Asymmetric Attention and State-Dependent Aggregate Demand and Supply

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Abstract

This paper studies how endogenous information acquisition by households and firms shapes state-dependent shock propagation. A new source of strategic interaction arises from the interdependence of information choices between households and firms. Theoretically, I show in a linear-quadratic-Gaussian framework that strategic motives in information acquisition depend not only on strategic motives in actions, but also on the volatility of underlying shocks. When applied to a standard macroeconomic model, two-sided information acquisition by households and firms generates non-monotonic movements in the slopes of aggregate demand and aggregate supply as volatility varies. Quantitatively, the model is consistent with the time variation in attention and the slopes of aggregate demand and aggregate supply in the U.S. economy, whereas predictions based on one-sided information acquisition contradict the data.

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1 Introduction

Business cycles feature fluctuations in aggregate uncertainty (e.g., Bloom, 2014; Jurado et al., 2015). Uncertainty, however, is not fully exogenous. Firms, households, and other economic agents choose how much information to acquire about the state of the economy. As shown in rational inattention theory (e.g., Sims, 2003; Maćkowiak et al., 2023) and in survey evidence (e.g., Weber et al., 2022; Link et al., 2023), agents' attention to macroeconomic and microeconomic conditions varies with the business cycle. Attention shapes how responsive decisions are to underlying shocks. In turn, fluctuations in attention provide a natural explanation for state-dependent effects of monetary and fiscal demand shocks and the time variation in macroeconomic volatility.

This paper studies the two-way feedback between uncertainty and attention and its implications for state-dependent shock propagation. Distinct from existing work, which typically analyzes this feedback with endogenous attention by either firms or households (e.g., Maćkowiak and Wiederholt, 2009; Kamdar and Ray, 2024), I emphasize *two-sided* endogenous information acquisition by households and firms. Interdependence in decisions makes information choices also interdependent. Intuitively, when firms acquire more information about disturbances in marginal costs, their prices are more responsive to shocks. Since household spending depends on prices, greater price sensitivity affects households' incentives to acquire information. The resulting change in demand then feeds back into firms' information choices via the dependence of prices on spending.

To understand the strategic interactions in information choices, I first analyze endogenous information acquisition in a linear-quadratic-Gaussian setting with general coordination motives. Others' attention affects an agent's marginal value of information by changing how aggregate actions load on different fundamentals and thus the uncertainty in the agent's best response. The main insight is that strategic motives in information acquisition depend not only on strategic motives in actions, but also on the volatility of the underlying shocks.

I then apply the framework to study how information acquisition by households and firms, as well as their interaction, shapes equilibrium shock propagation, focusing on the slopes of aggregate demand and aggregate supply. These slopes, defined as the relative pass-through of a supply or demand shock to the price level versus output, are endogenous to information choices. As shock volatility increases, equilibrium attention adjusts, which alters the slopes and generates state-dependent shock transmission. Moreover, the aggregate demand curve flattens only when firm attention is high, whereas the aggregate supply curve steepens only when household attention is high. The non-monotonicity arises from strategic interactions in information choices between households and firms, a prediction that is not obtained when inattention is confined to either side alone. In essence, the condition for aggregate demand to flatten requires that the negative feedback from firm attention to household attention be weak, while the condition for aggregate supply to steepen requires that the positive feedback along the same link be moderate.

Finally, I quantify the model's predictions for attention and the slopes of aggregate demand and supply in the U.S. over time. At the micro level, model-implied changes in inflation forecast dispersion, a proxy for attention, align with survey evidence. At the macro level, variation in the slope of aggregate supply is consistent with external empirical evidence. Using local projections of unemployment on inflation instrumented with identified oil supply news shocks from Känzig (2021), I find that the aggregate demand curve steepens from 1975–1984 to 1985–2019, in line with the model's implication. I then conduct counterfactual exercises that fix either firm or household attention at its sample average. The resulting counterfactual slopes are at odds with the data, indicating that two-sided endogenous attention is necessary to account for the joint behavior of aggregate demand and supply.

Theory. I begin by characterizing costly information acquisition in a linear-quadratic-Gaussian framework with heterogeneous groups. Each group contains a continuum of ex ante identical agents. Optimal action of each agent is linear in expectations of a group-specific fundamental and aggregation actions of all groups, which I refer to as the desired action. The fundamentals are jointly normally distributed. Interdependence in actions across groups is summarized by an interaction matrix, which allows asymmetric coordination motives.

I first solve for the joint determination of information acquisition and aggregate actions. Optimal information choice depends on an agent's prior uncertainty about its desired action. Each group's information determines how aggregate actions respond to fundamentals, thereby influencing other groups' uncertainty and information decisions. While this fixed-point logic is standard in rational inattention with a single group (e.g., Maćkowiak et al., 2023), linkages across groups generate richer strategic interactions in information acquisition.

To study these interactions, I analyze how others' attention affects an agent's marginal value of information. The effect depends on two factors: the comovement of desired actions and the propagation of others' actions to the agent's desired action through the interaction matrix. When the two factors share the same sign, greater attention by other agents increases the volatility of the desired action and raises the marginal value of information. When they have opposite signs, higher attention by others lowers the incentive to acquire information. In the single-group setting (e.g., Hellwig and Veldkamp, 2009; Myatt and Wallace, 2012; Colombo et al., 2014), information incentives mirror strategic motives in actions. With multiple groups, these incentives also rely on shock volatility, which shapes both factors.

Rationally Inattentive Households and Firms. Next, I apply the framework to a standard macroeconomic model with costly information acquisition by households and firms. Households choose consumption and firms set prices under uncertainty about two aggregate shocks: a discount rate (demand) shock and a productivity (supply) shock.

I show that the unique equilibrium admits an aggregate demand and aggregate supply representation. Real output and the price level are determined at the intersection of the two curves. Critically, their slopes are endogenous to attention. Holding households' information acquisition fixed, higher firm attention steepens aggregate supply, which increases the price response relative to the output response to an aggregate demand shock. Holding firms' information acquisition fixed, higher household attention flattens both aggregate demand and aggregate supply, which reduces the relative effects of an aggregate demand and supply shock on prices versus output.

Attention choices are endogenous to the economic environment, in particular to aggregate shock volatility. Consequently, the slopes of aggregate demand and aggregate supply are state-dependent. For aggregate demand, increases in shock volatility steepen the curve when equilibrium firm attention lies below a threshold. Rising volatility induces firms to acquire more information. Greater firm attention has two opposing effects on household attention: it raises the marginal value of information by increasing the exposure of households' desired consumption to supply shocks, but lowers the marginal value by further insulating desired consumption from demand shocks. With low firm attention, the second effect dominates the first and also outweighs the direct effect of shock volatility on household attention. Hence, equilibrium household attention falls, and the aggregate demand curve steepens.

For aggregate supply, when shocks are more volatile, the slope flattens if equilibrium household attention is below a threshold. In this case, both households and firms acquire more information, which pushes the aggregate supply slope in opposite directions. The direct effect of higher shock volatility, together with positive feedback from firm attention, raises household attention sufficiently to produce a flatter aggregate supply.

I contrast these predictions with cases in which one side, households or firms, is rationally inattentive while the other has perfect information. In those cases, the slopes of aggregate demand and aggregate supply are either invariant to underlying shock volatility or vary monotonically with it. The latter pattern results from the monotonic relationship between attention and volatility. These results imply that assumptions about the information structure of households and firms lead to different predictions for how shocks propagate. To gauge the empirical relevance of two-sided information acquisition, I quantify the model's predictions and assess the roles of household and firm attention in counterfactual exercises in the final part of the paper.

Quantitative Analysis. I calibrate the model to the conditional variances of U.S. real GDP growth and inflation estimated using a GARCH specification. The calibrated model generates time-varying attention and slopes of aggregate demand and aggregate supply.

At the micro level, I evaluate the model's predictions for household and firm attention by comparing the cross-sectional dispersion of one-year-ahead inflation forecasts implied by the model with evidence from two surveys, the Surveys of Consumers and the Livingston Survey. The model tracks variation in survey forecast dispersion over time, with correlations of 0.42 for households and 0.30 for firms.

At the macro level, the model matches empirically documented patterns in the slope of aggregate supply (Ball and Mazumder, 2011; Hazell et al., 2022; Cerrato and Gitti, 2025): it steepens from the 1960s to the 1970s, flattens from the 1970s to the Great Moderation, and steepens again after Covid. The slope of aggregate demand in the model moves in the opposite direction over these periods. Using local projections of unemployment on inflation instrumented with identified oil supply news shocks from Känzig (2021), I find evidence that the average aggregate demand slope is steeper over 1985–2019 than over 1975–1984.

To assess the role of attention in generating time variation in the slopes, I conduct counterfactual exercises that hold either firm or household attention fixed at its sample average. When household attention is constant, the slope of aggregate demand is invariant over time. When firm attention is constant, the model predicts a steeper aggregate supply after the Volcker disinflation. These counterfactual implications are inconsistent with the data. Therefore, endogenous information acquisition by both households and firms, rather than by one side alone, is necessary to match the joint behavior of aggregate demand and aggregate supply.

Related Literature. This paper contributes to the rational inattention literature.[1] Most macroeconomic applications model one-sided rational inattention by either firms or households, including price setting (e.g., Maćkowiak and Wiederholt, 2009; Paciello, 2012; Stevens, 2020; Miao et al., 2022; Turen, 2023; Afrouzi, 2024), consumption and saving choices (e.g., Sims, 2003; Luo, 2008; Tutino, 2013; Luo et al., 2017; Mitman et al., 2022), and labor supply decisions (e.g., Kamdar and Ray, 2024). In contrast, this paper incorporates rationally inattentive households and firms and shows that strategic interactions in information acquisition deliver new implications for state-dependent shock propagation, both theoretically and quantitatively.

The closest papers are Maćkowiak and Wiederholt (2015) and Zhang (2024), which also study two-sided information acquisition. Maćkowiak and Wiederholt (2015) show that lim-

[1] See Sims (2010), Wiederholt (2010), Veldkamp (2011) and Maćkowiak et al. (2023) for reviews.

ited attention by households and firms, as the only source of rigidity, generates inertia in the impulse responses of aggregate variables to multiple shocks that matches the data. Zhang (2024) accounts for divergent beliefs about inflation and output growth across households, firms, and professionals in surveys by allowing them to acquire information about different shocks. Complementing these results, my analysis focuses on how endogenous attention of both sides and their interactions shape the slopes of aggregate demand and aggregate supply, and generate state-dependent pass-through of shocks as shock volatility varies.

The attention mechanism links state dependence in shock propagation to uncertainty. A large empirical literature examines how effects vary with economic conditions for monetary policy shocks (e.g., Weise, 1999; Tenreyro and Thwaites, 2016), government spending multipliers (e.g., Auerbach and Gorodnichenko, 2012; Ramey and Zubairy, 2018), and tax multipliers (e.g., Candelon and Lieb, 2013; Demirel, 2021). This paper contributes to the literature by providing an explanation of state dependence based on endogenous attention, which is itself determined by uncertainty. It also contributes to the literature on endogenous uncertainty and its macroeconomic consequences (e.g., Kozeniauskas et al., 2018; Ludvigson et al., 2021; Chiang, 2024; Flynn and Sastry, 2024). My analysis emphasizes the two-way feedback between attention and uncertainty arising from both exogenous shock volatility and equilibrium forces.

My finding that the aggregate supply slope varies with attention and uncertainty also relates to the literature on the flattening of the Phillips curve (e.g., Ball and Mazumder, 2011; Blanchard, 2016; Hooper et al., 2020; McLeay and Tenreyro, 2020; Stock and Watson, 2020; Hazell et al., 2022; Cerrato and Gitti, 2025). Related work by Afrouzi and Yang (2021) studies how monetary policy alters the slope by shaping firms' incentives to acquire information. In contrast, this paper shows that the aggregate supply slope depends on attention of both firms and households. Flynn et al. (2025) show that the hedging incentive with respect to multiple sources of uncertainties shapes firms' supply function choices and induces variation in the slope of aggregate supply. My results indicate that uncertainty also affects incentives for information acquisition. In addition, I provide empirical evidence of time variation in the slope of aggregate demand guided by the theory, complementing the literature that has focused mainly on aggregate supply.

Finally, this paper contributes to research on information acquisition in generalized linear-quadratic games (e.g., Hellwig and Veldkamp, 2009; Myatt and Wallace, 2012; Colombo et al., 2014; Pavan, 2014; Denti, 2017; Myatt and Wallace, 2019; Hébert and La'O, 2023). Fang et al. (2025) studies complementarity in information acquisition in a production network with rationally inattentive firms. My analysis highlights the role of shock volatility in determining the strategic motives for information acquisition.

Outline. Section 2 studies information acquisition in a general linear best-response setting. Section 3 characterizes the equilibrium with endogenous slopes of aggregate demand and aggregate supply in a macroeconomic model with rationally inattentive households and firms. Section 4 estimates the model and validates its predictions for attention dynamics. Section 5 quantifies the model's predictions for the slopes of aggregate demand and aggregate supply over time and investigates the role of two-sided information acquisition in shaping these state-dependent slopes. Section 6 concludes.

2 Information Acquisition in General Strategic Settings

This section studies endogenous information acquisition in a canonical linear-quadratic-Gaussian setting with heterogeneous groups and general coordination motives. After describing the environment, I characterize the joint determination of attention and aggregate actions in equilibrium. I then analyze the strategic interactions in information acquisition by showing how others' attention affects an agent's marginal value of information.

2.1 Setup

The economy has n groups indexed by $i \in N = \{1, \dots, n\}$. Each group i is populated by a unit-mass continuum of agents $k \in [0, 1]$. I denote agent k in group i by (k, i). The exogenous state $\theta = (\theta_1, ..., \theta_n)$ follows a multivariate normal distribution with a general correlation structure, with each θ_i corresponding to a group-specific fundamental. Agents share the common prior $\theta \sim \pi_0 = \mathcal{N}(0, \Sigma)$.

Agent (k, i) takes an action $a_{ki} \in \mathbb{R}$ and has quadratic utility

$$u_i(a_{ki}, a, \theta) = -\frac{1}{2}a_{ki}^2 + a_{ki}\left(\sum_{j=1}^{n} g_{ij}a_j + \theta_i\right) + \mathcal{O}_i(a, \theta) \tag{2.1}$$

where $a_j = \int_0^1 a_{kj}\ \mathrm{d}k$ denotes the aggregate action of group j and $a = (a_1, \dots, a_n)$ is the vector of aggregate actions. The term $\mathcal{O}_i$ is an arbitrary function that does not depend on the agent's own action. The parameters g_{ij} capture the influence of group j's aggregate action on agents in group i. The strategic motives across groups are summarized by the interaction matrix

$$G = [g_{ij}]_{i,j \in N}.$$

Given the quadratic payoff, the best response of each agent is linear in expectations of the exogenous state and of others' actions. A second-order approximation to objective functions maps many environments into this framework.[2] For example, the monetary model in Woodford (2003) can be cast as a single group of firms with a scalar G. Each firm's pricing depends on the aggregate price and an exogenous money supply shock. Multi-sector New Keynesian models such as La'O and Tahbaz-Salehi (2022) correspond to a non-negative matrix G, whose entries reflect Cobb-Douglas input shares. Firms in each industry set prices to match a linear combination of an industry-specific fundamental and the prices of their supplier industries. In Section 3, I study a two-group application with households and firms in a standard neoclassical model, where G is determined by structural parameters and captures the interdependence of consumption and pricing decisions.

Agents are rationally inattentive. They are uncertain about the realization of θ and the aggregate action vector a and acquire costly information about these variables. Given their information set, each agent forms posterior beliefs over θ and a and chooses an action that maximizes expected utility.

The individual information choice is represented by a joint distribution over θ, a and the signal s_{ki} with the pdf $\pi_{ki}(\theta, a, s_{ki})$. Admissibility requires that the marginal over the state θ and aggregate actions a of π_{ki} is given by the distribution of $(\theta, f(\theta))$ with $\theta \sim \pi_0$ and $a = f(\theta)$ for some deterministic function f. Under rational expectations, $f(\theta)$ is consistent with aggregate actions in equilibrium.[3]

Following Sims (2003), I assume that the cost of acquiring information is given by the mutual information between the signal and the state:[4]

$$\mathcal{I}\left(\theta, a; s_{ki}\right) := \int \pi_{ki}(\theta, a, s_{ki}) \log\left(\frac{\pi_{ki}(\theta, a, s_{ki})}{\pi_{ki}(\theta, a)\pi_{ki}(s_{ki})}\right) \,\mathrm{d}\theta \,\mathrm{d}a \,\mathrm{d}s_{ki} \tag{2.2}$$

where $\pi_{ki}(\theta, a)$ and $\pi_{ki}(s_{ki})$ are the marginals of (θ, a) and s_{ki}.

Each agent chooses an information policy π_{ki} and an action plan $a_{ki} : \mathcal{S} \to \mathbb{R}$, where $\mathcal{S}$ is the signal space, to maximize expected utility net of information costs:

$$\max_{\pi_{ki}, a_{ki}} \; \mathbb{E}_{\pi_{ki}}\left[u_i(a_{ki}(s_{ki}), a, \theta)\right] - \omega_i \; \mathcal{I}(\theta, a; s_{ki}) \tag{2.3}$$

where $\omega_i > 0$ is the information cost parameter for group i, and $\mathbb{E}_{\pi_{ki}}$ is taken under the

[2] The linear-quadratic-Gaussian framework dates back to Radner (1962) and is widely used in strategic settings with uncertainty for its tractability. See, e.g., Vives (1984), Morris and Shin (2002), and Angeletos and Pavan (2007).

[3] That aggregate actions are functions of θ follows from the assumption that each agent is strategically small and the mutual information cost assumption specified below, under which agents do not acquire any signals with correlated nonfundamental noises (Hébert and La'O, 2023).

[4] Since the aggregate action is a deterministic function of the state, $a = f(\theta)$, the pair (θ, a) contains no more information than θ. Hence $\mathcal{I}\left(\theta, a; s_{ki}\right) = \mathcal{I}\left(\theta; s_{ki}\right)$.

distribution π_{ki}. I focus on equilibria in which agents within the same group take symmetric strategies. That is, agents in group $i \in N$ choose a common distribution π_i and an action plan $a_i(\cdot)$. Cross-sectional heterogeneity in realized actions a_{ki} for $k \in [0,1]$ then comes only from independent signal noise. I define an equilibrium as follows:

Definition 2.1 (Equilibrium)**.** *A symmetric equilibrium is a collection of strategies* $\{\pi_i, a_i\}_{i\in N}$ *and an aggregate mapping* f *such that:*

1. *For each agent* (k, i)*, the pair* (π_i, a_i) *solves* (2.3)*.*

2. *The aggregate mapping* f *is consistent with agents' optimal actions:*

$$f_i(\theta) = \int a_i(s_{ki})\pi_i(s_{ki} \mid \theta) \, \mathrm{d}s_{ki}, \quad \forall i \in N$$

where $f_i(\theta)$ *is the* i*-th component of* $f(\theta)$ *and* $\pi_i(s_{ki} \mid \theta)$ *is the conditional density of* s_{ki} *under* π_i*.*

2.2 Equilibrium

The optimal action for agents in group i under perfect observation of (θ, a), denoted by a_i^*, is given by:

$$a_i^* = \sum_{j=1}^{n} g_{ij} a_j + \theta_i. \tag{2.4}$$

When information is costly, the optimal signal s_{ki} is Gaussian and collinear with a_i^*.[5] The optimal action a_{ki} is simply the conditional expectation of a_i^* under the signal:

$$a_{ki} = \mathbb{E}\left[a_i^* \mid s_{ki}\right]. \tag{2.5}$$

Each agent's information and action choices can be summarized by a single variable $\lambda_i \in [0, 1]$, which is the squared correlation between a_{ki} and a_i^*. A higher λ_i implies more mutual information between the signal and the state encoded in the probability distribution π_i and a larger reduction in prior uncertainty about a_i^*. Accordingly, I refer to λ_i as agent (k, i)'s attention. Lemma 2.1 characterizes the optimal attention and action for each agent, taking the decisions of others as given.

[5]This form of one-dimensional Gaussian signal is a well-established result in the rational inattention literature, which arises from assumptions of quadratic payoffs, a Gaussian prior, and a one-dimensional action space. See, e.g., Maćkowiak and Wiederholt (2009) and Afrouzi (2024) in a single-group setting, and Fang et al. (2025) in a production network.

Lemma 2.1 (Individual Optimal Strategy). *The optimal attention for agent* (k,i) *is:*

$$\lambda_i = \max\left\{0, 1 - \frac{\omega_i}{V_i}\right\} \tag{2.6}$$

which implies that the optimal action follows:

$$a_{ki} = \lambda_i a_i^* + \epsilon_{ki}, \quad \epsilon_{ki} \sim \mathcal{N}(0, \omega_i \lambda_i) \tag{2.7}$$

where the noise ϵ_{ki} *is independent of* a *and* θ*,* a_i^* *is given by equation (2.4), and* $V_i = \mathrm{Var}(a_i^*)$ *denotes the unconditional variance of the desired action* a_i^**.*

Proof. See Appendix A.1. □

The optimal action tracks the desired action a_i^* more closely as attention increases. By the expression of noise variance in (2.7), higher attention implies greater cross-sectional dispersion in actions. To understand this result, consider an alternative interpretation of λ_i, which is the agent's optimal Kalman gain on a linear Gaussian signal about the desired action. Intuitively, with more information acquisition, signals are more informative with lower noise variances. Agents place more weight on those signals when forming posterior beliefs. These forces push the action dispersion in opposite directions. Under optimal information acquisition, the second weighting effect dominates. Although realized actions are more dispersed ex post and may incur large utility loss with extreme actions, optimal information choice trades off expected utility against information cost ex ante.

An agent may optimally choose not to acquire any information, that is, $\lambda_i = 0$, when the information cost parameter is very high or unconditional uncertainty is very low. Otherwise, optimal attention is decreasing in the information cost parameter and increasing in the prior variance of the desired action.

Each agent's prior uncertainty about the desired action depends on others' actions and information acquisition through the cross-group links summarized by the interaction matrix G. Attention determines how responsive aggregate actions are to the underlying fundamentals, which in turn affects how desired actions co-move with fundamentals. When agents in one group acquire more information, it may increase or decrease the unconditional variances of desired actions for other groups. In turn, other groups adjust their attention and actions, feeding back into the first group's choices.

Multiple equilibria may arise in this strategic environment. Before characterizing optimal actions and attention, I state conditions that ensure existence and uniqueness of an equilibrium in which all agents choose strictly positive attention.

Proposition 2.1 (Existence and Uniqueness). *There exists a unique equilibrium in which all agents acquire information under the following assumptions:*

$$
\begin{aligned}
&(A1) \quad \rho = \sigma_{\max}(G) < 1 \\
&(A2) \quad \max_{i \in N} \omega_i \ < \ \frac{\sigma_{\min}(\Sigma)}{(1+\rho)^2} \\
&(A3) \quad \frac{2\rho(1+\rho)^2}{(1-\rho)^3} \cdot \frac{\sigma_{\max}(\Sigma)}{\sigma_{\min}(\Sigma)} < 1
\end{aligned}
$$

where $\sigma_{\max}(\cdot)$ and $\sigma_{\min}(\cdot)$ denote the largest and the smallest singular values of a matrix, respectively.

Proof. See Appendix A.2. □

Under condition (A1), ρ measures the strength of network feedback among groups' actions. Imposing a strict unit upper bound on ρ ensures existence and uniqueness of equilibrium for any given attention vector λ. Multiplicity then arises only from attention choices. Equation (2.6) shows that agents choose not to acquire any information when the unit information cost parameter exceeds the prior uncertainty about the desired action, $\omega_i > V_i$. Condition (A2) ensures that information cost parameters are sufficiently small for all groups, which rules out corner solutions with no information acquisition for some agents.

Finally, condition (A3) guarantees uniqueness of an equilibrium with strictly positive attention for all groups. To establish this result, I define an attention best-response operator that maps an arbitrary attention vector to the attention vector implied by the optimality conditions in Lemma 2.1, and show that it is a contraction under the assumptions. More formally, let $\lambda = (\lambda_1, \cdots, \lambda_n) \in [0,1]^n$ denote an attention vector. I define the operator $\mathcal{T} : [0,1]^n \to [0,1]^n$ by:

$$
\mathcal{T}_i(\lambda) = 1 - \frac{\omega_i}{V_i\,(G, \Sigma, \lambda)}, \quad \text{for } i = 1, \ldots, n \tag{2.8}
$$

It suffices to prove that $\mathcal{T}$ is a contraction. Intuitively, the tightness of condition (A3) increases with the strength of network feedback, ρ, and with the condition number of the shock covariance matrix, $\frac{\sigma_{\max}(\Sigma)}{\sigma_{\min}(\Sigma)}$, both of which contribute to a larger response of prior uncertainty and thus of $\mathcal{T}(\lambda)$ to changes in λ. Uniqueness follows by restricting their combined effect. The equilibrium attention vector is the unique fixed point satisfying $\mathcal{T}(\lambda) = \lambda$.

I assume these conditions hold throughout the analysis in this section. The next proposition characterizes the equilibrium outcomes.

Proposition 2.2 (Equilibrium Attention and Aggregate Action)**.** *The vector of equilibrium aggregate actions is determined by:*

$$a = (I - \Lambda G)^{-1} \Lambda\theta \tag{2.9}$$

where Λ *is a diagonal matrix containing each group's attention* $\lambda_1, \cdots, \lambda_n$*.*

The optimal attention of group $i \in N$ *is given by:*

$$\lambda_i = 1 - \frac{\omega_i}{V_i}, \quad V_i = \mathrm{Var}(a_i^*) \tag{2.10}$$

with the vector of desired actions $a^* = (a_1^*, \cdots, a_n^*)$ *satisfying:*

$$a^* = \Lambda^{-1} a \tag{2.11}$$

Proof. See Appendix A.3. □

For comparison with the rational inattention equilibrium, first consider the frictionless case with no information costs. Agents have perfect information. The attention matrix is the identity, $\Lambda = I$. The equilibrium vector of aggregate actions, denoted by $a(I)$, is then given by:

$$a(I) = (I - G)^{-1}\theta.$$

In this case, the sensitivity of each group's aggregate action to fundamentals is governed solely by the interaction matrix.

In the equilibrium with costly information acquisition, agents' limited attention, $\lambda_i \in (0, 1)$, attenuates both the direct response of aggregate actions to shocks, captured by $\Lambda\theta$, and the indirect response operating through general equilibrium, captured by the term $(I - \Lambda G)^{-1}$. Hence, the response of aggregate actions to fundamentals depends not only on the interaction matrix but also on endogenous attention. Equilibrium attention itself is a function of the interaction matrix, the covariance matrix of fundamentals, and the information cost parameters. This characterization extends the information-adjusted network representation for symmetric networks in Denti (2017).

Proposition 2.2 characterizes the joint determination of aggregate actions, attention, and the uncertainty faced by agents. Relative to an exogenous information structure or a single-group information acquisition setting, a new source of equilibrium feedback arises from the interaction of information choices across groups. I illustrate these strategic interactions in more detail below.

2.3 Strategic Interaction in Attention Choice

I define the value of information for agent (k, i) as the difference between expected utility under the optimal signal structure and that under no information acquisition:

$$\frac{1}{2}\lambda_i V_i,$$

The marginal value of information, denoted by m_i, is then:

$$m_i = \frac{V_i}{2} \tag{2.12}$$

which measures the incentives to acquire information. Intuitively, when the desired action is more volatile, that is, when V_i is higher, agents have stronger incentives to acquire information.

To understand the interdependence of attention choices, I consider the comparative statics of how an exogenous shift in others' attention affects an agent's marginal value of information.[6] Using the characterization of V_i in Proposition 2.2, I next describe how m_i varies with each λ_j.

Proposition 2.3 (Sensitivity of the Marginal Value of Information to Attention)**.** *For any $i, j \in N$, the marginal value of information varies with attention as follows:*

$$\mathcal{M}_\lambda := \left[\frac{\partial m_i}{\partial \lambda_j}\right]_{ij} = G(I - \Lambda G)^{-1} \circ (I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1} \tag{2.13}$$

where $\circ$ denotes the element-wise (Hadamard) product.

Proof. See Appendix A.4. □

Relatedly, Fang et al. (2025) characterize strategic complementarity in information acquisition across firms in a production network. Proposition 2.3 nests their result, which corresponds to a specific positive matrix G and implies that information choices are strategic complements. Allowing for a general interaction matrix delivers a new prediction. That is, the strategic motives in attention choices depend not only on the strategic motives in actions but also on the underlying shock volatility. This dependence is especially evident when groups have negative linkages, as shown in Example 2 and in the next section.

The attention of other groups affects the uncertainty V_i and thus the marginal value of information by changing the propagation of underlying shocks to the desired actions.

[6] In the current setup, such an exogenous shift can arise from changes in the information cost parameter ω_j.

Proposition 2.3 shows that this effect is summarized by the Hadamard product of two factors. The right factor, $(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}$, is the unconditional covariance matrix of desired actions. It describes the current "state" of how aggregate actions co-move with each other across groups, which is determined by their responses to fundamentals. The left factor $G(I - \Lambda G)^{-1}$ maps how changes in the aggregate action of one group propagate to the desired actions of other groups. Hence, $\mathcal{M}_\lambda$ can be interpreted as an uncertainty-adjusted influence matrix.

The sign of $\frac{\partial m_i}{\partial \lambda_j}$ reflects whether more attention by group j increases or decreases the value of information for agents in group i. To illustrate its dependence on the two factors, suppose the desired actions a_i^* and a_j^* are positively correlated. If the (i, j) element of the left factor is also positive, the desired action a_i^* moves with the aggregate action a_j in the same direction. Hence, a more responsive a_j, due to higher attention, amplifies the response of a_i^* to shocks, increasing its unconditional volatility and thus the marginal value of information for i. Conversely, if that (i, j) element is negative, a_i^* responds to a_j and to shocks with the opposite sign. A more responsive a_j thus reduces the volatility of a_i^* and lowers the marginal value of information.

I illustrate the determination of $\mathcal{M}_\lambda$ using two simple examples. The first example considers the case with no interactions across groups. The second example examines two groups that are linked to each other.

Example 1 (Single-Group Beauty Contest Game)**.** The first example features a diagonal matrix G. With no interactions across groups, the environment is equivalent to n separate beauty contest games à la Morris and Shin (2002). The best response for agents in group i is:

$$a_{ki} = \mathbb{E}\left[g_{ii}a_i + \theta_i \mid s_{ki}\right]$$

where g_{ii} is the i-th diagonal element of G with $|g_{ii}| < 1$ under condition (A1), $\theta_i \sim \mathcal{N}(0, \sigma_i^2)$ is the shock to group i, and s_{ki} is agent (k, i)'s signal. The corresponding $\mathcal{M}_\lambda$ is also diagonal:

$$\mathcal{M}_\lambda = \operatorname{diag}\left(\frac{g_{ii}}{1 - \lambda_i g_{ii}}\right) \circ \operatorname{diag}\left(\frac{\sigma_i^2}{(1 - \lambda_i g_{ii})^2}\right).$$

As the desired actions are identical within each group, the sign of $\frac{\partial m_i}{\partial \lambda_i}$ depends on the first factor, in particular, g_{ii}. Attention choices are complements when actions are strategic complements, $g_{ii} > 0$, and strategic substitutes when $g_{ii} < 0$. This result echoes Proposition 1 in Hellwig and Veldkamp (2009), which shows that the strategic motives behind information choices mirror those inherent in the action space. $\triangle$

Example 2 (Two Connected Groups)**.** The second example considers two groups with the following interaction matrix and shock covariance structure:

$$G = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \qquad \Sigma = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

The matrix $\mathcal{M}_\lambda$ for this setting is given by:

$$\mathcal{M}_\lambda = \alpha \begin{bmatrix} g_{11} - \lambda_2 \det(G) & g_{12} \\ g_{21} & g_{22} - \lambda_1 \det(G) \end{bmatrix} \circ \begin{bmatrix} \mathrm{Var}(a_1^*) & \mathrm{Cov}(a_1^*, a_2^*) \\ \mathrm{Cov}(a_1^*, a_2^*) & \mathrm{Var}(a_2^*) \end{bmatrix}$$

where $\alpha = 1/\det(I - \Lambda G) > 0$.

Relative to the diagonal example, whether attention is a strategic complement within each group now depends on the sign of $g_{11} - \lambda_2 \det(G)$ for group 1 and the sign of $g_{22} - \lambda_1 \det(G)$ for group 2. The additional terms, $\lambda_2 \det(G)$ and $\lambda_1 \det(G)$, capture feedback from the other group. The strength of this feedback is governed by the other group's attention and by the structure of G. Critically, cross-group interaction can cause $\frac{\partial m_i}{\partial \lambda_i}$ to have the opposite sign of g_{ii}.

Figure 1a presents a numerical example that illustrates how cross-group interaction affects within-group strategic motives in information acquisition. In each panel, the colored dashed line plots g_{ii}. The solid line plots $g_{ii} - \det(G)$, which corresponds to the maximal cross-group feedback for any given G. Depending on the other group's attention $\lambda_{-i} \in (0, 1)$, the value $g_{ii} - \lambda_{-i} \det(G)$ lies between the two lines. As the upper off-diagonal term g in G varies, the left panel shows that $\frac{\partial m_1}{\partial \lambda_1}$ can have the opposite sign of g_{11} when g is sufficiently large. The right panel shows that $\frac{\partial m_2}{\partial \lambda_2}$ can have the opposite sign of g_{22} when g is sufficiently negative. In both cases, strong feedback from the other group overturns the direct within-group effect.

The analysis of within-group strategic motives highlights the role of G. I now fix $g = -0.5$ and continue the numerical example to show how shock volatility disciplines the strategic interaction in attention choices across groups in addition to G.[7]

Figure 1b plots how $\frac{\partial m_1}{\partial \lambda_2}$ (blue) and $\frac{\partial m_2}{\partial \lambda_1}$ (red) vary with σ_2^2, holding $\sigma_1^2 = 1$ fixed. From the expression for $\mathcal{M}_\lambda$, the sign of these cross-effects depends on the covariance between a_1^* and a_2^*. As shown in the figure, both signs flip once σ_2 exceeds a threshold.

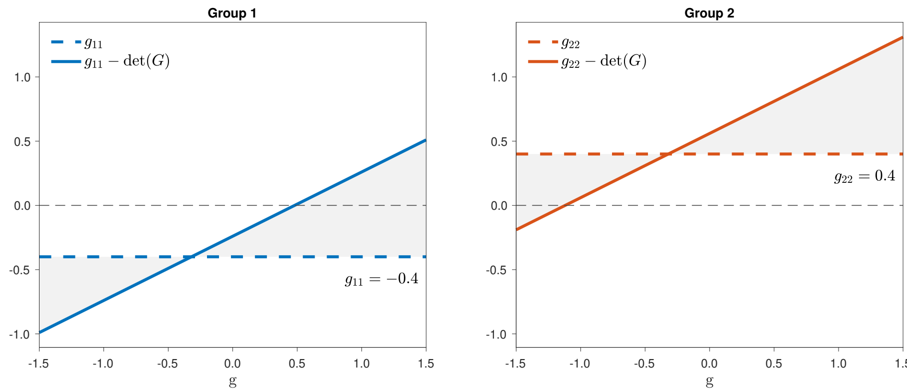
The intuition is as follows. When σ_2 is small, the shock θ_1 accounts for most of the variation in aggregate actions. The effect of θ_1 on group 2 operates through group 2's response to the aggregate action of group 1, i.e., g_{21}. The dominance of θ_1 and a positive g_{21} imply that the desired actions of the two groups are now positively correlated. Higher

[7] Appendix A.9 provides the theoretical characterization.

Figure 1: Strategic Interactions in Attention (Example 2)

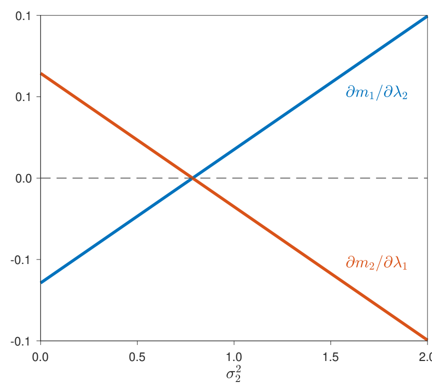
(a) Within-group

$$G = \begin{bmatrix} -0.4 & g \\ 0.5 & 0.4 \end{bmatrix}$$



(b) Cross-group

$$G = \begin{bmatrix} -0.4 & -0.5 \\ 0.5 & 0.4 \end{bmatrix}$$



attention by group 1 makes its aggregate action respond more strongly to θ_1, which raises the volatility of group 2's desired action. It is then optimal for group 2 to acquire more information, so $\frac{\partial m_2}{\partial \lambda_1} > 0$. By contrast, since $g_{12} < 0$, higher attention by group 2 dampens the volatility of group 1's desired action, so $\frac{\partial m_1}{\partial \lambda_2} < 0$. When σ_2 becomes large, the shock θ_2 plays a dominant role and the situation reverses.

$\triangle$

I end this section with another intuitive representation that illustrates how strategic interactions and shock volatility affect the equilibrium attention by perturbing the interaction matrix. For any given G, decompose it as $G = G_d + G_o$, where G_d collects the diagonal elements and G_o the off-diagonal ones. Let $G(\varepsilon)$ denote an ε-perturbation: $G(\varepsilon) = G_d + \varepsilon G_o$. I then approximate the equilibrium attention around $\varepsilon = 0$. To provide a clear intuition, I assume that shocks are independent.

Proposition 2.4. *The second-order approximation of equilibrium attention λ_i around $\varepsilon = 0$ is:*

$$\lambda_i(\omega, G(\varepsilon), \Sigma) = \overline{\lambda_i} + \left\{ \sum_{j \neq i} \alpha_{ij} \cdot g_{ij}^2 \sigma_j^2 + \sum_{j \neq i} \beta_{ij} \cdot g_{ij} g_{ji} \sigma_i^2 \right\} \cdot \varepsilon^2 + \mathcal{O}\left(\varepsilon^3\right) \tag{2.14}$$

where the coefficients satisfy $\alpha_{ij}, \beta_{ij} > 0$, σ_i^2 is the variance of the shock θ_i, and $\overline{\lambda_i} = \lambda_i(\omega, G(0), \Sigma)$ is the equilibrium attention for group i when $\varepsilon = 0$.

Proof. See Appendix A.5. □

Since Σ is diagonal, the first-order effect vanishes. In the second-order term, the first sum shows that the link g_{ij} introduces the group-specific shock θ_j into group i's desired action, which raises group i's incentive to acquire information. The second sum shows that the mutual response, captured by the product $g_{ij} g_{ji}$, can amplify or dampen the impact of group i's own shock on its desired action, and thus increase or reduce the uncertainty associated with θ_i. Although this approximation is derived under independent shocks, the intuition extends to more general shock structures.

3 Rationally Inattentive Households and Firms

I now apply the framework in Section 2 to study how endogenous information acquisition by households and firms shapes equilibrium shock propagation, with a focus on the slopes of aggregate demand and aggregate supply. The section proceeds as follows. First, I introduce rationally inattentive households and firms in a standard neoclassical model. Second, I show that the equilibrium has an Aggregate Demand and Aggregate Supply representation, with slopes determined by agents' attention. Third, I characterize how changes in shock volatility generate non-monotonic movements in both slopes, a new prediction that hinges on endogenous attention of households and firms.

3.1 Setup

Time is discrete and infinite $t \in \mathbb{N}$. Since households and firms make multiple decisions conditional on different information sets, I divide each time period into three stages for convenience.[8]

[8] The only rigidity in the model comes from information frictions. It is standard to impose different measurability restrictions for variables to clear markets in both the New Keynesian literature and the literature with imperfect information (Mankiw and Reis, 2002; Woodford, 2003; Maćkowiak and Wiederholt, 2009).

Firms. There is a continuum of monopolistic intermediate goods firms. Each firm $j \in [0,1]$ produces a differentiated variety with linear technology:

$$Y_{jt} = A_t L_{jt} \tag{3.1}$$

where L_{jt} is labor input and A_t is aggregate productivity, which follows an AR(1) in logs with time-varying volatility σ_{At}:

$$\log A_t = \rho_A \log A_{t-1} + \theta_{At}, \quad \theta_{At} \sim_{i.i.d} \mathcal{N}(0, \sigma_{At}^2). \tag{3.2}$$

Firm j faces demand from the competitive final goods producers, which combine intermediate goods to produce the final good Y_t at price P_t using a constant-elasticity-of-substitution technology:

$$Y_t = \left(\int_0^1 Y_{jt}^{\frac{\eta-1}{\eta}} \, \mathrm{d}j \right)^{\frac{\eta}{\eta-1}} \tag{3.3}$$

where $\eta > 1$ is the elasticity of substitution across varieties. Firms receive a wage subsidy at rate $\tau = \frac{1}{\eta}$ that offsets the monopolistic markup.

Intermediate goods firms choose their signal structure in stage 1 of each period t. In stage 2, they set prices based on realizations of their signals and prior information from previous periods. In stage 3, all shocks are publicly revealed. Firms then hire labor in a competitive labor market so that production meets demand at their posted prices.

Firm j's optimal (log) price under perfect information p_t^* equals its marginal cost of production:

$$p_t^* = \log \frac{W_t}{A_t} \tag{3.4}$$

where W_t is the nominal wage. Let p_{jt} be the (log) price set by firm j. After a quadratic approximation to the firm's profit function around the steady state, the loss from setting p_{jt} is given by:

$$\mathcal{L}(p_{jt}, p_t^*) = -\frac{\eta-1}{2}(p_{jt} - p_t^*)^2 \tag{3.5}$$

A higher η implies more elastic demand and a larger profit loss from mispricing.

Households. Each household $i \in [0,1]$ has expected discounted utility over final good consumption C_{it} and labor supply N_{it} given by:

$$\mathbb{E}_{i0}\left[\sum_{t=0}^{\infty} \beta^t Z_t \left(\frac{C_{it}^{1-\gamma}}{1-\gamma} - N_{it} \right) \right] \tag{3.6}$$

where $\log Z_t$ is a discount rate shock that follows an AR(1) with time-varying volatility σ_{Zt}:

$$\log Z_t = \rho_Z \log Z_{t-1} + \theta_{Zt}, \quad \theta_{Zt} \sim_{i.i.d} \mathcal{N}(0, \sigma^2_{Zt}) \tag{3.7}$$

Moreover, the innovations to the discount rate and aggregate productivity are independent.

Households choose their signal structure in stage 1, similarly to firms. Both households and firms have common knowledge of the shock processes in (3.2) and (3.7). Households also trade contingent financial claims that settle in stage 3. In stage 2, after observing their signals, households choose consumption. In stage 3, they supply labor, consume the chosen amount, and purchase risk-free bonds under perfect information about the economy.

The household budget constraint at time t is:

$$P_t C_{it} + \int Q_t(\widetilde{\iota}_{it}) X_{it}(\widetilde{\iota}_{it}) \, \mathrm{d}\widetilde{\iota}_{it} + \frac{B_{it+1}}{R_t} = W_t N_{it} + B_{it} + X_{it}(\iota_{it}) + \Pi_t + T_t \tag{3.8}$$

where $\iota_{it} = (\theta_{Zt}, \theta_{At}, C_{it})$, $Q_t(\widetilde{\iota}_{it})$ is the price of the state-contingent claim, $X_{it}(\widetilde{\iota}_{it})$ is household i's holdings, B_{it+1} is the risk-free nominal bond (in zero net supply) purchased at t, R_t is the nominal interest rate between t and $t+1$ set by the central bank, Π_t is the total profits of firms and T_t is a lump-sum tax financing wage subsidies.

Households have access to complete markets over ι_{it}. Individual consumption C_{it} is a random variable and contains signal noise due to rational inattention. By trading the contingent claims, households insure against the idiosyncratic noise in signals and consumption. Since households are ex ante identical and start from a degenerate wealth distribution at $t = 0$, this assumption eliminates wealth heterogeneity across households for all periods.[9]

Let c_t^* be the desired (log) consumption under full information. It depends positively on the real wage and satisfies:

$$c_t^* = \log \left(\frac{W_t}{P_t} \right)^{1/\gamma} \tag{3.9}$$

The actual (log) consumption, denoted by c_{it}, differs from c_t^* due to limited attention. After a quadratic approximation to the utility function, the flow utility loss of choosing c_{it} can be expressed as:

$$\mathcal{L}(c_{it}, c_t^*) = -\frac{\gamma}{2}(c_{it} - c_t^*)^2 \tag{3.10}$$

With a higher elasticity of marginal utility γ, the losses are larger when consumption deviates from c_t^*.

[9]The perfect insurance assumption to simplify the dynamic analysis goes back to Grossman (1985) and Lucas (1990). It is a standard assumption in canonical DSGE models. In this setting, agents can insure against idiosyncratic shocks arising from inattention. See also Lorenzoni (2010) and Angeletos and Sastry (2025).

Monetary Policy. To complete the model, I assume that the central bank sets the nominal gross interest rate R_t according to a Taylor rule:

$$\log R_t = \log \bar{R} + \phi_\pi \log(P_t/P_{t-1}) \tag{3.11}$$

where $\bar{R} = \beta^{-1}$ is the steady-state nominal rate, and ϕ_π is the response coefficient to inflation. While households and firms understand that monetary policy follows this rule, they do not observe the value of R_t until stage 3. Since R_t is a function of the current price level P_t, this timing assumption is consistent with the individual rational inattention problem.

Costly Information Acquisition. Let small letters denote the logs of the corresponding variables. Combining monetary policy, households' optimality conditions and market clearing, the equilibrium nominal wage is determined by:[10]

$$w_t = \theta_{Zt} + \phi_\pi p_{t-1} + \rho_Z z_{t-1} \tag{3.12}$$

Uncertainty in the nominal wage thus comes only from current shocks, and so does firms' desired price p_t^* as well as households' desired consumption c_t^*. Since contemporaneous shocks are perfectly observed in stage 3 of each period, households' and firms' information, consumption and price choices become static problems.

Formally, let aggregate consumption and price be $c_t = \int_0^1 c_{it}\, \mathrm{d}i$ and $p_t = \int_0^1 p_{jt}\, \mathrm{d}j$, and denote $\theta_t = (\theta_{Zt}, \theta_{At})$ as the vector of aggregate shocks. Household i chooses an information policy $\pi_{it}(\theta_t, c_t, p_t, s_{it})$, which is a joint distribution over the signal s_{it} and (θ_t, c_t, p_t), and a consumption rule $c_{it} : \mathbb{S}_{it} \to \mathbb{R}$, where $\mathbb{S}_{it}$ is the household's information set in stage 2 of period t. Household i maximizes expected utility net of information costs:

$$\max_{\pi_{it}, c_{it}} \quad \mathbb{E}_{\pi_{it}} \left[-\frac{\gamma}{2} (c_{it} - c_t^*)^2 \right] - \omega_H \mathcal{I}(\theta, c_t, p_t; s_{it}) \tag{3.13}$$

$$s.t. \quad c_t^* = \frac{1}{\gamma} \left(-p_t + \theta_{Zt} + \phi_\pi p_{t-1} \right) + const \tag{3.14}$$

where $\omega_H > 0$ is the unit information cost for households, and $\mathcal{I}(.;.)$ is the mutual information as before.

Similarly, firm j chooses an information policy $\pi_{jt}(\theta_t, c_t, p_t, s_{jt})$, a joint distribution over its signal s_{jt} and (θ_t, c_t, p_t), and a pricing rule $p_{jt} : \mathbb{S}_{jt} \to \mathbb{R}$, where $\mathbb{S}_{jt}$ is the firm's information

[10] The usual transversality condition eliminates non-fundamental fluctuations in nominal wages.

set in stage 2 of period t. Firm j maximizes expected profit net of information costs:

$$\max_{\pi_{jt}, p_{jt}} \quad \mathbb{E}_{\pi_{jt}}\left[-\frac{\eta-1}{2}(p_{jt}-p_t^*)^2\right] - \omega_F \mathcal{I}(\theta, c_t, p_t; s_{jt}) \tag{3.15}$$

$$s.t. \quad p_t^* = \theta_{Zt} - \theta_{At} + \phi_\pi p_{t-1} + const \tag{3.16}$$

where $\omega_F > 0$ is the information cost parameter for firms.

Mapping the economy to the framework of Section 2, the interaction matrix G between households and firms, and the shock covariance matrix Σ are:

$$G = \begin{bmatrix} 0 & -\frac{1}{\gamma} \\ 0 & 0 \end{bmatrix} \qquad \Sigma = \begin{bmatrix} \sigma_{Zt}^2/\gamma^2 & \sigma_{Zt}^2/\gamma \\ \sigma_{Zt}^2/\gamma & \sigma_{Zt}^2 + \sigma_{At}^2 \end{bmatrix} \tag{3.17}$$

Matrix G is upper triangular with a single nonzero off-diagonal entry $-\frac{1}{\gamma}$. Strategic interaction arises from the dependence of consumption on prices. Although this is a simplified case derived from standard preferences and technology assumptions, it generates rich predictions on the state dependency of shock propagation, as shown in the remainder of this section.

I focus on symmetric strategies within households and firms. Households choose the same information policy π_t^H and consumption policy $c_{it} : \mathbb{S}_{it} \to \mathbb{R}$. Firms choose the same information policy π_t^F and pricing policy $p_{jt} : \mathbb{S}_{jt} \to \mathbb{R}$.[11]

Definition 3.1 (Equilibrium). *An equilibrium consists of information choices* $\{\pi_t^H, \pi_t^F\}_{t\in\mathbb{N}}$*, price and consumption choices* $\{c_{it}, p_{jt}\}_{i,j\in[0,1],t\in\mathbb{N}}$*, and variables*

$$\{W_t, P_t, R_t, \Pi_t, T_t, \{Q_t(\widetilde{\iota})\}_{\widetilde{\iota}}, \{N_{it}, X_{it}(\widetilde{\iota}), B_{it+1}\}_{i\in[0,1]}\}_{t\in\mathbb{N}}$$

such that:

1. *Firms' information and price choices solve (3.15).*
2. *Households' information and consumption choices solve (3.13). Their choices of labor supply, risk-free bonds and state-contingent claims maximize utility subject to the budget constraint (3.8).*
3. *The nominal interest rate R_t evolves according to (3.11).*
4. *The markets for the intermediate goods, the final good, labor, bonds, and state-contingent claims all clear.*

[11] To avoid confusion between the individual consumption policy and aggregate consumption $c_t = \int_0^1 c_{it}\, \mathrm{d}i$, I keep the individual index i in the subscript of the symmetric consumption policy function. The same convention applies to firms' pricing policies.

3.2 Equilibrium AD/AS Representation with Endogenous Slopes

I first characterize the optimal information acquisition, consumption and pricing strategies for households and firms. By Lemma 2.1, the problems in (3.13) and (3.15) reduce to choosing attention $\lambda_t^H \in [0,1]$ for households and $\lambda_t^F \in [0,1]$ for firms.

Corollary 3.1 (Optimal Strategies for Households)**.** *Each household chooses attention* λ_t^H *and consumption* c_{it} *according to:*

$$\lambda_t^H = 1 - \frac{\omega_H}{\gamma\,\mathrm{Var}(c_t^*)} \tag{3.18}$$

$$c_{it} = \lambda_t^H c_t^* + u_{it}, \quad u_{it} \sim \mathcal{N}(0, \frac{\omega_H}{\gamma}\lambda_t^H) \tag{3.19}$$

where c_t^* *is defined in (3.14),* $\mathrm{Var}(c_t^*)$ *is the household's prior uncertainty of* c_t^**, and the idiosyncratic noise* u_{it} *is independent of* c_t^**.*

Proof. Follows from Lemma 2.1. □

Higher attention makes households' optimal consumption track the desired level more closely in expectation. Households acquire more information when the prior variance of c_t^* increases, since greater uncertainty raises expected utility loss and strengthens incentives to acquire information. Since c_t^* depends on the aggregate price p_t, firms' choices influence household attention by altering uncertainty about c_t^*. Holding $\mathrm{Var}(c_t^*)$ fixed, attention increases with the curvature of the loss function γ and decreases with the information cost parameter ω_H.

Corollary 3.2 (Optimal Strategies for Firms)**.** *Each firm chooses attention* λ_t^F *and price* p_{jt} *according to:*

$$\lambda_t^F = 1 - \frac{\omega_F}{(\eta - 1)\,\mathrm{Var}(p_t^*)} \tag{3.20}$$

$$p_{jt} = \lambda_t^F p_t^* + u_{jt}, \quad u_{jt} \sim \mathcal{N}(0, \frac{\omega_F}{\eta - 1}\lambda_t^F) \tag{3.21}$$

where p_t^* *is defined in (3.16),* $\mathrm{Var}(p_t^*)$ *is the firm's prior uncertainty of* p_t^**, and the idiosyncratic noise* u_{jt} *is independent of* p_t^* *and* u_{it}*.*

Proof. Follows from Lemma 2.1. □

Similarly, the firm's price is more closely correlated with its desired price when it has higher attention. Each firm's optimal attention rises with the prior variance of its desired price and with the demand elasticity, and falls with the information cost parameter.

Desired consumption and prices, and therefore their unconditional variances, are endogenous. I now characterize the equilibrium dynamics of the economy. Aggregate allocations can be represented by an Aggregate Demand and Aggregate Supply (AD/AS) framework, with slopes determined by the endogenous attention choices of households and firms.

Theorem 3.1 (Equilibrium AD/AS with Endogenous Slopes)**.** *Aggregate output and price in the unique equilibrium are determined by the following AD-AS equations:*

$$p_t = \overline{p}_t - \psi_t^D \left(y_t - \overline{y}_t\right) + \theta_{Zt} \tag{3.22}$$

$$p_t = \overline{p}_t + \psi_t^S \left(y_t - \overline{y}_t\right) - \frac{\lambda_t^F}{1-\lambda_t^F}\theta_{At} \tag{3.23}$$

where $\overline{p}_t$ and $\overline{y}_t$ are expected price and output at the first stage of time t and depend only on past shocks. The slopes are given by:

$$\psi_t^D = \frac{\gamma}{\lambda_t^H} \quad \text{and} \quad \psi_t^S = \frac{\gamma\lambda_t^F}{\lambda_t^H(1-\lambda_t^F)} \tag{3.24}$$

and the optimal firm and household attention are given by:

$$\lambda_t^F = 1 - \frac{\omega_F}{(\eta-1)(\sigma_{At}^2+\sigma_{Zt}^2)} \tag{3.25}$$

$$\lambda_t^H = 1 - \frac{\gamma\omega_H}{\left(\lambda_t^F\right)^2\sigma_{At}^2 + \left(1-\lambda_t^F\right)^2\sigma_{Zt}^2} \tag{3.26}$$

Proof. See Appendix A.6. □

Applying Proposition 2.2 yields the joint determination of equilibrium allocations and attention. The aggregate demand equation (3.22) and aggregate supply equation (3.23) follow from expressing the equilibrium so that demand shocks enter only the AD curve and supply shocks enter only the AS curve.

The aggregate demand curve describes how real output depends on the aggregate price and demand shocks. As illustrated in Figure 2b, its slope, ψ_t^D, captures the relative elasticities of prices and output to supply shocks. Specifically, consider a positive aggregate supply shock that lowers the aggregate price by one unit. As households observe the price change imperfectly, they perceive a rise in real income of λ_t^H and thus increase consumption by $\frac{\lambda_t^H}{\gamma}$. Output, equal to aggregate consumption, also rises by $\frac{\lambda_t^H}{\gamma}$. Since the response of output to supply shocks comes only from the dependence of consumption on prices, firm attention affects the responsiveness of output and price to supply shocks proportionally. Therefore, the slope of aggregate demand, ψ_t^D, depends only on household attention, λ_t^H. When households acquire more information, output is more responsive to prices and the aggregate demand becomes flatter.

The aggregate supply curve describes how the aggregate price depends on output and supply shocks. Its slope, ψ_t^S, reflects the relative elasticities of price and output to demand shocks, as shown in Figure 2a. To understand its determination, consider firms' price setting after an aggregate demand shock that raises output by one unit. Since households are inattentive, the unit change in output reflects changes in real wages imperfectly, implying an increase in real marginal costs of $\frac{\gamma}{\lambda_t^H}$. The total change in the aggregate price combines dampened responses to real marginal cost and to the nominal aggregate price under firms' incomplete information:

$$\lambda_t^F \times \frac{\gamma}{\lambda_t^H} + \left(\lambda_t^F\right)^2 \times \frac{\gamma}{\lambda_t^H} + \left(\lambda_t^F\right)^3 \times \frac{\gamma}{\lambda_t^H} + \cdots = \frac{\lambda_t^F}{1-\lambda_t^F} \times \frac{\gamma}{\lambda_t^H}$$

where the infinite sum arises from the feedback between individual prices and the aggregate price.[12] Holding household attention fixed, greater firm attention steepens the aggregate supply. Holding firm attention fixed, lower household attention implies that even a small increase in aggregate demand corresponds to a large movement in real wages. In response, firms set higher prices, and the supply curve becomes steeper.

The equilibrium attention of households and firms admits a closed-form solution. From (3.16), the desired price depends solely on aggregate shocks. Hence, its unconditional variance and equilibrium firm attention are determined by shock variances. Combining the expression of desired consumption (3.14) with the equilibrium aggregate price, households' desired consumption up to a constant can be written as

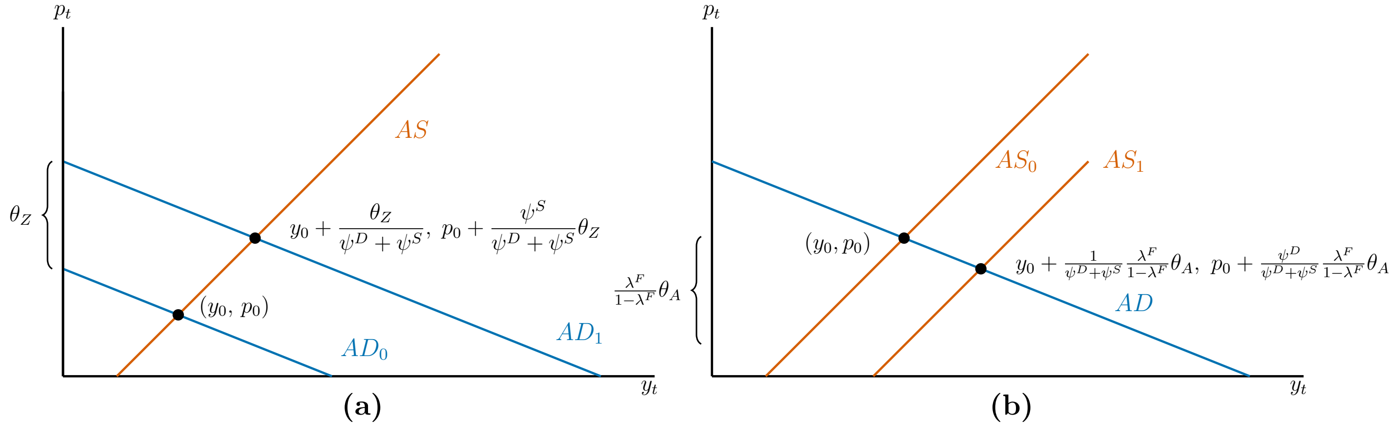
$$c_t^* = \frac{\lambda_t^F}{\gamma}\theta_{At} + \frac{1-\lambda_t^F}{\gamma}\theta_{Zt}.$$

Firm attention affects household uncertainty and attention by shifting the exposure of c_t^* to supply and demand shocks, as characterized in Propositions 2.3 and 2.4.

AD/AS with One-Sided Rational Inattention. Theorem 3.1 nests the one-sided rational inattention benchmarks by setting the information cost to zero for households or for firms. To compare their predictions with the two-sided inattention equilibrium, I characterize the slopes of aggregate demand and aggregate supply in each case.

[12]To clarify, the desired price p_t^* does not depend on the aggregate price p_t. That is, there is no general-equilibrium strategic complementarity in price-setting in the current setup. See also Flynn et al. (2025).

Figure 2: Equilibrium AD-AS Representation



Corollary 3.3. *If firms are rationally inattentive and households have perfect information, the slopes of AD and AS are:*

$$\psi_t^D = \gamma \quad \text{and} \quad \psi_t^S = \frac{\gamma\lambda_t^F}{1-\lambda_t^F} \tag{3.27}$$

where firm attention is given by (3.25). *If households are rationally inattentive and firms have perfect information, the slopes of AD and AS are:*

$$\psi_t^D = \frac{\gamma}{\lambda_t^H} \quad \text{and} \quad \psi_t^S = \infty \tag{3.28}$$

where household attention is determined by:

$$\lambda_t^H = 1 - \frac{\gamma\omega_H}{\sigma_{At}^2} \tag{3.29}$$

Proof. Follows from Theorem 3.1. □

Firm-side rational inattention implies a constant aggregate demand slope and an endogenous aggregate supply slope that increases with firm attention. Equilibrium firm attention is still given by equation (3.25), since the desired price has the same form as in the baseline model. In this case, the pass-through of aggregate demand shocks depends only on firm attention and has smaller real effects when firms are more attentive. The relative pass-through of supply shocks to prices versus quantities is invariant to economic conditions.

In contrast, household-side inattention implies a vertical aggregate supply and an endogenous aggregate demand slope that decreases with household attention. With no price rigidity, real output is determined by aggregate productivity. Firms adjust prices one-for-one with nominal wages, thereby insulating real wages from demand shocks. Fluctuations in the desired consumption are driven only by supply shocks. With higher household attention, supply shocks have a lower relative pass-through to prices versus output.[13]

These results show that alternative assumptions about the information structure of households and firms lead to different predictions for the slopes of aggregate demand and supply, and thus for how shocks propagate. As information choice is endogenous to the economic environment, the response of these slopes to changing conditions also differs across information assumptions. In what follows, I analyze and compare the state dependence of slopes.

3.3 State-Dependent Aggregate Demand and Supply

The comparative statics analyze how equilibrium slopes of aggregate demand and supply respond to changes in the shock volatility. The main result is that both slopes are nonmonotonic in volatility, in contrast to the monotone patterns obtained with one-sided inattention.

3.3.1 Response of Aggregate Demand to Shock Volatility

By Theorem 3.1, the slope of aggregate demand depends on equilibrium household attention. Shock volatility affects households' information choices both directly and indirectly through firm attention. Holding firm attention fixed, higher volatility induces households to acquire more information. However, the endogenous adjustment of firm attention may raise or lower households' incentives to acquire information, as stated in Proposition 2.3. The response of equilibrium household attention then depends on the direction and strength of the strategic interaction in information acquisition between households and firms.

The next theorem shows that, when firm attention exerts strong negative feedback on household attention, higher shock volatility can reduce household attention. In this case, the aggregate demand curve steepens.

Theorem 3.2 (How Shock Volatility Affects Aggregate Demand)**.** *The slope of aggregate demand curve varies with shock volatility as follows:*

1. *The AD curve steepens in demand shock volatility if and only if* $\lambda_t^F < \ell_{Zt}^F$*, i.e.,* $\frac{\partial \psi_t^D}{\partial \sigma_{Zt}} > 0$.
2. *The AD curve steepens in supply shock volatility if and only if* $\lambda_t^F < \ell_{At}^F$*, i.e.,* $\frac{\partial \psi_t^D}{\partial \sigma_{At}} > 0$.

where $\ell_{Zt}^F, \ell_{At}^F \in [0, 1]$ *are two thresholds depending on* σ_{At} *and* σ_{Zt}*.*

Proof. See Appendix A.7. □

[13] Another implication is that households' signals contain information only about supply shocks. As in Kamdar and Ray (2024) and Zhang (2024), households then perceive a negative correlation between output and inflation.

To interpret the theorem, it is helpful to distinguish two opposing effects of firm attention on $\mathrm{Var}(c_t^*)$, and thus on household attention. On the one hand, higher firm attention makes prices move more closely with the nominal wage, thereby better insulating households' desired consumption from demand shocks and reducing its uncertainty. On the other hand, higher firm attention strengthens the price response to aggregate supply shocks, increasing the component of $\mathrm{Var}(c_t^*)$ attributable to supply shocks.

By Proposition 2.3, the combined effect depends on the strategic interaction between consumption and prices, captured by $-\frac{1}{\gamma}$, and on which shock dominates the comovement of aggregate output and prices. The next corollary states the condition under which the attenuating effect dominates the amplifying effect on household attention.

Corollary 3.4. *Equilibrium household attention decreases with firm attention if the following condition holds:*

$$\lambda_t^F < \frac{\sigma_{Zt}^2}{\sigma_{Zt}^2 + \sigma_{At}^2} \tag{3.30}$$

Proof. Follows from Proposition 2.3. □

Aggregate output and prices are positively correlated in equilibrium, when firm attention satisfies (3.30). In this case, fluctuations are primarily driven by demand shocks. The dampening effect of firm attention dominates: higher firm attention reduces the volatility of households' desired consumption and lowers household attention.

When the volatility of demand or supply shock increases, firms always acquire more information. Holding the feedback from firms' attention fixed, higher volatility also increases households' incentives for information acquisition. If equilibrium firm attention is below the corresponding threshold, ℓ_{Zt}^F or ℓ_{At}^F, before the change in volatility, the attenuating feedback from firm attention is strong enough to dampen households' information acquisition. Compared with the value $\frac{\sigma_{Zt}^2}{\sigma_{Zt}^2+\sigma_{At}^2}$ in (3.30), both thresholds are smaller, implying that sufficiently strong negative feedback is required to further offset the direct effects of higher volatility on household attention. In this case, household attention decreases, and the aggregate demand curve steepens.

The two thresholds depend on both shock volatilities and increase with the relative volatility $\frac{\sigma_{Zt}}{\sigma_{At}}$. In the limiting cases, when fluctuations are driven solely by aggregate demand shocks, the threshold attains its upper bound, $\ell_Z^F = 1$. Firm attention remains strictly below this value. Thus, the aggregate demand curve steepens when demand shock uncertainty rises. In contrast, with only aggregate supply shocks, the threshold is at the lower bound $\ell_A^F = 0$. Aggregate demand is then flatter as supply shock volatility increases.

Corollary 3.5 (Single Shock Environment)**.** *The slope of aggregate demand changes with shock uncertainty in opposite directions, when the economy is subject to only aggregate demand shocks or supply shocks:*

1. *If $\sigma_{At} = 0$, when demand shocks are more volatile, households acquire less information, and ψ_t^D steepens.*

2. *If $\sigma_{Zt} = 0$, when supply shocks are more volatile, households acquire more information, and ψ_t^D flattens.*

Proof. Follows from Theorem 3.2. □

Intuitively, with only demand shocks, firm attention has only a dampening effect, insulating desired consumption from those shocks. Households then acquire less information as shock volatility rises. With only supply shocks, the amplifying force of firm attention prevails. Households' real wages and desired consumption are more responsive to supply shocks, leading them to acquire more information. It is clear from these examples that the effect of uncertainty on aggregate demand hinges on the source of volatility and on the interaction between households and firms in information acquisition.

Aggregate Demand Response with One-Sided Attention. I now compare these results with cases in which one side has perfect information and the other is rationally inattentive.

Corollary 3.6. *The following results hold under one-sided rational inattention:*

1. *With firm-side inattention and households perfectly informed, the AD curve is invariant to shock volatility.*

2. *With household-side inattention and firms perfectly informed, the AD curve is invariant to demand shock volatility, and flattens as supply shock volatility rises,*

Proof. Follows from differentiation of Equations (3.27), (3.28) and (3.29). □

The results follow directly from the expressions for the aggregate demand slope in Corollary 3.3. When households have perfect information, the demand slope is constant at the structural parameter γ, independent of firms' information choices and the economic environment. When firms have perfect information and households are rationally inattentive, real income and desired consumption are driven by supply shocks. Higher supply shock volatility increases the volatility of desired consumption. Households then acquire more information and the aggregate demand flattens.

3.3.2 Response of Aggregate Supply to Shock Volatility

By Theorem 3.1, both household and firm attention enter directly into the slope of aggregate supply. The slope's response to shock uncertainty depends on the relative change in attention between households and firms. As shock volatility rises, aggregate supply flattens if the increase in household attention is sufficiently large relative to the increase in firm attention.

Theorem 3.3 (How Shock Volatility Affects Aggregate Supply)**.** *The slope of aggregate supply curve varies with shock uncertainty as follows:*

1. *The AS curve flattens in demand shock volatility if and only if* $\lambda_t^H < \ell_{Zt}^H$*, i.e.,* $\frac{\partial \psi_t^S}{\partial \sigma_{Zt}} < 0$.
2. *The AS curve flattens in supply shock volatility if and only if* $\lambda_t^H < \ell_{At}^H$*, i.e.,* $\frac{\partial \psi_t^S}{\partial \sigma_{At}} < 0$.

where $\ell_{Zt}^H, \ell_{At}^H \in [0, 1]$ *are functions of* σ_{At}*,* σ_{Zt} *and* λ_t^F*.*

Proof. See Appendix A.8. □

To unpack the mechanisms, consider the responses of aggregate prices and output to a demand shock when the volatility of either demand or supply shocks increases. Firms acquire more information, and their prices respond more aggressively to the demand shock. As discussed earlier, the equilibrium response of household attention is state-dependent. If household attention decreases, output becomes less responsive to the demand shock and aggregate supply steepens. If household attention increases, the change in the aggregate supply slope is ambiguous.

This theorem states that when equilibrium household attention is low relative to the threshold, higher shock volatility leads to an increase in household attention large enough to flatten aggregate supply. From the expression for the supply slope, $\psi_t^S = \frac{\gamma \lambda_t^F}{\lambda_t^H (1-\lambda_t^F)}$, a rise in household attention from a low level mechanically produces a larger decline in the slope. In addition, when the theorem's conditions hold, an increase in shock volatility has a larger impact on the unconditional variance of desired consumption, strengthening households' incentives to acquire information. Together, these forces flatten aggregate supply.

While the two conditions are stated in terms of household attention, the impact of firm attention on the slope is reflected in the two thresholds. For example, when firm attention is sufficiently low, households acquire less information as shown in Theorem 3.2. In this case, both thresholds coincide with the boundary value of zero. Household attention then exceeds these thresholds, and the slope of aggregate supply increases as shock volatility rises.

The mapping from shock volatility to the thresholds is more complex than in the analysis of aggregate demand, since firm and household attention jointly determine the supply slope. In the limit with only demand shocks, the supply slope becomes steeper when the shock is more volatile. In the limit with only supply shocks, a similar non-monotonicity pertains.

Aggregate Supply Response with One-Sided Attention. The next corollary provides predictions for the state-dependent slope of aggregate supply under one-sided endogenous information acquisition. Similar to results in Corollary 3.6 for aggregate demand, the aggregate supply slope is also either invariant to shock volatility or varies with it monotonically. When firms are rationally inattentive and households have perfect information, higher volatility induces firms to acquire more information, leading to more responsive prices and a steeper aggregate supply. When households are rationally inattentive and firms have perfect information, aggregate supply is vertical and independent of volatility as well as households' information choices.

Corollary 3.7. *The following results hold under one-sided rational inattention:*

1. *With firm-side inattention and households perfectly informed, the AS curve steepens as the volatility of demand or supply shocks rises.*

2. *With household-side inattention and firms perfectly informed, the AS curve is vertical and invariant to shock volatility.*

Proof. Follows from differentiation of Equations (3.27), (3.28) and (3.29). □

The monotonic response of the aggregate supply slope to shock volatility arises in previous studies where firms have exogenously given signals (e.g., Lucas, 1973) or only firms acquire costly signals (e.g., Afrouzi and Yang, 2021). In Lucas (1973), firms observe their local prices, which is a noisy signal of the aggregate price with an exogenous variance of signal noise. More volatile nominal disturbances then generates a steeper aggregate supply curve, resulting in less "favorable" inflation-output tradeoff. In Afrouzi and Yang (2021), price-setting firms are rationally inattentive. A more hawkish monetary policy lowers demand shock uncertainty, yielding a flatter steady-state Phillips curve by changing firms' incentives to acquire information.

In contrast, under two-sided endogenous information acquisition, the slope of aggregate supply depends on the attention of both sides, and the interaction in their attention decisions can generate a non-monotonic relationship between the supply slope and uncertainty. Relatedly, Flynn et al. (2025) show that relative uncertainty about demand, real marginal cost, and the aggregate price shapes firms' supply function choices and thus the slope of aggregate supply. In this model, the level of uncertainty also matters because it determines the benefit of information acquisition.

4 Quantitative Analysis: Estimation and Validation

To quantify the model's predictions for equilibrium outcomes, I estimate the model on U.S. data and validate its micro implications for the time series of household and firm attention in this section. The model implies that attention is countercyclical. It is elevated from the 1970s to the early 1980s and again during Covid, and low during the Great Moderation. Using microdata on expectations from the Survey of Consumers and the Livingston Survey, I find that the time pattern of attention aligns with the survey evidence.

4.1 Calibration

Each model period corresponds to a quarter. There are two sets of parameters to calibrate: the structural parameters $(\gamma, \omega_H, \frac{\omega_F}{\eta-1})$ and the time-varying shock volatilities $(\sigma_{Zt}, \sigma_{At})$. From Theorem 3.1, firms' decisions and equilibrium allocations depend only on the ratio, $\widetilde{\omega}_F \equiv \frac{\omega_F}{\eta-1}$, rather than on ω_F and η separately, so it suffices to calibrate this effective information cost.

The calibration strategy is as follows. I first estimate the conditional heteroskedasticities of real GDP growth and inflation using a bivariate GARCH(1,1) specification. In the model, exogenous shock uncertainty and endogenous attention jointly determine the variances of output and inflation. As equilibrium attention in each period is a function of current volatilities of the demand and supply shocks given information costs, I back out the volatility series $(\sigma_{Zt}, \sigma_{At})$ by matching the conditional variances of real GDP growth and inflation estimated from the data. I also target two moments that are closely related to households' and firms' information costs: an average household attention level of 0.22 from Pfäuti (2023); and an average aggregate supply slope of 0.11 from Hazell et al. (2022). I set $\gamma = 1$ for standard log utility. I solve the model to jointly match these targeted moments over the pre-Covid period. Since uncertainty rises sharply after 2020, I keep the calibrated values for $(\gamma, \omega_H, \frac{\omega_F}{\eta-1})$ at their pre-Covid levels and recalibrate only the shock volatilities for 2020–2024. Appendix B.1 provides more details about the estimation of shock volatility.

Macro Uncertainty. To measure time-varying uncertainties in GDP growth and inflation, I estimate a GARCH(1,1) model (Bollerslev, 1990) using quarterly data on real GDP and the GDP price deflator from the BEA over 1960Q1–2024Q4. Specifically, let X_t denote the vector of log differences of the two variables and let ε_t be the vector of VAR residuals. Then

$$X_t = c + AX_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, H_t) \tag{4.1}$$

Table 1: Calibrated and Assigned Parameters

Parameter	Value	Moment Matched/Method
S.D. of demand shocks (σ_{Zt})	Fig. B2	GARCH estimates (Fig. B1)
S.D. of supply shocks (σ_{At})	Fig. B2	GARCH estimates (Fig. B1)
Household information cost (ω_H)	9×10^{-4}	Average household attention (Pfäuti, 2023)
Firm information cost ($\widetilde{\omega}_F$)	9×10^{-4}	Average supply slope (Hazell et al., 2022)
Risk aversion (γ)	1	Log preference

Note: This table reports calibrated parameter values and targeted moments. $\widetilde{\omega}_F = \frac{\omega_F}{\eta-1}$ is the effective unit information cost for firms. The time series of aggregate demand and supply shock volatilities, together with the constant information cost parameters for households and firms, are jointly calibrated to match the targeted moments in the last column.

where H_t is the covariance matrix of the residuals. The GARCH(1,1) model with constant conditional correlations assumes the following processes for H_t:[14]

$$H_t = D_t R D_t \quad \text{and} \quad h_{i,t} = s_i + \alpha_i h_{i,t-1} + \beta_i \varepsilon_{i,t-1}^2 \tag{4.2}$$

where R is the conditional correlation matrix, D_t is a diagonal matrix containing the time-varying standard deviations for the residuals, and $h_{i,t}$ are the conditional variances for $i \in$ {real GDP growth, inflation} at period t. The unknown parameters (s_i, α_i, β_i) are estimated by maximum likelihood.

Figure B1 in the Appendix plots the estimated conditional variances, which exhibit time variation similar to the macro uncertainty index in Jurado et al. (2015). Over the sample, output growth is more volatile than inflation, and both series rise in recessions. Inflation volatility is notably higher in the 1970s, early 1980s and after the onset of Covid, with peak variance roughly five times that in other periods. Output volatility displays a similar pattern, reaching its highest level during Covid, at about an order of magnitude above its peak in the Great Recession.

Calibrated Parameters. Table 1 reports the calibrated parameter values. Households and firms have the same effective information cost, although this is not imposed ex ante.[15] The calibrated demand shock uncertainty is lower than the supply shock uncertainty and

[14] In the GARCH specification, higher uncertainty arises from past large innovations in the levels of variables. This is consistent with the model mechanism, which suggests that both larger shocks and stronger responses in actions generate larger fluctuations in aggregate outcomes. Other statistical models, such as stochastic volatility (SV) models, also capture time-varying uncertainty, but GARCH estimates volatility at time t using only information up to $t-1$ and requires no additional observed variables, which makes its estimates comparable to the model.

[15] These estimates are close to the calibrated value in Maćkowiak and Wiederholt (2015), 6×10^{-4}.

has greater time variation. It rises in recessions and is higher from the 1970s to the mid-1980s and during the Great Recession. Both series change sharply during Covid. Appendix Table B3 compares model-implied moments with their targets and shows that the model matches them closely.

4.2 Model Validation

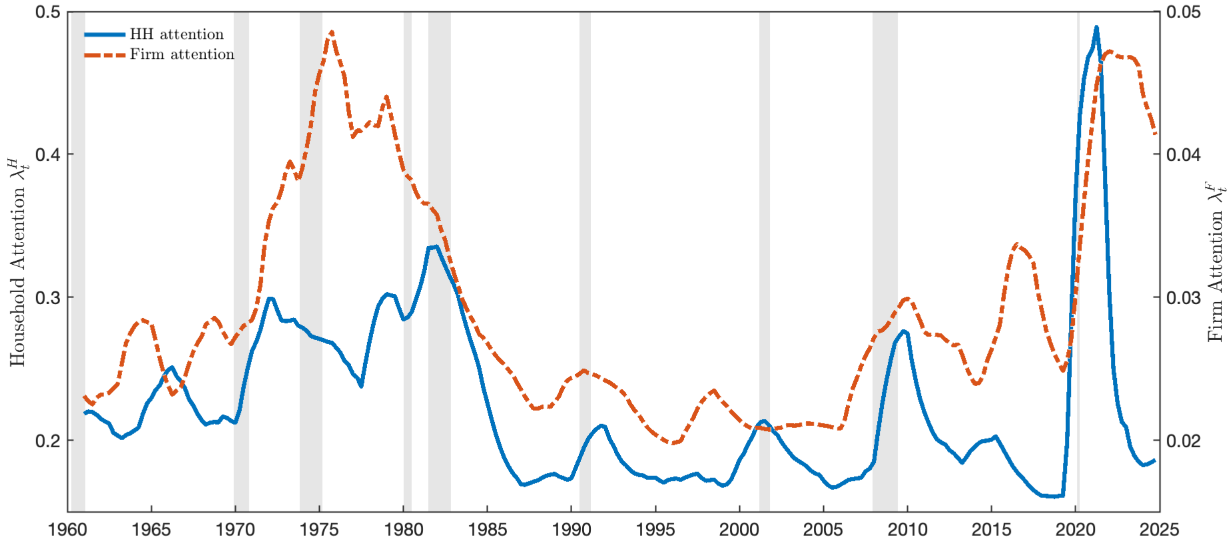
As shown in the theoretical analysis in the previous section, the key determinants of the slope of aggregate demand and aggregate supply are the endogenous attention of households and firms. I now present the model's predictions for attention over time and provide supporting survey evidence.

Time-Varying Attention in the Model Figure 3 plots the model-implied attention series for households and firms. Firms display low attention throughout the sample. This reflects the calibration target of a small average supply slope, which implies that aggregate prices respond only weakly to output movements driven by demand shocks. Price rigidities in the model arise solely from incomplete information. Hence, matching this moment requires low firm attention. This implication is consistent with evidence that firms pay less attention to aggregate conditions than to their own markets (e.g., Weber et al., 2022).

Attention is countercyclical, rising by 21% on average in recessions before Covid. This pattern aligns with evidence of cyclical information rigidities in survey data (e.g., Coibion and Gorodnichenko, 2015; Goldstein, 2023; Chiang, 2024), and with studies that find higher attention during downturns using natural-language-processing measures from firms' regulatory filings and conference calls (e.g., Flynn and Sastry, 2024). During Covid, attention rises sharply. Household attention more than doubles relative to its post-1990 average, and firm attention reaches a level comparable to its mid-1970s peak, consistent with recent evidence in Korenok et al. (2023), Pfäuti (2023), and Bracha and Tang (2025).

Beyond business-cycle movements, another salient pattern is a pronounced increase in attention during the 1970s, followed by a significant decline. Averaging within three periods, 1960-1969, 1970-1984, and 1985-2019, household attention rises by 28% from the first to the second period and then falls by 33%, while firm attention increases by 47% and then decreases by 36%. This time variation is in line with Coibion and Gorodnichenko (2015), who estimate the coefficient each quarter by regressing consensus forecast error on forecast revision for several macro variables using the Survey of Professional Forecasters (SPF). Their estimated degree of information rigidity, inversely related to attention, declines from the late 1960s to the early 1980s, rises through the Great Moderation until the mid-2000s, and falls in the Great Recession. Extending the sample through the pre-Covid period and adding nowcasts

Figure 3: Model-Implied Attention of Households and Firms



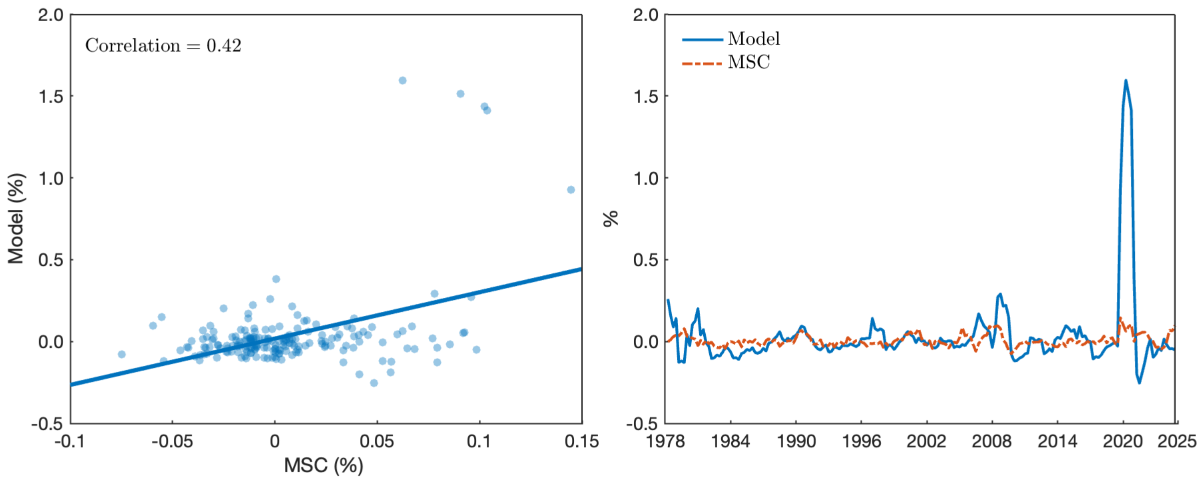
Note: This figure plots quarterly attention series from the calibrated model. The blue solid line, on the left y-axis, depicts household attention. The red dashed line, on the right y-axis, depicts firm attention. Units are interpreted as Kalman gains on private signals. Shaded regions indicate NBER recession dates.

of macro variables, Appendix B.3 reproduces this pattern using the SPF. As discussed in the later section, this pattern of attention leads to notable changes in the slopes of aggregate demand and supply curves over time.

Households' and firms' attention in equilibrium are determined by their prior uncertainty about desired consumption and prices, respectively. Periods of high attention coincide with increases in macroeconomic uncertainty, as indicated by the GARCH estimates. Moreover, condition (3.30) in Corollary 3.4 holds under the calibrated parameter values. It follows that greater firm attention lowers the marginal value of information for households, which is the force behind in generating the differing movements in firm and household attention in some periods, such as the late 1970s.

Forecast Dispersion in the Model and Surveys. To assess the plausibility of the model's predictions about information acquisition over time, I exploit the relationship between attention and forecast dispersion implied by Corollary 4.1. Since forecast dispersion increases with attention, I use dispersion as a proxy for attention. I then compare the percentage changes in inflation forecast dispersion predicted by the model with corresponding measures from two surveys, the Michigan Surveys of Consumers (MSC) and the Livingston Survey.

Figure 4: Percentage Changes in Household Inflation Forecast Dispersion (MSC vs. Model)



Note: This figure compares percentage changes in household inflation forecast dispersion from the model with that from the Michigan Survey of Consumers (MSC). Left panel: each dot is the quarterly pair (MSC, Model). Right panel: time series of survey dispersion (red, dashed) and model dispersion (blue, solid).

Corollary 4.1 (Inflation Forecast Dispersion in the Model)**.** *Define the forecast dispersion of inflation among firms and households by*

$$\text{Disp}_{p,firm} := \left\{ \mathbb{E}\left(\mathbb{E}\left[p_t \mid p_{jt}\right] - \overline{\mathbb{E}}\left[p_t \mid p_{jt}\right] \right)^2 \right\}^{1/2}$$

$$\text{Disp}_{p,hh} := \left\{ \mathbb{E}\left(\mathbb{E}\left[p_t \mid c_{it}\right] - \overline{\mathbb{E}}\left[p_t \mid c_{it}\right] \right)^2 \right\}^{1/2}$$

where $\overline{\mathbb{E}}$ *denotes the cross-sectional average expectation over firms or households. Then, for interior attention levels in* $(0, 1)$*, forecast dispersion co-moves with attention.*

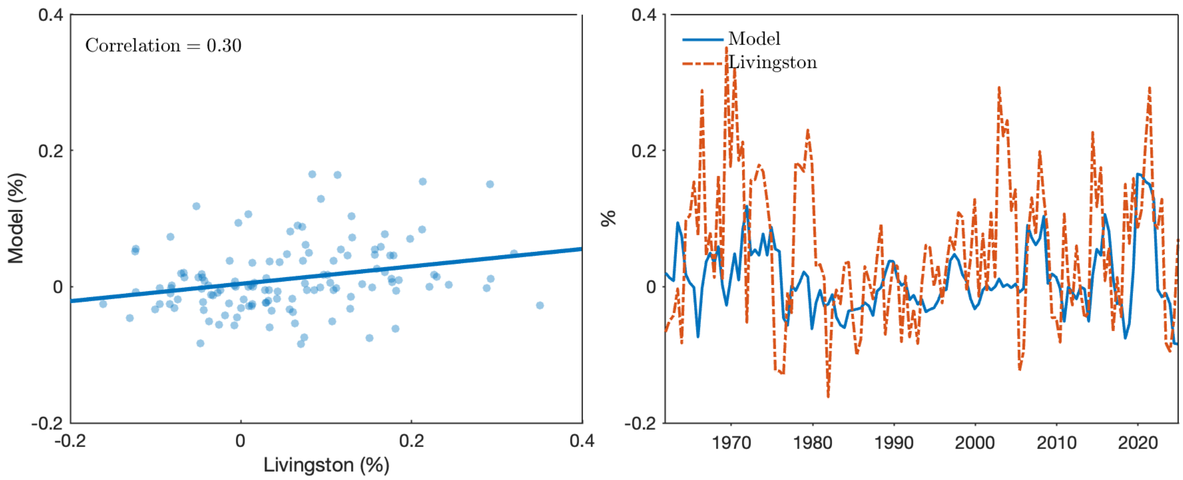
Proof. See Appendix A.10. □

In the model, each firm's price is a signal of the aggregate price. Because firms' attention is endogenous to prior uncertainty about the aggregate price, higher attention, for interior levels $\lambda_t^F \in (0, 1)$, unambiguously increases forecast dispersion among firms. For households, the private signal pertains to aggregate output. Hence, forecast dispersion among households depends on both attention and the informativeness of aggregate output for prices, which is endogenously determined in equilibrium and itself depends on attention.

As the empirical counterpart to measuring household attention, the MSC interviews a representative sample of around $500 - 1,000$ U.S. households each month starting from January 1978. Respondents are asked to make forecasts about one-year-ahead inflation.[16]

[16]The relevant question in the survey is "By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?"

Figure 5: Percentage Changes in Firm Inflation Forecast Dispersion (Livingston vs. Model)



Note: This figure compares percentage changes in firm inflation forecast dispersion from the model with that from the Livingston Survey. Left panel: each dot is the quarterly pair (Livingston, Model). Right panel: time series of survey dispersion (red, dashed) and model dispersion (blue, solid).

I measure forecast dispersion as the cross-sectional standard deviation of residual inflation forecasts after controlling for characteristics such as age and income (Fofana et al., 2025).

To ensure comparable units, I compute percentage changes in cross-sectional forecast dispersion over time in the model and in the MSC. Figure 4 plots the results. The right panel shows the time series of percentage changes in forecast dispersion, and the left panel shows the corresponding scatter plot. The two series are correlated, with a correlation of 0.42 over 1978-2024. This positive correlation supports the relevance of the model's mechanism for the survey-based variation in household attention.

I use the Livingston Survey to proxy for firms' beliefs, following Coibion and Gorodnichenko (2012). The Livingston Survey is the oldest continuous US expectations survey, started in 1946. It is conducted biannually in June and December, with about 50 forecasters per wave from industry, banking, government organizations, and academia. The first two categories account for approximately 80% of respondents. I measure forecast dispersion as the cross-sectional standard deviation of 12-month-ahead CPI inflation forecasts.

To match the survey's semiannual frequency, I construct June and December counterparts in the model by averaging adjacent quarters. June is the average of Q2 and Q3, and December is the average of Q4 and the following year's Q1. Figure 5 compares percentage changes in forecast dispersion from the model with those from the Livingston Survey over 1961-2024. The right panel shows the time series, and the left panel gives the scatter, with a correlation of 0.30 between the two series.

5 Aggregate Demand and Supply in the U.S.

In this final section, I first present the model's quantitative predictions for the slopes of aggregate demand and aggregate supply over time. Aggregate supply steepens and aggregate demand flattens during the 1970s through the early 1980s and in the post-Covid period. The time variation in the aggregate supply slope is consistent with empirical evidence. Using the local projection method, I also find evidence of time variation in the aggregate demand slope.

I then assess the role of endogenous attention in generating state-dependent slopes by fixing household and firm attention, one at a time, at their respective sample averages. Under these counterfactuals, the model's predictions contradict the data. Specifically, holding household attention constant yields a time-invariant slope of aggregate demand. Holding firm attention constant produces an aggregate supply slope that becomes steeper after the Volcker disinflation.

5.1 Time-Varying Slope of Aggregate Supply

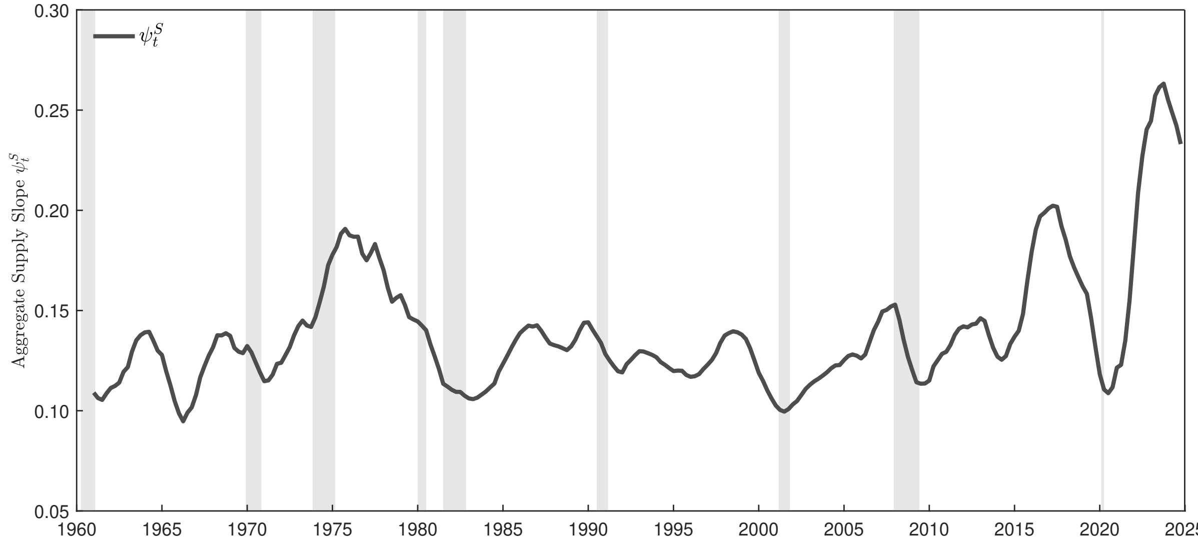
Figure 6 plots the model-implied slope of aggregate supply in the U.S. over time. The slope steepens in three episodes: the 1970s through the early 1980s, 2016–2019, and the post-Covid period. It generally flattens in recessions, with the 1973–75 recession as an exception.

Comparison with Empirical Estimates. I compare the model's predictions to empirical estimates of the Phillips curve. A number of papers estimate the slope over different periods using macro time series or disaggregated panel data (e.g., Ball and Mazumder, 2011; Blanchard, 2016; Hooper et al., 2020; McLeay and Tenreyro, 2020; Hazell et al., 2022). A recurring finding in this literature is that the slope declines during the Great Moderation relative to its level in the 1970s. The model-implied time series of the aggregate supply slope matches this pattern. I also compare the percentage changes in the slope across periods in the model to the estimates in Ball and Mazumder (2011) and Hazell et al. (2022), summarized in Panels (A) and (B) of Table 2.

Ball and Mazumder (2011) estimate the aggregate supply slope using CPI inflation and measured output gap over 1960–2007.[17] Their estimates indicate a steeper slope in 1973–1984 and a flatter slope thereafter. The model predicts a similar pattern, accounting for 13% of the initial steepening and 24% of the subsequent flattening in their estimates. Hazell et al. (2022) estimate the slope using cross-sectional state-level price data and an unemployment gap instrumented with either lagged unemployment or a shift-share instrument, addressing

[17] They also estimate the slope for 1985–2010 in that paper. I use the pre-financial-crisis estimate for comparison.

Figure 6: The Slope of Aggregate Supply Over Time



Note: This figure plots the model-implied slope of aggregate supply for the U.S. economy, given by equation (3.24). The slope, ψ_t^S, is defined as the relative elasticities of the price level and real output to an aggregate demand shock.

omitted-variable and simultaneity concerns that arise with aggregate data. They find a decline in the slope from 0.198 in 1978–1990 to 0.09 afterward. Consistent with this evidence, the model-implied aggregate supply slope falls by 4%, explaining 7% of the decline in their result. The modest decline in the model is due to the increase in the slope during 2016–19, when the estimated conditional variance of inflation rises and firms have higher attention.

The model also predicts that the aggregate supply slope rises after Covid and reaches its highest level in the sample. This steepening is consistent with Cerrato and Gitti (2025). Using regional data, they find that the slope of the Phillips curve increases sharply after Covid, from 0.07 over the 1990–pre-Covid period to 1.41 in March 2021–June 2022, as shown in Panel (C) of Table 2.

In sum, the model reproduces the key time variation in the aggregate supply slope. This suggests that endogenous attention is one contributing force behind those movements.

5.2 Time-Varying Slope of Aggregate Demand

Figure 7 shows the model-implied slope of aggregate demand in the U.S. over time. In contrast to aggregate supply, it is flatter over 1970–1984 and steeper from 1985 to the pre-Covid period. The slope flattens during recessions, with pronounced declines during the Great Recession and the Covid episode.

Table 2: Aggregate Supply Slope: Model vs. Empirical Estimates

(A) Ball and Mazumder (2011)	Data	Model
1960–1972	0.135	0.122
1973–1984	0.371 ($\uparrow$ 175%)	0.149 ($\uparrow$ 22%)
1985–2007	0.136 ($\downarrow$ 63%)	0.126 ($\downarrow$ 15%)

(B) Hazell et al. (2022)	Data	Model
1978–1990	0.198	0.135
1991–2018	0.090 ($\downarrow$ 55%)	0.130 ($\downarrow$ 4%)

(C) Cerrato and Gitti (2025)	Data	Model
Jan 1990–Feb 2020	0.07	0.13
Mar 2021–Jun 2022	1.41	0.17

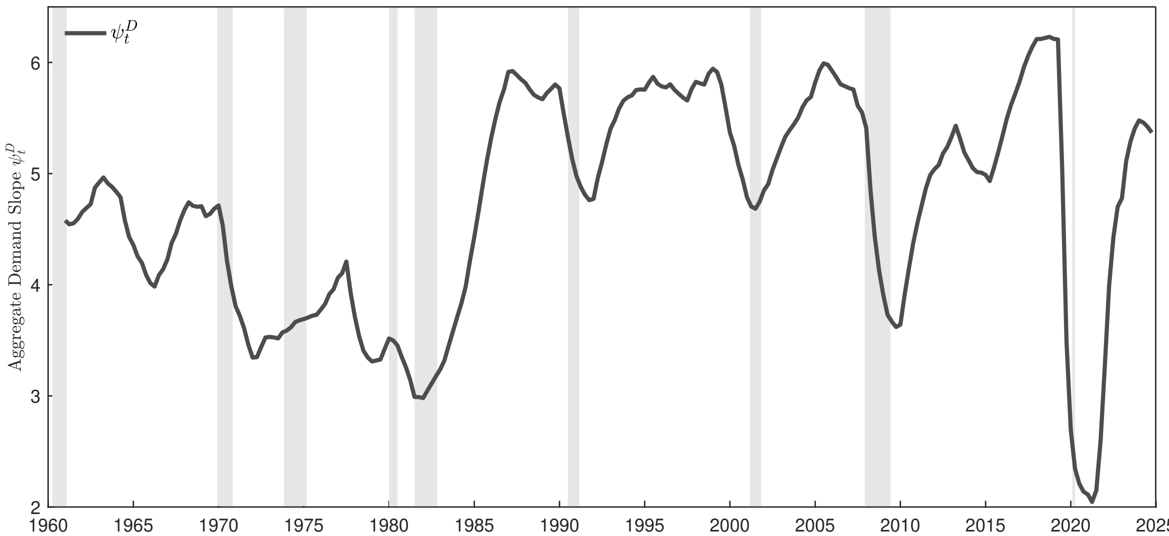
Note: Panels A to C compare the aggregate supply slope with estimates from Ball and Mazumder (2011), Hazell et al. (2022), and Cerrato and Gitti (2025), respectively. Parentheses report percentage changes relative to the preceding period. An upward arrow $\uparrow$ denotes an increase and a downward arrow $\downarrow$ denotes a decrease.

Comparison with Empirical Estimates. By analogy with the supply side, one might compare the aggregate demand slope with empirical estimates of the slope of the Euler equation, that is, the aggregate elasticity of intertemporal substitution. In this framework, however, the slope ψ_t^D does not map one-for-one to that object. As the nominal interest rate responds endogenously to current inflation, ψ_t^D reflects both the Euler equation slope and the contemporaneous inflation coefficient in the monetary policy rule that enters the nominal rate in the Euler equation.

To proceed, I use Jordà (2005)'s local projection and estimate the slope ψ_t^D as the ratio between the impulse responses of the price level and the impulse responses of real output following identified supply shocks, separately for two periods, 1975–1984 and 1985–2019.

In the baseline estimation, I use the monthly oil supply news shock from Känzig (2021) as a proxy for the aggregate supply shock, which spans 1975M1–2019M12. The shocks are identified in an oil market VAR that uses oil futures price surprises around OPEC production announcements as an external instrument. I use the monthly unemployment rate and CPI from the BLS over the same period as proxies for real output and the price level in the model, respectively. Although the model is quarterly, I use monthly data to increase sample

Figure 7: The Slope of Aggregate Demand Over Time



Note: This figure plots the model-implied slope of aggregate demand for the U.S. economy, given by equation (3.24). The slope, ψ_t^D, is defined as the relative elasticities of the price level and real output to an aggregate supply shock.

size. Appendix Table B2 reports the regression results using quarterly real GDP and the GDP deflator.[18]

Specifically, I estimate the following local projection, instrumenting the three-month-ahead CPI level with the identified shock:

$$y_{t+h} = \alpha_h + \beta_h p_{t+h} + \text{controls} + \varepsilon_{t+h} \tag{5.1}$$

where the horizon is $h = 3$, y_{t+h} is the three-month-ahead unemployment rate, p_{t+h} is the three-month-ahead CPI level instrumented with the current shock, and the control variables include 12 lags of unemployment, the shock, and four oil market variables (the oil price, oil production, oil inventories and world industrial production). The coefficient β_h then corresponds to the inverse of the slope, $1/\psi_t^D$. Hence, the model implies that β_h is higher in 1975-1984 than afterward.

Table 3a presents the regression results. The first two columns report estimates of the inverse slope, $\widehat{\beta}_h$, and the effective first-stage F statistics (Olea and Pflueger, 2013). I compute Newey and West (1987) standard errors with the lag length equal to the horizon. The first and second columns show that the estimated inverse slope is larger during 1975–1984 (0.29 vs. 0.17), consistent with the model's prediction. The final column reports the p-value

[18] I aggregate the monthly shocks to the quarterly frequency in these regressions.

Table 3: The Slope of Aggregate Demand

(a) Estimates of the Inverse Aggregate Demand Slope

	1975-1984	1985-2019	Anderson-Rubin p-value
$\widehat{\beta}_h$	0.29	0.17	0.01
	(.49)	(.21)	
Effective First-stage F	5.41	17.87	

Note: This table reports the estimated coefficients from the local projection in equation (5.1), which correspond to the inverse of the model's aggregate demand slope. Standard errors are reported in parentheses. Effective first-stage F statistics are computed following Olea and Pflueger (2013). The last column reports the Anderson–Rubin p-value for the null that the coefficients are the same before and after 1984.

(b) Aggregate Demand Slope: Model vs. Empirical Estimates

	1975-1984	1985-2019	Change (%)
Data ($1/\widehat{\beta}_h$)	3.45	5.88	70
	(5.76)	(7.26)	
Model (ψ_t^D)	3.54	5.35	51

Note: This table reports the aggregate demand slope obtained from the local projection estimates and implied by the model. The last column reports the percentage change in the slope from 1975–1984 to 1985–2019. Standard errors in parentheses are computed using the delta method.

from the HAC-robust Anderson–Rubin test of the null that the coefficients are equal across the two periods (Moreira and Moreira, 2019).

Table 3b compares the average demand slope estimated from the data (first row) with the model-implied slope (second row). Both measure indicate a steepening after 1984, and the model accounts for 73% of the increase in the data. While the flatter aggregate demand in 1975–1984 indicates a smaller *relative* pass-through of supply shocks to inflation compared with unemployment, it is consistent with evidence that supply shocks have stronger *absolute* effects on inflation in high-inflation periods than in low-inflation periods (Pfäuti, 2023).

5.3 Contribution of Asymmetric Attention to State Dependence

Having documented the time patterns of the aggregate demand and supply slopes, I now examine how attention shapes their state dependence. To assess the role of attention on each side, I conduct counterfactual exercises that fix either household or firm attention at its pre-Covid average, while the other side acquires information optimally. I then plot and compare the implied counterfactual slopes. The difference between the baseline and each counterfactual isolates the contribution of household and firm attention to the time variation in these slopes.

Aggregate Supply. Figure 8 plots three time series for the slope of aggregate supply: the baseline series in black, a counterfactual with firm attention held fixed at its 1961–2019 average in blue, and a counterfactual with household attention held fixed at its 1961–2019 average in red.

The time variation in the baseline slope reflects changes in both household and firm attention. Attention is higher in the 1970s and early 1980s than in the 1960s and during the Great Moderation. Although the effects of household and firm attention on the supply slope have opposite signs, changes in firm attention are more pronounced, driving the steepening of aggregate supply in the 1970s and its subsequent flattening. During Covid, attention again rises sharply. Household attention, however, increases more at the onset of Covid and then declines in the post-Covid period as uncertainty falls. This pattern yields an initial drop followed by a substantial increase in the aggregate supply slope. This resulting steepening contributes to post-pandemic inflation in the U.S., as shown in Cerrato and Gitti (2025).

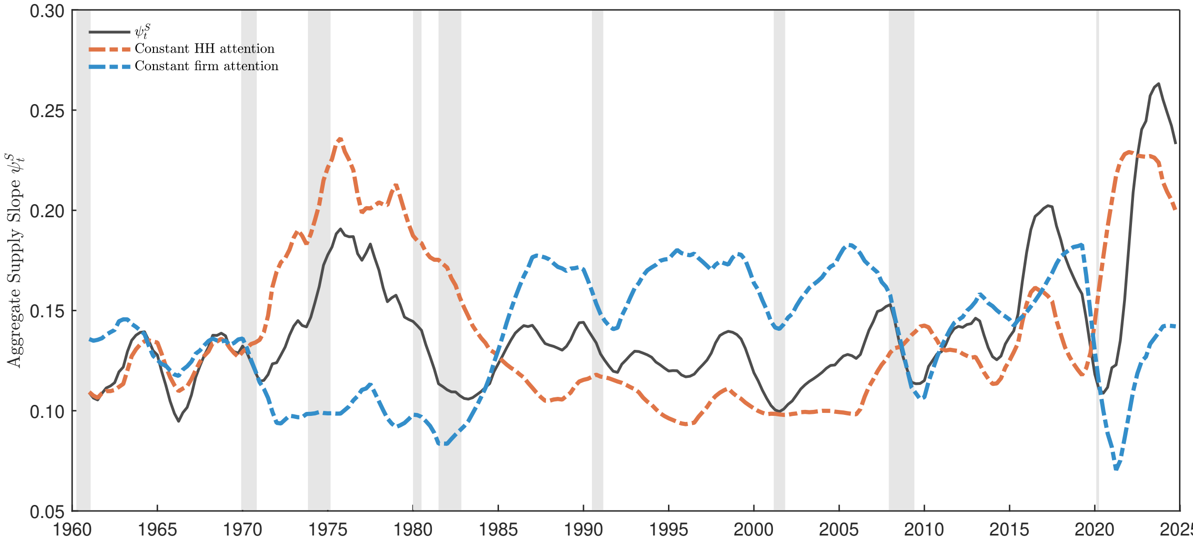
A similar mechanism operates during the 2008 financial crisis: when household attention increases substantially, the aggregate supply slope becomes flatter. The model thus offers an explanation for the "missing disinflation" during and after the Great Recession. Elevated attention, especially among households, driven by higher macro uncertainty endogenously flattens aggregate supply.

The time series for the aggregate supply slope aligns with patterns documented in Flynn et al. (2025). Consistent with their findings, periods of a steeper slope coincide with rising inflation uncertainty, and the Great Recession features a spike in real uncertainty and a flatter slope.[19] In Flynn et al. (2025), these shifts in uncertainty lead firms to choose different supply schedules. In the present model, they induce households and firms to adjust their attention.

In the counterfactual exercise where household attention is fixed, firm attention is determined solely by shock volatility and therefore remains unchanged. Differences between the counterfactual and baseline slopes are thus attributable to household attention. In the 1970s, baseline household attention exceeds its pre-2020 sample average. As the aggregate supply slope decreases with household attention, the counterfactual slope is steeper, about 32% higher on average than the baseline. After the mid-1980s, baseline household attention falls below the sample average, so the counterfactual slope is flatter, about 12% lower than the baseline. These results imply that fluctuations in household attention attenuate

[19] The current model also implies a steeper supply slope in 2016–2019. This is due to the combination of relatively low household attention and high firm attention. As shown in Figure B1, inflation uncertainty increases in this period, which raises firm attention.

Figure 8: Counterfactual Aggregate Supply Slope



Note: This figure plots the model-implied aggregate supply slope for three cases: baseline with endogenous household and firm attention (black); household attention fixed at its 1961–2019 average with firm attention endogenous (red); and firm attention fixed at its 1961–2019 average with household attention endogenous (blue).

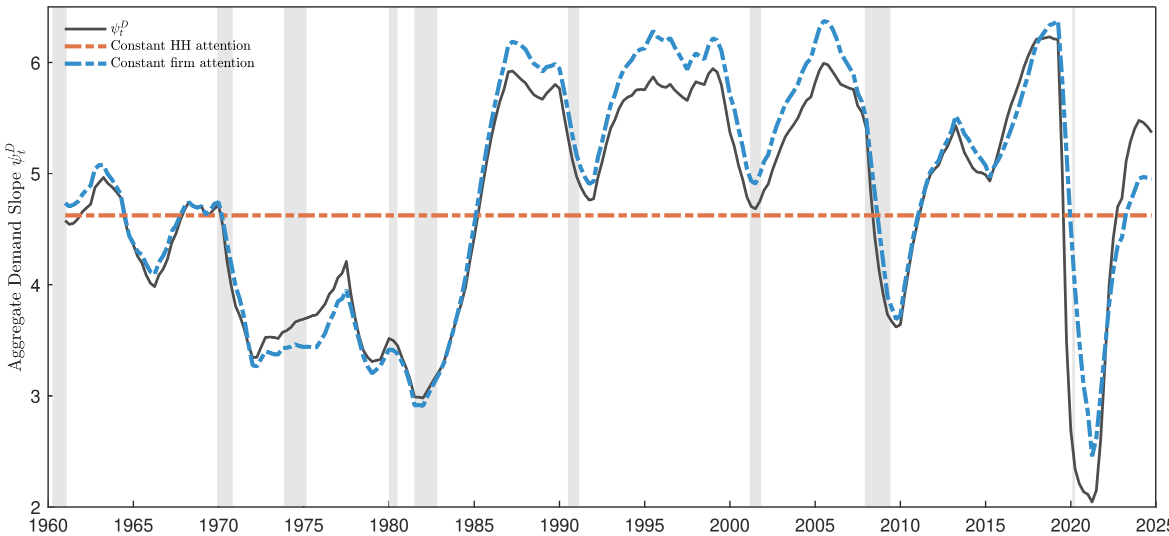
movements in the aggregate supply slope over time.

Although this counterfactual series retains similar time variation to the baseline, it predicts a steepening of the supply slope during the Great Recession and the Covid period. Given that household attention is constant, only firm attention rises during those periods, leading to a steeper slope. The resulting steepening would suggest a large increase in inflation, opposite to what the data indicate.

In the counterfactual exercise with firm attention held constant over time, the implied aggregate supply flattens in the 1970s and steepens thereafter. This pattern reflects higher household attention in the earlier period under the counterfactual. Intuitively, with firms' attention fixed, its impact on household attention is unchanged. Higher shock volatility in the 1970s then induces households to acquire more information.

The difference between this counterfactual slope and the baseline results from two forces. First, in the baseline, firm attention is higher in the 1970s than later. Fixing firm attention at its sample average therefore yields a lower counterfactual aggregate supply slope in this period. Second, because higher firm attention lowers the marginal value of information for households under the calibrated parameters, the strategic interaction in information choices leads to higher household attention in the counterfactual, thereby further flattening the slope. To illustrate this mechanism, Appendix Figure B5 plots the implied slope with firm attention fixed as in this exercise and household attention following its baseline path. The resulting

Figure 9: Counterfactual Aggregate Demand Slope



Note: This figure plots the model-implied aggregate demand slope for three cases: baseline with endogenous household and firm attention (black); household attention fixed at its 1961–2019 average with firm attention endogenous (red); and firm attention fixed at its 1961–2019 average with household attention endogenous (blue).

series lies between the counterfactual and the baseline, reflecting the negative feedback from firm to household attention.

Aggregate Demand. Figure 9 plots the aggregate demand slope generated by the baseline model (black) along with two counterfactual paths: one holding household attention at its sample average (red) and one holding firm attention at its average (blue). The slope of aggregate demand depends inversely on equilibrium household attention. It thus moves in the opposite direction to the household attention series. Notably, in the baseline model, during Covid the demand slope declines markedly and then rebounds in the post-Covid period, driven by underlying movements in household attention.

Fixing household attention yields a constant demand slope. However, the evidence in Table 3a shows that supply shocks exhibit a larger relative pass-through to output than to prices in 1975–1984 than in 1985–2019. A constant series, which implies a time-invariant relative pass-through, is inconsistent with this pattern.

When firm attention is held constant over time, differences between the counterfactual and baseline demand slopes reflect the strategic interaction in information choices as discussed above. The counterfactual series lies close to the baseline. This is because firm attention remains low despite its notable time variation.

6 Conclusion

This paper develops a framework in which households' and firms' information choices are jointly determined and shape the slopes of aggregate demand and aggregate supply. Endogenous attention links uncertainty to state-dependent shock transmission. Higher shock volatility shifts attention, which alters the relative pass-through of demand and supply shocks to aggregate prices and output. In the two-sided rational inattention setting, strategic interactions in information acquisition between households and firms generate non-monotonic responses of the slopes in shock volatility that do not arise under one-sided inattention.

Quantitatively, the calibrated model matches key patterns in U.S. data. At the micro level, forecast dispersion in the Surveys of Consumers and the Livingston Survey co-moves with the model's predictions for attention. At the macro level, the model reproduces the steepening of aggregate supply in the 1970s through the mid-1980s, its flattening during the Great Moderation, and its recent post-Covid steepening, while aggregate demand moves in the opposite direction. Local projections of real output on inflation, instrumented with identified oil-supply news shocks, indicate that the average aggregate demand slope is steeper in 1985–2019 than in 1975–1984. Counterfactual exercises that hold either household or firm attention fixed contradict the data, underscoring that two-sided endogenous attention is necessary to account for the joint behavior of aggregate demand and supply.

While the application focuses on positive implications for how shock effectiveness varies with attention and uncertainty, a direction for further exploration is optimal policy when information choices are interdependent across agents. In addition, the analysis of endogenous information acquisition in linear best-response games applies to other settings, such as asset pricing and models with heterogeneous households.

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Appendices

A Omitted Proofs

A.1 Proof of Lemma 2.1

Proof. Since mutual information is monotone in the Blackwell order, optimal information acquisition implies a one-to-one correspondence between signals and actions. Moreover, under a Gaussian prior and quadratic utility, the optimal action a_{ki} is also Gaussian and collinear with the desired action $a_i^* = \sum_{j=1}^n g_{ij} a_j + \theta_i$. That is, a_{ki} takes the following form:

$$a_{ki} = \lambda_i \left(\sum_{j=1}^n g_{ij} a_j + \theta_i \right) + \epsilon_{ki}$$

for some $\lambda_i \in [0,1]$, where the signal noise ϵ_{ki} is normal and independent of a and θ. This representation implies the following relationship between λ_i and the variance of the signal noise:

$$a_{ki} = \mathbb{E}\left[a_i^* \mid a_{ki}\right] \implies \operatorname{Var}(\epsilon_{ki}) = \lambda_i(1-\lambda_i) \operatorname{Var}(a_i^*)$$

where $\operatorname{Var}(a_i^*)$ is the unconditional variance of a_i^*. Moreover, the optimal form and use of the signal also imply that λ_i equals the squared correlation between a_{ki} and a_i^*

$$\operatorname{corr}(a_{ki}, a_i^*) = \sqrt{\lambda_i}$$

We can now rewrite the agent's problem as follows:

$$\begin{aligned}
&\max_{\pi_i, a_{ki}} \; -\frac{1}{2}\mathbb{E}_{\pi_i}\left[\left(a_{ki} - \sum_{j=1}^n g_{ij} a_j - \theta_i\right)^2\right] - \omega_i \mathcal{I}\left(a, \theta; s_{ki}\right) \\
&= \max_{a_{ki}} \; -\frac{1}{2}\mathbb{E}\left[\operatorname{Var}\left(a_i^* \mid a_{ki}\right)\right] - \omega_i \mathcal{I}(a_i^*; a_{ki}) \\
&= \max_{\lambda_i} \; -\frac{1}{2}\operatorname{Var}(a_i^*)(1-\lambda_i) + \frac{\omega_i}{2}\log(1-\lambda_i)
\end{aligned}$$

The first equality uses that a_{ki} is a sufficient statistic for the signal and that (a, θ) and a_{ki} are independent conditional on a_i^*. The second equality follows from the normal distribution of a_{ki}.

In sum, each agent's information and action strategies reduce to choosing a single variable, which is defined as their attention $\lambda_i \in [0,1]$:

$$\max_{\lambda_i \in [0,1]} \; -\frac{1}{2}\operatorname{Var}(a_i^*)(1-\lambda_i) + \frac{\omega_i}{2}\log(1-\lambda_i) \tag{A.1}$$

$$a_{ki} = \lambda_i a_i^* + \epsilon_{ki}, \quad \epsilon_{ki} \sim \mathcal{N}\left(0, \lambda_i(1-\lambda_i)\operatorname{Var}(a_i^*)\right) \tag{A.2}$$

Solving the problem (A.1) gives the optimal attention and corresponding signal noise:

$$\lambda_i = \max\left\{0, 1 - \frac{\omega_i}{\operatorname{Var}(a_i^*)}\right\}, \quad \text{and } \operatorname{Var}(\epsilon_{ki}) = \omega_i\lambda_i \tag{A.3}$$

Before acquiring any information, the prior uncertainty about a_i^* is $\operatorname{Var}(a_i^*)$. After information acquisition, the optimal posterior uncertainty about a_i^* is ω_i. This can be seen by:

$$\operatorname{Var}\left(a_i^* \mid a_{ki}\right) = \operatorname{Var}(a_i^*)(1-\lambda_i) = \operatorname{Var}(a_i^*)\left(1 - \left(1 - \frac{\omega_i}{\operatorname{Var}(a_i^*)}\right)\right) = \omega_i$$

Optimal attention λ_i then captures the fraction of uncertainty reduction about a_i^*:

$$\lambda_i = \frac{\operatorname{Var}(a_i^*) - \omega_i}{\operatorname{Var}(a_i^*)}.$$

□

A.2 Proof of Proposition 2.1

Proof. The proof uses the following standard notations. For $x \in \mathbb{R}^n$, $\|x\|_\infty := \max_{1\le i\le n}|x_i|$ is the ℓ_∞ norm of x. For a matrix $M \in \mathbb{R}^{n\times n}$, $\|M\|_2 := \sigma_{\max}(M)$ is the spectral norm, where $\sigma_{\max}(M)$ is the largest singular value of M. The smallest singular value is denoted by $\sigma_{\min}(M)$. $\|M\|_\infty = \max_i \sum_j |m_{ij}|$ is the infinity norm, equal to the maximum absolute row sum.

The rational inattention equilibrium boils down to solving for the attention vector $\lambda := (\lambda_1, \ldots, \lambda_n)$ that satisfies the following system of equations: $\forall i \in N$,

$$\lambda_i = \max\{0,\ 1 - \frac{\omega_i}{V_i}\} \tag{A.4}$$

$$V_i = e_i'(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}e_i \tag{A.5}$$

where e_i is the basis vector, and $\Lambda = \operatorname{diag}(\lambda)$ is a diagonal matrix with diagonal elements given by λ. To prove the existence and uniqueness of a positive-information-acquisition equilibrium, i.e., $\lambda \gg 0$, I impose the following three assumptions:

A1. The spectral norm of matrix G is smaller than 1.

$$\rho := \|G\|_2 < 1 \tag{A.6}$$

A2. Unit information costs ω_i have a strict upper bound defined by:

$$\overline{\omega} := \max_{1 \leq i \leq n} \omega_i < B := \frac{\sigma_{\min}(\Sigma)}{(1+\rho)^2} \tag{A.7}$$

A3. ω_i, G and Σ satisfy the following inequality:

$$L := \frac{2\rho(1+\rho)^2}{(1-\rho)^3} \cdot \frac{\sigma_{\max}(\Sigma)}{\sigma_{\min}(\Sigma)} < 1 \tag{A.8}$$

By assumption (A.6), the matrix inversion $(I - G\Lambda)^{-1}$ is well defined for any $\lambda \in [0,1]^n$. Define the operator $\mathcal{T} : [0,1]^n \to [0,1]^n$ as follows:

$$\mathcal{T}_i(\lambda) := \max\left\{0, 1 - \frac{\omega_i}{e_i'(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1} e_i}\right\}, \quad \Lambda = \mathrm{diag}(\lambda)$$

Lemma A.1. *Under assumptions [A1] and [A2], all agents acquire new information in any equilibrium.*

Proof. From equation (A.4), for agents to acquire information, the unit information cost must be smaller than the unconditional variance of target actions. Define $V(\lambda) := (I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}$, which is symmetric positive definite. Then:

$$\begin{aligned}
\sigma_{\min}\left(V(\lambda)\right) = \min_{\|x\|_2 = 1} x'V(\lambda)x &= \min_{\|x\|_2=1} \left((I - \Lambda G')^{-1}x\right)' \Sigma \left((I - \Lambda G')^{-1}x\right) \\
&\geq \sigma_{\min}(\Sigma) \cdot \|(I - \Lambda G')^{-1}x\|_2^2 \\
&\geq \sigma_{\min}(\Sigma) \cdot \left\{\sigma_{\min}\left((I - \Lambda G')^{-1}\right)\right\}^2 \cdot \|x\|_2^2 \\
&\geq \sigma_{\min}(\Sigma) \cdot \frac{1}{(1+\rho)^2} := B
\end{aligned}$$

where the first equality follows from the Rayleigh–Ritz characterization for SPD matrices, the second inequality follows from the multiplicative property of the $\|\cdot\|_2$ norm, the third inequality holds because $\Sigma \succeq \sigma_{\min}(\Sigma)I$, and the last inequality is derived from the following:

$$\sigma_{\min}\left((I - \Lambda G')^{-1}\right) = \frac{1}{\|I - \Lambda G'\|_2} \geq \frac{1}{1 + \|\Lambda\|_2 \|G'\|_2} \geq \frac{1}{1+\rho}$$

Since any diagonal element of $V(\lambda)$ satisfies $e_i' V(\lambda) e_i \geq \sigma_{\min}(V(\lambda))$ and assumption (A.7) holds, we have proved that any fixed point must satisfy $\lambda \gg 0$.

□

The metric space $([0,1]^n, d_\infty)$ with the metric induced by ℓ_∞ norm is complete. It remains to prove that $\mathcal{T}$ is a contraction to establish the equilibrium existence and uniqueness.

For any $\lambda, \widetilde{\lambda} \in [0,1]^n$, let $X := I - G\Lambda$ and $Z := I - G\widetilde{\Lambda}$. We then have:

$$V(\lambda) - V(\widetilde{\lambda}) = X^{-1}\Sigma X^{-T} - Z^{-1}\Sigma Z^{-T} = (X^{-1} - Z^{-1})\Sigma X^{-T} + Z^{-1}\Sigma(X^{-T} - Z^{-T}) \quad \text{(A.9)}$$

Moreover, by Assumptions (A.6) and (A.7) we obtain the following upper bound for $\|X^{-1}\|_2$:

$$\|X^{-1}\|_2 = \|\sum_{k=0}^{\infty}(G\Lambda)^k\|_2 \leq \sum_{k=0}^{\infty}\|(G\Lambda)^k\|_2 \leq \sum_{k=0}^{\infty}\|G^k\|_2 \leq \frac{1}{1-\rho} \quad \text{(A.10)}$$

Combining (A.10) with the identity

$$X^{-1} - Z^{-1} = X^{-1}(Z - X)Z^{-1} = X^{-1}G(\Lambda - \widetilde{\Lambda})Z^{-1}$$

we get:

$$\|X^{-1} - Z^{-1}\|_2 \;\leq\; \|X^{-1}\|_2 \cdot \|G\|_2 \cdot \|\Lambda - \widetilde{\Lambda}\|_2 \cdot \|Z^{-1}\|_2 \;\leq\; \frac{\rho}{(1-\rho)^2} \cdot \|\lambda - \widetilde{\lambda}\|_\infty \quad \text{(A.11)}$$

We get the following bound for the two additive terms in (A.9):

$$\begin{aligned} \|(X^{-1} - Z^{-1})\Sigma X^{-T}\|_2 \;&\leq\; \|X^{-1} - Z^{-1}\|_2 \cdot \|\Sigma\|_2 \cdot \|X^{-T}\|_2 \\ &\leq\; \frac{\rho}{(1-\rho)^3} \cdot \sigma_{\max}(\Sigma) \cdot \|\lambda - \widetilde{\lambda}\|_\infty \end{aligned}$$

where the second inequality follows from (A.11). Since matrix transpose does not change the spectral norm, the bound applies to the second term $\|Z^{-1}\Sigma(X^{-T} - Z^{-T})\|_2$ as well. Therefore, we obtain:

$$\|V(\lambda) - V(\widetilde{\lambda})\|_2 \;\leq\; \frac{2\rho}{(1-\rho)^3} \cdot \sigma_{\max}(\Sigma) \cdot \|\lambda - \widetilde{\lambda}\|_\infty \quad \text{(A.12)}$$

The last step is to show that the operator $\mathcal{T}$ is a contraction using the results established so far. From the definition of the operator $\mathcal{T}$ and assumption (A.7), we have:

$$\begin{aligned}
\|\mathcal{T}(\lambda) - \mathcal{T}(\widetilde{\lambda})\|_\infty = \max_{1\le i\le n}\left|\frac{\omega_i}{e_i'V(\widetilde{\lambda})e_i} - \frac{\omega_i}{e_i'V(\lambda)e_i}\right| &\le \left|\frac{\overline{\omega}e_i'\left(V(\lambda)-V(\widetilde{\lambda})\right)e_i}{\sigma_{\min}\left(V(\lambda)\right)^2}\right| \\
&\le \left|\frac{\overline{\omega}e_i'\left(V(\lambda)-V(\widetilde{\lambda})\right)e_i}{B^2}\right| \\
&\le \frac{1}{B}\|V(\lambda)-V(\widetilde{\lambda})\|_2 \\
&\le \frac{1}{B}\frac{2\rho}{(1-\rho)^3}\cdot\sigma_{\max}(\Sigma)\cdot\|\lambda-\widetilde{\lambda}\|_\infty \\
&\le L\|\lambda-\widetilde{\lambda}\|_\infty
\end{aligned}$$

With assumption (A.8), we have proved that $\mathcal{T}$ is a contraction on $[0,1]^n$ □

A.3 Proof of Proposition 2.2

Proof. By aggregating actions of agents in each group (A.2), we have:

$$a_i = \lambda_i a_i^* = \lambda_i\left(\sum_{j=1}^{n} g_{ij}a_j + \theta_i\right)$$

We can write it in vector form:

$$a = \Lambda(Ga+\theta)$$

Under the assumption (A1), we obtain the equilibrium action vector:

$$a = (I-\Lambda G)^{-1}\Lambda\theta \tag{A.13}$$

The equilibrium vector of the desired action a_i^* follows immediately:

$$a_i^* = \Lambda^{-1}a \tag{A.14}$$

And the equilibrium attention vector is given by Lemma 2.1 and equation (A.14). The uniqueness of equilibrium attention vector λ follows from conditions in Proposition 2.1.

□

A.4 Proof of Proposition 2.3

Proof. To ease notation, let $A = (I - G\Lambda)^{-1}$ and $h_i' = e_i'(I - G\Lambda)^{-1} = e_i'A$, where e_i is the standard basis vector. The prior variance of a_i^* can be written as $V_i = h_i'\Sigma h_i$.

The partial derivative of the marginal value of information m_i on attentionλ_j is given by:

$$\frac{\partial m_i}{\partial \lambda_j} = \frac{1}{2}\frac{\partial V_i}{\partial \lambda_j} = \frac{\partial h_i'}{\partial \lambda_j}\Sigma h_i$$

with

$$\frac{\partial h_i'}{\partial \lambda_j} = e_i'\frac{\partial A}{\partial \lambda_j} = e_i'AG\left(\frac{\partial \Lambda}{\partial \lambda_j}\right)A = e_i'(I - G\Lambda)^{-1}GE_{jj}(I - G\Lambda)^{-1}$$

where $E_{jj} = e_je_j'$. Combining the two equations above, we get:

$$\begin{aligned}\frac{\partial m_i}{\partial \lambda_j} &= e_i'(I - G\Lambda)^{-1}GE_{jj}(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}e_i \\ &= e_i'(I - G\Lambda)^{-1}Ge_je_j'(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}e_i \\ &= e_i'(I - G\Lambda)^{-1}Ge_j \times e_i'(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}e_j \\ &= e_i'G(I - \Lambda G)^{-1}e_j \times e_i'(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}e_j\end{aligned}$$

where the third equality holds as $e_j'(I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}e_i$ is a scalar. Writing the above in matrix form, we then obtain:

$$\mathcal{M}_\lambda = G(I - \Lambda G)^{-1} \circ (I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}$$

□

A.5 Proof of Proposition 2.4

Proof. When $\varepsilon = 0$, the interaction matrix G is diagonal, and the equilibrium attention $\overline{\lambda_i}$ for $i \in N$ is determined by the following equation, which follows from Example 1:

$$\frac{\sigma_i^2}{(1 - g_{ii}\overline{\lambda_i})^2} = \frac{\omega_i}{1 - \overline{\lambda_i}} \tag{A.15}$$

This equation equates the marginal value of attention with the marginal information cost. From this equation, the optimal attention for group i is solved by:

$$\overline{\lambda_i} = 1 - \omega_i\frac{\left(1 - g_{ii}\overline{\lambda_i}\right)^2}{\sigma_i^2} \tag{A.16}$$

Let $\overline{\lambda} = (\overline{\lambda_1}, \cdots, \overline{\lambda_n})$ be the attention vector, and $\overline{\Lambda}$ be the corresponding diagonal attention matrix. I start by deriving the first-order approximation.

First-order approximation. Applying the implicit function theorem to the equilibrium determination of attention $\lambda = \mathcal{T}(\lambda, \varepsilon)$, we obtain:

$$\frac{\mathrm{d}\lambda}{\mathrm{d}\varepsilon} = \left(I - \frac{\partial \mathcal{T}}{\partial \lambda}\right)^{-1} \frac{\partial \mathcal{T}}{\partial \varepsilon} \tag{A.17}$$

Let $V = (I - G\Lambda)^{-1}\Sigma(I - \Lambda G')^{-1}$, $M = (I - G\Lambda)^{-1}$ and $V_i = e_i' V e_i$. Evaluated at $\varepsilon = 0$, we have:

$$M\Big|_{\varepsilon=0} = (I - G_d\overline{\Lambda})^{-1} = \text{diag}\left(\frac{1}{1 - g_{ii}\overline{\lambda_i}}\right) := \text{diag}(d_i) = D$$

$$\frac{\partial M}{\partial \varepsilon}\Big|_{\varepsilon=0} = M\frac{\partial (G\Lambda)}{\partial \varepsilon}M\Big|_{\varepsilon=0} = DG_o\overline{\Lambda}D$$

$$\implies \quad \frac{\partial V}{\partial \varepsilon}\Big|_{\varepsilon=0} = DG_o\overline{\Lambda}D\Sigma D + D\Sigma D\overline{\Lambda}G_o'D \quad \text{and} \quad \frac{\partial V_i}{\partial \varepsilon}\Big|_{\varepsilon=0} = 2d_i^2 \sum_j d_j g_{ij}\overline{\lambda_j}\sigma_{ij}$$

where the expression for $\frac{\partial V_i}{\partial \varepsilon}\Big|_{\varepsilon=0}$ follows from the symmetry of $\frac{\partial V}{\partial \varepsilon}$ when $\varepsilon = 0$. Using the definition of the operator $\mathcal{T}$, $\mathcal{T}_i = 1 - \frac{\omega_i}{V_i}$, we then have:

$$\frac{\partial \mathcal{T}_i}{\partial \varepsilon}\Big|_{\varepsilon=0} = \frac{\omega_i}{V_i}\frac{\partial V_i}{\partial \varepsilon}\Big|_{\varepsilon=0} = \frac{\omega_i}{(d_i^2\sigma_i^2)^2} \cdot 2d_i^2 \sum_j d_j g_{ij}\overline{\lambda_j}\sigma_{ij} \tag{A.18}$$

The next step is to compute the feedback matrix $\left(I - \frac{\partial \mathcal{T}}{\partial \lambda}\right)^{-1}$. For each $j \in N$, we have:

$$\begin{aligned}\frac{\partial V}{\partial \lambda_j}\Big|_{\varepsilon=0} &= \frac{\partial M}{\partial \lambda_j}\Sigma M' + M\Sigma\frac{\partial M'}{\partial \lambda_j}\Big|_{\varepsilon=0} = M(G_dE_{jj})M\Sigma M' + M\Sigma M'(G_dE_{jj})M'\Big|_{\varepsilon=0} \\ &= 2D(G_dE_{jj})D\Sigma D\end{aligned}$$

Since D, G_d are diagonal matrices, then

$$\begin{aligned}\left[\frac{\partial V}{\partial \lambda_j}\Big|_{\varepsilon=0}\right]_{ii} = \frac{\partial V_i}{\partial \lambda_j}\Big|_{\varepsilon=0} &= 0, \quad \text{if } i \neq j \\ &= 2d_j^3 g_{jj}\sigma_j^2, \quad \text{if } i = j\end{aligned}$$

which implies the following equation:

$$I - \frac{\partial \mathcal{T}}{\partial \lambda} = \text{diag}\left(1 - \frac{\omega_i}{(d_i^2\sigma_i^2)^2}2d_i^3 g_{ii}\sigma_i^2\right) = \text{diag}\left(1 - \frac{2\omega_i}{d_i\sigma_i^2}g_{ii}\right) \tag{A.19}$$

Combine equations (A.17), (A.18), (A.19), we get the first-order approximation of λ around $\varepsilon = 0$:

$$\lambda_i(\omega, G(\varepsilon), \Sigma) = \overline{\lambda_i} + \frac{1}{1 - 2\frac{(1-\overline{\lambda_i})g_{ii}}{1-g_{ii}\overline{\lambda_i}}} \cdot \frac{2(1-\overline{\lambda_i})}{\sigma_i^2} \cdot \sum_{j \neq i} g_{ij} \frac{\overline{\lambda_j}}{1 - g_{jj}\overline{\lambda_j}} \sigma_{ij} \cdot \varepsilon + \mathcal{O}\left(\varepsilon^2\right) \tag{A.20}$$

where $\frac{1}{1-2\frac{(1-\overline{\lambda_i})g_{ii}}{1-g_{ii}\overline{\lambda_i}}} > 0$ captures the feedback effects. The linear term goes to zero when shocks are uncorrelated, i.e., $\sigma_{ij} = 0$, and the following derivations approximate λ_i up to second order for this case.

Second-order approximation. The following equation holds for the second-order term:

$$\frac{\mathrm{d}^2\lambda}{\mathrm{d}\varepsilon^2} = \left(\mathcal{T}_{\lambda\lambda}\frac{\mathrm{d}\lambda}{\mathrm{d}\varepsilon} + \mathcal{T}_{\lambda\varepsilon}\right)\frac{\mathrm{d}\lambda}{\mathrm{d}\varepsilon} + \frac{\partial \mathcal{T}}{\partial \lambda}\frac{\mathrm{d}^2\lambda}{\mathrm{d}\varepsilon^2} + \mathcal{T}_{\lambda\varepsilon}\frac{\mathrm{d}\lambda}{\mathrm{d}\varepsilon} + \mathcal{T}_{\varepsilon\varepsilon}$$

Since $\frac{\mathrm{d}\lambda}{\mathrm{d}\varepsilon}\Big|_{\varepsilon=0} = 0$ when Σ is diagonal, we have the following simplified expression for the second-order term:

$$\frac{\mathrm{d}^2\lambda}{\mathrm{d}\varepsilon^2} = \left(I - \frac{\partial \mathcal{T}}{\partial \lambda}\right)^{-1} \mathcal{T}_{\varepsilon\varepsilon} \tag{A.21}$$

Using the same notations as derivations above, we obtain:

$$M_{\varepsilon\varepsilon}\big|_{\varepsilon=0} = M_\varepsilon \frac{\mathrm{d}G\Lambda}{\mathrm{d}\varepsilon} M + M \frac{\mathrm{d}G\Lambda}{\mathrm{d}\varepsilon} M_\varepsilon \Big|_{\varepsilon=0} = 2DG_o\overline{\Lambda}DG_o\overline{\Lambda}D$$

$$V_{\varepsilon\varepsilon}\big|_{\varepsilon=0} = M_{\varepsilon\varepsilon}\Sigma M' + 2M_\varepsilon \Sigma M_\varepsilon' + M\Sigma M_{\varepsilon\varepsilon}' \Big|_{\varepsilon=0}$$

I now compute each of the (i,i) entry in $V_{\varepsilon\varepsilon}\big|_{\varepsilon=0}$. The first term is given by:

$$\begin{aligned} & e_i' M_{\varepsilon\varepsilon}\Sigma M' e_i \Big|_{\varepsilon=0} \\ & = 2e_i' DG_o\overline{\Lambda}DG_o\overline{\Lambda}D\Sigma De_i = 2d_i^3\overline{\lambda_i}\sigma_i^2 \sum_{j\neq i} d_j\overline{\lambda_j}g_{ij}g_{ji} = \frac{\overline{\lambda_i}\sigma_i^2}{\left(1-g_{ii}\overline{\lambda_i}\right)^3}\sum_{j\neq i}\frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}} \cdot g_{ij}g_{ji} \end{aligned}$$

The second term in $V_{\varepsilon\varepsilon}\big|_{\varepsilon=0}$ is:

$$\begin{aligned} & e_i' M_\varepsilon \Sigma M_\varepsilon' e_i \Big|_{\varepsilon=0} \\ & = d_i^2 \sum_{j\neq i} d_j^2 g_{ij}^2 \sigma_j^2 = \frac{1}{\left(1-g_{ii}\overline{\lambda_i}\right)^2}\sum_{j\neq i}\left(\frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}}\right)^2 \cdot g_{ij}^2\sigma_j^2 \end{aligned}$$

The third term in $V_{\varepsilon\varepsilon}\big|_{\varepsilon=0}$ is:

$$\begin{aligned} & e_i' M \Sigma M_{\varepsilon\varepsilon}' e_i \ \ \Big|_{\varepsilon=0} \\ &= e_i' M_{\varepsilon\varepsilon} \Sigma M' e_i \ \ \Big|_{\varepsilon=0} \end{aligned}$$

Combining the three terms above, we obtain the (i,i) entry in $V_{\varepsilon\varepsilon}\big|_{\varepsilon=0}$, that is, $\frac{\partial^2 V_i}{\partial \varepsilon^2} = [V_{\varepsilon\varepsilon}]_{ii} \ \Big|_{\varepsilon=0}$:

$$\frac{\partial^2 V_i}{\partial \varepsilon^2} \ \Big|_{\varepsilon=0} = 4\frac{\overline{\lambda_i}\sigma_i^2}{\left(1-g_{ii}\overline{\lambda_i}\right)^3} \sum_{j\neq i} \frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}} \cdot g_{ij}g_{ji} + 2\frac{1}{\left(1-g_{ii}\overline{\lambda_i}\right)^2} \sum_{j\neq i} \left(\frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}}\right)^2 \cdot g_{ij}^2\sigma_j^2 \tag{A.22}$$

Then,

$$\frac{\partial^2 \mathcal{T}_i}{\partial \varepsilon^2} \ \Big|_{\varepsilon=0} = \frac{\partial^2 \mathcal{T}_i}{\partial V_i^2}\left(\frac{\partial V_i}{\partial \varepsilon}\right)^2 + \frac{\partial \mathcal{T}_i}{\partial V_i}\frac{\partial^2 V_i}{\partial \varepsilon^2} \ \ \Big|_{\varepsilon=0} = \frac{\omega_i}{(d_i^2\sigma_i^2)^2} \cdot \frac{\partial^2 V_i}{\partial \varepsilon^2} \ \Big|_{\varepsilon=0} \tag{A.23}$$

Combining equations (A.19), (A.21), (A.22), (A.23), we then get the second order approximation as follows:

$$\begin{aligned} \lambda_i(\omega, G(\varepsilon), \Sigma) = \overline{\lambda_i} & \\ & + \alpha \cdot \left\{ 2\frac{\overline{\lambda_i}}{1-g_{ii}\overline{\lambda_i}} \sum_{j\neq i} \frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}} \cdot g_{ij}g_{ji}\sigma_i^2 + \sum_{j\neq i} \left(\frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}}\right)^2 \cdot g_{ij}^2\sigma_j^2 \right\} \cdot \varepsilon^2 \\ & + \mathcal{O}\left(\varepsilon^3\right) \end{aligned}$$

where the coefficient α is determined by the following:

$$\alpha = \frac{1-\overline{\lambda_i}}{1-2\frac{(1-\overline{\lambda_i})g_{ii}}{1-g_{ii}\overline{\lambda_i}}}\frac{1}{\sigma_i^2}.$$

To obtain the expression in Proposition 2.4, I defined the constants α_{ij} and β_{ij} by:

$$\beta_{ij} = 2\ \alpha\ \frac{\overline{\lambda_i}}{1-g_{ii}\overline{\lambda_i}} \cdot \frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}} > 0 \quad \text{and} \quad \alpha_{ij} = \alpha\left(\frac{\overline{\lambda_j}}{1-g_{jj}\overline{\lambda_j}}\right)^2 > 0$$

We then get the second-order approximation for $\lambda_i(\omega, G(\varepsilon), \Sigma)$ around $\varepsilon = 0$:

$$\lambda_i(\omega, G(\varepsilon), \Sigma) = \overline{\lambda_i} + \left\{ \sum_{j\neq i} \alpha_{ij} \cdot g_{ij}^2\sigma_j^2 + \sum_{j\neq i} \beta_{ij} \cdot g_{ij}g_{ji}\sigma_i^2 \right\} \cdot \varepsilon^2 + \mathcal{O}\left(\varepsilon^3\right) \tag{A.24}$$

$\square$

A.6 Proof of Theorem 3.1

Proof. From equations (3.14) and (3.16), households' and firms' prior expectations about aggregate output and price are given by:

$$\mathbb{E}[p_t \mid \mathcal{S}_{t,1}] = \mathbb{E}[p_t^* \mid \mathcal{S}_{t,1}] = \phi_\pi p_{t-1} + \rho_Z z_{t-1} - \rho_A a_{t-1} \tag{A.25}$$

$$\mathbb{E}[c_t \mid \mathcal{S}_{t,1}] = \mathbb{E}[c_t^* \mid \mathcal{S}_{t,1}] = \frac{1}{\gamma}\rho_A a_{t-1} \tag{A.26}$$

where $\mathcal{S}_{t,1}$ denotes the information set at the beginning of time t.

Mapping the economy to the framework of Section 2, the interaction matrix G between households and firms and the shock covariance matrix Σ are

$$G = \begin{bmatrix} 0 & -\frac{1}{\gamma} \\ 0 & 0 \end{bmatrix} \qquad \Sigma = \begin{bmatrix} \sigma_{Zt}^2/\gamma^2 & \sigma_{Zt}^2/\gamma \\ \sigma_{Zt}^2/\gamma & \sigma_{Zt}^2 + \sigma_{At}^2 \end{bmatrix} \tag{A.27}$$

Imposing the equilibrium market clearing condition that $c_t = y_t$, it follows immediately from Proposition 2.2 that the equilibrium attention satisfies (3.25) and (3.26), and the equilibrium allocation satisfies:

$$p_t = \lambda_t^F(-\theta_{At} + \theta_{Zt}) + \overline{p}_t \tag{A.28}$$

$$y_t = \frac{\lambda_t^H}{\gamma}\left(\lambda_t^F \theta_{At} + (1-\lambda_t^F)\theta_{Zt}\right) + \overline{y}_t \tag{A.29}$$

Combining (A.28) and (A.29) then gives the AD/AS representation such that demand shocks enter only the AD curve and supply shocks enter only the AS curve. □

A.7 Proof of Theorem 3.2

Proof. The inverse aggregate demand elasticity, $\psi_t^D = \frac{\gamma}{\lambda_t^H}$, depends inversely on household attention. Hence, it suffices to analyze how optimal household attention varies with shock uncertainty.

Denote $\mathcal{J}_\sigma(\lambda)$ as the Jacobian of optimal attention vector $\lambda_t = (\lambda_t^H,\ \lambda_t^F)$ with respect to aggregate demand and supply shock variances $(\sigma_{Zt}^2, \sigma_{At}^2)$. I also define V_t, y_{1t}, y_{2t} as follows to ease notation: $V_t := \sigma_{Zt}^2 + \sigma_{At}^2$, $y_{1t} := \frac{\omega_H \gamma}{\mathrm{Var}(c_t^*)^2}$ and $y_{2t} := \frac{\omega_F}{(\eta-1)\,\mathrm{Var}(p_t^*)^2}$. Lastly, momentarily ignore the time subscript t in all variables. Then,

$$\mathcal{J}_\sigma(\lambda) = \begin{bmatrix} y_1(1-\lambda^F)^2 + 2y_1y_2(\lambda^F V - \sigma_Z^2) & y_1(\lambda^F)^2 + 2y_1y_2(\lambda^F V - \sigma_Z^2) \\ y_2 & y_2 \end{bmatrix}$$

- Marginal response of household attention to demand shock volatility $\frac{\partial \lambda^H}{\partial \sigma_Z^2} < 0$ if:

$$y_1(1-\lambda^F)^2 + 2y_1y_2(\lambda^F V - \sigma_Z^2) < 0 \iff (1-\lambda^F)^2 + 2y_2(\lambda^F V - \sigma_Z^2) < 0$$
$$\iff \lambda^F < \frac{\sigma_Z^2 - \sigma_A^2}{V}$$

- Marginal response of household attention to supply shock volatility $\frac{\partial \lambda^H}{\partial \sigma_A^2} < 0$ if:

$$y_1(\lambda^F)^2 + 2y_1y_2(\lambda^F V - \sigma_Z^2) < 0 \iff (\lambda^F)^2 + 2y_2(\lambda^F V - \sigma_Z^2) < 0$$
$$\iff \lambda^F < 1 + \frac{\sigma_Z^2}{V} - \sqrt{1 + \left(\frac{\sigma_Z^2}{V}\right)^2}$$

We obtain the results in Theorem 3.2 by defining the thresholds ℓ_A^F and ℓ_Z^F as follows:

$$\ell_Z^F = \max\left\{0, \frac{\sigma_Z^2 - \sigma_A^2}{V}\right\} \qquad \ell_A^F = 1 + \frac{\sigma_Z^2}{V} - \sqrt{1 + \left(\frac{\sigma_Z^2}{V}\right)^2}$$

Moreover, $\ell_A^F \geq \ell_Z^F \iff \frac{\sigma_A^2}{\sigma_Z^2} \geq \frac{1}{3}$. □

A.8 Proof of Theorem 3.3

Proof. In this proof, I first obtain how the relative response of aggregate actions to each shock vary with shock volatility in the general LQG setting. I then apply the result to get how the slope of aggregate supply moves with demand and supply shock volatility.

Let $\mathbf{A}$ denote the equilibrium response matrix such that $a = \mathbf{A}\theta$, where A_{ij} denotes the (i, j) entry and captures the sensitivity of aggregate action of group i to shock θ_j. Consider the general case where Σ is not necessarily diagonal and can be decomposed as $\Sigma = K\widetilde{\Sigma}K'$, where $\widetilde{\Sigma}$ is diagonal with (j, j) entry σ_j^2. The following result characterizes how shock uncertainty σ_j^2 affects $\mathbf{A}$ and the relative elasticity $\frac{A_{il}}{A_{kl}}$ for any i, j, k, l.

Lemma A.2. *Shock volatility affects the equilibrium response matrix as follows:*

$$d\mathbf{A} = \left(\mathcal{S} \cdot \mathcal{J}_{\lambda,\sigma_j} \cdot \mathcal{Q}\right)\ d\boldsymbol{\sigma}_{\mathbf{j}}^{\mathbf{2}} \tag{A.30}$$

where $\mathcal{S} = (I - \Lambda G)^{-1}$ and $\mathcal{Q} = GA + K$. Here, $\mathcal{J}_{\lambda,\sigma_j}$ is a diagonal matrix with diagonal vector given by the j-th column of the Jacobian of attention λ with respect to shock variances, denoted by $\mathcal{J}_{\cdot j}$.

Moreover, the sensitivity of relative elasticity changes by:

$$\frac{d(A_{il}/A_{kl})}{A_{il}/A_{kl}} = (\mathcal{J}_{\cdot j} \circ \mathcal{Q}_{\cdot l}) \cdot \left(\frac{s_i}{A_{il}} - \frac{s_k}{A_{kl}} \right) \ d\sigma_{\mathbf{j}}^{\mathbf{2}} \tag{A.31}$$

where $\mathcal{Q}_{\cdot l}$ is the l-th column of $\mathcal{Q}$, and s_i is the i-th row of $\mathcal{S}$.

Proof. Denote $H = (I - \Lambda G)^{-1}$, then $A = (I - \Lambda G)^{-1} \Lambda K = H \Lambda K$. When shock volatility changes, the equilibrium A changes through the endogenous adjustments of attention matrix Λ. We thus have:

$$\begin{aligned} \mathrm{d}A &= (\mathrm{d}H)\Lambda K + H(\mathrm{d}\Lambda)K \\ &= H(\mathrm{d}\Lambda)GH\Lambda K + H(\mathrm{d}\Lambda)K = (I - \Lambda G)^{-1}\mathrm{d}\Lambda \left(K + GH\Lambda K\right) \end{aligned}$$

Holding the attention matrix fixed, the changes in the unconditional variances of desired actions are given by:

$$\frac{\partial V}{\partial \sigma_j^2} = (I - G\Lambda)^{-1} K E_{jj} K' (I - \Lambda G')^{-1}$$

$$\begin{aligned} \Longrightarrow \frac{\partial V_i}{\partial \sigma_j^2} = \left[\frac{\partial V}{\partial \sigma_j^2} \right]_{ii} &= e_i'(I - G\Lambda)^{-1} K E_{jj} K' (I - \Lambda G')^{-1} e_i = \left(e_i'(I - G\Lambda)^{-1} K e_j \right)^2 \\ &= \left[\ (I - G\Lambda)^{-1} K \circ (I - G\Lambda)^{-1} K \ \right]_{ij} \\ &:= \left[\ U \circ U \ \right]_{ij} \end{aligned}$$

where $\circ$ denotes the Hadamard product. I also use u_j to denote the j-th column of the matrix $U \circ U$, which gives $\frac{\partial v}{\partial \sigma_j^2}$.

Now consider how Λ responds to $\mathrm{d}\sigma_j^2$. Denote D as the diagonal matrix with diagonal elements given by $d_i = \frac{\omega_i}{V_i^2}$. From the equilibrium determination of λ_i:

$$\begin{aligned} \lambda_i &= 1 - \frac{\omega_i}{V_i} \\ V_i = e_i' V e_i &= e_i'(I - G\Lambda)^{-1} K \Sigma K' (I - \Lambda G')^{-1} e_i \end{aligned}$$

we have:

$$\mathrm{d}\lambda = D \ \mathrm{d}v \quad \text{and} \quad \mathrm{d}v = \mathcal{J}_{v,\lambda} \ \mathrm{d}\lambda + U \circ U \ \mathrm{d}\sigma$$

$$\Longrightarrow \frac{\partial \lambda}{\partial \sigma_j^2} = \left(I - D\mathcal{J}_{v,\lambda}\right)^{-1} D u_j$$

Therefore,

$$\frac{\partial A}{\partial \sigma_j^2} = (I - \Lambda G)^{-1} \operatorname{diag}\left(\left(I - D\mathcal{J}_{v,\lambda}\right)^{-1} D u_j \right) \left(I + G(I - \Lambda G)^{-1} \Lambda \right) K$$

And $\frac{\partial}{\partial \sigma_j^2} \frac{A_{il}}{A_{kl}}$ follows immediately from this expression, and we obtain:

$$d\frac{A_{il}}{A_{kl}} = (\mathcal{J}_{\cdot j} \circ \mathcal{Q}_{\cdot l}) \cdot \left(\frac{s_i}{A_{il}} - \frac{s_k}{A_{kl}}\right) \frac{A_{il}}{A_{kl}}\ d\boldsymbol{\sigma}_{\mathbf{j}}^{\mathbf{2}}$$

$\square$

I now apply Lemma A.2 to the household-firm setting. To ease notation, I ignore the time subscript of variables in the proof.

Denote the $(1,1)$ and $(1,2)$ entries of $\mathcal{J}_\sigma(\lambda)$ derived in A.7 as m_1 and m_2, respectively.

First, consider the impact of demand shock volatility σ_Z.

$$\begin{aligned}
\frac{\partial \psi^S}{\partial \sigma_Z^2} &= \left[\frac{-\lambda^F}{\lambda^H(1-\lambda^F)} \cdot m_1 \cdot (1-\lambda^F) + \frac{1}{1-\lambda^F} \cdot y_1 \cdot 1\right] \frac{1}{\lambda^H(1-\lambda^F)} \\
&= \left[-m_1 \frac{\lambda^F}{\lambda^H} + \frac{1}{V}\right] \frac{1}{\lambda^H(1-\lambda^F)} \\
&= \left[-\lambda^F(1-\lambda^F)y_1 - 2\lambda^F \frac{\lambda^F V - \sigma_Z^2}{V} y_1 + \frac{\lambda^H}{V}\right] \frac{1}{{\lambda^H}^2(1-\lambda^F)}
\end{aligned}$$

Since $\lambda^H, \lambda^F \in (0,1)$, we have:

$$\begin{aligned}
\frac{\partial \psi^S}{\partial \sigma_Z^2} < 0 \iff & -\lambda^F(1-\lambda^F)y_1 - 2\lambda^F \frac{\lambda^F V - \sigma_Z^2}{V} y_1 + \frac{\lambda^H}{V} < 0 \\
\iff & \frac{\lambda^H}{1-\lambda^H} < \frac{V}{\mathrm{Var}(c_t^*)} \lambda^F \left(1 + \lambda^F - 2\frac{\sigma_Z^2}{V}\right) = \frac{{\lambda^F}^2 V + (\sigma_A^2 - \sigma_Z^2)\lambda^F}{{\lambda^F}^2 \sigma_A^2 + (1-\lambda^F)^2 \sigma_Z^2} \\
\iff & \frac{\lambda^H}{1-\lambda^H} < \underbrace{1 + \frac{\lambda^F V - \sigma_Z^2}{{\lambda^F}^2 \sigma_A^2 + (1-\lambda^F)^2 \sigma_Z^2}}_{\ell_Z}
\end{aligned}$$

Equilibrium λ^F is a function of ω_F, η, σ_Z and σ_A, so is ℓ_Z. Define $\ell_Z^H = \frac{\ell_Z}{1+\ell_Z}$, then

$$\frac{\partial \psi^S}{\partial \sigma_Z^2} < 0 \iff \lambda^H < \ell_Z^H \tag{A.32}$$

Note that we also have:

$$\ell_Z > 0 \iff \lambda^F > \frac{\sigma_Z^2 - \sigma_A^2}{V}$$

Second, consider the impact of supply shock volatility σ_Z.

$$\begin{aligned}\frac{\partial \psi^S}{\partial \sigma_A^2} &= \left[\frac{-\lambda^F}{\lambda^H(1-\lambda^F)} \cdot m_2 \cdot (1-\lambda^F) + \frac{1}{1-\lambda^F} \cdot y_2 \cdot 1\right] \frac{1}{\lambda^H(1-\lambda^F)} \\ &= \left[-m_2 \frac{\lambda^F}{\lambda^H} + \frac{1}{V}\right] \frac{1}{\lambda^H(1-\lambda^F)} \\ &= \left[-\lambda^{F^2} y_1 - 2(\lambda^F V - \sigma_Z^2) y_1 y_2 + \frac{\lambda^H}{V}\right] \frac{1}{\lambda^{H^2}(1-\lambda^F)}\end{aligned}$$

We then have:

$$\begin{aligned}\frac{\partial \psi^S}{\partial \sigma_A^2} < 0 &\iff -\lambda^{F^2} y_1 - 2(\lambda^F V - \sigma_Z^2) y_1 y_2 + \frac{\lambda^H}{V} < 0 \\ &\iff \frac{\lambda^H}{1-\lambda^H} < \frac{\lambda^{F^2} V + 2(1-\lambda^F)(\lambda^F V - \sigma_Z^2)}{\mathrm{Var}(c_t^*)} = \frac{\lambda^{F^2} V + 2(1-\lambda^F)(\lambda^F V - \sigma_Z^2)}{\lambda^{F^2}\sigma_A^2 + (1-\lambda^F)^2 \sigma_Z^2} \\ &\iff \frac{\lambda^H}{1-\lambda^H} < \underbrace{1 + \frac{\lambda^F \sigma_Z^2 + (1-\lambda^F)(2V\lambda^F - 3\sigma_Z^2)}{\lambda^{F^2}\sigma_A^2 + (1-\lambda^F)^2\sigma_Z^2}}_{\ell_A}\end{aligned}$$

Similarly, ℓ_A depends only on ω_F, η, σ_Z and σ_A. Define $\ell_A^H = \frac{\ell_A}{1+\ell_A}$, then

$$\frac{\partial \psi^S}{\partial \sigma_A^2} < 0 \iff \lambda^H < \ell_A^H \tag{A.33}$$

And we have that

$$\ell_A > 0 \iff \lambda^F > \frac{V + \sigma_Z^2 - \sqrt{V^2 + \sigma_Z^4}}{V}$$

□

A.9 Proof of the 2-by-2 example

Proof. For the 2-by-2 example, the resulting $\mathcal{M}_\lambda$ is given by:

$$\mathcal{M}_\lambda = \frac{1}{\det(I - G\Lambda)} \begin{bmatrix} g_{11} - \lambda_2 \det(G) & g_{12} \\ g_{21} & g_{22} - \lambda_1 \det(G) \end{bmatrix} \circ \underbrace{\begin{bmatrix} \widetilde{\sigma}_1 & \widetilde{\sigma}_{12} \\ \widetilde{\sigma}_{12} & \widetilde{\sigma}_2 \end{bmatrix}}_{\widetilde{\Sigma}}$$

where the covariance matrix $\widetilde{\Sigma}$ is:

$$\widetilde{\Sigma} := (I - G\Lambda)^{-1} \Sigma (I - \Lambda G')^{-1} = \begin{bmatrix} \mathrm{Var}(a_1^*) & \mathrm{Cov}(a_1^*, a_2^*) \\ \mathrm{Cov}(a_1^*, a_2^*) & \mathrm{Var}(a_2^*) \end{bmatrix}$$

and $\widetilde{\sigma}_{12}$ is determined by:

$$\widetilde{\sigma}_{12} = \frac{(1-\lambda_2 g_{22})\lambda_1 g_{21} \cdot \sigma_1^2 + (1-\lambda_1 g_{11})\lambda_2 g_{12} \cdot \sigma_2^2}{\det(I - G\Lambda)^2}$$

Under assumption (A1), $\det(I - G\Lambda) > 0$. Since $\widetilde{\sigma}_1 > 0$ and $\widetilde{\sigma}_2 > 0$, the signs of $\frac{\partial m_1}{\partial \lambda_1}$ and $\frac{\partial m_2}{\partial \lambda_2}$ are determined by $g_{11} - \lambda_2 \det(G)$ and $g_{22} - \lambda_1 \det(G)$, respectively.

If $g_{12}, g_{21} > 0$, then $\widetilde{\sigma}_{12} > 0$. We have $\frac{\partial m_1}{\partial \lambda_2} > 0$ and $\frac{\partial m_2}{\partial \lambda_1} > 0$.

If $g_{12}, g_{21} < 0$, then $\widetilde{\sigma}_{12} < 0$. It still implies that $\frac{\partial m_1}{\partial \lambda_2} > 0$ and $\frac{\partial m_2}{\partial \lambda_1} > 0$.

If $g_{12} < 0$, $g_{21} > 0$, and

$$\frac{\sigma_1^2}{\sigma_2^2} > \frac{-(1-\lambda_1 g_{11})\lambda_2 g_{12}}{(1-\lambda_2 g_{22})\lambda_1 g_{21}} := \underline{r}$$

then $\widetilde{\sigma}_{12} > 0$. Hence, $\frac{\partial m_1}{\partial \lambda_2} < 0$ and $\frac{\partial m_2}{\partial \lambda_1} > 0$.

If $g_{12} > 0$, $g_{21} < 0$, and

$$\frac{\sigma_1^2}{\sigma_2^2} > \frac{-(1-\lambda_1 g_{11})\lambda_2 g_{12}}{(1-\lambda_2 g_{22})\lambda_1 g_{21}} := \underline{r}$$

then $\widetilde{\sigma}_{12} < 0$. It still holds that $\frac{\partial m_1}{\partial \lambda_2} < 0$ and $\frac{\partial m_2}{\partial \lambda_1} > 0$.

□

A.10 Proof of Corollary 4.1

Proof. To ease notation, define the effective unit information costs for firms and households as $\widetilde{\omega_F} := \frac{\omega_F}{\eta - 1}$ and $\widetilde{\omega_H} = \frac{\omega_H}{\gamma}$. By Corollary 3.2, firm j's private signal is given by:

$$p_{jt} = p_t + u_{jt}, \quad u_{jt} \sim \mathcal{N}(0, \widetilde{\omega_F}\lambda_t^F)$$

where I have used the aggregation result that $p_t = \lambda_t^F p_t^*$. Similarly, by Corollary 3.1, household i's private signal is:

$$c_{it} = y_t + u_{it}, \quad u_{it} \sim \mathcal{N}(0, \widetilde{\omega_H}\lambda_t^H)$$

where $c_t = \lambda_t^H c_t^*$ is obtained by aggregating consumption and $c_t = y_t$ in equilibrium.

First, consider firms' forecast formation and forecast dispersion. After observing its signal, firm j's expectation about aggregate price p_t follows the Bayesian updating rule:

$$\mathbb{E}[p_t \mid p_{jt}] = \frac{\text{Cov}(p_t, p_{jt})}{\text{Var}(p_{jt})} p_{jt} = \frac{\text{Var}(p_t)}{\text{Var}(p_{jt})} p_{jt}$$

Aggregating across all firms, the average forecast is given by:

$$\overline{\mathbb{E}}[p_t \mid p_{jt}] = \int_{j=0}^{1} \mathbb{E}[p_t \mid p_{jt}] \, \mathrm{d}j = \frac{\mathrm{Var}(p_t)}{\mathrm{Var}(p_{jt})} p_t$$

where $\overline{\mathbb{E}}[p_t \mid p_{jt}]$ denotes firms' average (mean) forecast. Firm j also forms the following conditional expectation about the aggregate output y_t:

$$\mathbb{E}[y_t \mid p_{jt}] = \frac{\mathrm{Cov}(y_t, p_{jt})}{\mathrm{Var}(p_{jt})} p_{jt} = \frac{\mathrm{Cov}(y_t, p_t)}{\mathrm{Var}(p_{jt})} p_{jt}$$

And their average forecast about output is:

$$\overline{\mathbb{E}}[y_t \mid p_{jt}] = \int_{j=0}^{1} \mathbb{E}[y_t \mid p_{jt}] \, \mathrm{d}j = \frac{\mathrm{Cov}(y_t, p_t)}{\mathrm{Var}(p_{jt})} p_t$$

From derivations above, we can also obtain how forecast dispersion varies with attention. Consider the forecast dispersion about price among firms.

$$\begin{aligned}
\mathrm{Disp}_{p,firm} &:= \left\{ \mathbb{E}\left(\mathbb{E}[p_t \mid p_{jt}] - \overline{\mathbb{E}}[p_t \mid p_{jt}] \right)^2 \right\}^{1/2} \\
&= \left\{ \mathbb{E}\left(\frac{\mathrm{Var}(p_t)}{\mathrm{Var}(p_{jt})} (p_{jt} - p_t) \right)^2 \right\}^{1/2} = \left\{ {\lambda_t^F}^2 \widetilde{\omega_F} \lambda_t^F \right\}^{1/2} = \left\{ \widetilde{\omega_F} {\lambda_t^F}^3 \right\}^{1/2}
\end{aligned}$$

The forecast dispersion about prices increases with firm attention. On one hand, higher λ_t^F means the signal-to-noise ratio is larger and individual price is more informative in forecasting the aggregate price level. Thus, firms put more weight on their signals in forecasting the aggregate price level. On the other hand, higher λ_t^F also implies greater dispersion in individual prices, conditional on any aggregate price level. Both forces contribute to the increase in forecast dispersion.

Note that, this monotonic relationship arises from the endogeneity of attention and signals. If the prior uncertainty about the desired price is fixed, forecast dispersion increases with λ_t^F when $\lambda_t^F \in (0, \frac{1}{2})$. However, λ_t^F in the current model is endogenous and depends on firms' prior uncertainty. Taking into account this endogeneity in attention and signal acquisition, forecast dispersion increases with attention when $\lambda_t^F \in (0, 1)$.

If the forecasting variable is output, we get:

$$\text{Disp}_{y,firm} := \left\{\mathbb{E}\left(\mathbb{E}[y_t \mid p_{jt}] - \overline{\mathbb{E}}[y_t \mid p_{jt}]\right)^2\right\}^{1/2} = \left\{\mathbb{E}\left(\frac{\text{Cov}(p_t, y_t)}{\text{Var}(p_{jt})}(p_{jt} - p_t)\right)^2\right\}^{1/2}$$
$$= \left\{\mathbb{E}\left(\frac{\text{Cov}(p_t, y_t)}{\text{Var}(p_t)}\frac{\text{Var}(p_t)}{\text{Var}(p_{jt})}(p_{jt} - p_t)\right)^2\right\}^{1/2} = \left\{\left(\frac{\text{Cov}(p_t, y_t)}{\text{Var}(p_t)}\right)^2 \widetilde{\omega_F}\lambda_t^{F^3}\right\}^{1/2}$$

The weight firms put on signals to forecast output depends on how informative their signals are, captured by the additional term, $\frac{\text{Cov}(p_t,y_t)}{\text{Var}(p_t)}$.

Next, consider households' forecast formation and forecast dispersion. It follows similar derivations as for firms, simply by renaming the variables.

$$\text{Disp}_{y,hh} = \left\{\widetilde{\omega_H}\lambda_t^{H^3}\right\}^{1/2} \qquad \text{Disp}_{p,hh} = \left\{\left(\frac{\text{Cov}(p_t, y_t)}{\text{Var}(y_t)}\right)^2 \widetilde{\omega_H}\lambda_t^{H^3}\right\}^{1/2}$$

Note that forecast dispersion in inflation among households now depends additionally on $\text{Cov}(p_t, y_t)$ and $\text{Var}(y_t)$, which are also determined by attention. □

B Additional Empirical and Quantitative Results

This Appendix provides additional results and details for the analysis in Sections 4 and 5.

B.1 Model Estimation

GARCH Estimation Results. Figure B1 presents estimates from the CCC-GARCH(1,1) model. Panel A reports the conditional variances for real GDP growth and inflation over 1960–2020, whereas Panel B extends the sample through 2025 to include the post-Covid period. Output growth exhibits higher volatility than inflation. Both volatility series spike surrounding the 1973-1975 and 1981-1982 recessions, the Great Recession and the COVID-19. Volatilities rose sharply in the 1970s and early 1980s, while declining significantly after 1984.

I assess the validity of CCC-GARCH(1,1) model by performing the following standard misspecification tests. The ARCH-LM test yields p-values of 0.997 (output growth) and 0.693 (inflation), failing to reject the null hypothesis that no ARCH effects remain in the residuals after fitting the GARCH(1,1) model. Ljung–Box tests on the squared residuals for 15 lags return p-values of 0.97 for output growth, and 0.85 for inflation, further supporting the absence of leftover ARCH dynamics.

To test the constant-correlation assumption, I consider an alternative DCC-GARCH(1,1) model. Denote D_t as the diagonal matrix that contains only the diagonal variance terms in H_t. DCC-GARCH(1,1) specifies the conditional covariance of standardized residuals $u_t = D_t^{-1}\varepsilon_t$ as

$$Q_t = (1-\alpha-\beta)Q + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1}, \quad \alpha \geq 0, \beta \geq 0, \alpha+\beta < 1$$

with correlation matrix

$$R_t = \operatorname{diag}(Q_t)^{-1/2}\, Q_t \operatorname{diag}(Q_t)^{-1/2}.$$

The likelihood-ratio test for the null hypothesis of $\alpha = \beta = 0$ gives $LR(2) = 2.0546$ with p-value=0.3580, failing to reject the null of constant conditional correlations.

Calibration of Time-Varying Shock Volatility. I illustrate in more detail the calibration strategy to obtain the volatility of aggregate demand and aggregate supply shocks. Let $z_t = (y_t, \pi_t)$ be the vector of equilibrium output and the price level, $e_t = (\theta_{Zt}, \theta_{At})$ be the shock vector, $\Sigma_{zt} = \mathbb{E}_t[z_t z_t']$ be the equilibrium covariance matrix for z_t, and $\Sigma_{et} = \mathbb{E}_t[e_t e_t']$ be the covariance matrix for e_t.

The model implies that z_t is a function of e_t in equilibrium. Moreover, the responsiveness of z_t to e_t depends on the shock covariance matrix, denoted by $X_t(\Sigma_{et})$, and we can write z_t as:

$$z_t = X_t(\Sigma_{et})e_t$$

The covariance matrix for z_t is then given by:

$$\Sigma_{zt} = X_t(\Sigma_{et})\Sigma_{et}X_t'(\Sigma_{et}) \tag{B.1}$$

The time series of demand shock volatility σ_{Zt} and supply shock volatility σ_{At} are then obtained by matching the model-implied outcome variances, the diagonal terms in Σ_{zt}, with the conditional variances of real output growth and inflation estimated from the GARCH model.

Figure B2 plots the estimated quarterly series of standard deviations of supply shocks and demand shocks from 1961Q1 to 2019Q4, and for the full sample.

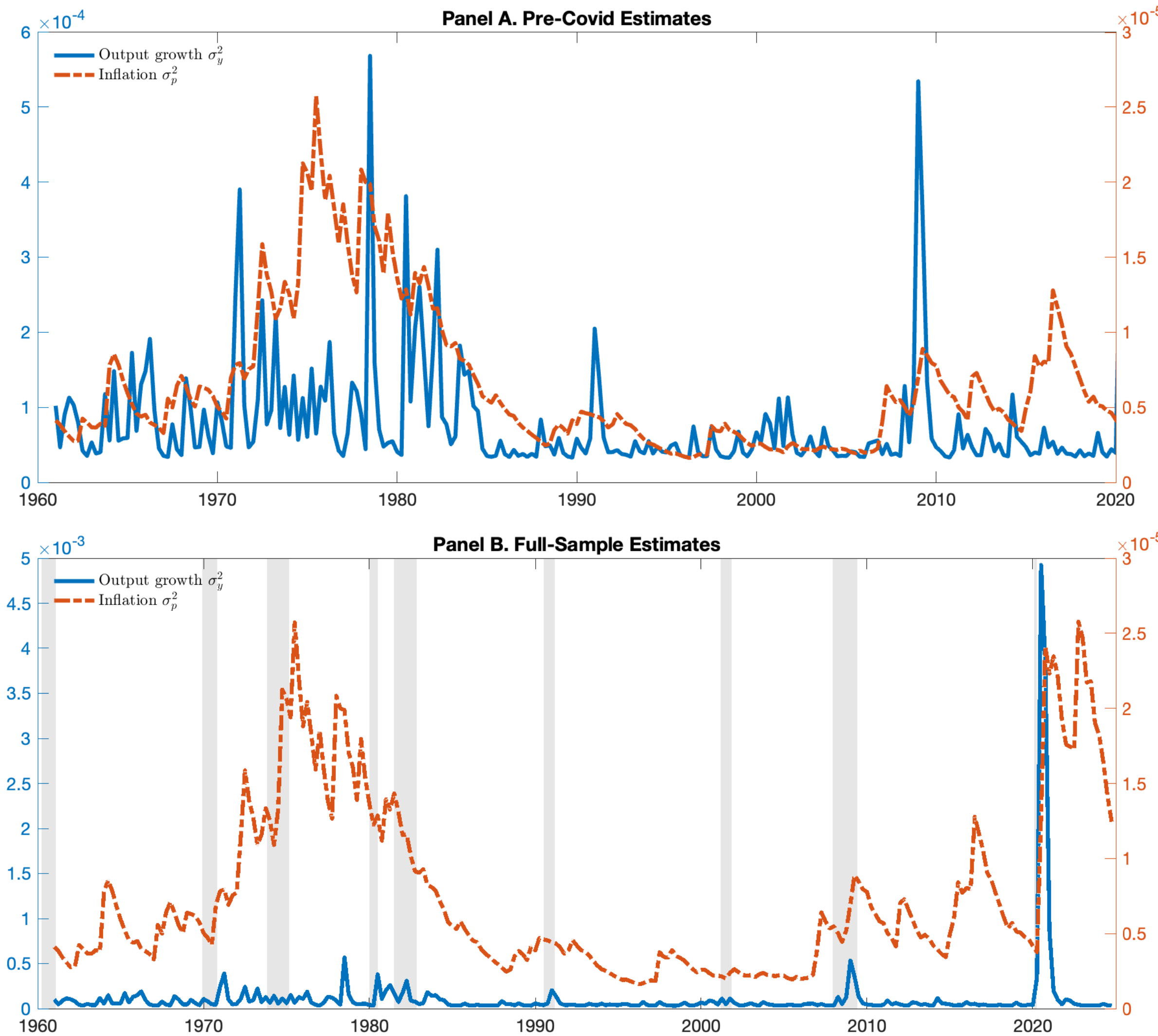
Model Fit. Figure B3 compares the model-implied uncertainties of output and inflation with the corresponding GARCH estimates. Table B1 summarizes the targeted moments in the data and as implied by the model. Overall, the calibrated model matches the targeted moments.

Table B1: Targeted Moments

Moment (1960-2020)	Data	Model
Variance of real output growth	Fig. B1	Fig. B3
Variance of inflation	Fig. B1	Fig. B3
Average household attention	0.22	0.2163
Average slope of the aggregate supply curve	0.11	0.1346

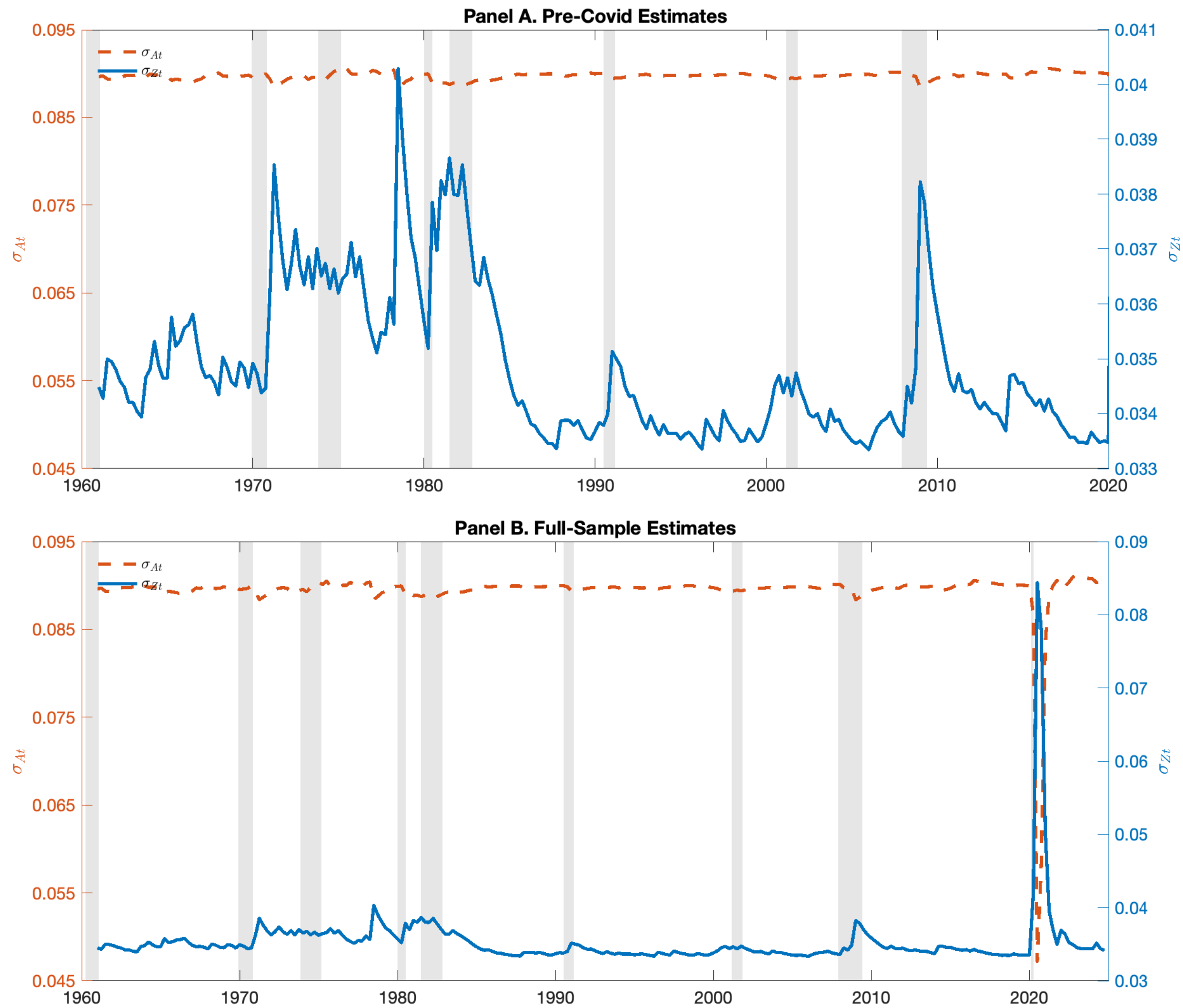
Note: The second and third columns compare the targeted moments in the data and as implied by the model.

Figure B1: Estimates of Inflation and Output Uncertainty in the U.S.



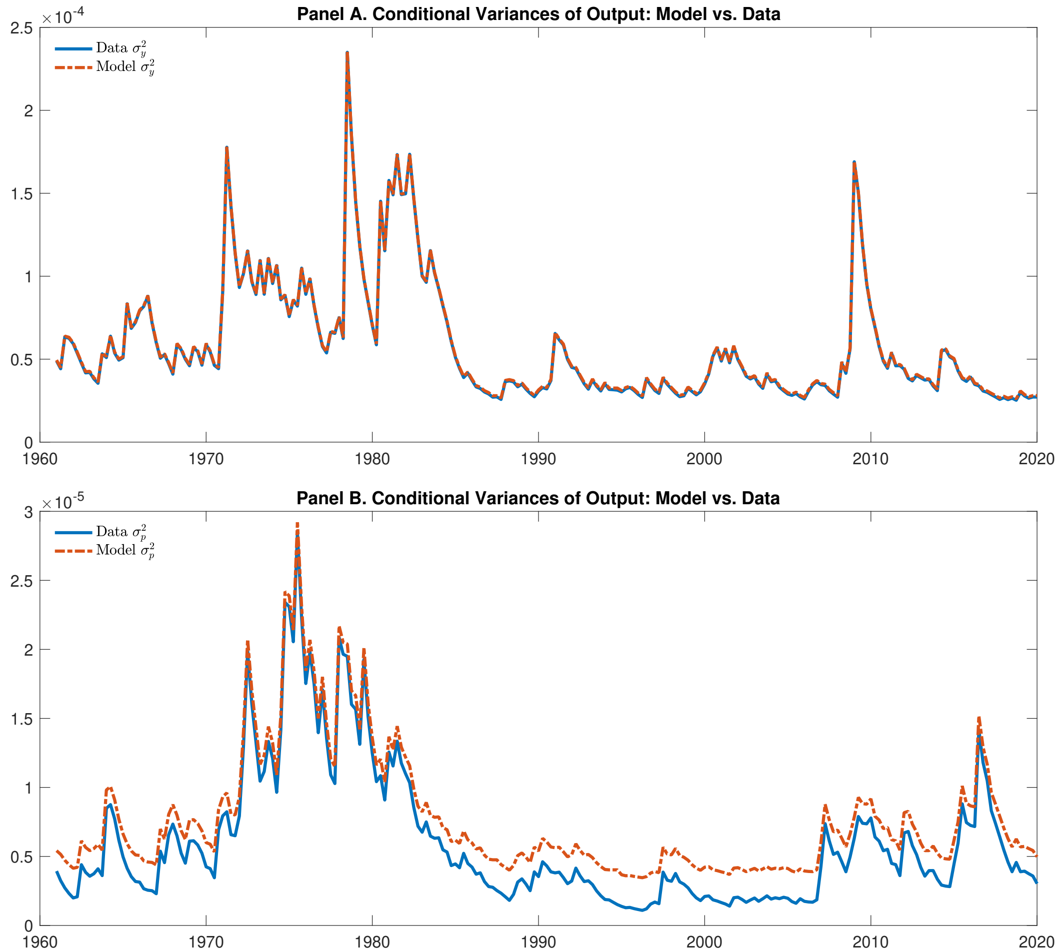
Note: This figure plots the estimated conditional variances for output growth (red dashed line) and inflation (blue solid line) obtained from the CCC-GARCH(1,1) model. The left axis measures output growth, and the right axis measures inflation. Panel A spans the period 1960–2020, whereas Panel B extends the sample through 2025 to include the post-Covid period.

Figure B2: Estimates of Time-Varying Shock Uncertainty



Note: This figure plots the estimated volatilities for aggregate supply shocks (red dashed line) and aggregate demand shocks(blue solid line). The left axis measures supply shock volatility, and the right axis measures demand shock volatility. Panel A spans the period 1960–2020, whereas Panel B extends the sample through 2025 to include the post-Covid period.

Figure B3: Model Fit



Note: Panel A plots the conditional variances of output implied by the model (red dashed line) and estimated from the GARCH specification (blue solid line). Panel B plots the conditional variances of inflation implied by the model (red dashed line) and estimated from the GARCH specification (blue solid line).

B.2 Empirical Estimates of the Aggregate Demand Slope

Table B2: Estimates of Inverse AD Slope

	1975-1984	1985-2019	Anderson-Rubin p-value
$\widehat{\beta}_h^Q$	-5.16	-0.89	0.04
	(4.37)	(1.01)	
Effective First-stage F	1.31	11.32	
$\widehat{\beta}_h$	0.29	0.17	0.01
	(.49)	(.21)	
Effective First-stage F	5.41	17.87	

Note: This table reports the estimated coefficients of the IV-LP regression, which refer to the inverse of aggregate demand elasticity. The upper panel presents results based on quarterly real GDP and inflation data, while the lower panel presents results based on monthly unemployment and inflation data. Standard errors are reported in parentheses. The effective first-stage F-statistics are computed following Olea and Pflueger (2013), which are robust to weak instruments and heteroskedasticity.

B.3 Information Rigidity Over Time

Coibion and Gorodnichenko (2015) provides a method to measure information rigidity using survey data. In particular, they run the following regression:

$$x_{t+h} - F_t x_{t+h} = c + \beta^{CG} \left(F_t x_{t+h} - F_{t-1} x_{t+h} \right) + error_t \tag{B.2}$$

where $F_t x_{t+h}$ is the consensus forecast of a given variable x_{t+h} made at time t and $F_t x_{t+h} - F_{t-1} x_{t+h}$ is the consensus forecast revision.

I first present the theoretical relationship between attention and information rigidity in the current model. I then use the SPF to estimate information rigidities over time in the U.S..

Lemma B.1. *The following relationships hold in the model:*

$$\beta^{CG}_{firm} = \frac{1-\lambda_t^F}{\lambda_t^F} \quad and \quad \beta^{CG}_{hh} = \frac{1-\lambda_t^H}{\lambda_t^H} \tag{B.3}$$

Proof. To ease notation, define the effective unit information costs as $\widetilde{\omega_F} := \frac{\omega_F}{\eta - 1}$ and $\widetilde{\omega_H} =$

$\frac{\omega_H}{\gamma}$. Then firm j's private signal is given by:

$$p_{jt} = p_t + u_{jt}, \quad u_{jt} \sim \mathcal{N}(0, \widetilde{\omega_F}\lambda_t^F)$$

where I have used $p_t = \lambda_t^F p_t^*$ in aggregation. Similarly, household i's private signal is:

$$c_{it} = c_t + u_{it}, \quad u_{it} \sim \mathcal{N}(0, \widetilde{\omega_H}\lambda_t^H)$$

where $c_t = \lambda_t^H c_t^*$ holds in aggregation.

First, consider firms' forecasts on output and the price level. After observing its signal, firm j's expectation about aggregate price p_t follows the Bayesian updating rule:

$$\mathbb{E}[p_t \mid p_{jt}] = \frac{\text{Cov}(p_t, p_{jt})}{\text{Var}(p_{jt})} p_{jt} = \frac{\text{Var}(p_t)}{\text{Var}(p_{jt})} p_{jt}$$

which is also firm j's forecast revision about p_t. Aggregating across all firms, the consensus forecast error and forecast revision are given by:

$$\overline{FE}_{p,firm} = p_t - \overline{\mathbb{E}}[p_t \mid p_{jt}] = \frac{\text{Var}(u_{jt})}{\text{Var}(p_{jt})} p_t, \quad \text{and} \quad \overline{FR}_{p,firm} = \overline{\mathbb{E}}[p_t \mid p_{jt}] = \frac{\text{Var}(p_t)}{\text{Var}(p_{jt})} p_t$$

where $\overline{\mathbb{E}}[p_t \mid p_{jt}] = \int \mathbb{E}[p_t \mid p_{jt}] \, \mathrm{d}j$ denotes firms' average (mean) forecast. Define $\beta^{CG}_{p,firm}$ as the coefficient of regressing consensus forecast error on forecast revision for the aggregate price. We have:

$$\beta^{CG}_{p,firm} = \frac{\text{Var}(u_{jt})}{\text{Var}(p_t)} = \frac{\widetilde{\omega_F}\lambda_t^F}{{\lambda_t^F}^2 \, \text{Var}(p_t^*)} = \frac{\widetilde{\omega_F}}{\text{Var}(p_t^*) - \widetilde{\omega_F}} = \frac{1 - \lambda_t^F}{\lambda_t^F} \tag{B.4}$$

where the last two equalities use the equation for optimal attention, $\lambda_t^F = 1 - \frac{\widetilde{\omega_F}}{\text{Var}(p_t^*)}$.

Firm j forms the following conditional expectation about the aggregate output c_t:

$$\mathbb{E}[y_t \mid p_{jt}] = \frac{\text{Cov}(y_t, p_{jt})}{\text{Var}(p_{jt})} p_{jt} = \frac{\text{Cov}(y_t, p_t)}{\text{Var}(p_{jt})} p_{jt}$$

which is also firm j's forecast revision about c_t. The consensus forecast error about the aggregate output among firms can be written as:

$$\overline{FE}_{y,firm} = y_t - \overline{\mathbb{E}}[y_t \mid p_{jt}] = y_t - \frac{\text{Cov}(y_t, p_t)}{\text{Var}(p_{jt})} p_t = \frac{\text{Cov}(y_t, p_t)}{\text{Var}(p_t)} p_t - \frac{\text{Cov}(y_t, p_t)}{\text{Var}(p_{jt})} p_t + \epsilon_t$$

where the second line has projected y_t onto p_t and the error ϵ_t is independent with p_t. The consensus forecast revision is:

$$\overline{FR}_{y,firm} = \overline{\mathbb{E}}[y_t \mid p_{jt}] = \frac{\text{Cov}(y_t, p_t)}{\text{Var}(p_{jt})} p_t$$

Again, define the CG regression coefficient as $\beta^{CG}_{y,firm}$. We then have:

$$\beta^{CG}_{y,firm} = \frac{\frac{\text{Cov}(y_t,p_t)}{\text{Var}(p_t)} - \frac{\text{Cov}(y_t,p_t)}{\text{Var}(p_{jt})}}{\frac{\text{Cov}(y_t,p_t)}{\text{Var}(p_{jt})}} = \frac{\text{Var}(p_{jt})}{\text{Var}(p_t)} - 1 = \frac{1-\lambda^F_t}{\lambda^F_t} \tag{B.5}$$

Hence, we obtain:

$$\beta^{CG}_{firm} := \beta^{CG}_{p,firm} = \beta^{CG}_{y,firm} = \frac{1-\lambda^F_t}{\lambda^F_t} \tag{B.6}$$

Next, the analysis for households' forecast follow exactly as above, simply by renaming the variables. We then conclude:

$$\beta^{CG}_{hh} := \beta^{CG}_{p,hh} = \beta^{CG}_{y,hh} = \frac{1-\lambda^H_t}{\lambda^H_t} \tag{B.7}$$

□

Data. SPF is a survey of professional forecasters run by the Federal Reserve Bank of Philadelphia starting from 1968. It surveys around 40 forecasters each quarter. Table B3 lists the macro variables used in the regression. I construct the consensus forecast and forecast revision by taking the mean of individual forecasts, after removing outliers that are more than 5 inter-quartile ranges away from the median. Forecast horizon ranges from current quarter to three quarters ahead. For real-time data, I follow the convention of using the initial releases from the Philadelphia Fed's Real-Time Dataset for Macroeconomists.

Table B3: List of Variables

Variable	SPF
Nominal GDP	1968:IV-2019:IV
Real GDP	1968:IV-2019:IV
Industrial production index	1968:IV-2019:IV
GDP price deflator	1968:IV-2019:IV
Housing starts	1968:IV-2019:IV
Unemployment rate	1968:IV-2019:IV
Consumer price index	1981:III-2019:IV
Real consumption	1981:III-2019:IV
Real nonresidential investment	1981:III-2019:IV
Real residential investment	1981:III-2019:IV
Federal government consumption	1981:III-2019:IV
State and local government consumption	1981:III-2019:IV

Figure B4: Information Rigidity in SPF

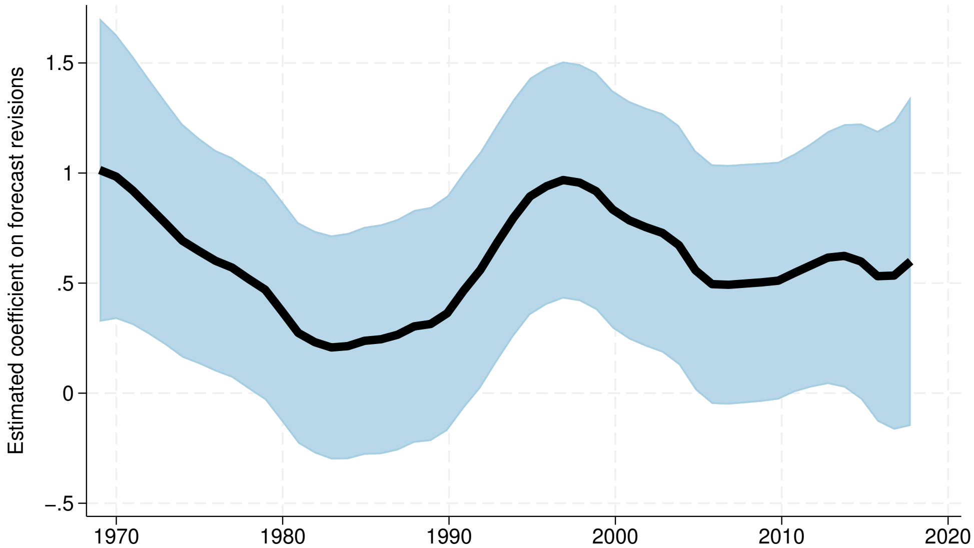
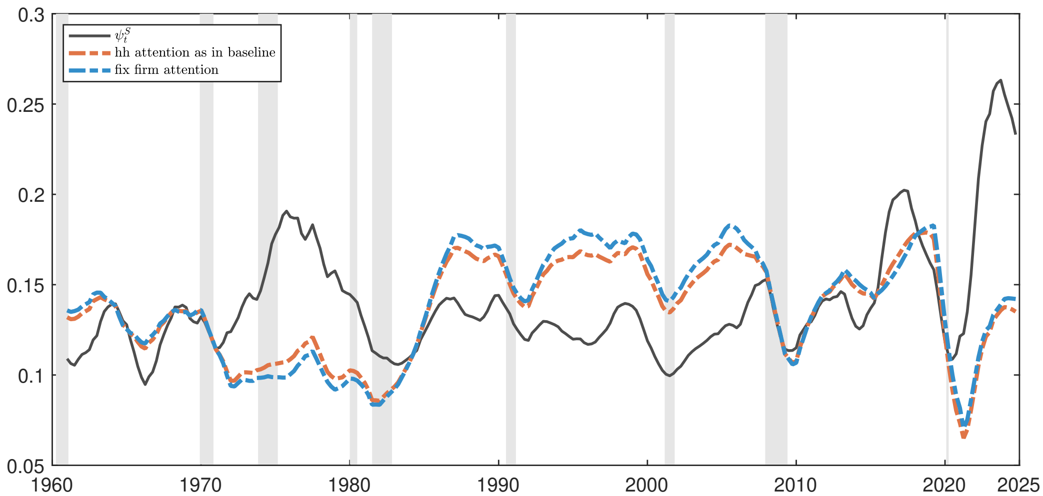


Figure B5: Counterfactual Aggregate Supply Slope



Note: This figure plots the model-implied aggregate supply slope for three cases: baseline with endogenous household and firm attention (black); household attention same as in the baseline model and firm attention fixed at its 1961–2019 average (red); and firm attention fixed at its 1961–2019 average with household attention endogenous (blue).