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Estimating Behavioral Inattention

CAMA Working Paper 34/2025
June 2025

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Keywords

cognitive discounting, myopia, attention, Bayesian estimation, behavioral macroeconomics

JEL Classification

E37, E52, E58, E70, E71

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ISSN 2206-0332

Estimating Behavioral Inattention*

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Abstract

Bounded rationality and limited attention significantly influence expectation formation and macroeconomic dynamics, yet empirical quantification of these behavioral phenomena remains challenging. This paper provides the first cross-country estimation of both micro- and macro-level attention parameters using a structurally identified behavioral New Keynesian model. Employing Bayesian techniques on harmonized data from 22 OECD countries (1996–2019) and ensuring robust parameter identification, we document substantial heterogeneity in behavioral inattention across countries. Our cognitive discounting estimates range from 0.76 to 0.98, with higher values indicating greater attention. We establish three key empirical regularities: (1) attention parameters are positively associated with macroeconomic volatility, supporting rational inattention theory; (2) surprise movements in key macroeconomic variables and online information-seeking behavior significantly influence attention allocation; and (3) institutional quality, particularly government effectiveness, is correlated with attention levels. These findings reveal that attention is both a behavioral and a structural phenomenon, responding to institutional factors and economic conditions. Our results provide an empirical foundation for calibrating country-specific models and yield important implications for the design and transmission of monetary policy under bounded rationality, showing that policy effectiveness may systematically vary with the macroeconomic environment.

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*The views expressed in this paper are those of the authors and do not necessarily represent the views of the Bank of Israel or the World Bank. The authors thank Joaquim Andrade, Anat Bracha (discussant), Assan Jallow, and participants at the Bank of Israel Research Department's Seminar and the 4th Behavioral Science Lab Seminars for their constructive comments.

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Please cite this paper as:

Benchimol, J., Bounader, L., and Dotta, M., 2025. Estimating Behavioral Inattention. Journal of Economic Behavior & Organization, vol. 236, number 107068.

1 Introduction

Behavioral inattention in economic decision-making has profound implications for macroeconomic dynamics and policy transmission, yet empirically estimating its extent across economic environments has remained elusive. This paper provides the first cross-country estimates of micro- and macro-level attention parameters using a micro-founded behavioral New Keynesian model. By analyzing OECD economies with harmonized data and employing Bayesian techniques, we document substantial heterogeneity in behavioral inattention across countries and demonstrate that this variation exhibits systematic patterns related to macroeconomic conditions and institutional factors.

A growing body of literature challenges the perfect attention (full rationality) assumption in standard macroeconomic models (Stiglitz, 2011; Blanchard, 2018). Behavioral economics and rational inattention theories suggest that agents have limited cognitive resources and optimally allocate attention based on costs and benefits (Sims, 2003b; Gabaix, 2014). Understanding economic agents' attention to macroeconomic variables and the drivers of cross-country differences in attention is key to understand expectation formation, macroeconomic dynamics, and monetary policy transmission.

While theoretical work on incorporating behavioral inattention into macroeconomic models has advanced significantly (Gabaix, 2014, 2019, 2020), empirical assessment of attention parameters has lagged behind. Existing research has relied primarily on expectation data from single-country surveys (Coibion and Gorodnichenko, 2012) or focused on specific episodes (Bracha and Tang, 2025). These approaches have illuminated important aspects of behavioral inattention but leave a critical gap: no study has systematically estimated and compared attention parameters across countries within a unified structural framework. This gap inhibits our understanding of how behavioral biases in expectation formation vary with economic environments and complicates the assessment of global applicability for behavioral macroeconomic models.

Cross-country estimation of attention parameters has proven difficult despite its theoretical importance. The challenges are fourfold: limited harmonized expectation data across countries; identification difficulties even in single-country settings; lack of coherent microfoundations linking micro and macro attention parameters; and methodological constraints in simultaneously identifying structural and behavioral parameters. Our approach addresses these challenges through harmonized data construction, robust identification strategies, and a micro-founded behavioral framework that establishes clear mappings between attention parameters at different levels. This cross-country approach allows us to examine how behavioral biases vary with economic environments and assess the global applicability of behavioral macroeconomic models.

Our paper makes three main contributions. First, we estimate a micro-founded behavioral New Keynesian model for OECD countries using Bayesian techniques, obtaining well-identified estimates of attention parameters for households and firms.

Our empirical strategy overcomes several identification challenges that have hindered previous attempts to estimate behavioral parameters. We estimate the model developed by Benchimol and Bounader (2023), which provides microfoundations for macroeconomic attention and establishes coherent relationships between micro and macro attention parameters.[1] This approach ensures that all parameter estimates are properly identified, addressing the concerns raised by Gabaix (2020) and Ilabaca et al. (2020).

Using quarterly data from 1996 to 2019, we estimate the model separately for each OECD country. Our key parameters of interest are the cognitive discounting parameter ($\bar{m}$), which captures the degree to which agents discount information about future states, and the micro attention parameters, which measure firms' attention to inflation (m_{π}^{f}) and the output gap (m_{x}^{f}), and households' attention to interest rates (m_r). Our results reveal substantial cross-country heterogeneity: the cognitive discounting parameter ranges from 0.76 to 0.98, with countries like Turkey, Mexico, and Colombia exhibiting values closer to 1 (indicating higher attention), whereas the UK and Chile show lower attention levels. This heterogeneity suggests that the degree of behavioral bias in expectation formation varies significantly with economic and institutional environments.

Second, we document a robust positive relationship between macroeconomic volatility and attention levels, providing novel cross-country evidence supporting rational inattention theory. Countries with more volatile inflation, output, and interest rates tend to exhibit higher estimated attention parameters. This finding aligns with theoretical predictions from Maćkowiak and Wiederholt (2015) that agents optimally allocate more attention to more volatile and important variables. The strength of this relationship varies among different types of attention, with inflation volatility exhibiting the strongest association with firm attention to inflation. Our results display an adaptive aspect of attention formation: economic agents appear to dynamically adjust their attention allocation based on the macroeconomic environment they face.

Third, we analyze the determinants of attention by combining the estimated attention parameters with panel data on economic variables and proxies for information acquisition. Results from fixed-effects panel regressions show that the intensity of Google searches for economic terms is consistently associated with attention levels, suggesting that active information-seeking behavior is a reliable predictor of cognitive allocation. Macroeconomic surprises—especially in inflation, GDP, and interest rates—also correlate significantly with attention shifts, consistent with theories of state-dependent attention (Maćkowiak and Wiederholt, 2015), where unexpected shocks lead agents to reallocate their focus. Variance measures, particularly for inflation and interest rates, further reinforce this pattern, highlighting the role of volatility in increasing the value of monitoring. Institutional quality also show context-dependent associations—particularly for government

[1] These parameters measure the share of attention given to economic variables by behavioral consumers and firms relative to fully rational agents (with rational expectations).

effectiveness—suggesting that its role in shaping attention may depend on the nature of the economic signal and the type of agent involved (Leeper et al., 2013).

To our knowledge, this is the first study to estimate both the slope and levels of the behavioral term structure of expectations as defined by Gabaix (2020) using identified Bayesian techniques with comparable cross-country data. Our international comparison of attention levels to macroeconomic volatility empirically contributes to the behavioral inattention literature (Gabaix, 2014, 2019) and addresses identification concerns raised in previous work.[2]

While Gabaix (2020) attempted a Bayesian estimation of a behavioral New Keynesian model in his 2018 working paper, identification concerns led to its omission from the final publication. Similarly, Ilabaca et al. (2020) employed Bayesian techniques to estimate Gabaix's model but refrained from estimating microeconomic attention parameters due to identification challenges, focusing instead on aggregate myopia. Our approach overcomes these limitations by using the model from Benchimol and Bounader (2023), which establishes more coherent microfoundations for macroeconomic behavioral parameters and precise relationships between micro and macro attention measures.

Following the established Bayesian estimation framework for New Keynesian DSGE models (An and Schorfheide, 2007; Smets and Wouters, 2007), we ensure that all our parameter estimates are properly identified through multiple criteria: reduced-form solution (Ratto, 2008; Adolfson et al., 2019), moments (Iskrev, 2010), minimal system (Komunjer and Ng, 2011), and spectral density (Qu and Tkachenko, 2012). Our study is the first to systematically estimate attention parameters across OECD economies using a unified methodological approach, enabling meaningful cross-country comparisons and generalizable policy implications.

Our findings contribute to the growing literature examining how attention relates to macroeconomic variables, levels, thresholds, and personal experiences (Malmendier and Nagel, 2016; Link et al., 2023; Bracha and Tang, 2025; Korenok et al., 2025; Weber et al., 2025). We extend this literature by establishing empirical connections between macroeconomic variance and both macro and micro attention parameters across diverse economic environments. Our results show that inflation volatility is associated with attention among both firms and households, while factors such as institutional quality and information-seeking behavior (measured through Google Trends) also influence attention allocation.

Our paper relates to Afsar et al. (2024), which develops a behavioral hybrid New Keynesian model incorporating habit formation and price indexation alongside attention parameters. While this hybrid approach provides improved empirical fit for

[2]See Footnote 25, Gabaix (2020):

> *(...) The 2018 working paper version of the present paper provides a tentative Bayesian estimation of the entire model (...). The estimation in that draft should be taken as preliminary at best since further well-identified empirical work will be necessary in order to reach definitive conclusions. (...) Gathering evidence on micro parameters* $\overline{m}$ *would be much more costly. However, using microdata, Ganong and Noel (2019) finds evidence for a form of micro-level cognitive discounting, so that progress is being made in that direction too.*

U.S. data with lower attention parameter estimates (around 0.46), our approach deliberately excludes backward-looking elements to focus on quantifying and explaining cross-country heterogeneity in attention. The difference in attention estimates likely stems from three factors: (1) backward-looking components may absorb persistence that manifests as attention in our model, (2) we allow for different degrees of attention across variables rather than a single parameter, and (3) our cross-country sample captures a broader range of institutional and macroeconomic environments than the U.S.-focused analysis. Our emphasis on explaining international heterogeneity through institutional quality, macroeconomic volatility, and information acquisition complements the finding in Benchimol and Bounader (2023) that behavioral elements improve model fit.

Our findings have important implications for macroeconomic modeling and monetary policy. The substantial heterogeneity in attention parameters across countries suggests that monetary policy transmission may vary significantly, even among advanced economies. This challenges the common practice of calibrating behavioral parameters based on single-country estimates. Moreover, the relationship between macroeconomic volatility and attention implies a potential trade-off for policymakers: while reducing volatility may be desirable for its own sake, it could lead to less attentive behavior, potentially amplifying the impact of future shocks. Our results contribute to the literature on monetary policy under bounded rationality (Woodford, 2010; Gabaix, 2020; Benchimol and Bounader, 2023) by highlighting that policy effectiveness may vary with the macroeconomic environment in subtle ways. During periods of stability, policy actions may have muted effects due to low attention, while in more volatile times, the same actions could have outsized impacts. This nonlinearity introduces new challenges for central banks and suggests the need for more sophisticated, state-dependent policy frameworks.

The remainder of the paper is organized as follows. Section 2 describes the behavioral New Keynesian model we estimate, highlighting how it incorporates attention at both the micro and macro levels. Section 3 outlines our data and estimation methodology, with a particular focus on our identification strategy and main estimation results, documenting the heterogeneity in attention levels across countries and over time. Section 4 analyzes the relationship between attention and macroeconomic volatility, providing both graphical evidence and statistical tests of the potential sources of behavioral inattention. Section 5 discusses possible mechanisms and investigates the determinants of attention using panel regressions, exploring the roles of institutional factors, macroeconomic surprises, and information acquisition. Section 6 interprets and discusses our findings to draw some policy implications, and Section 7 concludes.

2 The Model

This section presents the micro-founded behavioral New Keynesian framework that serves as the foundation for our empirical analysis. We use the model developed by

Benchimol and Bounader (2023), which offers relevant advantages over previous behavioral macroeconomic specifications in terms of both theoretical consistency and empirical tractability.[3]

2.1 Attention Parameters

The central innovation in our approach is the explicit modeling of bounded rationality through a set of attention parameters that capture distinct dimensions of cognitive limitations. These parameters formally quantify the degree to which economic agents deviate from full rationality when forming expectations about future economic conditions.

The behavioral expectations for any economic variable X are structured as:

$$\mathbb{E}_t^{BR}\left[\hat{X}_{t+k}\right] = m_X \overline{m}^k \mathbb{E}_t\left[\hat{X}_{t+k}\right], \tag{1}$$

where $\mathbb{E}_t^{BR}[.]$ represents the behavioral (boundedly rational) expectation operator, $\mathbb{E}_t[.]$ is the standard rational expectation operator, $\widehat{X}$ denotes the variable's deviation from steady state, m_X captures the contemporaneous attention (or level/intercept) specific to variable X, and $\overline{m}$ represents cognitive discounting (or slope of attention) that applies to expectations at all future horizons k.

This specification allows for both variable-specific attention (m_X differs across economic variables) and horizon-specific discounting ($\overline{m}^k$ applies exponential down-weighting to more distant future periods), providing a flexible yet tractable framework for modeling behavioral biases in expectation formation.

Our model incorporates five micro-level attention parameters. The cognitive discounting parameter ($\overline{m}$) that affects expectations at all future horizons for both households and firms. The households' attention to interest rates (m_r). The firms' attention to inflation (m_π^f). The households' attention to income (m_y). The firms' attention to the output gap (m_x^f).

These micro parameters aggregate into two key macro-level attention measures that govern the dynamics of the IS curve and Phillips curve, respectively:

$$M = \frac{\overline{m}}{R - m_y} \quad \text{and} \quad M^f = \frac{\theta \overline{m}}{1 - (1-\theta)\, m_\pi^f} \tag{2}$$

where $R = 1 + \bar{r} = 1/\beta$ is the gross steady-state interest rate, $\bar{r}$ is the steady-state real interest rate, β is the discount factor, and θ is the Calvo (1983) price stickiness parameter.

All attention parameters—both micro ($\overline{m}$, m_x^f, m_π^f, m_y, m_r) and macro (M, M^f)—are bounded within the interval $[0,1]$. The standard rational-expectations framework is nested as a special case when all attention parameters equal one. The

[3] The detailed theoretical background, microfoundations and derivations, as well as comparisons with Gabaix (2020)'s behavioral New Keynesian model, are described in Benchimol and Bounader (2023).

deviation from unity therefore quantifies the degree to which behavioral agents' expectations differ from those of fully rational agents. The macro parameters M and M^f moderate the excessive forward-looking behavior often associated with rational expectations models (Blanchard, 2009), providing a behavioral microfoundation for observed persistence in macroeconomic dynamics.

2.2 Model Dynamics

The behavioral New Keynesian model consists of three core equations that characterize macroeconomic dynamics. First, the micro-founded IS curve, derived from behavioral households' optimization of lifetime utility subject to budget and transversality constraints, takes the form:

$$\tilde{y}_t = M\mathbb{E}_t\left[\tilde{y}_{t+1}\right] - \sigma\left(i_t - \mathbb{E}_t\left[\pi_{t+1}\right] - r_t^n\right) + \varepsilon_{z,t}, \tag{3}$$

where $\tilde{y}_t$ represents the output gap (deviation of output y_t from its natural level y_t^n), i_t is the nominal interest rate, π_t is inflation, r_t^n is the natural real interest rate, and $\varepsilon_{z,t}$ is a preference shock. The parameter $\sigma = m_r/(\gamma R)$ captures behavioral relative risk aversion,[4] with γ representing the inverse intertemporal elasticity of substitution.

Unlike standard New Keynesian models, the behavioral IS curve features M as a coefficient on expected future output, directly incorporating limited attention into intertemporal consumption decisions. When $M < 1$, the impact of expected future output on current output is attenuated, reflecting households' imperfect consideration of future economic conditions.

The model's production technology incorporates decreasing returns to scale:

$$y_t = (1-\alpha)\, n_t + \varepsilon_{a,t} \tag{4}$$

where α quantifies the degree of decreasing returns, n_t represents aggregate labor (hours worked), and $\varepsilon_{a,t}$ is a technology shock. This specification of decreasing returns plays an important role in our identification strategy, as elaborated in Section 2.3.

The behavioral Phillips curve, derived from firms' profit maximization under behavioral expectations, is given by:

$$\pi_t = \beta M^f \mathbb{E}_t\left[\pi_{t+1}\right] + \kappa\tilde{y}_t + \varepsilon_{u,t}, \tag{5}$$

where $\varepsilon_{u,t}$ represents a cost-push shock and the slope parameter κ is defined as:

$$\kappa = \frac{(1-\theta)\,(1-\beta\theta)\, m_x^f}{1-(1-\theta)\, m_\pi^f}\Theta\left(\gamma + \frac{\phi+\alpha}{1-\alpha}\right) \tag{6}$$

[4] For identification purposes and analytical tractability, we set households' attention to income $m_y = 1$, which simplifies aggregate household attention to $M = \overline{m}$ and behavioral relative risk aversion to $\sigma = m_r/(\gamma R)$. This parameterization preserves the interaction between m_r and M in Equation 3 while enhancing identification.

with $\Theta = (1-\alpha) / (1-\alpha+\alpha\epsilon)$ and ϵ representing the elasticity of substitution between goods. The behavioral Phillips curve directly incorporates firms' limited attention through the coefficient βM^f on expected future inflation, which attenuates the impact of anticipated inflation on current price-setting decisions when $M^f < 1$.

The model is closed with a standard Taylor-type monetary policy rule:

$$i_t = r_t^n + \phi_\pi \pi_t + \phi_y \widetilde{y}_t + \varepsilon_{r,t}, \tag{7}$$

where policy parameters ϕ_π and ϕ_y capture the central bank's responsiveness to inflation and output gap deviations, respectively, and $\varepsilon_{r,t}$ represents a monetary policy shock. A supplementary flexible-price block is included to compute natural variables and output gaps, following Galí (2015).

All structural shocks follow standard AR(1) processes such that $\forall s \in \{z, a, u, r\}$, $\varepsilon_{s,t} = \rho_s \varepsilon_{s,t-1} + \eta_{s,t}$, where $\eta_{s,t} \sim N(0; \sigma_s)$ is i.i.d. over time, and ρ_s governs shock persistence.

This behavioral framework captures how limited attention affects macroeconomic dynamics through two primary channels: (1) by attenuating the impact of expected future conditions on current decisions, and (2) by modifying the structural relationships between key macroeconomic variables. While incorporating backward-looking components like habit formation or price indexation might improve empirical fit, we deliberately maintain a more parsimonious specification to focus clearly on cross-country heterogeneity in attention without confounding it with other sources of persistence.

2.3 Contributions

Our estimation approach addresses several identification challenges that have impeded previous attempts to estimate behavioral parameters in New Keynesian models.[5] We implement three key methodological innovations that collectively ensure robust identification of both micro and macro attention parameters.

First, we apply the behavioral expectations structure to deviations from steady state rather than to level variables. This seemingly technical distinction has profound implications for identification. By specifying the model in terms of gap variables, we establish consistent mappings between subjective (boundedly rational) and objective (fully rational) expectations that align with Gabaix (2014, 2019)'s theoretical framework. This approach generates coherent structural relationships between micro and macro attention parameters that provide crucial identifying restrictions absent in previous estimation attempts.

Second, our incorporation of decreasing returns to scale ($\alpha > 0$) introduces additional identifying variation through the Phillips curve slope (κ). This specification creates a distinct channel through which attention to the output gap

[5]These challenges are explicitly acknowledged in Footnote 25 of Gabaix (2020), where he notes that while his 2018 working paper attempted a Bayesian estimation of a behavioral New Keynesian model, identification issues prevented inclusion of these estimates in the final publication.

(m_x^f) affects inflation dynamics separately from attention to inflation (m_π^f). This additional source of variation, absent in constant-returns specifications (Gabaix, 2020), substantially improves the separate identification of these attention parameters.

Third, we employ a comprehensive identification assessment strategy that validates parameter estimates through multiple complementary approaches. We systematically analyze the Jacobian matrices of steady-state and reduced-form solutions, first and second moments, minimal system matrices, and frequency domain identification.[6] This multi-dimensional verification of identification, largely absent from previous estimation attempts of micro attention parameters, ensures that our results are not artifacts of weak identification or parameter conflation.

The empirical validity of our identification strategy is evident in several dimensions: (1) well-behaved posterior distributions for all attention parameters, (2) distinct identification patterns across different types of attention, (3) economically meaningful cross-country variation in estimated parameters that aligns with observable country characteristics, and (4) coherent relationships between estimated attention and macroeconomic conditions that conform to theoretical predictions.

This framework thus provides a theoretically consistent and empirically tractable approach to modeling bounded rationality in macroeconomic dynamics while ensuring robust identification of behavioral parameters—addressing a critical gap in the existing literature on behavioral macroeconomics.

3 Estimation

This section outlines our data construction, calibration strategy, and econometric methodology. We develop a cross-country dataset using harmonized sources and employ rigorous Bayesian techniques with particular attention to parameter identification.

3.1 Data

To facilitate cross-country comparison of behavioral inattention parameters, we construct a harmonized quarterly panel dataset spanning 22 OECD countries from 1996Q1 to 2019Q4. Our sample encompasses Australia, Canada, Chile, Colombia, Costa Rica, Czech Republic, Denmark, Hungary, Iceland, Israel, Japan, Korea, Mexico, New Zealand, Norway, Poland, Sweden, Switzerland, Turkey, United Kingdom, United States, and the Euro Area (Eurozone).[7] The dataset includes country-specific real GDP, GDP deflator, private consumption, short-term interest rates, population, employment, hours worked, and hourly compensation. The data

[6]Section 3.3 provides detailed information on these identification checks.

[7]Some economies in our sample, including Colombia and Costa Rica, formally joined the OECD after our analysis period. We include them because their data adhere to OECD statistical standards and their inclusion enriches our cross-country comparison by increasing variation in economic structures and development levels.

primarily come from harmonized OECD databases, supplemented by national statistical institutions when necessary. Where required, we extrapolate annual or missing data to a quarterly frequency. In some cases, manual collection and extrapolation are necessary for specific datasets.[8]

The time series data used in this analysis were seasonally adjusted and normalized. GDP and consumption data, derived via the expenditure approach, are expressed in US dollars adjusted for fixed purchasing power parity (PPP). Our dataset includes private consumption (private final consumption expenditures), short-term interest rates (calculated as 3-month averages of 12-month rates), employment levels, total population, annual hours worked, and compensation.

Necessary data transformations included extrapolating annual hours worked to a quarterly frequency and converting quarterly compensation data from current national currency to a 2015 base index. Although the OECD offered harmonized data for some countries (e.g., Australia, Denmark), coverage for others (e.g., Canada, Colombia) was incomplete. Consequently, the dataset was supplemented using time series from other official sources such as the Federal Reserve Economic Data (FRED), the World Bank, and national central banks and statistical agencies. Detailed descriptions of all data sources and the transformations applied to construct each series are available in the Appendix.

3.2 Calibration

We estimate all parameters except the discount factor (β), the Frisch elasticity of labor supply (ϕ), the Calvo (1983) parameter (θ), and the elasticity of household demand for consumption goods (ε). β is set at 0.992 to ensure that the annual steady-state real interest rate aligns with approximately three percent. ϕ, θ, and ε are set to one, 0.66, and six, respectively. These calibrations are consistent with those used in Galí (2008) and Walsh (2017).

Table 1 presents prior distributions for estimated parameters.

3.3 Methodology

We employ Bayesian estimation techniques to identify behavioral parameters across countries. This approach offers several advantages for our analysis: it incorporates prior information while allowing the data to drive posterior estimates, handles small-sample issues effectively, and enables rigorous identification diagnostics.

Following the literature on Bayesian estimation of New Keynesian DSGE models (An and Schorfheide, 2007; Smets and Wouters, 2007), we estimate the behavioral New Keynesian model for each country separately using quarterly data from 1996Q1 to 2019Q4. We implement the estimation procedure using Dynare 6.0 with the Metropolis-Hastings algorithm, utilizing three parallel chains and generating a total of 2,000,000 draws. We discard the first 1,000,000 draws as burn-in to ensure

[8] Detailed information on the data sources and transformations (including data collection and extrapolation steps) is provided in the Appendix A.

Table 1. Calibration - Priors

	Mean	Std.	Distribution		Mean	Std.	Distribution
γ	2.0	0.2	Normal	ρ_i	0.8	0.1	Beta
α	0.33	0.1	Beta	ϕ_π	2.5	0.2	Normal
ρ_z	0.5	0.5	Beta	ϕ_y	0.25	0.1	Normal
ρ_a	0.8	0.1	Beta	$\bar{y}$	0	0.01	Normal
ρ_u	0.7	0.1	Beta	$\bar{\pi}$	0	0.01	Normal
ρ_r	0.1	0.1	Beta	$\bar{\imath}$	0	0.01	Normal
m_x^f	1	0.2	Uniform	$\bar{n}$	0	0.01	Normal
m_π^f	1	0.2	Uniform	σ_z	0.01	Inf.	Inv.-Gamma
$\overline{m}$	1	0.2	Uniform	σ_a	0.01	Inf.	Inv.-Gamma
m_r	1	0.2	Uniform	σ_u	0.01	Inf.	Inv.-Gamma
				σ_r	0.01	Inf.	Inv.-Gamma

Notes: The parameters $\bar{y}$, $\bar{\pi}$, $\bar{\imath}$, and $\bar{n}$ are the measurement errors included in the observable equations presented in the Appendix. Inf. stands for infinity and Inv.-Gamma for the inverse-gamma distribution.

convergence. The tuning parameter on the covariance matrix is carefully calibrated to achieve acceptance rates between 20% and 40%, ensuring efficient exploration of the posterior distribution.

Our primary focus is on the behavioral parameter estimates: the cognitive discounting parameter ($\overline{m}$), firms' attention to inflation (m_π^f) and the output gap (m_x^f), households' attention to interest rates (m_r), and the derived aggregate attention parameters (M and M^f).[9]

A critical aspect of our methodology is ensuring robust parameter identification. We verify that all parameter estimates are identified through multiple complementary approaches. The reduced-form solution identification (Ratto, 2008; Adolfson et al., 2019) by analyzing the Jacobian matrix of the model's reduced-form solution with respect to the structural parameters, ensuring that the mapping between structural parameters and reduced-form coefficients is invertible. The moment-based identification (Iskrev, 2010), by verifying that the Jacobian of the first and second moments of the observable variables with respect to the structural parameters has full rank, confirming that different parameter values generate distinguishable patterns in the data moments. The minimal system identification (Komunjer and Ng, 2011) by examining the minimal state-space representation of the model to ensure that the parameters are identifiable from the observables. The spectral density identification (Qu and Tkachenko, 2012) by exploring the spectral density of the observable variables to confirm identification in the frequency domain.

The identification strategy we employ addresses concerns raised in previous

[9]The complete estimation results and replication files are available upon request. Our calibration approach allows for heterogeneous attention across variables and countries, as our focus is on understanding cross-country differences rather than maximizing model fit for a single country.

attempts to estimate behavioral parameters in New Keynesian models. By verifying identification through multiple criteria, we ensure that our parameter estimates genuinely reflect patterns in the data rather than artifacts of weak identification.

The Appendix provides the complete set of observable equations and a detailed description of all data transformations. The following sections present the results of our empirical investigation into attention.

3.4 Results

This section presents our cross-country estimates of attention parameters, documenting substantial heterogeneity across OECD economies. We first analyze results for the full sample period (1996–2019), then examine temporal variation through sub-sample analysis. We conclude with sensitivity analysis that validates the robustness of our findings.

3.4.1 Full Sample

Table 2 presents the estimates for all attention parameters ($\bar{m}$, m_{π}^{f}, m_{x}^{f}, m_r, M, and M^f) and key model parameters (κ and $\frac{1}{\sigma}$) across OECD countries. Darker shading in the column indicates higher attention to each variable.

Our cross-country analysis reveals striking heterogeneity in attention parameters. The cognitive discounting parameter ($\bar{m}$) varies substantially across OECD economies, ranging from 0.76 to 0.98. This parameter, which captures agents' discount rate for processing information about future states, exhibits a clear pattern: countries with historically volatile macroeconomic environments tend to have values closer to unity (indicating higher attention), while more stable economies show greater cognitive discounting. Three emerging economies—Turkey, Mexico, and Colombia—display the highest values of $\bar{m}$ (closest to 1), suggesting near-rational processing of future information. In contrast, advanced economies like the United Kingdom and Chile exhibit the lowest values, revealing greater behavioral bias in processing forward-looking information.

Firm-specific attention parameters also display systematic cross-country variation. Attention to inflation (m_{π}^{f}) ranges from 0.80 to 0.96, with Turkey and Mexico exhibiting the highest values—a finding consistent with their histories of inflation volatility. Japan and Chile, economies characterized by price stability, show the lowest attention to inflation. Similarly, attention to the output gap (m_{x}^{f}) varies between 0.84 and 0.92, with the highest values again observed in Turkey and Mexico, while Japan and Chile display comparatively lower attention to economic slack.

Households' attention to interest rates (m_r) shows less cross-country variation, with values clustering around 0.66 for most economies. Japan stands as a mild outlier with slightly higher interest rate attention. This relative homogeneity in interest rate attention, compared to the heterogeneity in other attention parameters, suggests that households' attention to monetary policy exhibits less sensitivity to macroeconomic conditions than firms' attention to inflation and output.

Table 2. Attention and Deep Parameter Estimates

Panel A: Full sample

	$\bar{m}$	m_π^f	m_x^f	m_r	M	M^f	κ	$\frac{1}{\sigma}$
Australia (AU)	0.897	0.862	0.893	0.663	0.897	0.832	0.231	3.530
Canada (CA)	0.947	0.862	0.899	0.664	0.947	0.879	0.243	3.540
Switzerland (CH)	0.945	0.880	0.900	0.665	0.945	0.884	0.277	3.493
Chile (CL)	0.862	0.808	0.855	0.663	0.862	0.780	0.154	3.558
Colombia (CO)	0.962	0.897	0.887	0.663	0.962	0.908	0.159	3.562
Costa Rica (CR)	0.916	0.885	0.887	0.663	0.916	0.860	0.177	3.568
Czech Republic (CZ)	0.923	0.884	0.906	0.663	0.923	0.866	0.287	3.573
Denmark (DK)	0.935	0.834	0.863	0.666	0.935	0.856	0.131	3.493
Euro Area (EA)	0.877	0.840	0.895	0.666	0.877	0.806	0.201	3.500
United Kingdom (GB)	0.871	0.834	0.887	0.664	0.871	0.798	0.219	3.522
Hungary (HU)	0.926	0.891	0.878	0.663	0.926	0.871	0.112	3.557
Israel (IL)	0.879	0.869	0.894	0.663	0.879	0.818	0.229	3.540
Iceland (IS)	0.948	0.850	0.902	0.665	0.948	0.875	0.296	3.524
Japan (JP)	0.879	0.815	0.843	0.685	0.879	0.798	0.069	3.158
Korea (KR)	0.918	0.847	0.866	0.664	0.918	0.846	0.116	3.559
Mexico (MX)	0.968	0.957	0.924	0.663	0.968	0.940	0.294	3.568
Norway (NO)	0.907	0.864	0.904	0.664	0.907	0.842	0.285	3.541
New Zealand (NZ)	0.902	0.829	0.870	0.664	0.902	0.824	0.165	3.547
Poland (PL)	0.885	0.877	0.901	0.664	0.885	0.827	0.229	3.547
Sweden (SE)	0.888	0.827	0.889	0.664	0.888	0.811	0.248	3.525
Turkey (TR)	0.989	0.962	0.924	0.662	0.989	0.963	0.274	3.614
United States (US)	0.879	0.821	0.870	0.664	0.879	0.801	0.107	3.498

Panel B: 1996Q1–2004Q1

	$\bar{m}$	m_π^f	m_x^f	m_r	M	M^f	κ	$\frac{1}{\sigma}$
Australia (AU)	0.769	0.847	0.859	0.683	0.769	0.708	0.209	3.145
Canada (CA)	0.789	0.845	0.859	0.680	0.789	0.727	0.174	3.156
Switzerland (CH)	0.765	0.849	0.868	0.685	0.765	0.706	0.208	3.122
Chile (CL)	0.736	0.841	0.865	0.681	0.736	0.676	0.212	3.163
Colombia (CO)	0.817	0.860	0.871	0.680	0.817	0.758	0.213	3.167
Costa Rica (CR)	0.760	0.841	0.858	0.680	0.760	0.699	0.192	3.176
Czech Republic (CZ)	0.771	0.851	0.863	0.680	0.771	0.712	0.181	3.170
Denmark (DK)	0.775	0.844	0.860	0.682	0.775	0.713	0.181	3.140
Euro Area (EA)	0.756	0.843	0.861	0.684	0.756	0.695	0.156	3.127
United Kingdom (GB)	0.778	0.844	0.857	0.680	0.778	0.716	0.202	3.167
Hungary (HU)	0.782	0.847	0.851	0.679	0.782	0.721	0.153	3.174
Israel (IL)	0.777	0.847	0.863	0.679	0.777	0.716	0.206	3.175
Iceland (IS)	0.785	0.849	0.863	0.684	0.785	0.724	0.230	3.127
Japan (JP)	0.710	0.837	0.849	0.728	0.710	0.652	0.093	2.873
Korea (KR)	0.735	0.845	0.864	0.680	0.735	0.677	0.207	3.173
Mexico (MX)	0.807	0.876	0.873	0.680	0.807	0.753	0.184	3.166
Norway (NO)	0.746	0.844	0.858	0.683	0.746	0.686	0.180	3.145
New Zealand (NZ)	0.751	0.840	0.860	0.682	0.751	0.690	0.187	3.152
Poland (PL)	0.773	0.847	0.857	0.680	0.773	0.712	0.173	3.158
Sweden (SE)	0.758	0.843	0.858	0.683	0.758	0.698	0.176	3.140
Turkey (TR)	0.908	0.946	0.934	0.699	0.908	0.878	0.305	3.001
United States (US)	0.771	0.842	0.869	0.683	0.771	0.709	0.185	3.132

Panel C: 2004Q2–2011Q4

	$\bar{m}$	m_π^f	m_x^f	m_r	M	M^f	κ	$\frac{1}{\sigma}$
Australia (AU)	0.771	0.841	0.854	0.681	0.771	0.708	0.179	3.154
Canada (CA)	0.800	0.848	0.858	0.683	0.800	0.737	0.189	3.127
Switzerland (CH)	0.818	0.848	0.862	0.683	0.818	0.754	0.206	3.112
Chile (CL)	0.761	0.842	0.856	0.683	0.761	0.700	0.151	3.136
Colombia (CO)	0.806	0.853	0.869	0.684	0.806	0.745	0.164	3.136
Costa Rica (CR)	0.747	0.848	0.861	0.679	0.747	0.689	0.188	3.179
Czech Republic (CZ)	0.814	0.844	0.861	0.686	0.814	0.749	0.216	3.099
Denmark (DK)	0.753	0.843	0.858	0.685	0.753	0.693	0.176	3.118
Euro Area (EA)	0.739	0.851	0.866	0.684	0.739	0.683	0.196	3.123
United Kingdom (GB)	0.747	0.843	0.859	0.684	0.747	0.688	0.168	3.125
Hungary (HU)	0.762	0.842	0.853	0.680	0.762	0.701	0.151	3.166
Israel (IL)	0.766	0.841	0.855	0.681	0.766	0.704	0.171	3.150
Iceland (IS)	0.789	0.848	0.865	0.683	0.789	0.727	0.224	3.136
Japan (JP)	0.776	0.845	0.861	0.751	0.776	0.715	0.166	2.761
Korea (KR)	0.744	0.841	0.847	0.690	0.744	0.683	0.106	3.086
Mexico (MX)	0.755	0.843	0.860	0.686	0.755	0.695	0.188	3.122
Norway (NO)	0.777	0.844	0.861	0.681	0.777	0.715	0.197	3.152
New Zealand (NZ)	0.756	0.843	0.857	0.682	0.756	0.695	0.180	3.147
Poland (PL)	0.738	0.841	0.852	0.687	0.738	0.678	0.146	3.119
Sweden (SE)	0.777	0.846	0.861	0.684	0.777	0.716	0.199	3.116
Turkey (TR)	0.772	0.857	0.880	0.683	0.772	0.715	0.198	3.150
United States (US)	0.707	0.849	0.862	0.684	0.707	0.652	0.160	3.127

Panel D: 2012Q1–2019Q4

	$\bar{m}$	m_π^f	m_x^f	m_r	M	M^f	κ	$\frac{1}{\sigma}$
Australia (AU)	0.776	0.843	0.847	0.680	0.776	0.714	0.171	3.177
Canada (CA)	0.796	0.849	0.860	0.682	0.796	0.734	0.194	3.141
Switzerland (CH)	0.788	0.845	0.861	0.681	0.788	0.726	0.186	3.159
Chile (CL)	0.769	0.854	0.856	0.685	0.769	0.711	0.218	3.104
Colombia (CO)	0.810	0.863	0.868	0.682	0.810	0.752	0.197	3.150
Costa Rica (CR)	0.758	0.846	0.857	0.681	0.758	0.698	0.162	3.151
Czech Republic (CZ)	0.749	0.842	0.846	0.696	0.749	0.689	0.110	3.041
Denmark (DK)	0.770	0.846	0.856	0.684	0.770	0.709	0.184	3.109
Euro Area (EA)	0.749	0.840	0.853	0.691	0.749	0.688	0.109	3.071
United Kingdom (GB)	0.719	0.844	0.847	0.698	0.719	0.662	0.087	3.038
Hungary (HU)	0.724	0.836	0.846	0.686	0.724	0.664	0.088	3.117
Israel (IL)	0.761	0.848	0.854	0.686	0.761	0.701	0.155	3.121
Iceland (IS)	0.768	0.845	0.863	0.695	0.768	0.707	0.214	3.034
Japan (JP)	0.834	0.852	0.873	0.854	0.834	0.770	0.182	2.364
Korea (KR)	0.781	0.842	0.856	0.681	0.781	0.718	0.168	3.155
Mexico (MX)	0.756	0.846	0.859	0.683	0.756	0.696	0.169	3.134
Norway (NO)	0.782	0.845	0.860	0.686	0.782	0.720	0.201	3.096
New Zealand (NZ)	0.727	0.843	0.847	0.690	0.727	0.669	0.106	3.091
Poland (PL)	0.752	0.842	0.848	0.686	0.752	0.691	0.113	3.113
Sweden (SE)	0.735	0.841	0.859	0.684	0.735	0.675	0.167	3.136
Turkey (TR)	0.809	0.877	0.886	0.682	0.809	0.756	0.229	3.156
United States (US)	0.732	0.839	0.852	0.688	0.732	0.672	0.119	3.103

Notes: The shading scheme is defined separately in relation to each column. The darker the shading is, the higher the attention.

Several patterns emerge when comparing different types of attention. First, attention to inflation and output (m_π^f and m_x^f, respectively) consistently exceeds attention to interest rates (m_r) across all countries. This asymmetry indicates that firms allocate more attention to price and production decisions than households devote to interest rates—potentially reflecting differences in information acquisition channels. Firms often employ professional services for guidance on pricing and production decisions (Thaler, 2016), while households typically rely on more limited, informal sources of information when forming interest rate expectations.

Second, aggregate household attention (M) typically exceeds aggregate firm attention (M^f) across most countries. This pattern may reflect differences in the breadth versus depth of attention: households maintain broader awareness of general economic conditions but with less specificity, while firms focus more narrowly on sector-specific information directly relevant to their operations. However, it is important to note that both macro parameters emerge from structural relationships involving multiple micro parameters, and their comparison serves primarily as a simplified means of distinguishing between household and firm attention at the aggregate level.

Third, attention to inflation (m^f_π) is generally lower than attention to the output gap (m^f_x). This finding aligns with salience theory in behavioral economics (Kahneman and Tversky, 1979), which suggests that in relatively stable inflation environments—characteristic of our sample period—firms would rationally allocate more attention to production and demand fluctuations than to price changes, which exhibit less variability and thus lower decision-relevance.

The estimated cross-country variation reveals instructive cases that illustrate the relationship between macroeconomic conditions and attention. Turkey exemplifies an economy where high macroeconomic volatility corresponds with near-rational attention parameters (values close to 1). During our sample period, Turkish inflation rates fluctuated dramatically, exceeding 80% at their peak and rarely falling below 6%, while GDP growth oscillated between -4.8% and 8% (IMF, 2019). This persistent macroeconomic volatility appears to have induced higher attentiveness among economic agents compared to environments with greater stability.

In contrast, Japan represents a case where macroeconomic stability coincides with comparatively low attention parameters. Despite experiencing GDP growth that varied between -5% and 4%, Japanese inflation remained close to zero throughout most of our sample period (IMF, 2020). This stability in price levels appears to have permitted more attenuated attention to macroeconomic variables, supporting the hypothesis that volatile environments induce heightened attentiveness while stable environments allow for greater cognitive economizing.

The pattern of cross-country differences in attention levels also appears related to other deep parameters of the model, particularly relative risk aversion (σ). In our sample, lower relative risk aversion is associated with higher attention, as exemplified by Turkey. While this relationship seems intuitive—less risk-averse agents may be more willing to invest in information acquisition—the similarity in risk aversion estimates across countries prevents definitive conclusions. We explore the determinants of cross-country differences in attention more systematically in Section 4.

The relationship between risk aversion and attention allocation represents a theoretically rich area with several plausible mechanisms, though the directional relationship remains ambiguous in the literature (Huang and Liu, 2007). The observed negative correlation—where lower relative risk aversion correlates with higher attention (as in the Turkey case)—can be rationalized through several theoretical channels.

More risk-averse agents may allocate disproportionate cognitive resources to risk-minimizing behaviors rather than to information acquisition and processing (Sims, 2003b). This creates an effective *crowding out* of attention capacity, consistent with cognitive resource allocation theory (Kahneman and Tversky, 1979).

The marginal utility of additional information varies systematically with risk preferences (Maćkowiak and Wiederholt, 2015). Risk-tolerant agents (lower σ) may derive greater expected utility from precise information because they can exploit opportunities more aggressively, whereas risk-averse agents might adopt conservative strategies regardless of marginal information improvements, reducing their incentive for costly information acquisition.

Risk-averse agents often employ satisficing rather than optimizing decision rules (Simon, 1955), requiring lower precision thresholds and thus less attention investment. This decision threshold effect suggests that higher risk aversion systematically reduces the desirable level of attention allocation in uncertainty-rich environments.

In our behavioral New Keynesian framework, this relationship manifests directly in the transmission parameters. For instance, in the IS curve formulation where $\sigma = m_r / (\gamma R)$, the sensitivity of output to real interest rates is jointly determined by interest rate attention (m_r) and risk aversion (σ). Higher σ attenuates the impact of changes in attention (m_r), suggesting that more risk-averse agents experience diminished marginal returns to attention allocation, creating an equilibrium in which lower attention becomes optimal.

These theoretical channels collectively explain the empirical pattern we observe, where economies characterized by lower relative risk aversion (such as Turkey) simultaneously exhibit higher attention parameters. This relationship underscores that attention allocation represents an endogenous response to both structural characteristics and the macroeconomic environment, rather than a fixed behavioral trait.

3.4.2 Sub-Samples

To examine temporal variation in attention parameters, we re-estimate our model over three sub-periods: 1996Q1–2004Q1 (Panel B), 2004Q2–2011Q4 (Panel C), and 2012Q1–2019Q4 (Panel D) in Table 2. This temporal disaggregation allows us to investigate whether attention parameters remain stable over time or evolve in response to changing economic conditions.

Our sub-sample analysis reveals relevant temporal dynamics in attention parameters for several countries, though most estimates demonstrate reasonable stability across periods. Turkey exhibits the most pronounced temporal variation, with attention parameters fluctuating substantially across sub-samples—likely reflecting episodes of macroeconomic instability experienced during the sample period. This finding reinforces our hypothesis that attention parameters respond endogenously to changes in the economic environment.

The sub-sample estimates demonstrate that attention varies not only across countries but also within countries over time in response to changing economic conditions. Moving from Panel B (1996Q1–2004Q1) to Panel D (2012Q1–2019Q4), we observe clear shifts in attention parameters for several economies. While the sub-period demarcations do not align perfectly with the Global Financial Crisis (GFC), the differences between Panels C and D suggest that this major economic disruption may have influenced attention patterns across countries.

Our estimates align well with both the empirical and theoretical literature on behavioral inattention. The cognitive discounting parameter estimates fall within the $[-0.15; +0.15]$ interval (with appropriate adjustment for the parameter space) documented by Coibion and Gorodnichenko (2015) and Bordalo et al. (2020). Our results are also broadly consistent with other Bayesian estimations of behavioral New Keynesian models in the literature (Ilabaca et al., 2020; Pfäuti and Seyrich, 2022), though our cross-country approach provides novel insights into systematic patterns of heterogeneity.

The sample and sub-sample periods encompass significant economic events, including the dot-com crisis and the GFC, making our analysis of temporal stability particularly informative. While we document meaningful differences in attention parameters both across countries and over time, our current analysis does not fully exploit the panel structure of our dataset. A more systematic analysis of how country characteristics relate to attention parameters represents an important avenue for future research. Such analysis could involve clustering countries based on attention patterns and examining common features within clusters.

3.5 Sensitivity Analysis

To assess the robustness of our estimates to calibration choices, we conduct sensitivity analysis on the Calvo parameter (θ), which governs price rigidity and plays a key role in the relationship between micro and macro attention parameters. We select two contrasting cases—the Eurozone and Turkey—representing economies with different structural characteristics and estimated attention levels. For each case, we vary θ by ± 0.1 from our baseline calibration ($\theta = 2/3$) and re-estimate the model.

Our analysis reveals a nuanced but modest relationship between nominal rigidities and attention parameters. When price flexibility increases in Turkey ($\theta = 2/3 - 0.1$), firms' attention to inflation rises from 0.96 to 0.99, approaching full rationality. Conversely, when price rigidity increases in the Eurozone ($\theta = 2/3 + 0.1$), attention to inflation shifts slightly from 0.83 to 0.82. Similar patterns emerge for other attention parameters: Turkish firms' attention to the output gap increases from 0.92 to 0.97 with greater price flexibility, while the Eurozone's declines from 0.89 to 0.85 with greater rigidity.

Despite these quantitative effects, the cross-country hierarchical patterns of attention remain qualitatively robust across calibrations. This stability is particularly noteworthy given the potential equilibrium feedback effects between price rigidities, macroeconomic volatility, and attention allocation. The theoretical mechanism operates through both direct effects on the Phillips curve slope (κ) and indirect effects via the endogenous relationship between price adjustment frequencies and optimal attention allocation.[10]

The relationship between price rigidities, price volatility, and attention parameters operates through multiple channels, as different values of θ mechanically affect the Phillips curve slope (κ), directly influencing the transmission of marginal costs to inflation (direct channel). In addition, modifications to θ could alter the frequency of price changes and thus price volatility, which our results suggest influences attention parameters (behavioral channel). Last but not least, the interaction between these channels may generate equilibrium feedback effects where attention and price-setting decisions are jointly determined (equilibrium effects). These channels are valid for any structural parameters.

Our sensitivity analysis indicates these effects are quantitatively modest in our sample. Turkey's attention parameters (m_x^f changing from 0.92 to 0.97, m_π^f from 0.96 to 0.99) and the Eurozone's (m_x^f changing from 0.89 to 0.85, m_π^f from 0.83 to 0.82) maintain their relative ordering even with adjusted θ values. Our analysis points toward a promising research agenda that involves building an integrated framework where structural parameters and attention are estimated jointly, thereby highlighting potential complementarities between pricing frictions and cognitive constraints.

4 Sources of Behavioral Inattention

Having established significant cross-country heterogeneity in attention parameters, we now investigate the economic determinants of this variation. This section systematically examines three key relationships: attention and macroeconomic volatility (Section 4.1), attention and shock volatility (Section 4.2), and attention and macroeconomic levels (Section 4.3). Our analysis traces how the economic environment shapes cognitive resource allocation, providing novel evidence on state-dependent attention that extends beyond experimental or survey-based approaches.

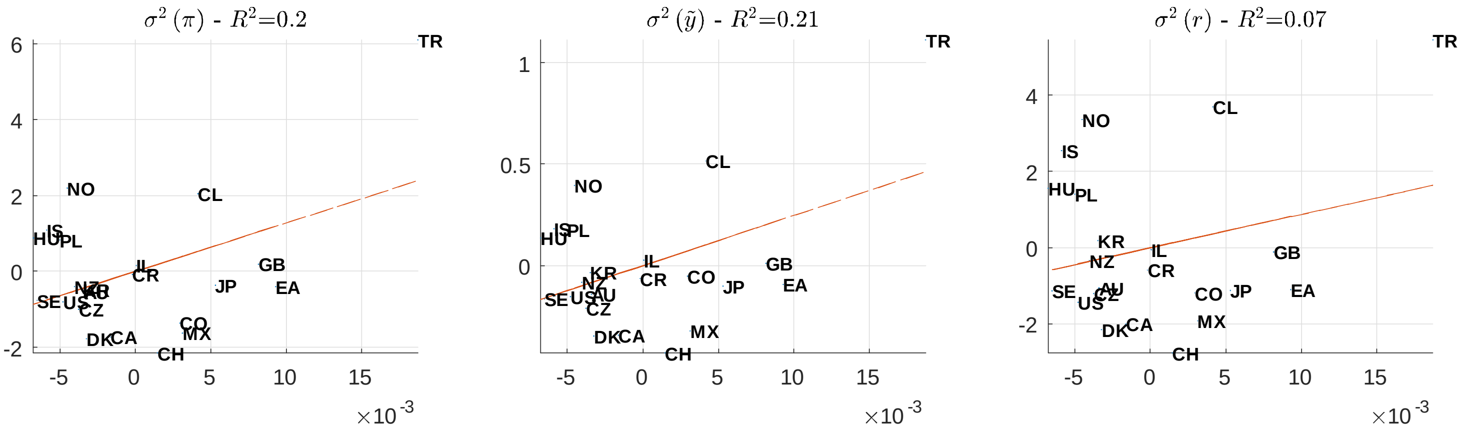
Two important caveats merit emphasis. First, the relationships we document should be interpreted as equilibrium correlations rather than causal effects. The behavioral economic literature suggests bidirectional influences: macroeconomic volatility affects optimal attention allocation (Sims, 2003a), while attention patterns simultaneously influence macroeconomic dynamics and amplify or dampen volatility (Gabaix, 2020). Second, we deliberately focus on reduced-form relationships rather than structural estimation of attention formation mechanisms, as the latter would require a more elaborate theoretical framework beyond our current scope. Despite these limitations, the empirical regularities we document provide valuable insights into how attention co-evolves with the macroeconomic environment.

[10]The analysis of these interaction effects, particularly the joint estimation of structural and behavioral parameters, represents an important avenue for future research. Such an approach could potentially explain some complex interplays between institutional features, such as price-setting mechanisms, and behavioral aspects like attention allocation.

4.1 Attention and Volatility

We begin by examining the relationship between macroeconomic volatility and cognitive attention—a central prediction of rational inattention theory. Figure 1 illustrates OLS regressions relating the estimated variances of key macroeconomic variables to the cognitive discounting parameter ($\bar{m}$).

Figure 1. Economic Volatility and $\bar{m}$.



Notes: σ^2 (.) represents the estimated variance. $\bar{m}$ (x-axis) and estimated variance (y-axis) are detrended for the regression. The Appendix presents additional results that further illustrate the relationship between attention and macroeconomic volatility.

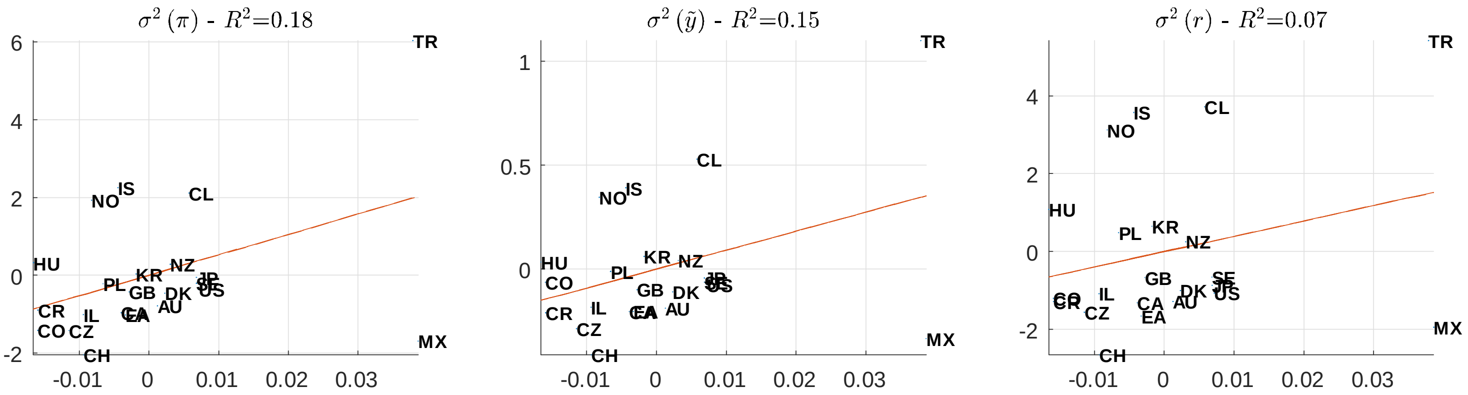
The results show strong positive correlations between macroeconomic volatility and the general cognitive attention parameter ($\bar{m}$). Countries experiencing greater variance in inflation, output gaps, and interest rates systematically exhibit higher levels of attention. This relationship is both statistically significant and economically important: inflation variance alone explains approximately 20% of cross-country variation in $\bar{m}$, while output gap variance explains 21%, and interest rate variance explains 7%. The pattern's consistency across all three panels provides compelling evidence for a fundamental link between economic stability and cognitive attention.

This finding offers strong empirical support for theories of rational inattention and salience. As Kahneman (2003) argues, even abstract concepts become more cognitively prominent when their manifestations are frequent and consequential. Macroeconomic volatility—transmitted through media coverage, personal financial experiences, and workplace dynamics—appears to heighten the cognitive accessibility of economic variables, leading agents to allocate greater attention to monitoring and processing economic information.

The cross-country distribution displays interesting patterns. High-volatility economies such as Turkey, Colombia, and Mexico cluster in the upper-right quadrant, exhibiting both high macroeconomic variance and elevated attention levels. Conversely, historically stable economies like Japan, Switzerland, and the Euro Area populate the lower-left quadrant, characterized by both low volatility and more attenuated attention. These patterns suggest that attention allocation responds systematically to the economic environment agents face, rather than reflecting fixed cultural or institutional factors.

To investigate whether this relationship extends to specific dimensions of attention, Figure 2 examines the connection between macroeconomic volatility and firms' specific attention to inflation (m^f_π).

Figure 2. Economic Volatility and m^f_π.



Notes: $\sigma^2(.)$ represents the estimated variance. m^f_π (x-axis) and estimated variance (y-axis) are detrended for the regression. The Appendix presents additional results that further illustrate the relationship between attention and macroeconomic volatility.

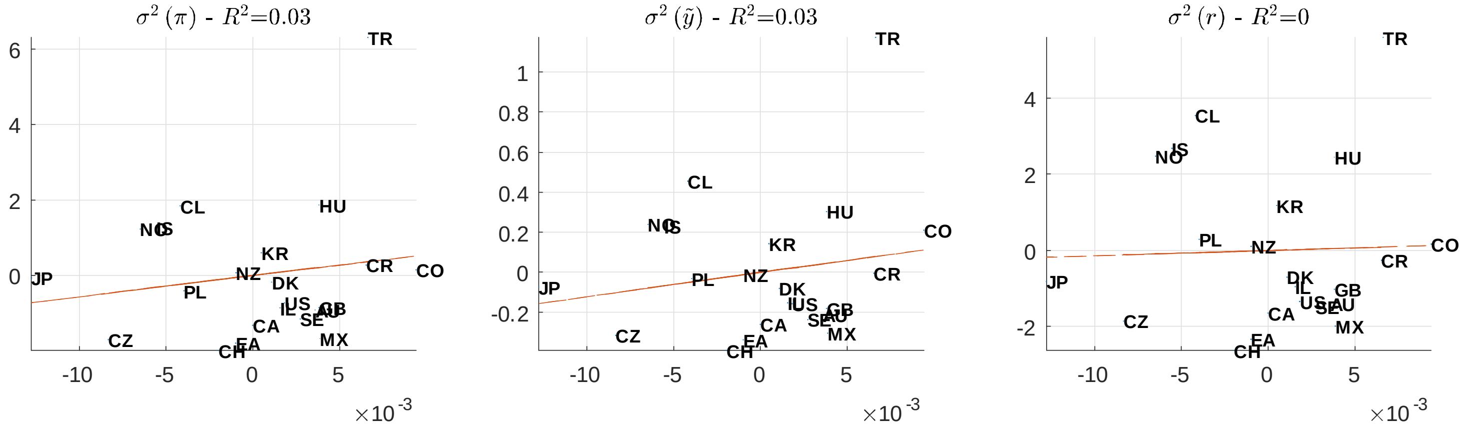
The relationship between macroeconomic volatility and firms' attention to inflation is remarkably strong. The leftmost panel shows that inflation variance alone explains 18% of cross-country variation in m^f_π. This finding directly supports the prediction from Maćkowiak and Wiederholt (2015)'s rational inattention model that firms optimally allocate more attention to variables with greater volatility. The middle panel further reveals that output gap volatility significantly predicts inflation attention ($R^2 = 0.15$), suggesting that firms recognize how real activity fluctuations often precede inflationary pressures and adjust their information processing accordingly.

The interest rate volatility panel shows a weaker but still positive relationship ($R^2 = 0.07$). This pattern is in line with the theoretical prediction that firms allocate relatively less attention to variables that affect them indirectly. While interest rates influence firms through financing and demand channels, these effects are more attenuated than direct price pressures, justifying more modest attention allocation to monetary policy fluctuations.

We similarly examine the relationship between macroeconomic volatility and firms' attention to the output gap (m^f_x) in Figure 3.

The positive relationship persists, though with somewhat lower explanatory power—inflation variance explains only 3% of cross-country variation in output gap attention, while output gap variance itself explains just 3%. This apparent disconnect highlights an important distinction: unlike inflation, the output gap is not directly observable to firms but must be inferred from multiple signals. Consequently, the relationship between output volatility and attention to output may involve more complex, non-linear dynamics not fully captured by our linear specification.

Figure 3. Economic Volatility and m_x^f.

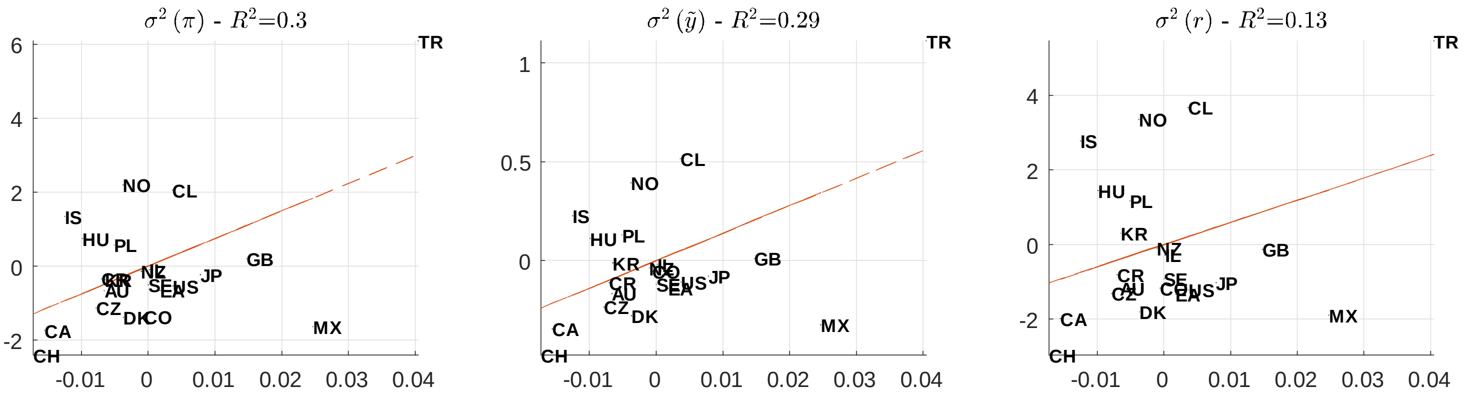


Notes: σ^2 (.) represents the estimated variance. m_x^f (x-axis) and estimated variance (y-axis) are detrended for the regression. The Appendix presents additional results that further illustrate the relationship between attention and macroeconomic volatility.

Despite these subtleties, the positive slope in all panels confirms that macroeconomic volatility enhances attention to all key variables, not just those experiencing direct volatility. This pattern suggests a generalized attention effect: economic instability increases vigilance toward the entire macroeconomic environment, not merely toward specific volatile variables.

Finally, we examine whether these micro-level relationships aggregate into macro-level patterns by analyzing the relationship between macroeconomic volatility and the aggregate firm attention parameter (M^f) in Figure 4.

Figure 4. Economic Volatility and M^f.



Notes: σ^2 (.) represents the estimated variance. M^f (x-axis) and estimated variance (y-axis) are detrended for the regression. The Appendix presents additional results that further illustrate the relationship between attention and macroeconomic volatility.

The relationship between macroeconomic volatility and aggregate firm attention (M^f) is remarkably strong. Inflation variance explains 30% of cross-country variation in M^f, while output gap variance explains 29%, and interest rate variance explains 13%. These explanatory powers substantially exceed those for the micro-level attention parameters, suggesting that macroeconomic volatility influences attention through multiple complementary channels that compound when aggregated.

The M^f parameter captures firms' overall attentiveness to forward-looking information in price-setting decisions. Its strong correlation with macroeconomic volatility across all specifications suggests that economic instability fundamentally alters how firms process information and form expectations—not merely which specific variables they track.

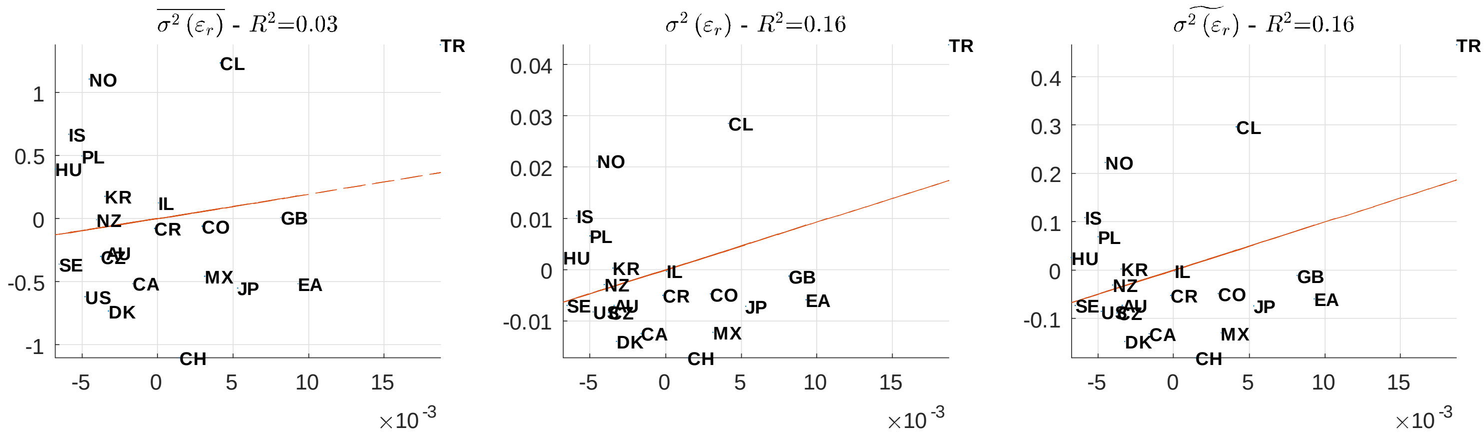
Our findings establish three key empirical regularities: (1) macroeconomic volatility is positively and robustly associated with attention allocation across countries; (2) this relationship holds for both micro-level and macro-level attention parameters; and (3) the relationship's strength varies across attention types, with inflation volatility exhibiting the most consistent connection to attention. These patterns support a state-dependent view of attention, where cognitive resource allocation responds optimally to the economic environment.

This evidence substantially extends the predominantly theoretical and experimental literature on rational inattention by documenting how attention varies systematically across diverse macroeconomic contexts. The findings suggest that stable economic environments may induce widespread cognitive inattention—a potential channel through which macroeconomic stability could paradoxically breed future instability by reducing vigilance.

4.2 Attention and Shock Volatility

Beyond observed macroeconomic outcomes, attention may respond to the volatility of underlying structural shocks that drive the economy. Figure 5 examines the relationship between the volatility of monetary policy shocks ($\varepsilon_{r,t}$) and the cognitive discounting parameter ($\bar{m}$).

Figure 5. Monetary Policy Shocks and $\bar{m}$.



Notes: $\overline{\sigma^2}(.)$ represents the estimated shock's posterior mean standard deviation, $\sigma^2(.)$ represents the estimated shock's posterior variance, and $\widetilde{\sigma^2}(.)$ represents the sup-inf spread of the estimated shock's standard error posterior mean. $\bar{m}$ (x-axis) and variances (y-axis) are detrended for the regression. The Appendix presents the results for all variables and shocks.

The figure shows a striking relationship: countries with more volatile monetary policy shocks systematically exhibit higher cognitive attention. This relationship holds across multiple measures of shock volatility: posterior mean standard deviation (left panel, $R^2 = 0.03$), posterior variance (middle panel, $R^2 = 0.16$), and the range of the posterior distribution (right panel, $R^2 = 0.16$). The substantially higher explanatory power of the latter two measures suggests that attention responds more strongly to the possibility of extreme policy surprises than to routine variability.

Countries like Turkey, Norway, and Chile, which experience substantial monetary policy variation, demonstrate higher attention levels compared to countries with more predictable monetary policy like Japan and the Euro Area. This pattern suggests that central bank predictability may paradoxically reduce economic agents' vigilance, potentially complicating policy transmission during regime changes.

The Appendix extends this analysis to other structural shocks: technology shocks ($\varepsilon_{a,t}$), preference shocks ($\varepsilon_{z,t}$), and cost-push shocks ($\varepsilon_{u,t}$). Technology and preference shocks exhibit strong positive correlations with attention parameters similar to monetary policy shocks, suggesting that unpredictability in productivity growth and consumer demand similarly enhances attention allocation.

Notably, cost-push shocks show weaker and less consistent relationships with attention. This anomaly may reflect two factors: First, most OECD countries have maintained low and stable inflation through credible inflation-targeting regimes during our sample period, reducing the relevance of pure inflationary disturbances. Second, cost-push shocks generate particularly complex dynamics—raising inflation while simultaneously reducing output—potentially making them harder for agents to interpret and respond to compared to other shock types.

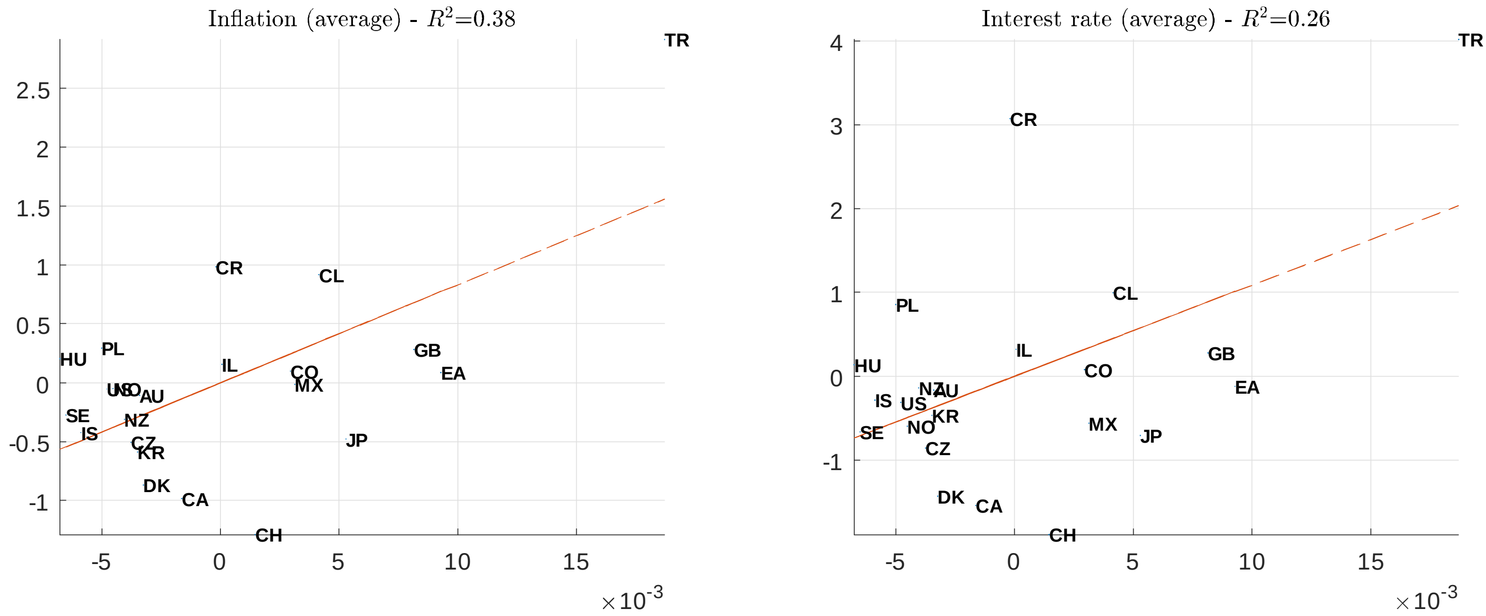
The strong relationship between structural shock volatility and attention complements our earlier findings regarding observed macroeconomic volatility. They suggest that economic environments characterized by greater unpredictability—whether in observed outcomes or underlying drivers—induce higher levels of attention from both households and firms. This reflects the core prediction of rational inattention theory: when the economic environment becomes more volatile or unpredictable, the expected welfare cost of inattention rises, justifying greater allocation of scarce cognitive resources to economic monitoring and information processing.

4.3 Attention and Levels

Beyond volatility, the absolute level of key macroeconomic variables may influence attention allocation. Behavioral economics suggests that higher nominal values may enhance the salience of economic variables through several channels: they receive greater media coverage, have larger impacts on household budgets, and create more consequential business planning environments. Figure 6 examines how average inflation and interest rate levels correlate with the cognitive discounting parameter ($\bar{m}$).

The figure also displays strong relationships: average inflation levels explain 38%

Figure 6. Inflation and Interest Rate Levels and $\bar{m}$.



Notes: average percentage variation based on quarterly data over the full sample. $\bar{m}$ (x-axis) and levels (y-axis) are detrended for the regression.

of cross-country variation in cognitive attention, while interest rate levels explain 26%. Countries with persistently higher inflation and interest rates—Turkey, Mexico, and Colombia—exhibit near-rational attention levels ($\bar{m}$ approaching 1), while countries with very low nominal rates—Japan, Switzerland, and the Euro Area—show substantially attenuated attention.

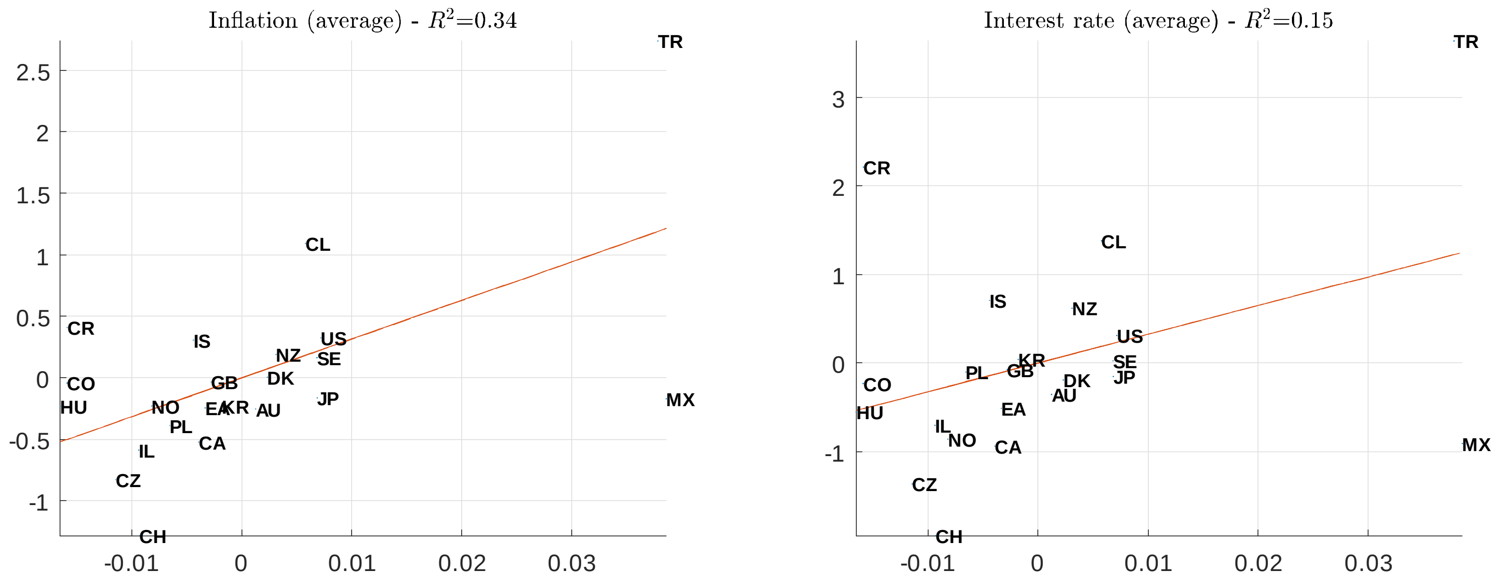
These patterns suggest that macroeconomic levels may be even more important than macroeconomic volatility in shaping attention allocation. This finding has important implications for economies operating in persistently low-inflation, low-interest-rate environments. Such regimes may induce widespread cognitive inattention to macroeconomic conditions, potentially complicating policy transmission and amplifying the impact of unexpected shifts in the macroeconomic environment.

The relationship between macroeconomic levels and firm-specific attention parameters reveals additional nuances. Figure 7 examines how inflation and interest rate levels correlate with firms' attention to inflation (m^f_π).

The relationship between inflation levels and firms' attention to inflation is particularly strong ($R^2 = 0.34$), while interest rate levels show a more modest association ($R^2 = 0.15$). The differential strength of these relationships suggests that firms' attention responds most strongly to variables that directly affect their operations; since inflation directly impacts pricing decisions while interest rates operate through more indirect channels, the stronger response to inflation levels is economically intuitive.

The cross-country distribution reveals an important pattern: the dispersion of m^f_π

Figure 7. Inflation and Interest Rate Levels and m_π^f.



Notes: average percentage variation based on quarterly data over the full sample. m_π^f (x-axis) and levels (y-axis) are detrended for the regression.

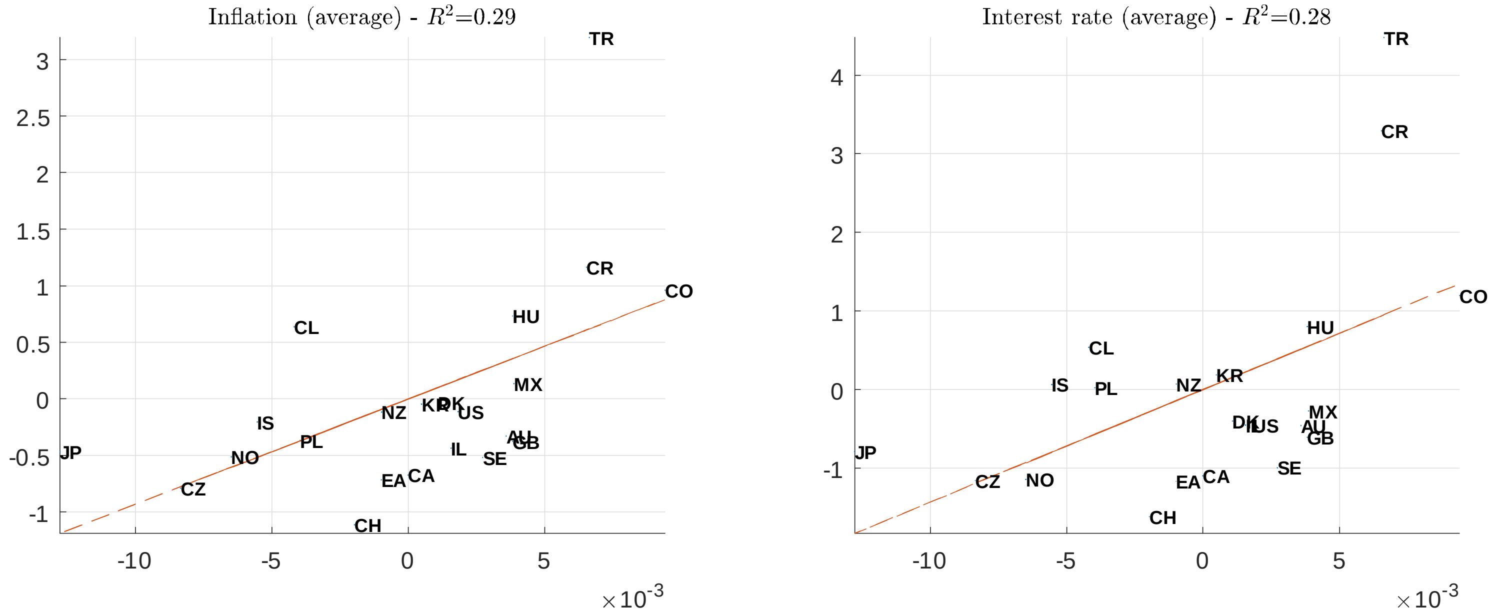
across countries is notably smaller than for the general cognitive parameter $\bar{m}$. This compressed distribution suggests that firms maintain a baseline level of inflation vigilance even in low-inflation environments, likely reflecting the critical importance of price-setting decisions for firm profitability. This interpretation aligns with evidence from Coibion and Gorodnichenko (2015) that firms typically allocate substantial information-processing resources to tracking inflation despite significant individual heterogeneity.

Figure 8 extends this analysis to firms' attention to the output gap (m_x^f), revealing equally strong relationships with both inflation levels ($R^2 = 0.29$) and interest rate levels ($R^2 = 0.28$).

This finding is particularly relevant given that the output gap is a theoretical construct not directly observable to firms. The strong association suggests that environments with higher nominal variables enhance attention to real economic conditions, not merely to nominal variables themselves. This broad enhancement of economic vigilance may reflect greater media coverage of economic conditions, more intensive business planning activities, or reduced opportunity costs of economic information processing in high-nominal environments.

The empirical regularities documented in this section substantially extend our understanding of state-dependent attention. They suggest that attention is not a fixed characteristic of economic agents but varies systematically with the economic environment. Specifically, we find robust evidence that attention increases with macroeconomic volatility (especially inflation volatility), structural shock volatility (especially monetary and technology shocks), and macroeconomic levels (especially inflation and interest rates levels).

Figure 8. Inflation and Interest Rate Levels and m_x^f.



Notes: Average percentage variation based on quarterly data over the full sample. m_x^f (x-axis) and levels (y-axis) are detrended for the regression.

5 Attention Drivers

Having established robust correlations between attention and macroeconomic conditions, we now investigate the deeper structural determinants of behavioral inattention. This section employs panel regression techniques to identify factors that influence attention allocation, extending beyond the cross-sectional relationships documented in Section 4. We focus on three categories of potential determinants: institutional factors, macroeconomic surprises, and active information acquisition behavior.

To examine these relationships, we construct a panel dataset covering two sub-periods (2004Q2–2011Q4, and 2012Q1–2019Q4) for our OECD sample.[11] This temporal disaggregation allows us to exploit not only cross-country variation but also within-country changes in attention over time, providing additional identifying variation and allowing for the inclusion of country fixed effects to control for time-invariant unobservables.

We collect institutional quality data from the World Bank's Worldwide Governance Indicators (WGI), which measure multiple dimensions of governance quality including corruption control, government effectiveness, political stability, regulatory quality, rule of law, and accountability. These indicators are constructed by aggregating survey responses from enterprises, citizens, and expert assessments

[11] We exclude the 1996Q1–2004Q1 period due to the unavailability of Google Trends data, which begins only in 2004. Additionally, our analysis includes 19 countries, as we exclude the Euro Area, Hungary, and Mexico due to data limitations. The OECD does not provide forecast data for Hungary and Mexico, while Google Trends data are not available for the Euro Area.

(Kaufmann et al., 2011), providing internationally comparable metrics of institutional quality. We average these indicators across each sub-period to construct our panel measures.

Additionally, we extract monthly Google Trends data from 2004 to 2019 on search intensity for four macroeconomic-related topics: CPI, GDP, price, and inflation. These search intensity metrics serve as proxies for active information acquisition behavior by economic agents. We also compile data on realized and forecast macroeconomic outcomes (inflation, GDP growth, and interest rates) to compute "surprise" components—the difference between expected and realized values—which capture unanticipated macroeconomic developments that may trigger shifts in attention allocation.[12]

To mitigate multicollinearity concerns, we conduct a systematic cross-correlation analysis to identify and eliminate highly correlated predictors (see the Appendix for detailed correlation matrices). Our final explanatory variable set includes: (i) government effectiveness, (ii) political stability, (iii) inflation surprises, (iv) GDP surprises, (v) interest rate surprises, (vi) inflation volatility, (vii) GDP volatility, (viii) interest rate volatility, and (ix-xii) Google Trends search intensity for CPI, GDP, price, and inflation.

We estimate panel regressions with country and time fixed effects, following the specification:

$$y_{it} = \alpha + \beta X_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \tag{8}$$

where y_{it} represents estimated attention parameters (M, M^f, m_x^f, and m_π^f), X_{it} is the vector of explanatory variables, γ_i and δ_t are country and time fixed effects, respectively, i indexes OECD countries, and t indexes sub-periods. The coefficient vector β captures the relationship between explanatory variables and attention parameters, controlling for country-specific time-invariant factors and common temporal shocks.

Our specification includes fixed effects to address potential endogeneity concerns stemming from omitted time-invariant country characteristics and common time trends. However, we acknowledge that these relationships should be interpreted as equilibrium correlations rather than strictly causal effects, given the potential for reverse causality and time-varying omitted variables.

[12]The difference between forecast/expected and realized values represents the surprise component for inflation, growth, and interest rates. Both data sets are sourced from the OECD and are measured as annual percentages. Specific data series were obtained from the following OECD pages: Inflation (`https://www.oecd.org/en/data/indicators/inflation-forecast.html`), Interest Rates (`https://www.oecd.org/en/data/indicators/short-term-interest-rates-forecast.html`), and GDP (`https://www.oecd.org/en/data/indicators/real-gdp-forecast.html`). According to the OECD, expected values are derived from forecast data generated through a comprehensive assessment of the economic climate at both the country and global levels. These forecasts incorporate a combination of model-based analyses and statistical indicator models to provide a structured outlook on macroeconomic conditions.

5.1 Attention and Google Trends Data

We examine the relationship between attention parameters and Google Trends search intensity, which captures active information-seeking behavior by economic agents. While several studies employ Google Trends data as a direct proxy for attention (Korenok et al., 2025), we adopt a more nuanced approach following Da et al. (2011), who establish search activity as a revealed-preference measure of attention allocation. This distinction is theoretically important, as Da et al. (2011) demonstrate that information acquisition through search represents an active cognitive engagement with economic variables, but may not fully capture the subsequent information processing that shapes expectation formation.

The theoretical relationship between information acquisition (measured by search intensity) and cognitive attention allocation (captured by our estimated parameters) is anchored in rational inattention theory (Sims, 2003b; Maćkowiak and Wiederholt, 2015), which posits that agents optimally decide how much information to acquire and subsequently how to process this information.[13] Da et al. (2011) provide empirical evidence for this framework by documenting that investors' search activity predicts subsequent market behavior, establishing search intensity as a valid measure of attentional allocation that precedes economic decision-making.

Using monthly Google Trends data from 2004 to 2019, we construct search intensity measures for four macroeconomic-related concepts: CPI, GDP, price, and inflation. Following the methodological approach of D'Amuri and Marcucci (2017), we normalize these measures within countries and aggregate them to match our three sub-periods, ensuring comparability across our panel structure while preserving intertemporal and cross-sectional variation.[14]

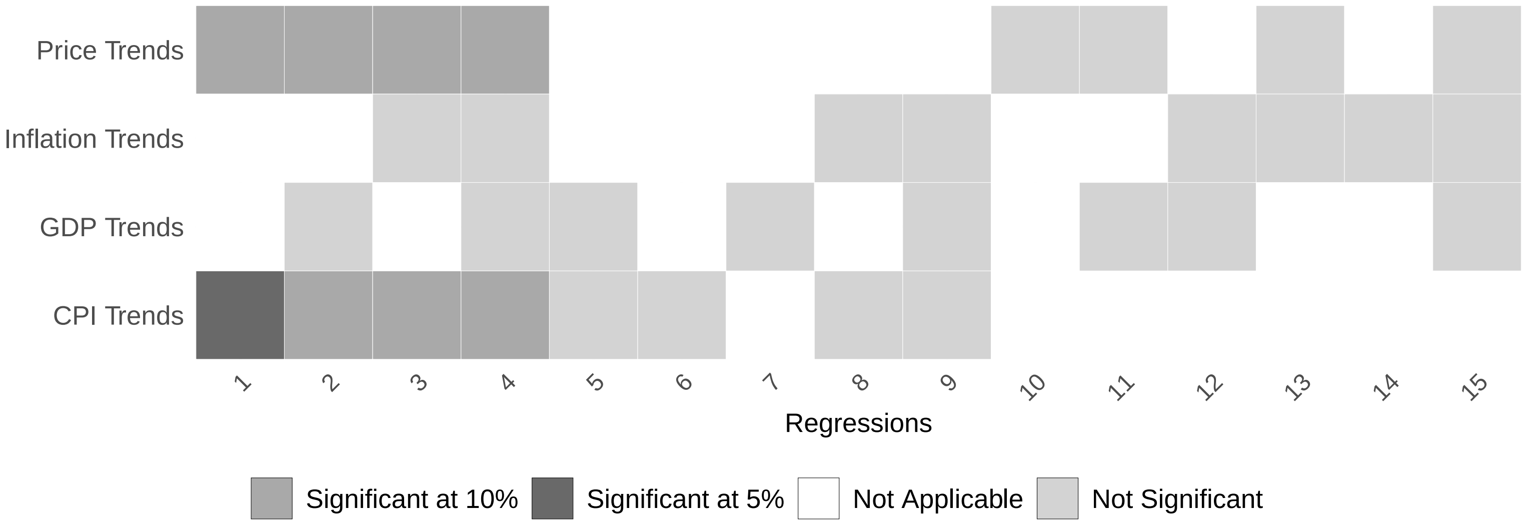
We estimate 15 regressions following Equation 8, using all possible combinations of four Google Trends variables as predictors. Figure 9 displays the results for household attention (M), using a heatmap to visualize coefficient significance across specifications.

The heatmap reveals a systematic pattern: CPI-related search intensity exhibits the strongest and most consistent relationship with household attention (M), achieving statistical significance at the 5% level in the first specification and at the 10% level in several others. This finding aligns with Coibion and Gorodnichenko (2015), who show that households form inflation expectations primarily through experiences with frequently purchased items, which heavily influence CPI. The positive coefficient indicates that greater public interest in consumer prices—revealed through active

[13] This distinction reflects the two-stage process of expectation formation in rational inattention models: agents first decide how much information to acquire, then determine how to process and incorporate this information into economic decisions.

[14] The relationship between search intensity and attention could go both ways. A negative sign might suggest that Google Trends primarily capture the initial information-gathering stage rather than the depth of information processing. For instance, households might search intensively for "inflation" data immediately after a shock, spiking Google Trends, yet still underweight that information when forming expectations as the shock subsides. Conversely, a positive sign could indicate inherent uncertainty, leading to higher search intensity as individuals struggle to effectively update their beliefs in challenging economic environments.

Figure 9. Google Trends Data on Dependent Variable M.



Notes: this heatmap displays the 15 regressions using only the selected Google Trends explanatory variables.

searches—correlates with higher cognitive attention to general economic conditions.

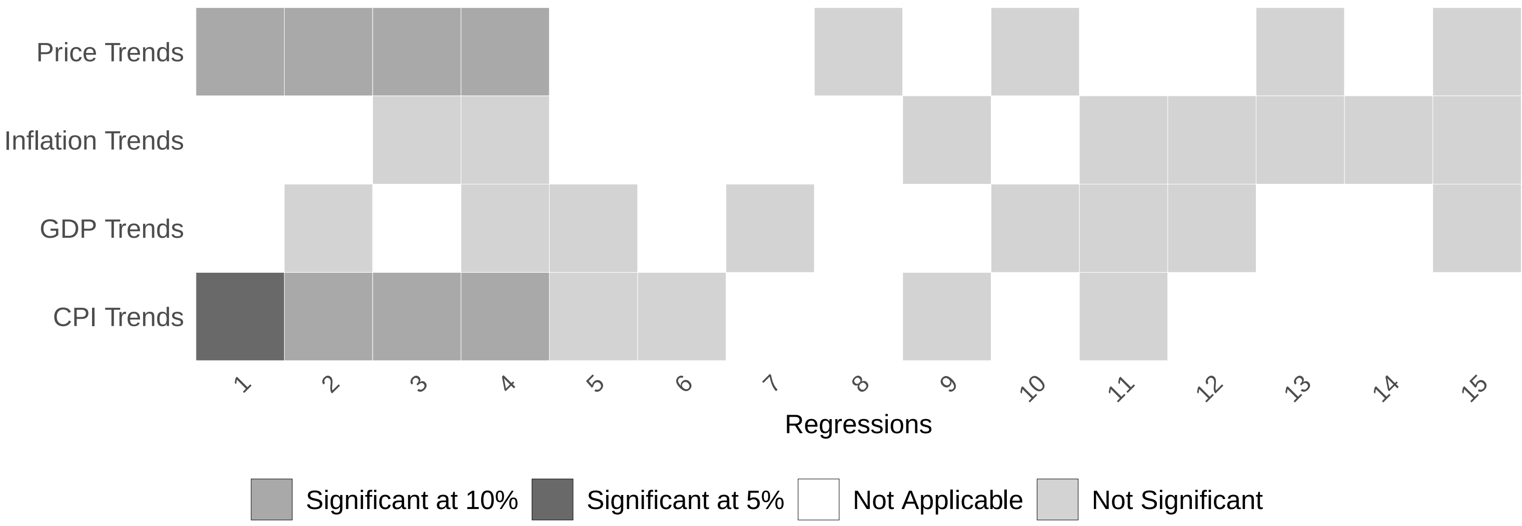
Price and inflation search trends show less consistent but still meaningful relationships with attention, achieving significance in several specifications. This pattern suggests that attention to these concepts may be more episodic or context-dependent than attention to the broader CPI measure. GDP-related searches demonstrate the weakest relationship with household attention, consistent with the observation that macroeconomic aggregates like GDP are abstract concepts with limited direct salience for most households compared to prices (Carroll, 2003).

Figures 10 through 12 present analogous results for firm attention parameters (M^f, m_x^f, and m_π^f), revealing similar patterns but with notable differences in the strength and consistency of relationships.

For aggregate firm attention (M^f) in Figure 10, CPI searches again show the strongest relationship, with price searches also demonstrating consistent significance. This pattern suggests that firms' information processing, like households', is particularly responsive to price-related information flows. For output gap attention (m_x^f) in Figure 11, CPI searches maintain significance in several specifications, though with generally weaker patterns than for aggregate attention measures. Notably, no Google Trends variables achieve statistical significance in explaining firms' inflation attention (m_π^f) in Figure 12.

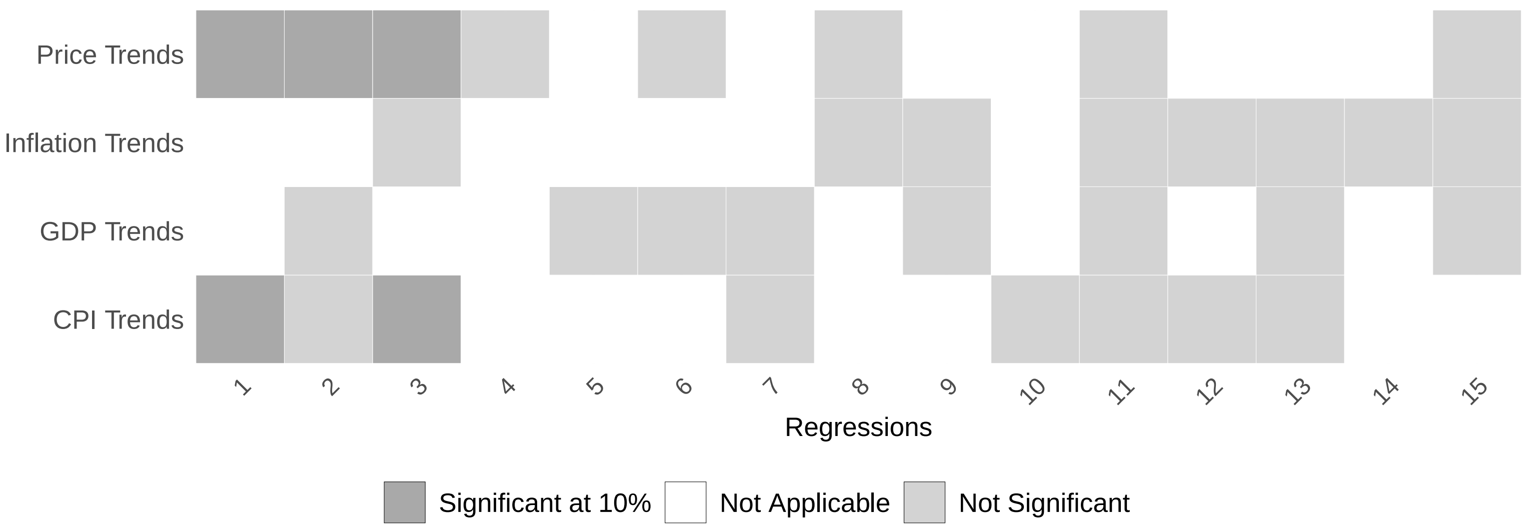
This difference in significance patterns across attention types suggests two important insights. First, information acquisition behavior appears more strongly related to general cognitive processing parameters (M and M^f) than to variable-specific attention measures (m_x^f and m_π^f). This aligns with theoretical models where general cognitive capacity constrains overall information processing, while specific attention allocation responds more to volatility and salience of individual

Figure 10. Dependent Variable: M^f.



Notes: this heatmap displays all the 15 regressions using only the selected Google Trends explanatory variables.

Figure 11. Dependent Variable: m_x^f.

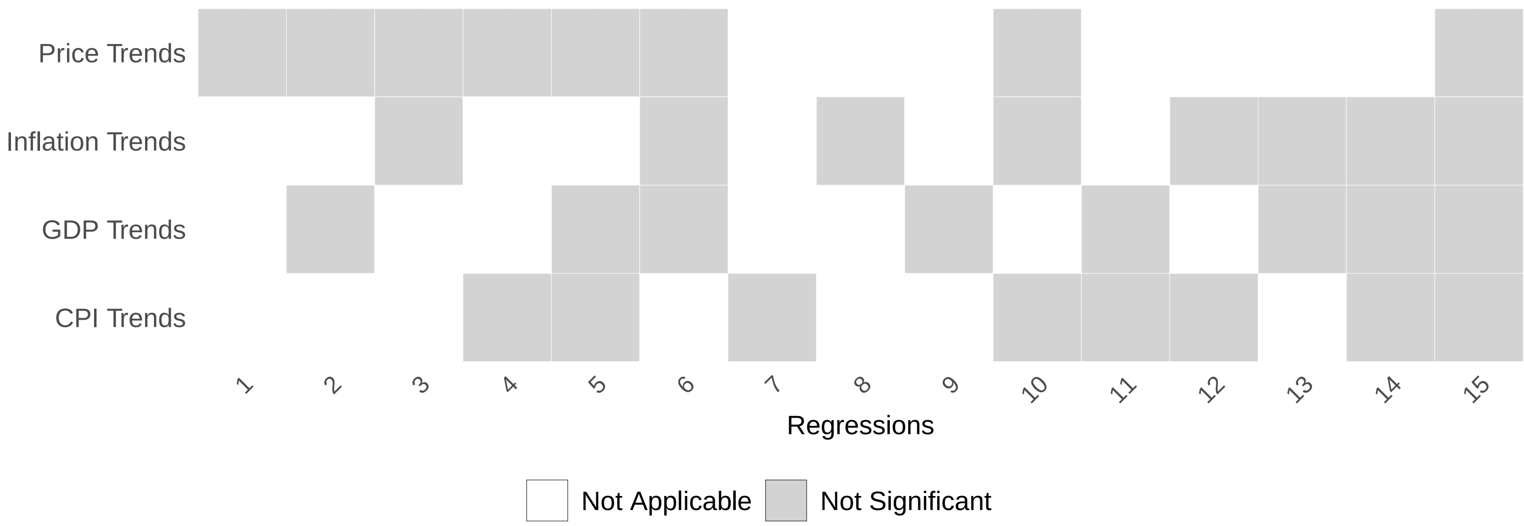


Notes: this heatmap displays all the 15 regressions using only the selected Google Trends explanatory variables.

variables (Sims, 2003b). Second, the weaker relationship between search activity and firms' variable-specific attention may reflect firms' use of specialized information sources beyond general web searches, such as professional forecasts, industry reports, and dedicated analysts.

These results establish that active information acquisition behavior correlates positively with cognitive attention parameters, particularly for more general measures of attention. The relationship appears strongest for price-related searches,

Figure 12. Dependent Variable: m^f_π.



Notes: this heatmap displays all the 15 regressions using only the selected Google Trends explanatory variables.

suggesting that price information may be especially salient in shaping economic vigilance. However, these search variables explain only a modest portion of variation in attention, indicating that other factors likely play important roles in determining attention allocation. This limited explanatory power is consistent with theoretical models that distinguish between information acquisition and information processing as separate components of expectation formation (Woodford, 2003).

5.2 Determinants of Behavioral Inattention

To analyze potential attention determinants, we expand our analysis to include institutional quality measures, macroeconomic surprise variables, and volatility measures alongside Google Trends data. This broader set of potential determinants allows us to assess the relative importance of institutional, informational, and volatility factors in shaping attention allocation.

We estimate 4,095 regressions—all possible combinations of our 12 explanatory variables—and select the 15 best-performing specifications based on a weighted combination of Adjusted R^2 and AIC.[15] Figure 13 presents results for household attention (M), with analogous results for firm attention parameters (M^f, m^f_x, and m^f_π) shown in Figures 14 through 16.

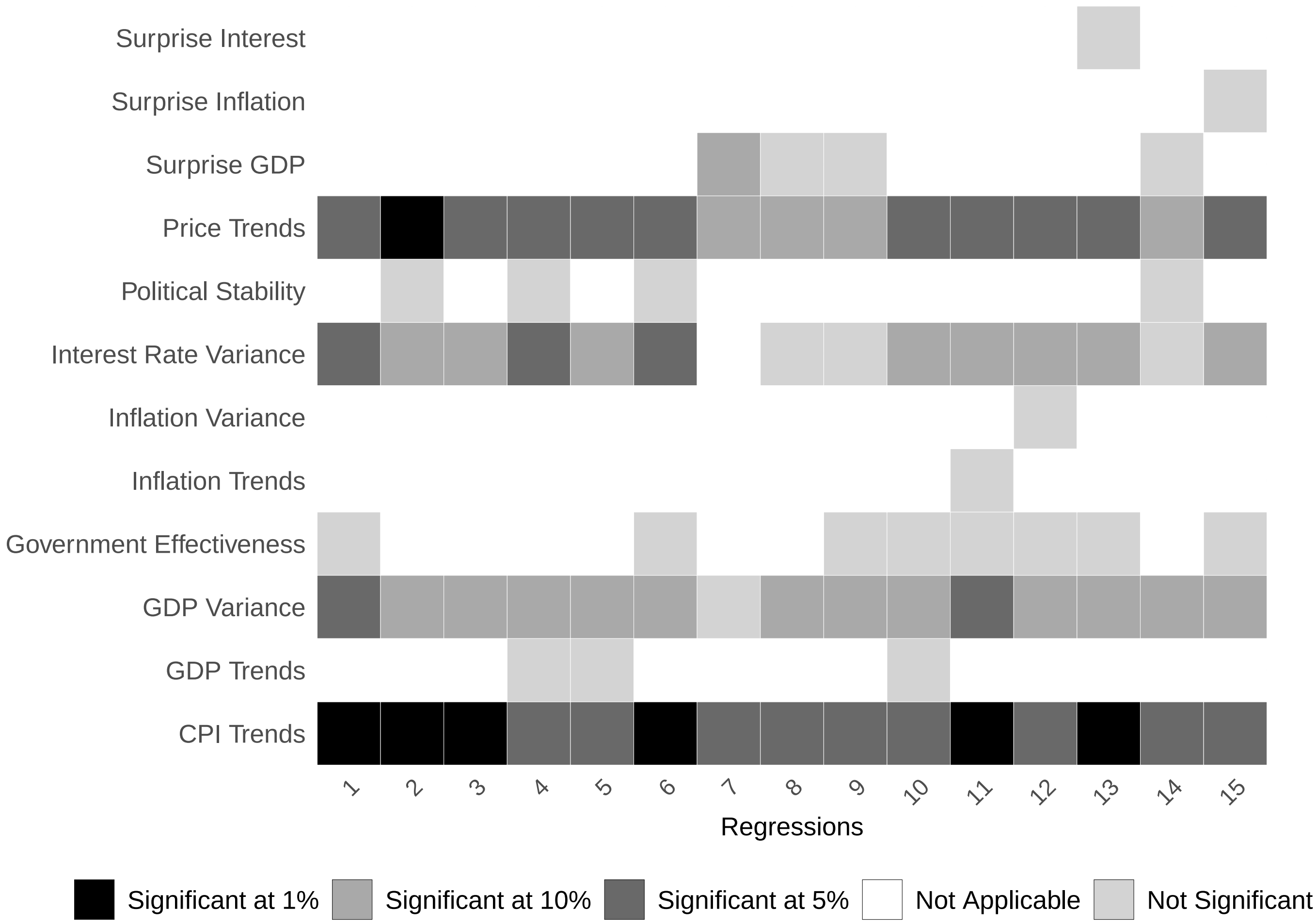
Figure 13 reveals that CPI and price trends emerge as the most consistently significant determinants of household attention, achieving statistical significance at the 5% level in the majority of specifications, with CPI Trends reaching the 1% significance level in multiple cases. This finding reinforces our earlier observation

[15]Regressions are ranked using normalized Adjusted R-squared and Akaike Information Criterion (AIC) metrics, combined into a weighted score, with the top 15 highest-scoring models selected.

regarding the importance of price-related information seeking for household attention allocation. GDP variance also demonstrates robust significance across specifications, suggesting that volatility in real economic activity substantially influences household attentiveness.

Interest rate variance appears significant in several specifications, though with less consistency than the price-related search variables. This pattern suggests a hierarchy of attention determinants, with price-related information flows and GDP variance playing primary roles, while monetary policy variability exerts a secondary influence. Notably, government effectiveness displays statistical significance for household attention in only a few specifications, suggesting a more limited role than anticipated by some theoretical frameworks that link institutional quality with attention.

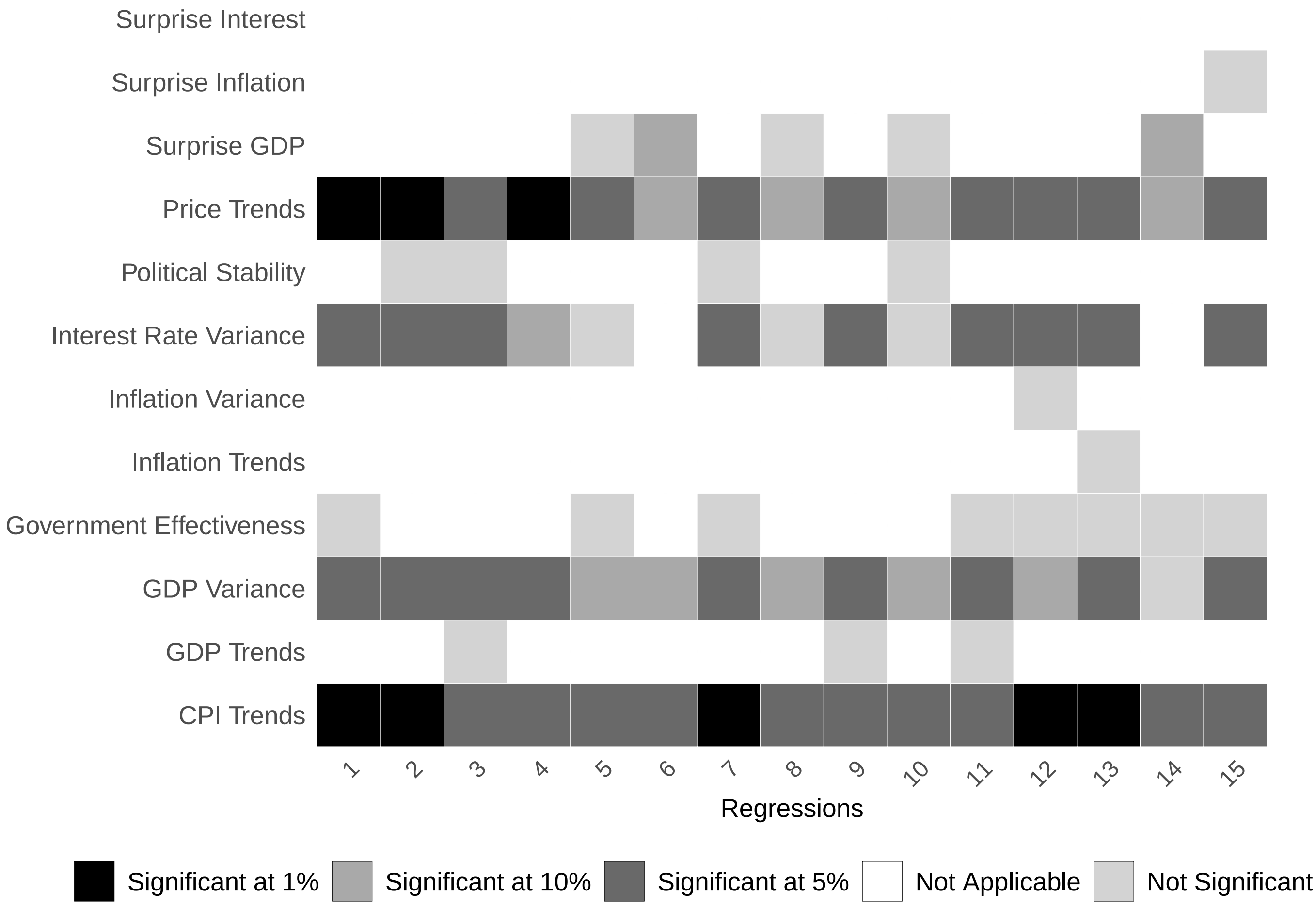
Figure 13. Dependent Variable: M.



Notes: this heatmap displays the best 15 regressions according to the weighted criteria for AIC and Adjusted R^2, using all of the selected explanatory variables (in addition to Google Trends data).

For aggregate firm attention (M^f) in Figure 14, both CPI and price trends again demonstrate significant relationships, with CPI trends reaching the 1% significance threshold in multiple specifications. This consistency across agent types suggests that price-related information seeking constitutes a fundamental determinant of economic vigilance for both households and firms. GDP variance maintains robust significance across specifications for firm attention, paralleling its importance for household attention. Interest rate variance exhibits more consistent significance for firms than for households, potentially reflecting the greater relevance of financing conditions for corporate decision-making. Measures of institutional quality, especially government effectiveness, exhibit only marginal significance in explaining aggregate firm attention. While this finding partially contradicts theoretical frameworks that underscore governance's impact on the information environment, it is consistent with the pattern observed for household attention. This suggests that, within our empirical framework, more immediate economic causes, such as price trends, volatility, and macroeconomic surprises, exert a greater influence on attentional behavior.

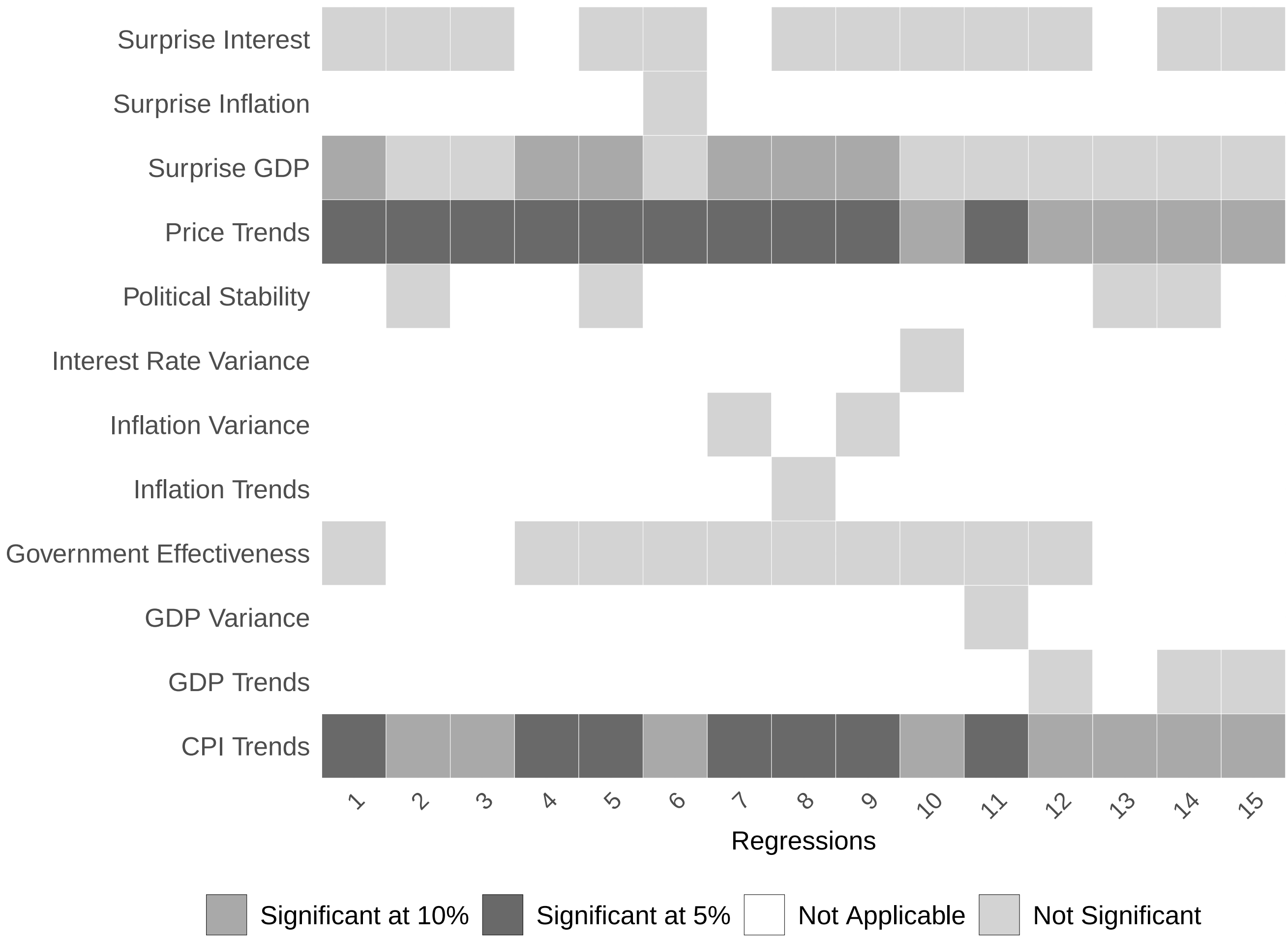
Figure 14. Dependent Variable: M^f.



Notes: this heatmap displays the best 15 regressions according to the weighted criteria for AIC and Adjusted R^2, using all of the selected explanatory variables (in addition to Google Trends data).

The results for firms' attention to the output gap (m_x^f), shown in Figure 15, reveal a distinct pattern relative to the aggregate attention measures discussed above. Google Trends indicators for price and CPI terms emerge as the most consistently significant variables, suggesting that firm-level perceptions of real activity are influenced by the intensity of price-related information seeking. Surprise GDP also demonstrates moderate statistical significance in several specifications, indicating that firms adjust their attention to output dynamics in response to unexpected changes in aggregate demand. While variables such as government effectiveness and political stability are not statistically significant across most regressions, their recurrent inclusion among top models suggests a possible—though limited—correlational role. Similarly, the influence of macroeconomic volatility appears diminished in this specification, implying that firm attention to the output gap is more sensitive to contemporaneous informational shocks and current signal salience than to variance structures.

Figure 15. Dependent Variable: m_x^f.



Notes: this heatmap displays the best 15 regressions according to the weighted criteria for AIC and Adjusted R^2, using all of the selected explanatory variables (in addition to Google Trends data).

Figure 16 presents robust evidence that firms' inflation-related attention (m_π^f) is shaped by a combination of real activity shocks, institutional quality, and macroeconomic volatility. GDP surprises are statistically significant across all specifications, suggesting that firms systematically adjust their inflation monitoring in response to unexpected output fluctuations. This supports the idea that attention is dynamically reallocated when new information deviates from expectations, a core prediction of rational inattention models.

Institutional quality, particularly government effectiveness, also plays a consistent role, with significance at the 5% level across most specifications. This aligns with the theoretical results of Leeper et al. (2013), arguing that institutional strength enhances the clarity and predictability of policy signals, thereby incentivizing agents to pay closer attention. When institutions are credible and policy frameworks transparent, the marginal value of processing economic signals rises, leading to more attentive behavior. In contrast, weak institutional environments may obscure the informational content of signals, rationalizing lower attention. Additionally, price trends and political stability emerge as relevant predictors in several specifications, while surprise inflation, surprise interest, and variance measures, particularly for interest rates and inflation, also show significant correlation patterns, suggesting that firms' inflation expectations are shaped by both second-moment dynamics and short-term information shocks.

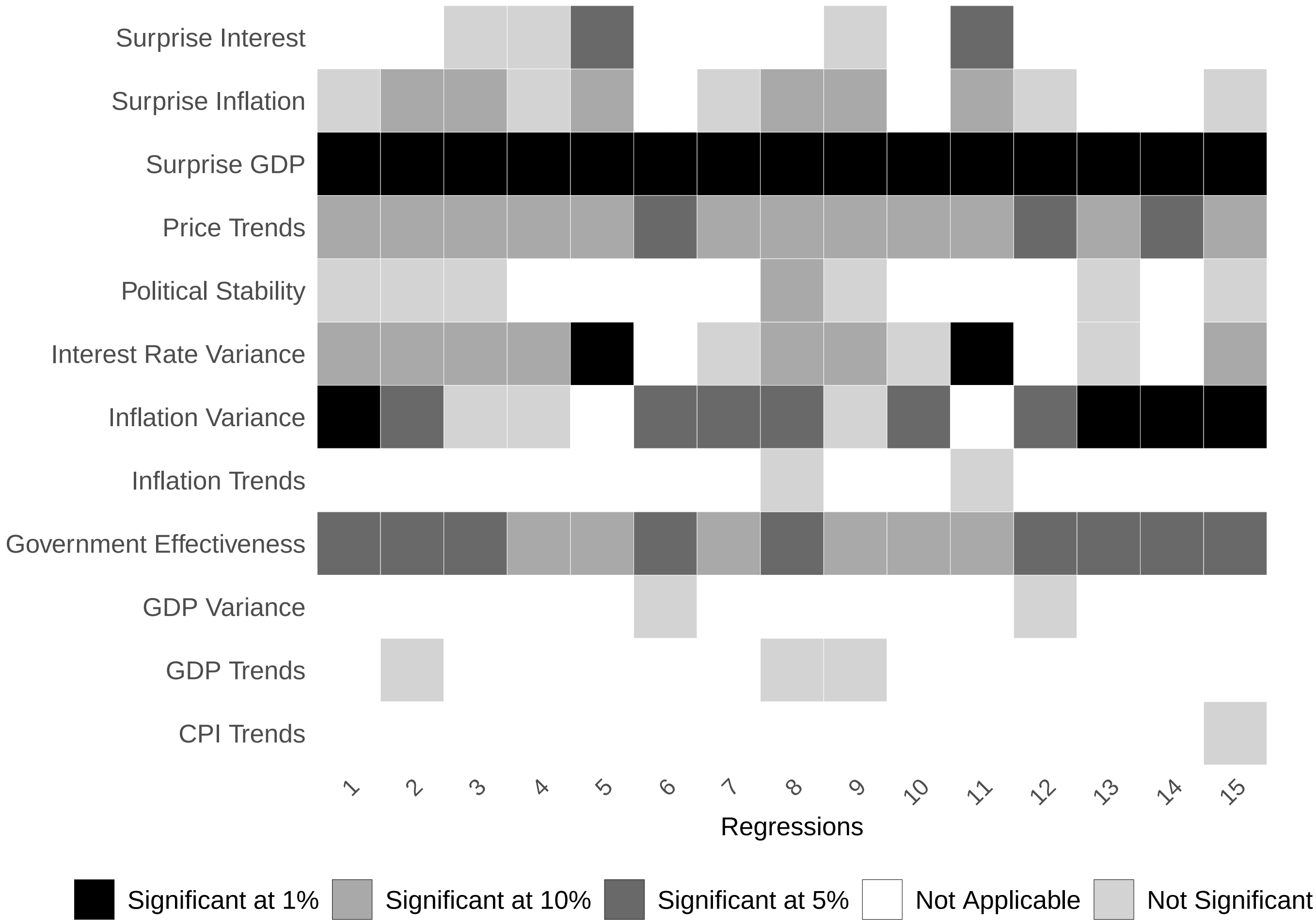
The relatively high sensitivity of firm inflation attention to institutional and volatility indicators, compared to household attention, reinforces the view that firms allocate cognitive resources more systematically, especially when misreading signals entails direct financial costs. This distinction is consistent with models in which firms process information more actively than households and adjust their attention based on both perceived credibility and the expected return to information (Maćkowiak and Wiederholt, 2015).

These panel regression results substantially extend our understanding of attention determinants beyond the cross-sectional relationships documented earlier. Four key empirical regularities emerge with important theoretical implications. First, price-related information seeking, measured through CPI and price trends, consistently influences both household and firm attention across specifications. This finding provides empirical support for theoretical models emphasizing the role of active information acquisition in expectation formation (Da et al., 2011).

Second, macroeconomic volatility, especially GDP variance, systematically enhances general cognitive attention, with particularly pronounced effects on household and aggregate firm attention. This finding provides panel-data confirmation of the cross-sectional patterns documented in Section 4 and further substantiates the state-dependent nature of attention allocation.

Third, surprise movements in macroeconomic variables (e.g., GDP surprises) correlate with inflation-specific attention parameters, providing novel evidence for theoretical models of state-dependent attention (Maćkowiak and Wiederholt, 2015). These surprise effects suggest that attention allocation responds dynamically to unexpected developments, introducing an additional source of state-dependence beyond average volatility levels.

Figure 16. Dependent Variable: m_{π}^{f}.



Notes: this heatmap displays the best 15 regressions according to the weighted criteria for AIC and Adjusted R^2, using all of the selected explanatory variables (in addition to Google Trends data).

Fourth, institutional quality plays a nuanced role in attention determination, with government effectiveness showing particular relevance for firms' inflation-specific attention while exerting limited influence on other attention parameters. This pattern suggests that institutional credibility may matter most for price-setting decisions, consistent with theories linking central bank independence and credibility to inflation expectations management (Leeper et al., 2013).

These findings suggest that attention allocation responds to the economic environment through multiple complementary channels: active information seeking about prices provides a foundation for general economic vigilance, macroeconomic volatility establishes baseline attention levels, surprise developments trigger reassessments of variable-specific attention, and institutional quality shapes the signal extraction problem facing economic agents. The distinct determinant patterns across different types of attention further suggest that attention allocation is a multidimensional process, with agents potentially employing different attention strategies for different economic variables based on their relative importance and informational characteristics.

While our panel approach with fixed effects addresses some potential endogeneity concerns, we acknowledge that causal identification remains challenging. Future research might leverage natural experiments, instrumental variables, or structural modeling approaches to more precisely isolate the causal determinants of attention allocation. Nevertheless, the robust correlations documented here provide valuable insights into how attention co-evolves with the economic environment, advancing our understanding of expectation formation under bounded rationality.

6 Policy Implications

The cross-country heterogeneity in attention parameters documented in this paper has significant implications for monetary policy transmission. Our estimates display that policy effectiveness varies with the economic environment, introducing state-dependent dynamics not captured in standard models with fixed attention parameters.

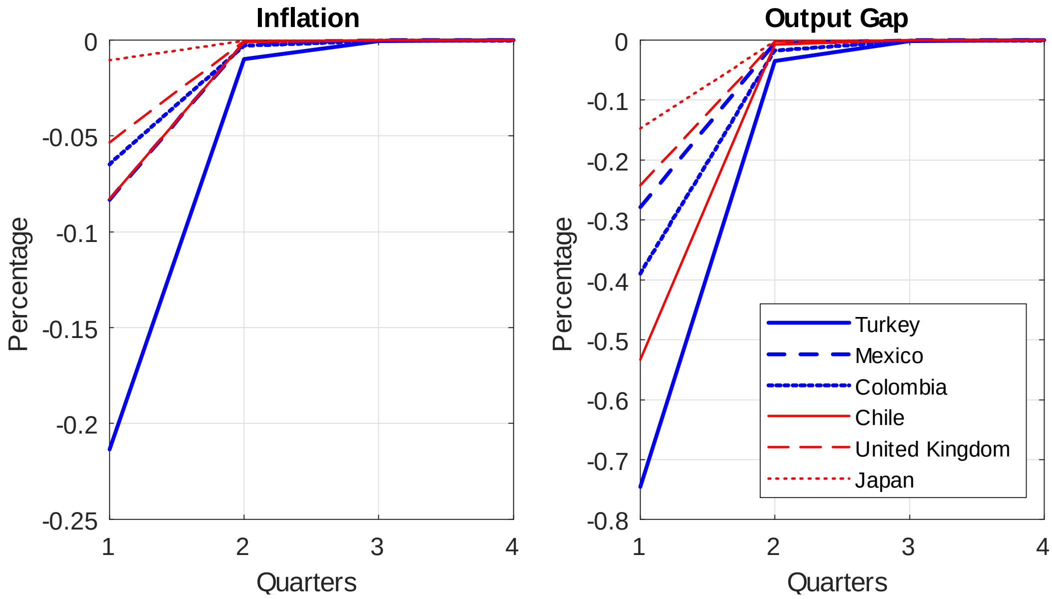
The impulse response functions in Figure 17 illustrate this state dependence empirically. Following an identical monetary policy shock, high-attention economies (Turkey, Mexico, Colombia) experience markedly larger and more persistent responses than low-attention economies (Chile, UK, Japan). Specifically, a 100 basis point monetary tightening in high-attention countries generates an approximately 20 basis point reduction in inflation and an 80 basis point contraction in the output gap at peak impact, while low-attention economies exhibit responses roughly half as large. This systematic difference in transmission strength challenges the conventional approach of applying uniform policy frameworks across different economic contexts.

Our findings suggest a previously unrecognized policy trade-off: macroeconomic stabilization, while desirable in itself, may reduce attention to economic variables, potentially attenuating future policy effectiveness. This creates a dynamic feedback loop where policy actions affect volatility, which influences attention, which then shapes subsequent policy transmission. Central banks thus face a more complex optimization problem than standard models imply, they must consider not only the immediate effects of their actions but also how these actions shape the attention environment that will condition future policy transmission.

For practical implementation, our results suggest potential benefits from state-contingent policy rules that adjust to prevailing attention regimes. During periods of high stability and low attention, policy actions may need to be more aggressive to achieve desired outcomes. Conversely, in volatile periods with heightened attention, more moderate interventions may suffice. The calibration of these state-contingent rules would depend on the estimated attention parameters for a particular economy.

The relationship between institutional quality and attention has particularly important implications for developing economies. Our finding that government

Figure 17. Responses to Monetary Policy Shocks.



Notes: impulse response functions to a 1% positive monetary policy shock for the three countries with the highest (Turkey, Mexico and Colombia, respectively) and lowest (Chile, United Kingdom, and Japan, respectively) general myopia ($\bar{m}$) levels.

effectiveness predicts attention levels suggests potential complementarities between institutional reforms and monetary policy effectiveness. Countries with weak governance institutions may face doubly challenging monetary policy environments: not only do they typically experience greater macroeconomic volatility, but weak institutions may also compromise the effectiveness of policy transmission by reducing the signal value of economic information, thereby discouraging attention allocation.

For inflation-targeting central banks operating in persistently low-inflation environments, our results raise important strategic questions. The strong positive correlation between nominal variable levels and attention suggests that prolonged periods of low inflation may induce widespread inattention to monetary policy signals. This dynamic may help explain the challenges many advanced economies have faced in generating inflation expectations despite unconventional monetary accommodation. While strictly maintaining a low inflation target remains theoretically optimal under rational expectations, our behavioral framework suggests potential benefits from occasionally permitting moderate inflation fluctuations to preserve attention to monetary policy. This perspective aligns with the conclusion that some inflation variability may be optimal under sticky information (Mankiw and Reis, 2002).

Communication strategies represent another channel through which central banks might influence attention dynamics. Our finding that surprise macroeconomic developments significantly affect attention allocation suggests that well-designed communication "surprises" could potentially enhance attention to policy. However, this approach carries risks of credibility loss if perceived as manipulation.

For international policy coordination, attention heterogeneity introduces additional complexity. Our results suggest that identical global shocks will generate asymmetric responses across countries with different attention regimes, complicating international policy coordination efforts. This heterogeneity underscores the potential value of tailoring policy advice to country-specific attention characteristics rather than prescribing uniform approaches.

The documented relationship between attention and policy effectiveness aligns with the theoretical prediction that optimal monetary policy depends critically on firms' attention to aggregate conditions (Paciello and Wiederholt, 2014). Our empirical findings extend their theoretical work by documenting that attention itself varies systematically with macroeconomic conditions, creating a more complex dynamic than previously recognized where policy actions influence future attention allocation through their effects on volatility.

For practitioners implementing behavioral macroeconomic models, our country-specific estimates provide empirically grounded calibration targets rather than relying on values estimated for a single country. The relationships we document between attention and macroeconomic conditions further allow for counterfactual analysis of how attention might evolve under alternative policy regimes or institutional reforms.

7 Conclusion

This paper advances the empirical foundation of behavioral macroeconomics by providing the first cross-country estimates of behavioral inattention parameters within a micro-founded framework. Using Bayesian techniques with a robust identification strategy, we document substantial heterogeneity in attention across countries and establish that this heterogeneity exhibits systematic patterns related to macroeconomic conditions and institutional factors.

Our analysis yields three principal contributions to the literature on expectation formation and macroeconomic dynamics. First, we deliver well-identified estimates of both micro- and macro-level attention parameters for 22 OECD economies, addressing the identification challenges that have hindered previous attempts to measure behavioral inattention empirically. Our cognitive discounting parameter estimates range from 0.76 to 0.98 across countries, with higher values indicating greater attention. This methodology establishes an empirical benchmark for measuring bounded rationality in macroeconomic contexts and provides calibration targets for future research.

Second, we document robust empirical support for rational inattention theory by establishing a positive relationship between macroeconomic volatility and attention allocation across countries. This novel cross-country evidence supports the theoretical prediction that agents optimally allocate more cognitive resources to more volatile variables (Maćkowiak and Wiederholt, 2015). This finding suggests that attention is not merely a fixed behavioral trait but responds endogenously to the economic environment in a manner consistent with optimizing behavior.

Third, our panel analysis identifies several robust determinants of attention, including macroeconomic volatility, institutional quality, surprise shocks, and information-seeking behavior. Trend variables—such as CPI and price-related Google search intensity—and macroeconomic variances (notably in GDP and interest rates) emerge as consistently significant predictors across multiple dimensions of attention. Institutional quality, particularly government effectiveness, also plays a relevant role in shaping attention, specially regarding firm attention. This establishes attention as both a behavioral and structural phenomenon, shaped by informational clarity, environmental volatility, and agents' active engagement with economic signals.

These findings have significant implications for macroeconomic modeling and theory. The state-dependent nature of attention we document challenges the common practice of assuming fixed attention or expectation formation parameters in macroeconomic models. Our results suggest instead that these parameters should vary systematically with economic conditions, potentially introducing nonlinearities in model dynamics and policy transmission that standard approaches may miss.

Several important avenues for future research emerge from our analysis. Methodologically, developing techniques to allow for continuous time variation in attention parameters would provide richer insights into attention dynamics. Extending the analysis to emerging market economies would test whether the relationships we document generalize to more diverse economic environments. Incorporating our estimated attention parameters into forecasting models could assess whether accounting for behavioral inattention enhances predictive performance.

More fundamentally, our empirical documentation of systematic relationships between economic conditions and attention parameters provides a foundation for deeper theoretical integration between rational inattention models (Sims, 2003b; Maćkowiak and Wiederholt, 2015), which formalize attention allocation as an optimal response to economic conditions, and behavioral approaches (Gabaix, 2014, 2020), which emphasize cognitive limitations in expectation formation. This integration would advance our understanding of how bounded rationality interacts with optimal behavior in shaping macroeconomic outcomes.

By establishing attention as a state-dependent parameter that varies with the economic environment, this paper enhances our understanding of expectation formation under bounded rationality and offers a more nuanced framework for analyzing policy transmission across diverse economic contexts. These insights contribute to the development of more realistic macroeconomic models that can better account for the behavioral foundations of economic decision-making and inform policymakers.

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8 Appendix

A Data

This appendix section documents our data sources and transformations. We employ quarterly data for 22 OECD countries from 1996Q1 to 2019Q4, ensuring consistent measurement and comparability across economies.

A.1 GDP

Real Gross Domestic Product (GDP) data are obtained from the OECD database for all countries (series code: VPVOBARSA). These data are constructed using the expenditure approach, denominated in US dollars at fixed purchasing power parity, seasonally adjusted, and reported at quarterly frequency.

For GDP deflators, we similarly rely on OECD expenditure-approach estimates (series code: DNBSA), denominated in national reference year and seasonally adjusted. To address data limitations for Colombia and Turkey, we implement linear extrapolation using World Bank data (series code: NY.GDP.DEFL.ZS) and FRED data (series code: TURGDPDEFAISMEI), respectively.

A.2 Consumption

Private final consumption expenditure data are collected from the OECD for all countries (series code: VPVOBARSA). These data are denominated in US dollars at fixed purchasing power parity, using the OECD reference year, seasonally adjusted, and reported at quarterly frequency.

A.3 Interest rates

Our primary interest rate measure is short-term (3-month) rates from the OECD's Monthly Monetary and Financial Statistics (MEI). For Mexico and Turkey, we supplement with immediate rates from the same OECD dataset due to data limitations. For Costa Rica, we linearly extrapolate lending interest rates from World Bank data (series code: FR.INR.LEND).

A.4 Labor

Employment data measure the number of persons employed according to each country's statistical definition. We also collect population data to construct per capita measures. These series are primarily drawn from the OECD's Quarterly National Accounts.

Due to OECD data limitations for certain countries, we supplement with employment data from FRED for Canada (series code: LFEMTTTTCAQ647S), Chile (LFEMTTTTCLQ647S), Costa Rica (EMPENGCRA148NRUG), Japan (LFEMTTTTJPQ647S), South Korea (LFEMTTTTKRQ647S), Mexico (SLEMPTOTLSPZSMEX), and Turkey (LFESEETTTRQ647N). For Colombia, we use World Bank data on total labor force (SL.TLF.TOTL.IN, linearly extrapolated to quarterly frequency). For New Zealand, we draw from the Reserve Bank of New Zealand (series code: HLFS.Q.L01G001.ns).

Population data are similarly supplemented with FRED series for Colombia (POPTTLCOA148NRUG, linearly extrapolated), Japan (POPTTLJPA647NWDB, linearly extrapolated), Mexico (POPTOTTMXA647NWDB), and Turkey (POPTOTTRA647NWDB).

We obtain employee compensation data primarily from the OECD (series code: CQRSA; national currency, current prices, quarterly levels, seasonally adjusted) and average annual hours worked (linearly extrapolated to quarterly frequency). Where OECD data are unavailable, we collect earnings data from FRED for Canada (LCEAMN01CAQ189N), Colombia (LABSHPCOA156NRUG), Israel (LCEAMN01ILQ189N), Iceland (LCEATT03ISQ661N), Japan (JPNCOMPQDSNAQ), Mexico (LCEAMN01MXM661S), South Korea (LCEAPR03KRQ189S), New Zealand (LCEATT01NZQ661N), and Turkey (TURHOUREAQISMEI). For Chile, we use the General Index of wages (nominal) from the Central Bank of Chile. For Costa Rica, we draw from World Bank data (GC.XPN.COMP.ZS, linearly extrapolated), and for Iceland we use World Bank data on total labor force (SL.TLF.TOTL.IN). For worked hours, we supplement with FRED data for Colombia (AVHWPECOA065NRUG) and South Korea (KORAHWEP).

B Observable Equations

This section details the data transformations used to construct observable variables for our estimation. We demean the first difference of each transformation to render the series stationary.

Real GDP per capita is constructed as:

$$y_{obs} = 100 \log\left(\frac{RealGDP_t}{POPIndex_t}\right) + \bar{y} \tag{9}$$

where $POPIndex_t = \frac{POP_t}{POP_{1996}}$

Hours worked per capita is transformed as:

$$n_{obs} = 100 \log \left(\frac{HOURSIndex_t \times EMPLOYMENTIndex_t \times 100}{POPIndex_t} \right) + \overline{n} \tag{10}$$

where $HOURSIndex_t = \frac{Hours_t}{Hours_{1996}}$ and $EMPLOYMENTIndex_t = \frac{EMPLOYMENT_t}{EMPLOYMENT_{1996}} \times 100$

Quarterly inflation is computed from the GDP deflator:

$$\pi_{obs} = 100 \log \left(\frac{GDPDeflator_t}{GDPDeflator_{t-1}} \right) + \overline{\pi} \tag{11}$$

The nominal interest rate is transformed to a quarterly frequency:

$$i_{obs} = \frac{INTEREST_t}{4} + \bar{\imath} \tag{12}$$

The parameters $\bar{y}$, $\overline{\pi}$, $\bar{\imath}$, and $\overline{n}$ represent measurement errors estimated within our model. Their prior calibration is centered at zero, consistent with our demeaned data.

C Additional Results

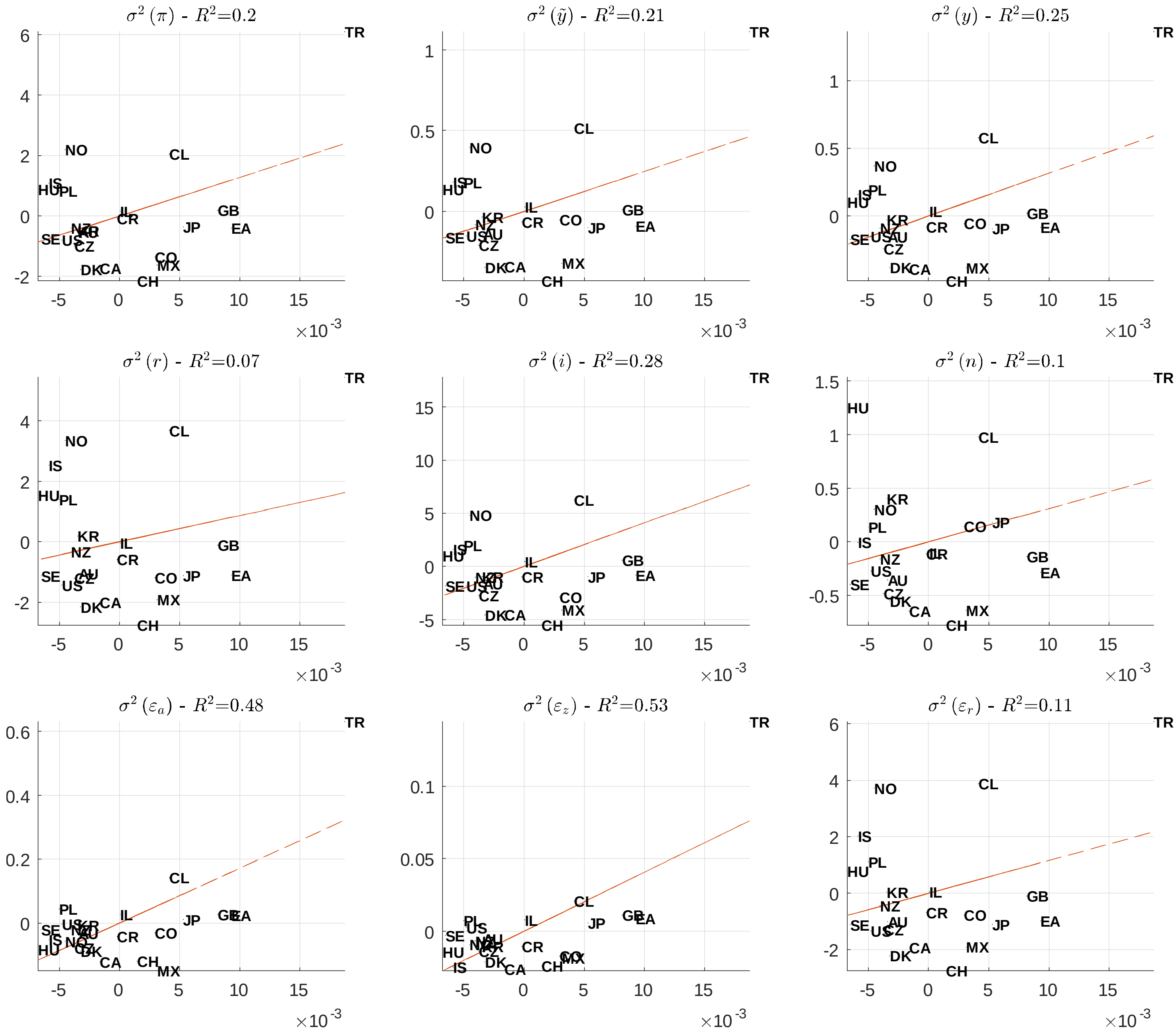
C.1 Attention and Volatility

Figure 18 presents the potential relationship between macroeconomic volatility and cognitive discounting ($\bar{m}$). The figure extends the main text analysis by examining a broader set of macroeconomic variances, including output variance, consumption variance, employment variance, technology shock variance, preference shock variance, and cost-push shock variance. The consistent positive relationship across all panels provides robust evidence that higher macroeconomic volatility is associated with greater attention. This pattern holds for both observed macroeconomic variables (top row) and for model-identified structural shocks (bottom row), suggesting that unpredictability in economic fundamentals broadly enhances attention allocation.

Figure 19 extends our analysis of firms' inflation attention (m_π^f) and macroeconomic volatility. The systematic positive relationship persists across all specifications, with particularly strong patterns for inflation variance and output gap variance. This evidence reinforces the interpretation that firms rationally allocate more attention to inflation in environments where price dynamics are more volatile and consequential.

Figure 20 similarly extends the analysis of firms' output gap attention (m_x^f) and macroeconomic volatility. While the positive relationship persists across specifications, the slope and explanatory power are generally lower than for inflation attention. This pattern is consistent with the output gap being a less directly observable variable compared to inflation, potentially complicating firms' attention allocation decisions.

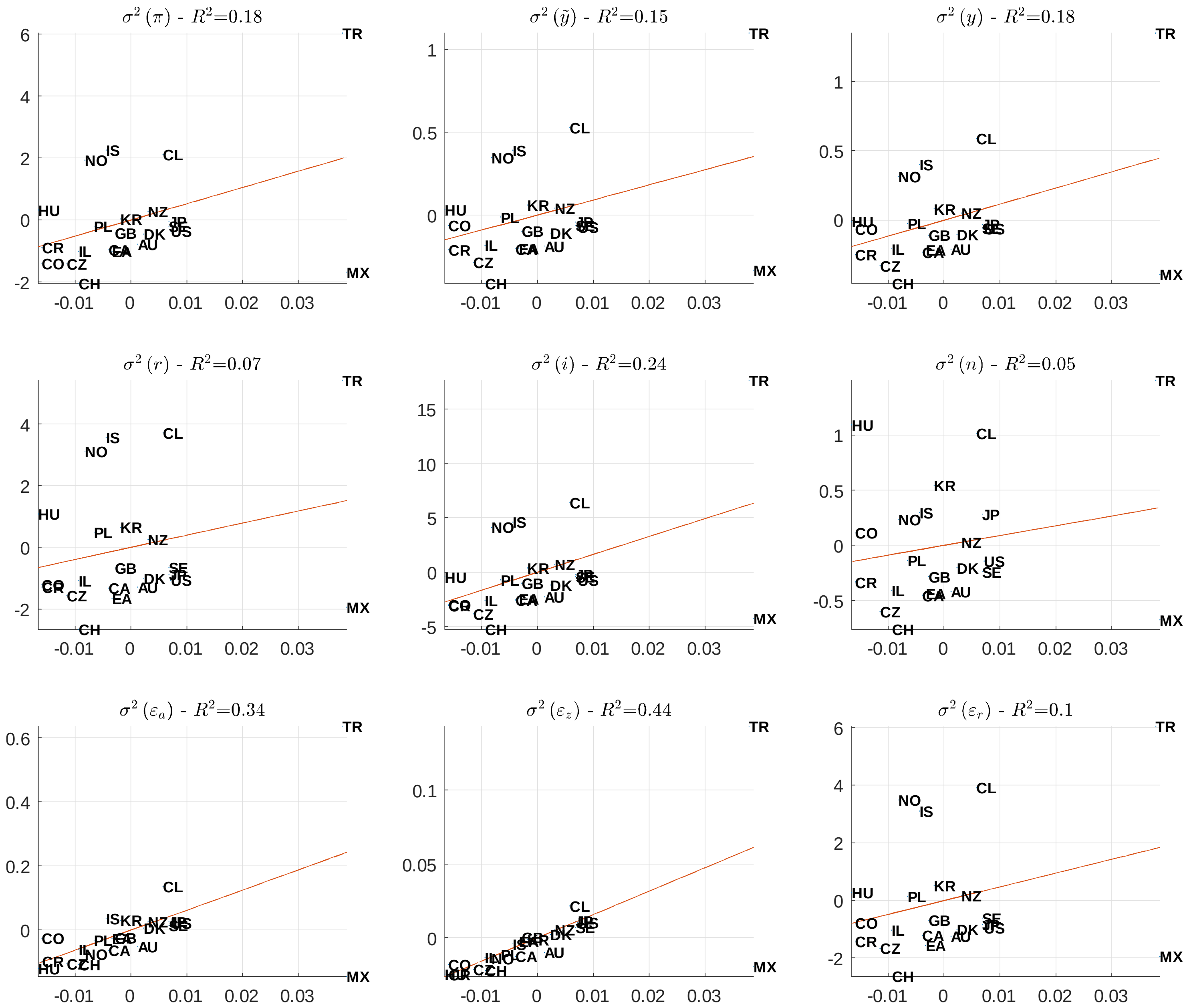
Figure 18. Economic Volatility and $\bar{m}$.



Notes: σ^2 (.) stands for the estimated variance. $\bar{m}$ (x-axis) and variances (y-axis) are detrended for the regression.

Figure 21 presents the relationship between macroeconomic volatility and aggregate firm attention (M^f), which captures firms' overall attentiveness to forward-looking information in price-setting decisions. The strong positive relationship across specifications, with particularly high explanatory power for inflation variance and output gap variance, suggests that macroeconomic volatility broadly enhances firms' forward-looking behavior. This pattern supports the interpretation that firms facing more volatile economic environments invest more cognitive resources in forward-looking information processing, leading to more

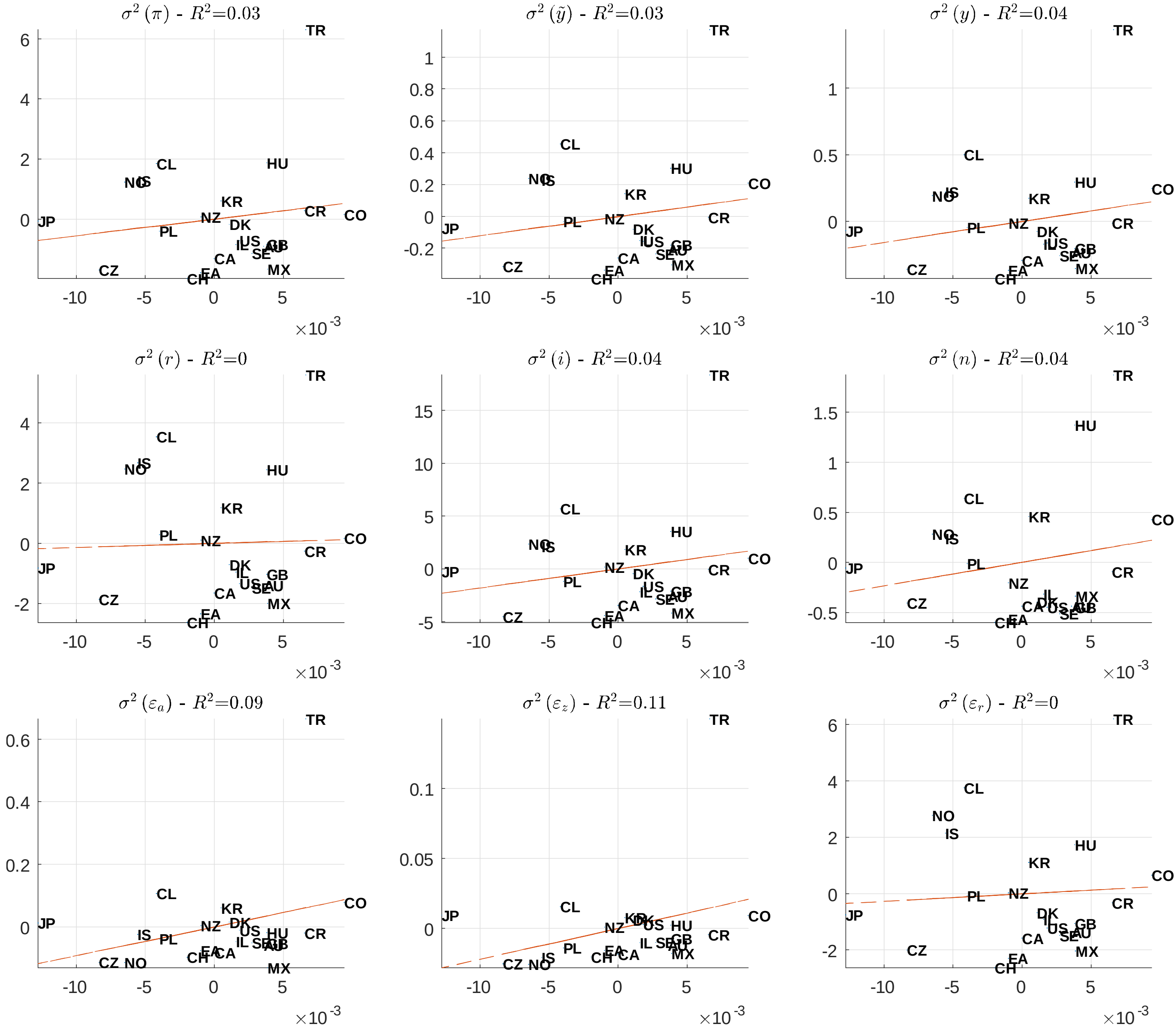
Figure 19. Economic Volatility and m^f_π.



Notes: $\sigma^2(.)$ stands for the estimated variance. m^f_π (x-axis) and variances (y-axis) are detrended for the regression.

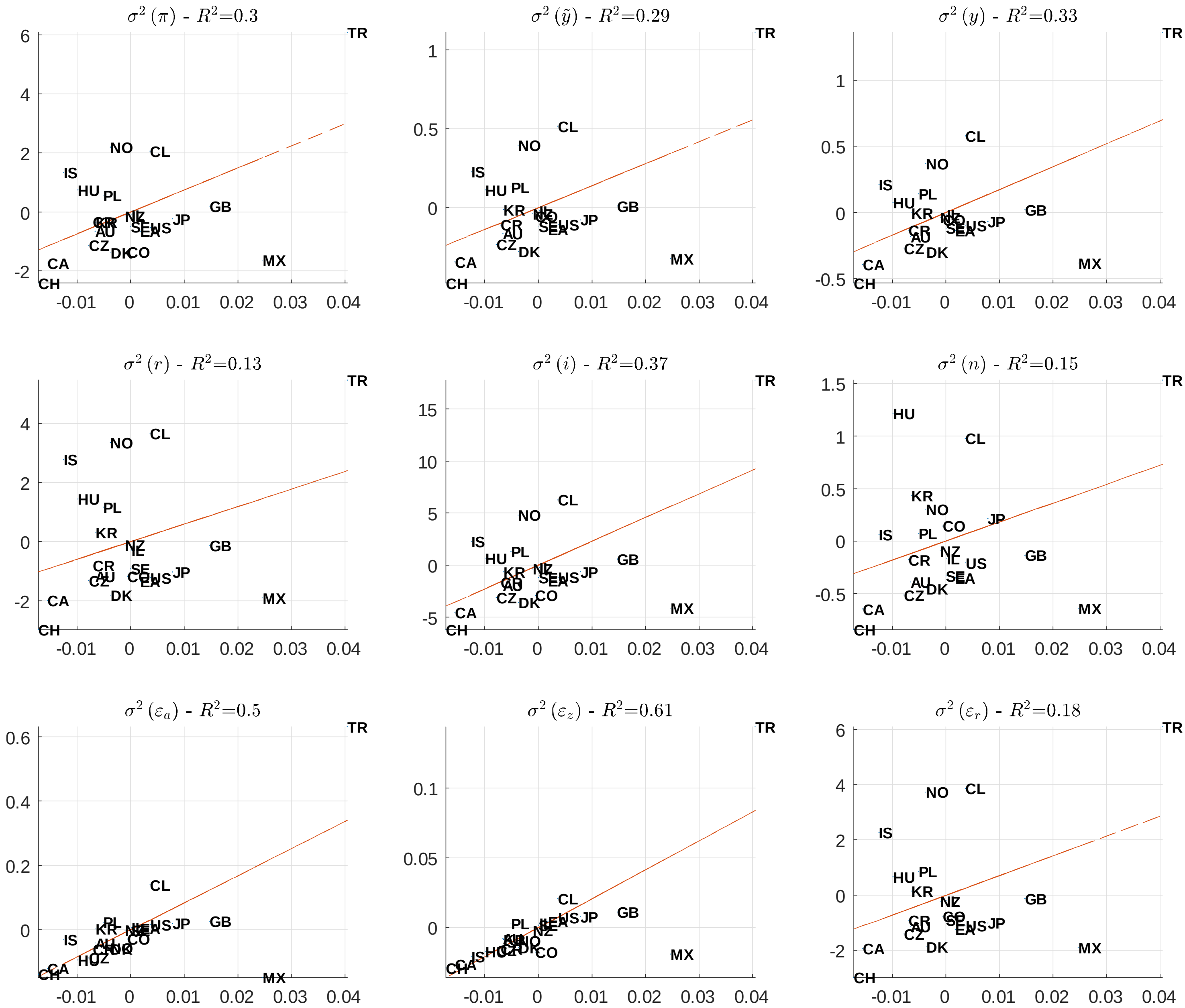
rational expectation formation.

Figure 20. Economic Volatility and m_x^f.



Notes: $\sigma^2(.)$ stands for the estimated variable's variance. m_x^f (x-axis) and variances (y-axis) are detrended for the regression.

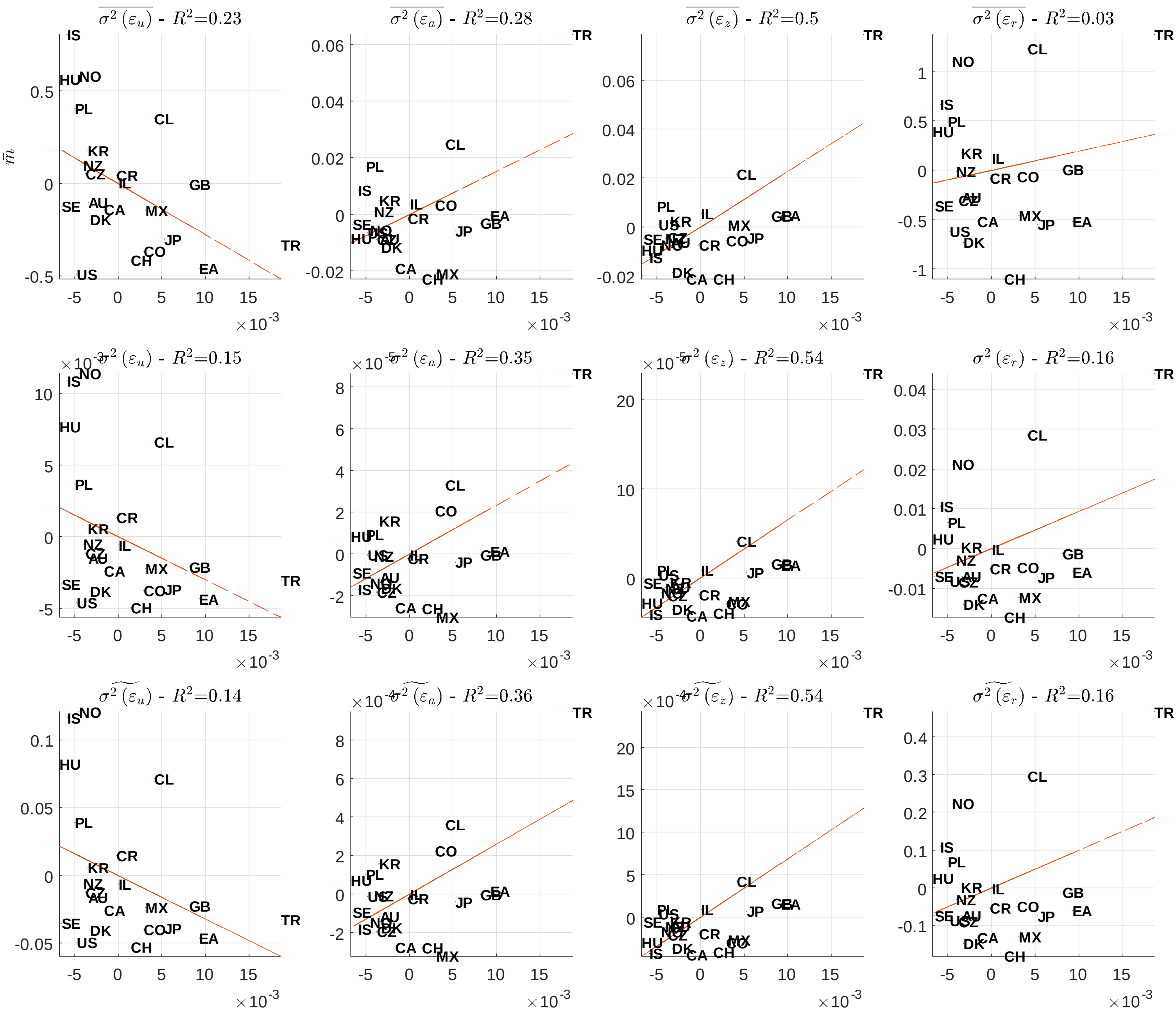
Figure 21. Economic Volatility and M^f.



Notes: $\sigma^2(.)$ stands for the estimated variance. M^f (x-axis) and variances (y-axis) are detrended for the regression.

C.2 Attention and Shock Volatility

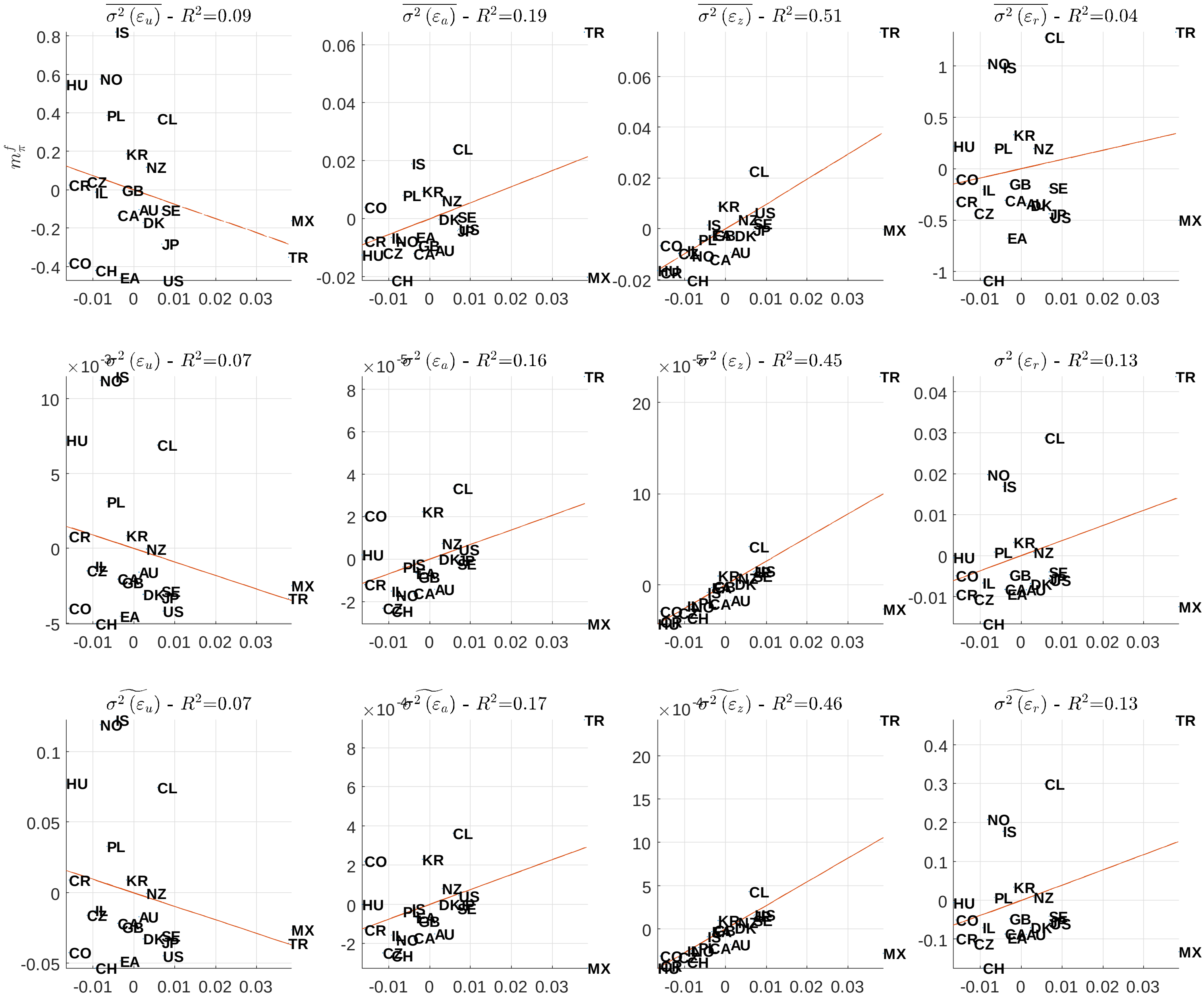
Figure 22. Shocks' Variance and $\bar{m}$.



Notes: $\overline{\sigma^2}\,(.)$ represents the estimated shock's posterior mean-standard deviation, $\sigma^2\,(.)$ represents the estimated shock's posterior variance, and $\widetilde{\sigma^2}\,(.)$ represents the sup-inf spread of the estimated shock's standard error posterior mean. $\bar{m}$ (x-axis) and variances (y-axis) are detrended for the regression.

Figure 22 extends our analysis of structural shock volatility and cognitive discounting ($\bar{m}$) to include all four structural shocks in our model: preference shocks ($\varepsilon_{z,t}$), technology shocks ($\varepsilon_{a,t}$), cost-push shocks ($\varepsilon_{u,t}$), and monetary policy shocks ($\varepsilon_{r,t}$). The consistent positive relationship across technology, preference, and monetary policy shocks indicates that greater unpredictability in these fundamental drivers enhances attention allocation. The weaker and less consistent relationship with cost-push shocks (third row) may reflect the complex nature of pure inflation disturbances, which induce countervailing movements in inflation and output that potentially complicate interpretation and attention allocation.

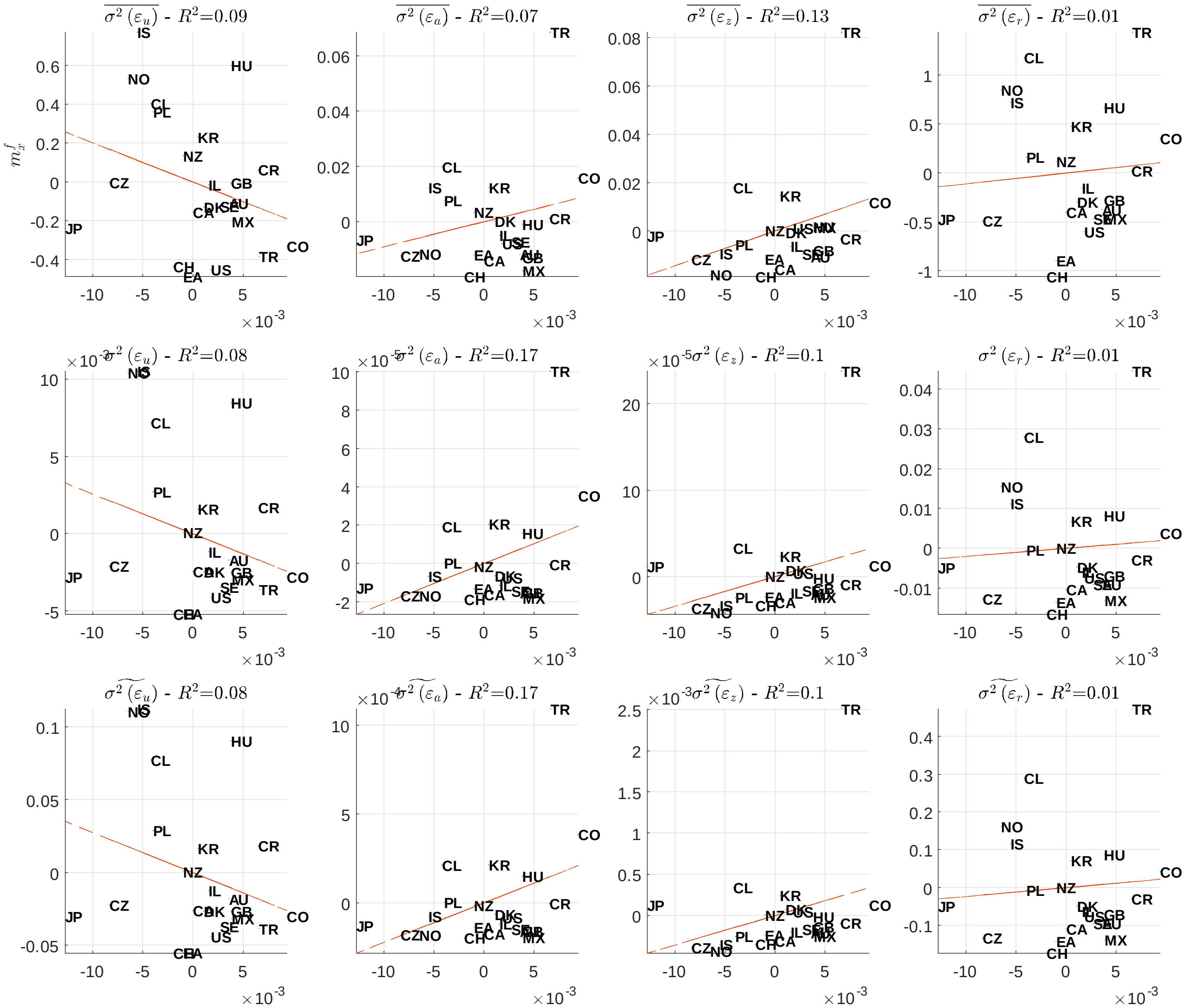
Figure 23. Shocks' Variance and m^f_π.



Notes: $\overline{\sigma^2(.)}$ represents the estimated shock's posterior mean-standard deviation, $\sigma^2(.)$ represents the estimated shock's posterior variance, and $\widetilde{\sigma^2(.)}$ represents the sup-inf spread of the estimated shock's standard error posterior mean. $\bar{m}$ (x-axis) and variances (y-axis) are detrended for the regression.

Figures 23, 24, and 25 extend this analysis to firms' inflation attention (m^f_π), output gap attention (m^f_x), and aggregate attention (M^f), respectively. The positive relationship between structural shock volatility and attention persists across these parameters, though with varying strength and consistency. For inflation attention, preference and technology shock volatility show particularly strong relationships, potentially reflecting firms' recognition that demand and supply fluctuations significantly influence inflation dynamics. For output gap attention, monetary policy shock volatility demonstrates the strongest relationship, consistent with the central role of monetary policy in stabilizing output fluctuations.

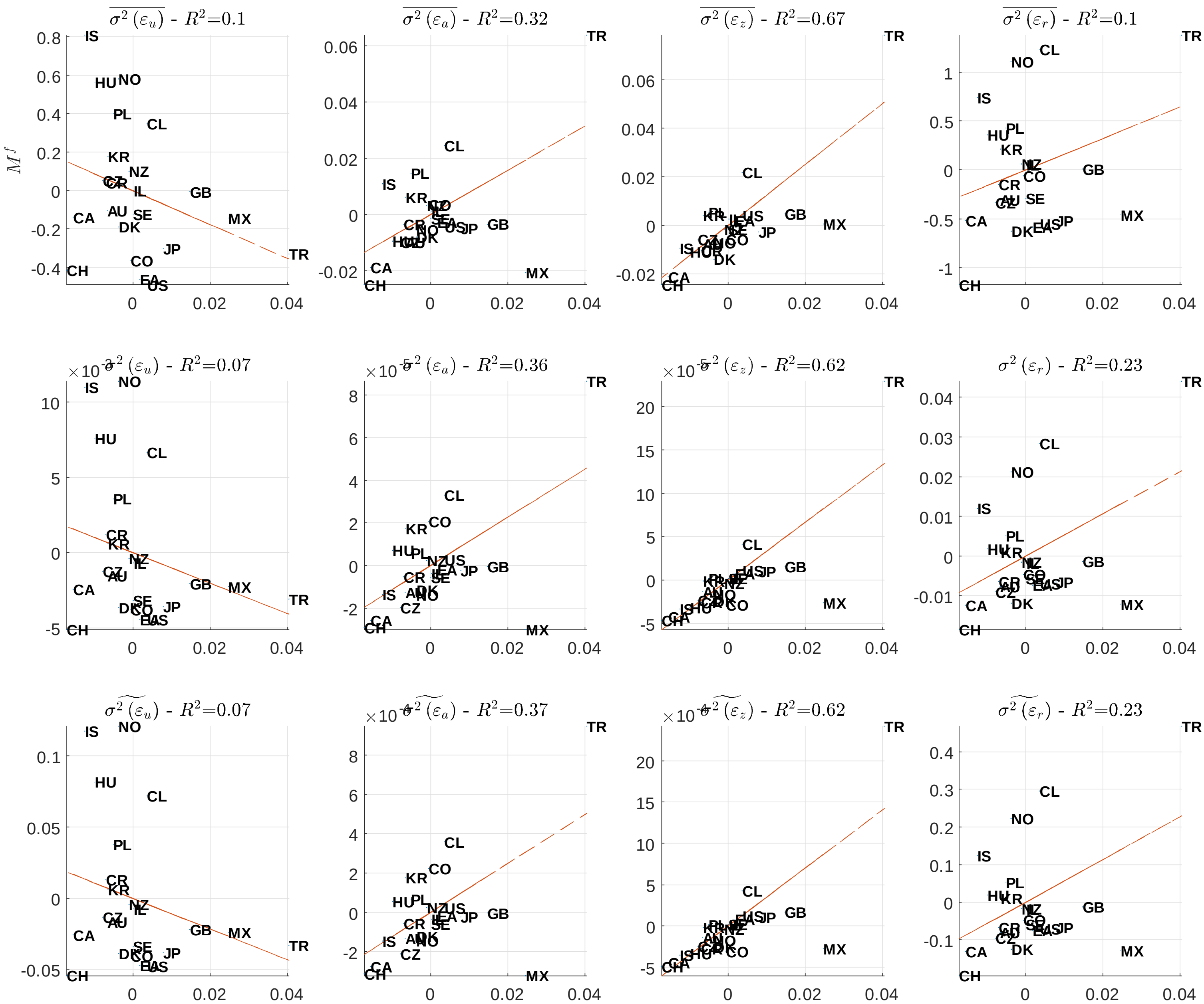
Figure 24. Shocks' Variance and m_x^f.



Notes: $\overline{\sigma^2(.)}$ represents the estimated shock's posterior mean-standard deviation, $\sigma^2(.)$ represents the estimated shock's posterior variance, and $\widetilde{\sigma^2(.)}$ represents the sup-inf spread of the estimated shock's standard error posterior mean. $\bar{m}$ (x-axis) and variances (y-axis) are detrended for the regression.

These additional results strengthen our conclusion that attention increases with macroeconomic unpredictability. The positive relationship holds across multiple measures of volatility (observed variables and structural shocks), different attention

Figure 25. Shocks' Variance and M^f.



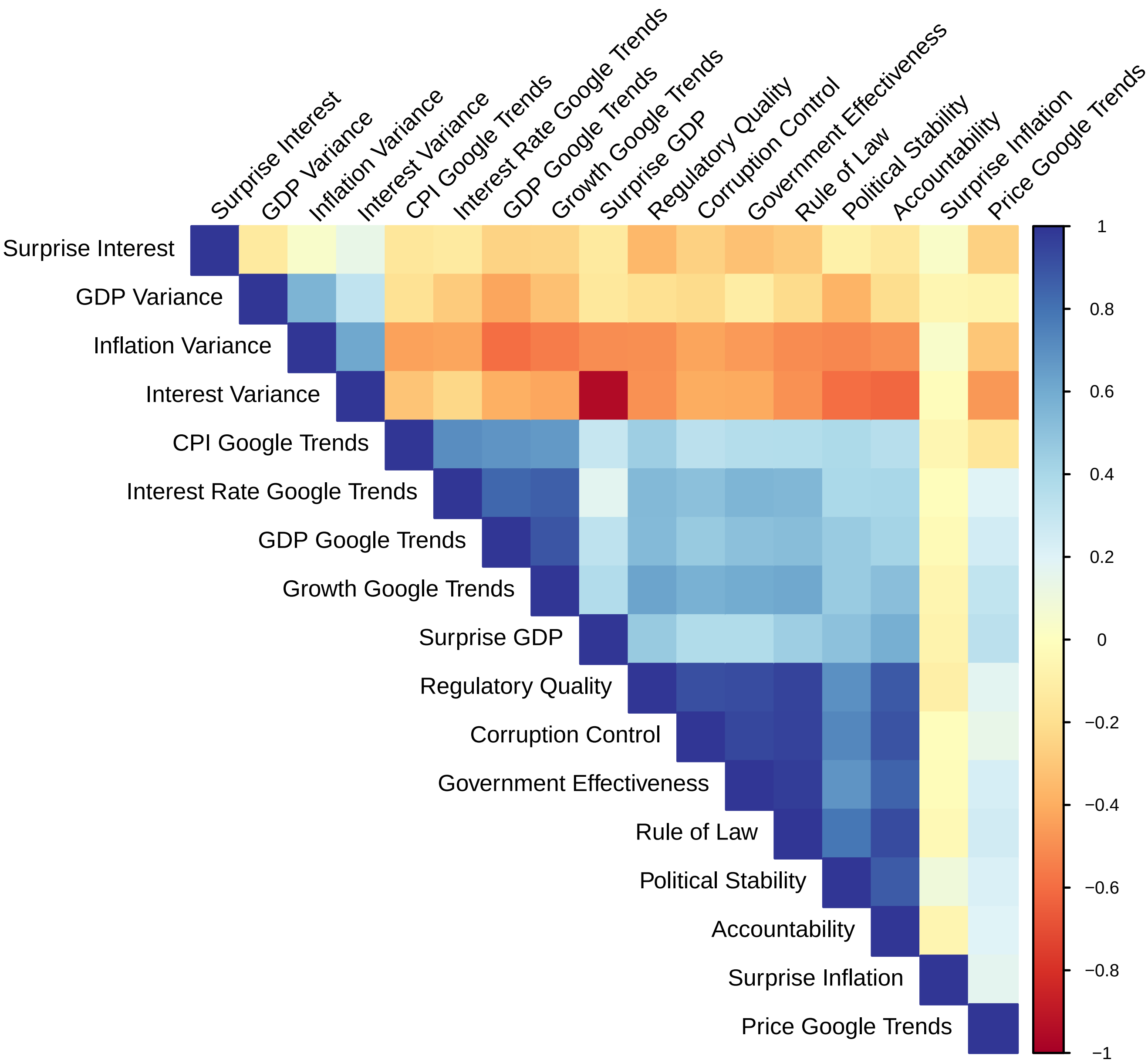
Notes: $\overline{\sigma^2(.)}$ represents the estimated shock's posterior mean-standard deviation, $\sigma^2(.)$ represents the estimated shock's posterior variance, and $\widetilde{\sigma^2(.)}$ represents the sup-inf spread of the estimated shock's standard error posterior mean. $\bar{m}$ (x-axis) and variances (y-axis) are detrended for the regression.

parameters (general cognitive discounting, variable-specific attention, and aggregate attention), and various statistical representations of uncertainty (mean posterior standard deviations, variances, and posterior distribution ranges). This evidence supports the rational inattention prediction that agents optimally allocate more cognitive resources to more volatile and consequential economic variables.

C.3 Cross-Correlations

Figure 26 presents the cross-correlation matrix for all potential explanatory variables considered in our panel analysis of attention determinants. Several notable patterns emerge.

Figure 26. Cross-Correlation Matrix of Panel Estimation Variables.



Notes: this plot presents the cross-correlation matrix for all data variables explained in Section 5.

First, institutional quality measures (government effectiveness, rule of law, regulatory quality, corruption control, accountability, and political stability) exhibit very high positive correlations with each other, justifying our decision to include only government effectiveness and political stability in our final specifications to avoid multicollinearity.

Second, Google Trends search variables (CPI, price, inflation, GDP, interest rate, and growth) show moderate positive correlations with each other, indicating that information-seeking behavior tends to be broad rather than narrowly focused on specific economic indicators. However, these correlations are not high enough to create severe multicollinearity concerns, supporting our inclusion of multiple search intensity measures in our regressions.

Third, macroeconomic volatility measures (inflation variance, GDP variance, and interest rate variance) exhibit more modest correlations with each other, suggesting that volatility in different macroeconomic dimensions represents distinct phenomena rather than reflecting a single underlying instability factor. This pattern supports our inclusion of separate volatility measures for different macroeconomic variables.

Fourth, macroeconomic surprise variables (surprise inflation, surprise GDP, and surprise interest) show relatively low correlations with each other and with volatility measures, indicating that unpredictable fluctuations in different economic indicators represent distinct phenomena that may influence attention through separate channels.

Finally, the institutional quality measures show negative correlations with volatility measures, consistent with the interpretation that stronger institutions foster greater macroeconomic stability. However, these correlations are modest enough that including both sets of variables in our regressions allows us to identify their distinct relationships with attention parameters.

The correlation structure represented in Figure 26 informed our variable selection for the panel regressions presented in Section 5. Our final set of explanatory variables balances informativeness about potential attention determinants with concerns about multicollinearity, allowing us to identify the distinct relationships between different factors and attention parameters.