts are essential to this analysis. The dispersion of individual forecast errors for long-term inflation provides key insights into the magnitude of heterogeneous signal noise regarding trend inflation. If economic agents form forecasts in a similar manner, yet their forecast errors vary, this dispersion may reflect differences in the signal noise they receive. The variance in long-run forecast errors is thus a valuable measure for estimating the magnitude of this noise in the Federal Reserve's communication. The analysis uses the 5-Year PCE Inflation Rate (PCE5YR) forecast responses from the SPF, which align with the Federal Reserve's PCE-based target.

In Section 1.3.3, I test the predictability of forecast errors to assess the extent to which the first moment—the conditional mean—of the subjective belief density is updated rationally. This analysis requires individual-level data on both forecast errors and forecast revisions. Forecast errors are defined as the difference between realized and forecasted inflation for the same period, where realized inflation is calculated using the GDP price index. To ensure alignment with forecasters' information sets, first-vintage data from the Philadelphia Fed's Real-Time Dataset for Macroeconomists is used for realized inflation. For instance, the inflation rate from 2000Q4 to 2001Q4 is calculated by dividing $PGDP_{2001Q4}$ value, published in the first (advance) release at 2002Q1, by the $PGDP_{2000Q4}$ value from the same release. As the SPF survey is conducted between the last week of the first month and the second week of the second month each quarter, forecasters likely incorporate this first release into their updated information set and adjust their forecasts accordingly [3].

1.3 Empirical Evidence

1.3.1 Statement on Longer-Run Goals and Monetary Policy Strategy

On January 24, 2012, the Federal Reserve released, for the first time, the "Statement of Longer-Run Goals and Monetary Policy Strategy". This statement, updated annually each January, conveys three primary pieces of information. First, it declares that a long-term inflation rate of 2% based on the Personal Consumption Expenditures (PCE) measure is most consistent with the Federal Reserve's statutory mandate. As mentioned in the statement, the Federal Reserve anticipates that this will not only reduce economic and financial uncertainty and enhance the effectiveness of monetary policy but also ensure that the public's longer-term inflation expectations become firmly anchored. The objective announced at the beginning of the year is consistently reaffirmed in subsequent Federal Open Market Committee (FOMC) statements.

The second piece of information pertains to the Federal Reserve's efforts to achieve the maximum level of employment. Unlike the clearly defined quantitative long-term inflation target, the Federal Reserve does not specify an employment rate target. This is because the maximum level of employment is determined not solely by monetary policy but also by nonmonetary factors that influence the structure and dynamics of the labor market. Accordingly, rather than announcing a specific numerical target, the Federal Reserve confirms that policy decisions would be based on assessments of the maximum level of employment, considering various indicators. Additionally, the statement provides the most recent projection of the longer-run normal rates of unemployment[4].

[3] The Bureau of Economic Analysis typically releases advance estimates of the current quarter in the last week of the first month of the next quarter.

[4] Information about Committee participants' estimates of the longer-run normal rates of output growth and un-

Lastly, the statement underscores the Committee's aim to mitigate deviations of inflation from its longer-term objective, while also addressing deviations of employment from its evaluations of the maximum sustainable level. These objectives are typically complementary; nevertheless, in cases where they may conflict, the Federal Reserve commits to a balanced approach in pursuing both goals. This "balanced approach" remains open to interpretation, as the statement does not define specific metrics or weights for each objective. Instead, it suggests that deviations in employment from the Committee's evaluations will be treated with equal consideration as inflation deviations from the long-term target, allowing for flexibility in response to prevailing economic conditions. Over time, this statement has undergone modifications. For instance, in 2016, the Committee introduced additional language as follow:

> The Committee would be concerned if inflation were running persistently above or below this objective. Communicating this *symmetric inflation goal* clearly to the public helps keep longer-term inflation expectations firmly anchored, thereby fostering price stability and moderate long-term interest rates and enhancing the Committee's ability to promote maximum employment in the face of significant economic disturbances.

The 2016 statement introduced a symmetric inflation goal, suggesting that the Federal Reserve was equally concerned about inflation falling below or exceeding the target. A further notable amendment occurred in 2020, when, in an uncommon move, the statement was revised in August, mid-year. Among the many changes, the following language is particularly noteworthy:

> In order to anchor longer-term inflation expectations at this level, the Committee seeks to achieve inflation that *averages 2 percent over time,* and therefore judges that, following periods when inflation has been running persistently below 2 percent,

---

employment is published four times per year in the FOMC's Summary of Economic Projections. The most recent projections, such as the median estimate of FOMC participants for the longer-run normal rate of unemployment at 4.6 percent, were omitted from the amended statement released in August 2020.

> appropriate monetary policy will likely aim to achieve inflation moderately above 2 percent for some time.

At this point, the Flexible Average Inflation Target (FAIT) was introduced. The Federal Reserve shifted its focus away from symmetric concerns about inflation moving either above or below the target and instead reflected a willingness to allow inflation to overshoot 2%, aiming to offset the persistent low inflation below 2% in the long run. This approach indicates the Federal Reserve's commitment to achieving an average of 2% inflation over time. In addition, the statement also emphasized that achieving the goals of price stability and maximum employment in a sustainable manner requires financial stability. It noted that policy decisions would also reflect a balance of risks, including risks to the financial system.

Despite these changes in tone, every statement issued from 2012 through the latest version in 2024 has consistently reaffirmed the 2% long-term inflation target. This reflects the Federal Reserve's clear and consistent signaling to the public, reinforcing the credibility of its commitment to price stability and anchoring inflation expectations. Moreover, while the core message remains unchanged, subtle modifications within these statements have provided the public with indirect yet smooth updates on current trend inflation. This nuanced communication allows the Federal Reserve to maintain flexibility in responding to evolving economic conditions without undermining the stability of long-term inflation expectations.

1.3.2 Subjective Uncertainty of Four-Quarter-Ahead Inflation Forecast

Since the announcement of the statement, numerous studies have examined whether the Federal Reserve's goal of firmly anchoring the public's longer-term inflation expectations has been achieved (Binder et al., 2023; Bundick and Smith, 2023; Orphanides, 2019; Buono and Formai, 2018). This section aims to empirically demonstrate that the statement has also influenced density forecasts, drawing on the theoretical foundations proposed by Ganics, Rossi and Sekhposyan (2024).

In each survey, participants provide annual inflation density forecasts for both the current and the following years, as illustrated in Figure A-2. The first step is to construct the cumulative distribution function (CDF) for a fixed-horizon density forecast, four quarters ahead ($h = 4$)[5]. This CDF, denoted as $F^{h,C}_{i,t,q}(\cdot)$, represents individual i's forecast for h-quarters-ahead of the quarter preceding time t. It is formulated as a convex combination of two separate CDFs: $F^{0}_{i,t,q}(\cdot)$, which represents individual i's density forecast for the *current year*, and $F^{1}_{i,t,q}(\cdot)$, corresponding to the density forecast for the *next year*. Before forming this convex combination I fit a normal distribution to the each of the individual CDFs $F^{0}_{i,t,q}(\cdot)$ and $F^{1}_{i,t,q}(\cdot)$. I borrow notations from Ganics, Rossi and Sekhposyan (2024).

$$F^{h,C}_{i,t,q}(\pi) \equiv \omega^{h}_{i,q} F^{0}_{i,t,q}(\pi) + (1-\omega^{h}_{i,q}) F^{1}_{i,t,q}(\pi), \text{ such that } 0 \leq \omega^{h}_{i,q} \leq 1, q \in \{1,2,3,4\}. \quad (1.3.1)$$

where $\omega^{h}_{i,q}$ denotes individual forecaster i's unknown weight in quarter q on the current calendar year forecast. Estimating $\{\omega^{h}_{i,q}\}^{4}_{q=1}$follows the methodology outlined by Ganics (2018), which is based on the principle that a density forecast is probabilistically well-calibrated if and only if its corresponding probability integral transform (PIT) follows a uniform distribution. Therefore the weights are calculated by minimizing the distance between the PIT of the combined distribution and the uniform distribution. Notably, the PIT is evaluated at h-quarters ahead realized inflation.

$$PIT^{h}_{i,t,q} \equiv F^{h,C}_{i,t,q}(\pi^{h}_{t,q}) = \omega^{h}_{i,q} F^{0}_{i,t,q}(\pi^{h}_{t,q}) + (1-\omega^{h}_{i,q}) F^{1}_{i,t,q}(\pi^{h}_{t,q}) \quad (1.3.2)$$

[5]This examination looks at annual inflation rate from quarter $t-1$ to quarter $t+3$

To calculate vertical difference between the empirical distribution function of the PIT and the CDF of the uniform distribution at quantile $r \in [0, 1]$, I define :

$$\Psi_{i,\mathcal{T}}(r, \omega^h_{i,q}) \equiv |\mathcal{T}|^{-1}\Sigma_{t\in\mathcal{T}}\mathbb{1}\left[PIT^h_{i,t,q} \leq r\right] - r \tag{1.3.3}$$

where $\mathcal{T}$ is the index set of an appropriate sample of size $|\mathcal{T}|$ and $\mathbb{1}[\cdot]$ denotes the indicator function. Thus, $|\mathcal{T}|$ corresponds to the total number of years in which forecaster i participates. However, this approach faces a challenge due to the small sample size. If $\omega^h_{i,q}$ is estimated separately for $q = 1, 2, 3, 4$, the amount of available data decreases, leading to considerable estimation uncertainty. This issue is particularly exacerbated in this study, as it focuses on measuring weights at the individual level. To address the small sample challenge, Ganics, Rossi and Sekhposyan (2024) propose an alternative method. Instead of estimating weights separately, they suggest parameterizing the weights using flexible exponential Almon lag polynomials, as outlined by Andreou, Ghysels and Kourtellos (2010). The weights are specified as follows.

$$\omega^h_{i,q} \equiv exp(\theta_{i,1}q + \theta_{i,2}q^2),\ \ q \in \{1, 2, 3, 4\}. \tag{1.3.4}$$

In addition to this, I adopt a rolling window estimation scheme by taking $\mathcal{T} = s-R+1, s-R+2, \cdots, s$ where $s = R, R+1, \cdots, T$ is the last observation of a rolling window of size R, and T is the last available density forecast observation in i's responses. In this analysis, the rolling window size is set to 20. The parameterization in the equation (1.3.4) ensures positive weights while pooling PIT across different quarters using an exponential polynomial.

The weights are collected in the vector $\omega^h_i \equiv (\omega^h_{i,1}, \omega^h_{i,2}, \omega^h_{i,3}, \omega^h_{i,4})$ and using this formulation, I estimate weights through the minimization of the scaled quadratic distance,

$$\hat{\omega}^h_{i,q} \equiv exp(\hat{\theta}_{i,1}q + \hat{\theta}_{i,2}q^2), \ \ q \in \{1, 2, 3, 4\} \tag{1.3.5}$$

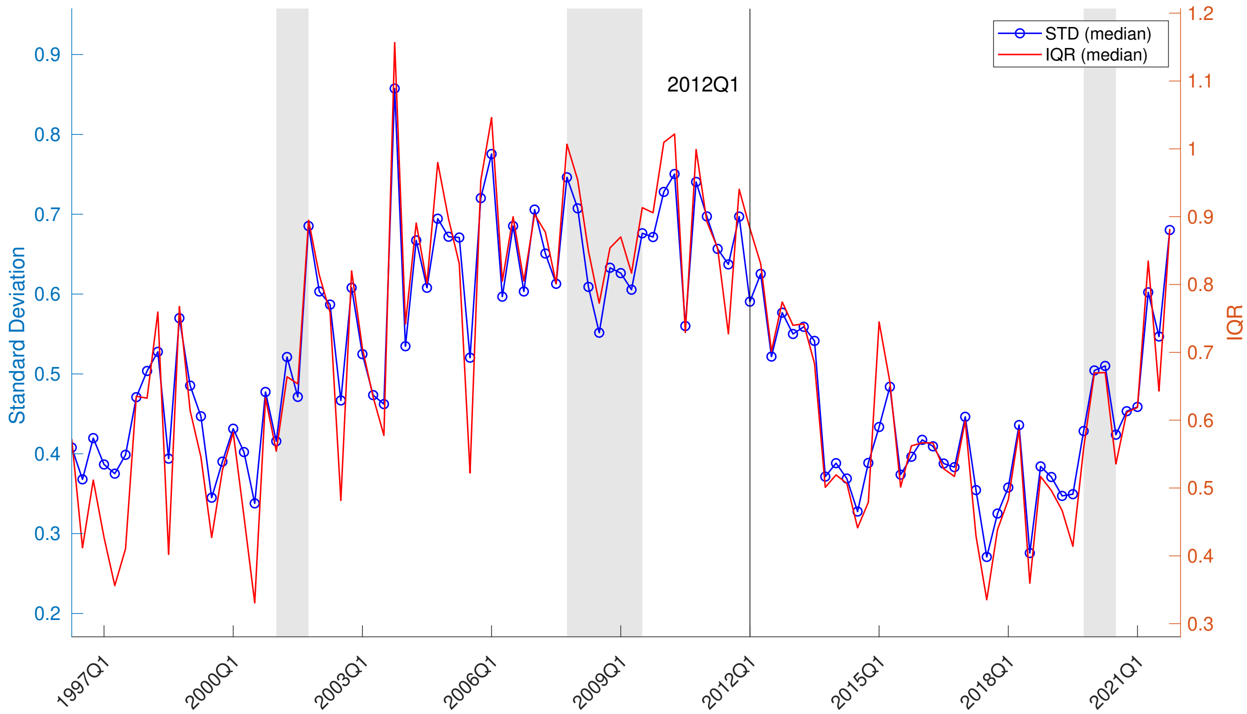
$$(\hat{\theta}_{i,1}, \hat{\theta}_{i,2})^\top \equiv \underset{\theta_{i,1},\theta_{i,2}\in\Theta}{argmin} \int_\rho \frac{\Psi^2_{i,\mathcal{T}}(r, \omega^h_{i,q})}{r(1-r)} dr \tag{1.3.6}$$

where the parameter space Θ is chosen to ensure that the estimated weights satisfy $0 < \hat{\omega}^h_{i,q} \leq 1$ for $q \in \{1, 2, 3, 4\}$, and they are non-increasing in q [6]. I use $\rho = [0, 1]$ that is a finite union of neither empty nor singleton, closed intervals on the unit interval, in which domain I want to minimize the distance between the empirical CDF of the PIT and the uniform CDF.

Using the estimated weights $\hat{\omega}^h_i \equiv (\hat{\omega}^h_{i,1}, \hat{\omega}^h_{i,2}, \hat{\omega}^h_{i,3}, \hat{\omega}^h_{i,4})$, derived from $\hat{\theta}_{i,1}$ and $\hat{\theta}_{i,2}$, the mixture distribution and its CDF $F^{h,C}_{i,t,q}(\pi)$ are obtained. The standard deviation of the fixed-horizon density forecast reflects subjective uncertainty. In Figure 1.1, the blue line with circles shows the median of the individual standard deviations for each time period. These standard deviations are computed for each individual's density forecast, and the median is plotted. Notably, the standard deviation begins to decrease after 2012Q1 and remains low until economic volatility rises again with the onset of Covid-19.

To provide a more robust measure of subjective uncertainty, I also use the interquartile range (IQR) of each forecaster's density forecast. Unlike standard deviation, the IQR provides the central 50% of the distribution and is less affected by outliers, making it particularly useful for skewed or multimodal distributions. By looking into the IQR, I minimize the influence of irregularities, especially when two fixed-event distribution means differ significantly or outliers are present. The

[6] The rationale behind this restriction is that, intuitively, as moving from quarter q to $q + 1$, I aim to avoid assigning greater weight to the current year's forecast in $q + 1$ than was assigned in quarter q



Note: The gray shaded areas indicate quarters in which there was an NBER-dated recession at any point in the quarter. Combined predictive densities for four-quarter-ahead inflation are derived at the individual level. The red line plots the median IQR for each period. The blue line with circles represents the median value of standard deviations for each period.

Figure 1.1: Subjective Uncertainty in Fixed-Horizon Forecast Densities

median IQR values offer a more robust measure of subjective uncertainty and are plotted as the solid red line.

Figure 1.1 illustrates that both the IQR and standard deviations confirm a sharp decline in inflation forecast uncertainty since 2012, suggesting that individual forecasters have become increasingly confident in their projections. It is important to note that this pattern does not result merely from data adjustments or transformations during the estimation process. To ensure a robust comparison, I calculate standard deviations from normal distribution-fitted fixed event densities for each survey vintage, avoiding the use of weighted averages. The median standard deviation is then derived for each quarter. The results reveal a significant reduction in subjective inflation forecast uncertainty across all horizons—from one to four quarters—since 2012, as further detailed in the Figure A-3. This trend corroborates the findings in Figure 1.1.

This declining pattern cannot be simply attributed to stable economic environments. While some may argue that it results from the stabilized conditions following the Great Recession of 2007–2009, this is not necessarily the case. If economic stability were the sole driver, we would expect a similar reduction in forecast uncertainty across other key macroeconomic variables. To test this, I assess forecasters' subjective uncertainty in real GDP and civilian unemployment rate predictions around 2012. However, the probabilistic forecast survey for the civilian unemployment rate only began in the second quarter of 2009, limiting the available early data. As a result, the Ganics, Rossi and Sekhposyan (2024) methodology restricts the ability to observe changes in uncertainty before and after 2012 [7]. To address this limitation, I fit a normal distribution to fixed-event density forecasts for real GDP growth and the unemployment rate, deriving standard deviations and plotting the quarterly median. Figures A-4 and A-5 show that there are no significant differences in probabilistic forecasts for these variables around 2012. This supports the conclusion that the Statement on Longer-Run Goals and Monetary Policy Strategy, which clarifies long-term inflation targets, has a direct impact on inflation forecasts without affecting uncertainty for other macroeconomic variables.

1.3.3 Over-reaction of Inflation Point Forecasts

As the second moment of the predictive density decreases, it naturally raises the question of whether the first moment, or conditional mean (point forecast), is also affected, potentially causing shifts in

[7] In the analysis, 20 quarters of survey data are used in a rolling window to estimate weights for density forecasts. For the civilian unemployment rate, responses up to 2014Q2 are used to produce the first fixed-horizon forecast for 2016Q1

forecast trends or directions before and after 2012. At the individual level, the average forecaster appears to overreact to private information, a phenomenon Bordalo et al. (2020) empirically verify and explain through the DE model. Coibion and Gorodnichenko (2015) introduce the CG test to provide evidence of information rigidities, with the CG test coefficient reflecting the degree of rigidity, consistent with both sticky-information and noisy-information models. They demonstrate that, at the aggregate level, systematic predictability of forecast revisions on forecast errors results in a positive CG test coefficient when information rigidities are present.

In contrast, Bordalo et al. (2020) apply the CG test at the individual level and find a negative CG coefficient, indicating individuals' over-reactive expectations in response to news. In my analysis, following Bordalo et al. (2020), I apply the CG test at the individual level by dividing the data into pre-2012 and post-2012 periods, where a distinct declining trend of subjective uncertainty is evident in Figure 1.1.

The version of the CG test by Bordalo et al. (2020) is

$$\pi_{t+4} - \pi^i_{t+4|t} = \beta_0 + \beta_1(\pi^i_{t+4|t} - \pi^i_{t+4|t-1}) + \epsilon^i_{t,t+4} \tag{1.3.7}$$

where forecast revisions, $\pi^i_{t+4|t} - \pi^i_{t+4|t-1}$, quantifies new information received by individual i and $\pi_{t+4} - \pi^i_{t+4|t}$ represents individual i's forecast errors. If $\beta_1 > 0$, it suggests that the average forecaster underreacts to her own information, whereas $\beta_1 < 0$ indicates overreaction. A negative β_1 indicates that the average forecaster is excessively optimistic when forecast revisions are positive - that is, when the current news points to a more favorable future state compared to the previous information set. Importantly, under rational expectations, $\beta_1 = 0$, even in the presence of information frictions. In the individual-level CG test, β_1 does not directly indicate the presence or absence of information

	1990Q2-2011Q4	2012Q1-2022Q1	1990Q2-2022Q1	1990Q2-2011Q4	2012Q1-2022Q1	1990Q2-2022Q1
β_0	-0.231^{***}	0.241	-0.062	-	-	-
	(0.079)	(0.238)	(0.105)			
β_1	-0.316^{***}	0.087	-0.147	-0.361^{***}	0.066	-0.194^{**}
	(0.070)	(0.175)	(0.103)	(0.069)	(0.128)	(0.090)
Obs.	2229	1142	3449	2221	1137	3438
FE	No	No	No	Yes	Yes	Yes

Note: CG test results using IV regression. Obs. indicates the sample size. Robust standard errors are in parentheses;***indicates significance at the 1% level. **indicates significance at the 5% level, and *indicates significance at the 10% level.

Table 1.1: CG Test Results at Individual Level

frictions. A rational forecaster may encounter information frictions stemming from inattention or noisy signals, but as long as the forecaster updates her beliefs rationally, forecast errors will remain unpredictable. If the forecaster has updated expectations rationally based on the available information, forecast revisions would not systematically predict forecast errors. Therefore, if there is no correlation between forecast revisions and forecast errors, it suggests that an average forecaster updates her expectations rationally, even with information frictions.

Table 1.1 exhibits that the pattern of overreaction in individual forecasts has weaken since 2012. Specifically, while β_1 turns positive after 2012, it remains statistically insignificant, suggesting that forecasters now form expectations closer to rational expectations for four-quarter-ahead inflation, with less sensitivity to new information. The Federal Reserve's additional communication on longer-run inflation has helped moderate overreaction in short-horizon inflation forecasts. As a result, forecasters incorporate this new message, leading to a decrease in subjective uncertainty, which in turn boosts their confidence in their beliefs without exaggerating extreme forecast scenarios. In sum, the Statement of Longer-Run Goals and Monetary Policy Strategy has *jointly* influenced both the first and the second moments of the predictive density, particularly for short-term horizons.

This observation suggests that clearer and more consistent communication from policymakers has been key to moderating overreaction patterns typically seen in individual forecasting behavior. Even when compared to the real GDP growth rate and the unemployment rate CG test results provided in the Table A-1, this is a distinctive feature of inflation forecasts. The point forecasts for the real GDP growth rate and the unemployment rate tend to exhibit slightly stronger overreaction to news since 2012. To investigate the mechanisms driving these changes – observed uniquely in inflation forecasts – I present the analysis using the Smooth DE framework.

1.4 Diagnostic Expectations and Smooth DE

The key distinction between Smooth DE and DE lies in changes in conditional uncertainty. In Smooth DE, the degree of overreaction depends on the current level of uncertainty about the state relative to the reference uncertainty formed in the past. Before delving into the specifics of Smooth DE, it is important to first understand the foundation laid by the DE model, which serves as the basis for these extensions.

1.4.1 Diagnostic Expectations

Bordalo, Gennaioli and Shleifer (2018) introduce the DE framework, which explains how survey forecasts become overly optimistic following good news and overly pessimistic after bad news. This overreaction, especially prominent in credit markets, challenges the assumptions of rational expectations theory. As an alternative, the authors propose the DE model, which draws on Kahneman and Tversky (1972)'s concept of 'representativeness heuristic'. The DE framework integrates both overextrapolation and the neglect of risk.

In the DE model, forecasters reassess the likelihood of future outcomes based on 'representativeness'. When forming forecasts about future economic states, individuals operating under the DE mechanism do not assess the distribution of a future state using the true conditional distribution given current news or realizations. Although this information is stored in their memory, when new information arrives, they compare the likelihood of certain future states given current news (updated information set) to that derived from reference information which has not incorporated the news. Because of memory limitations, agents cannot recall information perfectly; instead, they quickly recall certain 'representative' states—specifically, those that seem more likely based on new information. These states are the ones whose likelihood increases the most when compared to their previous beliefs or 'reference memory', which was shaped by past information. As a result, individuals overweigh these representative states, distorting the objective likelihood. Bordalo, Gennaioli and Shleifer (2018) formalize 'representativeness' as

$$rep_t = \frac{h(\hat{\omega}_{t+1}|G)}{h(\hat{\omega}_{t+1}|-G)},$$

where $\hat{\omega}_{t+1}$ is the forecasted variable, G represents updated information, serving as a posterior group that incorporates the latest news, while $-G$ denotes reference information, which serves as a reference group without incorporating the latest news. A certain expected outcome $\hat{\omega}_{t+1}$ is more representative if it occurs more frequently given news (G) *relative to* the reference memory ($-G$), and this state $\hat{\omega}_{t+1}$ comes to minds faster than other possible states. This representativeness distorts the objective density in the minds of decision-makers, leading them to form a biased subjective density. The distorted subjective density is expressed as

$$h_t^{\theta}(\hat{\omega}_{t+1}) = h(\hat{\omega}_{t+1}|G)\left[\frac{h(\hat{\omega}_{t+1}|G)}{h(\hat{\omega}_{t+1}|-G)}\right]^{\theta}\frac{1}{Z}$$

where Z is a normalizing constant. As θ increases, the tendency to oversample representative states becomes stronger, resulting in greater distortion of the objective density. Building on this distorted density, the diagnostic belief is formalized as follows.

Proposition 1. *When the process for $\omega_t$is AR(1) with normal $(0, \sigma^2)$ shocks, the diagnostic distribution $h_t^\theta(\hat{\omega}_{t+1})$ is also normal, with variance $\sigma^2$and mean*

$$\mathbb{E}_t^\theta(\omega_{t+1}) = \mathbb{E}_t(\omega_{t+1}) + \theta[\mathbb{E}_t(\omega_{t+1}) - \mathbb{E}_{t-1}(\omega_{t+1})].$$

Proof. See Appendix in Bordalo, Gennaioli and Shleifer (2018). □

$\mathbb{E}_t^\theta$ represents diagnostic expectations, while $\mathbb{E}_t$, the expectation operator without the superscript θ, represents rational expectations. Both $\mathbb{E}_t(\omega_{t+1})$ and $\mathbb{E}_{t-1}(\omega_{t+1})$ represent the conditional mean of rational expectations from the true density. It is assumed that the variance of diagnostic distribution σ^2 is identical to that of the fundamental shocks. Under rational expectations, θ equals zero, and the DE model collapses to rational expectations. This implies that agents have no memory limitations, allowing them to recall information perfectly and update their beliefs rationally. On the other hand, when $\theta > 0$, diagnostic expectations overreact to the information. A positive θ means that agents evaluate the likelihood ratio based on representativeness, and θ measures the severity of this distortion. Due to the distorted probability density in their incomplete memory, agents' oversampling of representative states significantly influences their expectations.

Consequently, while individuals may hold rational expectations in the back of their minds, diagnostic expectations are unconsciously distorted by the representativeness heuristic. This heuristic causes forecasters to overemphasize certain aspects of the information received, thereby distorting the objective distribution in their forecasts.

1.4.2 Smooth Diagnostic Expectations

Bordalo et al. (2020) and Bordalo, Gennaioli and Shleifer (2018) assume that subjective uncertainty is equivalent to objective uncertainty. A key innovation in Bianchi, Ilut and Saijo (2024)'s Smooth DE framework is the disconnection of objective and subjective uncertainty. They relax the rigid assumption that subjective uncertainty must mirror objective uncertainty. This shift acknowledges that if the first moment of expectations is distorted, it is reasonable to expect the second moment to be affected as well. Despite this intuition, the standard DE models do not focus on the role of uncertainty until Bianchi, Ilut and Saijo (2024) highlight the importance of changes in conditional uncertainty in shaping expectations.

The change in conditional uncertainty is represented as

$$R_{t+h|t,t-J} \equiv \frac{\sigma^2_{t+h|t}}{\sigma^2_{t+h|t-J}} \tag{1.4.1}$$

where $\sigma^2_{t+h|t-J}$ is the variance of the true density conditional on reference information set (in my model, reference information set is the information set from the immediately preceding period, $J = 1$) and $\sigma^2_{t+h|t}$ is the variance conditional on the current updated information set[8]. Forecasters retrieve memory selectively, leading to a distorted density $f^\theta(x_{t+h}|\mathcal{I}_t)$ affected by representativeness.

$$f^\theta(\hat{x}_{t+h}|\mathcal{I}_t) = f(\hat{x}_{t+h}|\mathcal{I}_t)\left[\frac{f(\hat{x}_{t+h}|\mathcal{I}_t)}{f(\hat{x}_{t+h}|\mathcal{I}_t^{ref})}\right]^\theta \frac{1}{Z} \tag{1.4.2}$$

In my model $\mathcal{I}_t^{ref}$ is the information set updated in the preceding period, $\mathcal{I}_{t-1}$.

[8] $J \geq 1$ allows distant memory for reference information set.

Proposition 2. *(Smooth DE) Consider the reference group given by density in equation*

$$f(\hat{x}_{t+h}|\mathcal{I}_{t-J}^{ref}) = \mathbb{N}(\hat{x}_{t+h}; \mu_{t+h|t-J}, \sigma^2_{t+h|t-J}).$$

Denote the ratio variances for the current and reference groups as

$$R_{t+h|t,t-J} \equiv \sigma^2_{t+h|t} / \sigma^2_{t+h|t-J}$$

If $R_{t+h|t,t-J} < (1+\theta)/\theta$, the Smooth DE density $f^{\theta}(\hat{x}_{t+h}|\mathcal{I}_t)$ in equation (1.4.2) is Normal with conditional mean

$$\mathbb{E}_t^{\theta}(x_{t+h}) = \mu_{t+h|t} + \theta \frac{R_{t+h|t,t-J}}{1+\theta(1-R_{t+h|t,t-J})}[\mu_{t+h|t} - \mu_{t+h|t-J}] \tag{1.4.3}$$

and conditional variance is

$$\mathbb{V}_t^{\theta}(x_{t+h}) = \frac{\sigma^2_{t+h|t}}{1+\theta(1-R_{t+h|t,t-J})}. \tag{1.4.4}$$

Proof. See Appendix in Bianchi, Ilut and Saijo (2024). □

$\mu_{t+h|t}$ and $\mu_{t+h|t-J}$ represent the conditional mean of rational expectations from the true density. The term $R_{t+h|t,t-J}$ plays a critical role in both the conditional mean, $\mathbb{E}_t^{\theta}(x_{t+h})$, and variance, $\mathbb{V}_t^{\theta}(x_{t+h})$. In Bianchi, Ilut and Saijo (2024), they highlight three key features of Smooth DE as introducing the effective distortion parameter

$$\tilde{\theta}_{t,t-J} \equiv \theta \frac{R_{t+h|t,t-J}}{1+\theta(1-R_{t+h|t,t-J})}. \tag{1.4.5}$$

The effective distortion parameter $\tilde{\theta}_{t,t-J}$ measures how much the conditional mean, in effect, overreacts to new information. This time-varying parameter reflects how much uncertainty is resolved as new information is incorporated. When current information significantly reduces uncertainty compared to reference information formed in the past, the role of retrieved memory diminishes. As uncertainty decreases, reliance on representativeness is reduced, allowing forecasters to depend more on precise information about the current state. This results in a conditional density, $f^{\theta}(\hat{x}_{t+h}|\mathcal{I}_t)$, that is closer to the true density.

Within the standard DE framework, it is impossible to demonstrate that the distortion parameter varies over time; it remains constant throughout. In contrast, in the smooth DE model, the effective distortion parameter, $\tilde{\theta}_{t,t-J}$, evolves over time, influenced by changes in the level of conditional uncertainty. Furthermore, the standard DE model does not support the evidence that agents tend to exhibit lower subjective uncertainty as they receive more transparent signals. In the standard DE model, agents' subjective uncertainty always aligns with true uncertainty. The smooth DE model is crucial because it explains joint changes in the conditional mean and variance of the belief distribution by incorporating $R_{t+h|t,t-J}$.

1.5 Model

In this section, with smooth DE, I propose a parsimonious model of individuals' expectations formation for four-quarter-ahead inflation. It is assumed that agents update their beliefs about unobservable components upon receiving signals that convey both information about the underlying states and noise.

1.5.1 Inflation Dynamics

Inflation is modeled as the sum of two unobserved components: a permanent trend component τ_t and transitory cyclical component (i.e., the inflation gap) ε_t, which follows an AR(1) process with persistence ρ_ε.

$$\pi_t = \tau_t + \varepsilon_t \tag{1.5.1}$$

This trend-cyclical decomposition builds upon the foundational work of Stock and Watson (2007) and is further developed by more recent studies, including those by Chan, Clark and Koop (2018), Mertens (2016), Mertens and Nason (2020), Nason and Smith (2021). Mertens and Nason (2020) and Nason and Smith (2021) analyze inflation forecasts within a sticky information framework incorporating average forecasts, demonstrating that gradual adjustments in forecasts during the high-inflation period of the 1970s led to persistent forecast errors until the Volcker disinflation. Their work also highlights the increased stickiness in inflation forecasts following this period.

This paper contributes to the existing literature by applying a noisy information model, analyzing individual-level panelist forecasts instead of aggregate forecast data, offering a novel perspective on the individual level expectations formation.

1.5.2 State-Space Model

Forecasters make multi-period-ahead inflation forecasts by combining their predictions of the trend component, τ_{t+h}, and the cyclical component, ε_{t+h}. To generate these forecasts separately, agents update their beliefs about the current states $\tau_{t|t}^{i,\theta}$ and $\varepsilon_{t|t}^{i,\theta}$, based on the information available at time t. Forecasters update in a forward-looking way in the sense that forecasts take the variable's true persistence into account, even if they overreact to news[9].

$$\begin{aligned}
\mathbb{E}_t^{i,\theta}(\pi_{t+h}) &= \mathbb{E}_t^{i,\theta}(\tau_{t+h}) + \mathbb{E}_t^{i,\theta}(\varepsilon_{t+h}) \\
&= \mathbb{E}_t^{i,\theta}(\tau_t) + \rho_\varepsilon^h \mathbb{E}_t^{i,\theta}(\varepsilon_t) \\
&= \begin{pmatrix} 1 & \rho_\varepsilon^h \end{pmatrix} \begin{pmatrix} \tau_{t|t}^{i,\theta} \\ \varepsilon_{t|t}^{i,\theta} \end{pmatrix}
\end{aligned}$$

where $h = 4$, $\tau_{t|t}^{i,\theta} = \mathbb{E}_t^{i,\theta}(\tau_t)$ and $\varepsilon_{t|t}^{i,\theta} = \mathbb{E}_t^{i,\theta}(\varepsilon_t)$ represent individual i's updated trend and cyclical components, respectively, both distorted by θ, given the information available at time t . The expectation operator $\mathbb{E}_t^{i,\theta}$ reflects individual i's Smooth DE. The parameter θ captures the extent of the departure from rational expectations.

The transition equation, a key part of the state-space model, remains unchanged before and after 2012, reflecting the (conservative) assumption that the data generating process for π_t does not change.

$$\begin{pmatrix} \tau_t \\ \varepsilon_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & \rho_\varepsilon \end{pmatrix} \begin{pmatrix} \tau_{t-1} \\ \varepsilon_{t-1} \end{pmatrix} + \begin{pmatrix} \sqrt{1-\gamma}\sigma & 0 \\ 0 & \sqrt{\gamma}\sigma \end{pmatrix} \begin{pmatrix} u_{t,\tau} \\ u_{t,\varepsilon} \end{pmatrix} \tag{1.5.2}$$

The total variance of the innovations to π_t, conditional on time $t-1$ information, is σ^2. The share of this variance attributed to shocks to the trend component τ_t is $1-\gamma$ while the remaining share γ is attributable to the cyclical component ε_t. $u_{t,\tau}$ and $u_{t,\varepsilon}$ are independent and follows standard normal distributions, $u_{t,\tau} \sim \mathbb{N}(0,1)$ and $u_{t,\varepsilon} \sim \mathbb{N}(0,1)$.

At each time t, the target variables $\tau_{t+h|t}$ and $\varepsilon_{t+h|t}$ are forecasted. To make these forecasts, forecasters must update their beliefs about the current states τ_t and ε_t, which are unobservable.

[9]Note that, since the expectations formation rule is forward-looking, $\tau_{t+h|t}^i = 1^h \tau_{t|t}^i$, given the random walk process, and $\varepsilon_{t+h|t}^i = \rho_\varepsilon^h \varepsilon_{t|t}^i$, given the AR(1) process.

Instead of direct observation, they rely on noisy signals that contain information about these states. Forecasters, therefore, infer τ_t and ε_t based on these signals. From this point forward, we assume the signal structure is exogenous.

5.2.1 Signal Structure Prior to the Statement: 1990Q2–2011Q4

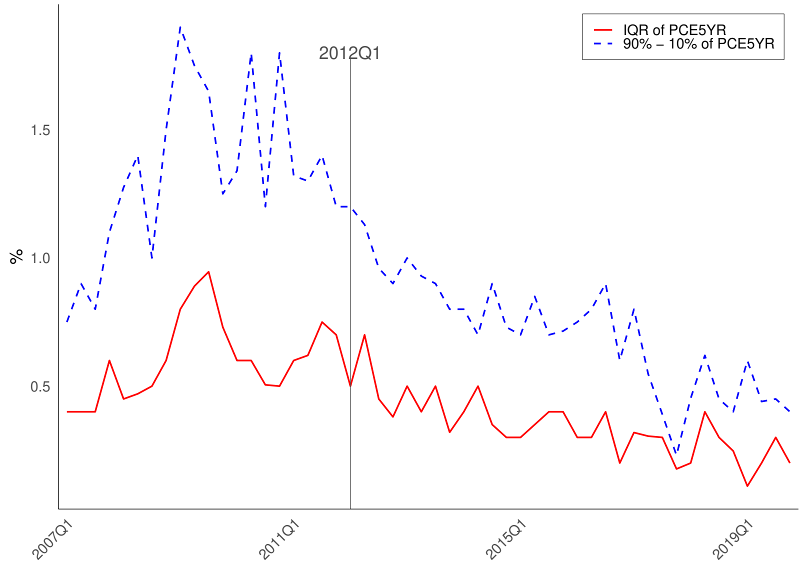
Before 2012, agents receive only one signal that contains information about both τ_t and ε_t, but they cannot disentangle which portion corresponds to each component. Agents receive private signals, leading to heterogeneity in forecasts. Each agent's signal noise is drawn from a standard normal distribution $\nu^i_{t,\tau\varepsilon} \sim \mathbb{N}(0, 1)$, and size of the noise is represented by $\sigma_{\nu,\tau\varepsilon}$

$$S^i_{t,\tau\varepsilon} = \begin{pmatrix} 1 & 1 \end{pmatrix} \begin{pmatrix} \tau_t \\ \varepsilon_t \end{pmatrix} + \sigma_{\nu,\tau\varepsilon} \nu^i_{t,\tau\varepsilon}. \tag{1.5.3}$$

I will henceforth refer to the signal $S^i_{t,\tau\varepsilon}$ as the 'mixed signal'.

5.2.2 Signal Structure After the Statement: 2012Q1–2021Q4

From 2012 onward, agents begin receiving an additional signal from the Statement on Longer-Run Goals and Monetary Policy Strategy, which clarifies the Federal Reserve's long-term inflation target. As its nuances evolve and shift over time, this signal indirectly conveys information about the current trend inflation, τ_t, while also providing the Federal Reserve's viewpoint on the current economic situation. The noise associated with this signal, $\nu^i_{t,\tau}$, varies across agents, reflecting different levels of trust in the Federal Reserve. For example, an agent with high confidence in the Fed's ability to maintain price stability would have $\nu^i_{t,\tau}$ close to zero, perceiving the signal with little noise. Conversely, an agent skeptical of the Federal Reserve's commitment, perhaps due to



Note: The red line represents the interquartile range of 5-year PCE forecasts. To capture a wider range of forecasts, the blue dashed line shows the difference between the 90th and 10th percentiles of 5-year PCE forecasts. The gap between forecasts ranked at the 90th and 10th percentiles among survey participants has significantly narrowed since 2012.

Figure 1.2: Belief Dispersion of 5-Year-Ahead PCE Forecasts

concerns about financial stability or labor market conditions, would perceive a much noisier signal, with $v^i_{t,\tau}$ deviating significantly from zero. These differences in trust are reflected in the SPF data. Even after the Federal Reserve's long-term target has been shared, disagreement in 5-year PCE forecasts across agents persists, as evidenced by the IQR of forecasts in Figure 1.2.

The IQR indicates that while disagreement in long-term inflation forecasts gradually decreases following the announcement, it does not completely dissipate. This gradually diminishing (but still existing) disagreement highlights the heterogeneity in agents' reception of publicly accessible signals. Even when exposed to the same information, agents interpret it differently based on their individual trust in the Federal Reserve's credibility, leading to heterogeneous signal reception.

The measurement equation since 2012 can be represented as

$$\begin{pmatrix} S^i_{t,\tau} \\ S^i_{t,\tau\varepsilon} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \tau_t \\ \varepsilon_t \end{pmatrix} + \begin{pmatrix} \sigma_{\nu,\tau} & 0 \\ 0 & \sigma_{\nu,\tau\varepsilon} \end{pmatrix} \begin{pmatrix} \nu^i_{t,\tau} \\ \nu^i_{t,\tau\varepsilon} \end{pmatrix}. \tag{1.5.4}$$

Here, $\sigma_{\nu,\tau\varepsilon}$ and $\sigma_{\nu,\tau}$ represent the magnitudes of the noise terms. The noise terms $\nu^i_{t,\tau\varepsilon}$ and $\nu^i_{t,\tau}$ are both assumed to follow a standard normal distribution, $\mathbb{N}(0,1)$, and $\sigma_{\nu,\tau}$ captures the magnitude of noise in the trend signal. I will refer to the signal $S^i_{t,\tau}$ as the 'trend signal'. Note that the signal structure represents each forecaster's perceived model of π_t, which is not necessarily the same as the true data-generating process.

1.5.3 Smooth Diagnostic Expectations

Given the state-space model, individuals update their information sets and beliefs. The true densities conditional on the current information set and the reference information set obtained in the preceding period are

$$f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h} | \mathcal{I}^i_t) = \mathbb{N}\left(\begin{matrix} \tau^i_{t+h|t} \\ \varepsilon^i_{t+h|t} \end{matrix}, \Sigma_{t+h|t} \right)$$

$$f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h} | \mathcal{I}^{i,ref}_t) = \mathbb{N}\left(\begin{matrix} \tau^i_{t+h|t-1} \\ \varepsilon^i_{t+h|t-1} \end{matrix}, \Sigma_{t+h|t-1} \right)$$

where $\tau^i_{t+h|t} = \mathbb{E}^i_t(\tau_{t+h})$ and $\varepsilon^i_{t+h|t} = \mathbb{E}^i_t(\varepsilon_{t+h})$ represent individual i's Bayesian rational expectations, unaffected by the heuristic. Instead of applying these true densities, forecasters use a distorted density, defined as

$$f^{\theta}(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^i) = f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^i)\left[\frac{f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^i)}{f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^{i,ref})}\right]^{\theta}\frac{1}{Z} \tag{1.5.5}$$

where Z is a constant of integration, and θ is assumed to be greater than zero ($\theta > 0$). If $\theta = 0$, this implies that forecasts are formed without distortion, in a fully rational manner. A key concept here is representativeness,

$$rep(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}) \equiv \frac{f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^i)}{f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^{i,ref})},$$

which measures the extent to which a forecaster, when faced with current news, subjectively assigns higher or lower likelihoods to future outcomes $(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h})$ relative to past reference information. This process triggers selective recall, with possible future outcomes of higher relative frequency being recalled more strongly. When $\theta = 0$, the heuristic does not influence expectations, and forecasts are based purely on the objective conditional probability $f(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h}|\mathcal{I}_t^i)$. Notably, $rep(\hat{\tau}_{t+h}, \hat{\varepsilon}_{t+h})$ is affected not only by changes in the conditional mean but also by changes in the conditional variance— by shifts in $\Sigma_{t+h|t}$ and $\Sigma_{t+h|t-1}$, which measure the uncertainty of the current distribution with respect to the reference distribution —when the information set is updated. As beliefs are updated, the ratio of conditional uncertainties, denoted by $R_{t+h|t,t-1}$, plays a crucial role in the smooth diagnostic expectations formation process. To account for this adjustment in conditional uncertainty in relation to the severity of distortion, the effective distortion parameter $\tilde{\theta}_{t,t-1}$ is adopted.

Proposition 3. *Let the reference group of variables, τ_t and ε_t, be given for the period immediately* *preceding the current one. The ratio of the conditional variance matrices between the current period, t, and the reference period, $t-1$, is defined as a 2-by-2 matrix given by*

$$R_{t+h|t,t-1} \equiv \Sigma_{t+h|t}\Sigma^{-1}_{t+h|t-1}.$$

If $R_{t+h|t,t-1} < \{\frac{1+\theta}{\theta}\}I$, where I is the 2-by-2 identity matrix, the smooth DE density is normally distributed with the conditional mean before 2012 expressed as

$$\begin{aligned}
\mathbb{E}^{i,\theta}_t(\pi_{t+h}) &= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\begin{pmatrix} \tau^{i,\theta}_{t|t} \\ \varepsilon^{i,\theta}_{t|t} \end{pmatrix} \\
&= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\left[\begin{pmatrix} \tau^{i}_{t|t-1} \\ \varepsilon^{i}_{t|t-1} \end{pmatrix} + \left(I+\tilde{\theta}_{t,t-1}\right) K_t \left(S^i_{t,\tau\varepsilon} - \tau^i_{t|t-1} - \varepsilon^i_{t|t-1}\right)\right] \\
&= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\left[\begin{pmatrix} \tau^{i}_{t|t-1} \\ \varepsilon^{i}_{t|t-1} \end{pmatrix} + \left(I+\tilde{\theta}_{t,t-1}\right) K_t \left(S^i_{t,\tau\varepsilon} - \begin{pmatrix} 1 & 1 \end{pmatrix}\begin{pmatrix} \tau^{i}_{t|t-1} \\ \varepsilon^{i}_{t|t-1} \end{pmatrix}\right)\right]
\end{aligned}$$

and the conditional mean after 2012

$$\begin{aligned}
\mathbb{E}^{i,\theta}_t(\pi_{t+h}) &= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\begin{pmatrix} \tau^{i,\theta}_{t|t} \\ \varepsilon^{i,\theta}_{t|t} \end{pmatrix} \\
&= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\left[\begin{pmatrix} \tau^{i}_{t|t-1} \\ \varepsilon^{i}_{t|t-1} \end{pmatrix} + \left(I+\tilde{\theta}_{t,t-1}\right) K_t \left(\begin{pmatrix} S^i_{t,\tau} \\ S^i_{t,\tau\varepsilon} \end{pmatrix} - \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}\begin{pmatrix} \tau^{i}_{t|t-1} \\ \varepsilon^{i}_{t|t-1} \end{pmatrix}\right)\right]
\end{aligned}$$

where effective distortion matrix $\tilde{\theta}_{t,t-1} = \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}$. The variance is for-

mulated as

$$\mathbb{V}_t^{\theta}(\pi_{t+h}) = \Sigma_{t+h|t}\left((1+\theta)I - \theta\Sigma_{t+h|t}\Sigma_{t+h|t-1}^{-1}\right)^{-1}$$
$$= \Sigma_{t+h|t}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}.$$

Proof. See Appendix 1.9. □

The Kalman gain matrix, K_t, changes over time. Since 2012, with the addition of a new signal, the K_t matrix shifts from a 2-by-1 to a 2-by-2 matrix structure. The reduction in uncertainty, $R_{t+h|t,t-1}$, takes the form of a 2-by-2 matrix throughout all periods[10]. $R_{t+h|t,t-1} < \{\frac{1+\theta}{\theta}\}I$ guarantees the variance of the resulting distorted normal distribution is finite and positive.

Proposition 4. *The effective distortion matrix $\tilde{\theta}_{t,t-1}$ decreases in a reduction in uncertainty $R_{t+h|t,t-1}$.*

$$\frac{\partial\tilde{\theta}_{t,t-1}}{\partial R_{t+h|t,t-1}} > 0$$

Proof. See Appendix 1.9. □

In the smooth DE model, $\tilde{\theta}_{t,t-1}$ is positively associated with the ratio of variances $R_{t+h|t,t-1}$. The distortion parameter θ captures the degree to which the diagnostic density inflates the probability of representative states and is constant. However, the *effective* degree of this amplification—represented by $\tilde{\theta}_{t,t-1}$ —varies over time, as it is scaled by $R_{t+h|t,t-1}$. Thus, if $\Sigma_{t+h|t}$ is much

[10]In Bianchi, Ilut and Saijo (2024), $R_{t+h|t,t-1}$ is defined as 'the ratio of conditional uncertainty,' which can rise or fall as the information set is updated. In particular, during an uncertainty shock—when updated information becomes more uncertain— $R_{t+h|t,t-1}$may increase. However, in my setting, I assume that as information is updated and the latest news is incorporated, uncertainty in the information set decreases, based on the assumption of a stable economy. For simplicity, I refer to $R_{t+h|t,t-1}$ as the reduction in uncertainty.

smaller than $\Sigma_{t+h|t-1}$, due to highly precise news in the current period, the *effective* magnitude of distortion declines as $R_{t+h|t,t-1}$ decreases. It directly relates to how excessively news influences agent's forecasts. Therefore the first moment of smooth DE density, $\mathbb{E}_t^{i,\theta}(\pi_{t+h})$, is influenced by $R_{t+h|t,t-1}$ adjusting $\tilde{\theta}_{t,t-1}$. In practice, the Federal Reserve's explicit communication about the 2% inflation target in early 2012 significantly contributed to reducing uncertainty surrounding the trend component τ_t which is embedded in $\Sigma_{t+h|t}$. This reduction in uncertainty is particularly sizable following the Federal Reserve's first statement in 2012. This clarity reduces forecasters' reliance on selectively recalled reference information when estimating the trend component.

Moreover, subjective uncertainty, denoted by $\mathbb{V}_t^{\theta}(\pi_{t+h})$, is tied to the ratio of conditional variances, $R_{t+h|t,t-1}$, implying that reduced uncertainty also diminishes subjective uncertainty in forecasts. Forecasters experience a reduction in uncertainty of the current distribution with respect to the reference distribution as incoming news delivers more precise information. Thus, they overstate how precise their updated belief is. This leads to lower uncertainty surrounding their point forecasts, higher confidence in their forecasts. This relationship is evident in the SPF data, where a notable decline in subjective uncertainty is observed following the Federal Reserve's communication in 2012. Consequently, forecasters base their estimates on clearer, current information, reducing reliance on the representativeness heuristic and imperfect memory recall, resulting in smaller distortions in belief updates.

Corollary 1. *As $\tilde{\theta}_{t,t-1}$ decreases, heterogeneity across individual forecasts decreases because less weight is given to signals that induce heterogeneity in the information individuals receive.*

Additionally, a reduction in uncertainty leads to less dispersion across inflation forecasts. The effective distortion parameter, $\tilde{\theta}_{t,t-1}$, serves as an amplifying factor for news. Forecast heterogeneity arises only from the heterogeneous signals that agents receive. When the amplifying factor decreases, each agent places less weight on news in forming their inflation expectations. Consequently, individual forecasts become more aligned with rational expectations as they become less sensitive to heterogeneous signals, thereby reducing disagreement among agents.

1.6 Estimation

The model is estimated in two stages. In the first stage, I estimate the parameters governing the law of motion in inflation using GDP Price Index data from 1990Q2 to 2021Q4. With these estimates, I proceed to estimate the distortion parameter and the magnitude of signal noises using the simulated method of moments (SMM). This two-step approach addresses the difficulty of estimating all parameters simultaneously through SMM, especially given the presence of latent variables, which complicates the selection of appropriate target moments. To overcome this, I first apply Bayesian estimation to pin down the parameters related to the law of motion, and subsequently use SMM to estimate the distortion parameter and signal noise.

1.6.1 Bayesian Estimation

Assuming that agents share true values for ρ_ε, γ and σ in the equation (1.5.2), I use Bayesian estimation along with a state space model to estimate the parameters ρ_ε, γ, and σ. In the state space model, a transition equation is same as equation (1.5.2) and the measurement equation is

$$y_t = \begin{pmatrix} 1 & 1 \end{pmatrix} \begin{pmatrix} \tau_t \\ \varepsilon_t \end{pmatrix} \tag{1.6.1}$$

Parameters	Prior	Posterior Mean	Std. Error	Posterior Distribution (90%)
ρ_ε	$\mathbb{N}$	0.377	0.105	[0.204, 0.551]
γ	$\mathbb{B}$	0.701	0.108	[0.509, 0.867]
σ^2	$\mathbb{IG}$	0.237	0.028	[0.195, 0.286]

Table 1.2: Estimated Parameters

where y_t represents realized inflation from Philadelphia Fed's Real-Time Dataset for Macroeconomists.

The parameter estimates are reported in Table 1.2. I report mean posterior estimates, along with the 90% posterior interval. I generate 100,000 draws using the Metropolis–Hastings algorithm and discard the first 10% as initial burn-in. Further methodological details are presented in the Appendix 1.9.

1.6.2 Simulated Method of Moments

The advantage of using SMM lies in its flexibility. SMM is highly flexible and can be applied to a wide variety of models, including non-linear and dynamic models where traditional estimation methods (e.g., maximum likelihood) may be difficult or impossible to use. Rather than relying on predefined distributions, SMM leverages simulated data from the model itself, allowing for greater flexibility in application. Furthermore, while the proposed expectations formation model benefits from simplicity and transparency, it is accompanied by the possibility of misspecification. In such cases, moment-based methods like SMM are generally more reliable than other estimation techniques.

Building on this foundation, I apply SMM to estimate key parameters by aligning the variances of forecast errors and forecast revisions—moments that are both observable in the data and tied closely to the parameters being estimated. According to the law of total variance, the variance of forecast errors can be broken down into two components: 1) the average variance of errors across agents and 2) the variance over time of consensus errors. The former provides information about size of noise in signals ($\sigma_{\nu,\tau\varepsilon}, \sigma_{\nu,\tau}$) while the latter captures the overreaction parameter θ. This reasoning similarly applies to the variance of forecast revisions.

The objective is to estimate parameter values that best align with the variances of forecast errors (FE) and forecast revisions (FR), aggregated across time and agents. I propose a range of possible values for θ, $\sigma_{\nu,\tau\varepsilon}$ and $\sigma_{\nu,\tau}$. The target moments are the variances of FE and FR for PGDP forecasts and the variance of FE for 5-Year PCE Inflation Rate (PCE5YR) forecasts. To identify the optimal parameters, I construct a three-dimensional grid, dividing the range of θ into 13 slices, $\sigma_{\nu,\tau\varepsilon}$ into 9 slices and $\sigma_{\nu,\tau}$ into 15 slices. Out of resulting 1,755 combinations $(13 \times 9 \times 15)$, I select the one that minimizes the distance between the variances of simulated and observed FE and FR in the survey data.

During the pre-2012 period, from 1990Q2 to 2011Q4, forecasters receive a signal containing a mixture of information about both τ_t and ε_t , which they use to update their forecasts $\tau_{t|t}^{i,\theta}$ and $\varepsilon_{t|t}^{i,\theta}$. For this period, I minimize the sum of two distances: the distance between the model-implied variance of forecast errors and the variance of observed forecast errors from PGDP inflation forecasts, and the distance between the model-implied variance of forecast revisions and the variance of observed forecast revisions. Long-run inflation forecast errors captured by the PCE5YR data from the SPF are unnecessary over this period, as the trend signal $S_{t,\tau}^{i}$ begins to play a role in the model starting in 2012.

Beginning in 2012, with the introduction of the long-run inflation target, an additional parameter, $\sigma_{\nu,\tau}$, is incorporated into the model. To accommodate this change, I utilize PCE5YR survey data, which provides long-run inflation forecasts. Accordingly, the minimization objective is adjusted to account for the distance between the variance of simulated long-run inflation forecast errors and the variance of observed long-run inflation forecast errors.

To estimate the model parameters, I employ a two-stage SMM approach. In the first stage, I search for parameter values that minimize the distance between simulated and observed moments.

$$\text{Pre-2012:}(\sigma^2_{FE,PGDP} - \hat{\sigma}^2_{FE,PGDP})^2 + (\sigma^2_{FR,PGDP} - \hat{\sigma}^2_{FR,PGDP})^2 \tag{1.6.2}$$

$$\text{Post-2012:}(\sigma^2_{FE,PGDP} - \hat{\sigma}^2_{FE,PGDP})^2 + (\sigma^2_{FR,PGDP} - \hat{\sigma}^2_{FR,PGDP})^2 + (\sigma^2_{FE,PCE5YR} - \hat{\sigma}^2_{FE,PCE5YR})^2 \tag{1.6.3}$$

Note that the last term $(\sigma^2_{FE,PCE5YR} - \hat{\sigma}^2_{FE,PCE5YR})^2$ in equation (1.6.3) is incorporated only for the period 2012Q1 to 2021Q4. The parameter space for θ is constrained by $\theta \geq 0$. In the second stage, I compute the empirical covariance of the three moments evaluated at the first-stage parameters $(\theta^{FS}, \sigma^{FS}_{\nu,\tau\varepsilon}, \sigma^{FS}_{\nu,\tau})$, invert it to derive the optimal weighting matrix W, and then estimate the second stage parameters $(\theta^*, \sigma^*_{\nu,\tau\varepsilon}, \sigma^*_{\nu,\tau})$ that minimize the following quadratic form

$$\left(\widetilde{\sigma^2_{FE,PGDP}}, \widetilde{\sigma^2_{FR,PGDP}}, \widetilde{\sigma^2_{FE,PCE5YR}}\right)^\top W \left(\widetilde{\sigma^2_{FE,PGDP}}, \widetilde{\sigma^2_{FR,PGDP}}, \widetilde{\sigma^2_{FE,PCE5YR}}\right) \tag{1.6.4}$$

where

$$\begin{aligned}
\widetilde{\sigma^2_{FE,PGDP}} &= \sigma^2_{FE,PGDP} - \hat{\sigma}^2_{FE,PGDP}(\theta, \sigma_{\nu,\tau\varepsilon}, \sigma_{\nu,\tau}) \\
\widetilde{\sigma^2_{FR,PGDP}} &= \sigma^2_{FR,PGDP} - \hat{\sigma}^2_{FR,PGDP}(\theta, \sigma_{\nu,\tau\varepsilon}, \sigma_{\nu,\tau}) \\
\widetilde{\sigma^2_{FE,PCE5YR}} &= \sigma^2_{FE,PCE5YR} - \hat{\sigma}^2_{FE,PCE5YR}(\theta, \sigma_{\nu,\tau\varepsilon}, \sigma_{\nu,\tau}).
\end{aligned}$$

It is important to note that $\widetilde{\sigma^2_{FE,PCE5YR}} = \sigma^2_{FE,PCE5YR} - \hat{\sigma}^2_{FE,PCE5YR}(\theta, \sigma_{\nu,\tau\varepsilon}\sigma_{\nu,\tau})$ is incorporated only for periods since 2012. For the time period between 1990Q2 and 2011Q4, only $\widetilde{\sigma^2_{FE,PGDP}}$

	θ	$\frac{\sigma_{\nu,\tau\varepsilon}}{\sqrt{(1-\gamma)}\sigma}$	$\frac{\sigma_{\nu,\tau\varepsilon}}{\sqrt{\gamma}\sigma}$	$\frac{\sigma_{\nu,\tau\varepsilon}}{\sigma}$	$\frac{\sigma_{\nu,\tau}}{\sigma}$
(1990Q2-2011Q4)					
Mixed signal only	0.956	5.961	3.894	3.260	-
	[0.85, 1]	[4.628, 7.105]	[3.023, 4.640]	[2.53, 3.885]	
Mixed signal&target	0.928	5.66	3.696	3.102	3.762
	[0.65, 1]	[3.736, 7.105]	[2.440, 4.640]	[2.01, 3.554]	[0.456, 9.176]
(1990Q2-2021Q4)					
Mixed signal&target	0.736	7.074	4.614	3.866	2.357
	[0.4, 1]	[4.914, 11.530]	[3.246, 5.03]	[3.05, 4.038]	[1.435, 3.443]

Note: The numbers in square brackets indicate a 90% confidence interval. θ is assumed to lie within the interval [0, 1].

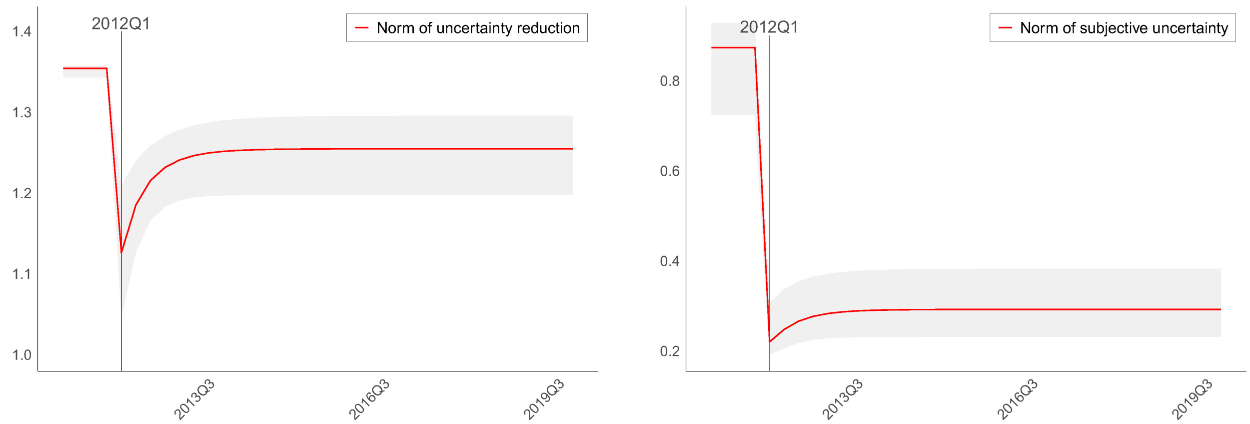
Table 1.3: SMM Estimates of θ, $\sigma_{\nu,\tau\varepsilon}$ and $\sigma_{\nu,\tau}$

and $\widetilde{\sigma^2_{FR,PGDP}}$ are taken into account. Finally, to construct confidence intervals for the parameter estimates, I perform 200 bootstrap replications.

1.6.3 Estimation of Parameters

By comparing Smooth DE based solely on the mixed signal with Smooth DE that incorporates both the mixed signal and an additional trend signal – representing the Federal Reserve's statement – it becomes evident that the inclusion of the long-term signal plays a crucial role in reducing the severity of the overreaction in forecasts. Table 1.3 shows that the value of θ declines from 0.956 during 1990Q2–2011Q4 to 0.736 over 1990Q2–2021Q4, which incorporates both mixed and trend signals. This clearly indicates a weakening in the severity of departure from rational expectations post-2012. To ensure that the decline in θ is not merely a result of introducing an additional parameter for estimation, I re-estimate the parameters using data from 1990Q2 to 2011Q4, incorporating not only the variances of FE and FR from four-quarter-ahead inflation forecasts as target moments, but also the variance of FE from long-run forecasts (PCE5YR)[11]. This

[11]The PCE5YR forecast survey only began in 2007. Therefore, I include the total variance of PCE5YR forecast errors over the period 2007Q1–2011Q4.



(a) The Frobenius Norm of Uncertainty Reduction (b) The Frobenius Norm of Subjective Uncertainty

Note: The figure shows the norm of the matrices $R_{t+4|t,t-1}$ (1.3a) and $\mathbb{V}_t^\theta$ (1.3b), transformed for comparison of their sizes over time. The shaded areas represent the 90% confidence interval. The red line indicates the mean, computed across 200 bootstraps, for each time period.

Figure 1.3: The Size of Reduction in Uncertainty and Subjective Uncertainty

approach allows me to assess whether adding the variance of long-run forecast errors as a new target moment significantly alters θ and $\sigma_{\nu,\tau\varepsilon}$ over the period 1990Q2 to 2011Q4. If there is no substantial change compared to estimates that exclude long-run forecast errors, this would suggest that the observed changes in θ and $\sigma_{\nu,\tau\varepsilon}$ from 1990Q2 to 2021Q4 are primarily driven by the policy change, rather than by the inclusion of the additional target moment. Notably, values for θ and $\sigma_{\nu,\tau\varepsilon}$ remain largely unchanged, implying that the announcement of the long-term target has a real effect, and that the smaller value of θ is not caused by the inclusion of an additional parameter.

Furthermore, I examine changes in the effective distortion parameter $\tilde{\theta}_{t,t-1}$, the reduction in uncertainty ratio $R_{t+4|t,t-1}$and subjective uncertainty before and after 2012Q1. Turning to the uncertainty ratio, represented as a 2-by-2 matrix, I use the Frobenius norm to compare its magnitude. In the left graph of Figure 1.3, a decline in the norm of $R_{t+4|t,t-1}$ is observed starting in 2012Q1, suggesting that the long-term inflation goal had an immediate effect in reducing uncertainty. This implies that the posterior variance from information updates decreases compared to the prior vari-

2011Q4	2012Q1	2012Q2	2012Q3
$\begin{pmatrix} 0.599 & -0.188 \\ -0.000 & 0.712 \end{pmatrix}$	$\begin{pmatrix} 0.513 & -0.145 \\ -0.000 & 0.713 \end{pmatrix}$	$\begin{pmatrix} 0.545 & -0.137 \\ -0.000 & 0.713 \end{pmatrix}$	$\begin{pmatrix} 0.559 & -0.133 \\ -0.000 & 0.712 \end{pmatrix}$

Note: For each of the matrices, the element at [1,1] reflects how much $\tau_{t|t}^{i,\theta}$overreacts (or underreacts) to news about τ_t. Similarly, the element at [1,2] indicates how much $\tau_{t|t}^{i,\theta}$ overreacts (or underreacts) to news about ε_t. The element at [2,1] measures how much $\varepsilon_{t|t}^{i,\theta}$ overreacts (or underreacts) to news about τ_t, while the element at [2,2] captures the extent to which $\varepsilon_{t|t}^{i,\theta}$ overreacts (underreacts) to news about ε_t. A positive value indicates overreaction, while a negative value indicates underreaction. Each element of the matrices is the mean computed across 200 bootstraps.

Table 1.4: Effective Distortion Matrix $\tilde{\theta}_{t,t-1}$ After 2012

ance before receiving new information as soon as the announcement is publicized. From 2014Q4 onward, this ratio converges and stabilizes at a lower level than pre-2012 levels. This reduction is primarily driven by a significant decline in uncertainty about the trend component. Across 200 bootstrap samples, the first element of $R_{t+4|t,t-1[1,1]}$, which captures the reduction in conditional posterior uncertainty around trend τ_t relative to conditional prior uncertainty before the information update, shows an average reduction of approximately 7.8% between 2011Q4 and 2012Q1. By contrast, the variance ratio reduction for the cyclical component ε_t, $R_{t+4|t,t-1[2,2]}$, remains consistently around 0.99, indicating that the decline in uncertainty for the cyclical component due to information updates is minimal, regardless of the presence of the additional signal. As shown in the right graph of Figure 1.3, subjective uncertainty $\mathbb{V}_t^{\theta}$ also declines alongside $R_{t+4|t,t-1}$ from 2012Q1, aligning with empirical evidence from survey data.

The effective distortion, $\tilde{\theta}_{t,t-1}$, reflects how the reduction in uncertainty affects overreaction to signals. Since $\tilde{\theta}_{t,t-1}$ is a 2-by-2 matrix, an element-wise comparison is required. Table 1.4 presents the effective distortion matrix around 2012Q1. In forecasting $\tau_{t|t}^{i,\theta}$, the degree of overreaction responding to news decreases since 2012, whereas in forecasting $\varepsilon_{t|t}^{i,\theta}$, there is little change in the degree of overreaction before and after 2012. A closer examination reveals that the overreaction in the belief updating process for $\tau_{t|t}^{i,\theta}$ naturally divides into two parts: 1) reaction to new information about the trend component and 2) reaction to new information about the cyclical component. The overreaction triggered by news regarding τ_t, captured by $\tilde{\theta}_{t,t-1[1,1]}$, clearly diminishes after 2012, suggesting that the announcement plays a role in making trend forecasts more rational. Interestingly, when it comes to news related to the cyclical component, captured by $\tilde{\theta}_{t,t-1[1,2]}$, individuals' forecasts consistently underreact to news both before and after 2012 ($\tilde{\theta}_{t,t-1[1,2]} < 0$). This suggests that, while individuals tend to overreact to news about the trend component when updating their beliefs, $\tau_{t|t}^{i,\theta}$, they counterbalance this by underreacting to news about the cyclical component, thereby helping to stabilize their long-term trend forecasts.

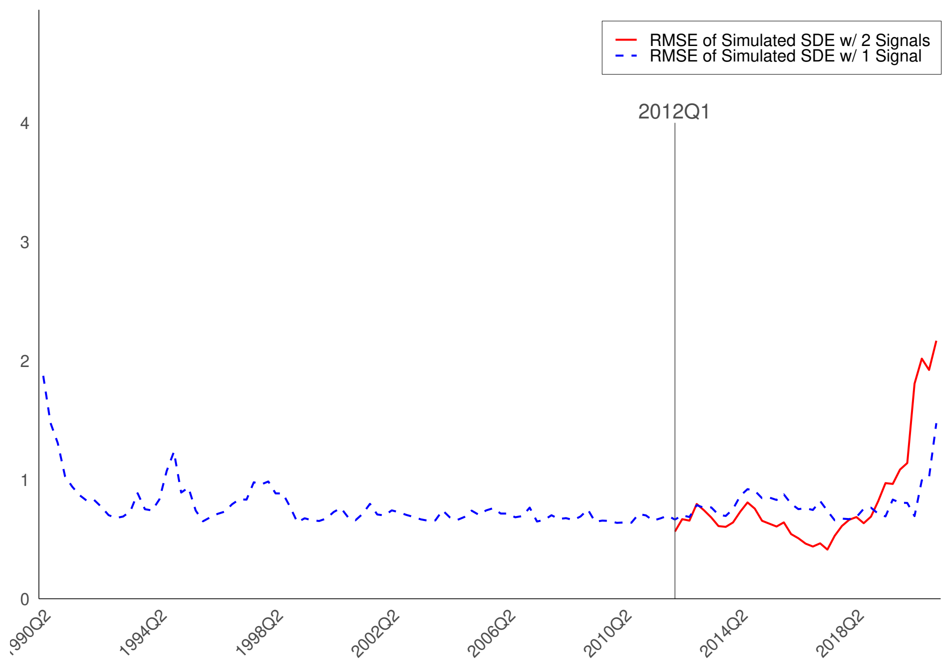
Moreover, there is no substantial difference in the severity of overreaction in terms of expectations regarding the cyclical component ε_t before and after 2012. The overreaction pattern of $\varepsilon_{t|t}^{i,\theta}$ can also be divided into 1) reaction to new information about the trend component, and 2) reaction to new information about the cyclical component. Forecasters clearly overreact to news about the cyclical component ($\tilde{\theta}_{t,t-1[2,2]} > 0$), and the magnitude of this overreaction does not change across the pre- and post-2012 periods. Interestingly, there is neither overreaction nor underreaction of forecasts $\varepsilon_{t|t}^{i,\theta}$ to news about the trend in either period. The element $\tilde{\theta}_{t,t-1[2,1]}$ which measures the extent to which forecasts of the cyclical component ε_t overreact to news about the trend, remains near zero both before and after 2012. This implies that when updating forecasts $\varepsilon_{t|t}^{i,\theta}$, individuals rationally adjust their forecasts even in the context of trend-related information, regardless of their awareness of government policy goals.

In conclusion, the evidence strongly suggests that the public announcement of the long-term inflation target reduces the extent of overreacting expectations related to the trend by lowering conditional variance. This, in turn, leads to greater confidence in forecasts, as reflected by a reduction in subjective uncertainty. However, the overreaction of the cyclical component remains largely unaffected.

1.6.4 Simulations

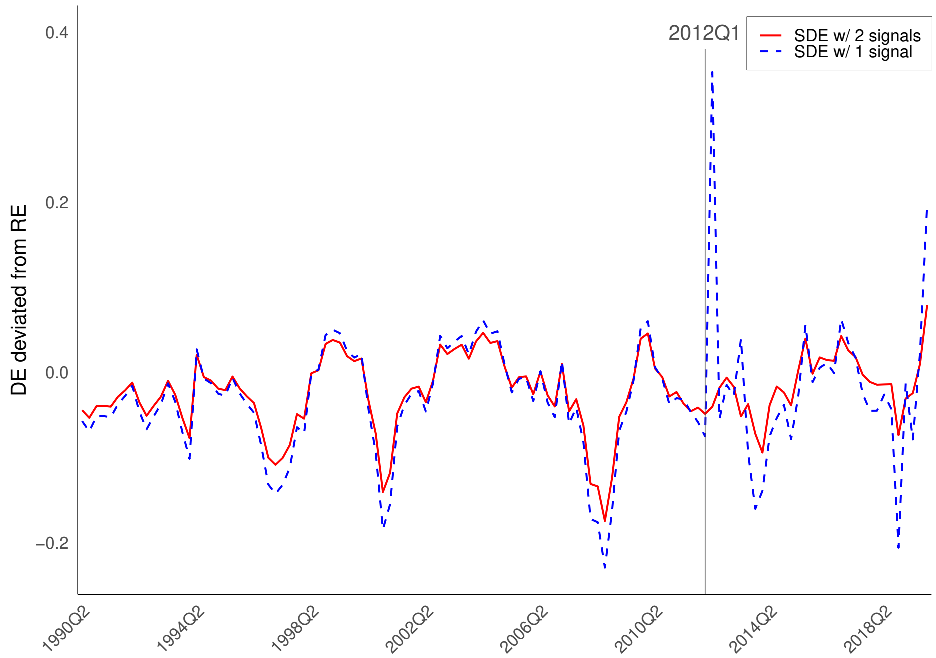
Building on the estimation results discussed earlier, I conduct simulations to explore what would have happened if there had been no policy change in 2012, meaning agents would have continued to receive only the mixed signal while the actual data remained unchanged. I assume a panel of 1,000 hypothetical agents predicting four-quarter-ahead inflation under two scenarios. In the first scenario, agents receive both the mixed signal and the trend signal since 2012. Using the parameters $\theta = 0.736$, $\frac{\sigma_{\nu,\pi}}{\sigma} = 2.357$, and $\frac{\sigma_{\nu,\tau\varepsilon}}{\sigma} = 3.866$, the agents form forecasts over the periods from 1990Q2 to 2021Q4. In the second, counterfactual scenario, the agents rely solely on the mixed signal, without receiving the long-term inflation target after 2012. For this scenario, the distortion parameter $\theta = 0.956$, and the mixed signal generated in the first scenario is applied over the period 1990Q2 to 2021Q4. This implies that, since 2012, the difference between the two lines in Figure 1.4 is driven solely by the trend signal.

The comparison between these two simulation scenarios highlights the impact of receiving an additional signal on inflation forecasts. Figure 1.4 presents the root mean squared error (RMSE) of simulated Smooth DE under both scenarios, illustrating which simulation aligns more closely with surveyed forecasts. Despite using different θ values in each scenario, prior to 2012, the Smooth DE with one signal and the Smooth DE with two signals display similar explanatory power. After 2012, however, the Smooth DE with two signals more closely fits the median SPF data, suggesting that this estimation better captures the formation of actual expectations. Following the onset of Covid-19, the RMSE under the two-signal case rapidly increases, illustrating a growing divergence



Note: The root mean squared error (RMSE) is calculated across 1,000 samples for each period. For actual data, I use the median forecast from the SPF, so $RMSE_t = \sqrt{\frac{\sum_{i=1}^{1000}(simulated\,SDE_{i,t} - med.SPF_t)^2}{1000}}$. This figure shows the time-varying $RMSE_t$: the red line represents the RMSE of the simulation with two signals, while the blue dashed line indicates the RMSE with only one signal after 2012. A lower RMSE indicates closer alignment with actual forecasts.

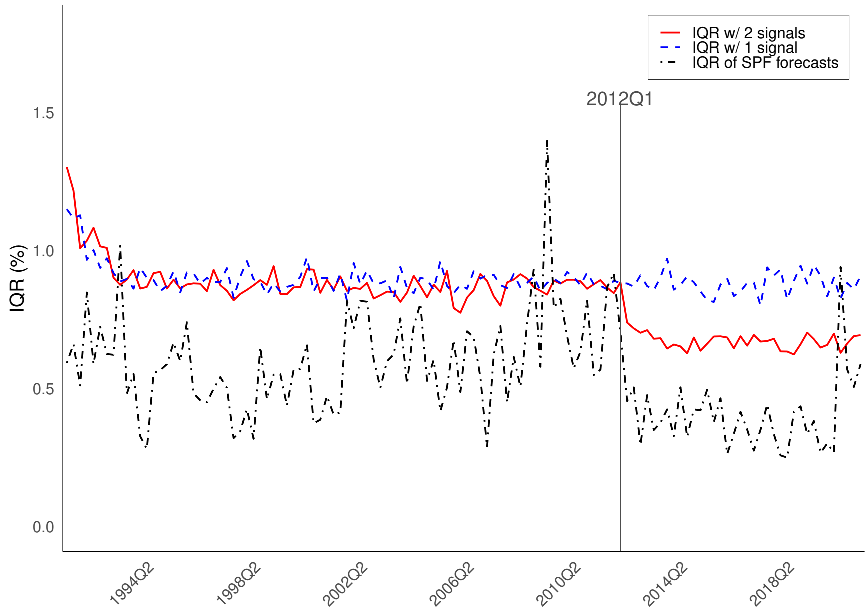
Figure 1.4: Simulated Four-Quarter-Ahead Inflation Forecasts



Note: The red line represents the magnitude of deviation of the simulated SDE with 2 signals from rational expectations (RE), while the blue dashed line indicates the extent to which the simulated SDE with one mixed signal deviate from RE.

Figure 1.5: The Extent of DE Deviation from RE

between simulated Smooth DE and the actual forecasts reported in the survey. In reality, the fundamental shock to the economy may have diminished trust in the Federal Reserve's messaging, leading forecasters to place less weight on direct information from the Federal Reserve about trend inflation. Instead, forecasters may have increasingly relied on the single mixed signal, adjusting their belief-updating behavior as though they were receiving only one signal. Consequently, since 2019, the counterfactual scenario where forecasters receive only the mixed signal might more accurately reflect actual forecasts observed in the SPF. Additionally, in August 2020, the Federal Reserve's adoption of Flexible Average Inflation Targeting, which shifted monetary policy toward a more lenient stance rather than strictly targeting 2% inflation, may have made the Federal Reserve's messages seem somewhat vague or less direct to recipients.



Note: The red line shows the interquartile range for each period based on forecasts with two signals received since 2012, while the blue dashed line represents the interquartile range under a counterfactual scenario in which agents, after 2012, continue to receive only one mixed signal.

Figure 1.6: Belief Dispersion of 1-Year Ahead Simulated Inflation Forecasts

Figure 1.5 further illustrates that including two signals significantly reduces the deviation from RE. The deviation from RE is calculated using the following formula [12]

$$\text{deviation} = \frac{Smooth\, DE - RE}{RE},$$

and the results are averaged across the 1,000 panelists and presented in Figure 1.5. The graph reveals that deviations are similar before 2012 across both scenarios, but post-2012, the scenario with only one signal becomes increasingly volatile. These findings suggest that sharing a long-term inflation target with the public brings individuals' expectations closer to rational expectations, thereby limiting over-reaction.

[12] Rational expectations (RE) are calculated under the assumption that $\theta = 0$.

In addition, the analysis of forecast dispersion, as shown in Figure 1.6, demonstrates that sharing a longer run target decreases disagreement among forecasters. The heterogeneity in expectations is primarily driven by information frictions, specifically by the heterogeneous signals that forecasters receive. If the Federal Reserve provides a transparent signal regarding a long-term trend, individuals' information sets will contain less uncertainty as they update them. With this current-period news, individuals recognize that the updated information is more accurate, prompting them to rely less on past memories and more on the true density conveyed by the current news. Consequently, representativeness, measured with respect to reference information, diminishes in its influence on belief updates, reducing the tendency for overreaction to heterogeneous news across agents. As the effect of heterogeneous signals on expectations formation decreases, disagreement among forecasts also declines. This aligns with previous studies showing that well-anchored inflation expectations are typically associated with lower dispersion in individual forecasts (Naggert, Rich and Tracy, 2023; Brito, Carriere-Swallow and Gruss, 2018; Ehrmann, 2018; Dovern, Fritsche and Slacalek, 2012).

To measure disagreement, I use the IQR of point forecasts following the methods of Abel et al. (2016), Glas and Hartmann (2016) and Lahiri and Sheng (2010). Figure 1.6 shows a noticeable decrease in the dispersion of four-quarter-ahead inflation forecasts after 2012, which aligns with the observed SPF data. This reduction in dispersion likely stems from a decrease in disagreement among forecasts about the trend component.

Parameters	Prior	Posterior Mean	Std. Error	Posterior Distribution (90%)
ρ_ε	$\mathbb{B}$	0.554	0.116	[0.345, 0.726]
γ	$\mathbb{B}$	0.739	0.110	[0.542, 0.904]
σ^2	$\mathbb{IG}$	0.195	0.023	[0.159, 0.235]

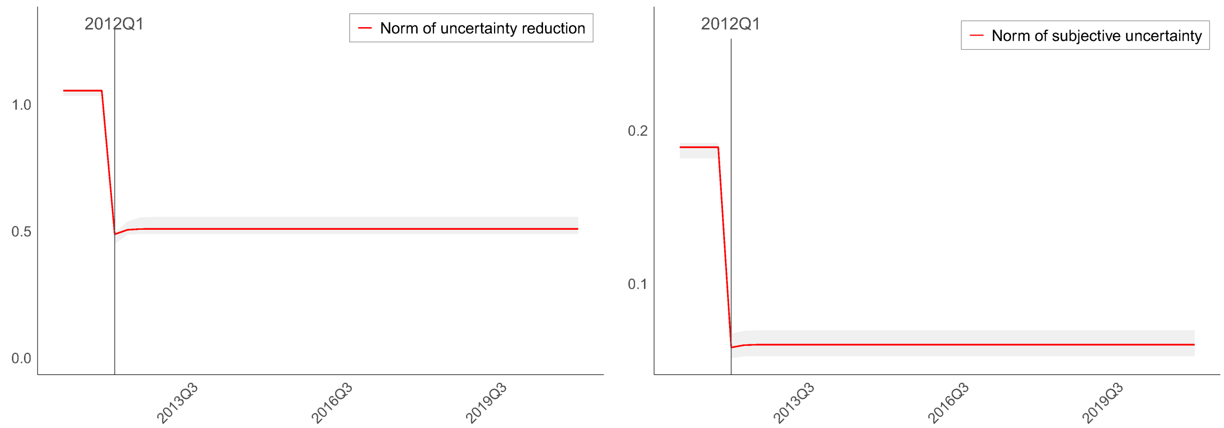
Table 1.5: Estimated Parameters

1.7 Robustness

I explored SMM estimates and analyzed changes and evolving patterns in subjective uncertainty, reduction in uncertainty, and the effective distortion parameter. These analyses build on fundamental parameters driving inflation dynamics, which were estimated through Bayesian estimation. However, the SMM estimates and simulations may be sensitive to the specific parameter values obtained from the Bayesian estimation. To assess robustness, I use alternative parameters derived from different prior distributions. If the new SMM estimates replicate the observed changes and evolving patterns in all three dimensions—subjective uncertainty, reduction in uncertainty, and the effective distortion parameter—it supports the model's validity.

Since the share of the inflation shock attributed to the cyclical component, γ, must lie between 0 and 1, and the volatility of the fundamental shock, σ, must be greater than zero, the priors for these parameters remain unchanged. However, the prior for ρ_ε is adjusted in this exercise by assuming a beta prior distribution. Table 1.5 indicates that the posterior mean of ρ_ε increases significantly from 0.377 to 0.554, while σ^2 decreases. Based on these results, I now assess whether alternative fundamental parameters affect the outcomes of the SMM estimation.

As shown in Table 1.6, the value for θ is 0.741, which is not substantially different from the previous value of 0.747. However, the size of the noise noticeably decreases in both mixed and trend signals. In particular, the noise in the trend signal is remarkably small, suggesting that individuals



(a) The Frobenius Norm of Uncertainty Reduction (b) The Frobenius Norm of Subjective Uncertainty
Note: The figure shows the norm of the matrices $R_{t+4|t,t-1}$(1.7a) and $\mathbb{V}_t^{\theta}$ (1.7b), transformed for comparison of their sizes over time. The shaded areas represent the 90% confidence interval. The red line represents the mean, computed across 200 bootstraps, for each time period.

Figure 1.7: The Size of Reduction in Uncertainty and Subjective Uncertainty

place a high level of trust in the Federal Reserve's announcements regarding long-term inflation targets. This reflects the fact that individuals heavily weigh the Federal Reserve's statements when updating their beliefs in response to new information. As a result, the ratio of posterior variance to prior variance, or uncertainty reduction, falls sharply in the first quarter of 2012 (Figure 1.7a).

	θ	$\frac{\sigma_{\nu,\tau\varepsilon}}{\sqrt{(1-\gamma)}\sigma}$	$\frac{\sigma_{\nu,\tau\varepsilon}}{\sqrt{\gamma}\sigma}$	$\frac{\sigma_{\nu,\tau\varepsilon}}{\sigma}$	$\frac{\sigma_{\nu,\tau}}{\sigma}$
(1990Q2–2021Q4)					
Mixed signal & target	0.741	1.643	0.977	0.840	0.338
	[0.4, 1]	[1.105, 1.696]	[0.657, 1.009]	[0.565, 0.867]	[0.236, 0.522]

Note: The numbers in square brackets indicate a 90% confidence interval. θ is assumed to lie within the interval [0, 1].

Table 1.6: SMM Estimates of θ, $\sigma_{\nu,\tau\varepsilon}$ and $\sigma_{\nu,\tau}$

Typically, the largest reduction in uncertainty occurs when the long-run inflation target is initially released, followed by a gradual increase in uncertainty as the effect dissipates over time. However, in this analysis, the high degree of trust in the Federal Reserve's announcements about the trend component lead to a prolonged effect, with uncertainty remaining low. Even after the

2011Q4	2012Q1	2012Q2	2012Q3
$\begin{pmatrix} 0.436 & -0.302 \\ -0.273 & 0.465 \end{pmatrix}$	$\begin{pmatrix} 0.022 & -0.016 \\ 0.046 & 0.244 \end{pmatrix}$	$\begin{pmatrix} 0.061 & -0.019 \\ -0.032 & 0.249 \end{pmatrix}$	$\begin{pmatrix} 0.063 & -0.019 \\ -0.035 & 0.249 \end{pmatrix}$

Note: For each of the matrices, the element at [1,1] reflects how much $\tau_{t|t}^{i,\theta}$overreacts (or underreacts) to news about τ_t. Similarly, the element at [1,2] indicates how much $\tau_{t|t}^{i,\theta}$ overreacts (or underreacts) to news about ε_t. The element at [2,1] measures how much $\varepsilon_{t|t}^{i,\theta}$ overreacts (or underreacts) to news about τ_t, while the element at [2,2] captures the extent to which $\varepsilon_{t|t}^{i,\theta}$ overreacts (underreacts) to news about ε_t. A positive value indicates overreaction, while a negative value indicates underreaction. Each element of the matrices is the mean computed across 200 bootstraps.

Table 1.7: Effective Distortion Matrix $\tilde{\theta}_{t,t-1}$ Post-2012

initial sharp decline, the graph shows only a very slight increase, indicating that the reduction in uncertainty has persisted for an extended period. Consequently, both the subjective uncertainty and the reduction in uncertainty graphs exhibit only minimal increases after 2012Q1, as shown in Figure 1.7.

As a result of the Federal Reserve's new policy, individuals rely less on memory and place greater emphasis on current news when forming forecasts, thereby mitigating over-reaction.

As shown in Figure 1.7 the key findings hold consistently, regardless of the parameter values estimated through Bayesian methodology. However, the persistence of the policy's impact depends on the level of trust in the Federal Reserve. The greater the trust, the longer individuals maintain confidence in their beliefs.

In addition, Table 1.7 shows a significant decline in the element $\tilde{\theta}_{t,t-1[1,1]}$, dropping from 0.436 to 0.022 in 2012Q1. This drop aligns with the pattern observed in previous analysis, reinforcing the idea that the announcement helped bring trend forecasts closer to rational expectations. Similarly, $\tilde{\theta}_{t,t-1[1,2]}$ and $\tilde{\theta}_{t,t-1[2,1]}$ retain their negative signs, in line with the findings reported in Table 1.4. In contrast to the earlier analysis, $\tilde{\theta}_{t,t-1[2,2]}$ exhibits a noticeable decrease after 2012.

1.8 Conclusion

The success of monetary policy hinges on clear and accurate communication of its plans and goals. Given that short-term inflation expectations can influence everyday decisions, such as consumer spending, it is essential to examine whether monetary policy affects short-term inflation forecasts. The key takeaway of this paper is that sharing precise numerical targets with the public not only anchors long-term inflation forecasts but also shapes short-term forecasts in a more rational and less distorted manner. When estimating future states, individuals rely on the representativeness heuristic, assigning greater weight to salient memories rather than objectively assessing probabilities. However, when provided with accurate information, individuals reduce their reliance on subjective recall and form expectations based on more objective likelihood of future outcome delivered, thereby mitigating over-reaction to news. This paper specifically focuses on the 2012 Statement on Longer-Run Goals and Monetary Policy Strategy, which provided concrete information on trend inflation, significantly reducing inflation forecast uncertainty and enhancing individuals' confidence in their forecasts.

Adding such an additional, reliable signal—compared to relying solely on one source— facilitates more rational belief updating and, consequently, reduces disagreement among individuals. While the decrease in long-term inflation forecast dispersion stems from the anchoring effect, the narrowing of short-term inflation forecast dispersion appears to result from lessened over-reaction to incoming information. This shift leads to expectations that align more closely with rational expectations, thereby reducing disagreement.

Moreover, I assume a stable economic environment, contributing to the broader understanding of how policy communication affects expectations in relatively calm periods. However, in times of severe disruptions—such as the Covid-19 pandemic or the war between Russia and Ukraine—subjective uncertainty and effective distortion may rise, particularly if agents doubt the sufficiency of transparent communication during such shocks. Future research could examine the role of fundamental shocks in shaping inflation expectations, specifically assessing how these shocks interact with policy communication strategies and whether these strategies can mitigate heightened subjective uncertainty in turbulent times.

Although this paper includes the Covid-19 period, it treats shocks from these disruptions as drawn from the same distribution as those in normal times. Extending this work could involve exploring policy guidance's role during extreme events modeled with a state-dependent approach, where shocks might come from a different normal distribution with a higher mean and variance. Such a model would capture how extreme shocks influence the degree of over-reaction and the shift in conditional uncertainty. This approach could also shed light on whether the interaction between uncertainty in news and fundamental shocks results in amplification or dampening effects. Understanding whether transparent communication by the Federal Reserve can reduce distortion and curb over-reactive belief adjustments under these conditions would provide valuable insights for policy design in periods of heightened uncertainty.

1.9 Appendices

Survey of Professional Forecasters

Please fill in forecast of the following U.S. business indicators.

		Quarterly Data						Annual Data [a]				
	L / G	2024:Q1	2024:Q2	2024:Q3	2024:Q4	2025:Q1	2025:Q2	2023	2024	2025	2026	2027
1. Nominal GDP		28284.5						27360.9				
2. GDP Price Index (Chain)		124.24						122.28				
3. Corporate Prof After Tax		.						2672.9				
4. Civilian Unemp Rate	L	3.8						3.6				
5. Nonfarm Payroll Employment [b]		157841						156066				
6. Industrial Prod Index		102.3						102.8				
7. Housing Starts		1.415						1.423				
8. T-Bill Rate, 3-month	L	5.23						5.07				
9. Moody's AAA Corp Bond Yield [c]	L	.						.				
10. Moody's BAA Corp Bond Yield [c]	L	.						.				
11. Treasury Bond Rate, 10-year	L	4.16						3.96				

Note: This question is included in the survey distributed in the second quarter of 2024.

Figure A-1: U.S. Business Indicators

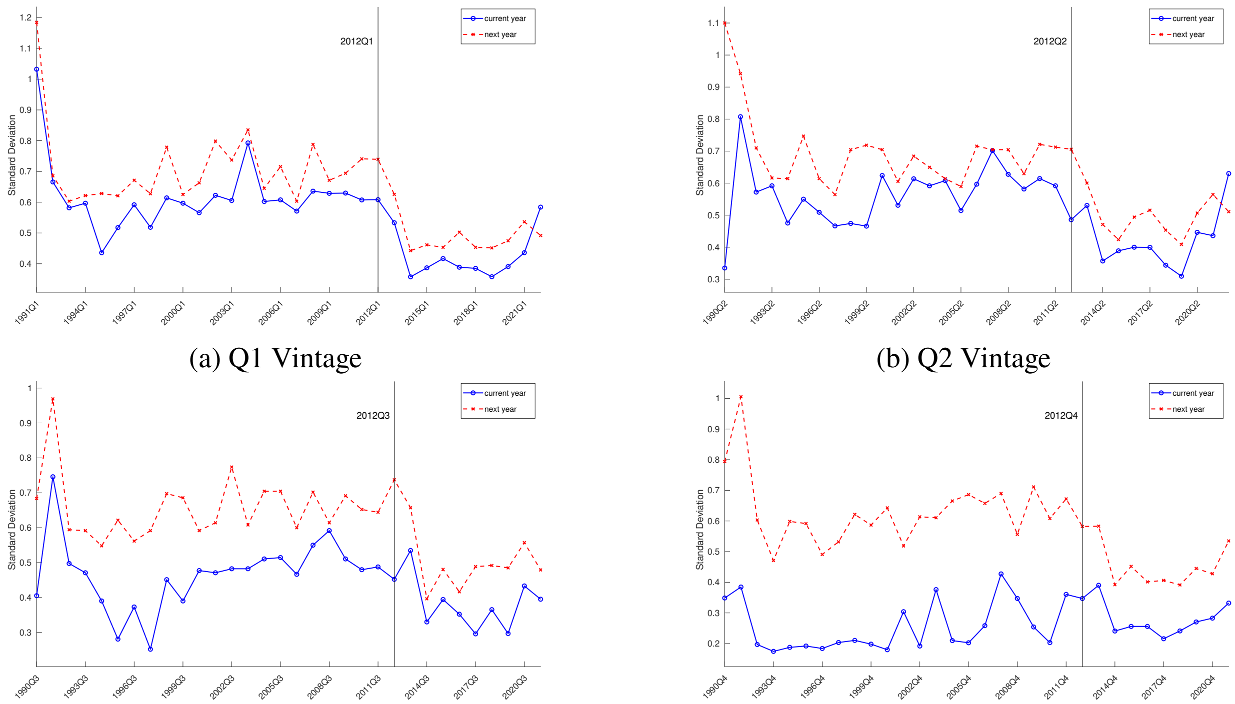
Please indicate what probabilities you would attach to the various possible percentage change (annual-average over annual-average) in the chain-weighted GDP price index. The probabilities of these alternative forecasts should add up to 100.

	Probability of indicated percent change in chain-weighted GDP price index	
	2023-2024	2024-2025
4 percent or more		
3.5 to 3.9 percent		
3.0 to 3.4 percent		
2.5 to 2.9 percent		
2.0 to 2.4 percent		
1.5 to 1.9 percent		
1.0 to 1.4 percent		
0.5 to 0.9 percent		
0.0 to 0.4 percent		
Will decline		
TOTAL	0	0

Note: This question is included in the survey distributed in the second quarter of 2024.

Figure A-2: Probabilities of Year-Over-Year Changes in the GDP Price Index

Subjective Uncertainty in Fixed-Event Inflation Forecasts



(a) Q1 Vintage

(b) Q2 Vintage

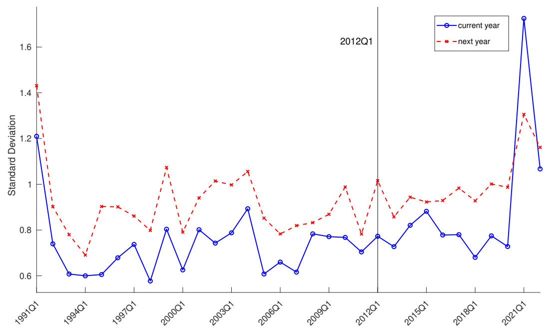
(c) Q3 Vintage

(d) Q4 Vintage

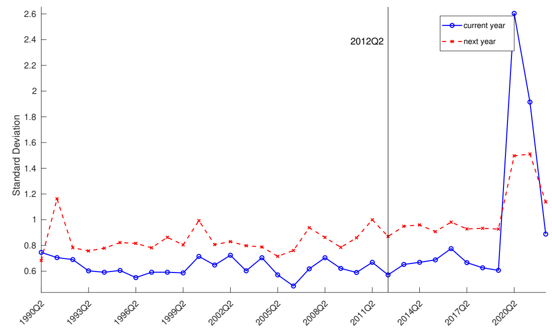
Note: The figure shows subjective uncertainty measured in fixed-event forecasts from the SPF. The blue line with circles depicts the median subjective uncertainty, expressed in standard deviations, for current-year inflation. The red dashed line illustrates the median subjective uncertainty, also expressed in standard deviations, for next-year inflation. A normal distribution is fitted to individual-level survey data, from which the standard deviations are derived.

Figure A-3: Inflation Rate

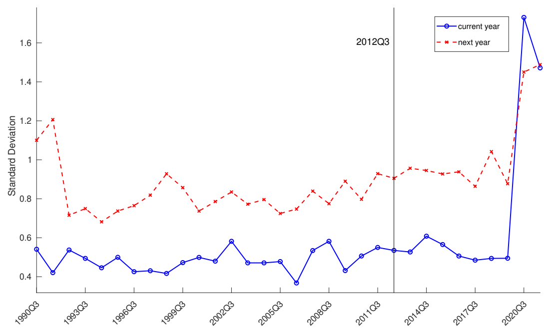
Subjective Uncertainty in Fixed-Event Non-Inflation Forecasts



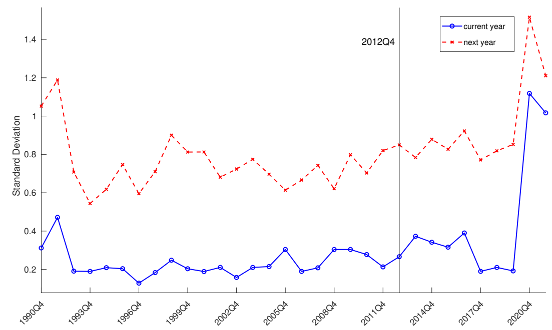
(a) Q1 Vintage



(b) Q2 Vintage



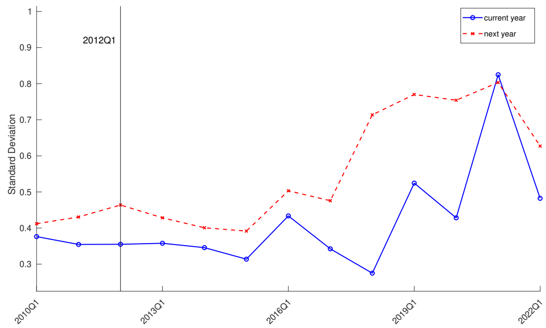
(c) Q3 Vintage



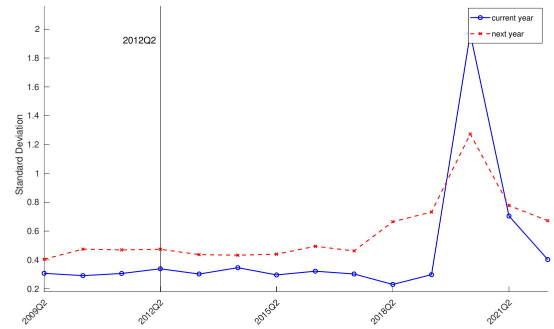
(d) Q4 Vintage

Note: The figure shows subjective uncertainty measured in fixed-event forecasts from the SPF. The blue line with circles depicts the median subjective uncertainty, expressed in standard deviations, for current-year percentage change in real GDP. The red dashed line illustrates the median subjective uncertainty, also expressed in standard deviations, for next-year percentage change in real GDP. A normal distribution is fitted to individual-level survey data, from which the standard deviations are derived.

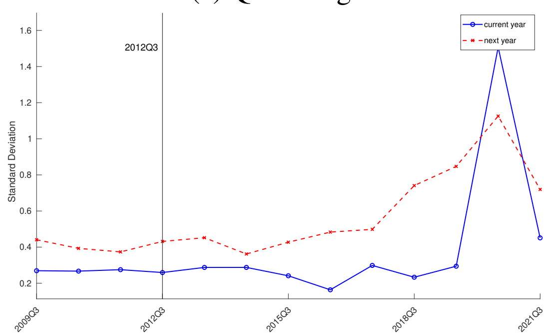
Figure A-4: Percentage Change in Real GDP



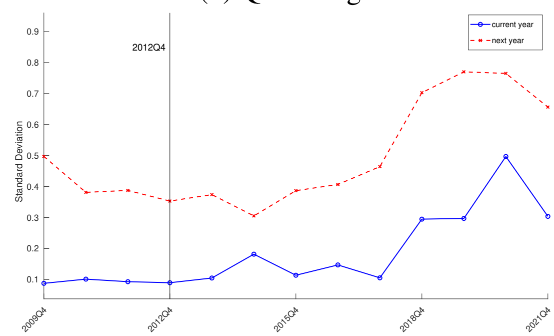
(a) Q1 Vintage



(b) Q2 Vintage



(c) Q3 Vintage



(d) Q4 Vintage

Note: The figure shows subjective uncertainty measured in fixed-event forecasts from the SPF. The blue line with circles depicts the median subjective uncertainty, expressed in standard deviations, for current-year civilian unemployment rates. The red dashed line illustrates the median subjective uncertainty, also expressed in standard deviations, for next-year civilian unemployment rates. A normal distribution is fitted to individual-level survey data, from which the standard deviations are derived.

Figure A-5: Unemployment Rate

CG Tests of Other Macroeconomic Variables

	1990Q2–2011Q4	2012Q1–2022Q1	1990Q2–2022Q1	1990Q2–2011Q4	2012Q1–2022Q1	1990Q2–2022Q1
β_0	-0.022 (0.151)	-0.799 (0.375)	-0.351^{**} (0.172)	-	-	-
β_1	0.225 (0.220)	-0.543^{*} (0.295)	-0.299 (0.266)	0.094 (0.194)	-0.557^{*} (0.310)	-0.345 (0.279)
Obs.	2320	1182	3554	2312	1177	3543
FE	No	No	No	Yes	Yes	Yes

Note: CG test results using IV regression. Obs. indicates the sample size. Robust standard errors are in parentheses;***indicates significance at the 1% level. **indicates significance at the 5% level, and *indicates significance at the 10% level.

(a) Percentage Change in Real GDP

	1990Q2–2011Q4	2012Q1–2022Q1	1990Q2–2022Q1	1990Q2–2011Q4	2012Q1–2022Q1	1990Q2–2022Q1
β_0	0.041 (0.094)	-0.146 (0.297)	0.023 (0.127)	-	-	-
β_1	0.670^{***} (0.230)	-0.472^{**} (0.188)	-0.279 (0.293)	0.530^{***} (0.200)	-0.492^{***} (0.190)	-0.307 (0.276)
Obs.	2413	1274	3741	2407	1270	3733
FE	No	No	No	Yes	Yes	Yes

Note: CG test results using IV regression. Obs. indicates the sample size. Robust standard errors are in parentheses;***indicates significance at the 1% level. **indicates significance at the 5% level, and *indicates significance at the 10% level.

(b) Unemployment Rate

Table A-1: CG Test Results at Individual Level

Bayesian Estimation

I assume prior distributions as

$$\rho_\varepsilon \sim \mathbb{N}(\mu_\rho, \sigma_\rho^2)$$

$$\gamma \sim \mathbb{B}(\alpha_\gamma,\beta_\gamma)$$

$$\sigma^2 \sim \mathbb{IG}(\alpha_{\sigma^2},\beta_{\sigma^2}),$$

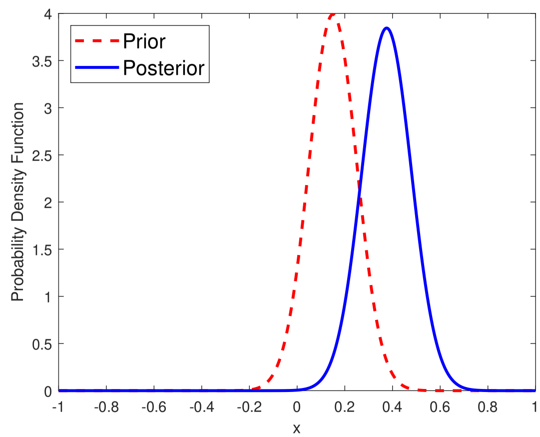
and set hyper-parameters as follows.

hyper-parameters	Value
μ_ρ	0.15
σ_ρ^2	0.01
α_γ	18
β_γ	3
α_{σ^2}	15
β_{σ^2}	11

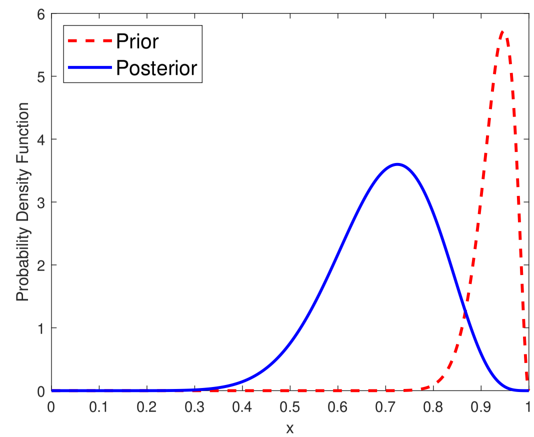
For initial values $x^{(0)} = (\rho_\varepsilon^{(0)}, \gamma^{(0)}, \sigma^{(0)})$, I guess unconditional mean of prior distributions.

A normal prior distribution is selected for ρ_ε, anticipating that isolating the cyclical component after removing the trend in inflation would result in lower persistence of shocks. While the trend component captures long-term patterns, the cyclical component focuses on short-term economic fluctuations. This may cause the autocorrelation coefficient in an AR(1) model to approach zero or even become negative. To account for this potential variability, a normal prior is considered appropriate for ρ_ε. In contrast, γ, representing a share ratio constrained to the interval [0, 1], is modeled using a beta distribution, which is optimal for such bounded parameters. Lastly, given that σ^2 is strictly positive, an inverse-gamma distribution is chosen for its prior. A burn-in period of 10,000 iterations out of 100,000 draws is employed, discarding the initial samples to stabilize the parameters and enhance the reliability of the posterior distribution.

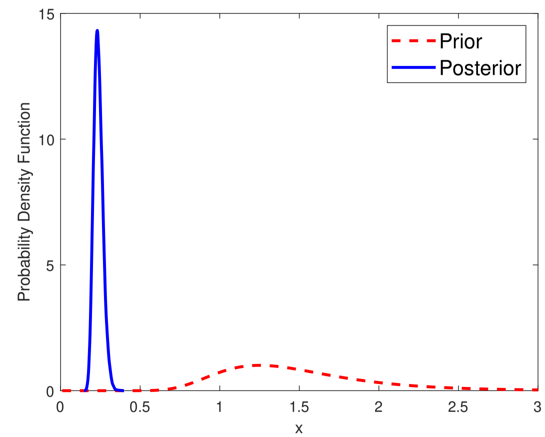
The following figure plots prior and posterior distributions.



(a) Distribution for ρ_ε



(b) Distribution for γ



(c) Distribution for σ^2

Proof of Proposition 3

We start by rewriting equation (1.5.5)

$$f^{\theta}(x_{t+h}) \propto \left[\begin{array}{l} \exp\left(-\frac{1}{2}(x_{t+h} - x^i_{t+h|t})^\top \Sigma^{-1}_{t+h|t}(x_{t+h} - x^i_{t+h|t})\right) \\ \left\{ \dfrac{\exp\left(-\frac{1}{2}(x_{t+h} - x^i_{t+h|t})^\top \Sigma^{-1}_{t+h|t}(x_{t+h} - x^i_{t+h|t})\right)}{\exp\left(-\frac{1}{2}(x_{t+h} - x^i_{t+h|t-1})^\top \Sigma^{-1}_{t+h|t-1}(x_{t+h} - x^i_{t+h|t-1})\right)} \right\}^{\theta} \quad \dfrac{1}{Z} \end{array} \right]$$

where $x_{t+h} = \begin{pmatrix} \tau_{t+h} & \varepsilon_{t+h} \end{pmatrix}^\top$ represents the actual realized inflation components, and $x^i_{t+h|t} = \begin{pmatrix} \tau^i_{t+h|t} & \varepsilon^i_{t+h|t} \end{pmatrix}^\top$ denotes individual i's h-ahead inflation forecast for the trend and cyclical components.

Since $\left\{\frac{exp(a)}{exp(b)}\right\}^{\theta} = exp(\theta(a-b))$,

$$f^{\theta}(x_{t+h}) \propto \left[\begin{array}{l} \exp\left(-\frac{1}{2}(x_{t+h} - x^i_{t+h|t})^\top \Sigma^{-1}_{t+h|t}(x_{t+h} - x^i_{t+h|t})\right) \\ \left\{\exp\left(\theta\left\{\left(-\frac{1}{2}(x_{t+h} - x^i_{t+h|t})^\top \Sigma^{-1}_{t+h|t}(x_{t+h} - x^i_{t+h|t})\right)\right.\right.\right. \\ \left.\left.\left. -\left(-\frac{1}{2}(x_{t+h} - x^i_{t+h|t-1})^\top \Sigma^{-1}_{t+h|t-1}(x_{t+h} - x^i_{t+h|t-1})\right)\right\}\right)\right\} \dfrac{1}{Z} \end{array} \right]$$

$$f^{\theta}(x_{t+h}) \propto \left[\begin{array}{l} \exp\left(-(1+\theta)\frac{1}{2}(x_{t+h} - x^i_{t+h|t})^\top \Sigma^{-1}_{t+h|t}(x_{t+h} - x^i_{t+h|t})\right. \\ \left. +\frac{1}{2}\theta(x_{t+h} - x^i_{t+h|t-1})^\top \Sigma^{-1}_{t+h|t-1}(x_{t+h} - x^i_{t+h|t-1})\right) \dfrac{1}{Z} \end{array} \right]$$

$$f^{\theta}(x_{t+h}) \propto \left[\begin{array}{l} \exp\left(-\frac{1}{2}\Sigma^{-1}_{t+h|t}\left\{(1+\theta)(x_{t+h} - x^i_{t+h|t})^\top (x_{t+h} - x^i_{t+h|t})\right.\right. \\ \left.\left. -\theta(x_{t+h} - x^i_{t+h|t-1})^\top \Sigma_{t+h|t}\Sigma^{-1}_{t+h|t-1}(x_{t+h} - x^i_{t+h|t-1})\right\}\right) \dfrac{1}{Z} \end{array} \right]$$

By developing the squared terms and focusing on the terms involving x_{t+h}, we arrive at

$$f^{\theta}(x_{t+h}) \propto \left[\begin{array}{l} \exp\left(-\frac{1}{2}\Sigma_{t+h|t}^{-1}\left\{(1+\theta)I - \theta\Sigma_{t+h|t}\Sigma_{t+h|t-1}^{-1}\right\}\left(x_{t+h}^{\top}x_{t+h}\right.\right. \\ -2(1+\theta)x_{t+h}\left((1+\theta)I - \theta\Sigma_{t+h|t}\Sigma_{t+h|t-1}\right)^{-1}x_{t+h|t}^{i} \\ \left.\left.+2\theta x_{t+h}^{\top}\left((1+\theta)I - \theta\Sigma_{t+h|t}\Sigma_{t+h|t-1}\right)^{-1}\Sigma_{t+h|t}\Sigma_{t+h|t-1}x_{t+h|t-1}^{i}\right)\right) \end{array}\right]$$

This equation represents the kernel of a normal density with the following mean

$$\begin{aligned}
\mathbb{E}_t^{i,\theta}(x_{t+h}) &= \left((1+\theta)I - \theta\Sigma_{t+h|t}\Sigma_{t+h|t-1}^{-1}\right)^{-1}\left((1+\theta)x_{t+h|t}^{i} - \theta\Sigma_{t+h|t}\Sigma_{t+h|t-1}^{-1}x_{t+h|t-1}^{i}\right) \\
&= \left((1+\theta)I - \theta R_{t+h|t,t-1}\right)^{-1}\left((1+\theta)x_{t+h|t}^{i} - \theta R_{t+h|t,t-1}x_{t+h|t-1}^{i}\right) \\
&= \left((1+\theta)I - \theta R_{t+h|t,t-1}\right)^{-1}x_{t+h|t}^{i} \\
&+ \theta\left((1+\theta)I - \theta R_{t+h|t,t-1}\right)^{-1}R_{t+h|t,t-1}(R_{t+h|t,t-1}^{-1}x_{t+h|t}^{i} - x_{t+h|t-1}^{i}) \\
&= \left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}x_{t+h|t}^{i} \\
&+ \theta\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}R_{t+h|t,t-1}(R_{t+h|t,t-1}^{-1}x_{t+h|t}^{i} - x_{t+h|t-1}^{i}) \\
&= \left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}x_{t+h|t}^{i} + \theta\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}R_{t+h|t,t-1}R_{t+h|t,t-1}^{-1}x_{t+h|t}^{i} \\
&- \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}x_{t+h|t-1}^{i} \\
&= (I + \theta I)\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}x_{t+h|t}^{i} - \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}x_{t+h|t-1}^{i}
\end{aligned}$$

where $R_{t+h|t,t-1} = \Sigma_{t+h|t}\Sigma^{-1}_{t+h|t-1}$. Since $I + \theta I = I + \theta(I - R_{t+h|t,t-1}) + \theta R_{t+h|t,t-1}$, it follows that

$$
\begin{aligned}
\mathbb{E}^{i,\theta}_t(x_{t+h}) &= \left(I + \theta(I - R_{t+h|t,t-1}) + \theta R_{t+h|t,t-1}\right)\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1} x^i_{t+h|t} \\
&- \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1} x^i_{t+h|t-1} \\
&= x^i_{t+h|t} + \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1} x^i_{t+h|t} \\
&- \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1} x^i_{t+h|t-1} \\
&= x^i_{t+h|t} + \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1} (x^i_{t+h|t} - x^i_{t+h|t-1}).
\end{aligned}
$$

Let me define the effective distortion parameter $\tilde{\theta}_{t,t-1} = \theta R_{t+h|t,t-1}\left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}$ reflecting the change in uncertainty $R_{t+h|t,t-1}$.

Due to information frictions, we assume that $x^i_{t|t} = x^i_{t|t-1} + K_t(s^i_t - x^i_{t|t-1})$ [13], and given that $\mathbb{E}^{i,\theta}_t(\pi_{t+h}) = \begin{pmatrix} 1 & 1 \end{pmatrix} \mathbb{E}^{i,\theta}_t(x_{t+h}) = \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix} \mathbb{E}^{i,\theta}_t(x_t)$,

$$
\begin{aligned}
\mathbb{E}^{i,\theta}_t(\pi_{t+h}) &= \begin{pmatrix} 1 & 1 \end{pmatrix}\left[\left(I + \tilde{\theta}_{t,t-1}\right) x^i_{t+h|t} - \tilde{\theta}_{t,t-1} x^i_{t+h|t-1}\right] \\
&= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\left(I + \tilde{\theta}_{t,t-1}\right)\left[x^i_{t|t-1} + K_t(s^i_t - x^i_{t|t-1})\right] - \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\tilde{\theta}_{t,t-1} x^i_{t|t-1} \\
&= \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix} x^i_{t|t-1} + \begin{pmatrix} 1 & \rho^h_\varepsilon \end{pmatrix}\left(I + \tilde{\theta}_{t,t-1}\right) K_t(s^i_t - x^i_{t|t-1})
\end{aligned}
$$

- Let us begin by considering the signal for individual i at time t which holds until the year of 2012.

$$
s^i_t = S^i_{t,\tau\varepsilon} = \begin{pmatrix} 1 & 1 \end{pmatrix}\begin{pmatrix} \tau_t \\ \varepsilon_t \end{pmatrix} + \sigma_{\nu,\tau\varepsilon}\nu^i_{t,\tau\varepsilon}
$$

[13] K_t denotes the Kalman gain matrix.

Using this, the expected inflation for individual i is given by

$$
\begin{aligned}
\mathbb{E}_t^{i,\theta}(\pi_{t+h}) &= \begin{pmatrix} 1 & \rho_\varepsilon^h \end{pmatrix} \left[x_{t|t-1}^i + \left(I + \tilde{\theta}_{t,t-1}\right) K_t (s_{i,t} - x_{t|t-1}^i)\right] \\
&= \begin{pmatrix} 1 & \rho_\varepsilon^h \end{pmatrix} \left(\begin{pmatrix} \tau_{i,t|t-1} \\ \varepsilon_{i,t|t-1} \end{pmatrix} + \left(I + \tilde{\theta}_{t,t-1}\right) K_t \left(\tau_t + \varepsilon_t + \sigma_{\nu,\tau\varepsilon} \nu_{t,\tau\varepsilon}^i - \tau_{t|t-1}^i - \varepsilon_{t|t-1}^i\right)\right).
\end{aligned}
$$

where K_t is a 2-by-1 Kalman gain matrix.

- For the year 2012 and beyond, the signal s_t^i is shifted to

$$
s_t^i = \begin{pmatrix} S_{t,\tau}^i \\ S_{t,\tau\varepsilon}^i \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \tau_t \\ \varepsilon_t \end{pmatrix} + \begin{pmatrix} \sigma_{\nu,\tau} & 0 \\ 0 & \sigma_{\nu,\tau\varepsilon} \end{pmatrix} \begin{pmatrix} \nu_{t,\tau}^i \\ \nu_{t,\tau\varepsilon}^i \end{pmatrix}.
$$

  Thus the expected inflation for individual i's updated as follows

$$
\begin{aligned}
\mathbb{E}_t^{i,\theta}(\pi_{t+h}) &= \begin{pmatrix} 1 & \rho_\varepsilon^h \end{pmatrix} \left[x_{t|t-1}^i + \left(I + \tilde{\theta}_{t,t-1}\right) K_t (s_t^i - x_{t|t-1}^i)\right] \\
&= \begin{pmatrix} 1 & \rho_\varepsilon^h \end{pmatrix} \left(\begin{pmatrix} \tau_{t|t-1}^i \\ \varepsilon_{t|t-1}^i \end{pmatrix} + \left(I + \tilde{\theta}_{t,t-1}\right) K_t \left(\begin{pmatrix} S_{t,\tau}^i \\ S_{t,\tau\varepsilon}^i \end{pmatrix} - \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \tau_{t|t-1}^i \\ \varepsilon_{t|t-1}^i \end{pmatrix} \right)\right)
\end{aligned}
$$

  where K_t is a 2-by-2 Kalman gain matrix.

Finally, the effective distortion matrix $\tilde{\theta}_{t,t-1} = \theta R_{t+h|t,t-1} \left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}$ is a 2-by-2 matrix. The first row captures how much the forecast on the trend component $\tau_{t|t}$ overreacts to news about τ_t and ε_t. Likewise the second row implies how much expectations about $\varepsilon_{t|t}$ are distorted in response to newly received information about τ_t and ε_t.

The subjective uncertainty is

$$
\begin{aligned}
\mathbb{V}_t^\theta(x_{t+h}) &= \Sigma_{t+h|t} \left((1+\theta)I - \theta \Sigma_{t+h|t} \Sigma_{t+h|t-1}^{-1}\right)^{-1} \\
&= \Sigma_{t+h|t} \left(I + \theta(I - R_{t+h|t,t-1})\right)^{-1}
\end{aligned}
$$

Proof of Proposition 4

$$\begin{aligned}
\frac{\partial\tilde{\theta}_{t,t-1}}{\partial R_{t+h|t,t-1}} &= \frac{\partial \theta R_{t+h|t,t-1}\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1}}{\partial R_{t+h|t,t-1}} \\
&= \frac{\partial \theta R_{t+h|t,t-1}}{\partial R_{t+h|t,t-1}}\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1} + \theta R_{t+h|t,t-1}\frac{\partial\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1}}{\partial R_{t+h|t,t-1}} \\
&= \theta I\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1} \\
&- \theta R_{t+h|t,t-1}\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1}(-\theta I)\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1} \\
&= \theta\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1} + \theta R_{t+h|t,t-1}\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1}\theta\left(I+\theta(I-R_{t+h|t,t-1})\right)^{-1}.
\end{aligned}$$

For $\frac{\partial\tilde{\theta}_{t,t-1}}{\partial R_{t+h|t,t-1}} > 0$, the resulting matrix must be positive definite. Given that the identity matrix I has any non-zero vector as an eigenvector, we can assume that I and $R_{t+h|t,t-1}$ share the same set of eigenvectors. Consequently, the eigenvalues of the matrix $I + \theta(I - R_{t+h|t,t-1})$ are given by

$$1 + \theta(1 - \lambda_i) \text{ for } i = 1, 2.$$

The matrix $I + \theta(I - R_{t+h|t,t-1})$ is positive definite if and only if

$$1 + \theta(1 - \lambda_1) > 0 \text{ and } 1 + \theta(1 - \lambda_2) > 0$$

given $\theta > 0$.

Since $|\Sigma_{t+h|t}| < |\Sigma_{t+h|t-1}|$, reflecting the fact that uncertainty decreases as the information set is updated,

$$|R_{t+h|t,t-1}| = \frac{|\Sigma_{t+h|t}|}{|\Sigma_{t+h|t-1}|} < 1.$$

Because the eigenvalues of a covariance matrix represent the uncertainty within the data, the eigenvalues of the updated posterior variance are smaller compared to the eigenvalues of the prior variance. This implies that

$$\lambda_i < 1 \text{ for } i = 1, 2.$$

As a result the following conditions hold.

$$1 + \theta(1 - \lambda_i) > 0 \text{ for } i = 1, 2$$

ensuring that

$$\frac{\partial \tilde{\theta}_{t,t-1}}{\partial R_{t+h|t,t-1}} > 0.$$

Chapter 2

Rationally Inattentive Behavior in Different Times

2.1 Introduction

> *"What information consumes is rather obvious: It consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention, and a need to allocate that attention efficiently among the overabundance of information sources that might consume it."*
>
> (Simon, 1971, p.40-41)

Efficient allocation of attention is essential when individuals are faced with an abundance of information. As a scarce resource, attention is allocated optimally, much like other economic resources. The rational inattention model, first proposed by Sims (1998) incorporates this cognitive process by framing attention as a costly resource. Sims (2003) introduces the concept of the rate of uncertainty reduction to quantify the flow of information, which has since become central to the literature on rational inattention. This framework has been widely used to study equilibrium behavior under limited attention.

Much of the existing research focuses on partial equilibrium analyses, examining specific sides of the economy. For example, Luo (2008) explores the joint dynamics of consumption and permanent income for rationally inattentive households and develops an analytical approach to solving the permanent income hypothesis model under rational inattention. Similarly, Tutino (2013) demonstrates that rationally inattentive households respond asymmetrically to income shocks, with negative shocks eliciting stronger and faster adjustments in consumption. On the firm side, Mackowiak and Wiederholt (2009) investigate the behavior of price-setting firms, showing that such firms prioritize firm-specific information over aggregate conditions.

Building on this foundation, Maćkowiak and Wiederholt (2015) design a DSGE model with rational inattention. In this model, households and firms deviate optimally from the behavior they would adopt under perfect information. These deviations, while incurring minor losses in utility or profit, reflect the costly nature of attention. Rationally inattentive agents determine their behavior by balancing the marginal benefit against the marginal cost of paying attention. The resulting utility or profit is slightly lower than it would be under perfect information; however, the loss is minimal and negligible. Importantly, their work demonstrates that rational inattention alone can account for the slow adjustment of macroeconomic aggregates, without relying on traditional assumptions such as Calvo pricing, habit formation in consumption, or Calvo wage-setting.

A key insight from the literature is that greater uncertainty draws more attention. For instance, both Maćkowiak and Wiederholt (2015) and Paciello (2012) find that firms are more attentive to aggregate technology shocks, which exhibit higher volatility, compared to monetary policy shocks. However, much of this research focuses on within-period variations in attention allocation, often limited to periods of low aggregate volatility, such as the Great Moderation (1982–2008). This leaves a critical gap: it remains unclear whether rational inattention models are valid across periods with markedly different levels of aggregate volatility. Validating the model in such contexts is crucial to demonstrate its robustness along both variable and temporal dimensions.

This paper addresses this gap by examining whether economic agents allocate more attention during periods of high aggregate volatility, such as the pre-Great Moderation period, and whether the DSGE model with rational inattention can consistently reproduce empirical findings across these periods. If, in the high-volatility pre-Great Moderation period, agents were perfectly attentive and adhered strictly to profit- or utility-maximizing behavior under perfect information, the model would fail to account for the slow adjustment of macroeconomic variables. This study examines whether the DSGE model with rational inattention can consistently reproduce empirical findings and capture slow adjustments, even during the pre-Great Moderation period—a context that has not been previously explored.

I make three contributions. First, I verify that the loss incurred by deviating from profit- or utility-maximizing behavior under perfect information is sufficiently small for firms and households to accept such deviations, regardless of the level of aggregate volatility. This behavior persists across both the pre-Great Moderation and Great Moderation periods. Agents facing information processing costs initially respond by deviating from the optimal behavior expected under perfect information. Subsequently, they adjust their behavior gradually toward optimal responses. In other words, rational inattention consistently serves as a source of slow adjustment in macroeconomic variables. My second contribution is that I show that economic agents allocate more attention to aggregate technology shocks during the pre-Great Moderation period, characterized by greater volatility. This finding aligns with the fact that rationally inattentive agents allocate more attention when uncertainty increases. This study extends the literature by confirming that this principle applies consistently across different periods, not just within a single time frame. Finally, I demonstrate that households and firms adjust their initially deviated responses more quickly during the pre-Great Moderation period, characterized by higher volatility. This is because agents allocate more attention and closely follow the profit- or utility-maximizing behavior under perfect information when volatility is high. Consequently, this paper reinforces the finding that firms and households pay closer attention to large uncertainties than to smaller ones over time.

This paper adopts the DSGE model developed by Maćkowiak and Wiederholt (2015), incorporating three fundamental shocks: monetary policy shocks, aggregate technology shocks, and firm-specific shocks. Consistent with their findings, both firms and households pay more attention to aggregate technology shocks than to monetary policy shocks, as the former exhibit greater volatility. Firms, in particular, prioritize firm-specific productivity and aggregate technology over monetary policy across both periods. By applying this model to periods with distinct volatility levels, this study sheds light on the temporal robustness of rational inattention as a source of macroeconomic adjustment dynamics.

2.2 Model Setup of DSGE

This section outlines the preferences and technology, market structure, asset structure, and monetary and fiscal policies. These features of the economy are almost identical to a simple New Keynesian model, with the key exception that assumptions such as Calvo pricing, Calvo wage-setting, and habit formation in consumption are removed. Since the model used in this research is identical to that in Maćkowiak and Wiederholt (2015), the detailed technical proofs and derivations of equations can be found in the online appendix of Maćkowiak and Wiederholt (2015).

The economy comprises three markets: the goods market, the labor market, and the asset market. In each market, one side determines the quantity, while the other sets the price. In the goods market, firms set the prices of goods, and households decide their level of consumption. In the labor market, households set wage rates, and firms determine the quantity of labor they will hire. In the sole asset market—the bond market—the government determines the interest rate, and households choose their bond holdings. Time is modeled as discrete.

2.2.1 Households

There are J households in the economy. These households consume goods, supply labor, and hold government bonds. Each household has market power in the labor market because they supply differentiated labor. The model assumes an infinite horizon, with each household maximizing the expected discounted sum of their period utility.

In each period, a household has a utility function of

$$U(C_{jt}, L_{jt}) = \frac{C_{jt}^{1-\gamma} - 1}{1-\gamma} - \varphi L_{jt} \tag{2.2.1}$$

with

$$C_{jt} = \left(\sum_{i=1}^{I} C_{ijt}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \tag{2.2.2}$$

C_{ijt} is the consumption for good i of j household at time t, and C_{jt} is the composite consumption by the household j. L_{jt} is the labor supply of household j at period t. The parameter $\theta > 1$ is the elasticity of substitution between the I different consumption goods, the parameter $\gamma > 0$ is the inverse of the intertemporal elasticity of substitution, and the parameter $\varphi > 0$ is the marginal disutility of labor.

The budget constraint of household j at time t is as follows.

$$\sum_{i=1}^{I} P_{it} C_{ijt} + B_{jt} = R_{t-1} B_{jt-1} + (1+\tau_w) W_{jt} L_{jt} + \frac{D_t}{J} - \frac{T_t}{J} \tag{2.2.3}$$

P_{it} is the price of good i at period t, and B_{jt} is the number of bonds held by household j and t. $R_{t-1}$is gross nominal interest rate on bond holdings between period $t-1$ and t, B_{jt-1} is the number of bonds held by household j from $t-1$ to t, W_{jt} is the nominal wage rate for labor supplied by household j at t,and L_{jt} is labor supplied by household j at t. τ_w is the wage subsidy, and D_t/J is a po-rata share of nominal aggregate profits and T_t/J is a pro-rata share of lump-sum taxes. Each household has initial bond holdings, and in order to prevent Ponzi schemes, bond holdings should always be positive, $B_{jt} > 0$. In every period, a vector of consumption $(C_{1jt,} \cdots, C_{Ijt})$, and wage rate W_{jt} are determined. Based on this wage rate, each household supplies any quantity of labor. Also each household takes nominal interest rate, the price of goods, and the aggregate wage index as given.

2.2.2 Firms

There exist I firms in the model. Each firm i supplies different good i. The production function of firm i is

$$Y_{it} = e^{a_t} e^{a_{it}} L_{it}^{\alpha} \tag{2.2.4}$$

with

$$L_{it} = \left(\sum_{j=1}^{J} L_{ijt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{2.2.5}$$

Y_{it} is output, L_{it} is composite labor demanded by firm i at t, and $e^{a_t} e^{a_{it}}$ is total factor productivity. e^{a_t} is aggregate component and $e^{a_{it}}$ is the idiosyncratic component of firm i's technology. L_{ijt} is labor demanded by firm i from household j at t, and the parameter $\eta > 1$ is the elasticity of substitution between different kinds of labor. The parameter $\alpha \in (0, 1]$ is the elasticity of output with respect to composite labor input. Nominal profit function of firm i is

$$(1 + \tau_p) P_{it} Y_{it} - \sum_{j=1}^{J} W_{jt} L_{ijt}. \tag{2.2.6}$$

τ_p is production subsidy provided by the government. In every period, each firm chooses price P_{it}, a labor mix $(\hat{L}_{i1t}, \cdots, \hat{L}_{i(J-1)t})$, where $\hat{L}_{ijt} = (L_{ijt}/L_{it})$ denotes relative input of type j labor at firm i in period t. Each firm supplies any quantity of the good at the price, and the quantity is decided by the chosen labor mix. Each firm takes wage rates and the aggregate price index as given.

2.2.3 Government

In the government part, we have a fiscal and a monetary authority. The nominal interest rate is determined by the Taylor rule.

$$\frac{R_t}{R} = (\frac{R_{t-1}}{R})^{\rho}[(\frac{\Pi_t}{\Pi})^{\phi_\pi}(\frac{Y_t}{Y_t^P})^{\phi_y}]^{1-\rho}e^{\varepsilon_t^R} \tag{2.2.7}$$

where R_t is the nominal interest rate in period t, $\Pi_t = (P_t/P_{t-1})$ is inflation. Y_t, aggregate output, is defined as

$$Y_t = \frac{\sum_{i=1}^{I} P_{it}Y_{it}}{P_t} \tag{2.2.8}$$

Y_t^P is equilibrium output under perfect information, and ε_t^R is a monetary policy shock. R is the nominal interest rate in the non-stochastic steady state. Likewise, Π is inflation in the non-stochastic steady state. The policy parameters satisfy $\rho \in [0, 1)$, $\phi_\pi > 1$ and $\phi_y \geq 0$. We have the government's budget constraint in period t:

$$T_t + B_t = R_{t-1}B_{t-1} + \tau_p(\sum_{i=1}^{I} P_{it}Y_{it}) + \tau_w(\sum_{j=1}^{J} W_{jt}L_{jt}). \tag{2.2.9}$$

Equation (2.2.9) indicates that the government collects lump-sum taxes or issues new bonds to finance maturing bond B_{t-1}, production subsidy τ_p and wage subsidy τ_w. Because both households and firms have market power, the government tries to correct market distortion by providing wage subsidy and production subsidy.

$$\tau_p = \frac{\tilde{\theta}}{\tilde{\theta} - 1} - 1 \tag{2.2.10}$$

where $\tilde{\theta}$ denotes the price elasticity of demand and

$$\tau_w = \frac{\tilde{\eta}}{\tilde{\eta} - 1} - 1 \tag{2.2.11}$$

where $\tilde{\eta}$ denotes the wage elasticity of labor demand.

2.2.4 Shocks

We consider monetary policy shocks, aggregate technology shocks, and idiosyncratic technology shocks. The stochastic processes $\{\varepsilon_t^R\}$,$\{a_t\}$, $\{a_{1t}, \cdots, a_{It}\}$ are independent. The monetary policy shock ε_t^R follows a Gaussian white noise process. Log of aggregate technology a_t and log of firm-specific technology $\{a_{1t}, \cdots, a_{It}\}$ follow a stationary AR(1) process with mean zero. The shock to log of aggregate technology a_t is denoted by ε_t^A, and the shock to log of firm-specific technology a_{it} is denoted by ε_{it}^I.

2.2.5 Notation

Throughout the paper, C_t is aggregate composite consumption, and L_t is aggregate composite labor input.

$$C_t = \sum_{j=1}^{J} C_{jt}, \quad L_t = \sum_{i=1}^{I} L_{it} \tag{2.2.12}$$

$\hat{P}_{it}$ and $\hat{W}_{jt}$ are relative terms.

$$\hat{P}_{it} = \frac{P_{it}}{P_t}, \quad \hat{W}_{jt} = \frac{W_{jt}}{W_t}$$

$\tilde{W}_{jt}$ denotes the real wage rate for type j labor, and $\tilde{W}_t$ denotes the real wage index.

$$\tilde{W}_{jt} = \frac{W_{jt}}{P_t}, \quad \tilde{W}_t = \frac{W_t}{P_t}$$

2.3 Rationally Inattentive Agents Model

The principle of the rational inattention model is that economic agents decide how much they allocate their attention by equating marginal benefit and the marginal cost of attention. The benefit of paying attention lies in the ability to adhere more closely to profit-maximizing or utility-maximizing behavior under perfect information. Conversely, the cost of paying attention is associated with the time and effort required to process information. To quantify the benefit of paying attention, I evaluate the utility or profit loss resulting from deviations from optimal actions under perfect information. For households, the utility loss from suboptimal consumption is interpreted as the benefit of paying attention to shocks within the rational inattention framework. Similarly, for firms, the profit loss due to suboptimal pricing represents the benefit of paying attention to shocks.

There are two key differences between the household's and firm's problems. First, firms' pricing decisions are influenced by monetary policy shocks, firm-specific shocks, and aggregate technology shocks, whereas households' consumption decisions are influenced only by aggregate technology shocks and monetary policy shocks. Second, firms determine both the labor demand for each firm and the prices of goods, while households decide their consumption bundle, wage rate, and bond holdings.

2.3.1 Profit Loss of an Inattentive Firm

It is necessary to identify demand for good i to derive the objective of a firm by guessing the following demand function

$$C_{it} = \vartheta \left(\frac{P_{it}}{P_t}\right)^{-\tilde{\theta}} C_t. \tag{2.3.1}$$

Here, $P_t = d(P_{1t}, \cdots, P_{It})$ represents a price index, where the function d is homogeneous of degree one, continuously differentiable, and symmetric. The coefficients ϑ and $\tilde{\theta}$ satisfy $\vartheta > 0$ and $\tilde{\theta} > 1$. Since the economy is an incomplete market economy, we must assume a general stochastic discount factor. In different states of the economy, firm owners face uncertainty regarding the valuation of their nominal profits. Consequently, it becomes necessary to account for $Q_{-1,t}$. In period -1, a decision-maker of a firm values nominal profit with the stochastic discount factor

$$Q_{-1,t} = \beta^t \Lambda(C_{1t}, \cdots, C_{Jt}) \frac{1}{P_t}. \tag{2.3.2}$$

C_{jt} represents the composite consumption of household j, Λ is a twice continuously differentiable function, and P_t is the price index used in the demand function above. I substitute the production functions (2.2.4), (2.2.5), and the demand function (2.3.1) into the profit function (2.2.6). Multiplying the resulting profit function by the stochastic discount factor (2.3.2), summing all over the periods and taking the expectation conditional on the firm's decision-maker's information in period -1, yields the objective function for the decision-maker in firm i. By taking a log-quadratic approximation to this objective function, we derive a simple expression for the expected discounted sum of profit losses resulting from rationally inattentive behavior that deviates from optimal behavior under perfect information:

$$\sum_{t=0}^{\infty}\beta^t\mathbb{E}_{i,-1}[\frac{1}{2}(x_t-x_t^*)'H(x_t-x_t^*)] \tag{2.3.3}$$

where

$$x_t=\begin{pmatrix} p_{it}\\ \hat{l}_{i1t}\\ \vdots \\ \hat{l}_{i(J-1)t}\end{pmatrix},\quad H=-\Lambda(C_1,\cdots,C_J)\hat{P}_i\hat{C}_i\begin{pmatrix}\tilde{\theta}(1+\frac{1-\alpha}{\alpha}\tilde{\theta}) & 0 & \cdots & \cdots & 0\\ 0 & \frac{2\alpha}{\eta^J} & \frac{\alpha}{\eta^J} & \cdots & \frac{\alpha}{\eta^J}\\ \vdots & \frac{\alpha}{\eta^J} & \ddots & \ddots & \vdots\\ \vdots & \vdots & \ddots & \ddots & \frac{\alpha}{\eta^J}\\ 0 & \frac{\alpha}{\eta^J} & \cdots & \frac{\alpha}{\eta^J} & \frac{2\alpha}{\eta^J}\end{pmatrix} \tag{2.3.4}$$

and the optimal actions under perfect information are given by

$$p_{it}^*=p_t+\frac{\frac{1-\alpha}{\alpha}}{1+\frac{1-\alpha}{\alpha}\tilde{\theta}}\left(\frac{1}{J}\sum_{j=1}^{J}c_{jt}\right)+\frac{1}{1+\frac{1-\alpha}{\alpha}\tilde{\theta}}\left(\frac{1}{J}\sum_{j=1}^{J}\tilde{w}_{jt}\right)-\frac{\frac{1}{\alpha}}{1+\frac{1-\alpha}{\alpha}\tilde{\theta}}(a_t+a_{it}) \tag{2.3.5}$$

and

$$\hat{l^*}_{ijt}=-\eta\left(\tilde{w}_{jt}-\frac{1}{J}\sum_{j=1}^{J}\tilde{w}_{jt}\right) \tag{2.3.6}$$

p_{it}^* is the log deviation from the non-stochastic steady-state price p under perfect information, and p_t denotes the log deviation from the non-stochastic steady-state price under rational inattention. In summary, lowercase letters represent log deviations from the non-stochastic steady-state variables. Equation (2.3.5) represents the log-linear optimal price. The profit-maximizing price in period t is expressed as a log-linear function of the price level, aggregate composite consumption, real wage rate, and total factor productivity. Equation (2.3.6) indicates that the relative labor input maximizing profit in period t depends solely on the relative wage rate of type j labor. Furthermore, as indicated by equation (2.3.3), the profit loss resulting from actual actions under rational inattention is only of the second order.

2.3.2 Attention Problem of a Decision-maker in a Firm

We now turn to the attention allocation problem faced by a rationally inattentive firm. In period -1, a rationally inattentive decision-maker in firm i determines how much attention to allocate over the infinite horizon to pricing decisions, labor mix decisions, and the laws of motion governing these variables. His objective is to maximize the firm's expected sum of discounted profit, net of the cost of paying attention

$$\max_{\kappa,B(L),C(L),\tilde{\eta},\chi} \{\sum^{\infty} \beta^t E_{i,-1}[\frac{1}{2}(x_t - x_t^*)'H(x_t - x_t^*)] - \frac{\mu}{1-\beta}\kappa\}, \tag{2.3.7}$$

subject to the law of motion for profit-maximizing actions under perfect information

$$p_{it}^* = A_1(L)\varepsilon_t^A + A_2(L)\varepsilon_t^R + A_3(L)\varepsilon_{it}^I \tag{2.3.8}$$

$$\hat{l}^*{}_{ijt} = -\eta \hat{w}_{jt}, \tag{2.3.9}$$

the law of motion for the actual actions under rational inattention when a decision-maker has a non-zero cost for paying attention

$$p_{it} = B_1(L)\varepsilon_t^A + C_1(L)\nu_{it}^A + B_2(L)\varepsilon_t^R + C_2\nu_{it}^R + A_3(L)\varepsilon_{it}^I + C_3(L)\nu_{it}^I, \tag{2.3.10}$$

$$\hat{l}_{ijt} = -\tilde{\eta}\hat{w}_{jt} + \chi\nu_{ijt}^L, \tag{2.3.11}$$

and the information constraint is

$$I(\{p_{it}^{*A}, p_{it}^{*R}, p_{it}^{*I}, l_{i1t}^{\hat{*}}, \cdots, \hat{l}^*{}_{i(J-1)t}\}; \{p_{it}^A, p_{it}^R, p_{it}^I, \hat{l}_{i1t}, \cdots, \hat{l}_{i(J-1)t}\}) \leq \kappa \tag{2.3.12}$$

$A_s(L), B_s(L), C_s(L)$ with $s = 1, 2, 3$ are infinite-order lag polynomials. The noise terms ν_{it}^A, ν_{it}^R, ν_{it}^I, ν_{ijt}^L follow Gaussian white noise processes with unit variance. These terms are independent of the underlying fundamentals, independent of each other, and independent across firms. The first term in equation (2.3.7) represents the expected discounted sum of profit losses resulting from deviations of actual actions under rational inattention from the profit-maximizing actions under perfect information. As previously discussed, the profit loss incurred from not closely tracking the profit-maximizing law of motion reflects the additional profit that could be earned with greater attention. Thus, these losses quantify the benefit of paying attention. The second term in equation (2.3.7) is the cost of paying attention. The parameter $\mu \geq 0$ is the per-period marginal cost of attention for the firm's decision maker, and the variable $\kappa \geq 0$ denotes the amount of attention allocated to shocks.

The profit-maximizing actions under perfect information are given by equations (2.3.8) and (2.3.9). According to equation (2.3.8), the optimal price identified in equation (2.3.5) is a linear function of current and past shocks, i.e., monetary policy shocks, aggregate technology shocks and idiosyncratic technology shocks in equilibrium. For example, $A_1(L)$ is the response of the optimal price to an aggregate technology shock in equilibrium.

The actual price and hiring of labor under rational inattention are specified in equations (2.3.10) and (2.3.11). There are two types of deviation in the law of motion for actual price. First, the price may behave differently under rational inattention than it would under perfect information ($B_s(L) \neq A_s(L)$ for some s). Second, the decision-maker may have some noises observing structural shocks ($C_s(L) \neq 0$ for some s). If there were no cost for acquiring and processing information, the law of motion for the actual price would be identical to that for the optimal price under perfect information. It implies ($B_s(L) = A_s(L)$) and ($C_s(L) = 0$) for $s = 1, 2, 3$. However, due to costly attention, the decision-maker sets an actual price that deviates. Similarly, labor mix decisions may diverge from their optimal responses under perfect information, as indicated by differences in relative wage rates ($\tilde{\eta} \neq \eta$), and the presence of noise ($\chi > 0$) in hiring decisions. Finally, The left-hand side of the information flow constraint in equation (2.3.12) measures the quantity of information incorporated into the agent's actions relative to profit-maximizing actions under perfect information. Agents should pay more attention if they want to follow the law of motion for profit-maximizing pricing and labor-mix decisions under perfect information. Furthermore, it quantifies the amount of information included in the agent's actions in relation to the underlying shocks to optimal behaviors with perfect information. This constraint, rooted in Sims (2003), quantifies the amount of information embedded in the agent's actions relative to underlying shocks. Further details can be found in Appendix C of Maćkowiak and Wiederholt (2015). A rationally inattentive decision-maker equates the marginal benefit of paying attention to each shock with its marginal cost, μ. For a given marginal cost, the optimal amount of attention to a particular shock is independent of the amount of attention to other shocks. For example, increasing attention to ε_t^A does not affect the attention allocated to ε_{it}^I and ε_t^R; Instead, κ increases by the amount of the additional attention. As a result, p_{it}^A more losely follows the optimal p_{it}^{*A}, whereas p_{it}^R and p_{it}^I remain unaffected.

2.3.3 Utility Loss of an Inattentive Household

Households also allocate their limited attention rationally. We begin by deriving a simple expression for the utility loss incurred when their actions, constrained by limited attention, deviate from the utility-maximizing actions under perfect information. We guess the following demand function for type j labor

$$L_{jt} = \zeta \left(\frac{W_{jt}}{W_t} \right)^{-\tilde{\eta}} L_t \tag{2.3.13}$$

Here $W_t = h(W_{1t}, \cdots, W_{Jt})$ is a wage index, where the function h is homogeneous of degree one, continuously differentiable, and symmetric. The coefficients ζ and $\tilde{\eta}$ satisfy $\zeta > 0$ and $\tilde{\eta} > 1$. When the labor demand function (2.3.13), the budget constraint (2.2.3), and the composite consumption (2.2.2) are substituted into the period utility function (2.2.1), an equation for period utility with those three constraints is obtained. By taking the expectation conditional on the information available to household j in period -1, multiplying it by β^t, and summing over all periods, we derive the household's objective. Using a log quadratic approximation, we estimate the following expression: the household's objective at a non-stochastic steady state. A household's actual actions with limited attention may differ from its utility-maximizing actions in the absence of information-processing costs. As a result, the discounted sum of utility losses is expressed as follows. This total utility loss represents the benefit of paying attention under the rational inattention framework.

$$\sum_{t=0}^{\infty} \beta^t \mathbb{E}_{j,-1}[\frac{1}{2}(x_t - x_t^*)' H_0 (x_t - x_t^*) + (x_t - x_t^*) H_1 (x_{t+1} - x_{t+1}^*)] \tag{2.3.14}$$

where

$$x_t = \begin{pmatrix} \tilde{b}_{jt} \\ \tilde{w}_{jt} \\ \hat{c}_{1jt} \\ \vdots \\ \hat{c}_{I-1jt} \end{pmatrix}, H_0 = -C_j^{1-\gamma} \begin{pmatrix} \gamma\omega_B^2(1+\frac{1}{\beta}) & \gamma\omega_B\tilde{\eta}\omega_W & 0 & \cdots & 0 \\ \gamma\omega_B\tilde{\eta}\omega_W & \tilde{\eta}\omega_W(\gamma\tilde{\eta}\omega_W + 1) & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix} \tag{2.3.15}$$

and

$$H_1 = C_j^{1-\gamma} \begin{pmatrix} \gamma\omega_B^2 & \gamma\omega_B\tilde{\eta}\omega_W & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix} \tag{2.3.16}$$

Here $\tilde{b}_{jt}$ denotes real bond holdings, $\tilde{w}_{jt}$ denotes the real wage rate, and $\hat{c}_{ijt}$ denotes relative consumption of good i of household j. After taking the log-quadratic approximation, the optimal actions under perfect information (no information processing cost) are derived as follows:

$$\omega_B \tilde{b^*}_{jt} = \frac{\omega_B}{\beta}(r_{t-1} - \pi_t + \tilde{b}^*_{jt-1}) + \omega_w \frac{\tilde{\eta}}{\tilde{\eta}-1}[(1-\tilde{\eta})\tilde{w}^*_{jt} + \tilde{\eta}\tilde{w}_t + l_t] + \omega_D \tilde{d}_t - \omega_T \tilde{t}_t - c^*_{jt}, \tag{2.3.17}$$

$$c^*_{jt} = \mathbb{E}_t[-\frac{1}{\gamma}(r_t - \pi_{t+1}) + c^*_{jt+1}], \tag{2.3.18}$$

$$\tilde{w}^*_{jt} = \gamma c^*_{jt} \tag{2.3.19}$$

and

$$\hat{c}^*_{ijt} = -\theta \hat{p}_{it}. \tag{2.3.20}$$

The expectation operator $\mathbb{E}_t$ represents conditional expectation given the complete history of the economy up to the current period t, and the ω's denote steady-state ratios, as provided in online Appendix D of Maćkowiak and Wiederholt (2015). Equations (2.3.17)-(2.3.20) are the standard log-linear optimality conditions that are general in the New Keynesian literature. The flow budget constraint (2.3.17) implies the following bond-holding deviation.

$$\omega_B(\tilde{b}_{jt} - \tilde{b}^*_{jt}) = \frac{\omega_B}{\beta}(\tilde{b}_{jt-1} - \tilde{b}^*_{jt-1}) - \tilde{\eta}\omega_W(\tilde{\omega}_{jt} - \tilde{\omega}^*_{jt}) - (c_{jt} - c^*_{jt}). \tag{2.3.21}$$

Substituting this equation for the bond deviation into equation (2.3.14) and rearranging it yields a simple expression for the expected utility loss from actual actions under rational inattention:

$$-C_j^{1-\gamma} \sum_{t=0}^{\infty} \beta^t \mathbb{E}_{j,-1} \left[\begin{array}{c} \frac{\gamma}{2}(c_{jt} - c^*_{jt})^2 + \frac{\tilde{\eta}\omega_W}{2}(\tilde{w}_{jt} - \tilde{w}^*_{jt}) \\ +\frac{1}{2} \begin{pmatrix} \hat{c}_{1jt} - \hat{c}^*_{1jt} \\ \vdots \\ \hat{c}_{I-1jt} - \hat{c}^*_{I-1jt} \end{pmatrix}' \begin{bmatrix} \frac{2}{\theta I} & \cdots & \frac{1}{\theta I} \\ \vdots & \ddots & \vdots \\ \frac{1}{\theta I} & \cdots & \frac{2}{\theta I} \end{bmatrix} \begin{pmatrix} \hat{c}_{1jt} - \hat{c}^*_{1jt} \\ \vdots \\ \hat{c}_{I-1jt} - \hat{c}^*_{I-1jt} \end{pmatrix} \end{array} \right]. \tag{2.3.22}$$

2.3.4 Attention Problem of a Household

Household j decides the amount of attention allocated to the intertemporal consumption decision, the wage-setting decision, and the consumption mix as well as the law of motion for composite consumption, wage rate, and consumption mix that maximize the expected discounted sum of utility net of the cost of paying attention in period -1.

$$\max_{\kappa, B(L), C(L), \tilde{\theta}, \xi} \{\sum_{t=0}^{\infty} \beta^t E_{j,-1}[\frac{1}{2}(x_t - x_t^*)' H_0 (x_t - x_t^*) + (x_t - x_t^*)' H_1 (x_{t+1} - x_{t+1}^*)] - \frac{\lambda}{1-\beta}\kappa\} \quad (2.3.23)$$

subject to equations (2.3.15) , (2.3.16) and (2.3.21), the law of motion for utility-maximizing actions under perfect information

$$c_{jt}^* = A_1(L)\varepsilon_t^A + A_2(L)\varepsilon_t^R, \quad (2.3.24)$$

$$\tilde{w}_{jt}^* = \gamma c_{jt}^*, \quad (2.3.25)$$

$$\hat{c}_{ijt}^* = -\theta \hat{p}_{it} \quad (2.3.26)$$

the law of motion for actual actions under rational inattention

$$c_{jt} = B_1(L)\varepsilon_t^A + C_1(L)\nu_{jt}^A + B_2(L)\varepsilon_t^R + C_2\nu_{jt}^R \quad (2.3.27)$$

$$\tilde{w}_{jt} = \gamma c_{jt} \quad (2.3.28)$$

$$\hat{c}_{ijt} = -\tilde{\theta}\hat{p}_{it} + \xi \nu_{ijt}^I \quad (2.3.29)$$

$$I(\{c_{jt}^{*A}, c_{jt}^{*R}, \hat{c}^*{}_{1jt}, \cdots, \hat{c}^*{}_{I-1jt}\}; \{c_{jt}^A, c_{jt}^R, \hat{c}_{1jt}, \cdots, \hat{c}_{I-1jt}\}) \leq \kappa \quad (2.3.30)$$

$A_s(L), B_s(L)$ and $C_s(L)$ with $s = 1, 2$ are infinite-order lag polynomials. The noise terms $\nu_{jt}^A, \nu_{jt}^R, \nu_{ijt}^I$ follow Gaussian white noise processes with unit variance. These noise terms are independent of the underlying fundamentals, independent of each other, and independent across households. Similar to a firm's decision-maker, a household equates the marginal benefit of paying attention with its marginal cost. The benefit of paying attention lies in the household's ability to track the law of motion for optimal actions under perfect information. For instance, if a household pays closer attention to a monetary policy shock, ε_t^R,its consumption response to that shock c_{jt}^R tracks more closely optimal response c_{jt}^{R*}. The first term in the objective function (2.3.23) is the expected utility loss of deviating from the law of motion for the utility-maximizing actions under perfect information. The per-period cost of paying attention is $\lambda \geq 0$, and the variable $\kappa \geq 0$ denotes the amount of attention allocated to intertemporal consumption decisions, wage-setting decisions, and consumption mix.

Unlike the attention problem faced by a firm's decision-maker, a household must also address deviations in bond holdings (2.3.21), wage-setting equations (2.3.25) and (2.3.28) additionally. First of all, equation (2.3.21) implies that the current bond holding deviation is a linear combination of past bond-holding deviations, current real wage deviations, and current consumption deviations.

Second, a household makes consumption and wage-setting decisions. A household sets the real wage rate according to equation (2.3.25) under perfect information. However, with limited attention, a household determines the actual real wage rate using equation (2.3.28). This reflects a fundamental result: a household always equates the real wage rate to the marginal rate of substitution between consumption and leisure.

This intratemporal optimality is expressed in equation (2.3.28) as log-deviations from a non-stochastic steady-state. Furthermore, because the household decides on the real wage rate and consumption, the household can satisfy the intratemporal optimality condition regardless of the nature of information flows available to the household[1]. Hence, a solution to the household's attention problem has to satisfy equation (2.3.28).

[1]Since composite consumption and the real wage rate contain the same information, it does not matter whether one uses the composite consumption behavior or the wage setting behavior in equation (42) to quantify the information flow to the household.

2.3.5 Equilibrium definition

An equilibrium with rational expectations is characterized as follows: firms solve equations (2.3.7)-(2.3.12), households solve equations (2.3.23)-(2.3.30), and aggregate variables are obtained by averaging individual actions. The nominal interest rate is determined according to the Taylor rule (2.2.7). Firms and households perceive the deviated actual laws of motion under rational inattention as identical to the perceived laws of motion for p_{it}^*, $\hat{l}_{ijt}^*$, c_{jt}^*,and $\hat{c}_{ijt}^*$. In my DSGE model, inattentive households and firms recognize that the actual laws of motion, which account for attention costs, align with the optimal laws of motion for profit-maximizing or utility-maximizing behavior. Thus, agents have rational expectations.

2.4 How to solve the model and calibration

2.4.1 How to solve the model

I derive the aggregate dynamics through an iterative procedure. First, I make an initial guess about the law of motion for the optimal actions under perfect information p_{it}^* and c_{jt}^*. Second, I solve the attention problem for firms and households separately. This step converts infinite-order lag polynomial terms into finite-order lag polynomial terms. As a result, each infinite-order lag polynomials $B_s(L)$ and $C_s(L)$ becomes a finite-order ARMA process. Following that, a standard non-linear optimization method is used to solve the attention problem. Third, I compute aggregate variables by averaging individual variables: $p_t = \frac{1}{I}\sum_{i=1}^{I} p_{it}$, $c_t = \frac{1}{J}\sum_{j=1}^{J} c_{jt}$, and the real wage rate $\tilde{w}_t = \frac{1}{J}\sum_{j=1}^{J} \tilde{w}_{jt}$. Fourth, I compute the law of motion for the nominal interest rate and set $y_t = c_t$, since there is no government expenditure or investment in the economy. Finally, I derive the laws of motion for profit-maximizing price and utility-maximizing consumption under perfect information by following equations (2.3.5) and (2.3.18). If the derived law of motion for the optimal actions differs from the initial guess, I update the guesses and repeat the process until a fixed point is obtained[2].

2.4.2 Calibration

Maćkowiak and Wiederholt (2015) first divide the parameters into two groups. The first group of parameters is rational inattention-related parameters. Therefore, the marginal cost of paying attention for the decision-maker in a firm μ and the marginal cost of paying attention for a household λ are included in the rational inattention-related parameter group. The other parameters are non-rational inattention parameters. They start by calibrating the non-rational-inattention parameters. Thereafter, they solve the model for a grid of values of μ and λ. The values of μ and λ are set in such a way as to minimize the gap between the impulse response to a monetary policy shock in the model and the impulse response to the same shock in the VAR of Altig et al. (2011).

I accept the values of λ, μ, and other non-rational-inattention parameters found in Maćkowiak and Wiederholt (2015), except for the persistence of aggregate productivity, the volatility of aggregate productivity shocks, and the volatility of monetary policy shocks. whether there are distinct rational inattentive responses during the pre-Great Moderation compared to the Great Moderation. The defining feature of the Great Moderation relative to the pre-Great Moderation is the significant decline in macroeconomic volatility. In this context, I calibrate parameter values to reflect differences in shock volatility, assuming other parameters remain stable across the periods. Additionally, the volatility of idiosyncratic technology shocks is assumed to remain constant across both periods. To calibrate the parameters for the stochastic processes of firm-specific productivity, Maćkowiak

[2]See online Appendix E of Maćkowiak and Wiederholt (2015) for more details.

	pre-GM	GM
β	0.99	
μ^a	0.0006	
λ^b	0.0006	
γ	1	
ϕ_π	1.5	
ϕ_y	0.125	
$\tilde{\theta}$	4	
$\tilde{\eta}$	4	
α	2/3	
ρ_I	0.3	
$sd(\varepsilon_{it}^I)$	0.231	
ρ_A	0.97	0.96
$sd(\varepsilon_t^A)$	0.0094	0.0055
$sd(\varepsilon_t^R)$	0.0018	0.0015

[a] marginal cost of information flow to firms as the fraction of revenue in non-stochastic steady state
[b] marginal cost of information flow to households as the fraction of consumption in non-stochastic steady state

Table 2.1: The Value of Parameters

and Wiederholt (2015) follow a common strategy in the menu cost literature. They determine the standard deviation of firm-specific shocks such that the absolute magnitude of price changes in the model aligns with the observed absolute magnitude of price changes in microdata. First, I assume the autocorrelation of idiosyncratic firm-specific productivity processes is 0.3, following Klenow and Willis (2007) and Nakamura and Steinsson (2008). Klenow and Kryvtsov (2008) find that the median absolute size of price changes equals 9.7% from 1988 to 2004. Consequently, the standard deviation of the firm-specific productivity shock, ε_{it}^{I}, is calibrated to 0.231 to match this observed absolute price change magnitude in the model. According to Nakamura et al. (2018), earlier studies focused solely on the Great Moderation period when inflation was low and stable. They overcome this obstacle by extending the microdata set on US consumer prices back to 1977. Their findings show no evidence that the absolute magnitude of price movements increased between 1977 and 1987, prior to the Great Moderation. They conclude that despite lower inflation during the Great Moderation, the average absolute magnitude of price changes from 1978 to 1987 was nearly comparable to that from 1988 to 2014. Based on these findings, I set the standard deviation of idiosyncratic productivity shocks, $\varepsilon_{it}^{I} = 0.231$ for both periods.

The monetary policy shock $\varepsilon_t^R = r_t - \rho r_{t-1} - (1-\rho)[\phi_\pi \pi_t + \phi_y (y_t - y_t^p)]$ is specified by equation (2.2.7). I use quarterly data on federal funds rate, the difference of the log of the GDP deflator, and the difference between the log of real GDP and the log of real potential GDP as measures of nominal interest rate, inflation, and the output gap, respectively. The standard deviation of the monetary policy shock, ε_t^R, is 0.0018 for the pre-Great Moderation period, and 0.0015 for the Great Moderation period.

For the stochastic process of aggregate technology, I use total factor productivity (TFP) data from Fernald (2014), following Nakamura and Steinsson (2008). I first regress the log of TFP on a constant and a time trend and then regress again the residual on its own lag. The persistence of aggregate technology, ρ_A, ia 0.97 for the pre-Great Moderation period, and 0.96 for the Great Moderation period. The standard deviation of the aggregate technology shock, ε_t^A, is 0.0094 for the pre-Great Moderation period and 0.0055 for the Great-Moderation period.

The datasets are divided into two groups for parameter calibration: the pre-Great Moderation period (1960Q1–1983Q4) and the Great Moderation period (1984Q1–2007Q2). Data on the federal funds rate, GDP deflator, real GDP, and real potential GDP are obtained from the Congressional Budget Office. I set $\beta = 0.99$, assuming that one period in the model corresponds to one quarter. In line with standard practice in business cycle models, the inverse of the intertemporal elasticity of substitution, γ , is set to 1, and the elasticity of output with respect to composite labor input, α, is set to 2/3. Following Clarida et al. (1999), I set $\rho = 0.85$, and following Taylor (1993), I set $\phi_\pi = 1.5$ and $\phi_y = 0.125$.

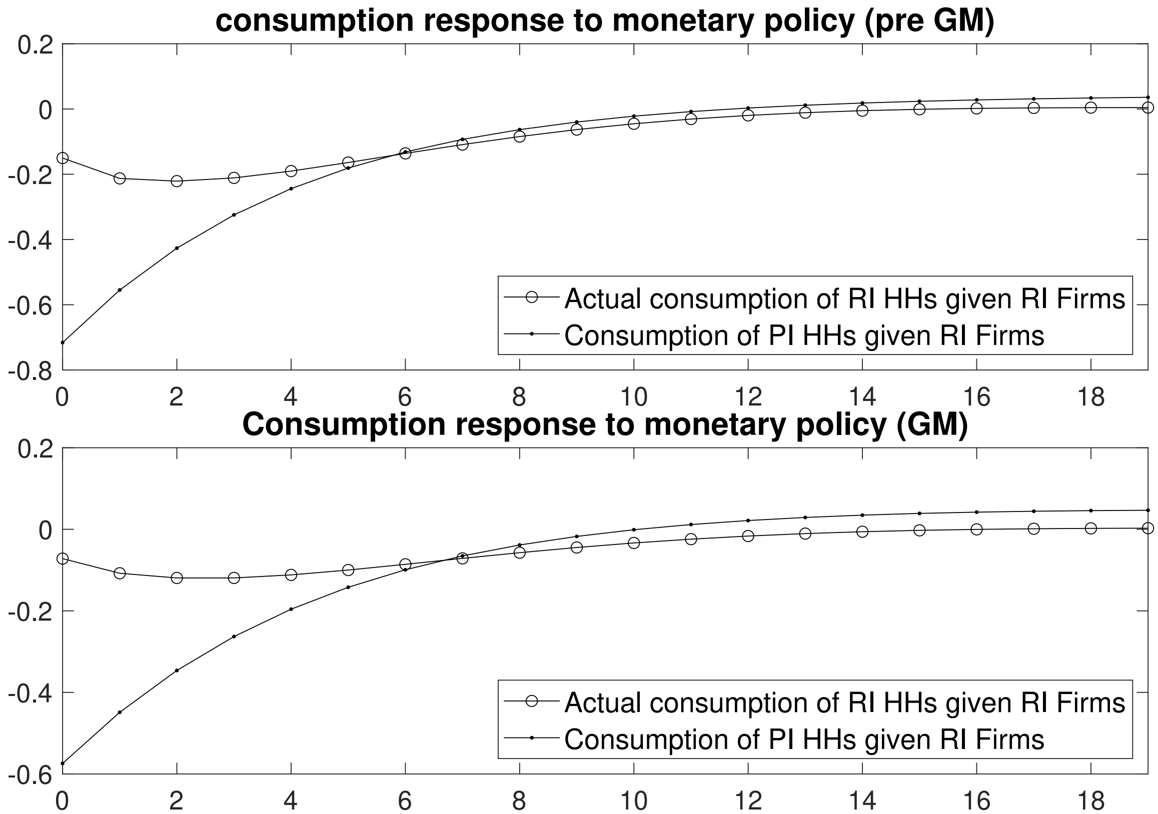
The preference parameter θ and the technology parameter η are determined to match a price elasticity of demand, $\tilde{\theta} = 4$, and a wage elasticity of labor demand, $\tilde{\eta} = 4$. Using the approach of Maćkowiak and Wiederholt (2015), I first set $\tilde{\theta} = \tilde{\eta} = 4$ and then compute the values of θ and η that satisfy these conditions. A price elasticity of demand of 4 lies within the range of estimates from Nakamura and Steinsson (2008; 2010). In the model, $I = J = 100$, representing 100 households and 100 firms. The ratio of wage income to consumption expenditure in the non-stochastic steady state, ω_W, is equivalent to 1.06, while $\omega_B, \omega_T, \omega_D$ do not influence the variables of interest. Parameters ω_B, ω_T and ω_D do not affect the solution to the household's attention problem. Holding the non-rational inattention parameters constant, the values of attention parameter λ and μ are set as $\lambda = 0.0006 * C_j^{1-\gamma}$ and $\mu = 0.0006 * \Lambda(C_1, \cdots, C_J)\hat{P}_i C_i$. These values are consistent with the settings in Maćkowiak and Wiederholt (2015).

2.5 Comparison of Impulse Responses Between in the Pre-Great Moderation and in the Great Moderation

2.5.1 Understanding Households' Behavior

Figure 2.1 documents the consumption response to a monetary policy shock. In the pre-Great Moderation period, households reduce consumption by 0.15%, while the utility-maximizing consumption under perfect information (henceforth, optimal consumption under PI) would decrease by 0.72%. This results in a deviation of 0.57% from the optimal consumption path when a contractionary monetary policy shock occurs in period zero. Households overconsume until the sixth quarter, incurring a utility loss. After the sixth quarter, households gradually adjust their consumption to restore the budget constraint while minimizing utility loss. This consumption pattern results in a utility loss equivalent to $0.0002 \times \gamma$ of steady-state consumption. Given the minimal magnitude of this utility loss, households tolerate the deviation from the optimal consumption path. This model aligns well with empirical findings. Empirically, output exhibits a hump-shaped response following a monetary policy shock, a feature that the model replicates. Rationally inattentive households with costly attention adjust their consumption gradually, supporting the empirical observation. When firms also have costly attention, prices evolve slowly after the shock; because of this, consumption is also affected by the monetary policy shock.

In the Great Moderation period, households initially respond to a contractionary monetary policy shock by overconsuming for the first seven quarters. The deviation from optimal consumption due to the shock is 0.5%. Households adjust their consumption to an optimal level by approximately the seventh quarter, one quarter later than in the pre-Great Moderation period. The utility loss per period from this deviation is $0.00003 \times \gamma$ of steady-state consumption. Across both periods, the

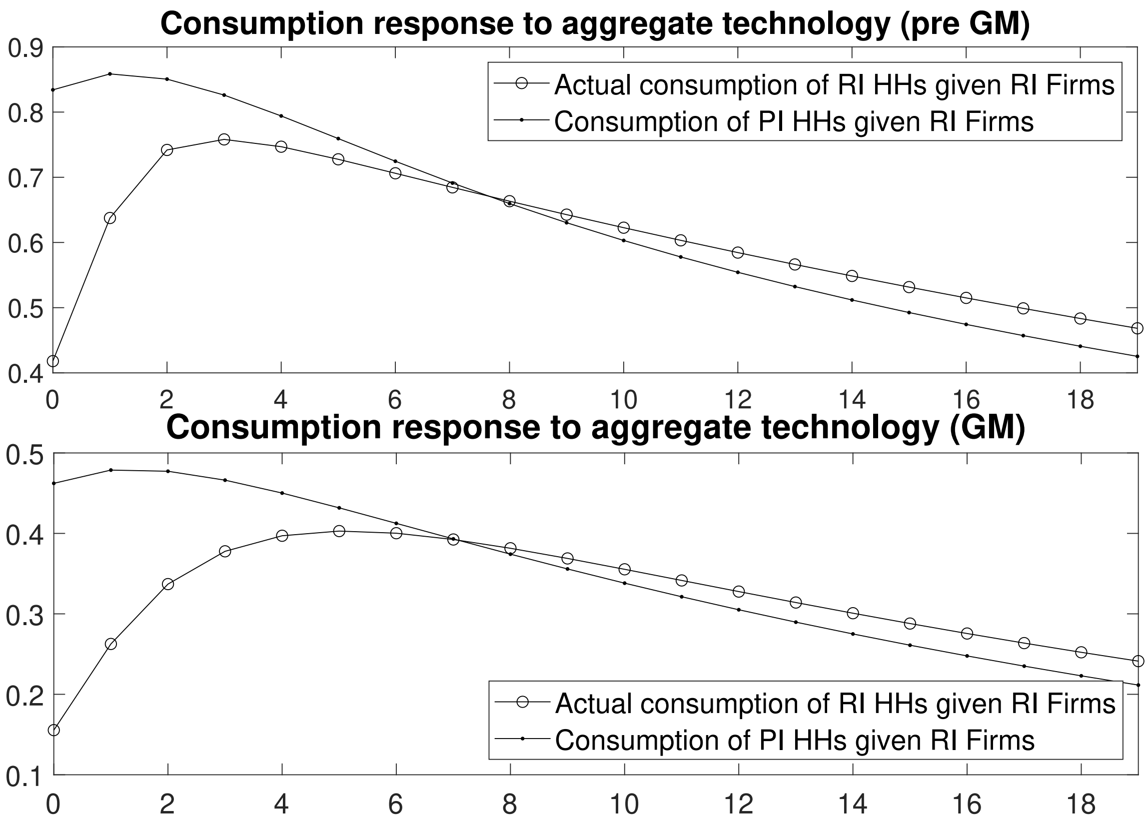


Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.1: Impulse responses of consumption to a monetary policy shock

utility loss from consumption deviation is negligible. This suggests that households consistently respond to contractionary monetary policy shocks by overconsuming in the early stages, irrespective of the volatility of the shock.

Figure 2.2 presents the case of a positive aggregate technology shock in the economy. Rationally inattentive households consume less than the optimal consumption under PI in both periods. In the pre-Great Moderation period, households consume more by 0.42% on impact, deviating from the optimal level of 0.83%. This results in a consumption deviation of 0.41% in period zero, which is gradually adjusted over time. By the seventh quarter, the deviated consumption converges to the optimal consumption under PI. The utility loss from this deviation is $0.0002 \times \gamma$ of steady-



Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.2: Impulse responses of consumption to an aggregate technology shock

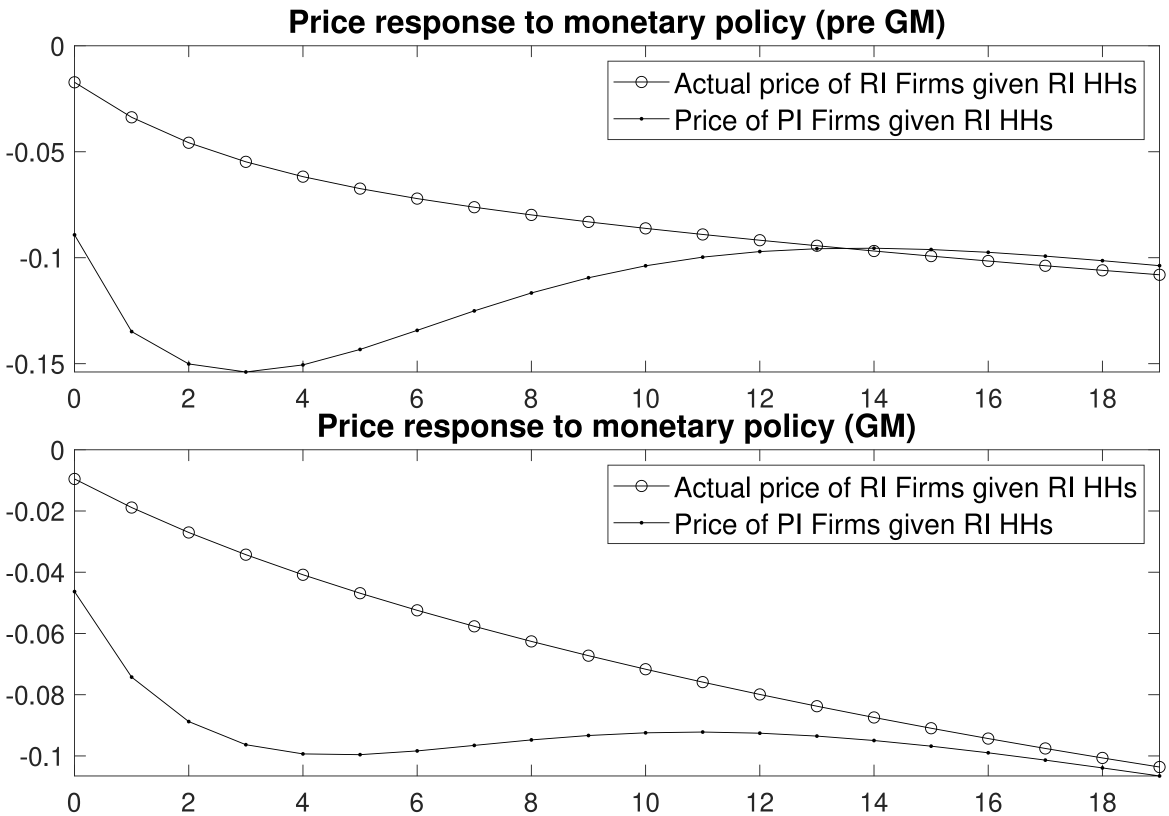
state consumption. In the Great Moderation period, households with limited attention increase consumption by 0.16%, compared to an optimal PI increase of 0.46%. The deviation of 0.3% in period zero similarly diminishes over time, with actual consumption converging to the PI optimal level by the seventh quarter. The utility loss in the Great Moderation period is $0.00009 \times \gamma$ of steady state consumption. In both periods, the expected utility loss is negligible, making it optimal for households to allocate only limited attention to aggregate technology shocks. Regardless of the period, households with limited attention consume less than the optimal PI consumption in response to a positive technology shock.

The utility loss that inattentive households tolerate per period remains trivial, regardless of the type or volatility of the shock. Consequently, households consistently choose to deviate from optimal PI consumption rather than closely track and respond to shocks, irrespective of the size or nature of aggregate volatility.

2.5.2 Understanding Firms' Behavior

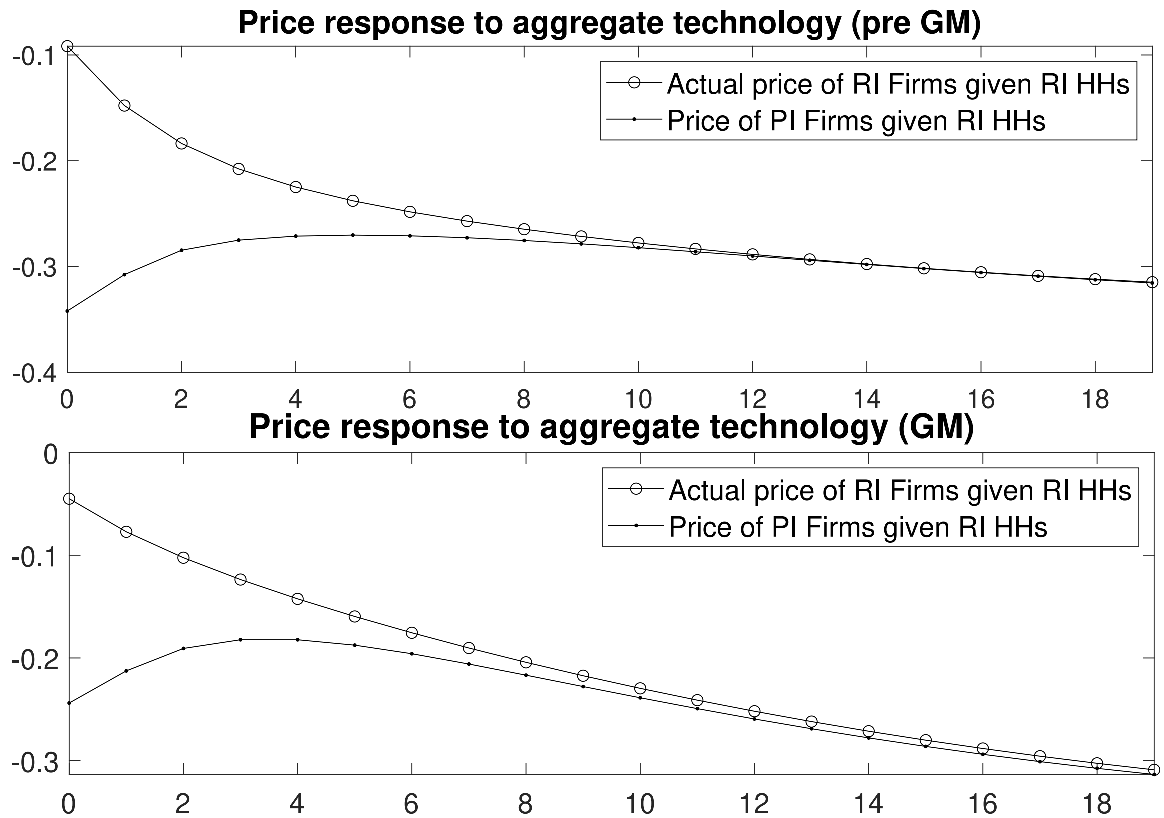
Now we turn to price-setting firms' responses to aggregate shocks. Figure 2.3 displays the impulse responses of price to a contractionary monetary policy shock. In the pre-Great Moderation period, the price adjusts around the fourteenth quarter after impact. A rationally inattentive decision-maker in a firm decides to lower the price of his product by 0.017%, responding to a contractionary monetary policy shock. The magnitude of the decrease is relatively smaller than the reduction in profit maximizing price - by 0.089% - under perfect information. As a result, the firm makes the expected loss per period (0.00006) of a firm's steady-state revenue due to imperfect tracking of aggregate technology.

In the Great Moderation period, the actual price set by a rationally inattentive firm converges



Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.3: Impulse responses of prices to a monetary policy shock

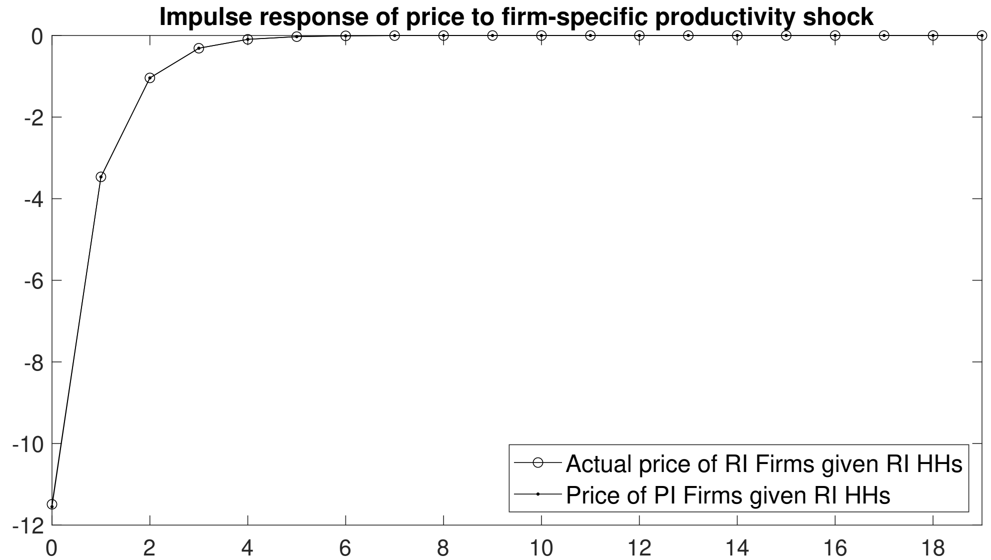


Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.4: Impulse responses of prices to an aggregate technology shock

to the profit-maximizing price under perfect information around the nineteenth quarter. This is because a decision-maker in a firm pays less attention in the Great Moderation period when the volatility of a technology shock significantly declines. The expected loss per period by deviating from the optimal course under PI is (0.00017) of a firm's steady-state revenue. The decision-maker reasonably pays little attention in both periods since the expected loss per period is insignificant enough. The endogenous attention allocation also implies that a monetary policy shock has a real effect while the profit loss is small. Firms respond slowly but surely to monetary policy.

Figure 2.4 shows that a decision-maker in a firm with limited attention consistently decides to cut the price down in response to a positive aggregate technology shock, with a relatively less



Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.5: Impulse responses of prices to an aggregate technology shock

than optimal price under PI in both periods. The expected loss per period is (0.00013) of a firm's steady-state revenue in both periods. Firms pay more attention to aggregate technology shocks than to monetary policy shocks. The actual price under rational inattention converges to the optimal price more quickly in the case of monetary policy shocks. Firms attend to more variable technology shocks closely. This supports the finding that the empirical impulse response of the price level responds much faster to aggregate technology shocks than to monetary policy shocks.

However, as you see, it still takes some time for the deviated price to monitor and keep up with the optimal price. It is because decision-makers still devote most of their attention to idiosyncratic technology. Figure 2.5 shows that the actual response of price to a firm-specific shock is almost identical to the optimal response of price under PI. That is, he tracks the optimal price under PI caused by an idiosyncratic shock very closely because the firm-specific shock is the most volatile and important[3]. This aligns well with findings of Mackowiak and Wiederholt (2009). They point

[3]The value of the amount of attention, κ, to the firm-specific shock is ten times greater than that to aggregate technology shock.

	Quantified Attention	pre-GM	GM	Δ%
Firm	Aggregate technology shock	0.2366	0.1842	-22.1
	Monetary policy shock	0.0946	0.0841	-11.1
Household	Aggregate technology shock	0.4713	0.2669	-43.4
	Monetary policy shock	0.1655	0.0903	-45.4

Table 2.2: Amount of allocated attention to each aggregate shock

out that firms decide to pay more attention to idiosyncratic variables when idiosyncratic conditions are more volatile and important than aggregate conditions.

2.5.3 Allocations of Attention

Table 2.2 shows the amount of attention across the two periods. The amount of allocated attention is decided following an information flow constraint. For instance, a firm's decision-maker's attention is quantified as the reduction in uncertainty about the optimal price. Specifically, it is measured by the difference between the prior uncertainty regarding the optimal price and the posterior uncertainty after observing the actual price response to shocks. This reduction in uncertainty is interpreted as the per-period amount of information acquired by the decision-maker. In the model's information flow constraint, the information about economic conditions is limited to not exceed the allocated attention κ. Therefore, the amount of information is processed is equated to the amount of attention allocated[4].

Both firms and households cut their attention during the Great Moderation period due to the decline in shock volatility. Households, in particular, cut their attention to both types of shocks by over 40%. In contrast, the reduction in firms' attention is relatively smaller. This difference arises because firm decision-makers primarily focus on idiosyncratic shocks, which are less affected

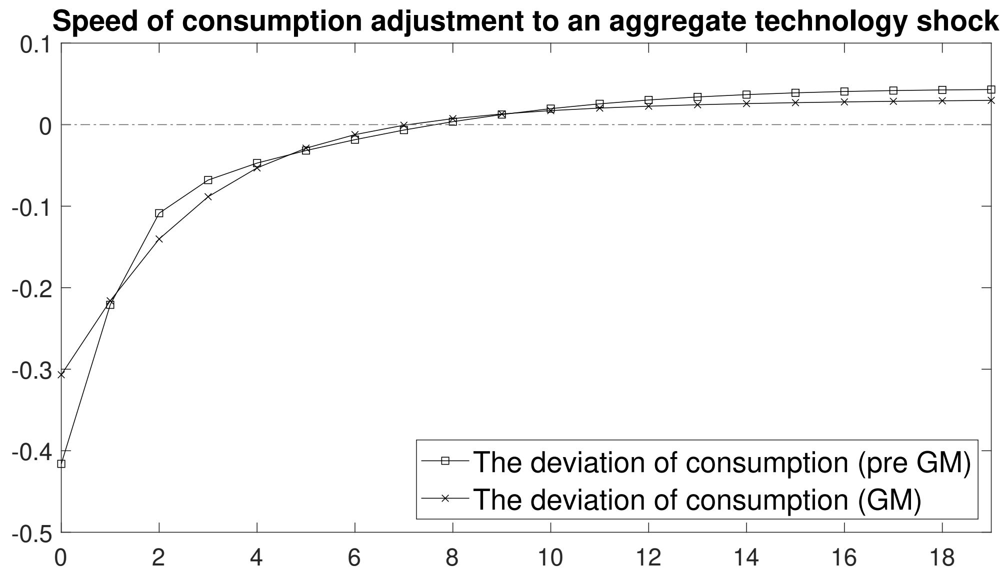
[4]Find more details in the online Appendix C of Maćkowiak and Wiederholt (2015)

by changes in aggregate volatility. Even in the pre-Great Moderation period, firms allocate less attention to aggregate shocks. As a result, the magnitude of the attention reduction for firms is not as pronounced as it is for households.

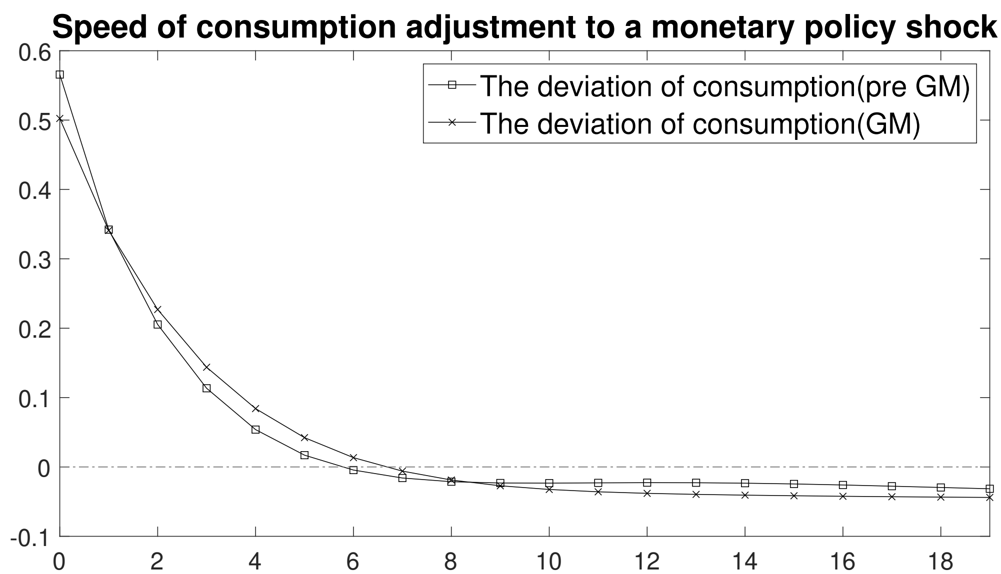
Figure 2.6 illustrates that households adjust their consumption more rapidly during the pre-Great Moderation period. The deviation in consumption is defined as the difference between actual consumption under rational inattention and optimal consumption under perfect information. This result can be attributed to differences in the amount of attention allocated. Households pay more attention to the volatility of each shock in the pre-Great Moderation period than in the Great-Moderation period. For aggregate technology shocks, the actual consumption response converges to the optimal level under perfect information at the same time in both periods, with the adjustment finalized by the seventh quarter after impact. However, the size of the initial deviation is larger in the pre-Great Moderation period, resulting in a faster adjustment speed during this period.

In the case of monetary policy shocks, consumption adjusts one quarter faster in the pre-Great Moderation period compared to the Great Moderation period. Additionally, the size of the initial deviation is larger in the pre-Great Moderation period. These findings confirm that households allocate more attention to shocks when volatility is higher, which in turn leads to faster behavioral adjustments.

Figure 2.7 displays the differing speeds of price adjustment across the two periods. The price deviation is defined as the difference between the actual price set by firms and the optimal price under perfect information. Firms correct the deviated price more quickly in response to each aggregate shock during the pre-Great Moderation period. This pattern is analogous to the adjustment of households' actual consumption



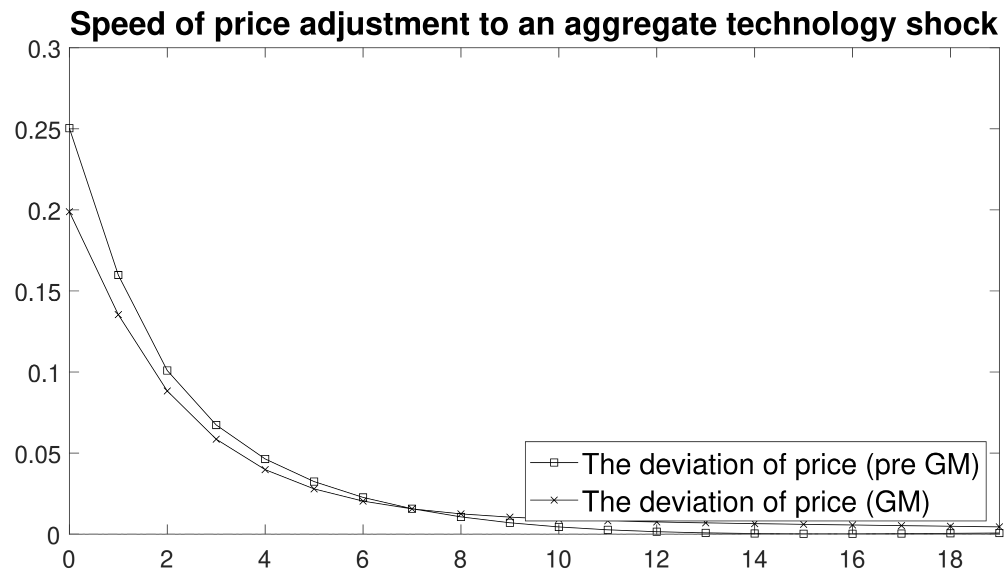
(a) The Adjustment of Consumption to an Aggregate Technology Shock



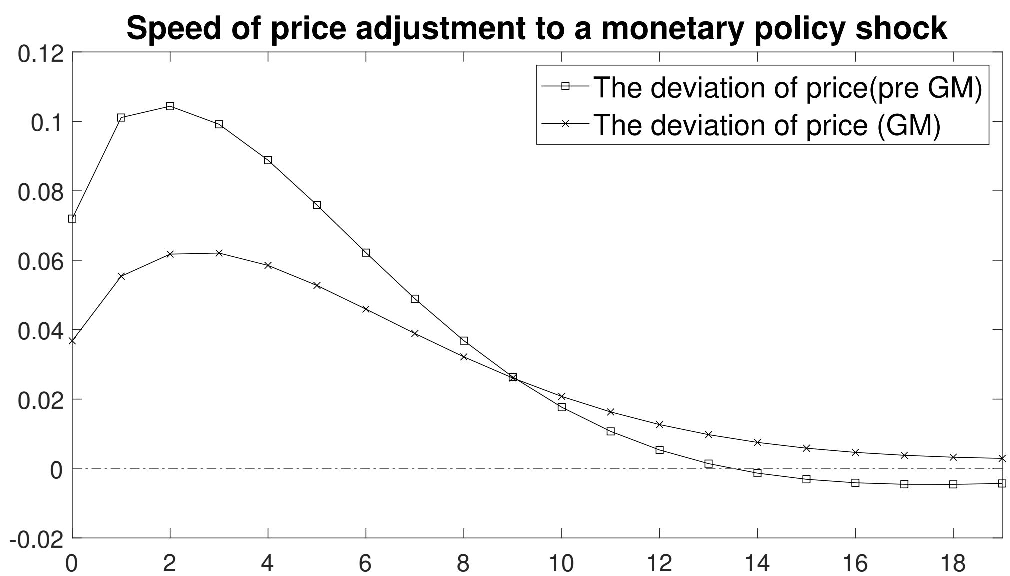
(b) The Adjustment of Consumption to a Monetary Policy Shock

Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.6: The Speed of Consumption Adjustment



(a) The Adjustment of Price to an Aggregate Technology Shock



(b) The Adjustment of Price to a Monetary Policy Shock

Note: An impulse response equal to 1 means a 1% deviation from the non-stochastic steady state.

Figure 2.7: The Speed of Price Adjustment

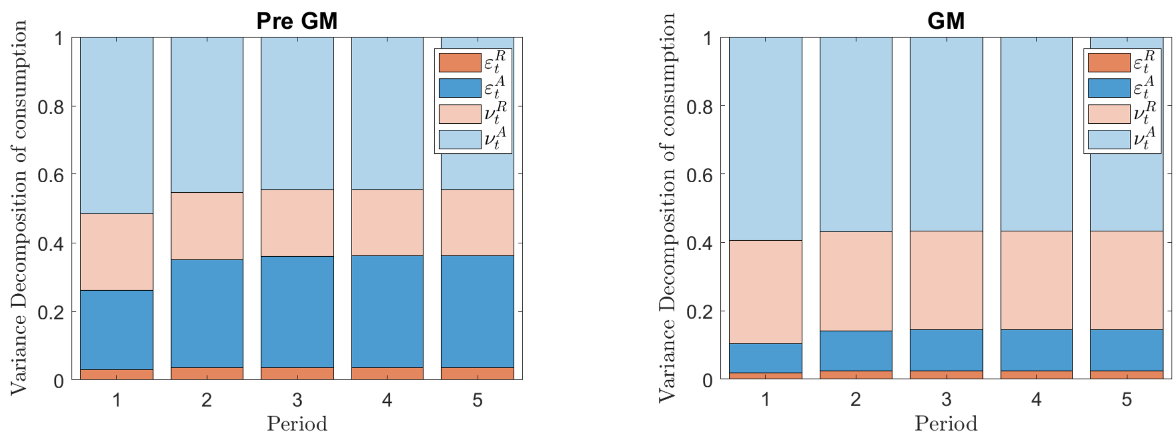


Figure 2.8: Forecast Error Variance Decomposition of Consumption

2.6 Forecast Error Variance Decomposition

Figure 2.8 shows the contribution of each shock to the forecast error variance of consumption. It is evident that the contribution of each structural shock decreases during the Great Moderation period. This is a natural consequence of the reduced volatility of aggregate shocks during this time. Instead, noise in observing structural shocks plays a larger role in explaining the variation in consumption during the Great Moderation. This aligns with the observation that households allocate less attention to shocks as they become less volatile. As a result, noise in observing fundamental shocks accounts for a larger share of consumption variation because households are less attentive to these shocks compared to the pre-Great Moderation period. Among the structural shocks, aggregate technology shocks contribute more to consumption variation than other shocks.

Figure 2.9 highlights that idiosyncratic shocks dominate other aggregate shocks in explaining the variation in prices. Interestingly, monetary policy shocks do not consistently contribute to price variation, while firm-specific technology shocks explain a significant portion. This finding supports the conclusion of Paciello (2012) that the higher volatility of aggregate technology shocks compared to monetary policy shocks leads firms to allocate more attention to aggregate technology

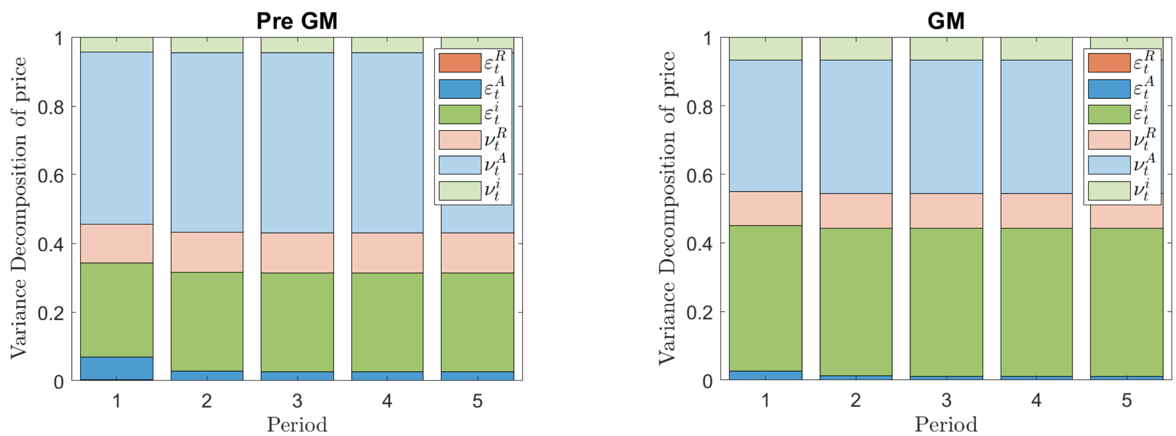


Figure 2.9: Forecast Error Variance Decomposition of Price

shocks. However, with the reduced volatility of aggregate technology shocks during the Great Moderation, their contribution to price variation diminishes significantly. Instead, the relative contribution of firm-specific shocks to price variation increases considerably.

2.7 Conclusion

Maćkowiak and Wiederholt (2015) demonstrate that rational inattention is another source of slow adjustment in macroeconomic variables. Their analysis focuses primarily on the Great Moderation period, spanning from the early 1980s to 2008. In this study, I assess whether their model is applicable to the pre-Great Moderation period, characterized by substantially higher volatility in macroeconomic variables. The model successfully matches empirical impulse responses to monetary policy shocks and aggregate technology shocks in both periods. Regardless of the level of volatility, the DSGE model with rational inattention consistently supports the observation of slow adjustment in real and nominal macroeconomic variables.

Furthermore, my findings reaffirm conclusions from existing literature: both firms and households allocate less attention to monetary policy shocks compared to aggregate technology shocks, irrespective of the period. This disparity arises because monetary policy shocks consistently exhibit lower variability than aggregate technology shocks. Notably, firm decision-makers allocate the majority of their attention to idiosyncratic technology shocks, which have the highest standard deviations.

The speed of behavioral adjustment is also slightly faster in the pre-Great Moderation period, as firms and households allocate more attention during this time. For households, increased attention to macroeconomic shocks means they monitor optimal consumption under perfect information more closely, leading to a faster reduction in deviations from optimal consumption. Similarly, firms take macroeconomic shocks more seriously in the pre-Great Moderation period. As a result, the actual prices set by firms converge more quickly to the optimal prices during this time.

Chapter 3

Forecasting the Future Through a Partisan Lens: Electoral Outcomes and Household Expectations

3.1 Introduction

Political polarization in the United States has increased dramatically over the past few decades, shaping not only partisan divisions but also broader societal and economic beliefs. As political identities become more entrenched, individuals increasingly interpret economic conditions and future prospects through a partisan lens. Recent economic research has documented the profound influence of political beliefs on economic expectations, showing that households revise their outlook on key economic indicators in response to shifts in political power. These revisions are not solely driven by actual policy changes but are deeply rooted in partisan perceptions of the economy. However, a critical yet underexplored question remains: how do economic expectations shift in the immediate aftermath of a presidential election, before any new policies are enacted? This paper explores how households adjust their economic expectations in response to election outcomes.

This study draws on two main strands of the literature. First, the relationship between political partisanship and individuals' economic outlook has been widely studied in both political science and economics. In political science, scholars have examined how voters' perceptions and expectations influence their voting behavior (Evans and Andersen, 2006; Wlezien et al., 1997; Stanig, 2013; Ladner and Wlezien, 2007). In economics, a growing body of work has documented that electoral outcomes causally shape macroeconomic expectations (Gillitzer and Prasad, 2018; Coibion et al., 2020;Kamdar and Ray, 2023; Mian et al., 2023; Binder et al., 2024). For instance, Coibion et al. (2020) show that individuals form significantly different economic expectations when asked to forecast conditionally on a given candidate winning the presidency, underscoring the partisan nature of these anticipations. Kamdar and Ray (2023) find substantial breakdowns in sentiment persistence after such political transitions. Huseynov and Murad (2024) explore how partisan alignment moderates the influence of news sources on inflation belief-updating, highlighting heterogeneity in information processing across political affiliations. While much of the existing literature focuses on changes in the level of expectations, we extend the analysis to the second moment—that is, subjective uncertainty, which captures how confident individuals are in their beliefs.

A second strand of literature emphasizes that political events, especially elections, have a pronounced and time-sensitive impact on household perceptions. For example, Mian et al. (2023) analyze Gallup and Michigan Survey data to show how aggregate expectation gaps evolve across political affiliations around the 2008 and 2016 elections. Kuang et al. (2024) demonstrate that under the hypothetical scenario of a Trump victory, Republican-leaning participants are more likely to perceive the Federal Reserve as an in-group institution, while the reverse holds for Democrat-leaning individuals. Building on this, Kuang et al. (2025) and Binder et al. (2025) conduct surveys surrounding the 2025 Trump inauguration, revealing pronounced partisan differences in trust in the Fed and in inflation expectations. This paper also shows that news of Trump's victory shifts the first moment of households' forecasts, with a particularly heterogeneous effect depending on political affiliation. DiGiuseppe et al. (2025) also report a strong effect of the election outcome on the updating of inflation expectations. They conducted a survey a few months before the Election 2024 and a follow-up survey one month after the election. Our study contributes to this literature by leveraging a quasi-experimental setting. We conducted a follow-up survey on November 6, 2024—the day after Trump's electoral victory—to directly examine how this electoral outcome, as an information shock, affects inflation and unemployment expectations and subjective uncertainty across partisan lines.

We offer three main contributions. First, consistent with prior findings, we document that Republican-affiliated households revise their unemployment expectations more optimistically following the election, while their aggregate inflation expectations remain largely unchanged. However, their inflation expectations become less dispersed, indicating convergence toward a central point. In contrast, Democrat-affiliated households revise both their inflation and unemployment expectations upward. Independents, without strong political preferences, do not significantly revise their expectations in response to the electoral outcome. Even in the absence of actual policy implementation, households update their forecasts based solely on the election result, revealing the salience of partisan identity in shaping economic expectations.

Second, we find that subjective uncertainty responds asymmetrically: Republican-affiliated households become more confident (i.e., their subjective uncertainty becomes smaller), while Democrat-affiliated households show no significant change. This suggests that individuals become more certain when electoral outcomes align with their prior beliefs.

Third, within-party disagreement narrows among Republicans but widens among Democrats following the election. Despite receiving the same public information, the direction of within-group belief dispersion diverges across party lines. Baker et al. (2020) find that economic policy uncertainty (EPU) increases by 28% during close and polarized U.S. presidential elections, compared to elections that are neither. According to their study, elections that are not close—or occur in low-polarization contexts—generate modest uncertainty. Although the 2024 presidential election ultimately resulted in a clear victory for Trump, it had been widely perceived as one of the closest races in American political history prior to Election Day. The heightened post-election disagreement among Democrats may reflect lingering uncertainty or disappointment stemming from the unexpectedly unfavorable outcome.

3.2 Survey Design

The primary objective of the survey is to study how households update their economic beliefs immediately after the election and to examine the role of political preferences and expectations about the election outcome in this process. To achieve these goal, we conducted two waves surveys.

The first wave took place on November 1–2, 2024, three days before the U.S. Presidential Election. This survey was part of the Randomized Control Trial (RCT) experiment described in Drobot (2025). In this wave, respondents were asked to provide their 12-month-ahead inflation and unemployment expectations in the form of density forecasts and point forecasts.

In designing the inflation expectations elicitation method, we followed the approach used in the well-known New York Fed Survey of Consumer Expectations (SCE). Armantier et al. (2017) provides an overview of the SCE and the rationale behind its question formatting. In addition, our survey included a series of open-ended questions, political affiliation questions, demographic questions, and other relevant inquiries. Respondents were also asked about their expectations regarding the election outcome.

The second wave was conducted on the morning of November 6, 2024, immediately after the election results were announced.[1] Respondents were first asked the same density forecast questions about inflation and unemployment as in the first wave. They were then shown a news post from The New York Times reporting Donald Trump's election victory. After this, they provided point

[1]To our knowledge, there were no significant policy announcements or newly released macroeconomic data that could have noticeably affected expectations. This suggests that the election outcome was likely the most salient signal respondents received during that short period.

forecasts for inflation and unemployment.

It is important to note that the information treatment in the second wave had no measurable effect, as most respondents were already aware of the election outcome (confirmed by a control question). This finding highlights how quickly major news spreads among the public.

3.3 Data

To collect a U.S. representative sample, we used the services of the Prolific platform. In the first wave of the survey, we collected 986 responses. From this sample, we randomly selected 417 individuals to participate in the follow-up survey (second wave). Table A-1 presents a summary of the demographic characteristics.

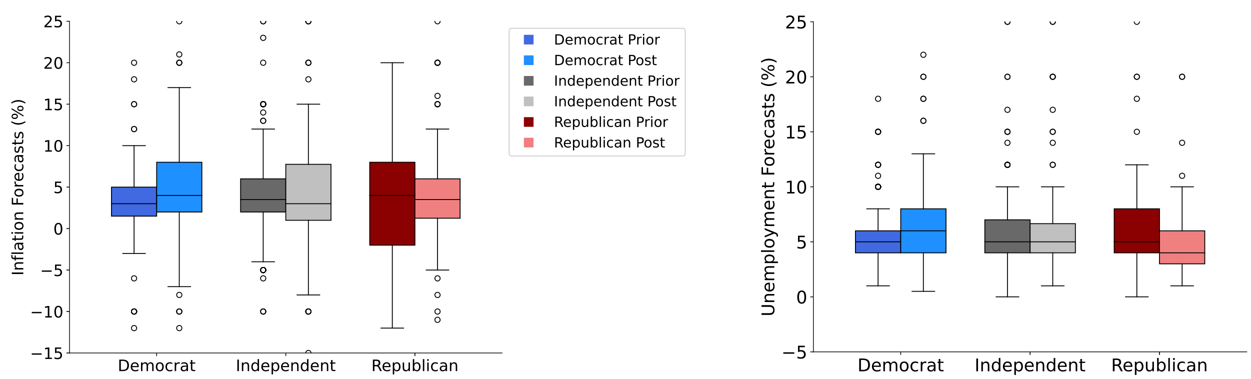
The partisan distribution in our sample closely resembles that of the U.S. population, though Republicans are slightly underrepresented. In terms of income, education, and race, Democrats and Republicans exhibit similar distributions. However, the Republican sample tends to be relatively older and has a lower share of female respondents. This difference, however, is not substantial enough to affect our analysis.

3.4 Analysis

3.4.1 Point Forecasts

In this section we focus on the analysis of point forecasts. Before the election, Democrats expected significantly lower inflation (mean: 1.86%) compared to Independents and Republicans (4.21% and 3.91%, respectively; see Table 3.1). However, after the election, when their candidate lost, Democrats were the only group to show a statistically significant upward revision in their inflation expectations. Given that this shift occurred the morning after the election, such a dramatic change was likely driven by a negative news shock stemming from the unexpected election outcome — 77% of Democrats in our sample had anticipated Kamala Harris to win (Figure A-1). A similar pattern emerged in unemployment expectations. Democrats substantially revised their forecasts upward, suggesting heightened concerns about economic conditions following the election outcome. Meanwhile, Republicans became noticeably more optimistic about unemployment, revising their expectations from 8.43% to 6.40%. Independents, as a group, did not revise their inflation and unemployment expectations after the election, highlighting the significant role of political polarization in the expectation formation mechanism in the U.S.

Figure 3.1: Changes in Point Forecasts Before and After Election



(a) Inflation (b) Unemployment

Beyond mean expectations, we examine cross-sectional disagreement using the interquartile range (IQR), as it is a robust measure that is less sensitive to outliers — a key advantage when analyzing household expectations data, which often contains extreme forecasts. Moreover, since the SCE also uses the interquartile range to measure disagreement, our analysis remains comparable to this major survey on household expectations (Armantier et al., 2017). Figure 3.1 and Table 3.1 reveal striking patterns. Although Republicans' mean expectations remained virtually stable, disagreement among Republican respondents declined sharply. In contrast, disagreement among Democrats slightly increased, indicating greater uncertainty or polarization in their post-election views.[2] This result warrants further analysis to better understand the underlying mechanisms driving these shifts in forecast dispersion.

Table 3.1: Summary Statistics of Inflation and Unemployment Expectations

(a) Two-sample t-test (Student's t-test) for equality of means

	Point Inflation Forecast				Point Unemployment Forecast			
	Mean Prior	Mean Post	Test Statistic	p-value	Mean Prior	Mean Post	Test Statistic	p-value
Democrat	1.86	4.40	-1.884	0.061	6.63	9.34	-1.864	0.064
Independent	4.21	4.81	-0.491	0.624	6.16	6.04	0.237	0.813
Republican	3.91	3.85	0.040	0.968	8.43	6.40	1.716	0.088

(b) Levene's test for equality of variances

	Point Inflation Forecast				Point Unemployment Forecast			
	Variance Prior	Variance Post	Test Statistic	p-value	Variance Prior	Variance Post	Test Statistic	p-value
Democrat	98.4	142.7	1.370	0.243	59.6	203.8	2.460	0.118
Independent	67.2	192.1	6.758	0.010	27.0	16.6	1.344	0.247
Republican	144.6	172.0	0.058	0.810	85.2	70.1	1.253	0.264

(c) Wald test on the ratio between interquartile ranges with pair bootstrap variance

	Point Inflation Forecast				Point Unemployment Forecast			
	IQR Prior	IQR Post	Test Statistic	p-value	IQR Prior	IQR Post	Test Statistic	p-value
Democrat	3.50	6.00	1.331	0.183	2.00	4.00	1.158	0.247
Independent	4.00	6.75	1.251	0.211	2.53	2.65	0.140	0.889
Republican	10.00	4.75	-2.896	0.004	4.50	3.00	-2.184	0.029

Note: This table presents summary statistics for point forecasts recorded before (Prior) and after (Post) the election for Democrats, Republicans, and Independents. It also reports test statistics and p-values for comparing the means, variances, and interquartile ranges (IQR) between the two samples: Prior and Post. Independents include "Independent, leaning towards Democrat" and "Independent, leaning towards Republican".

As an additional exercise, we analyze microdata from the Michigan Survey of Consumers (MSC). While the MSC tracks individuals over time, there are several key differences between our datasets. First, we survey the same respondents both before and after the election within a short time frame, whereas the MSC follows a rotating panel design, with respondents eligible for re-interviews approximately six and twelve months after their initial survey. Consequently, the

[2] We use Wald test on the ratio between IQRs with pair bootstrap variance. For a review of this test and other IQR tests, see Greco et al. (2024).

MSC sample we analyze consists of unique respondents each month. Second, we measure prior expectations precisely a few days before the election and posterior expectations on the morning the election results are announced. In contrast, the MSC collects data throughout each month. For example, the October 2024 data was gathered between September 24 and October 21, while the November data spans both the pre- and post-election periods, from October 22 to November 18. To isolate respondents surveyed exclusively after the election, we must rely on the December data, which covers the period from November 19 to December 16. Finally, the wording of the inflation question differs: we ask respondents about the inflation rate, whereas the MSC asks about price changes in general. Although our findings are not directly comparable to those from the MSC, this exercise still provides valuable insights.

In terms of similarities, the MSC sample (Table A-2) reveals that, prior to the election, Democrats had relatively lower inflation expectations and less disagreement compared to Republicans. Consistent with our findings, Democrats revised their expectations upward after the election. However, the MSC data also shows a stark contrast: while Democrats increased their inflation expectations, Republicans significantly revised theirs downward, even anticipating deflation by December 2025.[3] This difference can be partly explained by methodological factors. In our survey, we ask the same respondents before and after the election, effectively anchoring their posterior expectations to their prior beliefs. In contrast, the MSC surveys different respondents at each point in time, meaning those surveyed after the election lack a direct reference point, which could contribute to the observed divergence in revisions. Additionally, another key difference is that the monthly MSC data indicates a rise in overall disagreement among Democrats, with no

[3]Republicans' deflationary expectations may, in fact, reflect a more "optimistic" outlook, as multiple studies have shown that people generally dislike inflation (Stantcheva, 2024; Shiller, 1997).

changes among Republicans.

Combining insights from both datasets, we observe that Republicans' initial reaction to the election results was a reduction in disagreement without a shift in aggregate inflation expectations, but with a sharp decline in unemployment expectations. However, over time, they gradually adjusted their inflation beliefs to a more "optimistic" outlook while disagreement returned to previous levels. In contrast, Democrats' reaction was both immediate and persistent, remaining elevated even a month after the election. These findings highlight the highly dynamic and heterogeneous nature of expectation formation under partisan influence, suggesting that political affiliation not only shapes individuals' economic outlooks but also affects how quickly and persistently they respond to new information.

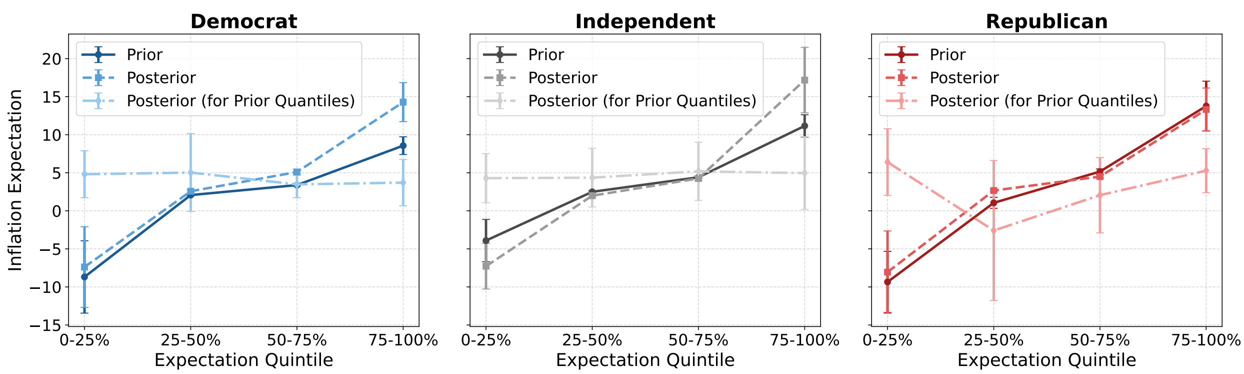
3.4.2 Forecast Revision

In the following section, we analyze how respondents across different quantiles updated their economic beliefs. We begin with inflation expectations. Figure 3.2 shows that the upward revision in inflation expectations of Democrats was primarily driven by the upper 25% of respondents. However, this shift was largely driven by individuals who had relatively low inflation expectations prior to the election (i.e., those in the first and second quartiles). In contrast, respondents who initially expected higher inflation tended to revise their expectations downward.

A similar pattern emerges among Independents and Republicans. Notably, Republicans in the first quartile of prior inflation expectations—who initially expected deflation—revised their expectations upward following the election. However, Republicans in the higher quartiles, who had anticipated higher inflation before the election, adjusted their expectations downward.

Why did Republicans who initially expected deflation revise their expectations upward, while those who expected inflation revised downward? One possible explanation is that both groups viewed their initial forecasts as extreme or unfavorable—either too low (deflation) or too high (inflation). Following the election, uncertainty diminished, leading them to adjust their expectations toward more moderate levels. Supporting this interpretation, we find evidence that Republicans who initially expected deflation and revised their inflation expectations upward also revised their unemployment expectations downward (see Figure A-2). This suggests they may have been influenced by a Phillips Curve-like belief, where they perceived rising inflation as a signal of improved economic conditions and lower unemployment. In fact, we see that around 30% of respondents in each political affiliation group exhibit Phillips Curve forecast thinking (Figure A-3).

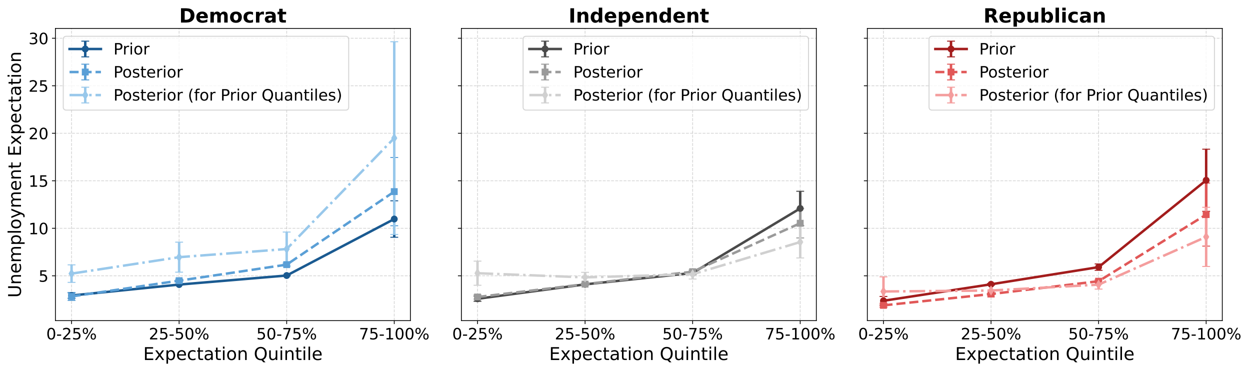
Figure 3.2: Inflation Expectations Before and After Election



Across demographic groups, older Democrats contribute the most to the upward revision in inflation expectations (see Figure A-4). Additionally, Republican men over 40 with a college degree also revise their forecasts upward. In contrast, Republican men and women with only a high school diploma adjust their forecasts downward.

We observe greater consistency in how respondents update their unemployment expectations (Figure 3.3). Among Democrats, all quartiles revise their expectations upward, indicating a broad-

Figure 3.3: Unemployment Expectations Before and After Election



based increase in expected unemployment. In contrast, most quartiles of Republicans adjust their expectations downward, suggesting a more optimistic labor market outlook among this group.

3.4.3 Uncertainty and Disagreement

We use density forecast questions to elicit individual uncertainty and examine how it changes after the election. Specifically, we measure uncertainty about the future using the variance of the density forecast. Following Engelberg et al. (2009) and Armantier et al. (2017), we fit a generalized beta distribution to the inflation forecast responses and compute the variance based on the estimated parameters. To measure individual uncertainty about unemployment forecasts, we adopt a different approach and calculate the variance using the midpoints of the reported density intervals.

Our first key finding is that, prior to the election, Democrats and Independents exhibit relatively lower levels of uncertainty about the future, as reflected in their smaller inflation and unemployment forecast variances. In contrast, Republicans are more uncertain before the election. However, after the election, the uncertainty among Republicans declines significantly, converging to the levels observed for Democrats and Independents.

Table 3.2: Variance of Inflation and Unemployment Expectations

(a) Two-sample t-test (Student's t-test) for equality of means

	Point Inflation Forecast				**Point Unemployment Forecast**			
	Mean Prior	Mean Post	Test Statistic	p-value	Mean Prior	Mean Post	Test Statistic	p-value
Democrat	18.48	16.58	0.452	0.651	2.85	2.82	0.085	0.932
Independent	21.30	15.34	1.354	0.177	3.21	2.28	3.124	0.002
Republican	32.67	15.64	2.990	0.003	4.04	2.82	2.663	0.008

The reduction in uncertainty among Republicans likely contributes to the observed decline in disagreement. Given that all quartiles shift toward a central point in the previous analysis, this suggests that lower uncertainty led to less overreaction to new information. As respondents narrow their perceived range of possible future inflation outcomes, their expectations become more aligned, facilitating greater convergence. Given that IQR is an aggregate measure and uncertainty is an individual-level measure, there is no easy way to directly test the relationship between the two. To overcome this challenge, we use bootstrap resampling to generate 10,000 samples. For each sample, we calculate the change in IQR (disagreement) and the change in mean uncertainty and run the following regression model:

$$\Delta\text{IQR}^{\text{boot}}_{j,t} = \alpha_j + \beta_j \cdot \Delta\text{Mean Uncertainty}^{\text{boot}}_{j,t} + \varepsilon_{j,t}, \tag{3.4.1}$$

where $\Delta\text{IQR}^{\text{boot}}_{j,t}$ is the change in the interquartile range of point forecasts in bootstrap sample t for variable j (inflation or unemployment expectations), and $\Delta\text{Mean Uncertainty}^{\text{boot}}_{j,t}$ is the change in the average individual uncertainty in bootstrap sample t for variable j. Thus, β_j captures the relationship between the change in uncertainty and the change in disagreement for inflation and unemployment separately.

As shown in Table 3.3, our hypothesis is confirmed: there is a positive, statistically significant relationship between the change in uncertainty and disagreement.

This approach recognizes that disagreement does not exist at the individual level but instead arises from the collective distribution of expectations. Since disagreement is a property of the group, not an individual characteristic, bootstrapping allows us to approximate how changes in individual uncertainty contribute to aggregate disagreement.

Table 3.3: Bootstrap Regression: Inflation vs. Unemployment Expectations (Republicans)

	Inflation	Unemployment
Δ Mean Uncertainty	0.457***	0.277***
	(0.001)	(0.020)
Constant	0.589***	-0.088***
	(0.039)	(0.001)
Observations	10,000	10,000
R^2	0.978	0.019

Note: This table presents the results of bootstrap regressions estimating the relationship between changes in individual uncertainty and changes in disagreement (measured as the interquartile range of point forecasts). The regressions are based on 10,000 bootstrap samples, where each sample is drawn with replacement from the original dataset. In each sample, we compute the change in mean individual uncertainty and the change in disagreement, then estimate the regression (1). Standard errors are shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

3.5 Conclusion

This paper empirically examines how electoral outcomes influence belief updating. To track changes in expectations at the individual level, we re-survey the same participants both before and after the 2024 U.S. presidential election. Our findings reveal heterogeneous forecast revision patterns across political affiliations. Democrat-affiliated households respond more pessimistically to the election result, raising their expectations for both inflation and unemployment, while Republican-affiliated households respond slightly more optimistically, lowering their unemployment forecast.

We also find that within-party disagreement, measured as the dispersion in expectations, narrows among Republicans but widens among Democrats following the election. This suggests that political affiliation shapes not only the direction but also the consistency of individuals' responses to shared public information.

Finally, focusing on the second moment of expectations, we observe that Republican-affiliated households report increased confidence, as reflected in reduced subjective uncertainty. In contrast, Democrat-affiliated households exhibit no significant change in their perceived uncertainty, suggesting that the election outcome failed to reduce their perceived uncertainty regarding the economic outlook.

3.6 Appendices

Table A-1: Demographic Characteristics of Respondents

		Democrats (170)	Republicans (133)	Independents (114)	Total (417)
share (%)					
Age					
	under 40	46.6	43.9	35.9	41.5
	40-60	21.8	32.5	21.8	24.7
	over 60	31.6	23.7	42.4	33.8
					100
gender					
	Female	56.4	40.4	44.7	47.2
	Male	43.6	59.6	55.3	52.8
					100
Race					
	White	66.9	71.9	67.6	68.6
	Non-white	33.1	28.1	32.4	31.4
					100
Education					
	High school	8.3	15.8	16.5	13.8
	Some college	33.8	26.3	34.7	32.4
	College	57.9	57.0	47.6	53.9
					100
Income					
	Under 50k	47.4	43.9	50.0	48.4
	50k-100k	32.3	38.6	34.1	35.5
	Over 100k	18.0	15.8	14.1	16.1
					100

Figure A-1: Perceived Election Outcome by Political Affiliation

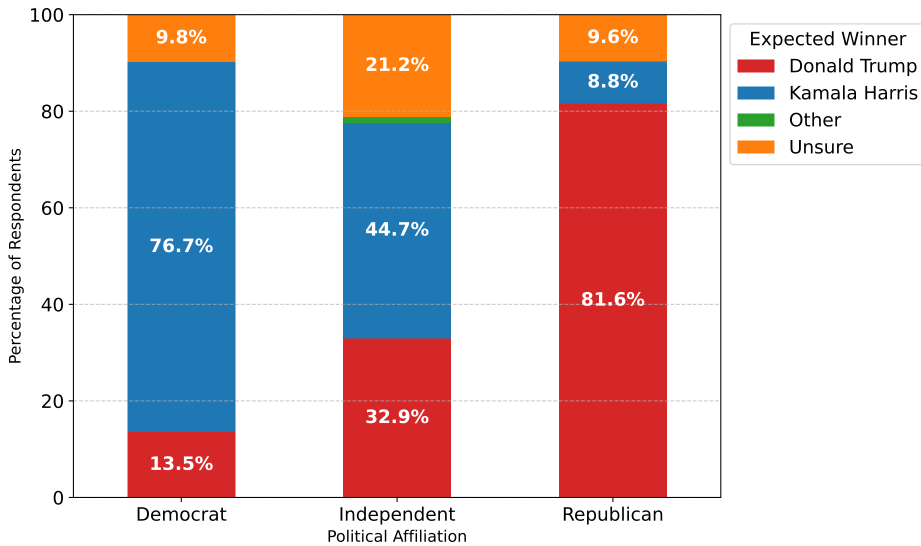


Table A-2: Summary Statistics of MSC Inflation Expectations

(a) Two-sample t-test (Student's t-test) for equality of means

	Sep.24-Oct.21 VS Oct.22-Nov.18				Sep.24-Oct.21 VS Nov.19-Dec.16			
	Mean Prior	Mean Post	Test Statistic	p-value	Mean Prior	Mean Post	Test Statistic	p-value
Democrat	2.29	4.90	-2.829	0.005	2.29	8.92	-6.676	0.000
Independent	4.32	4.18	0.240	0.810	4.32	4.12	0.327	0.744
Republican	6.85	-1.29	5.127	0.000	6.85	-3.62	7.582	0.000

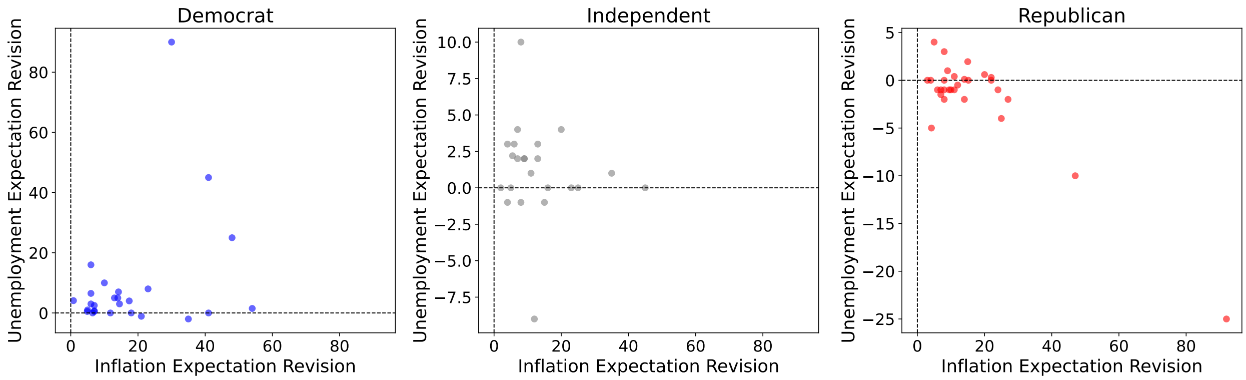
(b) Levene's test for equality of variances

	Sep.24-Oct.21 VS Oct.22-Nov.18				Sep.24-Oct.21 VS Nov.19-Dec.16			
	Variance Prior	Variance Post	Test Statistic	p-value	Variance Prior	Variance Post	Test Statistic	p-value
Democrat	57.9	99.7	5.408	0.021	57.9	127.0	11.849	0.001
Independent	80.0	104.0	1.010	0.315	80.0	120.0	6.203	0.013
Republican	173.6	144.2	0.083	0.773	173.6	82.8	3.244	0.073

(c) Wald test on the ratio between interquartile ranges with pair bootstrap variance

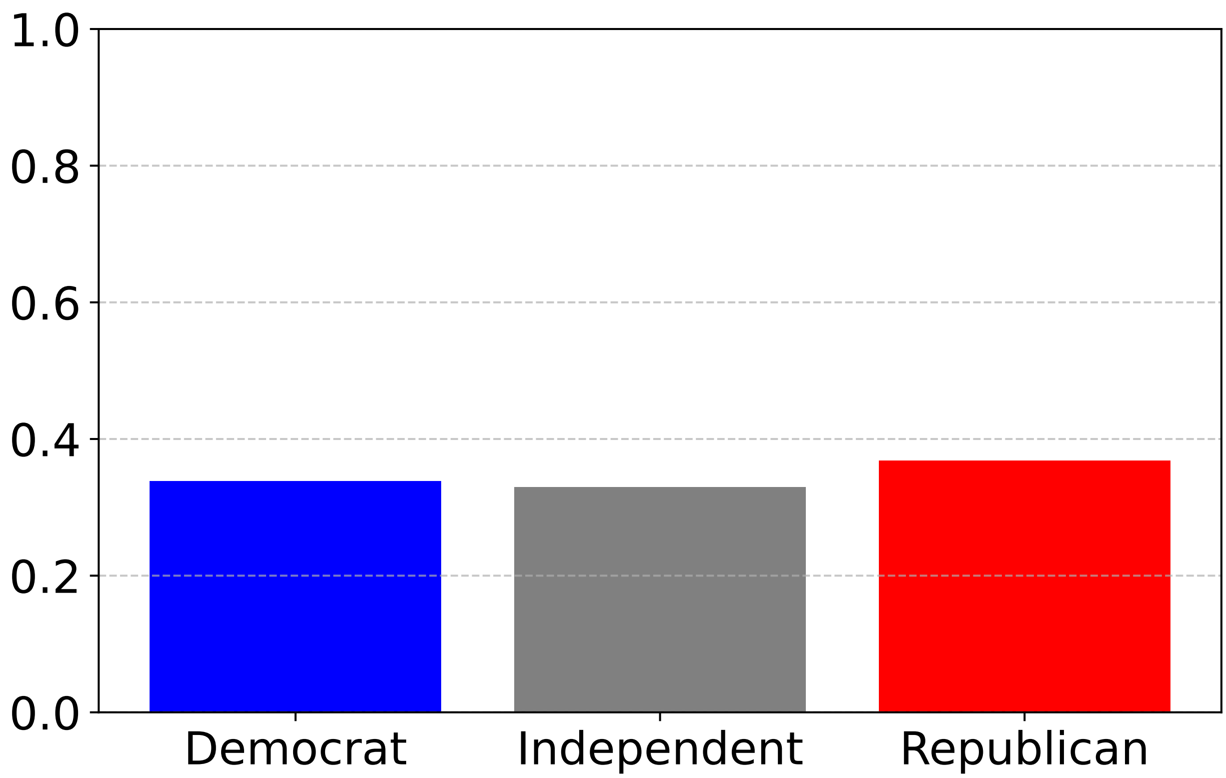
	Sep.24-Oct.21 VS Oct.22-Nov.18				Sep.24-Oct.21 VS Nov.19-Dec.16			
	IQR Prior	IQR Post	Test Statistic	p-value	IQR Prior	IQR Post	Test Statistic	p-value
Democrat	3.00	5.00	3.663	0.000	3.00	7.00	5.219	0.000
Independent	5.00	5.00	0.000	1.000	5.00	5.00	0.000	1.000
Republican	10.00	10.00	0.000	1.000	10.00	9.50	-0.143	0.886

Figure A-2: Deflationary Prior: Updating Inflation and Unemployment Expectations



Note: This figure presents the relationship between revisions in inflation expectations and unemployment expectations for respondents who initially expected deflation (i.e., those with negative prior inflation forecasts) and subsequently revised their inflation expectations upward following the election.

Figure A-3: Share of Respondents with Phillips Curve Forecast Thinking



Note: This figure presents the share of respondents who exhibit Phillips Curve forecast thinking, meaning they revised their inflation and unemployment expectations in opposite directions.

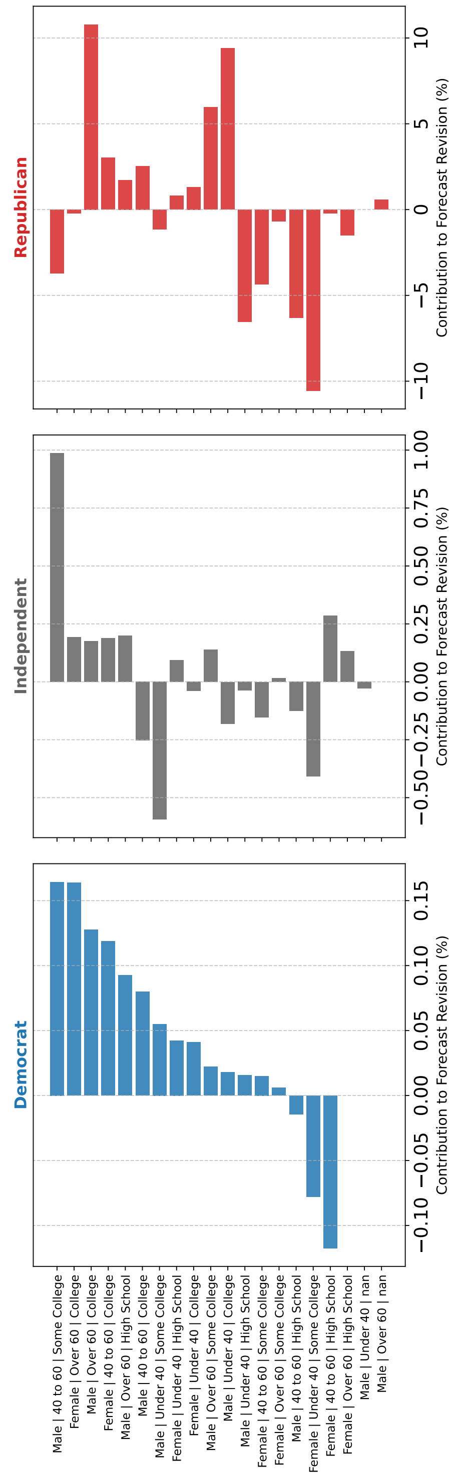


Figure A-4: Demographic Contributions to Inflation Forecast Revision

Bibliography

Abel, Joshua, Robert Rich, Joseph Song, and Joseph Tracy, "The Measurement and Behavior of Uncertainty: Evidence from the ECB Survey of Professional Forecasters," *Journal of Applied Econometrics*, 2016, *31* (3), 533–550.

Adam, Klaus and Stefan Nagel, "Chapter 16 - Expectations data in asset pricing," in "Handbook of Economic Expectations," Academic Press, 2023, pp. 477–506.

Altig, David, Lawrence J Christiano, Martin Eichenbaum, and Jesper Linde, "Firm-specific capital, nominal rigidities and the business cycle," *Review of Economic dynamics*, 2011, *14* (2), 225–247.

Andreou, Elena, Eric Ghysels, and Andros Kourtellos, "Regression models with mixed sampling frequencies," *Journal of Econometrics*, 2010, *158* (2), 246–261. Specification Analysis in Honor of Phoebus J. Dhrymes.

Armantier, Olivier, Giorgio Topa, Wilbert Van der Klaauw, and Basit Zafar, "An overview of the survey of consumer expectations," *Economic Policy Review*, 2017, (23-2), 51–72.

Baker, Scott R, Aniket Baksy, Nicholas Bloom, Steven J Davis, and Jonathan A Rodden, "Elections, political polarization, and economic uncertainty," Technical Report, National Bureau of Economic Research 2020.

Bernanke, Ben S, "Inflation Targeting," *Federal Reserve Bank of St. Louis Review*, 2004, *86* (4), 165–68.

Bianchi, Francesco, Cosmin Ilut, and Hikaru Saijo, "Diagnostic Business Cycles," *The Review of Economic Studies*, 2023, *91* (1), 129–162.

— **, Cosmin L Ilut, and Hikaru Saijo**, "Smooth Diagnostic Expectations," Report, National Bureau of Economic Research 2024.

Binder, Carola C., "Measuring uncertainty based on rounding: New method and application to inflation expectations," *Journal of Monetary Economics*, 2017, *90*, 1–12.

Binder, Carola, Cody Couture, and Abhiprerna Smit, "Partisan Trust in the Federal Reserve," Working Paper 33684, National Bureau of Economic Research April 2025.

Binder, Carola Conces, Rupal Kamdar, and Jane M Ryngaert, "Partisan expectations and covid-era inflation," *Journal of Monetary Economics*, 2024, p. 103649.

Binder, Carola, Wesley Janson, and Randal Verbrugge, "Out of Bounds: Do SPF Respondents Have Anchored Inflation Expectations?," *Journal of Money, Credit and Banking*, 2023, *55* (2-3), 559–576.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Diagnostic expectations and credit cycles," *The Journal of Finance*, 2018, *73* (1), 199–227.

— **,** — **, Rafael La Porta, and Andrei Shleifer**, "Diagnostic expectations and stock returns," *The Journal of Finance*, 2019, *74* (6), 2839–2874.

— **,** — **, Spencer Yongwook Kwon, and Andrei Shleifer**, "Diagnostic bubbles," *Journal of Financial Economics*, 2021, *141* (3), 1060–1077.

— , — , **Yueran Ma, and Andrei Shleifer**, "Overreaction in macroeconomic expectations," *American Economic Review*, 2020, *110* (9), 2748–82.

Brito, Steve, Yan Carriere-Swallow, and Bertrand Gruss, "Disagreement about Future Inflation: Understanding the Benefits of Inflation Targeting and Transparency," 2018.

Bundick, Brent and A. Lee Smith, "Did the Federal Reserve Break the Phillips Curve? Theory & Evidence of Anchoring Inflation Expectations," *The Review of Economics and Statistics*, 2023, pp. 1–45.

Buono, Ines and Sara Formai, "New evidence on the evolution of the anchoring of inflation expectations," *Journal of Macroeconomics*, 2018, *57*, 39–54.

Chan, Joshua C.C., Todd E. Clark, and Gary Koop, "A New Model of Inflation, Trend Inflation, and Long-Run Inflation Expectations," *Journal of Money, Credit and Banking*, 2018, *50* (1), 5–53.

Clarida, Richard, Jordi Gali, and Mark Gertler, "The science of monetary policy: a new Keynesian perspective," *Journal of economic literature*, 1999, *37* (4), 1661–1707.

Coibion, Olivier and Yuriy Gorodnichenko, "Information rigidity and the expectations formation process: A simple framework and new facts," *American Economic Review*, 2015, *105* (8), 2644–78.

— , **Dimitris Georgarakos, Yuriy Gorodnichenko, Geoff Kenny, and Michael Weber**, "The Effect of Macroeconomic Uncertainty on Household Spending," *American Economic Review*, March 2024, *114* (3), 645–77.

—, Yuriy Gorodnichenko, and Michael Weber, "Political polarization and expected economic outcomes," Technical Report, National Bureau of Economic Research 2020.

—, —, and —, "Monetary Policy Communications and Their Effects on Household Inflation Expectations," *Journal of Political Economy*, 2022, *130* (6), 1537–1584.

—, —, and Saten Kumar, "How do firms form their expectations? new survey evidence," *American Economic Review*, 2018, *108* (9), 2671–2713.

D'Acunto, Francesco, Daniel Hoang, Maritta Paloviita, and Michael Weber, "Effective policy communication: Targets versus instruments," *Chicago Booth Research Paper*, 2020, (20-38).

DiGiuseppe, Matthew, Ana Carolina Garriga, and Andreas Kern, "Partisan Bias in Inflation Expectations," 2025.

Dovern, Jonas, Ulrich Fritsche, and Jiri Slacalek, "Disagreement Among Forecasters in G7 Countries," *The Review of Economics and Statistics*, 11 2012, *94* (4), 1081–1096.

Drobot, Sergii, "News, Sentiment, and Inflation Expectations: Insights From Social Media Data and Experiments," 2025.

Ehrmann, Michael, "Targeting Inflation from Below: How Do Inflation Expectations Behave?," *41th issue (September 2015) of the International Journal of Central Banking*, 2018.

Engelberg, Joseph, Charles F Manski, and Jared Williams, "Comparing the point predictions and subjective probability distributions of professional forecasters," *Journal of Business & Economic Statistics*, 2009, *27* (1), 30–41.

Eusepi, Stefano and Bruce Preston, “Central Bank Communication and Expectations Stabilization,” *American Economic Journal. Macroeconomics*, 2010, *2* (3), 235–271.

Evans, Geoffrey and Robert Andersen, “The Political Conditioning of Economic Perceptions,” *The Journal of Politics*, 2006, *68* (1), 194–207.

Fernald, John G, “A Quarterly, Utilization-Adjusted Series on Total Factor Productivity, Working Paper 2012-19,” 2014.

Ganics, Gergely, “Optimal Density Forecast Combinations,” Working Paper 1751, Banco de Espana 2018. Available at SSRN: https://ssrn.com/abstract=3098761.

_ , Barbara Rossi, and Tatevik Sekhposyan, “From Fixed-Event to Fixed-Horizon Density Forecasts: Obtaining Measures of Multihorizon Uncertainty from Survey Density Forecasts,” *Journal of Money, Credit and Banking*, 2024, *n/a* (n/a).

Gillitzer, Christian and Nalini Prasad, “The Effect of Consumer Sentiment on Consumption: Cross-Sectional Evidence from Elections,” *American Economic Journal: Macroeconomics*, October 2018, *10* (4), 234–69.

Glas, Alexander and Matthias Hartmann, “Inflation uncertainty, disagreement and monetary policy: Evidence from the ECB Survey of Professional Forecasters,” *Journal of Empirical Finance*, 2016, *39*, 215–228. SI: Euro Zone in Crisis.

Goodfriend, Marvin, “Inflation targeting in the United States?,” in “The inflation-targeting debate,” University of Chicago Press, 2004, pp. 311–352.

Greco, Luca, George Luta, and Rand Wilcox, "On testing the equality between interquartile ranges," *Computational statistics*, 2024, *39* (5), 2873–2898.

Grishchenko, Olesya, Sarah Mouabbi, and Jean-Paul Renne, "Measuring Inflation Anchoring and Uncertainty: A U.S. and Euro Area Comparison," *Journal of Money, Credit and Banking*, 2019, *51* (5), 1053–1096.

Huseynov, Samir and Zahra Murad, "Seeing Through Different Lenses: Partisanship and Updating of Inflation Expectations," *Available at SSRN*, 2024.

Kahneman, Daniel and Amos Tversky, "Subjective probability: A judgment of representativeness," *Cognitive psychology*, 1972, *3* (3), 430–454.

Kamdar, Rupal and Walker Ray, "Polarized expectations, polarized consumption," *Polarized Consumption (September 19, 2023)*, 2023.

Klenow, Peter J and Jonathan L Willis, "Sticky information and sticky prices," *Journal of Monetary Economics*, 2007, *54*, 79–99.

— **and Oleksiy Kryvtsov**, "State-dependent or time-dependent pricing: Does it matter for recent US inflation?," *The Quarterly Journal of Economics*, 2008, *123* (3), 863–904.

Kostyshyna, Olena and Luba Petersen, "The Effect of Inflation Uncertainty on Household Expectations and Spending," Technical Report, National Bureau of Economic Research 2024.

Krüger, Fabian and Lora Pavlova, "Quantifying subjective uncertainty in survey expectations," *International Journal of Forecasting*, 2024, *40* (2), 796–810.

Kuang, Pei, Michael Weber, and Shihan Xie, "Perceived Political Bias of the Federal Reserve," Technical Report, National Bureau of Economic Research 2024.

_ , _ , and _ , "Central bank communication with the polarized public," Technical Report, National Bureau of Economic Research 2025.

Kumar, S, O Coibion, H Afrouzi, and Y Gorodnichenko, "Inflation targeting does not anchor inflation expectations: Evidence from firms in New Zealand," *Brookings Papers on Economic Activity*, 2015, *2015* (2), 151–208.

Ladner, Matthew and Christopher Wlezien, "Partisan preferences, electoral prospects, and economic expectations," *Comparative Political Studies*, 2007, *40* (5), 571–596.

Lahiri, Kajal and Xuguang Sheng, "Measuring forecast uncertainty by disagreement: The missing link," *Journal of Applied Econometrics*, 2010, *25* (4), 514–538.

L'Huillier, Jean-Paul, Sanjay R Singh, and Donghoon Yoo, "Incorporating Diagnostic Expectations into the New Keynesian Framework," *Review of Economic Studies*, 2023.

Luo, Yulei, "Consumption dynamics under information processing constraints," *Review of Economic dynamics*, 2008, *11* (2), 366–385.

Mackowiak, Bartosz and Mirko Wiederholt, "Optimal sticky prices under rational inattention," *American Economic Review*, 2009, *99* (3), 769–803.

Maćkowiak, Bartosz and Mirko Wiederholt, "Business cycle dynamics under rational inattention," *The Review of Economic Studies*, 2015, *82* (4), 1502–1532.

Maxted, Peter, "A Macro-Finance Model with Sentiment," *The Review of Economic Studies*, 2023, *91* (1), 438–475.

Mertens, Elmar, "Measuring the Level and Uncertainty of Trend Inflation," *The Review of Economics and Statistics*, 12 2016, *98* (5), 950–967.

— **and James M. Nason**, "Inflation and professional forecast dynamics: An evaluation of stickiness, persistence, and volatility," *Quantitative Economics*, 2020, *11* (4), 1485–1520.

Mian, Atif, Amir Sufi, and Nasim Khoshkhou, "Partisan bias, economic expectations, and household spending," *Review of Economics and Statistics*, 2023, *105* (3), 493–510.

Na, Seunghoon and Donghoon Yoo, "Overreaction and Macroeconomic Fluctuation of the External Balance," 2024.

Naggert, Kristoph N., Robert W. Rich, and Joseph Tracy, "The Anchoring of US Inflation Expectations Since 2012," *Economic Commentary (Federal Reserve Bank of Cleveland)*, 2023, (2023-11).

Nakamura, Emi and Jón Steinsson, "Five facts about prices: A reevaluation of menu cost models," *The Quarterly Journal of Economics*, 2008, *123* (4), 1415–1464.

— **and Jon Steinsson**, "Monetary non-neutrality in a multisector menu cost model," *The Quarterly journal of economics*, 2010, *125* (3), 961–1013.

— **, Jón Steinsson, Patrick Sun, and Daniel Villar**, "The elusive costs of inflation: Price dispersion during the US great inflation," *The Quarterly Journal of Economics*, 2018, *133* (4), 1933–1980.

Nason, James M. and Gregor W. Smith, “Measuring the slowly evolving trend in US inflation with professional forecasts,” *Journal of Applied Econometrics*, 2021, *36* (1), 1–17.

Orphanides, Athanasios, “Monetary policy strategy and its communication,” in “Federal Reserve Bank of Kansas City 2019 Jackson Hole Economic Policy Symposium, Challenges for Monetary Policy, Jackson Hole, August” 2019, pp. 22–24.

Paciello, Luigi, “Monetary policy and price responsiveness to aggregate shocks under rational inattention,” *Journal of Money, Credit and Banking*, 2012, *44* (7), 1375–1399.

Shiller, Robert J, “Why do people dislike inflation?,” in “Reducing inflation: Motivation and strategy,” University of Chicago Press, 1997, pp. 13–70.

Simon, Herbert A, “Designing organizations for an information-rich world,” *Computers, communications, and the public interest*, 1971, *72*, 37.

Sims, Christopher A, “Stickiness,” in “Carnegie-rochester conference series on public policy,” Vol. 49 Elsevier 1998, pp. 317–356.

— , “Implications of rational inattention,” *Journal of monetary Economics*, 2003, *50* (3), 665–690.

Stanig, Piero, “Political polarization in retrospective economic evaluations during recessions and recoveries,” *Electoral Studies*, 2013, *32* (4), 729–745.

Stantcheva, Stefanie, “Why do we dislike inflation?,” Technical Report, National Bureau of Economic Research 2024.

Stock, James H and Mark W Watson, “Why has US inflation become harder to forecast?,” *Journal of Money, Credit and banking*, 2007, *39*, 3–33.

Taylor, John B, "Discretion versus policy rules in practice," in "Carnegie-Rochester conference series on public policy," Vol. 39 Elsevier 1993, pp. 195–214.

Tutino, Antonella, "Rationally inattentive consumption choices," *Review of Economic Dynamics*, 2013, *16* (3), 421–439.

Wlezien, Christopher, Mark Franklin, and Daniel Twiggs, "Economic perceptions and vote choice: Disentangling the endogeneity," *Political Behavior*, 1997, *19* (1), 7–17.

Nayeon Kang

Education

Ph.D., Economics, Indiana University, Bloomington, IN, USA — Aug 2019 - May 2025

M.A., Economics, Korea University, Seoul, Korea — Mar 2014 - Feb 2016

B.A., Economics, Korea University, Seoul, Korea — Mar 2006 - Aug 2011

Fields of Specialization

Behavioral Macroeconomics, Monetary Economics, Expectations Formation, Survey

Working Papers

1. The Fed Explicitly Speaks: Numerical Inflation Targeting and Smooth Diagnostic Expectations (Job Market Paper)

2. Rationally Inattentive Behavior in Different Times

3. Forecasting the Future Through a Partisan Lens: Electoral Outcomes and Household Expectations (with Sergii Drobot)

Works-in-Progress

1. Diagnostic Expectations in ECB Survey

2. Misperception or Misconception? Dissonance in Households' Inflation Forecasts (with Sergii Drobot)

Honors, Fellowships & Awards

Adam Smith Fellowship recipient, Mercatus Center	2024-2025
Daniel J Duesterberg Fellowship, Indiana University	2022
M L Wilson Willis Globe Scholarship, Indiana University	2022
Top-up Fellowship, Indiana University	2019-2020
Brain Korea 21 Plus Scholarship, National Research Foundation of Korea	2014-2016
Foreign Exchange Student Scholarship, Mirae Asset Foundation	2008-2009
Scholarship for Academic Excellence, Korea University	2006

Presentations

KAEA Workshop at 2025 ASSA Annual Meeting (San Francisco)	2025
Midwest Economics Association 89th Annual Meeting (Kansas City)	2025
Spring 2025 Midwest Macroeconomics Meeting (Kansas City)	2025
KAEA Job Market Conference (Virtual)	2024
Hoosier Economics Conference at Indiana University (Bloomington)	2022

Teaching

Associate Instructor

ECON-B251 *Fundamentals of Economics for Business 1*

Spring 2023, Fall 2023, Spring 2024, Fall 2024

Teaching Assistant

ECON-B251 *Fundamentals of Economics for Business 1* Fall 2020, Fall 2021, Spring 2022

ECONE-E370 *Statistical Analysis for Business and Economics* Spring 2020

Graduate Assistant

ECON-E370 *Statistical Analysis for Business and Economics*

Spring 2021, Fall 2022, Spring 2025