Consumer Information Frictions and Monetary Non-Neutrality: A Sequential Search Approach *

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Abstract

This paper develops a model of monetary non-neutrality driven solely by consumer-side information frictions, in contrast to standard approaches that rely on firm-side nominal rigidity. Consumers face search costs when shopping and have imperfect information about average nominal marginal cost. After a monetary shock, consumers misattribute price increases to firm-specific shocks and search more. Firms limit passthrough of aggregate shocks to deter search. They still flexibly pass through idiosyncratic shocks, as information frictions only weakens strategic complementarity in pricing. Empirically, I identify shopping patterns and estimate search elasticity to inflation shocks, pining down search frictions. Embedding this mechanism in a DSGE, solved by sequence-space methods and estimated by impulse-response matching, I find information frictions explains about 70% of monetary non-neutrality. The mechanism also helps account for the pandemic's inflation surge.

Keywords: Monetary non-neutrality, Price Stickiness, Phillips Curve, Consumer Search, Sequential Search, information frictions, Incomplete Passthrough, Strategic Complementarity, Higher-Order Beliefs, Sequence-Space Methods, Inflation Surge

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"This paper presents a theory that justifies price stickiness, namely, that firms, fearing to upset their customers, attribute a cost to price changes."

— Rotemberg (1982)

Monetary policy is widely understood to have substantial real effects in the short run. A large body of empirical literature has shown that both output and inflation decline following an unexpected increase in the interest rate.[1] Still, a fundamental question persists: Why don't changes in nominal policy rates simply lead to proportional changes in nominal wages and prices, leaving real quantities unaffected? A classic answer, dating back to Friedman (1968) and Phelps (1967), is that policy shocks are *not anticipated*.[2] Lucas (1972) shows that this unanticipated nature of shocks can be interpreted as a form of *imperfect information* under fully rational expectations. Sims (2003, 2006) propose that the unawareness of policy shocks can stem from agents' limited capacity to pay attention to all the relevant information to their decisions.

Firms are the agents that set prices. If they are not well informed about aggregate demand and supply, they may fail to adjust prices accordingly. The literature has thus argued that informational frictions among the firms could rationalize non-trivial monetary non-neutrality at the aggregate level even if prices were flexible at the firm level (Woodford, 2003; Mankiw and Reis, 2002; Maćkowiak and Wiederholt, 2009). Moreover, the interaction between information frictions and standard nominal rigidities—such as Calvo-style price-setting or menu costs—helps account for the observed inertia and state-contingency in inflation dynamics (Angeletos and Huo, 2021; Gagliardone and Tielens, 2024).

Such a firm-centric approach, however, faces two challenges. First, it abstracts from how advances in computing and data storage are improving firms' ability to forecast demand using big data (Begenau et al., 2018; Farboodi and Veldkamp, 2021), which in turn could reduce the quantitative bite of the assumed friction. Second, and more crucially for my purposes, it abstracts from informational friction among consumers—thus also failing to account for how consumer-side frictions may influence the firms' pricing decision, even if the firms themselves had been fully informed. Empirical studies have documented several facts of consumer-side frictions: consumers misperceive inflation (Candia et al., 2023), overweight salient prices in forming expectations (Kumar et al., 2015), anchor their beliefs on recent shopping experiences and past experiences of high inflation (Malmendier and Nagel, 2016; D'Acunto et al., 2021), and overly attribute inflation to

[1] Christiano et al. (1999) identify this effect using timing restrictions in VAR. Recently, high-frequency identification approach helps resolve the endogeneity bias in the VAR approach and confirms this finding (Gertler and Karadi, 2015; Bauer and Swanson, 2023). Hazell et al. (2022) estimate the slope of Phillips curve to be very flat using cross-state variation in price indices. Ramey (2016) provides a great summary of this literature.

[2] Friedman famously noted, "there is always a temporary trade-off between inflation and unemployment; there is no permanent trade-off. The temporary trade-off comes not from inflation per se, but from unanticipated inflation, which generally means, from a rising rate of inflation" (1968, p. 11).

non-economic reasons (Binetti et al., 2024). Furthermore, the consumer search literature documents substantial price dispersion even for identical goods, consistent with frictions in price discovery (Stigler, 1961; Kaplan and Menzio, 2015).

By shifting the focus to such consumer-side frictions, and by studying how these frictions influence firm pricing behavior, my paper ends up echoing, and indeed micro-founds, the story told by Rotemberg (1982). He argues that sluggish adjustment of prices may arise as firms *fear* to upset consumers if they fully adjust prices (Rotemberg, 2005, 2010, 2011; Eyster et al., 2015). In my model, firms optimally choose to compress their markups and limit the passthrough of monetary shocks (as well as of aggregate supply shocks) to prices out of fear that price increases will upset their customers and trigger them to move to a competitor. It is therefore *as if* firms face a cost from adjusting prices, but this cost is not hardwired.[3]. Furthermore, the firms' "fear" is fully rational, and so is the customers' "upsetting". Customers are likely to leave a firm if that firm raises prices, not because they get angry, but rather because they are rationally confused and hope to get a better deal elsewhere. Firms, anticipating this behavior, optimally respond in a way that makes prices appear more rigid in the aggregate than at the micro level.

The model builds on standard sequential search models (Wolinsky, 1986; Anderson and Renault, 1999) where consumers decide where to buy goods and they search sequentially over firms to learn prices and their fit. Each search is associated with a cost. Consumers lack information about each firm's idiosyncratic production cost and they only receive a noisy signal about the average nominal marginal cost. As a result, they rationally confuse an increase in nominal costs produced in all firms with an increase in the relative price of the firm they happen to visit. For example, a higher price may be seen as evidence of low productivity rather than a common nominal shock—prompting search rather than purchase.

I begin by characterizing the full-information rational expectations equilibrium. Under full information about policy shocks, I show that monetary policy is neutral. While this result is often taken for granted, it is not immediate in this context, as search frictions can be interpreted as a form of information frictions on individual prices. Nonetheless, when consumers know the shock, they understand that, in equilibrium, all prices fully adjust proportionally to policy shocks. Relative prices remain unchanged, so do search decisions. The key insight is that search frictions alone are insufficient to generate monetary non-neutrality. Some form of imperfect information about aggregate shocks is still necessary to produce real effects.

One of the contributions of this paper is to show that the equilibrium in a setting with consumer sequential search, imperfect information about policy shocks, and heterogeneous firms can be summarized by a single equation, which resembles equation (2.7) in Woodford (2003) in its form,

$$\hat{p} = \Gamma \hat{mc} + (1 - \Gamma) E^c \hat{p} \tag{1}$$

[3]As is instead the case in standard models with nominal rigidity.

where Γ is average own-cost passthrough, namely passthrough of nominal marginal cost changes $\hat{mc}$, holding constant the response of other firms, and $E^c\hat{p}$ represents consumers' average expectation of price index. In Woodford (2003), firms only pass through what they know about the shock to prices. The mechanism here is more nuanced. Firms retain flexibility in responding to idiosyncratic shocks, since consumers correctly interpret firm-specific price changes as relative price movements. In such cases, firms optimally pass through a fraction Γ of the shock, letting marginal consumers decide whether to switch. By contrast, under aggregate shocks, imperfect information creates a wedge between expected and actual price indices. Full passthrough would trigger excessive searching, as consumers misinterpret aggregate price increases as firm-specific, which reflects Rotemberg's core insight. Indeed, this holds true for all firms: consumers are less likely to stay and purchase during search, regardless of firms' productivity.

To further clarify the intuition, consider an extreme case where policy shocks are completely unanticipated by consumers. Here, aggregate shocks are indistinguishable from idiosyncratic shocks, and optimal passthrough is Γ. This sharply contrasts with firm-side imperfect information models where firms fail to adjust prices altogether when shocks are fully unanticipated. The key difference lies in the information asymmetry: in this model, firms know the shock. However, they understand that the shock is completely unanticipated to consumers, so they cannot respond to changes in other firms' prices, via strategic complementarity, i.e., setting prices close to competitors'.

The paper's second contribution is empirical. I first extend the simple sequential-search framework to a multi-product environment in which consumers may buy, and stores may sell, multiple products. Using a large-scale consumer panel, I estimate the per-visit purchase probability by jointly matching (i) the distribution of the number of stores purchased from and (ii) the distribution of the number of products bought per store. The estimated per-visit purchase probability is $\hat{\rho} \approx 0.73$. I then estimate the elasticity of search with respect to inflation shocks: a 1 percentage-point, unanticipated, oil-driven increase in inflation raises search activity—measured by the number of distinct stores visited per household in a month—by about 2.85 percentage points. Following Coibion and Gorodnichenko (2015a), I identify consumer information frictions using oil price changes and oil news shocks as instruments to address endogeneity from missing inflation revisions; the implied Kalman gain is roughly 0.4, indicating large information frictions. Calibrating the sequential-search model to these moments yields an average own-cost pass-through of about 0.4, consistent with the literature (e.g., Gopinath et al. 2011; Amiti et al. 2019; Gagliardone et al. 2025) and indicative of strong pricing complementarities.

The third contribution is to develop a medium-scale DSGE model that places the consumer theory of price stickiness at its core, and to estimate the magnitude of information frictions using impulse response matching (Christiano et al., 2005). I incorporate two additional frictions: nominal price rigidity and nominal wage rigidity. Nominal price rigidity is motivated by the micro data evidence (Bils and Klenow, 2004; Nakamura and Steinsson, 2008); wage stickiness dampens the

response of own marginal costs to policy shocks (Christiano et al., 2005). Consumers learn about policy shocks gradually, forming expectations based on a history of private noisy signals. Learning renders the deviation of output from potential output more persistent as signal noise increases (Woodford, 2003). I then let these three frictions compete for explaining monetary non-neutrality in the model. I solve the model and compute impulse responses using the sequence-space method developed by Auclert et al. (2021), and follow Auclert et al. (2020) to accommodate learning dynamics in the sequence space. With this framework, I am able to address two central questions: (1) Can a model centered on consumer-side frictions with bells and whistles, match the empirical impulse responses to monetary shocks identified via SVAR? and (2) How much do consumer-side frictions contribute to monetary non-neutrality?

I estimate the model parameters to match the moments. In particular, the average own-cost passthrough is a sufficient statistic that summarizes all the parameters related to the search friction.[4] I calibrate it to match the empirical results from the second part of the paper. The degree of information frictions among shoppers is then estimated using impulse response matching. Specifically, I estimate an external IV-SVAR following Gertler and Karadi (2015), using standard macroeconomic variables alongside household inflation expectations from the Michigan Survey of Consumers. The results reveal that household inflation expectations underreact significantly to monetary shocks with estimated average duration of information frictions to be about 5 years, suggesting substantial information frictions. The key determinant of information frictions in estimation is the relative impulse responses of inflation and inflation expectation.

To analyze the monetary transmission mechanism, I first shut down nominal price rigidity. The result is stark: once information frictions are present, price rigidity contributes essentially nothing to monetary non-neutrality. The reason is that to match the empirical impulse responses requires substantial wage rigidity and information frictions. Conditional on these, adding modest price rigidity (e.g., Calvo $\lambda_p = 0.75$) is largely ineffective for output responses, consistent with Christiano et al. (2005). In the baseline calibration, wage rigidity accounts for about 30% of the cumulative output response to a monetary shock, leaving the remaining 70% to information frictions.

I also consider aggregate productivity shocks in this framework. In contrast to standard New Keynesian models, the inflation response in this framework features a sharp initial increase followed by a rapid decline. This arises because, although nominal wage responses are dampened by wage rigidity, and strategic complementarities are attenuated due to imperfect information, my model still allows firms to flexibly pass through a fraction Γ of the productivity shock to prices *immediately*, as implied by equation (1). The rapid decline is related to learning.

Finally, two puzzles—"missing disinflation" at the zero lower bound and the pandemic inflation surge—can be explained jointly by placing consumer information frictions in price setting. When

[4]There is a demand allocation term relies on particular parameters of search model (Baqaee et al., 2024). However, this effect is quantitatively small.

consumers pay little attention to inflation as in the Great Recession, firms face weak competitive discipline from marginal shoppers and pass through negative marginal cost shocks only modestly, yielding small disinflation. When attention is high as during the pandemic, firms are able to pass through positive marginal cost changes without worrying losing marginal customers, steepening the Phillips curve. Empirically, forecast errors co-move tightly with inflation when expectations are inert, but diverge when attention rises. Policy should therefore condition on information frictions: when salience of inflation is high, a more hawkish stance is suggested; when salience is low, greater weight on real activity is appropriate.

Related Literature – This paper contributes to several strands of literature. First, my study is motivated by the importance of consumers' reactions to price changes in price-setting models (Rotemberg 2005, 2010, 2011; Kleshchelski and Vincent, 2009; Nakamura and Steinsson, 2011; Eyster et al., 2015; Matějka, 2015; Rebelo et al., 2024; Sara-Zaror, 2024). These models usually assume that consumers experience disutility from perceived price unfairness or volatility. In contrast, this paper develops a consumer-based theory of price stickiness rooted in the tradition of Phelps (1969), Lucas (1972), Mankiw and Reis (2002), Woodford (2003), Maćkowiak and Wiederholt (2009), Angeletos and La'o (2010), and Angeletos and La'O (2013). The model demonstrates that firms may not fully adjust prices to monetary shocks if shocks are not anticipated by their consumers, even firms themselves are fully informed. Therefore, my model offers new avenues for rational micro-foundations of price stickiness, which is consistent with recent empirical evidence on firm and household expectations.

Several papers are closely related. Gaballo and Paciello (2021) show that paid prices remain sticky because consumers, unaware of the monopoly firm's marginal costs, reallocate toward a competitive market after the monopoly increases its price after an expansionary shock. In contrast, I consider a sequential search model where all firms have monopoly power. I find that it is markup compression, not demand reallocation, that drives sluggish price adjustment. Quantitatively, reallocation has minimal effect on inflation. In addition, Bénabou and Gertner (1993) and L'Huillier (2020) focus on the strategic role of individual prices consumers observe as revealing the information about aggregate shocks. To emphasize the channel of imperfect information in the sense of Friedman (1968) and Phelps (1967), I shut down this signaling channel. More broadly, my model remains tractable, accommodates standard DSGE features (Christiano et al., 2005; Smets and Wouters, 2007), and is solved efficiently using sequence-space methods (Auclert et al., 2021).

This paper takes a first step toward bridging recent empirical findings on consumer-side frictions with a model that takes these frictions as core of price stickiness. Evidence shows households misperceive inflation (Kumar et al., 2015; D'Acunto et al., 2021; Candia et al., 2023), and that expectations vary systematically by IQ and gender (D'Acunto et al., 2022, 2023). Household beliefs respond to Fed communication framing (Coibion et al., 2022) and are often attributed to political narratives like government spending (Binetti et al., 2024; Stantcheva, 2024). They tend

to be more attentive to inflation in high-inflation environment (Cavallo et al., 2017; Weber et al., 2025). Incorporating household expectations into standard models helps explain inflation puzzles such as the missing disinflation in the Great Recession and pandemic inflation surge (Coibion and Gorodnichenko, 2015b; Beaudry et al., 2024). This paper opens new venues for more research on linking empirical studies on people's inflation expectation to macroeconomic outcomes.

Outline – The rest of the paper is organized as follows. Section 1 presents the setup for static model. Section 2 characterizes the equilibrium. Section 3 presents the main theoretical results of this paper. Section 4 shows empirical evidences and calibration of search frictions and information frictions about oil shocks. Section 5 develops a DSGE model, estimates the information frictions about monetary shocks, and analyses the transmission mechanisms. Section 6 considers two applications. The last section concludes. Appendix A contains some of the proofs omitted from the text for the static model. Appendix B contains details of empirical setup and additional empirical evidence. Appendix C contains the proof of the dynamic model and details of calibration and estimation.

1 Static Model

In this section, I develop a macroeconomic model that has three types of agents: shoppers, firms, and a monetary authority. Shoppers face information frictions about monetary shocks and search frictions when deciding where to buy goods. In contrast, firms are fully informed. I start with the static model to explain the main mechanism.

Notation – I use lower case to denote $\log Y$ for any variable Y, i.e., $y = \log Y$ and lower case with hat to denote log-deviation from the steady-state value, i.e., $\hat{y} = \log Y - \log \bar{Y}$.

1.1 Setup

The timeline is as follows. Within a period, the monetary authority first sets the nominal wage. Shoppers are endowed with cash which also serves as the signal about the nominal wage. Firms post prices and shoppers search sequentially. A fraction of shoppers make the purchase in a given round and the remaining keep searching. The period ends until all shoppers make the purchase. I denote the round of search $r = 1, 2, 3, ...$ within a period. All rounds of search happen within one period.

Firm – The economy is populated with a unit mass of firms indexed $k \in [0, 1]$, each of which produces a differentiated product using the following production technology,

$$Y_k = A_k L_k \tag{2}$$

where L_k is the amount of labor employed. A_k is the firm's productivity, which is i.i.d. across firms. Specifically, I assume that $\log A_k$ is drawn from the normal distribution $\Phi_a(a) = \mathcal{N}(0, \sigma_a^2)$.

The marginal cost is $\frac{W}{A_k}$, where W is the nominal wage. The nominal wage represents the average nominal marginal cost. Labor is supplied outside this economy in the current setup.

Suppose consumers believe that the pricing strategy $p^* : \mathcal{R}^2 \to \mathcal{R}$ exists, which maps firm k's states $\{a_k, w\}$ to p_k, i.e., $p_k = p^*(a_k, w)$. If p^* is monotone in both arguments, then the inverse mapping from p_k to a_k given w can be denoted by $p^{*-1}(p, w)$.[5] Heterogeneity in a_k across firms induces an endogenous price distribution $F(p|w)$, which has a density distribution $f(p|w)$. The conditional price distribution is given by,

$$F(p|w) = 1 - \Phi_a(p^{*-1}(p, w)) \tag{3}$$

Monetary Authority – The monetary authority draws the log nominal wage from the normal distribution $\mathcal{N}(\bar{w}, \sigma_w^2)$, which serves as the prior for shoppers. Denote the monetary shock by $\hat{w} = w - \bar{w}$.

Shopper – The economy is populated with a continuum of shoppers indexed by $i \in [0, 1]$. At the beginning of the period, each shopper is endowed with cash X_i, which is centered around realized W. It follows,

$$X_i = W \exp\left(\sigma_x \varepsilon_{xi} - \frac{\sigma_x^2}{2}\right) \tag{4}$$

where ε_{xi} is i.i.d. across shoppers and it follows $\varepsilon_{xi} \sim \mathcal{N}(0, 1)$. It is also independent of any other shocks. The variance adjustment term $\sigma_x^2/2$ ensures that $\int X_i di = W$. The shopper treats X_i as signal about W. The expected log nominal wage is then given by $E(w|x_i) = \theta x_i + (1 - \theta)\bar{w}$, where $\theta = \frac{\sigma_x^{-2}}{\sigma_w^{-2} + \sigma_x^{-2}}$. It measures the information frictions. Higher θ implies that signals are more informative. Based on the Bayes' rule, shopper i's posterior belief $H(w|x_i)$ follows $\mathcal{N}(E(w|x_i), (\sigma_w^{-2} + \sigma_z^{-2})^{-1})$.[6] Using the posterior belief about w, shoppers can construct their perceived price distributions, $f(p|x)$, conditional on x:

$$f(p|x) = \int f(p|w)h(w|x)dw \tag{5}$$

The above equation yields two implications. First, when information is perfect, i.e., $x = w$, the perceived and objective price distributions coincide. Second, if $h(w|x_i)$ first-order stochastically dominates (FOSD) $h(w|x_j)$ and p^* increases in w, then $f(p|x_i)$ FOSD $f(p|x_j)$. Intuitively, if a shopper believes the nominal wage is on average lower, the perceived price distribution is shifted to the left, which would impact search decisions as we will show below.

[5] In rational expectations equilibrium, the believed pricing strategy is consistent with the objective pricing strategy, as shown in Section 2.

[6] The fact that cash also enters as a signal is inconsequential. One can take the limit $\sigma_x \to \infty$, and let shoppers receive another exogenous signal about wage. Modeling cash as a signal is thus a notational convenience.

Each shopper buys and consumes only one good.[7] The utility (or value) that shopper i gains from consuming good k is given by,

$$\log \frac{X_i}{P_k} + \frac{1}{\lambda}\epsilon_{ik} \tag{6}$$

where $\epsilon_{ik} \sim G$ is match utility between shopper i and good k, which is i.i.d across firms and shoppers.[8] G is triple continuously differentiable and its density function is g. It captures idiosyncratic consumer preferences for certain goods over others. Also, following the literature, I assume that G is *log-concave*.[9] The parameter λ controls the relative importance between two utilities. A larger λ implies more competition on prices. Since X_i only affects the level of utility and does not change the relative utilities across goods, I define the normalized utility as follows,

$$y_{ik} = -p_k + \frac{1}{\lambda}\epsilon_{ik} \tag{7}$$

According to (7), the value distribution of drawing a random good is a convolution of the perceived price distribution and the distribution of match utility,

$$\psi(y|x) = \int f(u-y|x)\lambda g(\lambda u)du \tag{8}$$

Shoppers search sequentially and randomly following Wolinsky (1986) and Anderson and Renault (1999). By incurring a search cost $\kappa > 0$, which is assumed to be a utility cost, the shopper can visit a firm to learn both its price and the associated match utility. Each shopper is assigned with the first good for free.[10] Shoppers have free recall, meaning there are no additional costs for purchasing goods from firms they have previously visited. In addition, shoppers do not commit to any plan made before setting out to search.[11] For now, I assume that shoppers do not learn about aggregate shocks from the prices they observe during search. Therefore, the perceived price distribution $f(p|x)$ remains fixed throughout the search. This assumption is plausible if the

[7] In Section 4, I extend the model by allowing shoppers to buy multiple goods in multiple stores.

[8] The price distribution is not degenerated and the optimal prices are related to firm's idiosyncratic states, if the random utility term is match-specific. Otherwise, if it is only shopper-specific, it does not matter for search decisions. Firms compete only on price. The price distribution is degenerated to a single optimal price. If it is only good-specific, the optimal prices are not related to firm's productivity.

[9] Note that some commonly used distribution functions are log-concave, e.g., normal distribution, uniform distribution, Gumbel distribution. See Bagnoli and Bergstrom (2005) for a broad discussion of log-concavity that do and do not satisfy this condition. The assumption of log-concavity ensures that the hazard rate $\frac{g(x)}{1-G(x)}$ is monotonically increasing.

[10] Shoppers always participate the market with free first good.

[11] If the shopper formulated her search plan prior to search and she committed to that plan, then she would take into account the expected total search costs of sampling, and she would stop with a lower quality match if she were unlucky and happened to sample a sequence of firms for which she ill-suited. In the case of a shopper doing sequential search without commitment, she ignores past fixed costs of search as sunk. Burdett and Judd (1983) considers a search problem with commitment and homogeneous firms.

variance of idiosyncratic productivity shocks is way larger than the variance of the monetary shocks, and the average number of draws is small. I make this assumption for tractability. As I will show, the main mechanism remains valid as long as information frictions exists. In Section 3.5, I discuss learning from prices and how good this approximation is. I also assume away security markets where shoppers can trade claims that are contingent on the search process and final choices.[12]

Now I state the shopper's problem. Let v_{ir} denote the maximum value among the firms visited by shopper i up to the rth round. By definition, $v_{i1} = y_{i1}$. For $r > 1$, v_{ir} is recursively given by,

$$v_{ir} = \max\{v_{ir-1}, y_{ir}\} \tag{9}$$

In the rth round of the sequential search, the state of the shopper is v_{ir}. The shopper has the option to stop searching and accept v_{ir} or continue searching. The value function for the shopper, $U : \mathcal{R} \to \mathcal{R}$, in each state $v \in \mathcal{R}$, satisfies,

$$U(v|x) = \max\left\{v, -\kappa + U(v|x)\int_{-\infty}^{v} \psi(y|x)dy + \int_{v}^{\infty} U(y|x)\psi(y|x)dy\right\} \tag{10}$$

The maximum represents that the shopper can either receive the maximum value v up to this round and stop searching, or continue searching by incurring a search cost κ and drawing a random good. If the value of that good is lower than v, which occurs with probability $\int_{-\infty}^{v} \psi(y|x)\, dy$, the shopper will retain the value $U(v)$, since she has free recall. Otherwise, she will obtain a higher value from the newly drawn good and update v according to (9). The shopper's problem is solved in two steps. First, she finds the U function that solves the functional equation (10). Second, she keeps sampling firms until v first exceeds the expression to the right of the comma in (10).

1.2 Equilibrium Definitions

The equilibrium concept is Perfect Bayesian Nash equilibrium (PBNE).[13] Formally, I define the equilibrium as follows:

Definition 1 (Equilibrium)**.** *A Perfect Bayesian Nash equilibrium is a triplet of allocation, prices, and beliefs such that*

1. *Firms choose the optimal pricing strategy p^* to maximize profits given the optimal search strategy.*

[12]For example, a security might provide positive returns if a shopper experiences a long sequence of unfavorable draws or if the final choice of store gives a low value. Mongey and Waugh (2024) show that the demand allocations in a standard discrete-choice model without search frictions can be different when the market is complete.

[13]In the standard search literature, prices are bounded and consumers know the range of prices. Therefore, consumers are able to detect the off-equilibrium prices. The literature imposes that consumers keep the same (passive) beliefs about the distribution of future prices on and off the equilibrium path. In our case, since productivity is assumed to have unbounded support, any positive price is an on-equilibrium price. The regulations on the off-equilibrium belief is not strictly needed in this model.

2. *Shoppers search without commitment. They do not update beliefs after observing prices during the search. Conditional on the information sets, they combine the optimal pricing strategy p^* and other exogenous distributions to compute $U(v|x)$ for each state v. Shoppers' optimal search strategy is then determined by the stopping rule as shown in (10).*

3. *Nominal wage and cash for each shopper are chosen exogenously.*

4. *Goods market clears.*

In addition, I define the full-information equilibrium in which shoppers know the nominal wage. It serves a natural benchmark for the incomplete-information equilibrium.

Definition 2 (Full-Information Equilibrium)**.** *A full-information equilibrium is the equilibrium defined above, except that shoppers know the nominal wage.*

2 Equilibrium Characterization

I now characterize the equilibrium. I proceed in three steps. First, I characterize the search and pricing strategies. Second, I show the existence and properties of full-information equilibrium. Third, I show the monetary neutrality under full information. Finally, I present search and pricing strategies under first-order approximation around the full-information equilibrium.

2.1 Characterization of Optimal Search Strategy

I first characterize the search strategy. Each shopper needs to first find the U function and then decide when to stop searching. The solution to the shopper's problem is presented in the following proposition,

Proposition 1. *The optimal search strategy follows a threshold rule. The threshold is denoted $v^*(x)$. If $v < v^*(x)$, the shopper keeps searching; otherwise, she stops and makes the purchase. The threshold $v^*(x)$ decreases in x. It is determined by,*

$$\int \int_{\lambda(v^*(x)+p)}^{\infty} \left(\frac{1}{\lambda}\epsilon - p - v^*(x)\right) g(\epsilon) d\epsilon f(p|x) dp = \kappa \tag{11}$$

where $f(p|x)$ is the perceived price distribution and κ is the search cost per search.

Proof. See Appendix A. ■

This result generalizes the standard threshold rule found in the literature (see Weitzman, 1979; Wolinsky, 1986) by incorporating both an endogenous price distribution and incomplete information.[14] Proposition 1 demonstrates that the optimal search strategy retains the threshold structure.

[14] In the canonical models, firms are homogeneous, implying a degenerate price distribution, and shoppers possess correct beliefs about this common price throughout their search.

The optimal search strategy is straightforward. The shopper keeps sampling firms until the target value $v^*(x)$ is reached. Indeed, in Appendix A, I show that the value function $U(v|x)$ is given by,

$$U(v|x) = \max\{v, v^*(x)\} \tag{12}$$

When $v < v^*(x)$, regardless of the current state v, the value of an additional search is constant, equal to the threshold $v^*(x)$, indicating that the shopper always opts to continue searching in this case. Conversely, when $v \geq v^*(x)$, the value function equals the state v, implying that the shopper accepts v.

The left-hand side of (11) represents the marginal utility of additional search at the threshold, i.e., when shopper's state is equal to $v^*(x_i)$. Suppose she samples another firm k, she will prefer the new good if $\frac{1}{\lambda}\epsilon_{ik} - p_k > v^*(x_i)$. Since the shopper can return without cost, the marginal utility obtained in this case is $\max\{\frac{1}{\lambda}\epsilon_{ik} - p_k - v^*(x_i), 0\}$. The threshold is achieved when the marginal utility is equal to the search cost. The threshold is decreasing in the shopper's signal x: A higher signal about the nominal wage leads to a lower threshold. Intuitively, when a shopper perceives the nominal wage to be lower, they believe the price distribution is shifted leftward. This increases the perceived probability of encountering a low-price firm, thereby raising the reservation value and increasing the likelihood of continued search.

2.2 Characterization of Optimal Pricing Strategy

I aggregate the optimal search decisions across shoppers and derive the demand allocation across firms and the resulting profits. Since shopper i only purchases the good k if $\frac{1}{\lambda}\epsilon_{ik} - p_k > v^*(x_i)$, the probability of purchasing from firm k is $1 - G\big(\lambda(v^*(x_i) + p_k)\big)$. This probability is the same for all rounds of search as learning from shopping is prohibited. The probability of any shopper purchasing from any firm in each search given w is given by,

$$\rho = \int \int \big(1 - G\big(\lambda(v^*(x) + p)\big)\big) d\Phi_x(x) f(p|w) dp \tag{13}$$

The probability ρ has following meaning. Suppose the mass of shoppers who visit any firm in the first round is one. A fraction ρ of these shoppers settle with the firms they visit in the first round. The remaining $1 - \rho$ shoppers search in the second round, a further $(1 - \rho)^2$ search in the third round, and so on. Then, the purchase follows a geometric distribution and the expected number of searches of each shopper is ρ^{-1}. Firms are atomistic and take ρ as given when setting prices. Furthermore, the total expenditure spent in firm k after all rounds of search is given by,

$$\omega_k = \frac{1}{\rho} \int \exp(x) \big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x) \tag{14}$$

The dispersion in the cash in hand affects the expenditure allocation through the dispersion of thresholds and the covariance between the cash in hand and the threshold, as more cash in hand

induces higher expectation of the nominal wage. Monopolistic firms compete on prices. Firm k maximizes the profit with respect to price,

$$\max_{P_k} \frac{\omega_k W}{P_k}(P_k - \frac{W}{A_k}) \tag{15}$$

The demand is derived by dividing the total expenditure spent in firm k by P_k. The profit is thus the total demand times the profit per sale. The following proposition characterizes the optimal pricing strategy.

Proposition 2. *Let μ_k denote the markup and e_k denote the elasticity of demand. Firm k charges a markup over its marginal cost,*

$$P_k = \mu_k \frac{W}{A_k}; \quad \mu_k = \frac{e_k}{e_k - 1} \tag{16}$$

The elasticity of demand e_k is determined by,

$$e_k = \lambda \frac{\int \exp(x) g\big(\lambda(v^*(x) + p_k)\big) d\Phi_x(x)}{\int \exp(x)\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x)} + 1 \tag{17}$$

Proof. See Appendix A. ■

The optimal price is a markup times the marginal cost. The elasticity of demand depends on the distribution of thresholds. This is a highly non-linear equilibrium. To understand the intuition, we first focus on the full-information benchmark.

2.3 Characterization of the Full-Information Equilibrium

In the full-information equilibrium, shoppers know the nominal wage. Let $v^*(w)$ denote the value of threshold in this equilibrium. From Proposition 1, it is given by,

$$\int \int_{\lambda(v^*(w)+p)}^{\infty} \big(\frac{1}{\lambda}\epsilon - p - v^*(w)\big) g(\epsilon) d\epsilon f(p|w) dp = \kappa \tag{18}$$

where $f(p|w)$ is the actual price distribution. The distribution of thresholds is reduced to a single value $v^*(w)$. It is easy to show that the average search per shopper $\rho = \int \big(1 - G(\lambda(v^*(w) + p))\big) f(p|w) dp$ and the optimal pricing strategy is given by,

$$P_k = \frac{e_k}{e_k - 1} \frac{W}{A_k} \tag{19}$$

$$e_k = \lambda \frac{g\big(\lambda(v^*(w) + p_k)\big)}{1 - G\big(\lambda(v^*(w) + p_k)\big)} + 1 \tag{20}$$

Firm's market power is determined by two factors. First, larger λ implies less dispersed taste shocks and more competition on prices, inducing higher elasticity.[15] However, larger λ may also

[15] Anderson et al. (1987) shows that without search frictions, if G is Gumbel distribution, the demand system is exactly CES and the elasticity of substitution is $\lambda + 1$.

decrease the elasticity for high-productivity low-price firms as p_k becomes sufficiently negative. I will discuss this point in detail in Section 4.

Second, the search friction naturally gives rise to monopoly power (Diamond, 1971). The effect of search friction on the elasticity is represented by a hazard function. The density g represents the number of marginal shoppers who are indifferent between making purchase and continuing searching that the firm will lose if it increases its price. The survival function $1 - G$ indicates that increasing prices will increase the profit obtained from all infra-marginal shoppers. The ratio between the two captures the trade-off when setting prices.

Moreover, since G is log-concave, the hazard function increases in its argument. As a result, the elasticity of demand increases in the threshold and firm's own price. It has two implications. First, when firms face pickier shoppers implied by the higher threshold, demand becomes more elastic. Second, there is unique solution for price given productivity. Next, I establish the existence of the full-information equilibrium.

Theorem 1 (Existence of the Full-Information Equilibrium)**.** *There exists a unique full-information equilibrium in which consumers search actively.*

Proof. See Appendix A. ■

This theorem is proved in two steps. First, the elasticity of demand increases in price. Individual prices are uniquely determined by (19) and (20). Second, there is a unique solution to (18) for a given price distribution derived from optimal pricing strategy in (19) for a fixed $v^*(w)$. The threshold $v^*(w)$ monotonically decreases with the search cost. The equilibrium is then the fixed point of the reservation value and the price distribution. Note that there always exist a continuum of equilibria in which firms charge sufficiently high prices and shoppers do not search. However, there is only one equilibrium in which shoppers search actively. The following theorem shows our first main result regarding monetary non-neutrality.

Theorem 2. *In the full information equilibrium, monetary policy is neutral. Monetary shocks are fully passed through to firms' prices.*

Proof. See Appendix A. ■

This theorem establishes that when shoppers know the monetary shock - shock to nominal wage, the passthrough from the monetary shock to prices is complete. This is true because in equilibrium, each firm understands that, if itself and all its competitors raise their prices one-to-one with a monetary shock, although consumers do not know individual prices of each firm, consumers understand the relative prices are unchanged and thus there is no gain from searching more or less. This belief is therefore consistent with firms' and shoppers' strategies. In sum, search friction alone is not sufficient to generate monetary non-neutrality. We need the interplay of both search and information frictions.

Due to the monetary neutrality of the full-information equilibrium, we can define the real reservation value as:

$$v^r = v^*(w) + w \tag{21}$$

Similarly, we can define the real price in full-information equilibrium by $p_k^r \equiv p_k - w$ and denote its density by $f(p^r)$, which is achieved by shifting $f(p|w)$ to the left by w. In this way, variables are transformed into real terms.

2.4 Approximate Optimal Strategies

Under incomplete information, both the threshold shown in Proposition 1 and the pricing strategy shown in Proposition (2) are highly non-linear. To proceed, I consider small monetary shocks from the full-information equilibrium where the reservation value and the real price are $v^*(\bar{w})$ and $\bar{p}_k$. Monetary shocks $\hat{w}$ drawn from a distribution with small standard deviation, i.e., $\sigma_w \to 0$. At the same time, I keep signal-to-noise ratio σ_w^2/σ_x^2 fixed, which correspond to a fixed level of information frictions, θ.

Let $\hat{p}_k$ denote the log change in price in firm k after a nominal marginal cost shock. Unlike the standard demand system where an aggregate demand function is available and then the price index is naturally defined, in the model with search frictions, there is no obvious way to define a price index. However, the standard theory (Hulten, 1973, 1978) offers a simple non-parametric formula for the *log change* in price index. If preference is homothetic and stable,[16], which is the case here, the log change in the price index is the expenditure share-weighted log changes in all the prices:

$$\hat{p} = \int \hat{p}_k \bar{\omega}_k dk \tag{22}$$

where $\bar{\omega}_k = \frac{1}{\rho}\big(1 - G\big(\lambda(v^*(\bar{w}) + \bar{p}_k)\big)\big)$ is the expenditure share in the full-information equilibrium. The following proposition presents the first-order approximation to the optimal search strategy in (11) and the optimal pricing strategy in (17).

Proposition 3. *Fix the variance ratio* $\frac{\sigma_z^2}{\sigma_w^2}, \frac{\sigma_x^2}{\sigma_w^2}$. *To the first order as* $\sigma_w \to 0$,
[Part 1] *The threshold* $v^*(x)$, *given information set* x, *is given by,*

$$v^*(x) = v^*(\bar{w}) + \hat{w} - E(\hat{p}|x) \tag{23}$$

[16]Homotheticity requires that the income elasticity of demand must equal one for each good. Stability requires that consumers adjust their spending only in response to changes in income and relative prices. Baqaee and Burstein (2023) show how to generalize the standard theory to more general preferences. In our case, according to 15, the demand for firm k is proportional to the aggregate income $W = \int X_i di$, which implies homotheticity. In addition, there is no other factors, such as taste shocks, state of nature, other than relative prices and income, that can affect the demand. The match-specific shocks are integrated out.

[Part 2] *The elasticity of demand is given by,*

$$e_k = \lambda \frac{g\big(\lambda(v^*(\bar{w}) + \bar{p}_k + \hat{p}_k - \bar{E}\hat{p})\big)}{1 - G\big(\lambda(v^*(\bar{w}) + \bar{p}_k + \hat{p}_k - \bar{E}\hat{p})\big)} + 1 \tag{24}$$

where $\bar{E}\hat{p} = \theta\hat{p}$*. In addition,* e_k *increases in* $\hat{p}_k - \bar{E}\hat{p}$*.*

Proof. See Appendix A. ■

This proposition shows that the threshold $\bar{v}^*(x)$ under incomplete information is equal to the real reservation value under full-information equilibrium as in (21), adjusted upward the difference between the shock and expected change in the price index. Shoppers who believe average price response is high have lower threshold. However, since the average expectation of price index moves less than the shock due to information frictions, this leads to increase in the average threshold. Firms therefore are as if facing facing pickier average consumers who are more prone to search.

The second part of the proposition characterizes the elasticity of demand. On the first order, the distribution of thresholds and covariance between cash in hand and thresholds vanish to zero and only $\bar{E}\hat{p}$ is retained. It is important that the elasticity depends on the perceived relative price, $\hat{p}_k - \bar{E}\hat{p}$, rather than the actual relative price typically seen in standard demand systems. When a consumer mistakes an individual firm's price increase for a rise in its relative price, they are more likely to initiate search. This is closely related to the intuition in Lucas (1972). Another perspective to understand the result is that firms behave as though they are competing against competitors who charge lower prices as $\bar{E}\hat{p} < \hat{p}$. They reduce prices accordingly.

3 Results on Passthroughs

In this section, I first present define passthroughs and present the main result: the passthrough of a aggregate nominal marginal cost shock to the price index is generically incomplete. Then, I show the main insight behind this results leveraging higher-order beliefs. Finally, I show monotone comparative statics and extensions.

3.1 Main Results

I first define passthroughs. Let φ_k denote the passthrough from the nominal wage shock $\hat{w}$ to price p_k. I refer to φ as aggregate-shock passthrough. Following Amiti et al. (2019), I define passthroughs as follows.

Lemma 1. *The price responds to both firm's own cost shocks and competitors' prices,*

$$\hat{p}_k = \gamma_k \hat{w} + \xi_k \bar{E}^c \hat{p} \tag{25}$$

where γ_k *is the own-cost passthrough,* ξ_k *is the cross-price passthrough, and* $\bar{E}^c$ *is the average expectation of shoppers.*

$$\gamma_k = (1 - \frac{d\log\mu_k}{dp_k}\Big|_{\hat{w}=0})^{-1}; \xi_k = \frac{d\log\mu_k}{dp}\Big|_{\hat{w}=0}\gamma_k \tag{26}$$

where μ_k is the markup. The aggregate-shock passthrough of each firm is given by,

$$\varphi_k = \gamma_k + \Phi\xi_k\theta \tag{27}$$

The average aggregate-shock passthrough Φ is given by,

$$\Phi = \frac{\Gamma}{1-\theta\Xi} \tag{28}$$

where $\Gamma = \int \gamma_k\omega_k dk$, $\Xi = \int \xi_k\omega_k dk$.

Proof. See Appendix A. ■

The lemma derives the own-cost and cross-price passthroughs using the markup elasticities. The aggregate-shock passthrough is defined as the combination of these two components. By integrating both sides, the average aggregate-shock passthrough is derived. Importantly, passthroughs does not depend on the information frictions θ as they are evaluated at the full-information equilibrium.

Note that shoppers know variables in the full-information equilibrium, so they know the distribution of γ, and they also understand the average information frictions θ as they know variances, so they know the distribution of φ and thus Φ. Therefore, the average expectation of the change in price index is $\bar{E}\hat{p} = \Phi\bar{E}\hat{w} = \Phi\theta\hat{w} = \theta\hat{p}$. The aggregate-shock passthrough is thus the weighted sum of two passthroughs, with weights related to information frictions.

I now state our main results on passthroughs under incomplete information.

Theorem 3. *The model economy can be summarized by the following equation,*

$$\hat{p} = \Gamma\hat{w} + (1-\Gamma)\bar{E}^c\hat{p} \tag{29}$$

where $\bar{E}^c\hat{p}$ represents shoppers' average expectation of $\hat{p}$. The average aggregate-shock passthrough is,

$$\Phi = \frac{\Gamma}{1-\theta(1-\Gamma)} \tag{30}$$

$\Phi < 1$ for any $\theta < 1$ given $\Gamma < 1$.

Proof. See Appendix A. ■

This is the main theorem of this paper. It establishes that strategic complementarity in pricing depends on *shoppers'* beliefs about the price index. For θ close to zero (meaning a sufficiently large departure from common knowledge of the shock), the average aggregate-shock passthrough is arbitrarily close to the average own-cost passthrough. But as θ increases (meaning a higher degree of common knowledge of the shock), passthrough increases rapidly. Therefore, by varying θ between 0 and 1, we can thus span all the values between the average own-cost passthrough and the full-information outcome.

Consider a positive monetary shock, such as a 1% increase in the nominal wage. In response, firms tend to raise prices. If firms increase prices by 1%, they risk losing marginal shoppers who

were previously indifferent between making a purchase and continuing their search. Conversely, if firms do not raise prices at all, they forgo profits from infra-marginal shoppers by charging lower markups. To maximize profits, firms choose prices somewhere in between. This case reflects Rotemberg's core intuition: firms, "fearing" to alienate marginal consumers, absorb some of the shock in their markups.

Now consider a negative monetary shock, such as a 1% decrease in the nominal wage. If firms reduce prices by 1%, they attract more shoppers, who perceive themselves as fortunate to have found a high-productivity firm. On the other hand, if firms do not lower prices, they gain more profit from infra-marginal shoppers who are willing to pay higher markups. To maximize profits, firms opt not to fully decrease their prices. In this case, the right interpretation should be that firms, who are "greedy" to extract more profits from infra-marginal consumers, limit the passthrough of the cost reduction.

Theorem 3 shows sharply that consumer-side information frictions can have very different implications on passthrough from firm information frictions models (Lucas, 1972; Woodford, 2003). To clarify the intuition, consider an extreme case where policy shocks are completely uninformed by consumers. Here, aggregate shocks are indistinguishable from idiosyncratic shocks, and optimal passthrough is Γ. The intuition is that when shoppers do not perceive any change in the price index, firms are not able to pass any of the change in other firms' prices to their own prices. This sharply contrasts with firm-side imperfect information models where firms fail to adjust prices altogether when shocks are fully uninformed. The key difference lies in the information asymmetry: in this model, firms know the shock. However, they understand that the shock is completely uninformed to consumers, so they cannot respond to changes in other firms' prices, via *strategic complementarity*, i.e., setting prices close to competitors.

3.2 Heterogeneity Across Firms

I define passthroughs on the primitive: $\varphi_k = \varphi(a_k)$, $\gamma_k = \gamma(a_k)$ and $\xi_k = \xi(a_k)$. The results also depends on the specific functional assumption on the distribution of match utility, G. Following the literature, I assume G is Gumbel distribution.

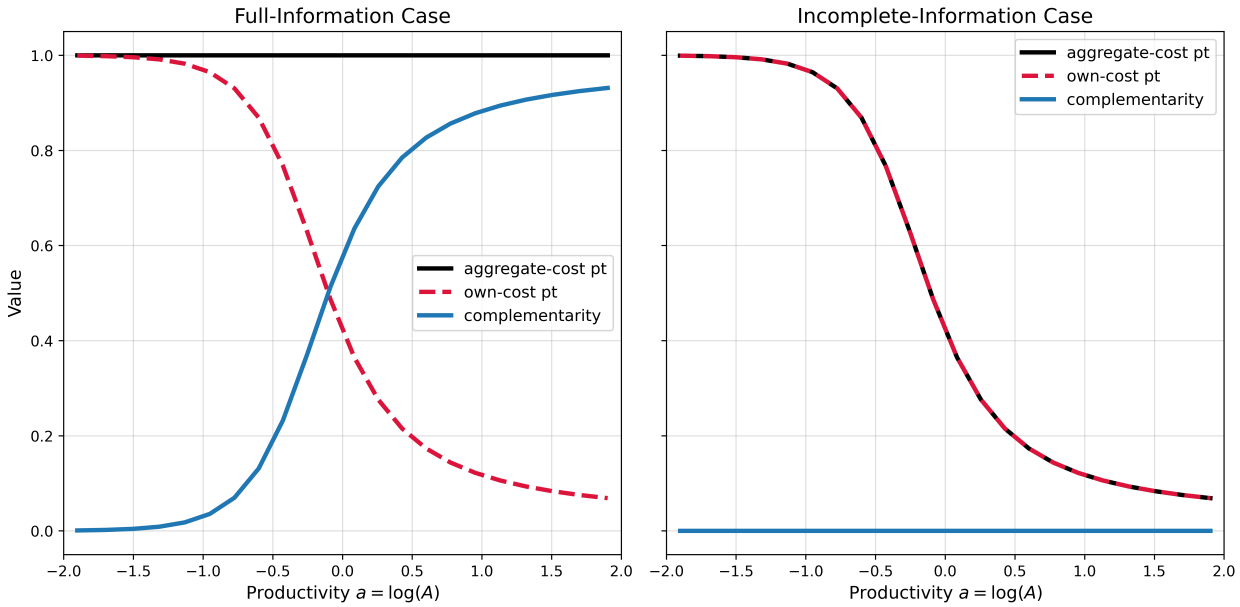
Proposition 4. *In a given equilibrium, markup $\mu(a)$ and cross-price passthrough $\xi(a)$ increases in productivity; own-cost passthrough $\gamma(a)$ and total passthrough $\varphi(a)$ decreases in productivity. Also, the following limit results hold:*

1. $\lim_{a\to\infty} \mu(a) = \infty$; $\lim_{a\to\infty} \varphi(a) = \Phi\theta$; $\lim_{a\to\infty} \gamma(a) = 0$; $\lim_{a\to\infty} \xi(a) = 1$
2. $\lim_{a\to-\infty} \mu(a) = \frac{\lambda+1}{\lambda}$; $\lim_{a\to-\infty} \varphi(a) = 1$; $\lim_{a\to-\infty} \gamma(a) = 1$; $\lim_{a\to-\infty} \xi(a) = 0$

Proof. See Appendix A. ■

To see the heterogeneity of passthroughs across firms, the left panel of Figure 1 illustrates that high-productivity firms pass through less of their own cost shocks and more of other firms' prices,

Figure 1: Distribution of three types of passthroughs under incomplete and complete information



Notes: The figure plots distributions of passthroughs based on one calibration of the model. The red line represents own-cost passthrough. The blue line represents cross-price passthrough. The black line represents aggregate-shock passthrough . The left and right panels show passthroughs in the incomplete and complete information cases, respectively.

as they have higher markups to absorb shocks. Under full information, the decrease in the own-shock passthrough over productivity is exactly offset by the increase in cross-price passthrough. The resulting aggregate-shock passthrough is always one for firms of any productivity. The left panel shows the case where shoppers have *zero* information about the shock. This result aligns with Theorem 2, where I prove the exact result. Notably, Amiti et al. (2019) establishes that the aggregate-shock passthrough is one for broad preferences including nested CES and first-order Kimball demand family. The theorem complements their results and emphasizes that the complete information about the price index is essential. Indeed, the complete knowledge of all prices is often assumed in these commonly used demand systems.

The left panel shows the case where shoppers have *zero* information about the shock. The cross-price passthrough is uniformly *zero* for any firm. As a result, the aggregate-shock passthrough equals the own-cost passthrough. Importantly, since information frictions dampen only the cross-price passthrough, high-productivity firms experience a more pronounced decline in cross-price passthrough and, therefore, aggregate-shock passthrough. Coupled with their high expenditure share, these firms disproportionately contribute to the incompleteness of average aggregate-shock passthrough.

In addition, according to the limit results in Proposition 4, the aggregate-shock passthrough is bounded below by $\Phi\theta$. This implies that $\hat{p}_k - \bar{E}\hat{p}$ is always positive, resulting in uniformly higher

perceived relative prices and more elastic demand for all firms. Consequently, following a positive shock, shoppers are more likely to search and passthroughs are incomplete for all firms.

The model delivers familiar implications for prices, markups, and pass-through: more productive firms charge lower prices and higher markups, and they exhibit lower own-cost pass-through; the admissible markup range has a lower bound governed by the dispersion of taste shocks and no finite upper bound. These patterns mirror standard preferences used in the literature (e.g., oligopolistic CES and Kimball-type demand) and align with the evidence that productive firms set higher markups and pass through less (Amiti et al., 2014, 2019). Taken together, these results suggest that a *sequential search* environment provides a natural microfoundation for the "standard" demand systems: with costly search, relative prices shape shoppers' stop-or-continue decisions, endogenously generating the curvature and strategic complementarity typically imposed in these preferences. When the search cost approaches zero, the preference reaches CES benchmark.

3.3 Strategic Complementarity Attenuation

In Proposition 3, we have discussed that elasticity of demand for individual firms increases due to increase in the perceived relative prices. Now, I "dig deeper" to show how such mechanism for *individual* firms relates to the attenuation on the strategic complementarity in pricing on the *aggregate* level. For this purpose, I will borrow heavily from game theory as in Morris and Shin (2002), Woodford (2003), and Angeletos and Lian (2023).

Corollary 1. *In the rational expectations equilibrium, the change in price index can be express as the infinite sum of higher-order beliefs of $\hat{w}$,*

$$\hat{p} = \Gamma \sum_{h=0}^{\infty} (1-\Gamma)^h \bar{E}^h \hat{w} \tag{31}$$

where shoppers' h-order average expectation $\bar{E}^h \hat{w} = \bar{E}(\bar{E}^{h-1}\hat{w})$, and $\bar{E}^0 \hat{w} = \hat{w}$. Using the fact that $\bar{E}^h \hat{w} = \theta^h \hat{w}$, the average aggregate-shock passthrough is given by,

$$\Phi = \Gamma \sum_{h=0}^{\infty} (1-\Gamma)^h \theta^h \tag{32}$$

Proof. See Appendix A. ■

Equation (31) can be derived by iterating (29) in Theorem 3 forward[17]. We can interpret this infinite sum as the aggregate response of price index unfolding in the notional time within a period. In the first round, when the monetary shock occurs, assume no firm has yet responded to the monetary shock and that firms expect other firms not to adjust their prices. The shock acts as

[17]To write the game into the infinite sum of higher-order beliefs as in (31), we need (i) firms are rational and (ii) shoppers know that firms are rational and (iii) the common knowledge of rationality among shoppers and (iv) firms know the common knowledge of rationality among shoppers. In Appendix A, I show which rationality is required in each step of derivation. The rational expectations equilibrium is a "super" concept that includes all these rationality.

an idiosyncratic shock to each firm, resulting in a price increase of $\Gamma\hat{w}$. In the second round, it becomes common knowledge among firms that the price index has increased by this amount. Due to the strategic complementarity of price-setting, firms pass an additional portion of the shoppers' perceived increase in the price index from the first round onto their prices, specifically $(1-\Gamma)\bar{E}\Gamma\hat{w}$, under the belief that other firms will not further adjust prices. This iterative process continues. In the $h+1$th round, the additional passthrough is $(1-\Gamma)^h\bar{E}^h\hat{w}$. The intuition connects to the literature on level-k thinking (García-Schmidt and Woodford, 2019; Farhi and Werning, 2019). Moreover, the information frictions attenuates more the high-order strategic complementarity, since the higher-order beliefs of shoppers are more anchored to the prior.

3.4 Monotone Comparative Statics

I present results on the comparative statics of aggregate-shock passthrough over search friction and information frictions. I establish that, all else equal, (i) the aggregate-shock passthrough is larger when the search cost is smaller for all firms, given G is Gumbel distribution, and (ii) the aggregate-shock passthrough is larger for all firms when the information frictions is smaller. In Appendix A, I show the results for own-cost and cross-price passthroughs.

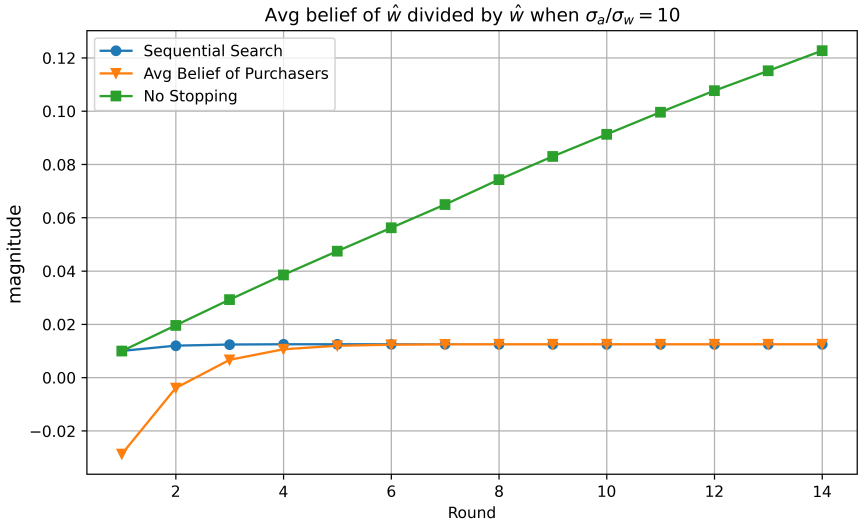
Proposition 5. *If $\varphi(a;\kappa)$ is aggregate-shock passthrough for given κ, then for $\kappa_2 > \kappa_1$, $\varphi(a;\kappa_2) < \varphi(a;\kappa_1)$ for $\forall a$, and $\lim_{\kappa\to\infty}\varphi(a) = 0$, $\lim_{\kappa\to 0}\varphi(a) = 1$; If $\varphi(a;\theta)$ is aggregate-shock passthrough for given θ, then for $\theta_2 > \theta_1$, $\varphi(a;\theta_2) > \varphi(a;\theta_1)$ for $\forall a$, and $\lim_{\theta\to 0}\varphi(a) = \gamma(a)$, $\lim_{\theta\to 1}\varphi(a) = 1$.*

Proof. See Appendix A. ■

This proposition shows that the two frictions are mutually reinforcing. Higher search costs raise markups for all firms and reduce own-cost pass-through, because thicker markups let firms absorb a larger share of cost shocks. As a result, strategic complementarity in pricing strengthens, which in turn amplifies the effect of information frictions on the passthrough of aggregate shocks. The limiting results imply that aggregate pass-through Γ can span the full range $[0,1]$, allowing for a wide spectrum of monetary non-neutrality. In particular, as search costs vanish ($\kappa \to 0$), $\Gamma \to 1$ and pass-through is full; under extreme search frictions, Γ can approach 0. Finally, in the dynamic model shoppers learn about the shock over time. If learning converges to common knowledge of the shock, monetary policy becomes neutral in the long run.

Taken together, Theorem 3 establishes that the passthrough from monetary shocks to the price index is generically incomplete. Corollary 1 identifies the core mechanism: information frictions attenuate strategic complementarities in pricing. Proposition 4 further show that the incomplete passthrough is primarily driven by high-productivity firms. Proposition 5 shows that aggregate passthrough declines as search and information frictions intensify.

Figure 2: Learning from Prices



Notes: The green line shows the average belief when there is no consumers stop searching. The blue line shows the average belief of consumers in a sequential search model. The orange line represents the average belief of consumers who have made purchase and stopped in the previous rounds.

3.5 Learning from Prices

In the above model, I assume that shoppers do not learn from prices during search. Here, I discuss the learning and validity of the assumption.

Suppose the prices can be linearized as $\hat{p} = \lambda a + \phi\hat{w}$.[18] The search threshold v^* is calibrated such that consumers stop with probability 75%, consistent with Section 4. I consider small shock and its impact on thresholds and prices are negligible. Then, I simulate a consumer panel and track average beliefs about the aggregate shock in Figure 2.

The green line shows the average belief of the shock in which all consumers continue searching and never stop and update beliefs from every observed price. Because the signal-to-noise ratio is low (aggregate shocks are small relative to idiosyncratic shocks), convergence is slow. The blue line allows a constant stopping hazard: in each round, 75% consumers exits after accepting a drawn price. With many consumers stopping early, the pool of active learners shrinks over rounds, so the population average belief never converges to the truth even with infinitely many search rounds. Selection further weakens learning. Early stoppers tend to observe low prices and form low beliefs; the orange line (stayers' average belief) remains below the overall average and can be very low. Because early stoppers never re-enter, their biased beliefs are not corrected.

[18]The pricing strategy is highly non-linear in productivity; the log-linearization is only to illustrate learning via shopping.

In short, when aggregate shocks are small and the average number of draws is limited, learning from prices is quantitatively weak—the average belief barely moves beyond the first search round.

3.6 Suggestive Evidence on Tariff Incidence –

Recent data reveals modest pricing responses to announced tariff rates in 2025 (Cavallo et al., 2025). Similarly, Cavallo et al. (2021) show that the incidence of the 2018 tariffs fell largely on U.S. firms. In U.S. stores, the impact on prices is more limited, suggesting compression of retail margins. It is natural to assume that firms understand these tariffs completely, as they source goods from exporters and face the border taxes directly. A plausible reason they do not fully pass tariff incidence to consumers is that consumers may not be fully informed the magnitude of the tariffs or the countries of origin of the products they buy. For many manufacturing goods, components are sourced from multiple countries, further complicating the situation. Such consumer-side information frictions imply low passthrough. We should also observe that, since retailers are not able to pass through tariff shocks, they substitute away from goods originating in tariffed countries (Sui et al., 2025).

4 Empirics: Micro to Macro

The key sufficient statistic for the magnitude of our mechanism is the aggregate own-cost pass-through, which is determined by the parameters governing search frictions—namely, the search cost κ and the dispersion of taste shocks λ. I estimate κ and λ using two informative empirical moments from a large-scale consumer shopping panel: the purchase probability ρ and the elasticity of search activity with respect to inflation. Because the search elasticity also depends on information frictions, I identify it using variation projected onto oil-price–induced inflation, and then separately estimate information frictions for oil-driven inflation from the Michigan Survey. Combining these estimates, I recover the two search parameters and the information-friction parameter relevant for oil shocks, and from them derive the implied aggregate own-cost pass-through. Since monetary shocks do not drive inflation, I identify information friction for monetary shocks by impulse-response matching in Section **??**.

4.1 Estimate Information Frictions to Oil Shocks

Suppose household learning can be modeled as a standard signal–extraction problem. Multiple shocks (e.g., oil and demand) drive inflation, and in each period households receive a noisy Gaussian signal for each shock.[19] In Proposition A.2, I show that the h-ahead forecast error is linearly related to the forecast revision:

$$\pi_{t+h} - \bar{E}_t[\pi_{t+h}] \;=\; K_{CG}\big(\bar{E}_t[\pi_{t+h}] - \bar{E}_{t-1}[\pi_{t+h}]\big) \;+\; v_{t+h,t}, \tag{33}$$

[19]Households are assumed to distinguish across shocks. Confusion between aggregate shocks can affect real variables and beliefs, as shown by Liu and Zhang (2024); we abstract from those dynamics for simplicity.

Table 1: Household information frictions: Regression Results

	(1)	(2)	(3)	(4)	(5)
	1975–2024 OLS baseline	1975–2019 Change in Oil Price	1975–2024 Change in Oil Price	1975–2019 Oil News Shock	1975–2024 Oil News Shock
Inflation	0.013	1.387***	1.723***	1.026	1.492**
	(0.165)	(0.517)	(0.544)	(0.728)	(0.686)
Obs.	196	179	196	180	196
F statistics		28	30	13	15

Notes: Robust standard errors in parentheses. Columns (2)–(3) use the change in oil prices as an instrument; Columns (4)–(5) use high-frequency oil news shocks. Reported first-stage F-statistics appear in the last row. Samples differ by column as indicated in the headers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

where $v_{t+h,t}$ is the full-information rational-expectations error, which contains multiple structural shocks, that is orthogonal to any information dated t or earlier. The slope K_{CG} is a weighted average of shock-specific slopes $K_{CG}(s)$, with weights proportional to each shock's contribution to the variance of forecast revisions in each horizon. Importantly, for each shock s, $K_{CG}(s) = \frac{1-G(s)}{G(s)}$, so $K_{CG}(s)$ is strictly decreasing in the Kalman gain $G(s)$. Following Coibion and Gorodnichenko (2015a), this regression diagnoses imperfect information about inflation and its magnitude; projecting the relation onto each shock delivers shock-specific information frictions via $K_{CG}(s)$.

In the Michigan Survey of Consumers, we only have one-year ahead inflation forecast and lack the consumer inflation forecast over horizons. That is, I can only run the following regression, and following the literature, I focus on forecast error on one-year horizon:

$$\pi_{t+3} - \bar{E}_t[\pi_{t+3}] = K_{CG}(\bar{E}_t[\pi_{t+3}] - \bar{E}_{t-1}[\pi_{t+2}]) + \epsilon_{t+3,t} \tag{34}$$

The error term $\epsilon_{t+3,t}$ now contains $\bar{E}_{t-1}[\pi_{t+2}] - \bar{E}_{t-1}[\pi_{t+3}]$. It is no longer an i.i.d. expectation error and becomes correlated with the forecast revision, rendering OLS biased if the true relationship is represented in (33). Following Coibion and Gorodnichenko (2015a), I estimate the specification by instrumental variables. The instruments are the log change in oil prices, and the high-frequency oil news shocks of Känzig (2021). These satisfy the usual conditions: relevance—they explain a substantial share of inflation variation—and exogeneity—they are realized in quarter t and are largely unforecastable, so they are orthogonal to agents' forecasts of future inflation in period $t-1$.[20] Importantly, when I use oil shocks as IV, I also project the forecast revision on oil shocks. In other words, the IV regression identifies the household learning about oil shocks, i.e., $K_{CG}(oil)$.

[20] In quarterly data, the first-order autocorrelation of log oil price changes is about 0.17, implying little persistence from one quarter to the next.

Table 1 reports the estimates. The OLS coefficient in Column (1) is small and statistically insignificant, either due to endogeneity issue or because households may overreact to some shocks and underreact to others (Bordalo et al., 2020). Using instrumental variables with oil price changes as the instrument, the coefficient rises from near zero to about 1.40 in the pre-pandemic sample and becomes statistically significant. A positive coefficient indicates information frictions; a larger coefficient implies a lower Kalman gain. In this case, the implied Kalman gain is about 0.42. The first stage is strong: oil price changes explain roughly 13% of the variation in forecast revisions. Extending the sample to include the pandemic (Column (4)) raises the coefficient to 1.723, implying a Kalman gain of about 0.37. Results are similar with the oil news shock instrument once the pandemic is included, but the pre-pandemic estimate is not significant given fewer oil shocks.[21] In sum, the Kalman gain for oil-driven inflation is about 0.4. This translates into a monthly Kalman gain 0.16.[22]

4.2 Shopping Behavior and Search Frictions in the Data

I then turn to estimate search frictions. First, I validate the basic implication of a sequential search model and derive the average number of search. Second, I estimate the elasticity of search activities to inflation shocks. Lastly, I compute the model counterparts and calibrate the parameters about search frictions.

Data – The data source is the NielsenIQ Consumer Panel Data set, which covers about 1,000 product modules grouped into over 100 product groups, representing roughly 30% of U.S. food and beverage spending and 2% of total household consumption.[23] The sample spans 2004m1–2019m12, tracking the shopping behavior of about 55,000 demographically balanced households annually across 49 states and 3,000 counties.[24] Households use in-home scanners to record purchases, providing trip-level detail on retailer, barcode, product category, expenditure, and purchase date, as well as annually updated demographics (e.g., age, education, employment, household size). I

[21] I interpret the evidence that includes pandemic with caution. Because the CPI consumption basket may be misspecified during lockdowns as consumption shifted away from services (Diewert and Fox, 2020; Guerrieri et al., 2022).

[22] If the state evolves between months and the gain is stationary, in each month, agents receive signals and three months later, the Kalman gain has to be 0.4. This implies $1 - (1 - K)^3 = 0.4$ and $K = 0.16$.

[23] Researcher's own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[24] I do not include later years because NielsenIQ reorganized product modules beginning in 2021, and constructing a concordance is beyond the scope of this paper.

aggregate the data to the household–quarter level; households remain in the panel for about nine years on average.[25] I focus purchases in the product departments that sell primarily food.[26]

Purchase Probability ρ – The sequential search framework models the shopping process as a geometric stopping problem with per-visit purchase probability ρ. However, the data does not record visits end without purchase. In addition, consumers buy multiple goods in the same store and across stores. To account for this discrepancy, I first extend the baseline sequential search model to incorporate multiple goods. Then, I show the household shopping patterns. Finally, I estimate ρ.

To parallel the basic structure in Section 1, I extend the model in a minimal way. First, shoppers have Cobb–Douglas preferences over K products, implying fixed and pre-determined expenditure shares across products. Second, each store carries all M products, with $M \geq K$. Shoppers draw match-specific taste shocks independently for each product in each store. Shocks follow the same distribution. They can buy any number of products in a given store, and once a product is purchased at one store it is not purchased again elsewhere.[27] Shoppers continue searching until they purchase a total of K products. On the supply side, there is a continuum of firms with heterogeneous productivity in producing each product. The productivity distribution is the same for every product, so the per-visit purchase probability for any given product is a common value ρ. Equivalently, each product is independently purchased at a store with probability ρ. In this extended model, with j products remaining, the per-visit purchase probability, and the number of products bought at that store, conditional on a purchase occurring, are:

$$p_{\text{buy}}(j) \;=\; 1-(1-\rho)^j; \quad \Pr(B=b \mid j) \;=\; \frac{\binom{j}{b}\rho^{\,b}(1-\rho)^{\,j-b}}{1-(1-\rho)^j}, \qquad b=1,\ldots,j,$$

Proposition A.4 characterizes in closed form (i) the distribution of the number of stores consumers purchase from, represented by L, given K, and (ii) the distribution of the number of products happen in a store, represented by B, given K. These results allow us to infer the purchase probability ρ even when the data include only stores at which purchases occur. Finally, the total number of products K may vary across households. The aggregate distributions of L and B are then mixtures over K using the empirical distribution of K.

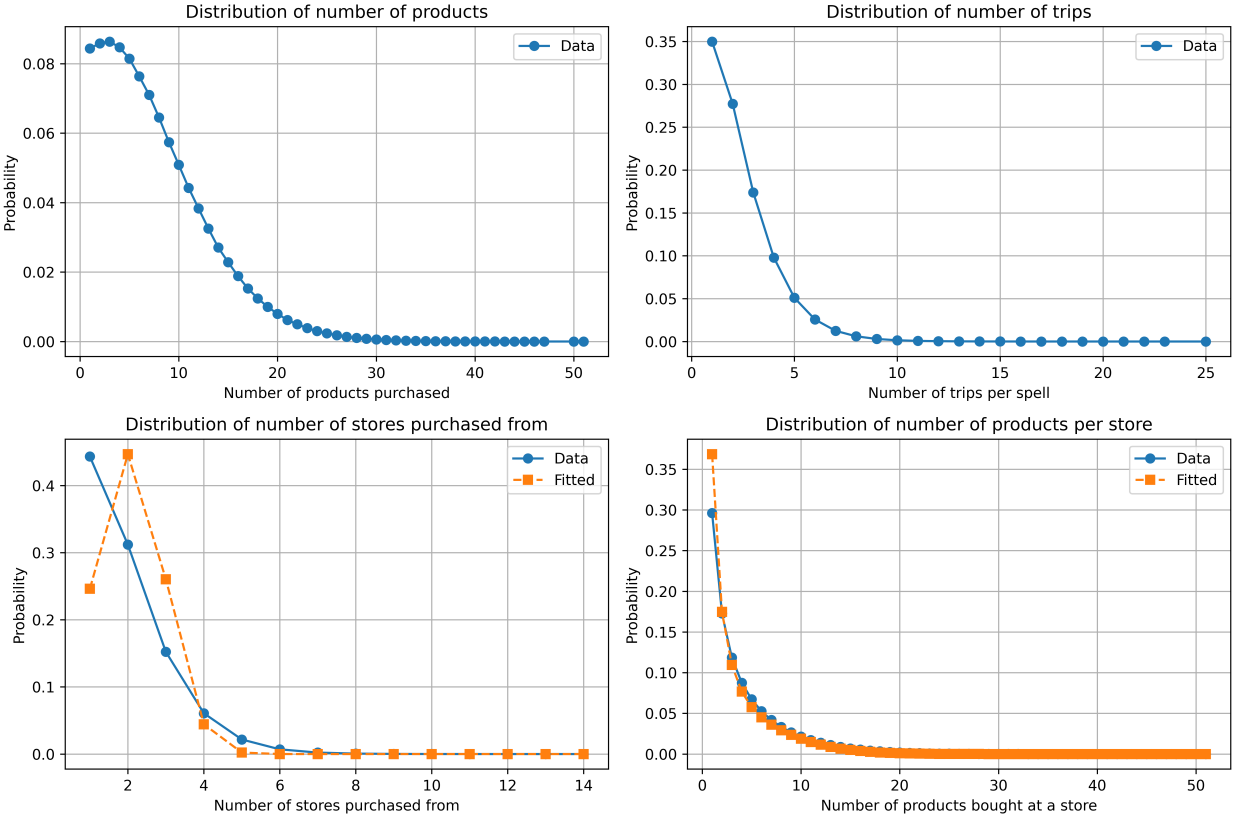
Now, Let us turn to data. Empirically, it is natural to think that households typically plan grocery shopping on a weekly horizon: they choose how many trips to make and which stores to visit (e.g., three trips across two stores). Empirically, in 2010 households visit on average two stores, make 2.5 trips, and buy about seven product groups per week. I will use "product" to refer

[25] See Broda and Weinstein (2010) and Jaravel (2019) for further discussion of NielsenIQ data.

[26] I exclude health and beauty care, alcoholic beverages and general merchandise, since households may have different shopping plans for these products.

[27] Empirically, the probability that consumers buy the *same* product category (e.g., milk or cheese) from two or more stores within a spell is below 5%, so this is a good approximation.

Figure 3: Distributions of Search-Relevant Indicators and Fit



Notes: The figure shows the empirical distributions of number of products, number of trips, number of distinct stores purchased from, and the number of products bought per store. The orange lines represent distributions from the model evaluated at the calibrated parameters.

to product groups from now on. There exists substantial heterogeneity across households. Figure 3 reports: in 2010, the number of products ranges from 1 to 50, the number of trips from 1 to 25, the number of distinct stores purchased from from 1 to 14, and the number of products bought per store from 1 to 50. Some households buy 50 products in one store, while others only buy one. I will demonstrate how these distributions discipline the search friction parameters.

I study search activities at the household–week level. Following Aguiar and Hurst (2007), I measure search intensity by the number of *distinct* stores visited. Unlike total trips, the distinct-store metric does not overstate search effort when a household makes multiple trips to the same store. This is especially relevant for larger households, which often revisit a single store within a week to meet needs or exploit promotions (Aguiar and Hurst, 2007; Argente and Lee, 2021). Such revisits are not counted as additional search in my model.

In estimation, I choose ρ to jointly fit (i) the distribution of the number of stores purchased from and (ii) the distribution of the number of products bought in a store. The resulting estimate is $\hat{\rho} \approx 0.73$. The orange lines in the bottom panel of Figure 3 show the model fit. The model-generated distribution of the number of products bought in a store aligns well with the data. With $\rho \approx 0.73$, the probability of buying exactly one product at a store is about 0.36, implying that consumers buy more than one product roughly half of the time conditional on making a purchase at that store. On the other hand, the model distribution of the number of stores purchased from misses a little. In the data, households on average buy about seven products; with a moderate ρ, they most often complete shopping in two stores. Raising ρ increases the probability of finishing in a single store, but it shrinks the tail for the distribution of number of stores purchased from, and it worsens the fit for the number of products bought in a store.

A plausible reason for this tension is that match-specific shocks across products within a store may not be independent. A positive correlation could drive more purchases in one store as households may encounter the 'jackpot" store.[28] However, introducing such correlation complicates interpretation and quantitative use of the model in this paper. To keep the extended framework minimal and transparent, I leave this enrichment to future work.

Elasticity of Search to Inflation – Next, I estimate the elasticity of search activity on inflation. Because inflation is observed at the monthly frequency, I aggregate the search measure to the month. Empirically, households plan a broader set of distinct stores to visit over a month than over a week. Consequently, simply averaging the weekly distinct–store counts within a month can underestimate the response of search to inflation. For example, before inflation rises, a household may visit its routine store plus store A every week; after inflation rises, it may visit the routine store plus store A in one week and the routine store plus store B in another week. A simple average across weeks would suggest no change in search effort, yet over the full month the number of distinct stores increases from two to three. Therefore, I construct monthly search measure as the number of distinct stores visited for each household within a month. On average, households go to 7.2 shopping trips and 3.4 distinct stores per month in the entire sample during 2004-2019. There is substantial heterogeneity across households. Figure B.1 shows the time trend of shopping time from American Time Use Survey and the distinct-store measure I build based on Nielsen Consumer Panel are aligned, bolstering the confidence of our measure.

To be consistent with estimation of information frictions, I consider the inflation driven by oil price shocks: the fitted value of inflation by regressing inflation on log change in oil price from a

[28]For example, a store-level taste component that additively shifts the utility of all products in that store would induce correlation across product-specific shocks and raise the probability of large within-store purchases. In Proposition A.5, I show a case where there is only store-level shock for all products in one store. The passthrough of product-level productivity shocks increases toward one when the number of products increases.

year ago. The baseline specification is:

$$y_{it+1} = \lambda_i + \gamma_{\text{month}(t)} + \beta\pi_t + \sum_{j=1}^{11} \beta_1 \pi_{t-j} + X_{it} + e_{it} \tag{35}$$

where t is month; i represents household. λ_i is the household fixed effect. $\gamma_{\text{month}(t)}$ is the calendar month fixed effect to control for the seasonality. π_t is the monthly inflation. β is the coefficient of interest. y_{it+1} is the log search measure in the next month. I use next-period value for two reasons. First, it avoids reverse causality because inflation and consumer search behavior are jointly determined in theory. Second, it may take time for consumers to adjust their shopping plan. I control for lagged inflation up to 11 months to absorb the persistent effect of lagged inflation on current search activities. The remaining variation in inflation is thus unpredictable by past inflation. X_{it} includes controls including current and 11-month lags of unemployment rates and the relative quality index for each household and month.

These controls help address an additional channel through which search activities may be affected. Higher inflation reduces real income and can therefore induce consumers to trade down to lower-quality varieties, increasing search intensity (Argente and Lee, 2021; Jaimovich et al., 2019). To alleviate this concern, I first control aggregate measure of real income: past and current unemployment rates. Then, I construct a household-month-level relative quality index following Argente and Lee (2021). The key idea is that relative prices provide a proxy for relative quality: within a product category, purchasing higher-priced varieties indicates higher quality. For each household and month, I compute the expenditure-share-weighted average of relative prices across purchased product categories, which yields a measure of the household's relative quality index. This index allows me to control for heterogeneity in the income–quality substitution channel at a granular level.

Table 2 shows that the elasticities of both the number of trips and the distinct–store measure with respect to inflation are positive and statistically significant, consistent with the theoretical prediction: positive inflation shock increases search activities.[29] Coefficients are generally larger for the number of trips than for the distinct–store measure, because households respond by adjusting both trips per store and number of distinct stores. Aguiar and Hurst (2007) and Argente and Lee (2021) show that households make more visits to the same store to redeem coupons.

Columns (1) and (4) report specifications without household fixed effects and yield larger coefficients than the corresponding estimates with fixed effects in Columns (2) and (5). This gap reflects compositional differences that pooled OLS cannot purge. For instance, retirees and larger households tend to search more on average and may be more price elastic; failing to account for these differences biases the estimated inflation effect upward. Once household fixed effects are included, a one–percentage–point increase in monthly inflation raises the number of trips by 2.8

[29] I omit coefficients on lags for space. The full table is in Table B.1 and Table B.2.

Table 2: Estimates of Elasticity of Search to Inflation

Panel A: Estimates using π						
log	Trip	Trip	Trip	Store	Store	Store
π	4.238***	2.848***	3.856***	3.555***	2.289***	3.166***
	(0.106)	(0.081)	(0.084)	(0.093)	(0.071)	(0.074)
quality index			1.415***			0.530***
			(0.212)			(0.180)
Panel B: Estimates using π_{oil}						
log	Trip	Trip	Trip	Store	Store	Store
π_{oil}	4.694***	2.899***	4.097***	3.594***	2.094***	2.853***
	(0.115)	(0.090)	(0.093)	(0.102)	(0.079)	(0.082)
quality index			1.400***			0.518***
			(0.215)			(0.182)
HH fixed effects	No	Yes	Yes	No	Yes	Yes
Unemployment rates	No	No	Yes	No	No	Yes

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Observations = 6,922,467. The panel unit is household $\times$ month. *Trip* denotes the number of shopping trips per household–month. *store* denotes the number of distinct stores visited. Columns indicate whether household fixed effects (HH FE) and current and past 12-month unemployment rates are included. Seasonality controls include month-of-year dummies. π is the baseline inflation measure; π_{oil} is an inflation measure constructed from oil-price movements. Coefficients on lagged inflation are omitted for space. Quality index is the relative quality of the consumption basket for each household.

pps for overall inflation and 2.9 pps for oil-driven inflation. The distinct-store measure increases by roughly 2.3 pps and 2 pps, respectively.

Columns (3) and (6) additionally control for past and current unemployment rates as well as the relative quality index. The elasticities increase, indicating that these controls are negatively correlated with inflation. This pattern arises because inflation and unemployment generally moved in opposite directions during the sample period, especially due to the Great Recession. In the final specification, the elasticity of the distinct-store measure with respect to oil-driven inflation is approximately 2.85, which I will use to calibrate the model.

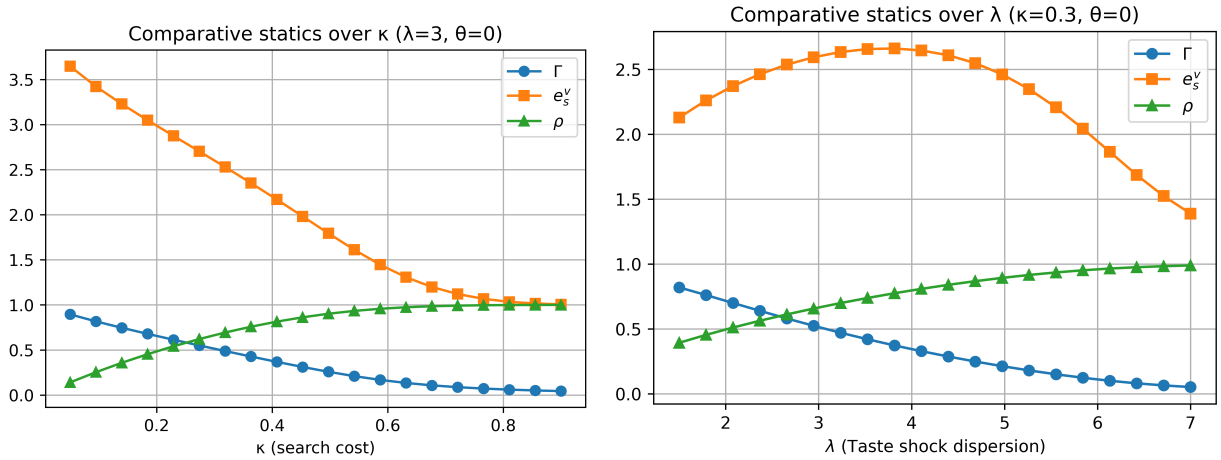
4.3 Mapping to Theory

I now show how the empirical objects estimated above map into the theory. The formula for the purchase probability ρ still takes the form as before, which I repeat here,[30]

$$\rho \;=\; \int \big[\,1 - G\big(\lambda\,[v^*(w) + p]\big)\big]\, f(p \mid w)\, dp, \tag{36}$$

[30]To ensure ρ is the same, the search cost has to be scaled with the number of remaining products shoppers need to buy. See Proposition A.3 for discussion.

Figure 4: Comparative statics over κ and λ



Denote the number of distinct stores a consumer visits by D, the probability of buying K number of goods by P_K. It is given by,

$$E_K[D] = \sum_{j=1}^{\infty} \left[1 - (1 - \rho(1-\rho)^{j-1})^K\right]$$

Denote the elasticity of number of visit to inflation by $e_s^v = \frac{d \log \rho^{-1}}{d\pi}$. The elasticity of D with respect to inflation is given by,

$$e_s \equiv e_s^v \sum_K P_K \frac{\log E_K[D]}{\log \rho^{-1}} \approx (1-\theta) \underbrace{\sum_K P_K \frac{\log E_K[D]}{\log \rho^{-1}} \int \omega(a)\, e(a)\, d\Phi(a)}_{\text{search elasticity to idio. shocks}} \tag{37}$$

where $\omega(a)$ is expenditure share of firm a, and $e(a)$ is demand elasticity. As discussed in Section 1, as information frictions about aggregate inflation increase (lower θ), consumers are more likely to misinterpret aggregate price changes as relative price changes, so search responds more to inflation. In the limiting case of purely idiosyncratic shocks at the firm level ($\theta = 0$), the search elasticity reaches maximal. Moreover, the elasticity of search is weighted sum of demand elasticity. This is because demand operates through an extensive margin: the sensitivity of demand to a price increase maps into the fraction of consumers who exit and continue searching when prices rise.

Two parameters shape both ρ and e_s^v: the dispersion of taste shocks, λ, and the search cost, κ. Figure 4 reports ρ, e_s^v when $\theta = 0$, and the average own-cost passthrough Γ, as we vary κ and λ.

Varying κ. As search cost κ rises, consumers search less aggressively and the search elasticity e_s^v declines, converging toward one as the demand elasticity approaches one and markup grows to infinity when search becomes prohibitively costly. Similarly, the purchase probability increases and tends to one. Passthrough Γ falls and tends to zero, consistent with Proposition 5.

Varying λ. For a given κ, increasing λ (reducing taste–shock dispersion) initially raises the demand elasticity when λ is small: with less dispersed idiosyncratic tastes, consumers are more price sensitive. Concurrently, high–productivity (low–price) firms attract more buyers and raise their markups. Beyond a threshold value of λ, this markup effect dominates, and the search elasticity begins to decline. The purchase probability continues to rise as lower taste dispersion reduces the incentive to keep searching. Aggregate passthrough Γ keeps falling: low–productivity firms already exhibit passthrough near one, while high–productivity firms reduce passthrough further as their markups increase, lowering the aggregate passthrough.

4.4 Estimation of Search Friction and Aggregate Passthrough

We estimate parameters using evidence based on oil price shocks in both sections. From Section 4.1, I calibrate the monthly information frictions (Kalman gain) to $\theta = 0.16$. From Section 4.2, I calibrate the purchase probability to 73%. The elasticity of search with respect to inflation in the case of oil-driven inflation is about 3. By plugging in the value of ρ and empirical distribution of K, the elasticity of expected number of stores purchased from, $E[E_K[D]]$ on ρ^{-1} is about 1.2. Using equation (37), the implied elasticity of search for an idiosyncratic price shock is about 2.83. The resulting calibrated parameters on search frictions are $\lambda = 3.94$ and $\kappa = 0.27$, with the associated real reservation value $v^* = -0.57$. The fit to these two empirical moments is nearly perfect.[31]

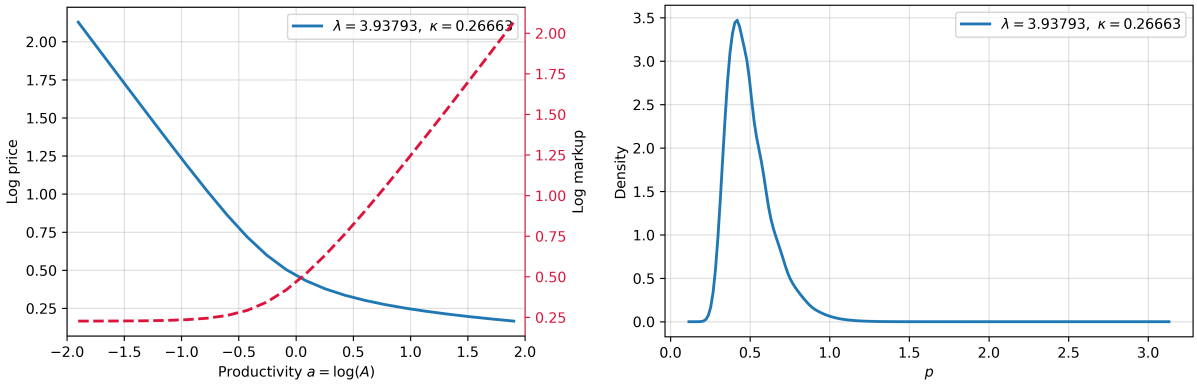
Figure 5 shows, in the left panel, the log price and markup over log productivity, and in the right panel, the equilibrium distribution of log prices obtained by Monte Carlo sampling. Prices decline gradually as productivity rises above zero, implying that log markup increases roughly linearly and markup itself rises exponentially. This asymmetry generates a price distribution concentrated to the left of $|v^*|$ and at the same time, it has a fatter right tail. These two forces balance out, giving a reservation value close to -0.57.

The implied aggregate own-cost passthrough is 0.4. This estimate is consistent with the literature. Amiti et al. (2019) and Gagliardone et al. (2025) estimate aggregate own-cost passthrough of about 0.4–0.5 using comprehensive Belgian manufacturing data.[32] Gopinath et al. (2011), using retail-chain data with wholesale costs, report heterogeneous own-cost passthrough: a median of about 0.5 for U.S. stores and 0.25 for Canadian stores. Because they cannot condition on the pricing behavior of all other firms as in Amiti et al., 2019, their estimates may be upward-biased by unobserved price movements of competitors. Taken together, the evidence points to strong strategic complementarities in pricing. Although I do not directly estimate passthrough due to

[31]The numerical estimation error is on the order of 10^{-6}.

[32]Whether own-cost and cross-price passthroughs sum to one depends on the specification. For example, Amiti et al. (2019) find that the sum is not statistically different from one, whereas Gagliardone et al. (2025), using a specification derived from standard New Keynesian models, estimate price stickiness of about 0.7, implying the sum is less than one. Moreover, buyer–seller relationships in tradable sectors often involve well-informed firms, so results can differ from those in final-goods retail settings.

Figure 5: Price, Markup and Price Distribution



Notes: The right panel plots the equilibrium distribution of log prices obtained by Monte Carlo sampling. Specifically, I draw a large number of productivity realizations $a \sim \mathcal{N}(0, \sigma_a^2)$ where $\sigma_a = 0.3$, and map each draw through the deterministic equilibrium pricing rule $p(a)$ implied by the model. The resulting p samples are used to approximate the density of log prices.

data limitations, the evidence above on shopping behavior provides a complementary perspective. Hence, in what follows I take $\Gamma = 0.4$ as a benchmark.

5 Quantification and Monetary Non-Neutrality

In this section, I present the full-fledged dynamic general equilibrium model, which completes and extends the static model. First, I close the model in Section 1, where the nominal wage and cash in hand are exogenous, in general equilibrium by introducing a new agent – worker. Second, I incorporate nominal rigidities on the firm side and nominal wage rigidity and let them compete for explaining the monetary non-neutrality. Finally, I dissect mechanisms of how each channel contributes to non-neutrality.

5.1 DSGE Model

Timeline – Time is discrete denoted by $t = 0, 1, 2, ...$ The timeline is as follows. The period is divided into morning and afternoon. In the morning, the monetary authority sets the interest rate, and the worker makes decisions on the labor supply, the bond position, and the aggregate consumption spending. In the afternoon, firms post prices, and shoppers search sequentially and decide where to buy. They are constrained by the amount of cash allocated to them. The worker has full information and shoppers have incomplete information about monetary shocks.

Monetary Authority – The monetary authority sets the nominal interest rate. It follows the Taylor rule,

$$i_t = \phi \hat{\pi}_t + v_{mt} \tag{38}$$

where v_{mt} follows,

$$v_{mt} = \rho_m v_{mt-1} + \sigma_m \varepsilon_{mt} \tag{39}$$

where ε_{mt} is the monetary shock and it follows $\varepsilon_{mt} \sim \mathcal{N}(0,1)$.

Firm – Firm k' productivity has two components,

$$\log A_{kt} = \log A_t + \log \tilde{A}_{kt} \tag{40}$$

where $\tilde{A}_{kt}$ is idiosyncratic productivity, which is i.i.d across firms and time, and A_t is the aggregate productivity. Let $a_t = \log A_t$. It follows the AR(1) process,

$$a_t = \rho_A a_{t-1} + \varepsilon_{At} \tag{41}$$

Shoppers are imperfectly informed about supply shocks. They receive noisy signals: $x_{it} = a_t + \varepsilon_{Ait}$.

Since both the nominal wage and the aggregate productivity affect prices only through the marginal costs, the optimal pricing strategy is homogeneous of degree zero in $\{W, A\}$, which implies,

$$p^*(a_{kt}, w_t, a_t) = p^*(a_{kt}, w_t - a_t) \tag{42}$$

Any positive change in aggregate productivity acts equivalently to a proportional decrease in the nominal wage. Therefore, as in Lemma 1, I can similarly define $\hat{p}_{kt} = -\varphi_k \hat{a}_t$ and average aggregate-shock passthrough Φ for supply shocks. Therefore, a more general pricing rule holds,

$$\hat{p} = \Gamma \widehat{mc} + (1 - \Gamma) E^c \hat{p} \tag{43}$$

where $\widehat{mc} = \hat{w} - \hat{a}$ is the log change in nominal marginal cost. The economic intuition mirrors that of monetary shocks. Following a negative productivity shock, e.g., an increase in input prices due to supply chain disruptions, shoppers with incomplete information may misattribute the resulting price increases to idiosyncratic productivity shocks. This misperception induces them to search more intensively for alternative firms. The resulting optimal pricing strategy, therefore, features incomplete passthrough of the productivity shock.

Worker – There is a representative household which consists of a single worker and a continuum of shoppers. The worker makes the labor supply and aggregate consumption spending decisions, leaving only the decisions about where to buy particular goods to the shoppers. I assume the worker has full information about the model economy, and there is no communication between the worker and the shoppers. Under this setup, a monetary shock can shift both nominal average marginal costs (observed by firms) and nominal aggregate demand (observed by the worker) while

remaining unknown to the shoppers. It also preserves the standard Euler equation. In particular, the worker's problem writes,

$$\max_{B_t, C_t, L_t} E_0 \sum_{t=0}^{\infty} \beta^t \left(\log(C_t - \lambda_c C_{t-1}) - \frac{L_t^{1+\eta}}{1+\eta} \right)$$
$$\text{s.t.} \quad P_t C_t + B_t = W_t L_t + R_{t-1} B_{t-1} + \Pi_t$$

where L_t is the labor effort, W_t is nominal wage, and Π_t is total nominal profits of firms. To match the hump-shaped response of output, following Smets and Wouters (2007), I assume that the worker's utility depends on last-period consumption due to habit. The parameter λ_c represents how consumption sticks to its last-period level. The risk-free bonds B_t is in zero net supply.

After determining the aggregate consumption, the worker distributes randomly the aggregate expenditure $X_t = P_t C_t$ to shoppers. Each shopper receives X_{it} and $\int \log X_{it} di = \log X_t$. Due to log utility, the level of consumption spending X_{it} does not influence the shopper's search decision, allowing the worker's and shoppers' problems to be separated.[33]

Using goods market clearing, the above optimization problem gives the first-order Euler equation,

$$\hat{y}_t = c_1 \hat{y}_{t-1} + (1 - c_1) \hat{y}_{t+1} - c_2 (\hat{i}_t - \hat{\pi}_{t+1}) \tag{44}$$

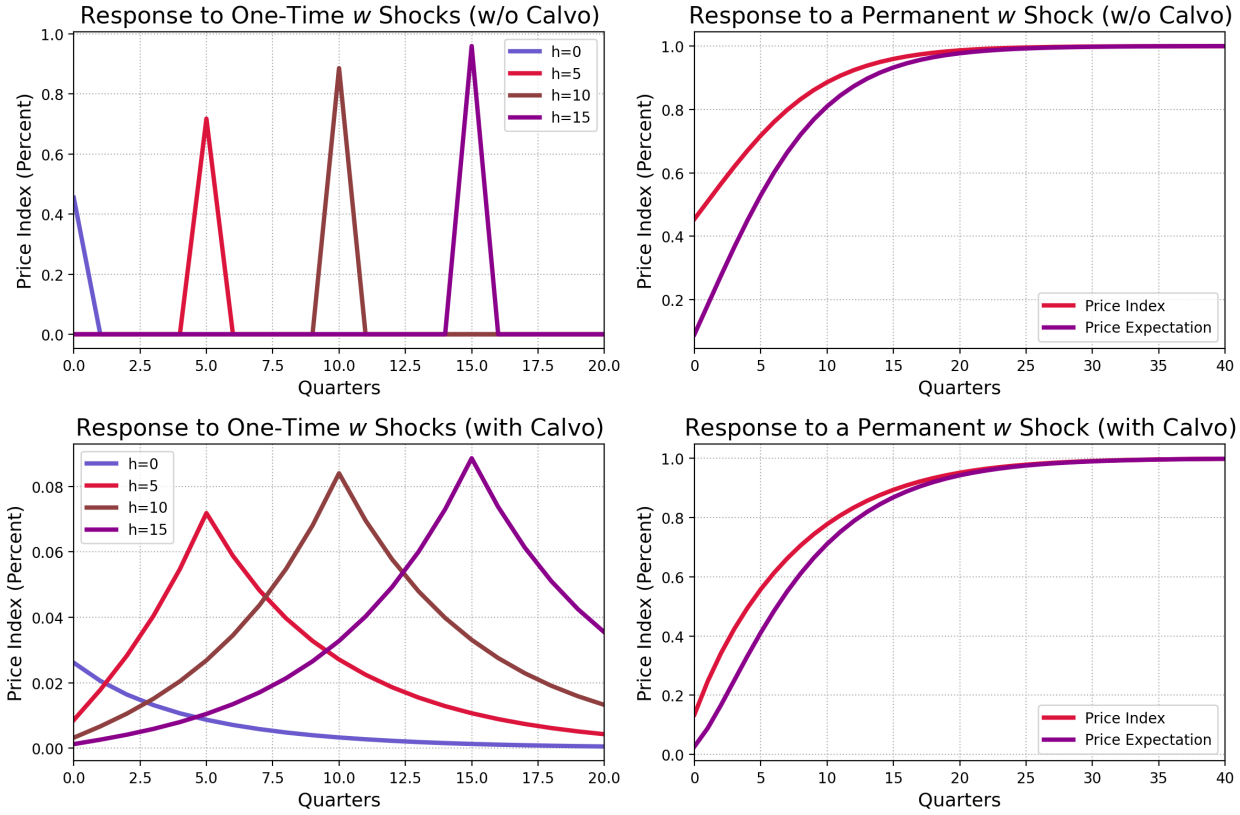
where $c_1 = \frac{\lambda_c}{1+\lambda_c}$ and $c_2 = \frac{1-\lambda_c}{1+\lambda_c}$. Larger λ_c not only dampens the response of output to the change in the real interest rate but anchor its level to the last-period output response.

Shopper – In the afternoon, each shopper receives the consumption spending X_{it} and solve the static problem in (10) period by period. In principle, they can infer the information that workers received in the morning from X_{it}. However, since X_{it} is a signal about endogenous variables, incorporating it would significantly increase computational complexity, which is beyond the scope of this paper (See Auclert et al. (2020) for a discussion.). For tractability, I set $\sigma_x \to \infty$ and only consider exogenous signals as follows.

Following Auclert et al. (2020) and Angeletos and Huo (2021), I assume that each shopper receives noisy information about the monetary shock. In particular, Auclert et al. (2020) model consumer learning about persistent monetary shocks by decomposing the shock into a sequence of independent news shocks $\{v_{mt}\}_{t=0}^{\infty}$. I adopt a similar framework, assuming that shoppers begin receiving signals about each news shock starting from date 0. Specifically, for a news shock that will hit at data t, shoppers receive independent private signals in each period $j \leq t$. Then, applying standard Bayesian updating, shoppers' average belief about this shock at date $j \leq t$ is $\bar{E}_j v = \frac{\sum_{\tau=0}^{j} \sigma_{s\tau}^{-2}}{\sigma_m^{-2} + \sum_{\tau=0}^{j} \sigma_{s\tau}^{-2}} v$. Following Auclert et al. (2020), I choose the sequence $\sigma_{s\tau}$ such

[33]Without habit $\lambda_c = 0$, the per period utility is equivalent to the integral of shoppers' utilities. With habit, the worker's objective is different.

Figure 6: Properties of the Passthrough Matrix $\mathbf{\Psi}$



Notes: The figure plots the responses of price index to one-time nominal wage shocks (left panel) and a permanent nominal wage shock (right panel) when $\theta = 0.1$, for both passthrough matrix with Calvo and without Calvo. The price adjustment frequency is 0.75. In addition, the average expectation of price index is plotted in the right panel.

that $\bar{E}_j v = 1 - (1-\theta)^j$, for $j = 1, 2, \ldots$, where θ is a constant representing both the degree of information frictions and the speed of learning for shoppers.[34] Stacking equation (29) across t into a vector-valued equation and rearranging, we obtain,

$$\hat{\boldsymbol{p}} = \underbrace{\Gamma(\boldsymbol{I} - (1-\Gamma)\mathbf{\Theta})^{-1}}_{\mathbf{\Psi}'} \widehat{\boldsymbol{mc}} \tag{45}$$

where $\mathbf{\Theta}$ is a diagonal matrix with entries $1 - (1-\theta)^j$ for $j = 0, 1, 2, \ldots$. Following Auclert et al. (2024), I denote the passthrough matrix as $\mathbf{\Psi} = \Gamma(\boldsymbol{I} - (1-\Gamma)\mathbf{\Theta})^{-1}$. It characterizes the response of the price level to nominal wage changes.

[34]The exponentially decaying information frictions induced by the time-varying sequence of variances of signals ensures that average beliefs about the monetary shock converge fast. In contrast, using a constant $\sigma_{s\tau}$ across all τ results in unrealistically slow learning. For example, if the signal-to-noise ratio is $1/9$, then even at date 100, the average belief remains 9% below the true shock.

The literature has extensively documented infrequent price adjustment in micro data. For example, Bils and Klenow (2004) and Nakamura and Steinsson (2008) report average adjustment frequencies on the order of three to four quarters. To accommodate such nominal rigidity on the firm side, I extend the model to allow for time-dependent price adjustment. Proposition A.1 shows that the pricing equation satisfies

$$\hat{\boldsymbol{p}} = \underbrace{\Gamma \boldsymbol{\Psi}^{TD} \left(\boldsymbol{I} - (1-\Gamma) \boldsymbol{\Psi}^{TD} \boldsymbol{\Theta} \right)^{-1}}_{\boldsymbol{\Psi}} \widehat{\boldsymbol{mc}}, \tag{46}$$

where $\boldsymbol{\Psi}^{TD}$ is the passthrough matrix in a model with purely time-dependent adjustment. As in Auclert et al. (2024), this specification nests commonly used time-dependent models such as Calvo and Taylor models.[35] Nominal rigidity dampens price responses through two channels. First, it directly attenuates the response to idiosyncratic shocks. Second, it further weakens the feedback operating through strategic complementarity, thereby amplifying the role of consumer information frictions. Intuitively, if consumers understand that many firms cannot adjust each period, the price distribution places more mass on the left tail, which induces additional search; anticipating this, firms further reduce passthrough.

The top-left panel of Figure 6 presents the responses of price index to one-time nominal wage shocks without Calvo. Two properties are worth noting. First, this information-based Phillips curve exhibits no forward-looking behavior: firms pass through the nominal wage shock to prices contemporaneously, at the time the shock occurs. This is consistent with the VAT evidences I discussed in Section 3.5. Second, for shocks that materialize later, shoppers have more time to acquire information, resulting in a larger price index response. Both properties resemble the firm-side information-based Phillips curve discussed in Mankiw and Reis (2002). With Calvo, firms start to increase prices long before the shock. The price increases by 1 percent now for a shock that will occur in 5 quarters. The right panel of Figure 6 shows the response of price index and average expectation of price index to a permanent nominal wage shock. When learning is slow, i.e., $\theta = 0.1$, the price index converges to 1 in about 10 years. The expectation initially undershoots significantly the price index and gradually converge to it over time. Calvo further dampens the initial response by $1/4$ as anticipated.

Following Auclert et al. (2024), I then derive the *generalized Phillips curve* by substituting $\hat{\boldsymbol{w}} = \hat{\boldsymbol{w}}^r + \hat{\boldsymbol{p}}$, where $\hat{w}^r$ is the log-deviation of real wage, and solving the fixed point,

$$\hat{\boldsymbol{\pi}} = \underbrace{(\boldsymbol{I} - \boldsymbol{L}) \boldsymbol{\Psi} \left(\boldsymbol{I} - \boldsymbol{\Psi} \right)^{-1}}_{\boldsymbol{K}} \widehat{\boldsymbol{mc}}^r \tag{47}$$

where $\boldsymbol{L}$ is the lag matrix with entries of 1 one line below the diagonal. Equation (47) maps any change in real wage $\hat{\boldsymbol{w}}$ to inflation. Matrix $\boldsymbol{K}$ represents the slope of the *generalized Phillips curve*.

[35] Auclert et al. (2024) also shows that on the first order, menu cost models are similar to a Calvo model with adjusted Calvo parameter. Therefore, focusing on Calvo model is without loss of generality.

The following proposition shows that in the limit of small monetary and technology shock, in the absence of other features of DSGE model, the impulse responses of output, inflation and interest rate satisfy a simple analog to the three-equation New Keynesian model.

Proposition 6. *As $\sigma_m, \sigma_a \to 0$, the equations characterizing $\{\hat{\pi}_t, \hat{c}_t, \hat{i}_t, \hat{v}_t, \hat{a}_t\}$ converges to:*

$$\begin{aligned}
\hat{y}_t &= \hat{y}_{t+1} - (\hat{i}_t - \hat{\pi}_{t+1}) \\
\hat{\boldsymbol{\pi}} &= (\eta + 1)\boldsymbol{K}(\hat{\boldsymbol{y}} - \hat{\boldsymbol{a}}) \\
\hat{i}_t &= \phi \hat{\pi}_t + \hat{v}_t
\end{aligned}$$

where v_t represents monetary shocks, $\hat{a}_t$ represents aggregate productivity shocks, and $\boldsymbol{K}$ is the slope of generalized Phillips curve.

Labor Union – Following Erceg et al. (2000) and Auclert et al. (2021), the worker supplies labor to unions, which differentiate the labor into types of labor services denoted by L_{jt}. A competitive labor packer aggregates these differentiated services using a Kimball aggregator (Kimball, 1995), and sells the composite labor input to firms at a nominal wage W_t. Firms use the aggregated labor service L_t in production, where aggregation satisfies:

$$\int_j G_w\left(\frac{L_{jt}}{L_t}\right) dj = 1, \tag{48}$$

with G_w denoting the Kimball aggregator. The aggregator satisfies $G_w'(x) = \exp\left\{\frac{1-x^{\frac{\zeta_w}{\varepsilon_w}}}{\zeta_w}\right\}$, where ε_w is the elasticity of substitution across labor types and ζ_w is the super-elasticity. Wages are set by unions subject to nominal rigidities à la Calvo: with probability $1 - \lambda_w$, unions can re-optimize wages in each period, while otherwise wages are indexed to past inflation.[36] Let w^r be the real wage. The union's optimization problem implies, to the first-order, the following wage Phillips curve:

$$\hat{w}_t^r = w_1(\hat{w}_{t-1}^r + \pi_{t-1}) + w_2(\mathbb{E}_t\hat{w}_{t+1}^r + \pi_{t+1}) - \pi_t - \kappa_w(\hat{w}_t^r - \eta\hat{l}_t - \hat{y}_t), \tag{49}$$

where $w_1 = \frac{1}{\beta}$, $w_2 = \frac{\beta}{1+\beta}$, and the slope parameter $\kappa_w = \frac{(1-\beta\lambda_w)(1-\lambda_w)}{\lambda_w}\frac{\varepsilon_w}{\varepsilon_w - 1 + \zeta_w}$. The slope κ_w governs the extent to which the gap between the real wage and the marginal rate of substitution between leisure and consumption is passed to the real wage.

Reallocation and Aggregate Productivity – A positive monetary shock induces more search under incomplete information, with larger information frictions leading to even greater search intensity and vice versa. Shoppers are more likely to be drawn to high-productivity, low-price firms, leading to an expansion in demand for these firms and a contraction for low-productivity firms.

[36] Christiano et al. (2016) derive wage inertia from their specification of how firms and workers negotiate wages. They argue that this micro-foundation outperforms a variant of the standard New Keynesian Calvo sticky wage model.

This reallocation of demand improves allocative efficiency and enhances aggregate productivity (Baqaee and Farhi, 2020; Baqaee et al., 2024). To see this formally, the aggregate production function is given by:

$$\hat{y}_t = \hat{a}_t + \hat{l}_t + (\hat{v}_t - \hat{p}_t) \tag{50}$$

where $\hat{v}_t = \hat{w}_t \int \bar{\alpha}_k \varphi_{kt} \, dk$ and $\bar{\alpha}_k = \frac{\omega_k \bar{\mu}_k^{-1}}{\int \omega_k \bar{\mu}_k^{-1} dk}$ represents the labor demand share in the full-information equilibrium, where $\bar{\mu}_k$ represents markup. Importantly, markups are not uniform across firms, so the change in aggregate productivity is nonzero.

To determine its sign, since high-productivity firms have higher markups, the weight $\bar{\alpha}_k$ effectively down-weights the incomplete passthrough φ_{kt} for high-productivity firms and up-weights it for low-productivity firms. Given that φ_{kt} is lower for more productive firms, it follows that:

$$\hat{v}_t / \hat{w}_t > \hat{p}_t / \hat{w}_t$$

Thus, a positive monetary shock induces an increase in aggregate productivity through endogenous reallocation of demand. Higher productivity dampens the response of price index and amplifies the monetary non-neutrality. Following the same method as computing $\hat{p}_t$, $\hat{v}_t$ is given by,

$$\hat{\boldsymbol{v}} = \underbrace{\tilde{\Gamma}(\boldsymbol{I} - (1 - \tilde{\Gamma})\boldsymbol{\Theta})^{-1}}_{\tilde{\boldsymbol{\Psi}}} \widehat{\boldsymbol{mc}} \tag{51}$$

where $\tilde{\Gamma} = \int \bar{\alpha}_k \gamma_k dk$ and $\tilde{\Gamma} > \Gamma$. Then, the aggregate production function is given by,

$$\hat{\boldsymbol{y}} = \hat{\boldsymbol{a}} + \hat{\boldsymbol{l}} + (\tilde{\boldsymbol{\Psi}} - \boldsymbol{\Psi})\widehat{\boldsymbol{mc}} \tag{52}$$

Equilibrium – In the limit of small monetary shock and technology shock, the equilibrium dynamics of variables $\{\hat{\pi}_t, \hat{p}_t, \hat{w}_t^r, \hat{w}_t, \hat{v}_t, \hat{c}_t, \hat{i}_t\}$ is governed by equations (44), (49), (52), (38), (51) and two equations that connect nominal and real variables: $\hat{w}_t = \hat{w}_t^r + \hat{p}_t$ and $\hat{\pi}_t = \hat{p}_t - \hat{p}_{t-1}$.

5.2 Calibration of information frictions

I first introduce data and present the empirical findings. Then, I use impulse response matching to estimate the information frictions.

Data and Method – The dataset for the main specification includes six monthly variables: the industrial production index; average hourly earnings of private production employees deflated by the GDP deflator; the consumer price index (CPI) including food and energy; consumer inflation expectations from the Michigan Survey of Consumers; the excess bond premium; and the one-year government bond rate. I use headline CPI to ensure consistency between realized inflation and what households observe when forming expectations. Then, I construct the monthly forecast from Michigan Survey of Consumers using the lagged one-month-ahead inflation forecast divided by

12. I then take the cumulative sum of this monthly forecast to construct the expectation of price index.[37] The sample covers 1978m1–2019m12.

I begin by estimating the reduced form of a monthly six-variable VAR, using twelve lags for each variable. The six reduced-form residuals are modeled as linear combinations of six underlying structural shocks. The goal is to identify how the structural shocks to monetary policy affect the contemporaneous reduced-form residuals. Once these shocks are identified, the VAR can be used to trace out their dynamic effects on the macroeconomic variables. To identify exogenous variation for the monetary shocks, I employ external instruments for the one-year government bond rate based on high-frequency surprises in futures market prices around FOMC announcements following the approach in Gertler and Karadi (2015) and Bauer and Swanson (2023). I use the monetary policy shock series provided by Bauer and Swanson (2023).

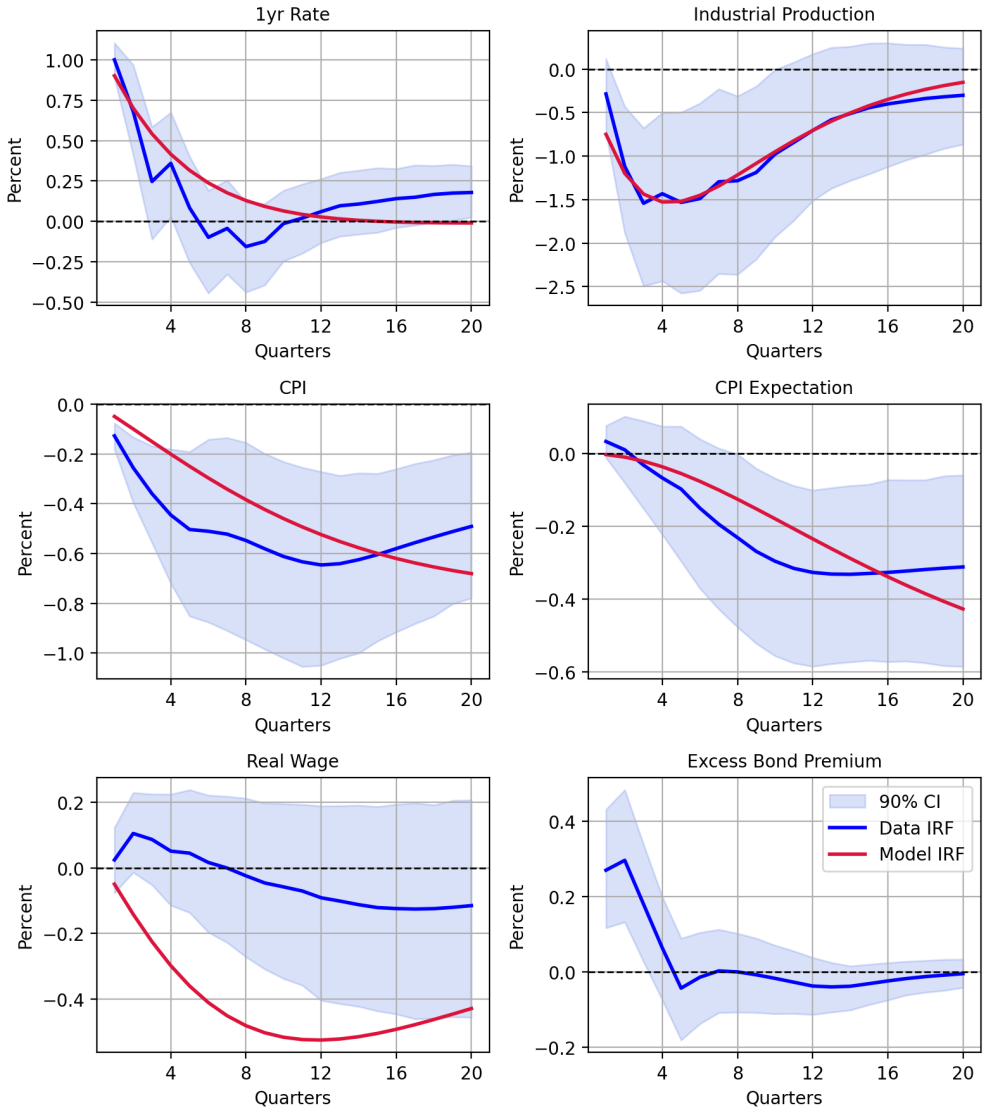
Empirical Findings – Figure 7 presents the main results. The blue lines depict the empirical impulse responses of four macroeconomic variables following a 100 basis point increase in the one-year government bond rate. Industrial production exhibits a hump-shaped response, consistent with existing literature (Gertler and Karadi, 2015), declining by approximately 150 bps in one to two years. CPI falls on impact by about 10 bps and continues to decline, reaching a total reduction of 45 bps over three years. In contrast, price index expectation increases a little on impact, then gradually declines, falling by about 30 bps over the same horizon.[38] These empirical patterns have two key implications. First, inflation expectations systematically undershoot realized inflation, supporting the core assumption of the model—namely, that consumers possess incomplete information about monetary shocks. Second, consumer learning appears remarkably slow: even after three years, consumers have internalized only about two-third of the total decline in CPI. If we just focus on the relative responses of CPI and CPI expectation, a simple back-of-the-envelope calculation shows: $1-(1-\theta)^{20}=2/3$, which yields $\theta=0.053$, implying an average duration about 18 quarters. I will show in what follows that this provides a useful reference point for the structural estimate of θ obtained through impulse response matching.

Impulse Response Matching – Following Christiano et al. (2005), I use impulse response matching to estimate 4 parameters: nominal wage rigidity λ_w, shoppers' average information frictions θ, worker's habit λ_c, and persistence of monetary shock ρ_m. Collecting them in the vector $\Lambda=\{\lambda_w,\lambda_c,\theta_s,\rho_m\}$. Let $\boldsymbol{J},\widehat{\boldsymbol{J}}$ denote model and empirical impulse responses. The estimator

[37] To make price expectation and price index consistent, I also transform the raw headline CPI series into the same format as the expectation of price index. Specifically, I compute yearly inflation as the year-over-year percentage change in CPI, divide this by 12, and take the cumulative sum of the resulting monthly series to construct the adjusted CPI series. The results are robust to instead using the raw CPI series (see Appendix C).

[38] The initial rise in inflation expectations is noteworthy and somewhat puzzling, though a full explanation lies beyond the scope of this paper.

Figure 7: Empirical and Baseline Model Impulse Responses



Notes: The figure plots the impulse responses for 6 variables following a 100 bp shock on the 1-year government bond rate. The sample period is 1978M1–2019M12. The blue lines represent the empirical impulse responses and the red lines represent the model counterparts. The shaded areas are 90% confidence intervals derived from wild bootstrap. The red line represents the impulse responses implied in Section 5. The x-axis denotes quarters from the shock, starting at 0. The y-axis denotes percent.

$\hat{\Lambda}$ solves,

$$\min_{\Lambda} \left(J(\Lambda) - \widehat{J} \right)' \boldsymbol{\Sigma}^{-1} \left(J(\Lambda) - \widehat{J} \right)$$

$\boldsymbol{\Sigma}$ is a diagonal matrix that has confidence interval of empirical impulse responses in its entries. Since the main parameter of interest is θ, I give CPI and CPI expectation more weight.[39]

[39] I double the original weights indicated by the confidence intervals.

Table 3: Calibrated and Estimated Parameters.

Panel A: Calibrated parameters			Panel B: Estimated parameters		
Param.	**Description**	**Value**	**Param.**	**Description**	**Value**
σ	EIS	1	θ	information frictions	0.048
η	Frisch elasticity	0.5	λ_c	Habit formation	0.802
β	Discount factor	0.99	λ_w	Calvo wage stickiness	0.930
ϕ	Taylor rule coefficient	2	ρ_m	Persistence of monetary shock	0.824
ε_w	Elasticity across labor types	3			
ζ_w	Superelasticity across labor types	10			
λ_p	Calvo price stickiness	0.75			
Γ	average own-cost passthrough	0.4			
$\tilde{\Gamma}$	Demand reallocation	0.426			

Table 3 summarizes the calibrated parameters. The average own-cost passthrough as the associated passthrough matrix that describes the effect of demand reallocation are calculated based the parameters regarding the search friction calibrated in Section 4. In addition, I follow the standard procedure in the literature (Smets and Wouters, 2007) of assuming a wage markup of 1.5 which implies the elasticity across labor types equal to 3, and a Kimball superelasticity for wages of $\zeta_w = 10$.

The model-implied impulse responses at the estimated parameters are shown in red in Figure 7. The model closely matches standard macroeconomic variables and also replicates the response of inflation expectations. The estimated information-friction parameter for consumers, $\theta = 0.048$, implies an average duration of incomplete information of about 20 quarters. This aligns with the earlier back-of-the-envelope calculation, indicating θ is primarily identified from the relative responses of CPI and CPI expectations. The relatively low estimate is consistent with recent evidence: Cavallo et al. (2017); Weber et al. (2025) show that in low-inflation environments households place greater weight on newly provided information indicating noisy prior about inflation. Korenok et al. (2023); Pfäuti (2024) find that attention rises only once inflation exceeds a threshold of about 4%, rarely observed in the United States during 1985-2019. This estimate is also significantly lower than the estimate of Kalman gain for oil-driven inflation in Section 4. This is consistent with the evidence that households are usually more attentive to salient prices (Kumar et al., 2015). However, monetary shocks are in general small and households may not understand the inflation dynamics following monetary shocks (Candia et al., 2023). Auclert et al. (2020) similarly estimate household information frictions in a HANK model, obtaining an average duration of about 15 quarters, which is one year shorter than my estimate. They target the hump-shaped output response, while I target the response of inflation expectations directly.

Figure C.1 in Appendix C reports results from estimating a Calvo model in which the wage rigidity and the persistence of the monetary policy shock are fixed at the values shown in Table 3. The Calvo parameter is estimated to be about 0.89, implying that 89% of firms are unable to adjust prices in a given quarter, which is consistent with the literature (Christiano et al., 2005; Smets and Wouters, 2007). Figure C.1 demonstrates that the model provides a reasonable fit for the responses of inflation and output. However, it fails to replicate the dynamics of inflation expectations. This is not surprising: under full information, expectations move one-for-one with realized inflation. Consequently, the Calvo framework lacks the mechanism needed to generate the observed wedge between actual and expected inflation. By contrast, the ability of my model to jointly match both series highlights a key strength of the proposed mechanism.

The estimated wage rigidity in Table 3 is $\lambda_w = 0.93$. This parameter is identified from two sources. First, it must capture the impulse response of real wages, which show little adjustment over the horizon, consistent with substantial rigidity. Second, wage stickiness influences CPI inflation: less frequent nominal wage adjustment dampens the price response. Raising λ_w above the reported value would improve the fit for real wages but would weaken the CPI and inflation-expectation responses, worsening the overall fit. Because firms in this model rely solely on labor, the estimation involves a trade-off between matching CPI and real wages.[40] Nonetheless, the estimate is comparable to Auclert et al. (2020), who calibrate a similar model with labor unions to match Romer and Romer (2004) shocks and obtain wage stickiness around 0.9.

Figure C.2 shows model impulse responses over a horizon of 80 quarters. The CPI falls to about 80 bps after 20 quarters and then stabilizes, while inflation expectations adjust more slowly and converge only after 80 quarters, underscoring substantial information frictions. Real wages display a highly persistent response, consistent with strong wage stickiness. Nominal wages initially drop by 110 bps, reflecting declines in both real wages and the price index; as the real wage effect dissipates, they gradually recover and stabilize about 80 bps below baseline.

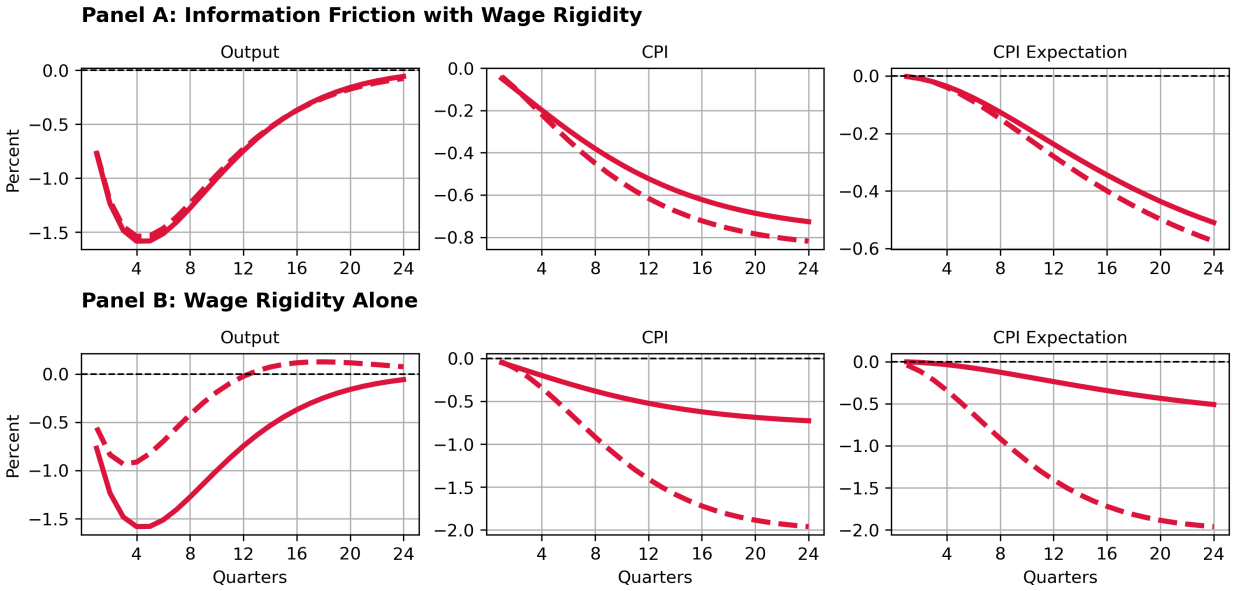
In sum, the relative responses of CPI and CPI expectation discipline the degree of information frictions; wage rigidity governs the persistence of real wage dynamics; together with nominal rigidity a là Calvo, they account for the remaining part of sluggishness of CPI inflation; habit formation is crucial for generating the hump-shaped output response; and the persistence of the monetary shock determines both the duration of the impulse responses and the magnitude of the output response.

5.3 Monetary Policy Transmission Channels

Now, I discuss monetary policy transmission channels in the dynamic general equilibrium model. In particular, there are two channels contributing to monetary non-neutrality: information

[40] In richer models with multiple production inputs including inputs whose prices move fast, this trade-off may be mitigated.

Figure 8: Decomposing the Transmission Channels of Monetary Policy



Notes: For both panels, the solid line plots the baseline impulse responses at the estimated parameters in Table 3 as the benchmark. In Panel A, dashed lines represent the case with $\lambda_p = 0$, holding all other parameters at their estimated values. Panel B shows the case when $\lambda_p = 0$ and $\theta = 1$.

frictions, Calvo price stickiness and nominal wage rigidity. In the following experiments as shown in Figure 8, I exploit contribution of each force.

In Panel A, I shut down Calvo pricing alone. The solid line represents the impulse responses generated from the baseline model. The dashed line shows the responses of this counterfactual case. The price index rises only marginally, and the output response is essentially unchanged. Therefore, conditional on the information frictions and wage rigidity, Calvo pricing frictions contribute little to monetary non-neutrality. The intuition is as follows. First, in a model without strategic complementarity, Christiano et al. (2005) show that removing nominal rigidity in a model with frictions on both wage and price adjustments has a small impact on output: when wage rigidity is large, marginal costs move little, so the price difference between adjusters and non-adjusters is small. With strategic complementarity, introducing price rigidity can further dampen the prices chosen by adjusters because firms fear consumer search and substitution toward firms that have not adjusted. This is why, with wage rigidity alone, adding price rigidity can amplify monetary non-neutrality by about two-thirds. However, sizable information frictions already weaken strategic complementarities. This explains why price rigidity has small impact conditional on both frictions.

In Panel B, I further shut down both Calvo pricing and information frictions. As expected, the decline in the price index is more than three times as large as in the baseline model, and the expected price index now tracks the actual price index almost exactly. Monetary non-neutrality

is substantially reduced: the cumulative output response falls by about 70% and the peak output response shrinks by roughly one half.[41] Information frictions account for a large share of monetary non-neutrality for two reasons. First, they dampen firms' price responses to changes in other firms' prices. Second, because the shock is less persistent than the information friction, perceived aggregate prices lag behind actual prices even after the shock has dissipated, generating persistent output effects as shown in Section 5. This result also implies that wage rigidity alone accounts for about 30% of monetary non-neutrality; as discussed in Section 5, wage rigidity is crucial for dampening marginal-cost movements in the model.

I conduct additional robustness checks reported in Appendix C: (i) replacing adjusted CPI with the raw CPI series; and (ii) replacing the industrial production index with the Brave–Butters–Kelley real GDP index. While the estimated persistence of monetary shocks and the degree of wage stickiness vary across these specifications, the estimate of information frictions remains robust. Across exercises, the implied average duration of information frictions ranges from 15 to 20 quarters. The information frictions explains 60% to 70% of monetary non-neutrality.

Taken together, the three experiments imply that information frictions account for about 70% of monetary non-neutrality; the remainder is due to wage rigidity, while price rigidity has negligible effect once the other two frictions are present.

5.4 Supply Shocks

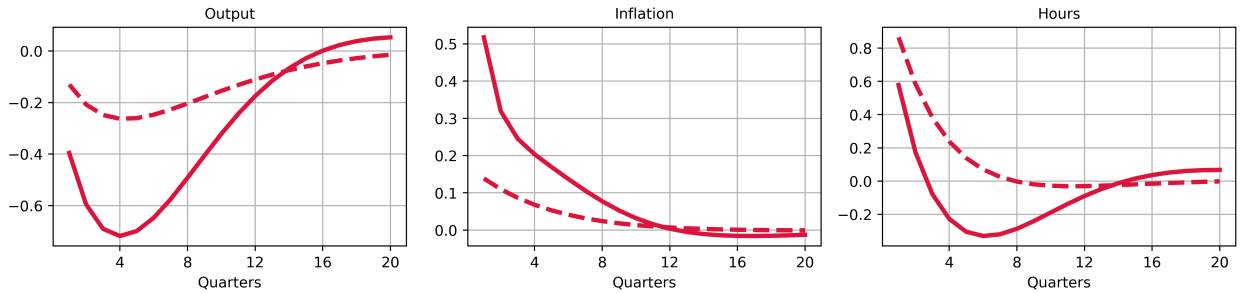
In this section, I show the impulse responses generated from this model compared to the standard Calvo model with wage rigidity and habit formation.

For calibration, I hold wage rigidity and habit formation fixed at the benchmark values reported in Table 3. To compare the model performance with a standard DSGE model, I shut down Calvo price rigidity in my model. Moreover, motivated by the evidence in Section 4, if we treat supply shocks as oil price changes, then the information frictions can be calibrated to $\theta = 0.4$. The solid lines in Figure 9 plot the impulse responses of output, inflation, and hours to a 100 basis-point *negative* productivity shock in my model; the dashed lines report the DSGE model with Calvo price rigidity set to 0.75. The two models differ sharply. In my model, inflation jumps by about 50 bps on impact and output features a peak response of about 70 bps. By contrast, the Calvo model delivers a much more muted rise in inflation (roughly 15 bps) and a peak output response of about 20 bps.

The contrast reflects how nominal marginal cost shocks transmit to prices. In my model, information frictions attenuate strategic complementarities, and wage rigidity dampens part of the nominal marginal cost increase; nevertheless, the exogenous productivity shock raises overall nominal marginal cost by 100 bps, generating a price increase of about 40 bps from firms' optimal passthrough of idiosyncratic shocks, with an additional $\sim$10 bps coming from consumer learning

[41] The cumulative response is calculated by summing the output response over 500 periods, weighted by β^t for $t = 0, 1, 2, \ldots$.

Figure 9: Model Impulse Responses After a Productivity Shock



Notes: The figure plots the impulse responses for 3 variables following a 100 bp shock on the aggregate productivity. The solid lines represent the impulse responses calibrated to values in Table 3 and $\theta = 0.4$, $\rho_a = 0.8$. The dashed lines represent the Calvo model with wage rigidity and habit formation in preferences. The x-axis denotes quarters from the shock. The y-axis denotes percent.

($\theta = 0.4$). In the Calvo model, passthrough of the *entire* marginal cost, including wage and productivity components, is dampened, yielding the much smaller inflation response. Figure C.3 shows that the baseline IRFs are closest to a Calvo specification with $\lambda_p = 0.45$, indicating that information frictions that differ across shocks can materially alter the Phillips curve slope and generate shock–dependent Phillips curves.

It is worth noting that inflation falls back quickly—by roughly 20 bp within one quarter. The shock drives a sharp rise in nominal marginal costs and thus inflation, but price index expectations adjust more slowly. Under the pricing rule (29), firms prefer to set prices close to the expected price index. As the initial cost pressure dissipates, firms reduce prices rapidly relative to the inertia in expectations. This "jump–and–fade" pattern for inflation after supply shocks is consistent with recent evidence that oil–shock inflation responses are large but short–lived (Kilian and Zhou, 2023).

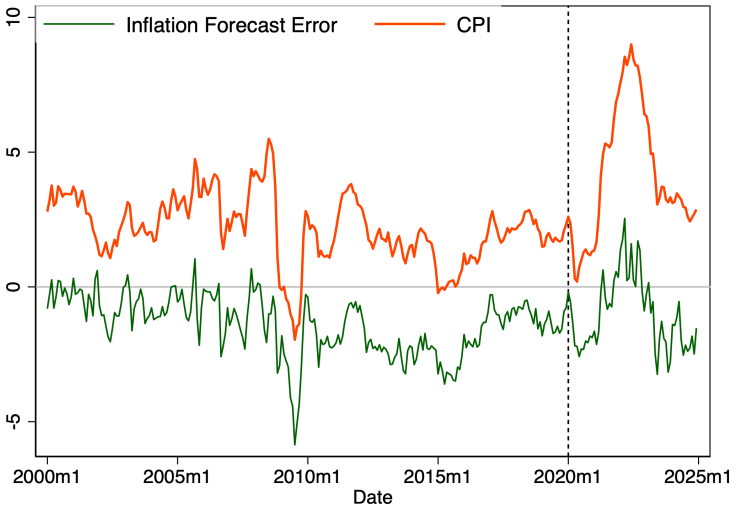
The behavior of hours is also intriguing. As emphasized by Galí (1999), when prices adjust slowly, aggregate demand is then above the contemporaneous potential output, inducing an initial increase in hours before they decline. With Calvo pricing, hours decrease slowly and eventually turn only slightly negative. In the baseline, the initial rise in hours is smaller and reverses more quickly: hours become negative within a year, with a peak decline of about -35 bp, which is more consistent with the evidence in Galí (1999).

Together, these results show that the baseline model flexibly matches two empirical regimes: (i) damped responses of inflation and inflation expectations, alongside substantial monetary non-neutrality, following monetary shocks; and (ii) pronounced but less persistent inflation spikes and more decline in labor supply, following productivity shocks.

6 Applications

The literature has focused on two puzzles. First, the standard New Keynesian model predicts sizable disinflation at the zero lower bound during the Great Recession, yet inflation barely turned

Figure 10: Inflation and Inflation Forecast error

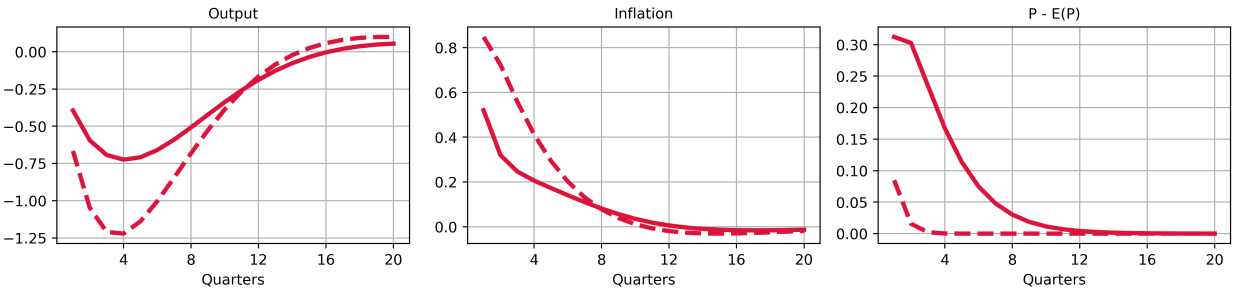


Notes: The figure plots headline CPI and inflation forecast error. The inflation forecast error is defined as the difference between realized inflation and the lagged one-month-ahead forecast: $\pi_t - \bar{E}_{t-1}\pi_t$.

negative—a puzzle termed "missing disinflation." Coibion and Gorodnichenko (2015b) argue that consumer inflation expectations remained elevated during this episode and passed through to current inflation. Second, after the onset of COVID-19, inflation—likely triggered by supply-chain disruptions—surged rapidly and remained persistently high, in stark contrast to the predictions of a flat Phillips curve estimated on pre-COVID data (Hazell et al., 2022). Several explanations have been advanced: Benigno and Eggertsson (2023) emphasize non-linearities in the New Keynesian Phillips curve; Blanchard and Bernanke (2023) highlight the central role of cost shocks; and Bianchi et al. (2023) attribute the surge to unfunded fiscal expansions.

Figure 10 shows that the inflation forecast error comoves closely with headline CPI for most of the sample, especially during the Global Financial Crisis when expectations barely moved; as a result, the decline in inflation passed through one-for-one into forecast errors. The pandemic period looks different: headline inflation spiked above 8%, yet the inflation forecast error rose by only about 1.5%, implying substantial pass-through from realized inflation to expectations. This pattern is consistent with Korenok et al. (2023) and Pfäuti (2024), who argue that attention to inflation rises sharply once inflation exceeds a 3–4% threshold. Relatedly, Cavallo et al. (2017) and Weber et al. (2025) show that in high-inflation environments households become more attentive and informed, making them less responsive to exogenous information treatments. During the pandemic, elevated attention was plausibly driven by unprecedented media coverage and public discourse around supply-chain disruptions and inflation.

Figure 11: Pandemic Inflation Surge and inflation Forecast error



Notes: The figure plots the impulse responses for 6 variables following a 100 bp shock on the aggregate productivity. The solid lines represent the impulse responses calibrated to values in Table 3 and $\theta = 0.4$. The dashed lines represent the Covid case by setting $\theta = 0.9$. The x-axis denotes quarters from the shock, starting at 0. The y-axis denotes percent.

My theory provides a joint explanation for both puzzles. During the Great Recession, when consumers paid little attention to inflation, firms passed through negative marginal cost shocks less aggressively: with inattentive marginal consumers who did not believe other firms had lowered prices, higher prices could extract more surplus from infra-marginal consumers without triggering search. Gilchrist et al. (2017) present a related mechanism based on higher firm discount rates during periods of elevated exit risk; here, limited passthrough arises instead from information frictions. By contrast, during the pandemic inflation surge, greater attention increased the pass-through of positive marginal cost shocks, amplifying inflation. Beaudry et al. (2024) find that household inflation expectations were a dominant driver of the surge; my framework explains why those expectations matter for realized inflation.

Supporting this interpretation, Cavallo et al. (2017) and Weber et al. (2025) show that in high-inflation environments households become more attentive and informed, making them less responsive to exogenous information treatments. In particular, Weber et al. (2025) document that prior uncertainty about inflation fell by a factor of nine inferred by the belief updating after information provision during the pandemic. Motivated by this evidence, I increase the information-friction parameter from $\theta = 0.4$ (baseline) to $\theta = 0.9$ for aggregate productivity shocks. The resulting dynamics are shown in Figure 11.

In the figure, solid lines correspond to $\theta = 0.4$ and dashed lines to $\theta = 0.9$. As information becomes more precise, the inflation response on impact rises by more than 30 bps, and the price-index forecast error shrinks to zero within one quarter. Inflation also reverts more slowly than under $\theta = 0.4$: faster learning accelerates the update of price-index expectations, leading consumers to infer that other firms have raised prices as well. This "higher peak, slower fade" pattern is consistent with Pfäuti (2024), who find that supply shocks exert stronger and more persistent effects on inflation when household attention is elevated. The model also predicts an output decline of

roughly 40 bps. In practice, output fell by less than the model implies, likely reflecting concurrent fiscal stimulus (Bianchi et al., 2023), which further boosted inflationary pressure.

The policy implication is that the slope of the Phillips curve is endogenous to the information environment faced by consumers. Shocks that generate extensive media coverage, public debate, and salient policy communication around inflation raise household attention to inflation, steepening the Phillips curve. In such environments, a more aggressive monetary stance is warranted because prices become more responsive to shocks. When unemployment and the output gap are more salient to households and attention to inflation is low, monetary policy should instead place greater weight on real activity within the dual mandate.

7 Conclusion

This paper develops a new framework for understanding monetary non-neutrality, driven entirely by consumer-side frictions. At the heart of the model is the information asymmetry about nominal marginal costs between consumers and firms. Specifically, the framework integrates a heterogeneous firm block and incomplete consumer information into a standard sequential search model. When consumers observe a price increase, they attribute it to adverse productivity shocks rather than increases in nominal wages, prompting them to search for outside options. Firms, in turn, internalize this consumer search behavior, compressing markups and limiting the passthrough of cost changes to prices. The framework also accommodates aggregate supply shocks, providing a toolbox for analyzing a wide range of shocks, each with potentially different information frictions.

Empirically, I use two informative empirical moments to estimate parameters about search frictions. The elasticity of search to inflation shocks is positive and sizable. The extended search model with multiple products fits the data fairly well. Future research can be directed to developing a quantitative search model with correlated taste shocks across products and stores. Furthermore, consumer information frictions for oil-driven inflation is estimated using Michigan Survey. Calibrating the sequential search model to these estimates yields an average own-cost passthrough within the range reported in the literature.

I further present a quantitative model that incorporates both price and wage rigidity. To match the extremely gradual adjustment in household inflation expectations observed in the data, the estimated model features significant information frictions. It accounts for about 70% of the total monetary non-neutrality. The key determinant of information frictions in estimation is the relative impulse responses of CPI and CPI expectation. Calvo friction has basically zero effect on monetary non-neutrality, consistent with Christiano et al. (2005). For aggregate supply shock, the quantitative model features pronounced but less persistent inflation spikes, larger decline in output and labor supply, compared to standard DSGE model.

Several further topics of inquiry are left for future research. First, although this paper focuses on final goods markets, the framework can be extended to any market with many sellers and buyers,

such as upstream and downstream firms in supply chains. An interesting extension would be embedding this model into production network models. Second, applying the model to the labor market could yield valuable insights. Workers' incomplete information about the average posted wage could influence their job-search decisions as documented in the recent literature. Finally, to better calibrate the model and assess the quantitative importance of the mechanism, incorporating both firm- and consumer-side frictions into the model is necessary.

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Appendix

A Omitted Proofs

Proof of Proposition 1:

Proof. We consider the case where the first draw does not need the search cost. Shoppers are randomly assigned a firm for free in the first round of search. This guarantees that they always participate the market. I prove that for given x, if $\int U(v|x)\psi(y|x)dy = -\infty$, then $v^*(x) = -\infty$; if $\int U(v|x)\psi(y|x)dy > -\infty$, there exists a unique threshold defined as follows.

$$v^*(x) = -\frac{\kappa}{1-\Psi(v^*(x)|x)} + \frac{\int_{v^*(x)}^{\infty} y\psi(y)dy}{1-\Psi(v^*(x)|x)} \tag{A.1}$$

First, given x, I consider two limits. When $v \to -\infty$,

$$-\kappa + U(v|x)\int_{-\infty}^{v}\psi(y|x)dy + \int_{v}^{\infty} U(y|x)\psi(y|x)dy = -\kappa + \int U(y|x)\psi(y|x)dy$$

Then, if $\int U(v|x)\psi(y|x)dy > -\infty$, $U(v|x) > v$. Intuitively, when the agent has the worst value whatsoever, i.e., $v \to -\infty$, the agent should choose to continue searching. In the other limit where $v \to \infty$,

$$-\kappa + U(v|x)\int_{-\infty}^{v}\psi(y|x)dy + \int_{v}^{\infty} U(y|x)\psi(y|x)dy = -\kappa + U(v|x)$$

Then, $U(v|x) = v$. Intuitively, when the agent has the best value whatsoever, the agent should stop search because she cannot get any other good that offers better value.

Second, I claim that if $U(v|x) > v$, then $U'(v|x) = 0$. To prove the claim, suppose there exist values of v on its support (at least at $-\infty$) such that $U(v) > v$. Then, $U(v)$ satisfies,

$$U(v|x) = -\kappa + U(v|x)\int_{-\infty}^{v}\psi(y|x)dy + \int_{v}^{\infty} U(y|x)\psi(y|x)dy \tag{A.2}$$

Equivalently,

$$U(v|x) = -\frac{\kappa}{1-\Psi(v|x)} + \frac{\int_{v}^{\infty} U(y|x)\psi(y|x)dy}{1-\Psi(v|x)} \tag{A.3}$$

It is easy to show that

$$U'(v|x) = \frac{\psi(v|x)}{(1-\Psi(v|x))^2}\left\{\int_{v}^{\infty} U(y|x)\psi(y|x)dy - U(v|x)(1-\Psi(v|x)) - \kappa\right\} = 0 \tag{A.4}$$

The second equation holds due to (A.3). Then, it is easy to see that $U(v|x)$ is a constant in $(-\infty, v^*]$, which is equal to $v^*(x)$, and then $U(v) = v$ in (v^*, ∞). v^* is unique. In addition, for $v < v^*$,

$$-\kappa + U(v|x)\int_{-\infty}^{v}\psi(y|x)dy + \int_{v}^{\infty} U(y|x)\psi(y|x)dy = -\kappa + v^*(x)\Psi(v^*(x)) + \int_{v^*(x)}^{\infty} y\psi(y|x)dy = v^*(x) \tag{A.5}$$

The search problem in (10) is therefore simplified to

$$U(v|x) = \max\{v, v^*(x)\} \tag{A.6}$$

This implies that the value of an additional search does not depend on the state v. No matter what state the shopper has, she always compare the state with $v^*(x)$.

Now, we prove the second part: $v^*(x)$ decreases in x. First, notice that from (A.5), the threshold can be written alternatively by the following,

$$\int \int_{\lambda(v^*(x)+p)}^{\infty} \big(\frac{1}{\lambda}\epsilon - p - v^*(x)\big) g(\epsilon) d\epsilon f(p|x) dp = \kappa \tag{A.7}$$

For $x_1 < x_2$, $f(p|x_1)$ is FOSD over $f(p|x_2)$. Since the inner integral in LHS decreases in p, that implies

$$v^*(x_1) > v^*(x_2)$$

We consider the case in which $\int U(v|x)\psi(y|x)dy = -\infty$ for any x. This happens when firms charge arbitrarily high prices, which implies $\psi(y|x)$ is a Dirac function at $y = -\infty$. Then, it is optimal to accept any firm in the first round and the resulting $v^*(x) = -\infty, \forall x$. This is the case considered in Diamond (1971). ■

Proof of Proposition 2:

Proof. Fix a firm k with marginal cost $c_k = W/A_k$ and (log) price $p_k = \log P_k$. A shopper with signal x accepts upon sampling iff

$$y_{ik} \;=\; -p_k + \tfrac{1}{\lambda}\epsilon \;\geq\; v^*(x) \quad\Longleftrightarrow\quad \epsilon \;\geq\; \lambda\big(v^*(x) + p_k\big),$$

so $\Pr(\text{accept} \mid x, p_k) = 1 - G(\lambda(v^*(x) + p_k))$. Conditional on acceptance, the purchased quantity equals X_i/P_k (from utility $\log(X_i/P_k)$). Averaging over x (with $X_i = We^x$ and $\int e^x d\Phi_x(x) = 1$) gives the firm's demand

$$Q_k(P_k) = \frac{1}{P_k}\int \exp(x)\Big[1 - G\big(\lambda\big(v^*(x) + p_k\big)\big)\Big]\, d\Phi_x(x) = \frac{B(p_k)}{P_k}, \tag{A.8}$$

where $B(p) := \int e^x \big[1 - G(\lambda(v^*(x) + p))\big]\, d\Phi_x(x)$. Because the firm is atomistic, a unilateral change in p_k does not affect $v^*(x)$.

Lerner rule. Profits are $\pi_k(P_k) = (P_k - c_k)Q_k(P_k)$. The first-order condition $d\pi_k/dP_k = 0$ yields

$$\frac{P_k - c_k}{P_k} \;=\; -\frac{Q_k(P_k)}{P_k Q_k'(P_k)} \;=\; \frac{1}{e_k},$$

where $e_k := -Q_k'(P_k)\, P_k/Q_k(P_k)$ is the own-price elasticity. Hence $\mu_k := P_k/c_k = e_k/(e_k - 1)$, proving (16).

Elasticity formula. Differentiate (A.8) using $p_k = \log P_k$ and $dp_k/dP_k = 1/P_k$:

$$\frac{dQ_k}{dP_k} = -\frac{B(p_k)}{P_k^2} + \frac{1}{P_k}\,B'(p_k)\,\frac{1}{P_k} = -\frac{B(p_k)}{P_k^2} + \frac{B'(p_k)}{P_k^2}.$$

Thus

$$e_k = -\frac{dQ_k}{dP_k}\frac{P_k}{Q_k(P_k)} = \left(\frac{B(p_k)}{P_k^2} - \frac{B'(p_k)}{P_k^2}\right)\frac{P_k}{B(p_k)/P_k} = 1 - \frac{B'(p_k)}{B(p_k)}.$$

Since $v^*(x)$ is fixed with respect to p_k,

$$B'(p_k) = \int e^x \Big[-g(\lambda(v^*(x) + p_k))\Big]\,\lambda\,d\Phi_x(x) = -\lambda \int e^x\, g(\lambda(v^*(x) + p_k))\; d\Phi_x(x).$$

Substituting into the expression for e_k gives

$$e_k = 1 + \lambda\,\frac{\displaystyle\int \exp(x)\, g(\lambda(v^*(x) + p_k))\; d\Phi_x(x)}{\displaystyle\int \exp(x)\left[1 - G(\lambda(v^*(x) + p_k))\right] d\Phi_x(x)},$$

which is (17). This completes the proof. ■

Proof of Theorem 1: I first prove a lemma that is useful for proving Theorem 1.

Lemma A-1. *The full-information threshold $v^*(w)$ decreases with the search cost, κ.*

The Lemma establishes a one-to-one correspondence between the full-information threshold and the search cost. A lower search cost directly raises the value of additional search. But at the same time, it reduces this value indirectly by increasing prices through (20). The Lemma show that the direct effect outweighs the indirect effect.

Proof. We first define the markup elasticity,

$$\Lambda_k = -\frac{d\log\mu_k}{dp_k} = \frac{1}{e_k(e_k - 1)}\frac{\partial e_k}{\partial p_k}$$

Since G is log-concave, $\frac{\partial e_k}{\partial p_k} > 0$. Therefore, the markup elasticity is positive. We can further write out the definition,

$$\Lambda_k = \frac{\frac{g'}{g}\frac{1-G}{g} + 1}{\frac{1}{\lambda}\frac{1-G}{g} + 1}$$

Here, I omit the argument of functions for simplicity. The argument is $\lambda(v^*(w) + p_k)$. Note that full-information equilibrium price is a function of $v^*(w)$ and p_k. I now rewrite the LHS of (A.7) in terms of the integral over productivity distribution, which is exogenous,

$$\int \int_{\lambda(v^*(w)+p^*(a;v^*(w)))}^{\infty} \big(\frac{1}{\lambda}\epsilon - p^*(a; v^*(w)) - v^*(w)\big) g(\epsilon) d\epsilon \phi_a(a) da = \kappa \tag{A.9}$$

where $\phi_a(a)$ is the pdf of productivity distribution. Fix $p^*(a; v^*(w))$, the LHS is decreasing in $v^*(w)$. However, higher $v^*(w)$ also decreases optimal prices. To know the net effect of these two forces, we need to derive $\frac{\partial p^*(a_k; v^*(w))}{\partial v^*(w)}$. From now on, we use $x_k(v^*(w))$ to denote $x(v^*(w), a_k)$ for any variable x.

$$\frac{\partial p_k(v^*(w))}{\partial v^*(w)} = \frac{\partial \log \mu_k(v^*(w))}{\partial v^*(w)} = -\frac{1}{e_k(v^*(w))(e_k(v^*(w)) - 1)} \frac{\partial e_k(v^*(w))}{\partial v^*(w)} \tag{A.10}$$

It is easy to show that

$$\frac{\partial e_k(v^*(w))}{\partial v^*(w)} = \lambda^2 \frac{g'(1-G) + g^2}{(1-G)^2} \left(1 + \frac{\partial p_k(v^*(w))}{\partial v^*(w)}\right) \tag{A.11}$$

Combine the above two equations, we have:

$$\frac{\partial p_k(v^*(w))}{\partial v^*(w)} = -\frac{\Lambda_k}{1 + \Lambda_k} \tag{A.12}$$

Since $\Lambda_k > 0$, $\frac{\partial p_k(v^*(w))}{\partial v^*(w)} \in (-1, 0)$. This implies that $\frac{\partial (v^*(w) + p_k(v^*(w)))}{\partial v^*(w)} \in (0, 1)$. Therefore, the LHS of (A.7) decreases in $v^*(w)$. ■

Now, I prove Theorem 1.

Proof. Under full information, the reservation value $v^*(w)$ is pinned down by

$$\mathcal{S}(v; w) \;:=\; \int\int_{\lambda\,(v+p)}^{\infty} \left(\tfrac{1}{\lambda}\epsilon - p - v\right) g(\epsilon)\, d\epsilon\; f(p \mid w; v)\, dp \;=\; \kappa, \tag{A.13}$$

where $f(\cdot \mid w; v)$ is the price distribution induced by firms' optimal pricing $p^*(a; v)$ when the reservation value is v.

Step 1: Monotonicity and continuity of $\mathcal{S}(v; w)$ in v (by Lemma A-1). Lemma A-1 establishes that the solution $v^*(w)$ to (A.13) is strictly decreasing in κ. This comparative statics result is equivalent to $\mathcal{S}(v; w)$ being strictly decreasing (and continuous) in v; hence we take $\partial \mathcal{S}(v; w)/\partial v < 0$ and continuity as given by the lemma and do not reprove it here.

Step 2: Boundary behavior. As $v \to +\infty$, the lower limit $\lambda(v + p) \to +\infty$ for all p, so $\mathcal{S}(v; w) \to 0$. As $v \to -\infty$, the lower limit $\lambda(v + p) \to -\infty$, implying $\int_{\lambda(v+p)}^{\infty} (\frac{1}{\lambda}\epsilon - p - v) g(\epsilon) d\epsilon = -(p + v) + o(1)$, hence $\mathcal{S}(v; w) \to +\infty$.

Step 3: Existence and uniqueness. By Step 1, $\mathcal{S}(v; w)$ is continuous and strictly decreasing in v, and by Step 2 it spans $(0, +\infty)$ as v ranges over $\mathbb{R}$. Therefore, for any $\kappa > 0$ there exists a *unique* $v^*(w) \in \mathbb{R}$ solving (A.13). This $v^*(w)$ pins down firms' optimal prices $p^*(a; v^*(w))$ and the induced price distribution $f(p \mid w)$, verifying equilibrium.

Step 4: Active search. Given finite $v^*(w)$, the per-draw acceptance probability is

$$\rho \;=\; \int \Big[1 - G\big(\lambda(v^*(w) + p)\big)\Big]\, f(p \mid w)\, dp,$$

which lies strictly between 0 and 1 because G has full support and $f(\cdot \mid w)$ places positive mass on its support. Hence the expected number of draws is $1/\rho > 1$, so consumers search actively.

This proves existence, uniqueness, and active search in the full-information equilibrium. ■

Remarks on Computation of the Full-information Equilibrium:

Remark 1 (Remark on Computing Steady-State Equilibrium)**.** *The proof of Theorem 1 provides insights on the computational method for the full-information equilibrium.*

1. *First guess a $v^*(w)$*
2. *Calculate the optimal price distribution given $v^*(w)$*
3. *Plug guessed $v^*(w)$ and derived price distribution and plug it into 18 and check if LHS is equal to the given search cost κ.*
4. *Increases guessed $v^*(w)$ if LHS is larger than search cost, according to Lemma A-1. Vice versa.*
5. *Loop the procedure 1-4 until the difference between the LHS and the RHS of 18 is smaller than the given tolerance*

Proof of Theorem 2:

Proof. Suppose the nominal wage increases from w to w'. Notice $\Delta w = w' - w$ does not need to be small. We guess that all the optimal prices increase proportionally, i.e., $p'_k = p_k + \Delta w$. Then the price distribution $f(p|w)$ shifts to the right and becomes $f(p - \Delta w|w')$. The threshold is determined by,

$$\int \int_{\lambda(v^*(w')+p)}^{\infty} \big(\frac{1}{\lambda}\epsilon - p - v^*(w')\big) g(\epsilon) d\epsilon f(p - \Delta w|w') dp = \kappa \tag{A.14}$$

Let $z = p - \Delta w$. Then we can rewrite the LHS of the above equation,

$$\int \int_{\lambda(v^*(w')+\Delta w+z)}^{\infty} \big(\frac{1}{\lambda}\epsilon - z - (\Delta w + v^*(w'))\big) g(\epsilon) d\epsilon f(z|w') dz = \kappa \tag{A.15}$$

This implies that $v^*(w') = v^*(w) - \Delta w$. According to (20), the elasticity of demand is given by,

$$\begin{aligned} e'_k &= \lambda \frac{g\big(\lambda(v^*(w') + p'_k)\big)}{1 - G\big(\lambda(v^*(w') + p'_k)\big)} + 1 \\ &= \lambda \frac{g\big(\lambda(v^*(w) - \Delta w + p_k + \Delta w)\big)}{1 - G\big(\lambda(v^*(w) - \Delta w + p_k + \Delta w)\big)} + 1 \\ &= e_k \end{aligned}$$

Since the elasticity of demand does not change, the optimal prices is given by,

$$p'_k = \log(\frac{e_k}{e_k - 1}) + w' - a_k = p_k + w' - w = p_k + \Delta w \tag{A.16}$$

Therefore, we verify the guess that the optimal prices increase proportionally with the nominal wage. Based on Theorem 1, the equilibrium is unique. Therefore, the above constructed equilibrium is the only equilibrium when the nominal wage is w'. ■

Proof of Proposition 3: Here, I provide separate proofs for two parts of Proposition 3. I start with the proof of the first part.

Proof of Part 1. First, we can rewrite 11 in terms of integrating over the exogenous productivity distribution and posterior belief about nominal wage,

$$\int\int\int_{\lambda(v^*(x)+p^*(a,\hat{w}))}^{\infty}\big(\frac{1}{\lambda}\epsilon - p^*(a,\hat{w}) - v^*(x)\big)g(\epsilon)d\epsilon\phi_a(a)dah(\hat{w}|x)d\hat{w} = \kappa \tag{A.17}$$

where $v^*(x)$ is implicitly determined by the above equation. On the first order, the posterior belief of the nominal wage collapses to a Dirac function at $E(w|x)$. Also, combining the passthrough $\varphi(a)$, the above equation becomes,

$$\int\int_{\lambda(v^*(x)+\bar{p}_k+\varphi(a)E(\hat{w}|x))}^{\infty}\big(\frac{1}{\lambda}\epsilon - \bar{p}(a) - \varphi(a)E(\hat{w}|x) - v^*(x)\big)g(\epsilon)d\epsilon\phi_a(a)da = \kappa \tag{A.18}$$

Take the total derivative on $E(\hat{w}|x)$ on both sides,

$$\int\Big(\varphi(a) + \frac{dv^*(x)}{dE(\hat{w}|x)}\Big)\big(1 - G(\lambda(v^*(x) + \bar{p}(a) + \varphi(a)E(\hat{w}|x)))\big)\phi_a(a)da = 0$$

On the first order, it can be written as follows,

$$\frac{dv^*(x)}{dE(\hat{w}|x))} = -\int\varphi(a)\omega(a)\phi_a(a)da = -\int\varphi_k\omega_k dk \tag{A.19}$$

where $\omega(a)$ is the expenditure share of firms with productivity a in the full-information equilibrium. Then, the threshold, on the first order, is given by,

$$v^*(x) = v^*(\bar{w}) - \frac{\partial v^*(x)}{\partial v^*(x)}v^*(x) = v^*(\bar{w}) - \Phi E(\hat{w}|x)$$

Recall $\hat{p} = \Phi\hat{w}$. We have the result. ■

Proof of Part 2 . First, plug the result in Part 1 into the elasticity of demand in (17), the elasticity becomes,

$$e_k = \lambda\frac{\int Xg\big(\lambda(v^*(\bar{w}) - \Phi E(\hat{w}|x) + p_k)\big)d\Phi_x(x)}{\int X\big(1 - G\big(\lambda(v^*(\bar{w}) - \Phi E(\hat{w}|x) + p_k)\big)\big)d\Phi_x(x)} + 1 \tag{A.20}$$

with some abuse of notation, Φ is the average aggregate-shock passthrough and $\Phi_x(x)$ is the cdf of information sets. Let $y = \lambda\Phi\big(E(\hat{w}|x) - \bar{E}(\hat{w})\big)$ and its pdf is $\phi_y(y)$, which is a Gaussian distribution with mean zero and standard deviation $\sigma = \lambda\Phi\theta\sigma_s$, where σ_s^2 is the variance of distribution of $E(\hat{w}|x) - \bar{E}(\hat{w})$ and is proportional to $\sigma_{\hat{w}}^2$. Further, we denote $z = \lambda(v^*(w) - \Phi\bar{E}(\hat{w}) + p_k)$. One

should think of z as mean and y is the error caused by idiosyncratic noises in private signals. The elasticity is rewritten as follows,

$$e_k = \lambda \frac{\int X g(z+y)\phi_y(y)dy}{\int X\big(1-G(z+y)\big)\phi_y(y)dy} + 1 \tag{A.21}$$

It is easy to show that the first-order approximation to the ratio is equivalent to separately approximating numerator and denominator and then combining them. Following this result, we first expand the numerator.

$$g(z+y) = g(z) + g'(z)y + \frac{g''(z)}{2}y^2 + \mathcal{O}(y^3)$$

Substitute this expansion into the integral and also notice that $X \propto \exp(y+\bar{w})$,

$$\begin{aligned}
\int \exp(y) g(z+y)\phi_y(y)dy &= \int (1+y)\Big(g(z) + g'(z)y + \frac{g''(z)}{2}y^2 + \mathcal{O}(y^3)\Big)\phi_y(y)dy \\
&= g(z) + \int \Big((g'(z) + \frac{g''(z)}{2})y^2 + \mathcal{O}(y^3)\Big)\phi_y(y)dy \\
&= g(z) + \big(g'(z) + \frac{g''(z)}{2}\big)\sigma^2 + \mathcal{O}(\sigma^3)
\end{aligned}$$

Therefore, $\int g(z+y)\phi_y(y)dy \to g(z)$ on the order of σ_w^2, which is second-order term. Similarly, $\int \big(1-G(z+y)\big)\phi_y(y)dy \to 1-G(z)$ on the order of σ_w^2. On the other hand, the average expectation of monetary shock $\bar{E}(\hat{w})$ approaches zero on the order of σ_w. Therefore, on the first order, the noises coming from the idiosyncratic noises converge to zero faster than the mean. As a result, elasticity, on the first order, is given by,

$$e_k = \lambda \frac{g(z)}{1-G(z)} + 1 = \lambda \frac{g(\lambda(v^*(w) - \Phi\bar{E}(\hat{w}) + p_k))}{1 - G(\lambda(v^*(w) - \Phi\bar{E}(\hat{w}) + p_k))} + 1 \tag{A.22}$$

■

Proof of Lemma 1:

Proof. First, log price is given by,

$$p_k = \log \mu_k + w - a_k$$

Total differentiate on both sides,

$$\hat{p}_k = \frac{\partial \log \mu_k}{\partial p_k}\hat{p}_k + \frac{\partial \log \mu_k}{\partial p}\bar{E}\hat{p} + \hat{w} \tag{A.23}$$

We further define $\gamma_k = (1 - \frac{d\log\mu_k}{dp_k}\Big|_{\hat{w}=0})^{-1}$ and $\xi_k = \frac{d\log\mu_k}{dp}\Big|_{\hat{w}=0}\gamma_k$. Then, we have,

$$\hat{p}_k = \gamma_k\hat{w} + \xi_k\bar{E}\hat{p} \tag{A.24}$$

Since $\hat{p} = \Phi\hat{w}$ and $\bar{E}\hat{p} = \theta\hat{p}$, the aggregate-shock passthrough for individual firm satisfies,

$$\varphi_k = \gamma_k + \Phi\xi_k\theta$$

Integrate on both sides,

$$\Phi = \frac{\Gamma}{1-\theta\Xi}$$

where $\Gamma = \int \gamma_k\omega_k dk$, $\Xi = \int \xi_k\omega_k dk$. ■

Proof of Theorem 3: I first prove the "Incompleteness" part of the Theorem. Then I prove an important lemma and finally I prove the comparative statics results.

Proof. Notice that for any function $f(w)$, the first-order approximation to its derivative is,

$$f'(w) = f'(\bar{w}) + f''(\bar{w})\hat{w} \tag{A.25}$$

Then, $f'(w)|_{\hat{w}=0} = f'(\bar{w})$ on the first order. I claim that the approximation gives the same result if we reverse the order of the operations. Let's first take the first-order approximation to $f(w)$,

$$f(w) = f(\bar{w}) + f'(\bar{w})\hat{w} \tag{A.26}$$

Then if we take derivative w.r.t. $\hat{w}$ and then make $\hat{w} = 0$, we get the same result.

Now, following this result, $\frac{\partial e_k}{\partial p_k}\Big|_{\hat{w}=0}$ and $\frac{\partial e_k}{\partial p}\Big|_{\hat{w}=0}$ can be computed by first first-order approximating e_k as we did in Proposition 3 and then take derivative to $\hat{p}_k$ and $\hat{p}$. For simplicity, I omit the argument of the functions, in particular, $F = F(v^*(\bar{w}) + \bar{p}_k)$ for any function F. It is straightforward to show that, on the first order,

$$\frac{\partial e_k}{\partial p_k}\Big|_{\hat{w}=0} = \lambda^2\frac{g'(1-G)+g^2}{(1-G)^2} \tag{A.27}$$

We can derive that γ_k does not depend on θ. In addition, we have

$$\frac{\partial e_k}{\partial p}\Big|_{\hat{w}=0} = -\theta\lambda^2\frac{g'(1-G)+g^2}{(1-G)^2} \tag{A.28}$$

Then, we have $\frac{\partial \log \mu_k}{\partial p} = -\theta\frac{\partial \log \mu_k}{\partial p_k}$. According to Lemma 1, we have

$$\xi_k = \theta(1-\gamma_k) \tag{A.29}$$

Substitute back to Lemma 1,

$$\hat{p}_k = \gamma_k(\hat{w} - \hat{a}_k) + \theta(1-\gamma_k)\hat{p} \tag{A.30}$$

Integrate on both sides,

$$\hat{p} = \Gamma\hat{w} + \theta(1-\Gamma)\hat{p} \tag{A.31}$$

Or equivalently,

$$\hat{p} = \Gamma\hat{w} + (1-\Gamma)E^c\hat{p} \tag{A.32}$$

■

Proof of Corollary 1:

Proof. The aggregation in (A.31) requires every firm is individually rational, so they know (A.30). Suppose every shopper believe that firms and other shoppers are rational. Then every shopper believes (A.31) holds. Shoppers' average expectation of $\hat{p}$ satisfies,

$$\bar{E}\hat{p} = \Gamma\bar{E}\hat{w} + (1-\Gamma)\bar{E}^2\hat{p} \tag{A.33}$$

where $\bar{E}^2[\cdot] = \bar{E}[\bar{E}[\cdot]]$ denotes the second-order belief. Iterating ad infinitum, the change in the actual price index $\hat{p}$ can be expressed in terms of the higher-order beliefs of the monetary shock $\hat{w}$:

$$\hat{p} = \Gamma\sum_{h=0}^{\infty}(1-\Gamma)^h\bar{E}^h\hat{w} \tag{A.34}$$

"Iterating ad infinitum" amounts to imposing common knowledge of rationality. The first iteration requires that shoppers know that firms and other shoppers are rational, the second iteration requires that shoppers know that others know they are rational and firms are rational, and so on. ■

Proof of Proposition 4 and 5: Before proving Proposition 4 and 5, I first state and prove the following lemma.

Lemma A-2. *Let* $\Lambda_k = -\frac{d\log\mu_k}{dp_k}\Big|_{\hat{w}=0}$ *denote the steady-state markup elasticity. When G is Gumbel distribution, it has the following property,*

$$\frac{d\Lambda(y)}{dy} < 0$$

In addition, $\Lambda(y)\to 0$ *as* $y\to\infty$ *and* $\Lambda(y)\to\infty$ *as* $y\to-\infty$.

Proof. To simplify notation, I denote $y_k = \lambda(v^*(\bar{w}) + \bar{p}_k)$. I assume that G follows standard type-I extreme-value distribution, i.e., $G(y) = \exp(\exp(-y))$, $g(y) = \exp(-y-\exp(-y))$. It also follows that $\frac{g'}{g} = e^{-y} - 1$.

First, since G is log-concave, g is also log-concave. This implies the following property,

$$(\frac{g'}{g})' < 0; \quad (\frac{1-G}{g})' < 0$$

Additionally, using G is Gumbel, I have $\frac{1-G}{g}\to 1$ as $y\to\infty$ and therefore $\frac{1-G}{g} > 1$.

Second, we write out markup elasticity,

$$\Lambda = \frac{\frac{g'}{g}\frac{1-G}{g}+1}{\frac{1}{\lambda}\frac{1-G}{g}+1} \tag{A.35}$$

Then the derivative of markup elasticity w.r.t y is given by,

$$\begin{aligned}
\frac{d\Lambda(y)}{dy} &= \left(\frac{g'}{g}\right)'\left(\frac{1-G}{g}\right)^2\frac{1}{\lambda} - \left(\frac{1-G}{g}\right)'\frac{1}{\lambda} + \left(\frac{g'}{g}\frac{1-G}{g}\right)' \\
&= -e^{-y}\left(\frac{1-G}{g}\right)^2\frac{1}{\lambda} + \frac{1}{\lambda}(1+\frac{g'}{g}\frac{1-G}{g}) + \left(\frac{g'}{g}\frac{1-G}{g}\right)' \\
&< -e^{-y}\left(\frac{1-G}{g}\right)\frac{1}{\lambda} + \frac{1}{\lambda}(1+(e^{-y}-1)\frac{1-G}{g}) + \left(\frac{g'}{g}\frac{1-G}{g}\right)' \\
&= \frac{1}{\lambda}\left(1-\frac{1-G}{g}\right) + \left(\frac{g'}{g}\frac{1-G}{g}\right)'
\end{aligned}$$

The inequality is due to $\frac{1-G}{g} > 1$. The first term of the last equation is negative. We need to deal with the second term. Notice that

$$\left(\frac{g'}{g}\frac{1-G}{g}\right)' = \left(\frac{g'}{g}\right)'\left(\frac{1-G}{g}\right) + \left(\frac{g'}{g}\right)\left(\frac{1-G}{g}\right)'$$

It is straightforward that when $y < 0$, $\frac{g'}{g} = e^{-y} - 1 > 0$. Then, $\left(\frac{g'}{g}\frac{1-G}{g}\right)' < 0$. We now focus on the case where $y > 0$.

$$\begin{aligned}
\left(\frac{g'}{g}\frac{1-G}{g}\right)' &= -e^{-y}\frac{1-G}{g} + (1-e^{-y}) - (1-e^{-y})^2\frac{1-G}{g} \\
&< -e^{-y}\frac{1-G}{g} + (1-e^{-y}) - (1-e^{-y})\frac{1-G}{g} \\
&= (1-e^{-y}) - \frac{1-G}{g} \\
&< 0
\end{aligned}$$

The first inequality is due to $1 - e^{-y} \in (0,1)$ when $y > 0$. The second inequality is due to $\frac{1-G}{g} > 1$. Combine all together, we have

$$\frac{d\Lambda(y)}{dy} < 0$$

For limit results, first recall $\frac{1-G}{g} \to 1$ as $y \to \infty$. Plug into (A.35), we get $\Lambda \to 0$ when $y \to \infty$. Second, since $\frac{1-G}{g} \to \infty$ when $y \to -\infty$, $\Lambda \approx \lambda g'/g \to \infty$ since $g'/g \to \infty$. ■

Next, we turn to the result on comparative statics.

Proof of Proposition 4: First, notice that to show φ_k decreases in a_k, it is sufficient to show that γ_k decreases in a_k. From Lemma 1, $\gamma_k = (1+\Lambda_k)^{-1}$. Since Λ_k decreases in P_k based on Lemma A-2, it implies γ_k increases in P_k. Since P_k decreases in a_k, it implies γ_k decreases in a_k.

Since the markup μ_k decreases in p_k, it increases in a_k. It is easy to show that $\lim_{a\to-\infty} e_k = 1 - \lambda\frac{g'}{g} = 1+\lambda$ and $\lim_{a\to\infty} e_k = 1$. Then, $\lim_{a\to-\infty}\mu_k = \frac{\lambda+1}{\lambda}$ and $\lim_{a\to\infty}\mu_k = \infty$.

Also, we know $\xi_k = \theta(1-\gamma_k)$, so ξ_k increases in a_k. Also, in the limit when $a \to \infty$, $p \to -\infty$. Then $\Lambda \to \infty$ and $\gamma \to 0$, $\xi \to \theta$. In the opposite limit, $p \to \infty$, and $\Lambda \to 0$, implying $\gamma \to 1$ and $\xi \to 0$. ■

Proof of Proposition 5: I first consider the comparative statics on κ. From Lemma A-1, an increase in the search cost κ implies lower threshold $v^*(\bar{w})$. Since the steady-state markup elasticity decreases in $v^*(\bar{w})$, γ_k decreases for all k. As a result, φ_k decreases in κ for all k. When $\kappa \to 0$, $v^*(\bar{w}) \to \infty$ and therefore $\Lambda_k \to 0$, resulting in $\gamma_k \to 1$ for any k. This implies $\varphi_k = 1$ for any k. When $\kappa \to \infty$, $v^*(\bar{w}) \to -\infty$, and therefore $\Lambda_k \to \infty$, resulting in $\gamma_k \to 0$ for any k. This implies $\varphi_k = 0$ for any k. Then, I consider the comparative statics on θ. An increase in the information friction, which means a decrease in θ, induces lower φ_k. When $\theta \to 0$, $\Phi = \Gamma$. When $\theta \to 1$, $\varphi_k = 1$. ■

Proof of Proposition A.5:

Proof. The profit of a firm that has N products indexed by j is given by,

$$\pi_k = \frac{1}{\rho} \sum_{j=1}^{N} \int X\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x) \frac{1}{P_{jk}} (P_{jk} - \frac{W}{A_{jk}}) (\frac{P_{jk}}{P_k})^{-\sigma} \tag{A.36}$$

where $P_k = (\sum_{j=1}^{N} P_{jk}^{1-\sigma})^{\frac{1}{1-\sigma}}$. Denote the total expenditure share on firm k as $\omega_k = \omega(P_k)$, then,

$$\pi_k = \frac{1}{\rho} \sum_{j=1}^{N} \omega(P_k) \frac{1}{P_{jk}} (P_{jk} - \frac{W}{A_{jk}}) (\frac{P_{jk}}{P_k})^{-\sigma} \tag{A.37}$$

Firm k will internalize the effect of change in P_{jk} on overall price index P_k of the firm. The first-order condition w.r.t. P_{jk} is given by,

$$P_{jk} = \mu_k \frac{W}{A_{jk}} = \frac{\sigma}{\sigma - 1 - P_k^{-1} \tilde{\pi}_k (e_k - 1 + \sigma - 1)} \frac{W}{A_{jk}} \tag{A.38}$$

where e_k is the same as in (17). Notice that the markup is the same across all the products within the firm. Also, we have $\tilde{\pi}_k = (1 - \mu_k) P_k$. Plug in the above equation, we have,

$$\mu_k = \frac{e_k}{e_k - 1} \tag{A.39}$$

The passthrough of productivity shock to a given product j is proportional to the expenditure share of this product over all products on the market.

$$\gamma_{jk} = \frac{\omega_{jk}}{\omega_k} \gamma_k \tag{A.40}$$

Therefore, when $N = 1$, $\gamma_{jk} = \gamma_k$; when $N \to \infty$, $\gamma_{jk} \to 0$. ■

Proposition A.1. *With time-dependent nominal rigidities, the pricing equation becomes,*

$$\hat{P} = \Gamma \Psi^{TD} (I - (1 - \Gamma) \Psi^{TD} M)^{-1} \hat{M} C \tag{A.41}$$

Proof. In time-dependent (TD) pricing models, price adjustments are governed by an exogenous *survival function* Φ_s, which represents the fraction of firms that have not yet adjusted their price after s periods. The function is weakly decreasing in s, i.e., $\Phi_s \in [0, 1]$ and $\Phi_0 = 1$.

Each period, firms get opportunities to reset their prices based on the survival function and the time since the last adjustment. The optimal reset price is given by:

$$x_t^* = \arg\min_x \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \Phi_s \frac{1}{2} \left(x - \gamma \sum_{r=1}^{s} \epsilon_{it+r} - \gamma \log MC_{t+s} - (1-\gamma) E_{t+s}^c \log P_{t+s} \right)^2 \tag{A.42}$$

where $x - \gamma \sum_{r=1}^{s} \epsilon_{it+r}$ is the price gap of firm i at date $t+s$ if it starts with a price gap of x at date t and does not adjust between t and $t+s$. $E_t^c \log P_{t+s}$ is the consumers' average expectation of price index at date $t+s$. The adjustment hazard at horizon s is defined as: $\lambda_s = \frac{\Phi_{s-1} - \Phi_s}{\Phi_{s-1}}$, $\lambda_s \in [0,1]$ when $\Phi_{s-1} = 0$, we set $\lambda_s = 1$. The law of motion for individual price gaps follows:

$$x_{it} = \begin{cases} x_t^* & \text{with probability } \lambda_s \\ x_{it-1} - \epsilon_{it} & \text{otherwise} \end{cases} \tag{A.43}$$

Denote by a_s the share of prices that last adjusted s periods ago, that is, the share of prices with age s. The age distribution of prices in the steady state is given by,

$$a_s = \frac{\Phi_s}{\sum_{r=0}^{\infty} \Phi_r} \tag{A.44}$$

The reset price gap x_t^* satisfies the FOC of the problem in (A.42),

$$x_t^* = \Gamma \frac{\sum_{s \geq 0} \beta^s \Phi_s \widehat{MC}_{t+s}}{\sum_{s \geq 0} \beta^s \Phi_s} + (1-\Gamma) \frac{\sum_{s \geq 0} \beta^s \Phi_s E_{t+s}^c \widehat{P}_{t+s}}{\sum_{s \geq 0} \beta^s \Phi_s} \tag{A.45}$$

Equation (A.45) shows that, with strategic complementarity, the optimal reset price gap is a weighted average of future nominal marginal cost shocks and price index changes. In addition, due to the information friction, consumers' average expectation of price index changes is typically dampened compared to the actual changes, which leads to dampened response of reset price gap.

The price index is a weighted average of past reset price gaps, with the age distribution as weights,

$$\hat{P}_t = \int x_{it} di = \sum_{s \geq 0} a_s x_{t-s}^* = \frac{\sum_{s \geq 0} \Phi_s x_{t-s}^*}{\sum_{s \geq 0} \Phi_s} \tag{A.46}$$

Both SD and TD models describe a mapping between nominal marginal cost $\{MC_t\}$ and the aggregate price level $\{P_t\}$. This can be expressed as:

$$P_t = \mathcal{P}_t(\{MC_s\}) \tag{A.47}$$

which, when log-linearized around steady state, gives:

$$\hat{P}_t = \sum_{s=0}^{\infty} \frac{\partial \log P_t}{\partial \log MC_s} \hat{MC}_s \tag{A.48}$$

Defining the pass-through matrix $\Psi_{t,s}$ as:

$$\Psi_{t,s} = \frac{\partial \log P_t}{\partial \log MC_s} \tag{A.49}$$

we can express the aggregate price level response as:

$$\hat{P} = \Psi \hat{MC} \tag{A.50}$$

We denote by $\Psi^{TD}_{\Phi_s}$ the canonical pass-through matrix when the strategic complementarity and the information friction are absent. It takes the form as equation (12) in Auclert et al. (2024).

$$\Psi^{TD} \equiv \frac{1}{(\sum_{s\geq 0}\Phi_s)(\sum_{s\geq 0}\beta^s\Phi_s)} \begin{pmatrix} \Phi_0 & 0 & 0 & \cdots \\ \Phi_1 & \Phi_0 & 0 & \cdots \\ \Phi_2 & \Phi_1 & \Phi_0 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \begin{pmatrix} \Phi_0 & \beta\Phi_1 & \beta^2\Phi_2 & \cdots \\ 0 & \Phi_0 & \beta\Phi_1 & \cdots \\ 0 & 0 & \Phi_0 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

Combining the policy function (A.45) and the law of motion (A.46), I obtain the pass-through matrix for a TD model with both strategic complementarity and information friction as:

$$\hat{P} = \Gamma\Psi^{TD}(I - (1-\Gamma)\Psi^{TD}M)^{-1}\hat{MC} \tag{A.51}$$

where M is a diagonal matrix that captures both strategic complementarity and information friction.

■

Proposition: CG slope with multiple learned shocks

Proposition A.2. *Let the n-dimensional state s_t evolve as*

$$s_t = As_{t-1} + \varepsilon_t, \qquad z_t = Hs_t + \eta_t,$$

and let inflation be $\pi_t = c's_t$. Agents form $\bar{E}_t[\cdot]$ using the steady-state Kalman filter with gain K. For a fixed horizon $k \geq 0$, define the revision and forecast error

$$R_t \equiv \bar{E}_t[\pi_{t+k}] - \bar{E}_{t-1}[\pi_{t+k}], \qquad FE_t \equiv \pi_{t+k} - \bar{E}_t[\pi_{t+k}].$$

Consider the Coibion–Gorodnichenko regression $FE_t = K_{CG}R_t + v_{t+k,t}$. Let $\nu_t \equiv z_t - H\hat{s}_{t|t-1}$ be the innovation with covariance $S \equiv (\nu_t)$. Then

$$K_{CG} \;=\; \frac{c'A^k(I-KH)\,S\,K'(A^k)'c}{c'A^kK\,S\,K'(A^k)'c}.$$

Special case: *If $H = I$, $A = \mathrm{diag}(\rho_i)$, $K = \mathrm{diag}(G_i)$, $S = \mathrm{diag}(\sigma^2_{\nu,i})$, and $c = (\alpha_1, \ldots, \alpha_n)'$, then*

$$K_{CG} = \frac{\sum_{i=1}^n \alpha_i^2\rho_i^{2k}\,G_i(1-G_i)\,\sigma^2_{\nu,i}}{\sum_{i=1}^n \alpha_i^2\rho_i^{2k}\,G_i^2\,\sigma^2_{\nu,i}} = \sum_{i=1}^n \omega_i\,\frac{1-G_i}{G_i}, \qquad \omega_i \equiv \frac{\alpha_i^2\rho_i^{2k}\,G_i^2\,\sigma^2_{\nu,i}}{\sum_{j=1}^n \alpha_j^2\rho_j^{2k}\,G_j^2\,\sigma^2_{\nu,j}}.$$

Proof. **Setup and notation.** Let $\hat{s}_{t|t-1}$ and $\hat{s}_{t|t}$ denote the Kalman predictor and filter at time t; in steady state

$$\hat{s}_{t|t} = \hat{s}_{t|t-1} + K\nu_t, \qquad \nu_t := z_t - H\hat{s}_{t|t-1}, \qquad S := (\nu_t).$$

For $k \geq 0$,

$$\bar{E}_t[\pi_{t+k}] = c'A^k\hat{s}_{t|t}, \qquad \bar{E}_{t-1}[\pi_{t+k}] = c'A^k\hat{s}_{t|t-1}.$$

(1) Revision.

$$R_t = \bar{E}_t[\pi_{t+k}] - \bar{E}_{t-1}[\pi_{t+k}] = c'A^k(\hat{s}_{t|t} - \hat{s}_{t|t-1}) = c'A^kK\nu_t. \tag{1}$$

(2) Forecast error decomposition. Write the k-ahead state error

$$e_{t+k|t} := s_{t+k} - \hat{s}_{t+k|t} = A^k(s_t - \hat{s}_{t|t}) + \sum_{j=1}^{k} A^{k-j}\varepsilon_{t+j}.$$

Hence

$$FE_t = \pi_{t+k} - \bar{E}_t[\pi_{t+k}] = c'e_{t+k|t} = c'A^k(s_t - \hat{s}_{t|t}) \; + \; \underbrace{\sum_{j=1}^{k} c'A^{k-j}\varepsilon_{t+j}}_{=:\xi_{t+k,t}}. \tag{2}$$

By construction $\xi_{t+k,t}$ is orthogonal to any t-dated object (in particular to ν_t and to R_t).

(3) Innovations representation for the t-dated component. We project the t-dated term $c'A^k(s_t - \hat{s}_{t|t})$ onto ν_t. Two standard Kalman identities in steady state are

$$(s_t, \nu_t) = PH', \qquad K = PH'S^{-1},$$

where $P = (s_t - \hat{s}_{t|t-1})$. Then the linear projection of s_t on ν_t is $K\nu_t$, while $\hat{s}_{t|t} = \hat{s}_{t|t-1} + K\nu_t$ has the same projected part. Therefore

$$\left[s_t - \hat{s}_{t|t} \,\middle|\, \nu_t\right] = [s_t \,|\, \nu_t] - [\hat{s}_{t|t} \,|\, \nu_t] = K\nu_t - K\nu_t = 0.$$

The orthogonal complement of $s_t - \hat{s}_{t|t}$ relative to ν_t is nevertheless *not* zero; using the filter update,

$$s_t - \hat{s}_{t|t} = (I - KH)(s_t - \hat{s}_{t|t-1}) - K\eta_t = (I - KH)\underbrace{(s_t - \hat{s}_{t|t-1})}_{\perp \eta_t} - K\eta_t.$$

Since $\nu_t = H(s_t - \hat{s}_{t|t-1}) + \eta_t$, a standard projection argument yields

$$c'A^k(s_t - \hat{s}_{t|t}) = c'A^k(I - KH)\,\nu_t \; + \; \zeta_t, \tag{3}$$

where ζ_t is orthogonal to ν_t (hence to R_t). Combining (2)–(3),

$$FE_t = c'A^k(I - KH)\,\nu_t \; + \; \underbrace{(\zeta_t + \xi_{t+k,t})}_{\perp \nu_t}. \tag{4}$$

(4) CG slope as a projection coefficient. From (1) and (4),

$$(FE_t, R_t) = \big(c' A^k (I - KH) v_t,\, c' A^k K v_t\big) = c' A^k (I - KH)\, S\, K' (A^k)' c,$$

$$(R_t) = \big(c' A^k K v_t\big) = c' A^k K\, S\, K' (A^k)' c.$$

Thus

$$K_{CG} \;=\; \frac{(FE_t, R_t)}{(R_t)} = \frac{c' A^k (I - KH)\, S\, K' (A^k)' c}{c' A^k K\, S\, K' (A^k)' c}.$$

(5) Special case with $H = I$. Let $A = \mathrm{diag}(\rho_i)$, $K = \mathrm{diag}(G_i)$, $S = \mathrm{diag}(\sigma^2_{v,i})$, $c = (\alpha_i)$. Then $(I - KH) = \mathrm{diag}(1 - G_i)$ and matrices commute elementwise, yielding

$$K_{CG} = \frac{\sum_{i=1}^n \alpha_i^2 \rho_i^{2k}\, G_i (1 - G_i)\, \sigma^2_{v,i}}{\sum_{i=1}^n \alpha_i^2 \rho_i^{2k}\, G_i^2\, \sigma^2_{v,i}} = \sum_{i=1}^n \underbrace{\frac{\alpha_i^2 \rho_i^{2k} G_i^2 \sigma^2_{v,i}}{\sum_{j=1}^n \alpha_j^2 \rho_j^{2k} G_j^2 \sigma^2_{v,j}}}_{=:\,\omega_i} \; \frac{1 - G_i}{G_i}.$$

This is a variance-weighted average of $(1 - G_i)/G_i$, not an unweighted average of G_i. ■

Proposition of extended search model

Proposition A.3 (Purchase Probability is invariant in j under scaled search cost)**.** *Let v^* solve the single-product reservation equation*

$$\bar\kappa \;=\; S(v) \;\equiv\; \iint_{\epsilon \ge \lambda(v+p)} \Big(\tfrac{1}{\lambda}\epsilon - p - v\Big)\, g(\epsilon)\, d\epsilon\, f(p)\, dp,$$

and define the associated acceptance probability

$$\rho(v) \;=\; \int \Big[1 - G\big(\lambda(v + p)\big)\Big] f(p)\, dp.$$

Suppose a store provides $j \in \mathbb{N}$ i.i.d. product draws, the consumer may buy any subset of products, and the per-store search cost scales with the number of remaining products as $\kappa_j = j\,\bar\kappa$. Then the optimal per-product reservation level satisfies $v_j^* = v^*$ for all j, and the per-product acceptance probability is constant:

$$\rho_j \;=\; \rho(v_j^*) \;=\; \rho(v^*) \quad \textit{for all } j \in \mathbb{N}.$$

Proof. **Step 1 (single-product option value and monotonicity).** For a cutoff v, define

$$S(v) \;=\; \Big[\Big(\tfrac{1}{\lambda}\epsilon - p - v\Big)_+\Big] \;=\; \iint_{\epsilon \ge \lambda(v+p)} \Big(\tfrac{1}{\lambda}\epsilon - p - v\Big) g(\epsilon)\, d\epsilon\, f(p)\, dp.$$

Under standard regularity, S is continuous and strictly decreasing in v. Hence, for any $\bar\kappa > 0$, the equation $S(v) = \bar\kappa$ has a unique solution v^*.

Step 2 (additivity with j products at a store). Fix $j \ge 1$ and a symmetric per-product cutoff v. The net option value from one more store equals

$$\Big[\sum_{k=1}^{j} \Big(\tfrac{1}{\lambda}\epsilon_k - p_k - v\Big)_+\Big] \;=\; \sum_{k=1}^{j} \Big[\Big(\tfrac{1}{\lambda}\epsilon - p - v\Big)_+\Big] \;=\; j\, S(v),$$

by linearity and independence.

Step 3 (reservation equation with scaled search cost). With j products remaining and symmetric cutoff v_j^*, the reservation condition is

$$\kappa_j \;=\; j\,S(v_j^*).$$

Impose $\kappa_j = j\,\bar{\kappa}$. Then $j\,\bar{\kappa} = j\,S(v_j^*)$ implies $S(v_j^*) = \bar{\kappa}$. By uniqueness from Step 1, $v_j^* = v^*$ for all j.

Step 4 (acceptance probability invariance). Therefore,

$$\rho_j \;=\; \rho(v_j^*) \;=\; \rho(v^*) \quad \text{for all } j,$$

as claimed. ■

Proposition A.4 (Distributions of L and B under independence)**.** *Fix $K \geq 1$. Let $\pi_{j,b}$ denote the truncated-binomial kernel at j remaining goods and $b \in \{1,\dots,j\}$. Then:*

(i) The pmf of the number of purchase stores L satisfies

$$\Pr(L = \ell \mid K) = G_K(\ell), \qquad G_0(0) = 1,\; G_0(\ell \geq 1) = 0, \quad G_j(\ell) = \sum_{b=1}^{j} \pi_{j,b}\, G_{j-b}(\ell - 1) \quad (j \geq 1,\; \ell \geq 1).$$

(ii) Let $T_j := [L \mid j]$ and $E_{j,b} := [\#$ of size-b baskets in a spell $\mid j]$. They solve

$$T_0 = 0, \quad T_j = 1 + \sum_{s=1}^{j} \pi_{j,s}\, T_{j-s}, \qquad E_{0,b} = 0, \quad E_{j,b} = \pi_{j,b} + \sum_{s=1}^{j} \pi_{j,s}\, E_{j-s,b}.$$

The (unconditional, pooled-over-purchases) basket-size pmf is

$$\Pr(B = b \mid K) = \frac{E_{K,b}}{T_K}, \qquad b = 1,\dots,K.$$

(iii) With heterogeneous K and weights w_K ($\sum_K w_K = 1$),

$$\Pr(L = \ell) = \sum_K w_K\, G_K(\ell), \qquad \Pr(B = b) = \frac{\sum_K w_K\, E_{K,b}}{\sum_K w_K\, T_K}.$$

Proof. Notation. For $j \geq 1$, $\pi_{j,b} = \Pr(B = b \mid j)$ is the binomial(j, ρ) pmf truncated to $\{1,\dots,j\}$:

$$\pi_{j,b} = \frac{\binom{j}{b}\rho^b(1-\rho)^{j-b}}{1-(1-\rho)^j}, \qquad b = 1,\dots,j.$$

(i) Distribution of $L \mid K$. First-step analysis at j goods: the first purchase store yields basket b with probability $\pi_{j,b}$ and leaves $j - b$ goods. The total number of purchase stores equals $1 + L'$ where $L' \overset{d}{=} L \mid (j-b)$. Conditioning on b yields

$$G_j(\ell) = \sum_{b=1}^{j} \pi_{j,b}\, G_{j-b}(\ell - 1), \qquad j \geq 1,\; \ell \geq 1,$$

with $G_0(0) = 1$ and $G_0(\ell \geq 1) = 0$. This gives $\Pr(L = \ell \mid K) = G_K(\ell)$.

(ii) Mean T_j and expected counts $E_{j,b}$. The same first-step decomposition for the mean gives

$$T_j = [L \mid j] = 1 + \sum_{s=1}^{j} \pi_{j,s}\, T_{j-s}, \qquad T_0 = 0.$$

For expected counts of size-b baskets, write N_b for the total number of size-b baskets in the spell. At the first purchase store,

$$N_b = \mathbf{1}\{B = b\} + N_b', \qquad N_b' \text{ from the continuation with } j - B.$$

Taking expectations and conditioning on $B = s$,

$$E_{j,b} = \sum_{s=1}^{j} \pi_{j,s}\big(\mathbf{1}\{s = b\} + E_{j-s,b}\big) = \pi_{j,b} + \sum_{s=1}^{j} \pi_{j,s}\, E_{j-s,b}, \qquad E_{0,b} = 0.$$

Under the common empirical sampling scheme that pools *all* purchase stores across spells, the basket-size pmf is the ratio of expected counts to the expected total number of purchases:

$$\Pr(B = b \mid K) = \frac{[N_b \mid K]}{[L \mid K]} = \frac{E_{K,b}}{T_K}.$$

(iii) Mixture over K. By the law of total probability and linearity of expectation,

$$\Pr(L = \ell) = \sum_K w_K \Pr(L = \ell \mid K) = \sum_K w_K\, G_K(\ell).$$

For baskets pooled over spells, the total expected number of size-b purchases equals $\sum_K w_K E_{K,b}$ and the expected total number of purchases equals $\sum_K w_K T_K$, hence

$$\Pr(B = b) = \frac{\sum_K w_K\, E_{K,b}}{\sum_K w_K\, T_K}.$$

This completes the proof. □ ■

Extension to Multiple Goods with Only Store-level Taste Shock The baseline model only allows firms to produce one good and each shopper purchases and consume one good from one firm. In this extension, I allow multiple goods to be produced by one firm. The firm produces goods with different productivity for each good.

$$\log A_{kj} = \log A + a_k + a_{kj}$$

where a_{kj} is the productivity of producing good j by firm k. It is i.i.d following $a_{kj} \sim \mathcal{N}(0, \tilde{\sigma}_{ap}^2)$. I assume that there is no search frictions when shopping within a firm. Shoppers draw a taste shock to the entire firm and decide which firm to purchase form and then buy the CES aggregation of all the goods in the firm. Let P_k denote the CES price index of multiple goods in firm k. We have the following result.

Proposition A.5. *Each firm charges same markup over all the products it sells.*

$$P_{kj} = \frac{e_k}{e_k - 1}\frac{W}{A_{kj}} \tag{A.52}$$

where e_k is the elasticity of demand uniform for all j. It is determined by

$$P_k = \frac{e_k}{e_k - 1}\frac{W}{A_k}; e_k = \lambda \frac{\int \exp(x)\big(g\big(\lambda(v^*(x) + p_k)\big)\big)d\Phi_x(x)}{\int \exp(x)\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big)d\Phi_x(x)} + 1 \tag{A.53}$$

where P_k is the CES price index of P_{kj} and $p_k = \log(P_k)$. The passthrough of product-level productivity shocks a_{kj} increases toward one when the number of products increases.

Proof. See Appendix A. ■

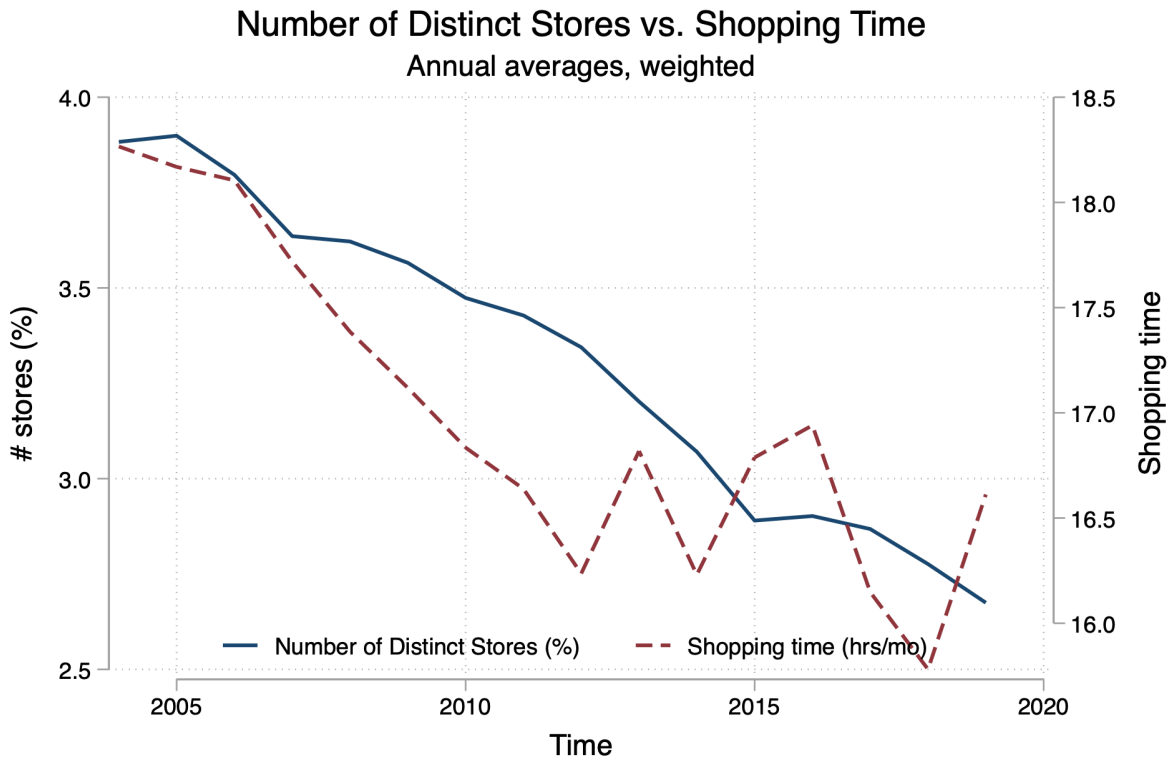
This extension is consistent with the result in Hottman et al. (2016) and speaks to the empirical literature on passthrough of exchange rate shock to retail prices. Goldberg and Hellerstein (2013) and Nakamura and Zerom (2010) find complete passthrough of wholesale prices to retail prices for beer and coffee sales in retail stores.[42] The proposition shows that when there are many goods in one store, the passthrough of product-specific idiosyncratic shocks is closed to one. However, this does not mean that the passthrough of aggregate shocks and firm-specific shocks is complete.

[42]See Gopinath et al. (2011) for a summary of this literature.

B Additional Results on Empirics

Time Trend of Shopping Time and Distinct-Store Measure Figure B.1 shows the time trend of average shopping time from ATUS and average distinct-store measure from Nielsen Consumer Panel data. They show the similar trends. The overall effort spent on shopping is declining. This could reflect the fact that the increasing concentration in the retail industry decreases the benefit of searching since stores within the same retail chain set similar prices (DellaVigna and Gentzkow, 2019).

Figure B.1: Time Trend of Search Activities



Search Elasticity of Inflation Shocks Table B.1 shows the full results that are omitted in Panel A in Table 2. Column (1) and (2) corresponds to Column (1) and (2) in Table 2. Column (4) and (5) corresponds to Column (3) and (4) in Table 2. The results show that the past inflation has long-lasting effects on current search activities.

Finally, Columns (3) and (6) add controls for household size, age, and total spending, and the estimates decline markedly, indicating substantial heterogeneity of the effect of inflation on search across size and age. Specifically, larger and older households increase search more when inflation picks up. In our data, about 40% of households change household size and about 65% transition across age categories over the sample period,[43] so conditioning on these time–varying characteristics absorbs a sizable share of the effect of inflation.

Similarly, Table B.2 shows the full results that are omitted in Panel B of Table 2. The results still show that the past inflation has long-lasting effects on current search activities.

[43] NielsenIQ defines nine age categories; "household size" is the number of members in the household.

Table B.1: Estimates Using π (Dependent variables: trips and stores)

	(1)	(2)	(3)	(4)	(5)	(6)
	Trip	Trip	Trip	Store	Store	Store
π	4.856***	2.683***	1.853***	3.797***	1.980***	1.338***
	(0.139)	(0.112)	(0.110)	(0.122)	(0.099)	(0.098)
$L.\pi$	0.305***	-0.032	-0.707***	1.036***	0.654***	0.154
	(0.118)	(0.111)	(0.116)	(0.108)	(0.102)	(0.104)
$L2.\pi$	5.666***	4.404***	3.509***	4.107***	2.856***	2.127***
	(0.139)	(0.119)	(0.123)	(0.124)	(0.108)	(0.109)
$L3.\pi$	4.084***	2.393***	0.999***	3.493***	1.980***	0.967***
	(0.135)	(0.116)	(0.120)	(0.124)	(0.106)	(0.108)
$L4.\pi$	2.720***	1.811***	0.938***	2.526***	1.574***	0.902***
	(0.138)	(0.119)	(0.124)	(0.124)	(0.109)	(0.110)
$L5.\pi$	3.926***	2.424***	1.386***	3.256***	1.829***	1.034***
	(0.140)	(0.120)	(0.125)	(0.127)	(0.109)	(0.111)
$L6.\pi$	3.143***	1.731***	0.825***	2.749***	1.447***	0.753***
	(0.136)	(0.120)	(0.125)	(0.124)	(0.109)	(0.111)
$L7.\pi$	3.343***	2.371***	1.667***	2.676***	1.733***	1.172***
	(0.131)	(0.117)	(0.122)	(0.118)	(0.107)	(0.109)
$L8.\pi$	4.898***	3.101***	1.883***	3.977***	2.340***	1.435***
	(0.137)	(0.120)	(0.124)	(0.125)	(0.109)	(0.110)
$L9.\pi$	2.998***	1.568***	0.431***	2.803***	1.441***	0.583***
	(0.131)	(0.116)	(0.121)	(0.119)	(0.106)	(0.108)
$L10.\pi$	3.423***	2.520***	1.862***	2.703***	1.851***	1.334***
	(0.126)	(0.116)	(0.121)	(0.114)	(0.106)	(0.108)
$L11.\pi$	6.835***	4.152***	2.379***	5.524***	3.049***	1.722***
	(0.153)	(0.118)	(0.115)	(0.135)	(0.104)	(0.102)
Total_Spending			0.125***			0.072***
			(0.001)			(0.001)
Constant	175.215***	178.133***	126.034***	101.109***	103.823***	74.111***
	(0.257)	(0.088)	(0.436)	(0.236)	(0.073)	(0.336)
Observations	6,922,774	6,921,646	6,921,359	6,922,774	6,921,646	6,921,359

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table omits the constant as requested.

Table B.2: Estimates Using π_{oil} (Dependent variables: trips and stores)

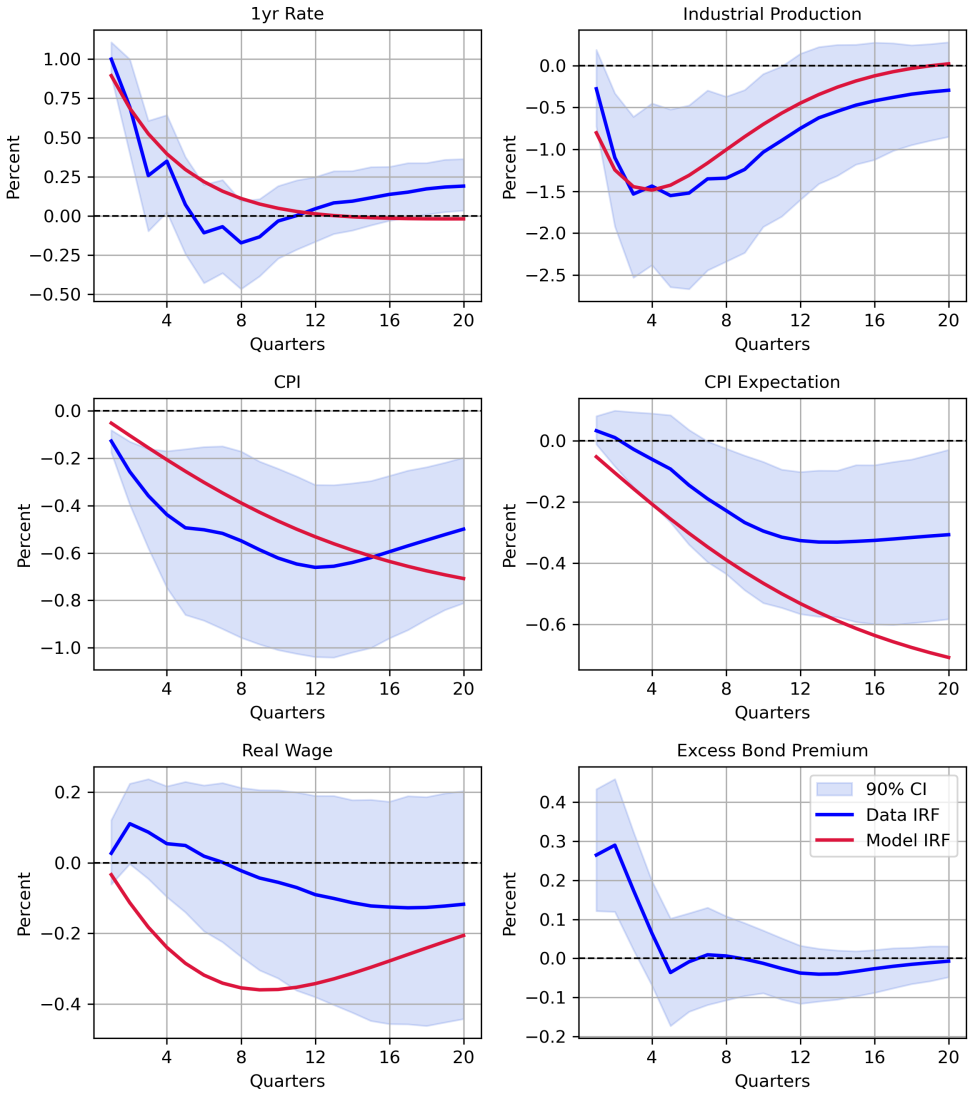
	(1)	(2)	(3)	(4)	(5)	(6)
	Trip	Trip	Trip	Store	Store	Store
π_{oil}	5.728***	2.883***	2.179***	4.688***	2.465***	1.610***
	(0.206)	(0.167)	(0.167)	(0.180)	(0.148)	(0.147)
$L.\pi_{\text{oil}}$	4.679***	3.097***	2.356***	3.954***	2.481***	1.732***
	(0.177)	(0.161)	(0.161)	(0.158)	(0.145)	(0.146)
$L2.\pi_{\text{oil}}$	3.482***	2.286***	1.343***	3.130***	1.903***	1.019***
	(0.179)	(0.162)	(0.162)	(0.161)	(0.146)	(0.147)
$L3.\pi_{\text{oil}}$	5.846***	4.271***	3.296***	4.500***	3.037***	2.106***
	(0.186)	(0.164)	(0.163)	(0.167)	(0.149)	(0.149)
$L4.\pi_{\text{oil}}$	5.255***	3.285***	2.237***	4.434***	2.639***	1.581***
	(0.187)	(0.163)	(0.163)	(0.168)	(0.147)	(0.148)
$L5.\pi_{\text{oil}}$	4.974***	2.514***	1.097***	4.783***	2.408***	1.174***
	(0.195)	(0.166)	(0.166)	(0.172)	(0.148)	(0.148)
$L6.\pi_{\text{oil}}$	4.125***	2.713***	1.945***	3.364***	2.082***	1.363***
	(0.184)	(0.166)	(0.166)	(0.164)	(0.148)	(0.149)
$L7.\pi_{\text{oil}}$	4.733***	3.027***	2.055***	3.775***	2.212***	1.365***
	(0.191)	(0.163)	(0.163)	(0.170)	(0.148)	(0.149)
$L8.\pi_{\text{oil}}$	6.252***	4.182***	3.073***	5.048***	3.145***	2.087***
	(0.193)	(0.165)	(0.164)	(0.172)	(0.149)	(0.149)
$L9.\pi_{\text{oil}}$	3.025***	1.531***	0.713***	2.931***	1.579***	0.709***
	(0.186)	(0.165)	(0.165)	(0.166)	(0.148)	(0.149)
$L10.\pi_{\text{oil}}$	5.579***	3.788***	2.513***	4.706***	3.011***	1.905***
	(0.200)	(0.168)	(0.167)	(0.177)	(0.151)	(0.151)
$L11.\pi_{\text{oil}}$	10.353***	6.412***	4.476***	8.059***	4.448***	2.661***
	(0.228)	(0.174)	(0.173)	(0.201)	(0.153)	(0.151)
Total_Spending						0.072***
						(0.001)
Constant	172.108***	176.240***	178.417***	98.542***	102.311***	73.130***
	(0.297)	(0.135)	(0.133)	(0.269)	(0.112)	(0.344)
Observations	6,922,774	6,921,646	6,921,646	6,922,774	6,921,646	6,921,359

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Additional Details on Calibration and Estimation

Estimated Calvo model: I present the estimated Calvo model where the wage rigidity and the persistence of the monetary policy shock are fixed at the values reported in Table 3. The estimated Calvo parameter is 0.9. Figure C.1 shows the result. The model yields a good fit for the inflation and output responses. However, it fails to capture the response of inflation expectations.

Figure C.1: Empirical and Calvo Model Impulse Responses



Notes: The figure plots the impulse responses for 4 variables following a 100 bp shock on the 1-year government bond rate. The sample period is 1978M1–2019M12. The blue lines represent the empirical impulse responses and the red lines represent the Calvo model counterparts. The shaded areas are 90% confidence intervals derived from wild bootstrap. The red line represents the impulse responses implied in Section 5. The x-axis denotes quarters from the shock, starting at 0. The y-axis denotes percent.

Figure C.3: Calvo-Equivalence to Baseline Model

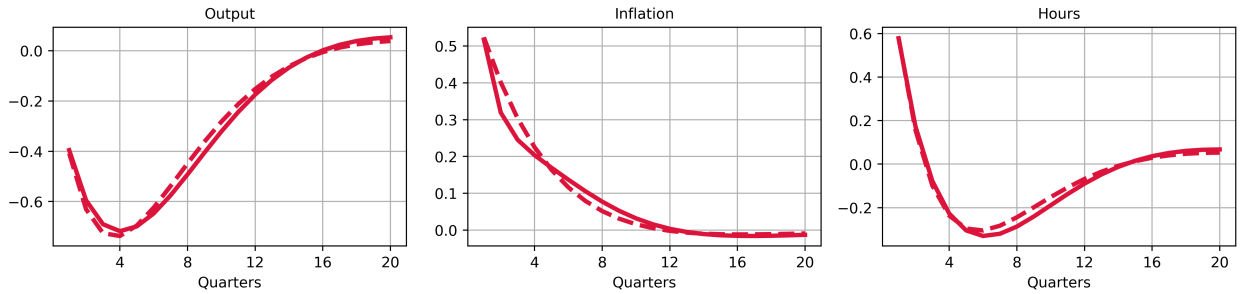
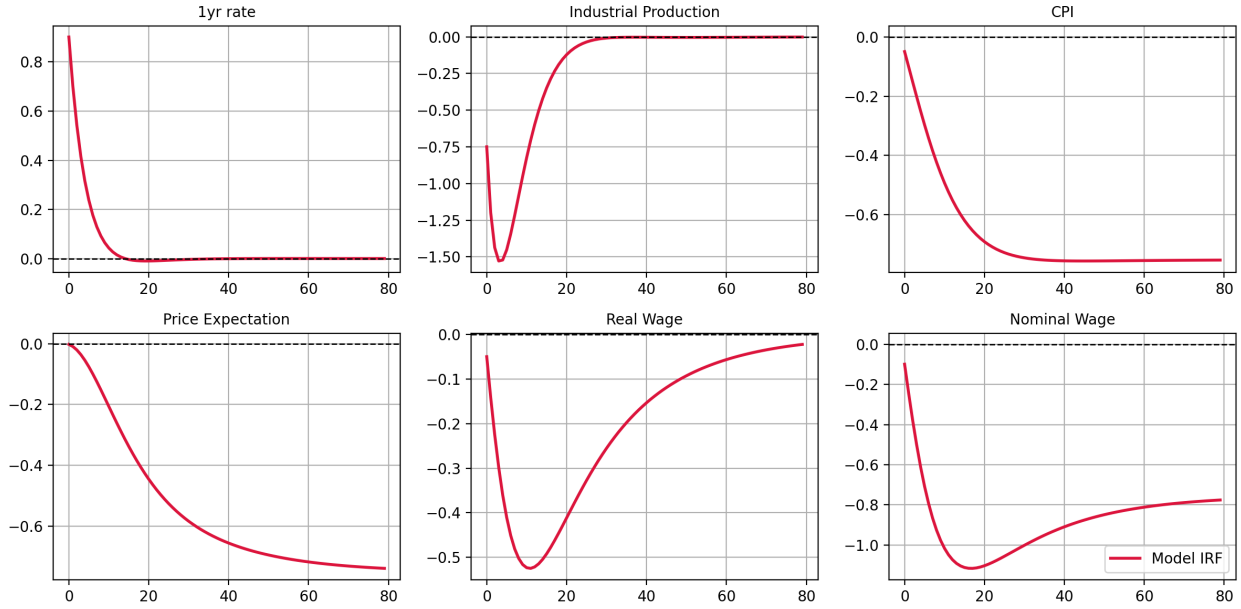


Figure C.2: Longer-Horizon Model Impulse Responses

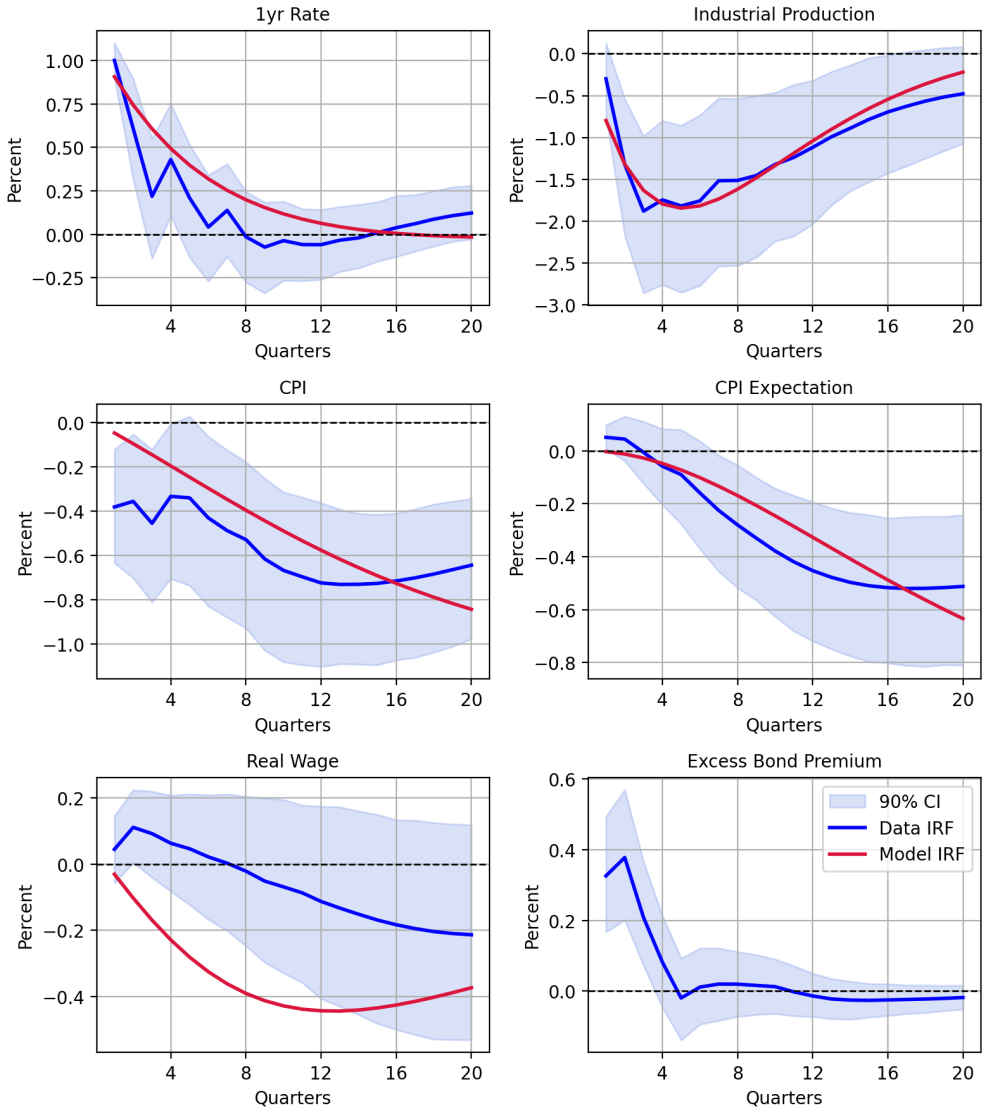


Notes: The figure plots the impulse responses for the longer horizons. The x-axis denotes quarters from the shock, starting at 0. The y-axis denotes percent.

Figure C.3 shows that a Calvo model with $\lambda_p = 0.45$ aligns well with the model with $\theta = 0.4$, indicating shock-dependent Phillips curve.

Other Robustness Checks – Figure C.4 shows the first robustness check where I use the raw CPI instead of adjusted CPI. The estimated persistence now increases to 0.84, and the information friction is 0.067, implying the average duration of information friction is 15 quarters. Now, the wage rigidity alone accounts for 35% monetary non-neutrality. Conditional on having information friction and wage rigidity, the price rigidity accounts for about 4.5% non-neutrality, which is still extremely small. The information friction thus accounts for about 60% monetary non-neutrality.

Figure C.4: Robustness: CPI



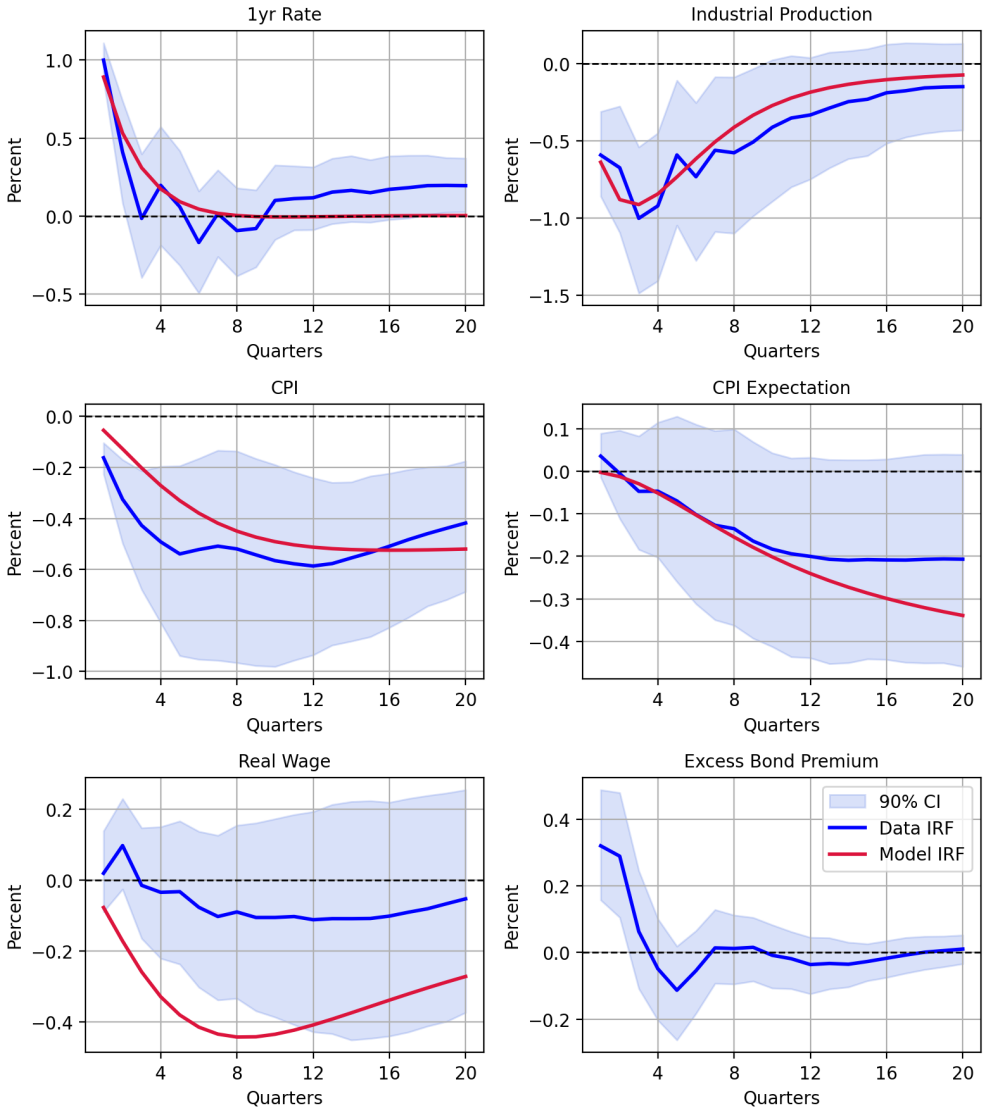
Notes: I use the raw CPI instead of adjusted CPI.

Figure C.5 shows the second robustness check where I use the monthly Brave-Butters-Kelley real GDP instead of the Industrial Production Index. The response of GDP index is much smaller than IP index, inducing a smaller persistence of monetary shock, which is estimated to be 0.72. The wage stickiness is also smaller, 0.88, as the shock is less persistent. However, the estimated information friction is 0.05, almost the same as the result of the baseline result.

The wage rigidity alone accounts for 23% monetary non-neutrality. Conditional on having information friction and wage rigidity, the price rigidity accounts for almost zero non-neutrality. The information friction thus accounts for about 77% monetary non-neutrality.

Overall, although the persistence of monetary shock and the degree of wage stickiness vary across specifications, the estimate of information friction is robust. The average duration of information friction is between 15 quarters to 20 quarters.

Figure C.5: Robustness: GDP



Notes: I use the Brave-Butters-Kelley Real Gross Domestic Product Index instead of the Industrial Production Index.