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

Xiaojie Liu†

November 12, 2024

Click here to view the latest version

Abstract

This paper develops a model of monetary non-neutrality driven by information asymmetry between consumers and firms about nominal marginal costs in a sequential search framework. With only consumer-side frictions, this approach is distinguished from the standard one that relies on firm-side pricing frictions. Under incomplete information, consumers' perceived price distribution determines their subjective value of search. As a result, firm's elasticity of demand depends on shoppers' expectation of the price index. The passthrough of aggregate shocks to prices is therefore incomplete. The key mechanism is that, following a monetary shock, consumers attribute some of the resulting price changes to firm-specific adverse shocks, inducing them to search for alternatives. To dissuade search, firms compress the markup and limit the passthrough of the shock. Furthermore, the Phillips curve shows that the monetary non-neutrality is proportional to the nowcast error of inflation. Despite its parsimonious nature, the calibrated model can generate substantial monetary non-neutrality. Consistent with the mechanism, higher inflation is associated empirically with more active consumer search, and regions with higher search frictions exhibit lower passthrough.

Keywords: Monetary non-neutrality, Phillips curve, search, information frictions, information asymmetry, passthrough

*I am grateful for comments and discussions with Alireza Tahbaz-Salehi, Lawrence Christiano, Sara Moreira, George-Marios Angeletos, Benjamin Jones, Alessandro Pavan, Harry Pei, Diego Kanzig, Chen Lian and Huo Zhen, Ryungha Oh.

†Kellogg School of Management, Northwestern University. Email: xiaojie.liu@kellogg.northwestern.edu

"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 known to have large real effects on the economy in the short run. Both output and inflation decline following an unexpected increase in interest rate,. This pattern has been repeatedly uncovered in the empirical literature.[1] Most of existing theories explain this phenomenon by focusing on frictions on the firm side. Models of price stickiness posit that price adjustments are infrequent due to either exogenous factors (Taylor, 1980; Calvo, 1983) or fixed costs (Mankiw, 1985; Golosov and Lucas, 2007). Another theory which dates at least back to Phelps (1969) and Lucas (1972) suggests that firms set prices based on incomplete information about aggregate shocks. Reis (2006) and Alvarez et al. (2016b) further argue that costs of acquiring and processing information contribute to price rigidity.

Growing evidence suggests that consumers are subject to more severe frictions than firms. For instance, consumers have misperception about inflation (Binetti et al., 2024; Candia et al., 2023) and pay particular attention to salient prices (Kumar et al., 2015; D'Acunto et al., 2021b). Moreover, Kaplan and Menzio (2015) and Kaplan et al. (2019) document a large price dispersion for an identical product even within the same market and week. This indicates some friction that hinders consumers from finding the cheapest one. These evidence motivates two central questions: Can we micro-found monetary non-neutrality using only the consumer-side frictions? How do these consumer-side frictions affect the transmission of monetary policy?

To address these questions, I develop a new monetary paradigm that places consumer-side frictions at the center. Consumers have two frictions: (i) information friction about firms' nominal marginal costs and (ii) search frictions on the good market. On the other hand, firms have full information about the model economy and set the prices flexibly. The main mechanism operates as follows. Following a positive monetary shock, the nominal wage increases. Firms tend to increase prices. However, shoppers with incomplete information about the nominal wage attribute much of this price increase to firm-specific adverse shocks. Shoppers who are initially indifferent between

[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.

purchasing and searching are now incentivized to seek outside options. To dissuade search, firms compress markups, thereby limiting the passthrough of the monetary shock.

I first characterize the full-information equilibrium in which only search friction is present, and show the monetary neutrality in this case. Then, I characterize the passthrough from the monetary shock to the price index under incomplete information and show that, generically, the passthrough is incomplete. Larger frictions further decrease the passthrough. Next, I characterize the slope of Phillips curve in terms of the two frictions. I further show that the output gap is proportional to the consumers' inflation nowcast error. Finally, I develop a dynamic general equilibrium model which can be solved by a three-equation system. The model exhibits substantial monetary non-neutrality under parsimonious calibration. The persistence of the output response is endogenously determined.

Model − I start with a static model to show the core mechanism. There are shoppers, firms and a monetary authority who sets the nominal wage. A monetary shock is considered as a shock to the nominal wage. Shopper's problem follows the sequential search literature (Wolinsky, 1986; Anderson and Renault, 1999). Specifically, shoppers search sequentially and randomly without commitment. Also, shoppers must incur a search cost to visit a firm and learn both the price and the associated match utility of its good. I extend this framework in two ways. First, I introduce firms with heterogeneous productivity, which induces a price distribution. Second, shoppers have incomplete information about the nominal wage. They construct their own perceived price distributions as the weighted average of the objective price distributions conditional on a given nominal wage. The value of an additional search now depends on both the perceived price distribution and the exogenous match utility distribution.

Each shopper receives a signal about the nominal wage before shopping. For tractability, I assume that shoppers do not learn the nominal wage from individual prices they observe throughout the search. Under this assumption, the optimal search strategy maps shopper's signal to a unique threshold. The optimal search strategy is then characterized by a threshold rule: if the value of a good exceeds the threshold, the shopper proceeds with the purchase. Otherwise, the shopper continues shopping. Firm's demand is derived from the aggregation of individual shopper's optimal search decisions. Firms then select the optimal pricing strategy that maps the idiosyncratic productivity and the nominal wage to its price.

Monetary Neutrality Result under FIRE – I first focus on the full-information rational expectations (FIRE) equilibrium. Under FIRE, shoppers can derive the actual price distribution conditional on the nominal wage, which is now the common knowledge. First, I prove the existence of a unique FIRE equilibrium in which shoppers search actively. Then, I show the first main result of this paper: under the full information about the nominal wage, the real quantities, e.g., the aggregate output and the demand allocation across firms remain the same after the monetary shock. Thus, the monetary policy is neutral. The key takeaway of this result is that the search friction alone is not sufficient to generate monetary non-neutrality. We need the interplay of two frictions.

Monetary Non-Neutrality Result under IIRE – In the incomplete-information rational expectations (IIRE) equilibrium, the optimal strategies are highly non-linear. To proceed, I consider a small monetary shock and hold the signal-to-noise ratio fixed. Then, I approximate the optimal search and pricing strategies to the first order. Specifically, I show that the threshold decreases with shopper's expectation of the price index. The intuition is simple: shoppers are more inclined to make purchases when they expect higher price index and therefore, worse outside options. Next, I show that the elasticity of demand increases in the perceived relative price, defined as the ratio between the actual firm's price and the average expectation of the price index. Average expectation is typically dampened due to the information friction. As a result, firms behave as if they are competing against other firms setting lower prices. The key property here is that firms respond to shopper' expectation of the price index rather than the actual one. In response, firms lower their prices, which compresses the markup and limits the passthrough of the shock.

I derive the aggregate total passthrough, i.e., the passthrough from the shock to the price index on the first order, based the passthroughs of own-cost shocks and competitors' prices derived from optimal pricing strategy. I present the main theorem of this paper that shows (i) the aggregate total passthrough is generically incomplete and (ii) high-productivity firms contribute more to the incompleteness because they have lower passthrough and larger market share and (iii) the aggregate total passthrough decreases with both frictions, with one friction amplifies the effect of the other.

Main Insight – We can understand the main insight of this result in the tradition of the beauty contest models (Morris and Shin, 2002; Angeletos and Lian, 2023). The model can be written as a game where the firm sets its price with respect to the shock on cost, as well as shoppers' expectation of the price index. The latter depends on the whole spectrum of the higher-order shoppers' beliefs about the shock. With the presence of the information friction, the higher-order beliefs are more anchored to the prior and less responsive to shocks. Intuitively, if the shopper thinks that other shoppers are not responsive to the shock, the best response is to react even less. Since firms only respond to shoppers' expectation of the price index, the price response is thus dampened.

To understand how firms, taking the shopper's expectation as given, react to each order of the shoppers' belief, I borrow tools from Level-k thinking (Farhi and Werning, 2019). I consider the rational expectation case in which $k \to \infty$. In the language of Level-k thinking literature, level-1 thinkers believe other firms do not respond to the shock. The passthrough of the shock to prices is then equal to the own-cost passthrough. Iteratively, level-k thinkers believe other firms are $k-1$th level thinkers. They thus pass through additional amount of the shock due to strategic complementarity in pricing, which is mitigated by the information friction. The magnitude of the mitigation is equal to how much shopper's kth-order belief anchors to the prior.

Phillips curve – I characterize the Phillips curve. The slope of Phillips curve can be decomposed into two parts, each associated with a specific friction. The slope decreases in both frictions. The curve has following properties. First, it is static and does not depend on the future inflation expectation. In particular, the output gap is proportional to the nowcast error of inflation. Second, unlike the modern Phillips curve literature that emphasizes the role of firm's expectation in the determination of the slope, this model provides a mechanism that household expectations can influence firms' pricing decision.

Dynamic Model and Calibration – I develop a dynamic general equilibrium model. In the model, monetary policy sets the nominal interest rate. Shopper's problem is still static as before. In each period, they receive a signal about the inflation and learn about the shock over time. I present a three-equation system that describes the joint dynamics of aggregate consumption, inflation and interest rate. I then calibrate the model parameters to match the moments from the literature and my own empirical evidence. In particular, the aggregate own-cost passthrough is a sufficient statistic that summarizes the "deep" parameters related to the search friction. The aggregate own-cost passthrough is estimated to be 0.5 for the manufacturing firms (Amiti et al., 2019) and varies from 0.2-0.5 for retail sector (Gopinath et al., 2011). Next, I estimate the empirical impulse responses of inflation and inflation expectation following a main inflation shock (Angeletos et al. (2020)). This shock drives a large bulk of variation in inflation and has little footprint in real variables. The dynamics of the responses indicates the "generic" way of how consumers learn inflation. I calibrate the information friction such that the time needed for the nowcast error shrinking to zero in the model is similar to the empirical counterpart.

Despite the model's parsimonious nature, the calibrated model can generate substantial monetary non-neutrality comparable to a standard New-Keynesian model with Calvo parameter equal to 0.7. That is, 70% firms cannot adjust prices in each period. The new insight in the dynamic model is that (i) learning enables the persistent output response and increases the accumulative monetary non-neutrality and (ii) since the output response depends on the gap between the actual inflation and inflation nowcast, rapid learning can close this gap before the shock fully dissipates, leading to endogenously reduction in the persistence of the output response.

Empirics – My mechanism is consistent with empirical evidence. In particular, I use the 2006-2019 NielsenIQ Consumer Panel data, which encompasses approximately 55,000 households annually, with each household participating in the panel for an average of 30 quarters. I find that a one-percentage-point increase in unanticipated inflation for food and drinks results in 0.55 additional trips in the retail sector. Consumers also visit 0.17 more distinct stores and spread their spending more evenly across trips within a quarter. It indicates that consumers explore different stores probably in search of better prices in response to rising prices.

Next, I test the main comparative statics: higher search costs implies lower passthrough conditional on same information frictions. I propose a novel measure of search frictions at the county level—establishment density—drawing on insights from urban literature. I construct the search index based on the weighted establishment density for non-tradeable industries using the County Business Pattern (CBP) data. I then construct price indices at the MSA (Metropolitan Statistical Area) level using NielsenIQ Retail Scanner data. Price indices are created for MSAs with at least 20 stores. The final data set covers about 250 MSAs. To address endogeneity concerns, I first control for county fixed effects and then interact with exogenously identified shocks. Then, I control for variables that represent local economic conditions and time-fixed effects. I find that a one standard deviation increase in the search index makes a region's price index approximately 12% more responsive to both monetary shocks (Bauer and Swanson, 2023) and oil news shocks (Känzig, 2021). This supports the model's prediction that regions with lower search costs exhibit larger responses in the price index. Then, I conduct similar analysis on unemployment rate. I find that regions with lower search costs also exhibit 20% less response in the unemployment rate following a monetary shock. This implies that higher passthrough to the price index induces less monetary non-neutrality. For the oil news shock, the response in unemployment rate is also dampened, which is in line with the predictions from the local wage Philipps curve when the real wage rigidity is present (Blanchard and Galí, 2010).

Related Literature – This paper contributes to three strands of literature. The first studies the price stickiness and monetary non-neutrality. Large-scale menu cost models have been advanced to match both the micro price moments and impulse response of macro variables (Golosov and Lucas, 2007; Midrigan, 2011; Alvarez et al., 2016a; Blanco et al., 2023). Efforts have been made on micro-founding non-neutrality through information frictions on firm side (Lucas, 1972; Woodford, 2003; Angeletos and La'o, 2010). One trend of literature focuses on using the consumer-side mechanisms to explain price stickiness as this paper. The prominent paper in this literature is Matějka (2015). He shows that firms set discrete prices as consumers "hate" price fluctuations, which increases their costs of attention. My paper has the similar flavor in the sense that the price stickiness originates from the strategic interaction between consumers and firms. However, my paper has different mechanisms and investigates these mechanisms in general equilibrium. Other papers like Gabaix and Graeber (2024) and Rebelo et al. (2024) propose consumer behavioral theories of price stickiness. My paper is within the realm of rational expectations.

Second, it adds to the research on the role of search frictions in monetary non-neutrality. This literature is divided into two main streams based on different search frameworks. The first stream follows Burdett and Judd (1983) where firms adopt a mixed pricing strategy where a range of prices is optimal when market has both shoppers and non-shoppers. Head et al. (2012) show that price stickiness can result from this strategy. As nominal price increases, profit can still be maximized despite a fall in real price. Similarly, Burdett and Menzio (2018) incorporate same mechanism into a menu-cost model, where a broader range of optimal prices leads to larger price adjustments.

The second stream leverages the sequential search framework. Benabou (1988) shows that when monopolistic competition arises from costly consumer search, the inaction region in a menu-cost model expands with increasing search costs. More recently, Sara-Zaror (2024) document that price dispersion for identical goods varies with inflation levels. This paper advances this second stream by integrating search models a là Wolinsky (1986) and Anderson and Renault (1999) with a heterogeneous firm block, a monetary general equilibrium framework, and incomplete information on the consumer side.

Third, this paper contributes to the literature on consumer-side information frictions and monetary non-neutrality. Bénabou and Gertner (1993), L'Huillier (2020) and Gaballo and Paciello (2021) focus on the role of individual prices consumers observe during the search as revealing the information about aggregate shocks. I shut down this learning channel. Instead, consumers form beliefs based on exogenous signals which they receive before the search. This facilitates a simple characterization of the optimal search strategy. My analysis shows that the main mechanism that generates the monetary non-neutrality is not related to learning from individual prices. This paper also broadly contributes to the literature on information frictions and the transmission of monetary policy. For example, Angeletos and La'O (2013) model aggregate demand fluctuations driven by sentiment in beliefs. Venkateswaran (2014) examines an incomplete-information version of the Diamond–Mortensen–Pissarides model. Angeletos and Lian (2018) show that incomplete information games among consumers can mitigate the forward guidance puzzle.

Outline − The rest of the paper is organized as follows. Section 1 presents a static model and establishes the main results on the passthrough. Section 2 presents the dynamic model and the calibration results. Section 3 shows empirical evidences. The last section concludes. Appendix A contains some of the proofs omitted from the text. Appendix B contains results from alternative calibrations. Appendix C contains procedure of variable construction and additional empirical evidence.

1 Static Model

I develop a macroeconomic model with (i) information asymmetry between shoppers and firms about marginal costs and (ii) search frictions on the goods market. I proceed in two steps. First, I present a static model to explain the core mechanism. Second, I present a full-fledged dynamic general equilibrium framework in the next section.

I first consider static partial equilibrium model in which there are firms, shoppers and a monetary authority and then close the model in the general equilibrium.

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 States, Strategies and Distributions

At the beginning of each period, the Nature draws the aggregate state w from a given distribution Φ_w, idiosyncratic states for each firm a_k from Φ_a, idiosyncratic noisy signals for each shopper x_i from Φ_x about the aggregate state w. $\Phi_w, \Phi_x, \Phi_a, G$ are the common knowledge for all agents. Each firm produces a good and selects the optimal pricing strategy that maps its state $\{a_k, w\}$ to the price of its good, i.e., $p_k = p^*(a_k, w)$, where $p : \mathcal{R}^2 \to \mathcal{R}$. The optimal pricing strategy p^* monotonically decreases in a_k and increases in w. Variation in a_k across firms induces a price distribution $F(p|w)$, which has a density distribution $f(p|w)$. Let $p^{*-1}(p, w)$ denote the inverse mapping from p_k to a_k given w. It is straightfoward to show that p^{*-1} also monotonically decreases in a_k and increases in w. The price distribution conditional on w is given by,

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

In the rational expectations equilibrium, shoppers know the equilibrium pricing strategy p^*. Conditional on knowing p^* and w, the shoppers are able to derive the price distribution. However, they have incomplete information about w. Their posterior belief about w is denoted by $H(w|x)$. The shopper's perceived price distribution conditional on x, $f(p|x)$, is given by,

$$f(p|x) = \int f(p|w)h(w|x)dw \tag{2}$$

The above equation has two implications. First, when $x = w$, the perceived and objective price distributions coincide. Second, if $h(w|x_i)$ first-order stochastically dominates (FOSD) $h(w|x_j)$, then $f(p|x_i)$ FOSD $f(p|x_j)$. Intuitively, when the shopper places more probability weights on low w, since prices increase in w, the perceived price distribution is stochastically smaller.

Moreover, the shopper forms the expected idiosyncratic state of firm k after observing the price p_k,

$$E(a_k|x) = \int p^{*-1}(p_k, w)h(w|x)dw \tag{3}$$

Similarly, it is obvious to show that $E(a_k|x_i) < E(a_k|x_j)$ when $h(w|x_i)$ FOSD $h(w|x_j)$. The shopper who believes the nominal wage is low will perceive the firm's a_k as lower than its actual value.

Finally, shoppers search sequentially and have free recall. Each shopper's search strategy depends on the perceived price distributions $F(p|x)$. The optimal search strategy can therefore be represented as a function that maps x to an optimal utility level, $v_i = v^*(x)$, where $v^* : \mathcal{R} \to \mathcal{R}$.

This strategy then determines the demand allocation across firms on the aggregate. In the rational expectations equilibrium, firms know the equilibrium search strategy v^* and select optimal pricing strategy p^* that maximizes the profit.

1.2 Setup

Now, I state the model. Time is discrete and infinite $t \in \mathbf{N}$. The timeline is as follows. Within a period, the monetary authority first sets the nominal wage. Shoppers are endowed with cash and form a conditional distribution about prices. 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,

$$Y_k = A_k L_k \tag{4}$$

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 $\log A_k$ draw from the normal distribution $\mathcal{N}(0, \sigma_a^2)$. 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 partial economy.

Monetary Authority $-$ The monetary authority directly controls the nominal wage W. It draws w from the normal distribution $\mathcal{N}(W, \sigma_w^2)$. Monetary shock is defined as $\hat{w} = w - W$.

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. It follows,

$$X_i = W \exp\left(\sigma_x \varepsilon_{xi} - \frac{\sigma_x^2}{2}\right) \tag{5}$$

where ε_{xi} is i.i.d. across shoppers and it follows $\varepsilon_{xi} \sim \mathcal{N}(0, 1)$. It is also independent of productivity shocks and monetary shocks. The shopper treats X_i as signal about w. The expected (log) nominal wage is then given by,

$$E(w|x_i) = \theta_x x_i + (1 - \theta_z - \theta_s)W \tag{6}$$

where $\theta = \frac{\sigma_x^{-2}}{\sigma_w^{-2}+\sigma_x^{-2}}$. Let $H(w|x_i)$ denote the posterior belief about the nominal wage with density $h(w|x_i)$. Based on Bayes' rule, it follows $\mathcal{N}(E(w|x_i), (\sigma_w^{-2} + \sigma_z^{-2})^{-1})$. Then, shoppers construct their perceived price distribution according to (2).

The shopper consume one good.[2] The utility that shopper i gains from consuming good k is given by,

$$\log \frac{Z_i}{P_k} + \frac{1}{\lambda}\epsilon_{ik} \tag{7}$$

where $\epsilon_{ik} \sim G$ is match utility between shopper i and good k. G is twice continuously differentiable and its density function is g. It captures idiosyncratic consumer preferences for certain goods over others. ϵ_{ik} are i.i.d across firms and shoppers.[3] Also, following the literature, I assume that G is log-concave. Note that some commonly used distribution functions are log-concave, e.g., normal distribution, uniform distribution, Gumbel distribution.[4] The parameter λ controls the relative importance between the two types of utility. A larger λ implies that the shopper places greater value on utility from consumption relative to match utility. Relative prices are less important in the purchase decision. 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,

$$y_{ik} = -p_k + \frac{1}{\lambda}\epsilon_{ik} \tag{8}$$

Shoppers search sequentially and randomly following Wolinsky (1986) and Anderson and Renault (1999). By incurring a search cost $\kappa > 0$, the shopper can visit a firm to learn both its price and the associated match utility. Shoppers have free recall, meaning there are no additional costs for purchasing goods from firms they have previously visited. The shopper continues to search if the expected value of searching is larger than making the purchase at the firm that provides the maximum value until now. According to (8), the distribution of value of drawing a random firm y

[2]In Section 1.5, I extend the model by allowing shoppers to get access to a bunch of goods by incurring one search cost.

[3]The price distribution is not degenerated if the random utility term is match-specific. If it is only shopper-specific, it does not matter for the search strategy. Firms compete only on price. The price distribution is degenerated to a single optimal price. If it is only good-specific, the price distribution will be exogenous.

[4]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.

is a convolution of the perceived price distribution and the distribution of match utility,

$$\psi(y|x) = \int \lambda g(\lambda(y+p))f(p|x)dp \tag{9}$$

I assume that $h(w|x_i)$ remains fixed throughout all rounds of search. In particular, I impose the following restriction on shoppers' information sets.

Assumption 1. *Shoppers do not learn about the nominal wage from individual prices they observe during the search.*

This assumption is plausible if the idiosyncratic variations, contributed by productivity shocks, in prices are way larger than the aggregate variations induced by the nominal wage. Even when a shopper consistently encounters firms charging high prices, she attributes this to bad luck rather than an increased nominal wage. I make this assumption for tractability. If shoppers' information sets depend on the whole search history, it leads to exploding states. The model becomes intractable and this complexity is not relevant to the main mechanism of the model as I will show below. In the dynamic model, I assume that shoppers receive a signal about the current change in the inflation before searching as an alternative way to incorporate learning from shopping.

I now state the shopper's problem. The shopper undertakes sequential search with perfect recall and without being restricted by any plan made before setting out to search. I refer to the latter as search without commitment.[5] Let v_{ir} denote the maximum value of previously visited firms in rth round. In particular, after sampling the first firm, $v_{i1} = y_{i1}$. I define v_{ir} for $r > 1$ as follows,

$$v_{ir} = \max\{v_{ir-1}, y_{ir}\} \tag{10}$$

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,

$$U(v|x) = \max\left\{v, -\kappa + U(v|x)\int_{-\infty}^{v}\psi(y|x)dy + \int_{v}^{\infty}U(y|x)\psi(y|x)dy\right\} \tag{11}$$

[5]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.

The maximum represents that the shopper can either receive the maximum value v until this round and stop searching more, 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 $\int_{-\infty}^{v_{ir}} \psi(y|x_i)\, dy$, 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 (11). The value function U is stationary only when Assumption 1 holds. Otherwise, with the information sets expanding over the rounds of search, the value function U should be indexed by the search round.

The shopper's problem is solved in two steps. First, she finds the U function that solves the functional equation (11). Second, she keeps sampling firms until v first exceeds the expression to the right of the comma in (11).

Partial Equilibrium – The equilibrium concept is Perfect Bayesian Nash equilibrium (PBNE). 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.[6] 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.*

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 (11).*

3. *Nominal wage is 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 to analyze the incomplete-information equilibrium.

[6] In the standard search literature, consumers know the firms' marginal cost and there is no correlated cost shocks. Consumers, therefore, are able to detect the off-equilibrium prices.

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

1.3 Equilibrium Characterization

I now characterize the equilibrium. I proceed in three steps. First, I characterize the search strategy and the pricing strategy. Second, I show the existence and properties of full-information equilibrium. Third, I show the monetary neutrality under full information.

Characterization of the Search Strategy – I first characterize the search strategy. The 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. *Under Assumption 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 is unique for each x. It is determined by,*

$$v^*(x) = -\frac{\kappa}{1 - \Psi(v^*(x)|x)} + \frac{\int_{v^*(x)}^{\infty} y\psi(y|x)dy}{1 - \Psi(v^*(x)|x)} \tag{12}$$

where $\Psi(p|x_i)$ is the perceived distribution of the value of a random draw.

Proof. See Appendix A. ■

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

$$U(v|x) = \max\{v, v^*(x)\} \tag{13}$$

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

This search strategy is optimal due to two assumptions. First, shoppers cannot commit to a plan prior to search. To understand the intuition, consider a shopper who draws a long sequence of goods that offer consistently low values. The shopper will keep searching even when the total search costs paid in this period is already very large. Indeed, there is a measure zero of shoppers who search forever and pay infinitely large search costs. This is apparently not optimal from the ex ante view. Second, the standard threshold rule may fail without Assumption 1. Rothschild (1974) shows that if shoppers do not know the price distribution, they may buy at high price because they infer from prices that the average price can be even higher. On the other hand, they may continue searching at a low price. Bénabou and Gertner (1993), L'Huillier (2020), Gaballo and Paciello (2021) focus on the role of individual prices in revealing information about aggregate shocks. Their analysis is thereby often restricted to two-firm case. [7]

The result extends the standard threshold result in the literature (Weitzman, 1979 and Wolinsky, 1986) by incorporating both endogenous price distribution and incomplete information. In their analysis, firms are homogeneous and shoppers have correct belief about the optimal price. Here, firms are heterogeneous and shoppers have incomplete information about the price distribution. Proposition 1 shows that under Assumption 1 ,the optimal search strategy still follows the threshold rule. The threshold depends on the shopper's information set x.

To make clear how two distributions affect the threshold, the following Corollary shows an alternative way to solve the threshold.

Corollary 1. *The threshold $v^*(x)$ is given by,*

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

where $f(p|x)$ is the perceived price distribution.

Proof. See Appendix A. ■

The left-hand side represents the expected additional benefit of this search. To see this, consider a shopper who has the state $v^*(x_i)$. From Proposition 1, she is indifferent between sampling another firm and stopping searching. 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 additional utility obtained in this case is $\max\{\frac{1}{\lambda}\epsilon_{ik} - p_k - v^*(x_i), 0\}$. The threshold is achieved when the expected additional utility is equal to the search cost.

Aggregation − I now show the aggregation of optimal search decisions. In particular, I show the expenditure allocation across firms and the resulting profits. According to the optimal search strategy, the shopper only purchases the good k if $\frac{1}{\lambda}\epsilon_{ik} - p_k > v^*(x)$. The shopper's probability of purchasing from firm k in each round is $1 - G\big(\lambda(v^*(x) + p_k)\big)$. Since learning from shopping is prohibited, this probability is the same for all rounds. The probability of any shopper purchasing

[7] Janssen et al. (2017) investigates the non-reservation property in a search equilibrium.

from any firm in each search given w is given by,

$$\rho = \int \int \big(1 - G\big(\lambda(v^*(x) + p)\big)\big) d\Phi_x(x) f(p|w) dp \tag{15}$$

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. It is straightforward to show that the expected number of contacts 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,

$$\omega_k = \frac{1}{\rho} \int X\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x) \tag{16}$$

The dispersion in the cash in hand affects the expenditure through the dispersion of thresholds. The inequality also matters through the covariance between the cash in hand and the threshold. The more cash in hand is positively correlated with higher expectation of the nominal wage. The profit for firm k is given by,

$$\pi_k = \frac{1}{\rho} \int X\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x) \frac{1}{P_k}(P_k - \frac{W}{A_k}) \tag{17}$$

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.

Characterization of the Pricing Strategy – Monopolistic firms compete on prices. They maximize the profit in (17) with respect to its price. The following proposition presents the optimal pricing strategy,

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

$$P_k = \mu_k \frac{W}{A_k}; \quad \mu_k = \frac{e_k}{e_k - 1} \tag{18}$$

The elasticity of demand e_k is determined by,

$$e_k = \lambda \frac{\int X\big(g\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x)}{\int X\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big) d\Phi_x(x))} + 1 \tag{19}$$

Proof. See Appendix A. ■

The optimal price is a markup times the marginal cost. There are two factors that contribute to the firm's market power. One is the relative importance of the utility of a match with the utility of consumption, λ. Larger λ implies higher elasticity.[8] Another factor is that search friction naturally gives rise to monopoly power (Diamond, 1971). In particular, the effect of search friction is represented by a hazard function, where the density g represents the marginal shoppers who are indifferent between making purchase and continuing searching. The survival function $1 - G$ indicates that the adjustment of the price will affect the profit obtained from all infra-marginal shoppers. The ratio between these two captures the trade-off that setting a higher price motivates shoppers to search, while extracting more profit from the infra-marginal shoppers.

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. Similar to Corollary 1, it is given by,

$$\int \int_{\lambda(v^*(w)+p)}^{\infty} \big(\frac{1}{\lambda}\epsilon - p - v^*(w)\big) g(\epsilon) d\epsilon f(p|w) dp = \kappa \tag{20}$$

where $f(p|w)$ is the actual price distribution. It is easy to show that firm's profit is given by,

$$\pi_k = \frac{1}{\rho}\Big(1 - G\big(\lambda(v^*(w) + p_k)\big)\Big)\frac{W}{P_k}(P_k - \frac{W}{A_k}) \tag{21}$$

where $\rho = \int \big(1 - G(\lambda(v^*(w) + p))\big) f(p|w) dp$. The difference between (21) and (17) is two-fold. First, the distribution of thresholds is reduced to a single value $v^*(w)$. Second, the inequality in cash in hand is no longer correlated with the threshold. I can similarly define the expenditure allocation in the full-information case,

$$\omega_k = \frac{1}{\bar{\rho}}\Big(1 - G\big(\lambda(v^*(w) + p_k)\big)\Big) \tag{22}$$

The first-order condition of firm's problem results in,

$$P_k = \frac{e_k}{e_k - 1}\frac{W}{A_k} \tag{23}$$

$$e_k = \lambda \frac{g\big(\lambda(v^*(w) + p_k)\big)}{1 - G\big(\lambda(v^*(w) + p_k)\big)} + 1 \tag{24}$$

Since G is log-concave, the elasticity of demand is increasing in firm's own price. The decrease in the density on the right tail is dominated the decrease in $1 - G$. The intuition is that the incentive

[8] 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 $\lambda + 1$.

to extract more profit from infra-marginal shoppers overwhelms the concern of losing marginal consumers. Therefore, high-productivity firms will set lower price and higher markup. Moreover, higher threshold implies pickier shoppers, which drives up the elasticity.

Now, I present an important property of $v^*(w)$. It is a crucial step in proving the existence of the equilibrium. This property is also useful to understand the effect of search frictions on other equilibrium objects I will discuss in Section 1.5.

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

Proof. See Appendix A. ■

The increase in the threshold $v^*(w)$ increases elasticity for all firms. I prove that the decrease in price is less than the increase in the threshold for any firm. Therefore, the left-hand side of (20) is strictly deceasing in $v^*(w)$. I now establish the existence of the full-information steady-state equilibrium.

Theorem 1 (Existence of the Full-Information Steady-State Equilibrium)**.** *There exists a unique full-information steady-state 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. It implies that higher price induces higher elasticity and lower markup. Therefore, the individual prices are uniquely determined by (23) and (24). Second, from Lemma 1, the threshold $v^*(w)$ is uniquely determined by (20) for the given price distribution that is derived from optimal pricing strategy. The equilibrium is then the fixed point of the reservation value and the price distribution.

Note that there always exist equilibria in which firms charge sufficiently high prices and shoppers do not search. However, there is only one equilibrium in which shoppers search actively. From now on, I will call the full-information equilibrium in which $w = \bar{w}$ the full-information steady state.

Now, I present the first main result about monetary non-neutrality.

Theorem 2. *In the full information equilibrium, monetary policy is neutral.*

Proof. See Appendix A. ■

This theorem establishes that the passthrough from the monetary shock to the price index is complete under full information. It indicates that search friction alone is not sufficient to generate monetary non-neutrality. This theorem is the exact result. To understand this theorem, consider a scenario where the monetary authority raises the nominal wage by $b\%$. If firms respond by increasing prices by $b\%$, then their values decrease by $b\%$ according to (8). The key step in the proof is that the threshold $v^*(x)$ also decreases by $b\%$. This implies that search decisions remain unchanged, as the relative positioning of the threshold and value distribution is preserved. Consequently, expenditure allocation remains the same as before, validating the guess that firms respond by increasing prices by $b\%$.

1.4 Approximate Optimal Strategies

Both the threshold shown in Proposition 1 and the pricing strategy shown in Proposition (2) are highly non-linear. Following the literature, I consider the case in which the monetary authority draws monetary shocks from a distribution with small standard deviation, i.e., $\sigma_w \to 0$. At the same time, I keep variance ratio $\frac{\sigma_x^2}{\sigma_w^2}$ fixed, which correspond to fixed values of θ. The fixed ratio preserve the same level of information frictions about the nominal wage. An implication is that $\sigma_x \to 0$. The existence of the full-information equilibrium allows us to approximate the non-linear strategies to the first order around the full-information steady state.

To proceed, first note that the posterior belief about the nominal wage, $H(w|x)$, follows $\mathcal{N}(E(w|x), (\sigma_w^{-2} + \sigma_z^{-2})^{-1})$. As all $\sigma_w, \sigma_x \to 0$, $H(w|x)$ collapses to a Dirac function centered at $E(w|x)$. Then, I approximate the perceived price distribution $f(p|x)$ to the first order,

$$f(p|x) = \int f(p|w)h(w|x)dw = f(p|E(w|x)) \tag{25}$$

On the first order, only the expectation of the nominal wage matters for the perceived price distribution.

Second, I define the passthrough from the monetary shock $\hat{w}$ to prices in equilibrium. The first-order approximation to the optimal pricing strategy p^* is given by,

$$p^*(a_k, w) = p^*(a_k, \bar{w}) + p_w^*(a_k, \bar{w})\hat{w} \tag{26}$$

I call $\varphi_k = p_w^*(a_k, W)$ the total passthrough, as it reflects the sum of two passthroughs which I will show in Section 1.5. Shoppers know the total passthrough as they know p^*. The total passthough is determined in the equilibrium. The shopper's expected price conditional on x is given by,

$$E(p_k|x) = p^*(a_k, \bar{w}) + \varphi_k E(\hat{w}|x) \tag{27}$$

Finally, 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, Hulten, 1978) offers a simple non-parametric formula for the change in the price index. Under the assumptions of homotheticity and preference stability[9], the log change in the price index is the expenditure share-weighted, as measured in the base period, log changes in all the prices. Apparently, both conditions are satisfied here, I define the expenditure share-weighted log change in the price index.

$$\hat{p} = \Phi \hat{w} \tag{28}$$

where $\Phi = \int \varphi_k \bar{\omega}_k dk$ and $\bar{\omega}_k$ is the expenditure share in the full-information steady state. The aggregate effect of a monetary shock on price index is measured by the aggregate total passthrough Φ. Furthermore, the average expectation of the price index is $\bar{E}\hat{p} = \theta\hat{p}$. The response of $\bar{E}p$ is dampened compared to the actual change in price index since the signals about the shock are noisy.

Now I state the results on the approximation of the non-linear equilibrium. In particular, the following proposition presents a first-order approximation to the threshold in (14) and the elasticity in (19).

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

$$v^*(x) = v^*(\bar{w}) - E(\hat{p}|x) \tag{29}$$

where Φ is the aggregate total passthrough.
[Part 2] *The elasticity of demand is given by,*

$$e_k = \lambda \frac{g\big(\lambda(v^*(w) + \bar{p}_k + \hat{p}_k - \bar{E}\hat{p})\big)}{1 - G\big(\lambda(v^*(w) + \bar{p}_k + \hat{p}_k - \bar{E}\hat{p})\big)} + 1 \tag{30}$$

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 under incomplete information is equal to the threshold under full-information steady state minus the expected change in the price index. In particular, higher signal about the nominal wage implies a lower threshold. To understand the intuition,

[9]Homotheticity requires that income effects are uniform, meaning 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.

consider a shopper who has a higher expectation of the price index. She is more likely to purchase from the current firm since the expected value of a random draw is lower. As a result, the threshold is reduced. Moreover, notice that $E(\hat{p}|x) = \Phi E(\hat{w}|x)$. The aggregate total passthrough, Φ, governs the passthrough from the expected monetary shock to the threshold for shoppers with any information sets. The aggregate total passthrough encapsulates all the changes in the price distribution following the shock. To see the intuition, suppose the distribution of passthrough is a singleton, i.e., $\varphi_k = \varphi_0$, then $\Phi = \varphi_0$. An increase in the perceived nominal wage would shift every point in the distribution to the right by the same amount. This is the case in the full-information equilibrium. On the other hand, if the distribution of passthrough is not degenerate, the shape of the price distribution also changes after the shock. Importantly, the aggregate passthrough depends on the covariance between the distribution of expenditure shares and the distribution of passthrough. In particular, If firms with higher average expenditure shares also pass through more of the increase in nominal costs to prices, it decreases the option value of search, thereby lowering the threshold. We can achieve the average change in the threshold compared to the benchmark $v^*(\bar{w})$ by integrating on both sides of (29),

$$\int v^*(x)dx = v^*(\bar{w}) - \theta\hat{p} \tag{31}$$

Shoppers, on average, believe the increase in the price index is not as large as the actual one, which motivates them to search for outside options more than in the full-information case. This will have significant impact on the elasticity of demand.

The second part of the proposition provides a simple characterization of the elasticity of demand. On the first order, only the average expectation of the price index is retained. The distribution of the thresholds and covariance between cash in hand and thresholds are second-order. The proposition shows that the elasticity depends on perceived relative price. Shoppers, on average, believe the relative price is larger than it actually is. As a result, firms behave as if they are competing with others that set prices lower than the actual levels, which induces them to reduce their own prices in response. This leads to compressed markups and incomplete passthroughs. This is the key driver of the main results presented in Section 1.5.

1.5 Characterization of Passthroughs in General Equilibrium

I now characterize passthroughs in the general equilibrium. I present the main finding: the aggregate passthrough of a money supply shock to the price index is generically incomplete. The slope of Phillips curve is flat if the information friction is large.

The total passthrough is composed of the own-cost passthrough and the cross-price passthrough. Decomposing the total passthrough into these two elements is crucial to understand the intuition behind results. Following Amiti et al. (2019), I define both passthroughs using markup elasticities. I present the following Lemma,

Lemma 2. *The price responds to both firm's own cost shocks and competitors' prices,*

$$\hat{p}_{kt} = \gamma_k \hat{w} + \xi_k \hat{p} \tag{32}$$

where γ_{kt} is own-cost passthrough and ξ_{kt} is cross-price passthrough.

$$\gamma_k = (1 - \frac{d\mu_k}{dp_k}\Big|_{\hat{w}=0})^{-1}; \xi_k = \frac{d\mu_k}{dp}\Big|_{\hat{w}=0}\gamma_k \tag{33}$$

The total passthrough of each firm is given by,

$$\varphi_k = \gamma_k + \Phi \xi_k \tag{34}$$

The aggregate total passthrough Φ is given by,

$$\Phi = \frac{\Gamma}{1 - \Xi} \tag{35}$$

where $\Gamma = \int \gamma_k \bar{\omega}_k dk$, $\Xi = \int \xi_k \bar{\omega}_k dk$.

Proof. See Appendix A. ■

The lemma links passthroughs with the elasticity of demand through the markup elasticity. As a result, passthroughs also depend on perceived relative prices as presented in Proposition 3. Plugging the definition of the total passthrough, the lemma then derives the total passthrough for each firm in equilibrium. Integrating on both sides, the aggregate total passthrough is obtained. Since the passthroughs are defined at the steady state, the own-cost passthrough, γ, does not depend on the information friction θ. Firms pass part of their own cost shocks to prices in all cases.

I now state our main results on passthroughs under incomplete information. To push the results on monotone comparative statics as far as possible, I assume that the distribution of the match utility, G, follows the Gumbel distribution.

Theorem 3 (Total Passthrough under Incomplete Information)**.** *Under incomplete information about the nominal wage, the aggregate total passthrough has following properties,*

1. ***[Incompleteness]*** $\Phi < 1$
2. ***[Composition]*** *φ_k decreases in productivity; $\bar{\omega}_k$ increases in productivity.*
3. ***[MCS on κ]*** *Φ decreases in search friction κ given θ. Limits: $\lim_{\kappa\to\infty}\Phi = 0$; $\lim_{\kappa\to 0}\Phi = 1$*

   [MCS on θ] *Φ increases in information friction θ given κ. Limits: $\lim_{\theta\to 1}\Phi = 1$; $\lim_{\theta\to 0}\Phi = \Gamma$*

Proof. See Appendix A. ■

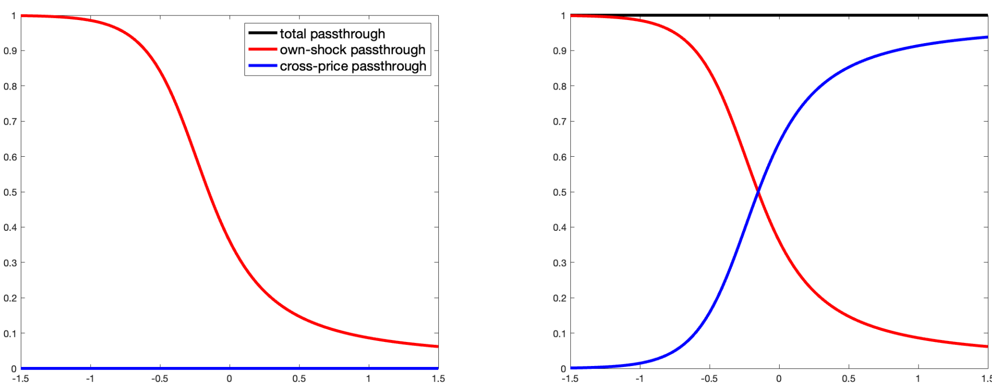
This is the main theorem of this paper. It establishes that the total passthrough is generically incomplete if there exists any information friction. The full-information case is a knife-edge case. I first explain the result on incompleteness. The key equation to understand the intuition of this result is:

$$1 - (\gamma_k + \xi_k) = (1 - \gamma_k)(1 - \theta) > 0 \tag{36}$$

It shows that the difference between the sum of the passthroughs, $\gamma_k + \xi_k$, and one can be decomposed into two terms. The first term captures the role of the search friction. The own-cost passthrough is not related to the information friction. The second term captures the role of information asymmetry about the nominal wage between consumers and firms. They are both positive. Figure 1 illustrates the three passthroughs. The right panel shows that under full information, the decrease in the own-shock passthrough over productivity is exactly offset by the increase in cross-price passthrough. The resulting total passthrough is always one for firms of any productivity. This result corresponds to Theorem 2 in which I prove the exact result. Notably, Amiti et al. (2019) shows that the total passthrough is one for broad preferences including nested CES and first-order Kimball demand family as well as for the broad homothetic families of demand considered in Matsuyama and Ushchev (2017). The theorem complements their results and emphasizes that the complete information about the price index is also essential. In fact, in all these commonly used demand system, the complete knowledge of prices set by individual firms is often assumed.

On the other hand, in the absence of any information as shown in the left panel, the cross-price passthrough is zero for any firm. Then, the total passthrough equals the own-cost passthrough. The intuition is that when shoppers do not perceive any change in the price index, firms find it optimal not to pass any of the actual change in the price index onto their own prices, in order to dissuade marginal shoppers from search. In the intermediate case when information is incomplete, the increase in cross-price passthrough is still not sufficient to offset the decrease in own-shock passthrough, leading to incomplete total passthroughs. This effect is particularly pronounced for high-productivity firms, as they are more sensitive to changes in the price index which information frictions have a larger bite on.

Figure 1: Distribution 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 total passthrough. The left and right panels show passthroughs in the incomplete and complete information cases, respectively.

Main Insight: General Equilibrium Attenuation – The strategic complementarity in pricing, as denoted by ξ, is the key object to understand the main insight. The strategic complementarity is a general equilibrium channel as it relates how firms respond to other firms' price changes. In this section, I "dig deeper" to show how the mechanism developed so far relates to the attenuation on the strategic complementarity.

First, on the micro-level, the individual total passthrough is defined as $\varphi_k = \gamma_k + \Phi\xi_k$. The effect of strategic complementarity is dampened by the aggregate total passthrough as $\Phi < 1$. This induces a even smaller individual total passthrough. Intuitively, the fact that shoppers understand that aggregate total passthrough is incomplete reduces the expected price index even more. Firms then reduce prices in response, resulting in even lower passthrough. Therefore, the incompleteness of the total passthroughs is amplified by the firms' incentive of setting prices close to the price index, which is a form of real rigidity (Klenow and Willis, 2016).

Second, on the macro-level, the information friction affects the aggregate total passthrough by attenuating the strategic complementarity. The following proposition presents the result.

Proposition 4. *Under the incomplete information, the aggregate total passthrough is given by,*

$$\Phi = \frac{\Gamma}{1-\theta(1-\Gamma)} \tag{37}$$

where $\theta(1-\Gamma)$ represents the degree of strategic complementarity. Compared to the full information equilibrium, the strategic complementarity is reduced, and the more so the larger the information friction, as measured by θ.

Proof. See Appendix A. ■

By varying θ between 0 and 1, we can thus span all the values between the aggregate own-cost passthrough and the full-information outcome. For θ close to zero (meaning a sufficiently large departure from common knowledge), the aggregate total passthrough is arbitrarily close to the own-cost passthrough. But as θ increases (meaning a higher degree of common knowledge), the effect of strategic complementarity becomes more and more important.

Higher-Order Beliefs – We can understand (37) in two ways. First, from the shopper's perspective, it relates to a certain property of higher-order beliefs (the beliefs of the beliefs of others). For this purpose, I will borrow heavily from game theory as in Morris and Shin (2002) and Woodford (2003), and I will follow the analysis in Angeletos and Lian (2023). To proceed, I first aggregate the pricing equation in (32) and write it as a beauty contest,

$$\hat{p} = \Gamma\hat{w} + (1-\Gamma)\bar{E}\hat{p} \tag{38}$$

This equation shows that firms only respond to shoppers' average expectation of other firms' prices. I call it strategic complementarity in price expectation. Suppose every shopper believe that firms and other shoppers are rational. Then every shopper believes the above condition holds. Shoppers' average expectation of $\hat{p}$ satisfies,

$$\bar{E}\hat{p} = \Gamma\bar{E}\hat{w} + (1-\Gamma)\bar{E}^2\hat{p} \tag{39}$$

where $\bar{E}^2[\cdot] = \bar{E}[\bar{E}[\cdot]]$ denotes the second-order belief. The equation shows that the shoppers' average expectation of the change in price index is in turn strategically complement in the second-order belief. The intuition is that how shoppers believe the other shoppers think about the price index will influence how these shoppers think about the price index and, in turn, affects the actual price index. 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 $\hat{w}$:

$$\hat{p} = \Gamma \sum_{h=0}^{\infty} (1-\Gamma)^h \bar{E}^h \hat{w} \tag{40}$$

where $\bar{E}^h \hat{w} = \bar{E}(\bar{E}^{h-1}\hat{w})$, and $\bar{E}^0 \hat{w} = \hat{w}$. It shows that all the high-order beliefs influence the actual price index and their impact decays by $1-\Gamma$. Note that $\bar{E}^h(\hat{w}) = \theta^h \hat{w}$. Substitute $\hat{p} = \Phi \hat{w}$, I obtain,

$$\Phi = \Gamma \sum_{h=0}^{\infty} \theta^h (1-\Gamma)^h \tag{41}$$

The above equation converges to the rational-expectations equilibrium outcome in (37) thanks to $1-\Gamma < 1$. It shows that the information friction dampens more the movements in the high-order beliefs than beliefs of lower-order. Higher-order beliefs are more anchored to the prior and less responsive to shocks. This is a robust feature and has been extensively discussed in the literature (Morris and Shin, 2002; Angeletos and Lian, 2018). The dampened responses of shoppers' higher-order beliefs contribute to the incompleteness of the aggregate total passthrough.

Level-k Thinking – We can also understand (37) from the firm's perspective. I borrow the tool of analysis from the literature on level-k thinking (García-Schmidt and Woodford, 2019 and Farhi and Werning, 2019). In the analysis, I will keep rational expectation and let the rounds of thinking $k \to \infty$.

Firms have full information and they take the shoppers' average expectation as given. For $k = 0$, firms do not respond to the monetary shock. For $k = 1$, firms think all the other firms are level-0 thinker. The shock is equivalent to an idiosyncratic cost shock. The change in price index is thus $\hat{p}^1 = \Gamma \hat{w}$. The level-1 thinkers therefore just understand partial equilibrium effect of the shock. For $k = 2$, firms think all the other firms are now level-1 thinker. Their prices further respond to $\hat{p}^1$. This amount is $\Gamma\theta(1-\Gamma)$, which is dampened by θ. The level-2 thinkers therefore incorporates a single round of general equilibrium effect. Similarly, in the kth round, the additional passthrough from the shock to the price index is $\Gamma\theta^{k-1}(1-\Gamma)^{k-1}$. All these adjustments in prices over the iterations happen instantaneously, not over real time. After summing up all the adjustments, we obtain (41). The incompleteness of the aggregate total passthrough can be interpreted as dampened general equilibrium effects in all rounds.

Price, Elasticity and Passthrough – I now connect the results so far to understand the relationship between price, elasticity and passthrough. Suppose the nominal wage increases by 1%. The aggregate total passthrough in equilibrium is 0.4. Thus, firms on average raise their prices by 0.4%. If a firm deviates and instead raises its price by 1%, according to Proposition 3, its elasticity will increase, reducing the markup by 0.6%. More specifically, the increase in the marginal shoppers g outweighs the increase in the infra-marginal shoppers $1 - G$. In this situation, the firm is more concerned about losing marginal shoppers to other firms than extracting additional profits from infra-marginal shoppers. This refrains the firm from passing fully through the shock to its price. This interpretation echos the message in Rotemberg (1982), which is that firms, fearing to upset consumers, limit the passthrough.

On the other hand, suppose the nominal wage decreases by 1%. If a firm reduces its price by 1%, its elasticity will decrease, resulting in a higher markup. In particular, since the firm will attract more shoppers as shoppers do not believe the price index has decreased by 1%, the firm is incentivized to extract more profits from infra-marginal shoppers. This again refrains the firm from fully decreasing price in response to the shock. In this case, the appropriate interpretation is that firms limit the passthrough to gain more profits from infra-marginal consumers.

As a final remark, one may think that, if passthroughs from the shock to prices are complete, while shoppers are motivated to search more in each round, mass of shoppers still increases in subsequent rounds of shopping, since the total mass of shoppers is fixed. Firms may end up with same demand as in the steady state under some conditions.[10] However, this argument overlooks the fact that firms treat ρ as exogenously given. Since firms cannot collude on prices or impose penalties for deviations, each individual firm has a strong incentive to deviate from the strategy of fully passing the shock through to prices. It thus cannot be a Perfect Bayesian Nash Equilibrium.

Results on Individual Passthroughs – In this section, I complete the picture by showing the properties of individual total passthroughs and their limit results.

I first present results on cross-sectional markups and passthroughs within an equilibrium. I define passthroughs on primitives: $\varphi_k = \varphi(a_k)$, $\gamma_k = \gamma(a_k)$ and $\xi_k = \xi(a_k)$.

[10] The conditions are that firms have same productivity and shoppers do not back out money supply from price.

Proposition 5. *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 limiting results hold:*

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

Firms with higher productivity set lower prices, attract more shoppers to purchase and choose higher markup. Similar in oligopolistic CES, the low end of markup is solely determined by the measure of substitutability between goods and the high end of markup is infinity. High-productivity firms have both lower total passthrough and higher expenditure share. They contribute a lot more to the incompleteness of the aggregate total passthrough. Proposition 5 also aligns with with empirical evidence highlighted in the literature: (i) more productive firms charge higher markups (Amiti et al., 2014); (ii) more productive firms pass through less exchange rate shocks (Amiti et al., 2019).

Second, to understand the results of comparative statics of the aggregate total passthroughs in Theorem 3, I state the following comparative statics results on the total passthroughs of individual firms. In particular, I establish that, all else equal, (i) the total passthrough is larger when the search cost is smaller for any given productivity and (ii) the total passthrough is larger when information friction is smaller for any given productivity.

Proposition 6. *Let equilibrium passthrough distributions $\gamma(a;\kappa), \xi(a;\kappa), \varphi(a;\kappa)$ for given κ. Given $\sigma_z > 0$, for $\kappa_2 > \kappa_1$,*

1. *Own-cost passthrough:* $\forall a, \gamma(a;\kappa_2) < \gamma(a;\kappa_1)$; $\lim_{\kappa\to\infty} \gamma(a) = 0$; $\lim_{\kappa\to 0} \gamma(a) = 1$
2. *Cross-price passthrough:* $\forall a, \xi(a;\kappa_2) > \xi(a;\kappa_1)$; $\lim_{\kappa\to\infty} \xi(a) = \theta$; $\lim_{\kappa\to 0} \xi(a) = 0$
3. *Total passthrough:* $\forall a, \varphi(a;\kappa_2) < \varphi(a;\kappa_1)$; $\lim_{\kappa\to\infty} \varphi(a) = 0$; $\lim_{\kappa\to 0} \varphi(a) = 1$

This proposition establishes that, all else equal, total passthrough is lower in an economy with higher search costs for any given productivity. It indicates that the search friction can amplify the effect of the information asymmetry on total passthroughs. As we know from Lemma 1, higher search cost lowers the thresholds. Lower thresholds results in lower elasticity of demand and higher markup elasticity. In Section 3.2, I present empirical evidence on this comparative statics result.

Furthermore, the limiting result implies that the total passthrough can vary from zero to one, implying the possibility of large degree of monetary non-neutrality.

Proposition 7. *Let equilibrium passthrough distributions $\gamma(a;\theta), \xi(a;\theta), \varphi(a;\theta)$ for given θ. For $\theta_2 > \theta_1$,*

1. *Own-cost passthrough: $\forall a, \gamma(a;\theta_2) = \gamma(a;\theta_1)$*

2. *Cross-price passthrough: $\forall a, \xi(a;\theta_2) > \xi(a;\theta_1)$; $\lim_{\theta\to 1} \xi(a) = 1 - \gamma(a)$; $\lim_{\theta\to 0} \xi(a) = 0$*

3. *Total passthrough: $\forall a, \varphi(a;\theta_2) > \varphi(a;\theta_1)$; $\lim_{\theta\to 1} \varphi(a) = 1$; $\lim_{\theta\to 0} \varphi(a) = \gamma(a)$*

This proposition highlights that the cross-price passthroughs increase at any given productivity as information becomes more precise. Intuitively, all else equal, if shoppers are more aware of changes in price index, firms will be more responsive to changes in competitors' prices. In contrast, the own-cost passthrough is irrelevant to the information frictions. In the dynamic model, shoppers will learn the shock over time. This proposition shows that learning can increase the total passthrough towards one, which implies monetary neutrality in the long run. The limit result also implies that if shoppers receive no information, firms only pass their own shocks to prices.

Taken together, Theorem 3 shows that the passthrough from changes in the nominal wage to price index is generically incomplete. The incompleteness is mostly contributed by high-productivity firms. The aggregate passthrough is lower when there is more search frictions and information frictions. Proposition 4 shows the main insight. Propositions 5-7 yield more disaggregated predictions of three types of passthroughs for individual firms and additional limit results.

1.6 General Equilibrium Model

In this section, I close the above partial equilibrium model in the general equilibrium. Following Mongey and Waugh (2024), I assume that shoppers first choose labor supply and consumption expenditure, and then search sequentially and consume. Unlike in the partial equilibrium model, the cash in hand X_i is determined endogenously.

The timeline is as follows. The period is divided into morning and afternoon. In the morning, the monetary authority sets the nominal GDP, and shopper make decisions about labor supply and the cash they will spend on shopping in the afternoon. In the afternoon, firms post prices, and shoppers are constrained by the amount of cash allocated to them in the morning.

Notably, there is no ex-ante securities market in which shoppers could trade contingent claims that are paid off conditional on final choices of goods and the number of searches. For example, a security might provide positive returns if a shopper experiences a long sequence of unfavorable draws or if the final choice only slightly exceeds the threshold.[11]

I state the shopper's problem in the morning. The shopper maximizes the expected value that she will obtain in the afternoon, net of the disutility associated with labor supply.

$$\max_{X_i, L_i} E_i U_i\left(\frac{X_i}{P_i}\right) - L_i$$
$$\text{s.t.} \quad X_i = W_i L_i + \Pi_i$$

where X_i is the cash left for the shopping. U_i is the shopper's value. It contains both match utility and utility from consumption. P_i is the price of good that the shopper accepts in the search process. Since both U_i and P_i are random, the shopper takes expectation on U_i and P_i when making the decision in the morning. L_i is the labor effort, W_i is shopper i' specific nominal wage, and Π_i is firms' total nominal profit that is allocated to the shopper. Due to the log utility, we know from (7), the cash X_i only shifts the level of the value and does not affect the search strategy. I rewrite the shopper's problem as follows,

$$\max_{X_i, L_i} \log X_i - L_i$$
$$\text{s.t.} \quad X_i = W_i L_i + \Pi_i$$

The first-order conditions imply $X_i = W_i$. Also, by definition, $p_i + c_i = x_i$. Aggregation gives,

$$\hat{p} + \hat{c} = \hat{w} \tag{42}$$

This implies that monetary authority who controls the nominal GDP also controls nominal wage. I also assume that shoppers only learn the aggregate nominal wage W from W_i. W_i draws from the distribution $\mathcal{N}(0, \sigma_x^2)$ same as in (5). For simplicity, I assume that shoppers do not treat Π_i as a signal. In the afternoon, shoppers search sequentially. This part of the model is the same as in the partial equilibrium model.

[11] 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.

Aggregate Supply Shocks I now study the responses of price index and output following an aggregate supply shock. I only consider one aggregate shock a time. Specifically, when analyzing aggregate supply shocks, the nominal wage is held constant and is known to all agents. The firm productivity now has two components,

$$\log A_k = \log A + \sigma_a \varepsilon_{ak} \tag{43}$$

where A is the aggregate productivity shock. Let $a = \log A$. It draws from $\mathcal{N}(0, \sigma_A^2)$. The shopper also receives noisy signal about a.

$$s_{ai} = a + \sigma_{as} \varepsilon_{ai} \tag{44}$$

where ε_{ai} is i.i.d across shoppers and it follows $\varepsilon_{ai} \sim \mathcal{N}(0, 1)$.

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

$$p^*(a_k, w, a) = p^*(a_k, w - a) \tag{45}$$

Any positive change in aggregate productivity acts equivalently to a proportional decrease in the nominal wage. Therefore, I can similarly define $\hat{p}_k = -\varphi_k \hat{a}$ and aggregate total passthrough Φ. The value of Φ is different from the one in the case of monetary shock because shoppers receive different signals about the aggregate shock.

Phillips Curve – In this section, I present the Phillips curve. The following proposition shows how two consumer-side frictions influence the slope of Phillips curve.

Proposition 8. *The Phillips curve is given by,*

$$\hat{p} = \frac{\Gamma}{1 - \Gamma} \frac{1}{1 - \theta} (\hat{c} - \hat{a}) \tag{46}$$

where θ is the average information friction about the particular shock of interest.

Proof. See Appendix A. ∎

This proposition shows that the slope of Phillips curve is composed by two parts. First, the slope increases with the aggregate own-cost passthrough Γ, which decreases in the search cost. Second, the slope is inversely related to the degree of information asymmetry. Under full information, the slope becomes vertical, implying monetary neutrality. In the other extreme, the slope approaches $\frac{\Gamma}{1-\Gamma}$, which implies that the lower bound of the slope is governed by the aggregate own-cost passthrough, corresponding to the limit results in Theorem 3. Moreover, the aggregate own-cost passthrough is a sufficient statistic that summarizes the effects of the "deep" parameters on the slope, i.e., $\kappa, \lambda, \sigma_a$. As I have shown in Proposition 6, the own-cost passthrough in principle can vary from 0 to 1.

This Phillips curve has two important differences from the standard New-Keynesian Phillips curve. First, I rewrite the Phillips curve in (46) in the following way,

$$\hat{p} - \bar{E}\hat{p} = \frac{\Gamma}{1-\Gamma}(\hat{c} - \hat{a}) \tag{47}$$

The Phillips curve involves the expectation of current price index instead of expectation of future inflation. This is the classic Lucas-type static Phillips curve. Importantly, the output gap is proportional to the nowcast error. In a seminal paper, Coibion and Gorodnichenko (2015) test the full-information rational expectation hypothesis in various surveys, including the Michigan Survey of Consumers. They find that average household expectation underreacts to aggregate shocks. It implies a positive gap $\hat{p} - \bar{E}\hat{p}$ for positive monetary shock and vise versa.

Second, in modern Phillips curve models, firms' expectations play a central role in driving current inflation. Even in Lucas (1972), firms' confusion about the idiosyncratic and aggregate demand shocks gives rise to monetary non-neutrality. However, the Phillips curve here presents an alternative view that household expectations can influence firms' pricing decisions as well. This has implications on how to estimate the slope of Phillips curve using the survey data. Recent efforts have been devoted to conducting new surveys of firms' expectations (Candia et al., 2023). I argue that household survey should be given enough emphasis as well.

2 Dynamic Model

I now present the full-fledged dynamic general equilibrium model. I introduce a new agent: worker. In particular, there is a representative household which consists of a single worker and a continuum of shoppers. I assume that the worker has full information about the model economy. The division between worker and shopper in a household is only used to simplify the problem. In particular, without information frictions on the worker side, we can obtain the standard Euler equation. This helps us focus on the monetary non-neutrality generated only by the frictions on the shopper side.[12]

The timeline is as follows. Each 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 total consumption expenditure transferred to shoppers. In the afternoon, firms post prices, and shoppers search sequentially and they are constrained by the cash in hand. I assume that the worker and shoppers cannot communicate. Also, there is no security markets where shoppers can trade claims that are contingent on the search process and results.

Firm – Let A_{kt} denote the firm's productivity

$$\log A_{kt} = \log A_t + \sigma_a \varepsilon_{akt} \tag{48}$$

where $\varepsilon_{akt} \sim \mathcal{N}(0,1)$ A_t is the aggregate productivity. Denote $a_t = \log A_t$. It follows an AR(1) process,

$$a_t = \rho_A a_{t-1} + \varepsilon_{At} \tag{49}$$

where ε_{At} is the shock to aggregate productivity. It follows $\varepsilon_{At} \sim \mathcal{N}(0, \sigma_A^2)$.

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

$$i_t = \phi \hat{\pi}_t + \upsilon_{mt} \tag{50}$$

where υ_{mt} follows,

$$\upsilon_{mt} = \rho_m \upsilon_{mt-1} + \varepsilon_{mt} \tag{51}$$

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

Worker – The worker maximizes the expected discounted utility with discount factor $\beta \in (0,1)$ and period utility defined over the sum of values which shoppers will obtain in the afternoon, i.e., $\int U_{it}(\frac{X_{it}}{P_{it}})di$. Definitions of $U_{it}(\frac{X_{it}}{P_{it}})$ are the same as in Section 1.6. Worker can save in risk-free

[12] In the extension, I consider the case with only a continuum of shoppers. Auxiliary shocks are added to "noise up" variables that contain information about the monetary shock, such as wage, interest rate and profit. I obtain incomplete-information Euler equation as in Angeletos and Lian (2018).

bonds B_t (in zero net supply) that pay an interest rate of R_t.

$$\max_{B_t, X_t, L_t} E_0 \sum_{t=0}^{\infty} \beta^t \left(\int U_{it}(\frac{X_{it}}{P_{it}}) di - L_t \right)$$

$$\text{s.t.} \quad X_t + B_t = W_t L_t + R_{t-1} B_{t-1} + \Pi_t$$

$$X_{it} = X_t \exp\left(\sigma_z \varepsilon_{xit} - \frac{\sigma_x^2}{2}\right)$$

where X_t is the total consumption expenditure transferred to shoppers and $\int X_{it} di = X_t$. L_t is the labor effort, W_t is nominal wage, and Π_t is firms' nominal profits. Again, the worker's problem can be simplified due to the log utility.

Shopper − The shopper solves the static problem in (11) period by period given the history of signals. I assume that each shopper receives a noisy signal about $\hat{\pi}_t$ at the beginning of each period. In this way, we both accommodate the learning from current prices and avoid specify two different information structures for two type of shocks. In addition, I make the simplifying assumption that shoppers observe the past price level but do not extract information from it. This assumption can be interpreted as a form of bounded rationality. It can also be motivated on empirical grounds: in the data, inflation contains little statistical information about the aggregate shocks. Instead, it is dominated by the "markup shocks".

Dynamic Equilibrium I present the proposition that describes the dynamics of consumption, price index and interest rate in equilibrium.

Proposition 9. *The equilibrium dynamics of* $\{\hat{p}_t, \hat{c}_t, i_t\}$ *is described by the following system of three equations:*

$$\hat{c}_t = E_t \hat{c}_{t+1} - (i_t - E_t \hat{\pi}_{t+1})$$

$$\hat{\pi}_t - \bar{E}^s \hat{\pi}_t = \frac{\Gamma}{1-\Gamma}(\hat{c}_t - \hat{a}_t)$$

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

where Γ *is the aggregate own-cost passthrough and* $\bar{E}^s$ *is the shoppers' average expectation.*

With simplifying assumptions, this system of equations is only different from the standard New-Keynesian model in terms of the Phillips curve, which facilitates the comparison. In the next section, I will show the impulse response functions and their properties. In the Appendix B, I present the system and impulse responses in which shoppers do not know the past price level and monetary authority adopts a price-level targeting rule.

2.1 Calibration

In this section, I present a calibration of the model. I proceed in two steps. First, I calibrate the aggregate own-cost passthrough and deep parameters that are related to the search friction. Second, I calibrate the information friction.

Aggregate own-cost passthrough – The aggregate own-cost passthrough is a sufficient statistic for deep parameters. Amiti et al. (2019) document that the average own-cost passthrough is around 0.5 in the universe of Belgian manufacturing firms. Interestingly, Amiti et al. (2019) also show that the sum of own-cost and cross-price passthroughs cannot be rejected from being one. This seems to indicate that the passthrough from the shock to prices is closed to one in the model. However, search frictions are more prevalent in the non-tradeable industries, such as retail and broad service sectors. In contrast, the buyer-seller relationships in tradable industries are often governed by contracts, typically involving bargaining between a final-good producer and multiple intermediate-good suppliers (Gopinath et al., 2011). Alternatively, Gopinath et al. (2011) use a retail chain database containing information on wholesale costs and demonstrate substantial variation in own-cost passthrough estimates, with a median of around 0.5 for U.S. stores and 0.25 for Canadian stores. Own-cost passthrough estimates are often biased upward because, without controlling for all competitors' prices, the estimates may capture strategic complementarity effects due to omitted price changes of other firms that respond to correlated shocks. Therefore, I pick $\Gamma = 0.3$ which is closed to the lower end of the median estimates.

Although the deep parameters are not relevant for impulse responses, it will still be valuable to check the sanity of the implied values of these parameters from moment matching. To proceed, I use the estimate of elasticity of substitution from DellaVigna and Gentzkow (2019). They use NielsenIQ Retailer Scanner database and find that the average elasticity of substitution across stores and products is 0.25, implying a markup of 1.67. In the extension, I show that retailers charge the same markup for all products that they sell in Proposition 10. In addition, the productivity dispersion σ_a is set to be consistent with Decker et al. (2020), i.e., $\sigma_a = 0.3$. The following table shows the baseline calibration for deep parameters that do not relate to the information friction.

Table 1: Baseline calibration of the model

Parameter	Description	Value
κ	Search cost	0.22
λ	Relative importance of match utility	5.51

Notes: The table reports the calibrated values for parameters that are related to the aggregate own-cost passthrough.

Table 2: Model fit

	Moment	Model	Data	Source
M1	Average markup	1.67	1.67	DellaVigna and Gentzkow (2019)
M2	Average own-cost passthrough	0.3	0.3	Amiti et al. (2019);Gopinath et al. (2011)

Notes: The table summarizes the moments, model and data values of these moments, and the sources of the empirical values of these moments.

Table 1 summarizes the calibrated parameters, and Table 2 presents the fit of the model to data. Despite its parsimonious structure, the model is successful in matching key moments in the data. Let us examine the implications of the calibrated value for two parameters. First, although the targeted elasticity of substitution is 2.5, the implied $\lambda+1$, which represents the elasticity of demand when $\kappa \to 0$ as shown in Proposition 6, is about 6.5. This suggests that the search friction accounts for a substantial bulk of the market power. Second, Based on the calibrated values of deep parameters, we can infer the average contact per shopper ρ^{-1} equal to 1.26. This suggests a relatively large search cost and about 80% shoppers make the purchase on the first search. Therefore, Assumption 1 is plausible, as shoppers only visit a limited number of firms.

Information friction – To calibrate the sequence of $\{\theta_t\}$, I intend to examine the impulse responses of inflation and inflation nowcast following identified shocks. However, I face two issues. First, the household inflation nowcast are not available in the popular survey data. For example, Michigan Survey of Household only asks households about their 1-year ahead inflation expectation.

Second, households may learn different shocks in different ways. For instance, Kumar et al. (2015) shows that households pay particular attention to salient prices, such as oil prices. Also, D'Acunto et al. (2021a) documents that households learn from their shopping experiences. This renders impulse responses to specific shocks, e.g., monetary shocks and oil shocks, less informative in understanding the household inflation expectation formation, which is the key component in generating monetary non-neutrality in our model. To proceed, I assume that households adopt a "generic" way of learning inflation, regardless of the specific nature of underlying shocks. In particular, households may incorporate various sources of information conditional on shocks but will always receive a noisy signal about inflation as a way to learn about inflation. To isolate this "generic" learning, I will use the main inflation shock from Angeletos et al. (2020). This shock is identified by maximizing its contribution to the business-cycle variation in inflation. The key feature of this shock is that it has a very small footprint on real quantities and zero footprint on TFP. It is thus akin to the cost-push shocks in the DSGE literature.

The main empirical strategy is to estimate impulse responses directly using the local projection method of Jordà (2005). The specification is,

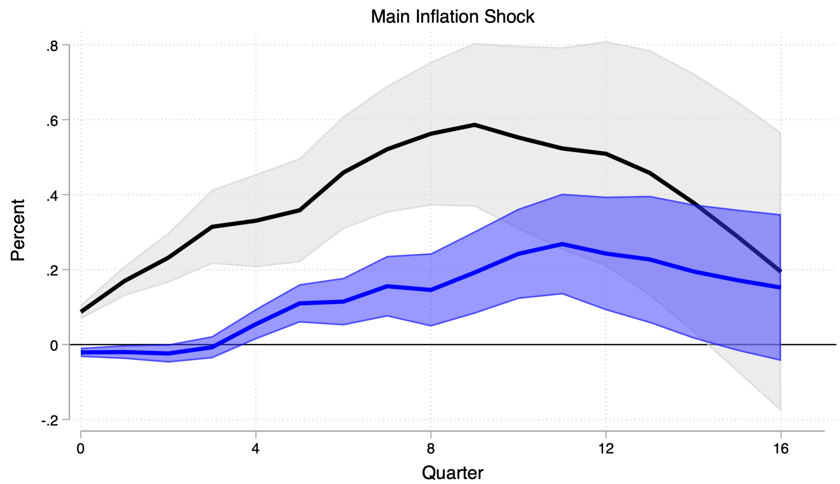
$$y_{t+h} = \alpha_h + \beta_h \varepsilon_t + \mathbf{\Gamma}' \mathbf{X}_t + u_{t+h} \tag{52}$$

where $\{\beta_h\}_{h=0}^{H}$ trace out the dynamic responses of the outcome. y_t is the inflation π_t and the household average inflation expectation a year ago $\bar{E}_{t-12}\pi_t$. X_t is a vector of controls. It includes 12 lags of shock itself, inflation, inflation expectation a year ago, 1-year government bond rate, growth rate of industrial production. I construct standard errors for the coefficients that are heteroskedasticity and autocorrelation robust (HAC). All reported error bands are 90% confidence intervals.

Figure 2 shows that the main impulse response estimates. The black line represents the impulse responses of inflation and the blue line represents the responses of inflation expectation a year ago. Since the shock is unanticipated, inflation expectations remain unchanged for the first year. They begin to adjust only when households observe and learn about the inflation. Given that this shock impacts only inflation, with no effect on other real variables, therefore, households' learning relies solely on observing the inflation itself. The key takeaway from this figure is that learning from inflation is slow. The inflation responses are always above the inflation expectation responses. The two error bands of the impulse responses begin to overlap at the end of the third year, and the impulse response lines intersect at the end of the fourth year.

I assume that, in the model, the shopper receives a noisy signal about unexpected inflation $\hat{\pi}_t$ in each period. I calibrate the signal-to-noise ratio of this signal such that two impulse responses of the inflation and the inflation nowcast coincide in 3 years after the shock. In Appendix B, I show the same impulse responses following identified oil news shocks and monetary policy surprises.

Figure 2: Impulse Responses of Inflation and Household Inflation Expectation



Notes: Dynamic responses: outcomes and forecasts. The sample period is Q3 1979–Q4 2017. The black line represents the impulse responses of inflation and the blue line represents the impulse responses of inflation expectation. The shaded areas are 90% confidence intervals based on heteroskedasticity and autocorrelation robust standard errors and 12 lags. The x-axis denotes months from the shock, starting at 0. The y-axis denotes percent.

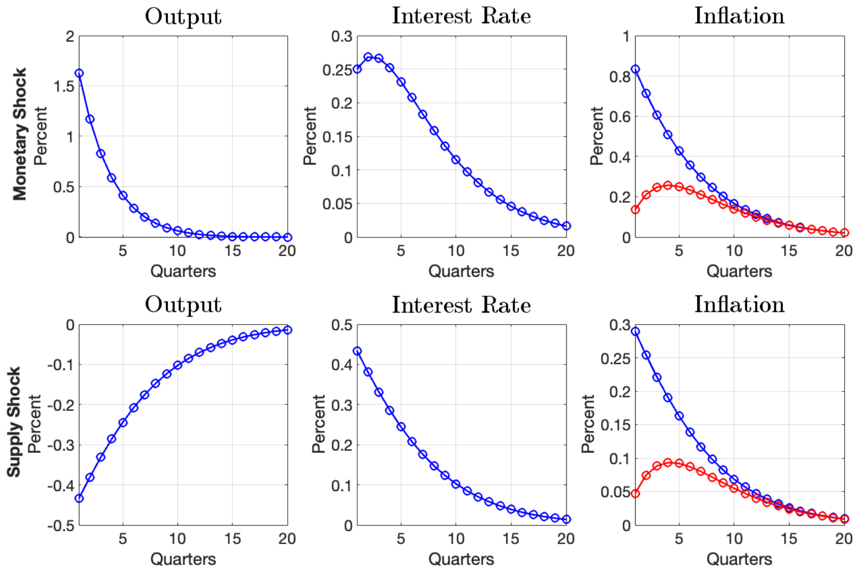
The plot with oil news shocks gives similar responses as the main inflation shock. The responses following the monetary shock are quite different. I provide a detailed discussion in Appendix B. In addition, the Taylor rule parameter is calibrated as $\phi = 1.5$.

2.2 Impulse Responses of the Calibrated Model

In this section, I discuss the impulse responses of the calibrated model. The calibrated model is computed using the frequency-domain methods based on Rondina and Walker (2021), Huo and Takayama (2023), and Han et al. (2022). Figure 3 presents the results. The first row shows the impulse responses of output, interest rate, inflation and inflation nowcast following a 100 basis-point interest rate cut based on the calibrated model. The second row presents the responses following a 100 basis-point reduction in the aggregate productivity. In the third column, the blue line represents the inflation and the red line represents the inflation nowcast. Our theory predicts that the gap between these two lines is proportional to the output response.

There are three key implications about the monetary non-neutrality from the calibration analysis. First, with exogenously calibrated parameters Γ and $\{\theta_t\}$, the model exhibits substantial

Figure 3: Impulse responses of price index and output in the calibrated economy



Notes: The figure shows the impulse responses of output, interest rate, inflation and inflation nowcast following a 100 basis-point interest rate cut and a 100 basis-point decrease in the aggregate productivity based on the calibrated model. In the third column, the blue line represents the inflation and the red line represents the inflation nowcast. The x-axis is quarters. The y-axis is percent.

monetary non-neutrality. A 100 basis-point cut in the interest rate results in an initial output increase of approximately 160 basis points. This response is comparable to that in a standard New-Keynesian model where the probability of not adjusting price being around 70%. This probability aligns with the value that is usually calibrated from a DSGE model based on impulse response matching or Bayesian estimation (Christiano et al., 2005 and Smets and Wouters, 2007). This suggests that the degree of monetary non-neutrality generated by our mechanism is sufficient to explain and match the macro-level impulse-response evidence.

Second, in the New-Keynesian Phillips curve, the future inflation feeds in and amplifies the current inflation. This leads to larger inflation response and smaller output response.[13] However, due to the static nature of our Phillips curve, the inflation response is dampened by around 15 basis points compared to the New-Keynesian model with Calvo parameter 70%. Another way to think about static versus dynamic Phillips curve is that monetary non-neutrality does not rely on

[13]One can prove that if the Calvo parameter is lower than the persistence of the shock, larger discount rate will decrease the output response.

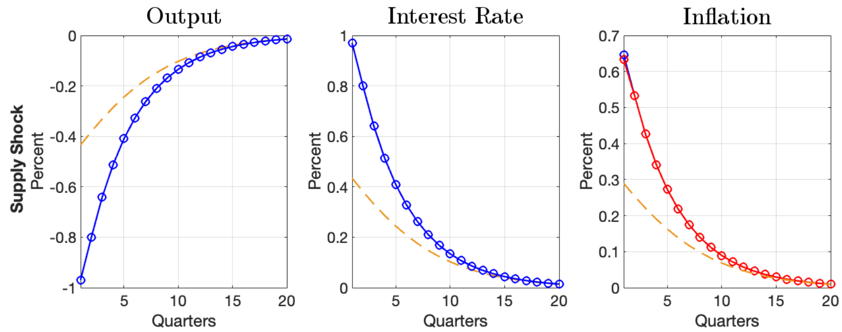
the future inflation. It is there as a by-product of Calvo adjustment friction. On the contrary, whether firms are forward-looking when setting prices or not does have significant impact on our understanding of the news shock. For example, a news about the future aggregate productivity shock considered in Lorenzoni (2009) will not have any effect on the real and nominal variables under static Phillips curve. Recent studies of anticipated VAT reforms reveal a rapid passthrough of VAT-induced cost changes to prices, typically within four months (Buettner and Madzharova, 2021), indicating a small future inflation expectation term in the Phillips curve.

Third, since the output response depends on the gap between actual inflation and the inflation nowcast, rapid learning can close this gap before the shock fully dissipates. Consequently, the persistence of the output response may be shorter than the persistence of the monetary shock. This is consistent with the empirical evidence. As shown in Figure 3 of Bauer and Swanson (2023), following a monetary shock, industrial production reaches its trough within 10 months, while the CPI continues to decline and approximately reaches its trough after 40 months. This suggests that the persistence of the output response is shorter than that of the inflation response. Our mechanism provides an endogenous explanation for the less persistent output response.

Now, I turn to supply shock. Following a 100 basis-point reduction in the aggregate productivity is rather not surprising, the output declines and the inflation increases by less than 100 basis points. This occurs because firms, wary of upsetting shoppers, limits the passthrough of the shock. As a result, prices remain below the full-information benchmark, which sustains aggregate demand above the natural output level. This also leads to a higher labor supply in equilibrium. The persistence of the output response inherits the shock's persistence, when the gap between inflation and inflation nowcast narrows to zero. This differs from the case of a monetary shock, as the aggregate productivity shock directly impacts output.

Overall, our mechanism can generate substantial monetary non-neutrality, comparable in magnitude to the calibrated Calvo parameter commonly used in DSGE models. The future news about aggregate productivity shock is not relevant since the Phillips curve is static. The persistence of the output response is endogenously determined, with faster learning leading to lower persistence. In addition, the economy is less responsive to a supply shock when the slope of the Phillips curve is flatter.

Figure 4: Impulse Responses of Inflation and Household Inflation Expectation



Notes: The figure shows the impulse responses of output, interest rate, inflation and inflation nowcast following a 100 basis-point decrease in the aggregate productivity in a calibrated model with a large signal-to-noise ratio. The orange dashed line represents our benchmark calibrated model. In the third column, the blue line represents the inflation and the red line represents the inflation nowcast. The x-axis is quarters. The y-axis is percent.

Applications – Now, I consider the application of the model to explaining the post-pandemic high inflation. The similar mechanism can be used to explain the differential inflation responses after demand and supply shocks. Then, I discuss the policy implications.

There was extensive public discussion and media coverage surrounding the onset of supply chain disruptions and labor shortages due to concerns about infections. Simultaneously, many restaurants posted notices informing consumers that they needed to increase prices because labor and material costs had risen. These public signals likely reduced information asymmetry, enabling households to learn more quickly about the rising costs faced by firms. Translating this scenario into the model setup implies that the signal regarding unexpected inflation becomes highly precise. As a result, the Phillips curve slope steepens, and cost changes are rapidly passed through to prices.

Figure 4 illustrates the impulse responses in this case. The orange dashed line represents the impulse responses based on our benchmark calibrated model. Compared to the benchmark, the decrease in output and inflation are more than doubled in the case of very precise signal about inflation. This is consistent with the empirical observation that the inflation shot up to almost 9% in June 2022. The output and unemployment rate did not show a significant decline, probably due to the concurrent fiscal stimulus.

A related application is to offer a possible explanation for the puzzle that inflation rises significantly following oil shocks (Känzig, 2021) but remains relatively modest after demand shocks (Bauer and Swanson, 2023). More concretely, Figure B.2 shows that household inflation expectations after an oil news shock converge to actual inflation more quickly than in response to the main inflation shock, as shown in Figure 2. This aligns with the evidence documented in Kumar et al. (2015) that consumers are highly sensitive to gasoline price fluctuations. As a result, the attention to oil prices reduces the information asymmetry associated with cost changes due to oil price shocks and therefore leads to a higher passthrough of the shock to prices. In contrast, households in low-inflation countries seem unaware of even dramatic monetary policy announcements, and more generally display almost no knowledge of what central banks do (see, e.g., Bachmann et al., 2015; Candia et al., 2020; D'Acunto et al., 2021a). This suggests that information asymmetry may be large and persistent following a monetary shock, leading to dampened and prolonged inflation responses and substantial monetary non-neutrality.

Policy Implication – The main policy lesson from these applications is that the slope of the Phillips curve is endogenous to the level of information available on the consumer side. Conventional Phillips curves, derived from reduced-form assumptions such as infrequent price adjustments and menu costs, are vulnerable to the Lucas Critique. Specifically, economic shocks are not isolated from the broader society; while individuals may not immediately recognize the shock itself, they often discuss its consequences. Certain shocks, in particular, may trigger a sequence of public events, policy communications, and announcements—such as FOMC meetings and direct fiscal transfers to households—which significantly increase households' awareness of the shock, resulting in a steeper slope of Phillips curve. This has important implications for the conduct of monetary policy. The monetary authority should adopt a more aggressive stance when information asymmetry is low, as prices are more responsive to the shock in such environments.

2.3 Extensions

I discuss two extensions. In the first 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 $a_{kj} \sim \mathcal{N}(0, \tilde{\sigma}^2_{ap})$. I assume that there is no search frictions when shopping within a firm. Shoppers 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 10. *Each firm charges same markup over all the products it sells.*

$$P_{kj} = \frac{e_k}{e_k - 1}\frac{W}{A_{kj}} \tag{53}$$

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

$$P_k = \frac{e_k}{e_k - 1}\frac{W}{A_k}; e_k = \lambda\frac{\int X\big(g\big(\lambda(v^*(x) + p_k)\big)\big)d\Phi_x(x)}{\int X\big(1 - G\big(\lambda(v^*(x) + p_k)\big)\big)d\Phi_x(x))} + 1 \tag{54}$$

where P_k is the CES price index of P_{kj}. The passthrough of product-level productivity shocks a_{kj} increases toward one when the number of products increases.

This extension 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.[14] 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.

In the second extension, I generalize the static general equilibrium model to accommodate finite labor supply elasticity. The details of setup and equilibrium are delegated to Appendix B. I present the following result.

Proposition 11. *The Phillips curve, when the elasticity of labor supply is η, is given by,*

$$\hat{p}_t = \frac{\Phi}{1 - \Phi - \frac{\eta(1-\tilde{\Phi})}{1+\eta}}(\hat{c}_t - a_t) \tag{55}$$

where $\tilde{\Phi} \leq 1$ is defined in the Appendix B. $\tilde{\Phi} = 1$ if $\theta_t = 1$. ε_{mt} is the monetary shock.

This proposition presents a Phillips curve with an additional term capturing the effect of incomplete information on labor supply. Due to the log utility assumption, changes in the nominal wage should not influence labor supply. However, under incomplete information, shifts in search behavior following shocks lead to a different customer allocation across firms. For instance, in the case of an expansionary monetary shock, increased search activity by consumers drives higher demand for high-productivity firms, resulting in a more efficient allocation of demand. Consequently, the aggregate labor demand increases. In equilibrium, both labor supply and nominal wage increase, exerting upward pressure on the price index. As a result, the slope of the Phillips curve becomes steeper.

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

3 Empirics

The model offers rich theoretical predictions. I empirically test two of them that indicate role of information asymmetry and search frictions respectively. First, I provide empirical support for the information asymmetry between firms and consumers about marginal cost. A key mechanism of the model suggests that due to such information asymmetry, an unanticipated inflation leads to increased search activity. I use a detailed consumer panel dataset, which contains households' shopping trips, spending, stores, and demographic characteristics to test whether higher inflation is associated with an increase in measures of search behavior. Second, I present evidence that supports the comparative statics on search frictions and passthroughs. I contribute to the literature by developing a novel measure of search frictions. I exploit regional variations in search frictions by treating each region as a separate model economy with heterogeneous search frictions and similar information frictions.

3.1 Evidence on Information Asymmetry

I present evidence that supports the information asymmetry between firms and consumers. After an unanticipated inflation shock, search behaviors remain unchanged if information about the shock is fully known to consumers. However, when information is incomplete, the shock leads to a significant increase in various measures of search behavior.

Data – The data source is the NielsenIQ Consumer Panel Data set.[15] NielsenIQ tracks the shopping behavior of average 55,000 households every year. Each household uses in-home scanners to record purchases. Households also record any deals used that may affect the price. These households represent a demographically balanced sample of households in 49 states and about 3,000 counties in the United States. Each household stays in the panel for 30 quarters on average. The dataset has over 1,000 NielsenIQ-defined product modules and covers around 30% of all expenditure on goods in the CPI.[16]

[15] 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.

[16] For further discussion of the NielsenIQ data, see Broda and Weinstein (2010).

The dataset contains information about each shopping trip the household takes, such as the retailer, the total spending, the date of the transaction. This enables me to construct various measures of search behavior. Moreover, the data includes households' demographic information such as age, education, employment, marital status, which are updated annually. I collapse the dataset to the household-quarter level.

Measurement – The number of trips each household undertakes in a given quarter serves as a direct measure of search behavior in the model. Households typically purchase multiple items per trip. To analyze the composition of spending across trips, I use the Herfindahl–Hirschman Index (HHI) to measure spending concentration for each household per quarter. A lower HHI indicates that spending is distributed more evenly across trips. The theory suggests that a higher HHI occurs when households are satisfied with most items encountered in fewer trips. Additionally, I measure the number of distinct retail stores visited by households in a quarter to capture the distribution of trips across retailers. According to theory, higher unanticipated inflation should drive households to search for alternative stores. In Appendix C.1, I also measure the fraction of items purchased on deal to assess households' efforts to find lower prices. Table 1 presents the summary statistics for these search measures. On average, households make 3.5 shopping trips per week with spending HHI equal to 7.6%, visit approximately 12 retailers per quarter, and purchase 26% of items with a deal. The variance of these search behavior is substantial, indicating large heterogeneity among the population.

Table 3: Descriptive Statistics of Household Search Behavior

	Mean	S.D.	10th Percentile	90th Percentile	Observations
Number of Trips	41.49	29.13	12	80	3,353,048
Spending HHI(%)	7.55	6.32	2.69	14.11	3,353,048
Number of Distinct Retailers	11.70	7.16	4	21	3,353,048

Notes: The table reports summary statistics for key household search behavior variables in my data. Number of Trips is the total number of shopping trips per quarter per household. Number of Retailers is the distinct retailers visited by a household per quarter. Spending HHI is the Herfindahl–Hirschman Index of spending across trips. Deal Fraction is the proportion of items purchased with a deal.

Unanticipated Inflation – Following the literature, I use a Vector Autoregression (VAR) model, which includes inflation for food and drinks, the log of industrial production, and the 1-year government bond rate, to forecast inflation based on historical data. I assume that households derive the anticipated inflation in this way. Specifically, I estimate a simple OLS regression of inflation on four lags of these three variables. The residual from this regression is treated as unanticipated inflation for households. I also consider the measure based on the inflation for overall goods and services. Moreover, I use exogenously identified shocks, i.e., monetary policy surprises based on Bauer and Swanson (2023)[17] and oil news shocks based on Känzig (2021), as direct measures of unanticipated inflation. Monetary policy surprises are supposed to decrease the inflation and oil news shocks should increase the inflation. Appendix C.1 provides further details and discusses several robustness checks.

Impact of Unanticipated Inflation on the Households' Search Behavior – I use measures of household search behavior, along with measures of unexpected inflation., to assess the changes in search behavior after an unanticipated inflation shock. I use the following empirical specification:

$$y_{it+1} = \lambda_i + \beta\tilde{\pi}_t + X_{it} + e_{it} \tag{56}$$

where t is time; i represents household. λ_i is the household fixed effect. $\tilde{\pi}_t$ is the unanticipated inflation. β is the coefficient of interest. It measures the magnitude of the correlation between the unanticipated inflation and the households' search behavior. y_{it+1} is different measures of search behavior in the next period. I use next-period value for two reasons. First, it avoids reverse causality because inflation and household search behavior are jointly determined in theory. Second, it may take time for households to change their shopping habits. X_{it} is the time-varying household controls. These controls include household age, employment, education, marital status, having children or not, and household i's total spending in time t. As pointed out by (Aguiar and Hurst, 2007), these variables have large affect on shopping behavior. For regressions using exogenously identified shocks, I also add log industrial production and 1-year government bond rate to control the effect of shocks on search behavior through other macroeconomic channels.

The results are presented in Table 4. The first row shows that a one standard-deviation increase in unanticipated food and drink inflation is associated with: (i) 0.545 additional trips, (ii) a 0.066 decrease in the spending HHI, (iii) a 0.17 increase in the number of different retailers visited, and (iv) a 0.156 increase in the number of different retailers visited conditional on the number of trips.

[17]Bauer and Swanson (2023) provide a clean monetary policy shock series by orthogonalizing the surprises identified using high-frequency methods with respect to the Greenbook and Blue Chip forecasts that pre-date the announcement.

Table 4: Search and Unanticipated Inflation

	Number of trips	Number of distinct stores	Number of dist. stores|Trips	Spending HHI
Panel A: $\tilde{\pi}$-FD	0.545***	0.170***	0.156***	-0.066***
	(0.015)	(0.004)	(0.004)	(0.005)
Panel B: $\tilde{\pi}$-ALL	0.118***	0.034***	0.033***	-0.014**
	(0.013)	(0.004)	(0.003)	(0.004)
Panel C: Oil News	0.217***	0.066***	0.046***	-0.004
	(0.012)	(0.003)	(0.003)	(0.004)
Panel D: MPS (BS23)	-0.145***	-0.067***	-0.057***	0.035***
	(0.012)	(0.003)	(0.003)	(0.005)
Observations	3,148,375	3,148,375	3,148,375	3,148,375
HH fixed effects	√	√	√	√
HH time-varying effects	√	√	√	√

Notes: The table reports the estimates in specification (18). Number of trips is the total number of trips. Number of distinct stores refers to the number of distinct stores visited by households. Number of distinct stores|Trips refers to the number of distinct stores conditional on the number of trips taken in a given quarter. Each observation is at the household×quarter level covering from 2006 Q1 to 2019 Q4. The coefficient represents the corresponding change in different measures of search behavior after a 1 percentage point change in unanticipated inflation. Household fixed and time-varying effects are controlled. Standard errors are clustered at the household level. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

These correlations suggest that households facing higher price indices engage in more active search, are less likely to satisfy with most of items in a few trips. They also tend to explore new stores, even when controlling for the number of trips. This indicates a reallocation of trips from familiar to new retailers. Additionally, Appendix C.1 shows that households are more likely to purchase items on deal, though this effect is small, suggesting it is not the primary adjustment mechanism in response to higher prices.

The second row uses unanticipated inflation in overall goods and services. As expected, the effect is smaller because the NielsenIQ data primarily covers food and beverages, and search behavior is more sensitive to inflation in these sectors. The third and fourth columns, which use exogenous shocks, show similar results. Appendix C.1 further explores the dynamic effect of unanticipated inflation on measures of search behavior. It shows that the effect is persistent and decreasing over time. As predicted by theory, households' adjustment of search behavior diminishes as they become aware of rising prices.

The economic magnitude of the coefficients are not large compared to the weighted mean reported in Table 3. For instance, the number of trips only experiences less than 2% increase compared to the average after inflation shocks, even though it is statistically significant. There are several reasons. First, consumers only records purchases from the stores that NielsenIQ includes. NielsenIQ tends to cover large retail stores. Therefore, the coefficient is biased down if consumers switch to other stores that are not included or online purchases. This can be implied from the substantial within-household variations trips across quarters.[18] Second, there may be substantial substitution happening within one trip, e.g., consumer may trade down quality of goods within the store (Jaimovich et al., 2019). This hampers consumer learning the underlying shock over shopping. Third, increasing search activities also dampens the inflation responses in the model. This generates a reverse causality issue in the estimation. Finally, there can be heterogeneous responses of different stores to the inflation shock. It can be originated from various frictions on the store side. For instance, stores may have information frictions about the shock. Retail stores may be affected by inflation shock less as their suppliers have absorbed part of the shock.

Overall, this evidence supports a key aspect of the main mechanism. As prices rise after an aggregate shock, consumers are incentivized to search for alternatives, indicating the existence of information asymmetry between retailers and consumers about increasing average marginal cost. The magnitude of responses in search activities may be contaminated by various reasons.

3.2 Evidence on the Effect of Search Frictions on the Passthrough

I now present second set of evidence that supports the comparative statics on search frictions and passthroughs. I construct novel measure of search frictions on the county level.

3.2.1 MSA-Level Search Index

Search frictions bridges the information asymmetry and the incomplete passthrough in the model. At the same time, the model captures search friction in a reduced form, i.e., a single utility cost. Finding a counterpart in the data poses a challenge. To address this, I draw on findings from urban economics literature. Duranton and Puga (2020) emphasize that regions with higher establishment density bring goods and services closer to consumers, reducing the need for travel. Duranton

[18] The within-household standard deviation is about 15 trips.

and Turner (2018) provide evidence that increased density leads to less time spent traveling by individual drivers. Similarly, Agarwal et al. (2017) show, using credit card records, that greater density of sales locations is associated with a decline in travel for shopping and personal services. Building on these insights, I use establishment density as a measure for search frictions. Higher density indicates lower search friction.

To construct establishment density from 2005 to 2019, I use annual data from the 1998-2019 *County Business Pattern* (CBP) published by the US Census Bureau. They contain administrative data on employment, payroll, and establishment counts for approximately 1,000 industries, classified according to 2-6 digit NAICS codes, by county and year. For each year of the CBP data, I calculate the establishment density for each industry, defined as the number of establishment divided by the relevant economic area, e.g, central business area. I restrict our sample to the following 2-digit NAICS industries: Retail Trade, Real Estate Rental and Leasing, Health Care and Social Assistance, Arts, Entertainment, and Recreation, Accommodation, Food Services and Other Services. These sectors are more likely to be affected by the search frictions and consumer search behavior can be best described by our model.[19] I then construct county-level search index by aggregating establishment density for each industry within a county,

$$SI_{cy} = \log(\sum_{j} \text{Share}_{jc\tau} \frac{N_{jcy}}{A_c}) \tag{57}$$

where SI denotes search index. y is year. N_{jcy} represent the number of establishments in industry j in county c during year y. A_c is the size of economic area. The specific choice of A_c is not crucial since I will demean the search index for each county. Ideally, $Share_{jc\tau}$ should be the local consumer expenditure share. However, due to the unavailability of county-level consumer expenditure data, I use total labor income as a proxy. Assuming that output elasticity of labor and markups are same across industries, labor income share exactly equals consumer expenditure share (Decker et al., 2020). Data on payroll and employment is required for computing labor income. However, due to confidentiality concerns, data on annual payroll and employment is often incomplete, with over 50% of the information on payroll missing in 2000. To address this issue, I use imputed employment data provided in Eckert et al. (2020).[20] Then, I utilize CBP data at the state level, which has way less

[19] I include Finance and Insurance, and Educational Services as robustness check in Appendix C.2.

[20] Eckert et al. (2020) develop a linear programming method that exploits the large set of adding-up constraints implicit in the hierarchical arrangement of the data to impute missing employment.

missing values, to calculate the annual wage for each industry within each state. I use it as a proxy for wage in all counties within that state. Lastly, I also fix the labor income share at pre-period τ to mitigate the concern that changes in expenditure share might affect inflation responses through channels other than search frictions, e.g., structural change. Specifically, I average labor income share over the period 1998-2000 to reduce the measurement error and missing values. I calculate the labor income share as follows:

$$Share_{jc\tau} = \frac{\text{annual wage}_{js\tau} \times \text{employment}_{jc\tau}}{\sum_j \text{annual wage}_{js\tau} \times \text{employment}_{jc\tau}} \tag{58}$$

where s is state and τ is period 1998-2000. One concern is that search indices across counties may be correlated with local economic conditions, such as local income and housing prices.[21]

Correlation with local economic conditions can bring following issues. First, higher local wage may affect inflation through other channels. For example, housing prices are usually positively correlated with wages. Stroebel and Vavra (2019) shows that regions with higher housing prices also have higher retail prices. In addition, Bilal (2023) documents persistent job-losing rates across regions, resulting in different unemployment rates. In regions with low job-losing rates, productive firms hire more aggressively. It may increase the regional inflation response to aggregate shocks. Last but not least, denser areas may carry more varieties (Handbury and Weinstein, 2015). More varieties may have impact on search time per variety, which means that the opportunity cost of searching in one good category is high if there are a lot other categories waiting to purchase.

To mitigate such concern, I subtract the permanent heterogeneity of search indices across counties by taking out the mean of search index over the period 2006-2019 for each county. Denote this mean as $\overline{SI}_c$. The demeaned search index is given by,

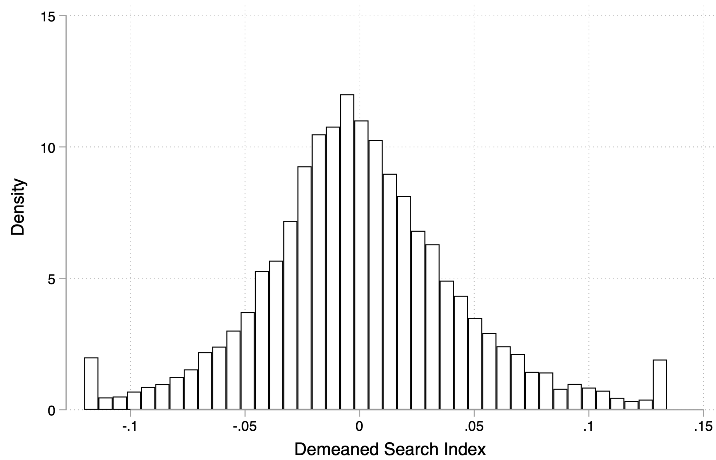
$$\Delta SI_{cy} = SI_{cy} - \overline{SI}_c \tag{59}$$

Positive ΔSI_{cy} indicates increase in establishment density above its mean in year y. I take the median of demeaned search indices across counties within a Metropolitan Statistical Area (MSA) and Mitropolitan Statistical Area (MicroSA).[22] Figure 1 shows the density distribution of

[21] In Appendix C.2, Table C.2-1 show these correlations are highly significant and relevant. I treat the relevant economic area as county geographic size and reduce the bias by taking medium within higher-level administrative geographical areas, such as MSA.

[22] I aggregate the search index to the higher-level administrative geographic areas since the price indices are constructed at MSA level. Aggregation also helps reduce measurement errors at the county level.

Figure 5: Density distribution of demeaned search index



Notes: The figure plots the density distribution of demeaned search index defined in (21).

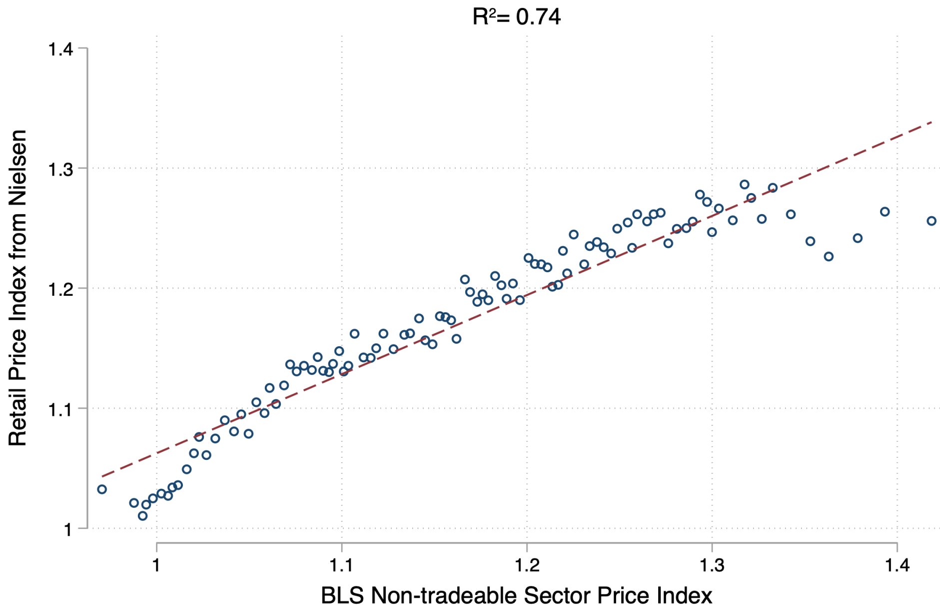
demeaned search index on the MSA and MicroSA level. The distribution is similar to a normal distribution with mean at approximately zero and the variance is 0.044. I construct variables that describe local economic conditions from the CBP data. I first derive county-level annual wage and total employment from the CBP data. I then construct a measure of concentration for non-tradeable industries using employment data based on Eckert et al. (2020). Finally, I import MSA, MicroSA-level unemployment rate data from BLS. The details of variable construction is delegated to Appendix C.2. Table C.2-2 shows that in contrast with the search index defined in (57), the demeaned search index is not significantly correlated with local economic conditions. This indicates that the fluctuation in search index around the mean for each county may indeed reflect the changes in the easiness of accessing a store in non-tradeable industries.

3.2.2 MSA-Level Price Index

To construct price indices, I utilize another dataset collected by the NielsenIQ Retail Scanner Database. The Retail Scanner data consist of weekly revenue and quantities for each Universal good Code (UPC) from approximately 40,000 individual stores selling food, drugs, and mass merchandise across all U.S. markets between 2006 Q1 and 2019 Q4. Each UPC is classified into one of the 1,070 product modules. The database covers stores from 377 MSAs, 533 MicroSAs, and 2,500 counties.

I construct price indices for MSAs, which NielsenIQ has better coverage. I restrict the attention to MSAs that (i) have at least 20 stores (ii) have at least 500 product modules which exist through

Figure 6: Correlation between Retail Scanner price indices and HHNS Non-tradeable price indices



Notes: The figure presents the binscatter plot of price indices for each quarter and state for Retail Scanner price indices and HHNS Non-tradeable price indices. The dashed red line is the linear fit of both price indices.

out the sample. Details are left to Appendix C.2.[23] I follow the BLS construction of the CPI with some adjustments. In the first stage, I clean the data such that the unit is same across all UPCs within each product module.[24] Then, I aggregate revenue and units in each product module and quarter and calculate the average price for a product module. I treat a product module a product.[25] Since all modules for all MSAs exist throughout the sample, the procedure is completely free from "chain drift" problem (Ivancic et al., 2011). In the second stage, I compute the Törnqvist price index for product modules by setting 2006 Q1 as the base period:

$$P_T = \prod_{i=1}^{n} \left(\frac{p_{i,t}}{p_{i,0}}\right)^{\frac{1}{2}\left[\frac{p_{i,0}\cdot q_{i,0}}{\Sigma\left(p_{i,0}\cdot q_{i,0}\right)}+\frac{p_{i,t}\cdot q_{i,t}}{\Sigma\left(p_{i,t}\cdot q_{i,t}\right)}\right]} \tag{60}$$

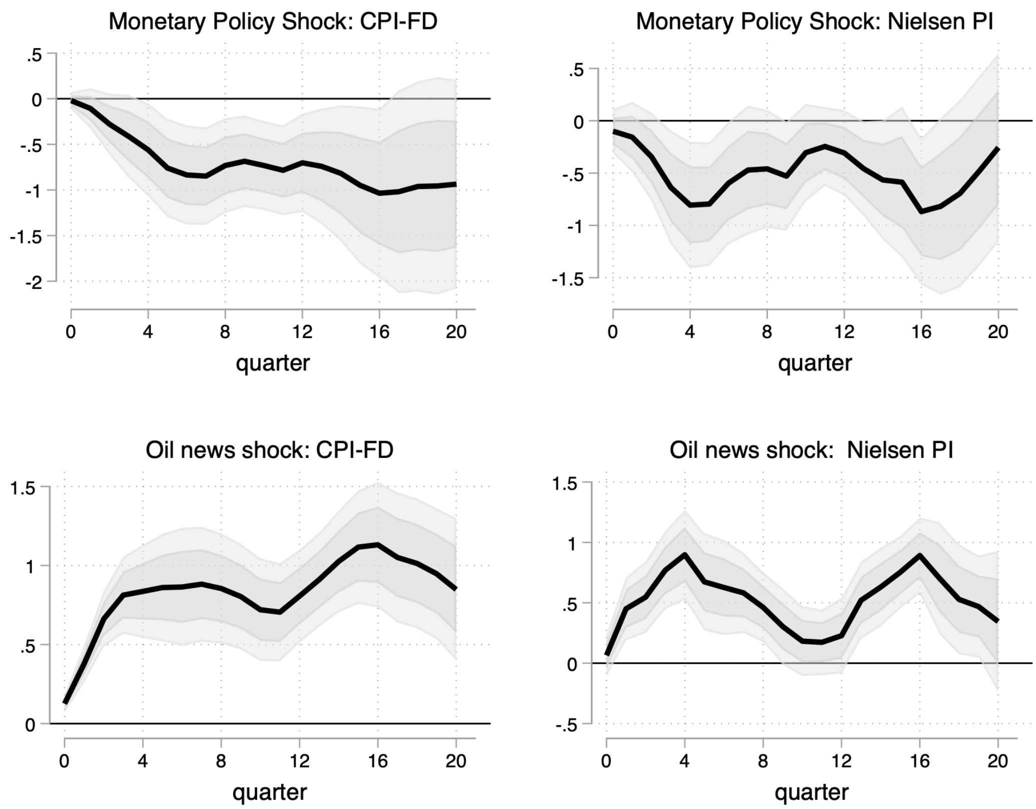
[23]In the robustness check, I also consider MicroSAs. I allow areas at least 10 stores instead of 20 stores.

[24]I only consider the UPCs appear in both the NielsenIQ Homescan database and Retail Scanner database. Homescan database has unit for each UPC.

[25]This step is different from BLS and papers that follow BLS, e.g., procedure Beraja et al. (2019). In particular, BLS construct chained price indices at the UPC level. However, for small MSAs, missing values from period to period lead to severe "chain drift" problem in my context. I discuss this in detail in Appendix C.2.

where $p_{i,0}$ and $q_{i,0}$ are base-period price and quantity of module i. $p_{i,t}$ and $q_{i,t}$ are current-period price and quantity of module i. I normalize $P_0 = 1$. The Törnqvist index serves as a natural benchmark because it provides a second-order approximation to any twice continuously differentiable, homothetic expenditure function (e.g., Diewert 1976). For robustness, I consider other standard price indices in Appendix C.2.

Figure 7: Impulse responses of cumulative inflation to shocks



Notes: The left panel presents the impulse responses of accumulative inflation to monetary policy shocks estimated (C.2-4). The right panel shows presents the impulse responses of accumulative inflation to oil news shock estimated (C.2-4). The inflation is calculated based on aggregate CPI-FD from BLS and aggregate Retail Scanner price indices derived by aggregating regional price indices with respective revenue weights. Dark and light shaded area represents 68% and 90% confidence interval respectively.

To examine the relationship between retail price indices and those for broader non-tradeable industries, I utilize the state-level price indices developed by Hazell et al. (2022) based on BLS micro-price data. Hazell et al. (2022) construct price indices for both tradeable and non-tradeable sectors at the state level, where the non-tradeable sector encompasses a wide range of services, excluding certain transportation services that may follow different pricing mechanisms (Nakamura and Steinsson, 2008). Notably, their definition excludes the retail industry, which allows us to explore the relationship between retail and other non-tradeable industries. I aggregate our price indices to the state level. Figure 6 shows a highly significant correlation between our retail price indices (derived from NielsenIQ RMS) and the HHNS price indices for service industries built from BLS data, with an R2 of 74%. This indicates that a substantial portion of the variation in general non-tradeable industries is explained by Retail Scanner price indices, giving us confidence that our price indices are broadly representative of price movements in the overall non-tradeable industries. Similarly, Beraja et al. (2019) use Retail Scanner price index as representative of price index of all sectors on the state level.

Moreover, I calculate inflation on different horizons based on CPI for food and drinks (CPI-FD) and CPI constructed from Retail Scanner database aggregated to US level. Figure 7 shows the impulse responses of cumulative inflation to monetary policy shocks and oil news shock. It has three implications. First, the responses are similar to both series for both shocks. This indicates that our price indices capture the variations we want even conditional on shocks. Second, the responses of cumulative inflation to oil new shocks exhibit double-hump shape. This is especially true for the constructed price indices. This second hump may result from the indirect effect of oil news shocks going through production networks, which typically takes some time (Rubbo, 2023). Details of specification of regressions are left to Appendix C.2.

3.2.3 Main Results on Passthroughs

After merging the MSA-level search index and MSA-level quarterly unemployment rates from BLS with MSA-level price indices, the final dataset contains 248 MSAs of which total revenues over the whole sample range from 0.4 billion to 124 billion dollars. The mean of unemployment rate is 6.32 and standard deviation is 2.78. I am interested in how changes in search frictions impacts the passthrough of shocks to price indices.

Specification − I now estimate our main baseline specification là Jorda (2005),

$$\sum_{l=0}^{h} \pi_{kt+l} = \lambda_{kq} + \eta_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=1}^{4} \kappa_{lh} u_{kt-l} + \mathbf{\Gamma}' \mathbf{X}_{ky} + e_{kth} \tag{61}$$

where h is the forecast horizon. k denotes MSA. t denotes quarterly time. y denotes year. λ_{kq} is quarter fixed effect for each MSA to capture MSA-specific seasonality effects. η_t is quarterly time fixed effect. ϵ_t represent shocks. I use oil news shocks and monetary policy shocks defined as before. ΔSI_{ky-1} is yearly demeaned search index in the previous year relative to the quarterly time t for MSA k. π_{kt} is quarterly inflation at time t and MSA k, defined as $\pi_{kt} = p_{kt} - p_{kt-1}$. u_{kt} is quarterly unemployment rate. $\sum_{l=0}^{h} \pi_{kt+l}$ is the accumulative inflation. I control 4 lags for the baseline. X_{kt} is a vector of controls. It includes ΔSI_{ky-1} and variables that measure local economic conditions defined before, i.e., log annual wage, log total employment, log HHI for non-tradeable industries. Our main coefficient of interest is β_h, which we call interaction coefficient. It measures, at different horizons, how passthrough of shock to inflation depends on search frictions measured by demeaned search index. To get aggregate impact of search frictions, I weight the regression using MSA's total personal income in 2006. I cluster standard errors at MSA level to account for correlation within MSA.

I use the last year's demeaned search index to address endogeneity concern that the entry and exit decisions of establishments are influenced by local economic conditions because firms cannot base their decisions on a random shock that had not yet occurred in the previous year. I also control for the time fixed effects to account for the effect of other macroeconomic variables that may affect the effects of shocks on cumulative inflation. For instance, Hazell et al. (2022) use time fixed effect to absorb changing inflation expectation. I control for lagged inflation to account for autocorrelation of inflation as standard in the literature.

One concern regarding the interpretation of β_h as what we intend is that an increase in search index relative to the sample mean in a MSA could increases labor demand and, therefore, local wages. This channel biases upward the estimates. To alleviate the concern, I directly control for local annual wages and total employment to account for the effects of changing local labor market conditions in response to the shock,. Further, I control for the Herfindahl–Hirschman Index (HHI) for non-tradeable industries, Since concentration could potentially influence employment growth through labor market power, the HHI for non-tradeable industries is controlled as well.

To know the economic magnitude of the interaction coefficient, we need to study the average effect of shocks on cumulative inflation. To do so, I removes the time fixed effects from the above specification and add more aggregate controls since the average effect of shocks can be contaminated by other macroeconomic variables,

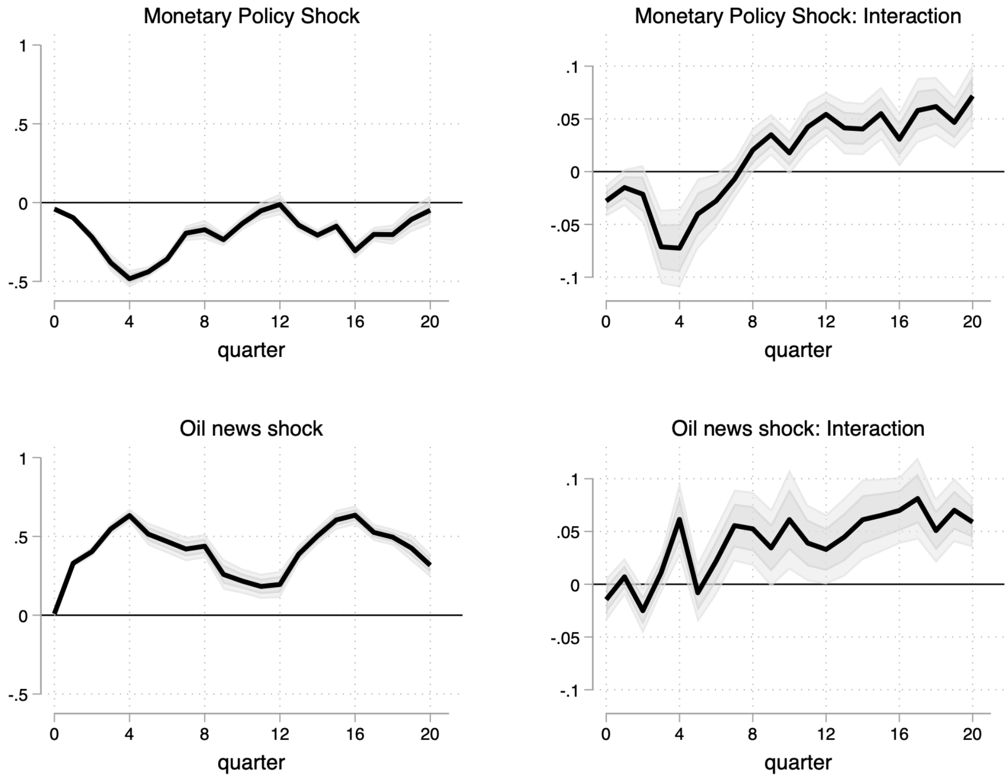
$$\sum_{l=0}^{h} \pi_{kt+l} = \lambda_{kq} + \alpha_h \epsilon_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=0}^{4} \kappa_{lh} u_{kt-l} + \sum_{l=1}^{4} \eta_{lh} X_{t-l} + \mathbf{\Gamma}' \mathbf{X}_{ky} + e_{kth} \tag{62}$$

where X_t represents the aggregate control, i.e., inflation calculated from CPI for food and drinks. The main coefficient of interest here is α_h, which measures the passthrough of shocks to inflation at different horizons. The average effect provides a natural benchmark to interpret the magnitude of the interaction coefficients.

Results – Figure 8 reports the results from estimating the baseline specification (61) and average effect of shocks in (62). I standardize two shocks and MSA's demeaned search index over the entire sample to facilitate interpretation of the interaction coefficients.

The left panel in Figure 8 shows the average effect of both monetary policy shocks and oil news shocks on cumulative inflation. Conditional on controls, one standard-deviation monetary policy shock decreases the inflation, with the peak of impact of -0.5 percentage point within one year. For oil news shocks, the impulse responses exhibits double-hump shape as shown in Figure 6. The cumulative inflation increases sharply within the first year by 0.6 percentage point after a standard-deviation increase in the shock and then decline slowly over time. In the fourth year, inflation picks up again, leading to cumulative responses of a similar magnitude as the initial increase.

Figure 8: Search frictions and passthroughs to price indices



Notes: The left panel presents the average effect of monetary policy shocks and oil news shock on cumulative inflation, which is estimated in (62). The right panel shows dynamics of the interaction coefficient over time estimated in (61). Dark and light shaded area represents 68% and 90% confidence interval respectively. The standard errors are clustered at MSA level.

The right panel illustrates the interaction coefficients at different horizons. It shows that if we assume MSAs have the same information frictions, then MSAs with higher demeaned search indices and, therefore, lower search frictions experience a greater passthrough of shocks to cumulative inflation for both monetary policy shocks and oil news shocks. The interaction coefficients are statistically significant and economically large. One standard-deviation increase in the demeaned search index implies about 12% additional passthrough of the shock to the cumulative inflation for both shocks. The result is consistent with Proposition 6.

Following a negative monetary shock, the interaction coefficients are initially negative but later turn positive. The intuition is that the shock initially reduces the price index, and the total passthroughs are greater in regions experiencing increases in establishment density. Over time, consumers gradually learn about the monetary shock and come to expect a lower price index. At the same time, the index begins to rise after reaching a trough, producing positive interaction coefficients due to the same underlying mechanism. However, we do not observe a reversal of sign in the interaction coefficients in response to oil news shocks. This may be due to the relatively moderate decline in the average effect by the third year, after which inflation starts to increase again afterward.

Overall, under the interpretation that the higher demeaned search index implies lower search friction, the empirical results (i) support the comparative statics presented in Proposition 6 and (ii) indicate that search frictions have large effect on passthroughs. Appendix C.2 further presents robustness checks for the main results. First, I verify that the results remain consistent when the search index includes additional industries, such as Finance and Insurance, as well as Educational Services. Second, I perform robustness checks by including more regions. I allow MSAs and MicroSAs which have at least 10 stores as opposed to 20 stores in the main analysis.

3.2.4 Main Results on Unemployment Rate

I next show that following the increased passthrough of shocks to price indices, there is less monetary non-neutrality, i.e., less impact on unemployment rate.

Specification – The main specification is the following,

$$u_{kh} = \lambda_{kq} + \eta_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=1}^{4} \kappa_{lh} u_{kt-l} + X_{ky} + e_{kth} \tag{63}$$

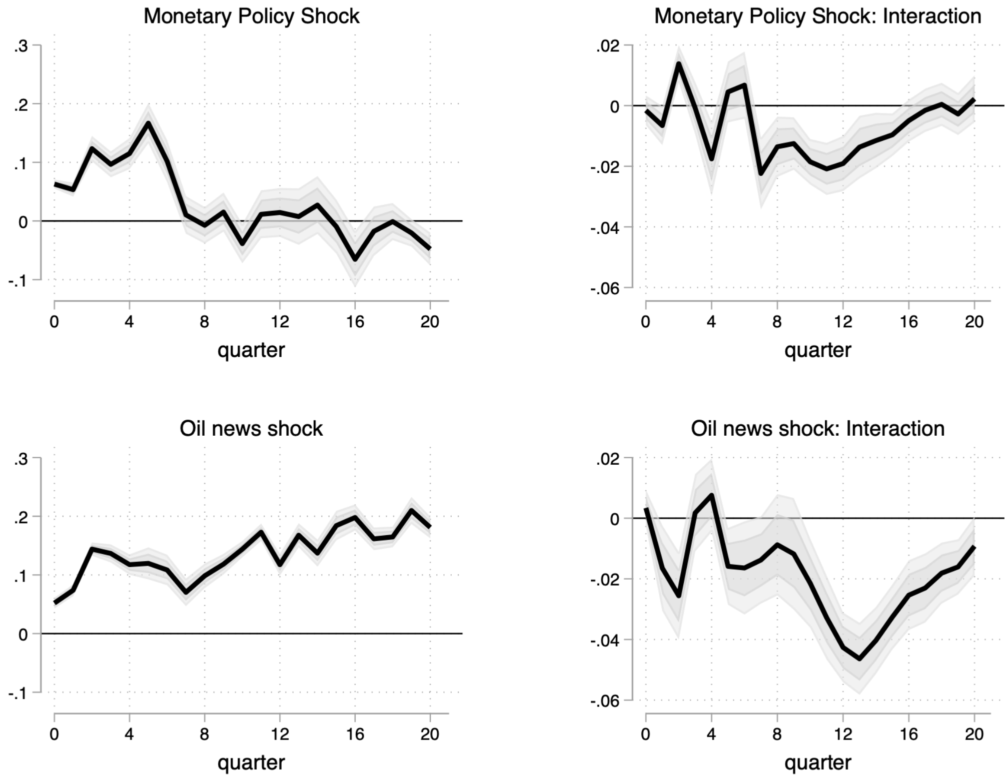
Notations are the same as in (61) except that the dependent variable is unemployment rate in MSA k at horizon h. The coefficient of interest is β_h. I estimate the average effect of shocks on unemployment rate as follows,

$$u_{kt+h} = \lambda_{kq} + \alpha_h \epsilon_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=1}^{4} \kappa_{lh} u_{kt-l} + \sum_{l=1}^{4} \eta_{lh} X_{t-l} + X_{ky} + e_{kth} \tag{64}$$

Again, notations are the same as in (24) and I add additional controls X_t: inflation calculated from CPI for food and drinks and 1-year rate of government bond.[26]

[26] In Appendix C.2, I show that the responses of aggregate unemployment rate to both shocks with these controls are similar to the left panel in Figure 9

Figure 9: Search frictions and unemployment rate



Notes: The left panel presents the average effect of monetary policy shocks and oil news shock on unemployment rates, which is estimated in (64). The right panel shows dynamics of the interaction coefficient over time estimated in (63). Dark and light shaded area represents 68% and 90% confidence interval respectively. The standard errors are clustered at MSA level.

Results – Figure 9 reports the results from estimating (63) and (64).

The left panel in Figure 9 shows the average effect of both monetary policy shocks and oil news shocks on unemployment rate. Conditional on controls, one standard-deviation monetary policy shock increases the inflation, with the peak of impact of over 0.1 percentage point within one year. Similarly, one standard-deviation oil news shock increases the inflation, with the peak of impact of about 0.2 percentage point within one and a half year.

The right panel illustrates the interaction coefficients at different horizons. It shows that MSAs with higher demeaned search indices and, therefore, lower search frictions have less responses in unemployment rate. The interaction coefficients are statistically significant and economically large.

For monetary shocks, one standard-deviation increase in the demeaned search index implies 20% less responses of unemployment rate. The result is consistent with the theory in the sense that following a monetary policy shock, more passthrough of the shock to price indices in regions with lower search frictions as shown in Figure 8 decreases the monetary non-neutrality.

Similar patterns hold for oil news shock. A one standard-deviation increase in the demeaned search index also results in about 20% less responses to unemployment rate. The result should be understood through the local wage Phillips curve. Blanchard and Galí (2010) shows that real wage rigidity within standard framework of labor market friction leads to a trade-off between inflation and unemployment under aggregate supply shocks. Consistent with this view, when passthrough to price indices is large after an oil news shock as shown in Figure 8, the associated downward pressure on unemployment is lower.

In sum, the empirical results in Section 3.2 demonstrate that, consistent with the theory, for both monetary policy shocks and oil news shocks, the passthrough to price indices is 12% larger in regions with one standard-deviation lower search frictions. This leads to a 20% smaller response in the unemployment rate, implying reduced monetary non-neutrality and highlighting a trade-off between inflation and unemployment as discussed in the literature.

4 Conclusion

This paper provides a new framework of monetary non-neutrality solely driven by the consumer-side frictions. At the center of the model is the information asymmetry about marginal costs between consumers and firms. Monetary non-neutrality increases with both search and information frictions. The paper also presents a Phillips curve that links inflation to households' expectations of average marginal costs, highlighting the critical role of these expectations in shaping firms' pricing decisions and, consequently, inflation dynamics.

To empirically test the role of information asymmetry, I utilize the NielsenIQ Consumer Panel. The findings indicate that an unanticipated inflation spike leads to increased search activity across various measures. I then examine the comparative statics of search frictions and passthrough effects. In this analysis, I propose a novel measure of search friction based on establishment density and construct MSA-level price indices. The results demonstrate that greater search frictions amplify the effects of information asymmetry, thereby generating more pronounced monetary non-neutrality.

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 involve embedding this model into production network models. Second, applying the model to the labor market could yield valuable insights. Given the parallels in the literature between search behavior in goods and labor markets, this extension might be straightforward. Workers' incomplete information regarding the average posted wage could influence their job-search decisions, prompting firms to adjust wage-setting and potentially generating wage stickiness. Third, to better calibrate the model and assess the quantitative importance of the mechanism, a micro-foundation for search costs is necessary. A spatial and industrial organization model would be a promising candidate. Finally, it would be crucial to use household expectation data to explore how these expectations influence firms' pricing decisions.

Bibliography

Agarwal, S., Jensen, J. B., and Monte, F. (2017). Consumer mobility and the local structure of consumption industries. NBER Working Paper 23616, National Bureau of Economic Research. Revision Date: January 2020.

Aguiar, M. and Hurst, E. (2007). Life-cycle prices and production. *American Economic Review*, 97(5):1533–1559.

Alvarez, F., Le Bihan, H., and Lippi, F. (2016a). The real effects of monetary shocks in sticky price models: A sufficient statistic approach. *American Economic Review*, 106(10):2817–2851.

Alvarez, F. E., Lippi, F., and Paciello, L. (2016b). Monetary shocks in models with inattentive producers. *The Review of Economic Studies*, 83(2):421–459. Published: 29 October 2015.

Amiti, M., Itskhoki, O., and Konings, J. (2014). Importers, exporters, and exchange rate disconnect. *American Economic Review*, 104(7):1942–1978.

Amiti, M., Itskhoki, O., and Konings, J. (2019). International shocks, variable markups, and domestic prices. *The Review of Economic Studies*, 86(6):2356–2402.

Anderson, S. P., Palma, A. D., and Thisse, J.-F. (1987). The ces is a discrete choice model? *Economics Letters*, 24(2):139–140.

Anderson, S. P. and Renault, R. (1999). Pricing, product diversity, and search costs: A bertrand-chamberlin-diamond model. *The RAND Journal of Economics*, 30(4):719–735.

Angeletos, G.-M., Collard, F., and Dellas, H. (2020). Business-cycle anatomy. *American Economic Review*, 110(10):3030–3070.

Angeletos, G.-M. and La'O, J. (2013). Sentiments. *Econometrica*, 81(2):739–779.

Angeletos, G.-M. and La'o, J. (2010). Noisy business cycles. *NBER Macroeconomics Annual*, 24(1):319–378.

Angeletos, G.-M. and Lian, C. (2018). Forward guidance without common knowledge. *American Economic Review*, 108(9):2477–2512.

Angeletos, G.-M. and Lian, C. (2023). Dampening general equilibrium: Incomplete information and bounded rationality. In Handbook of Economic Expectations, V. ., editor, *Handbook of Economic Expectations*, pages 613–645. Elsevier.

Bachmann, R., Berg, T. O., and Sims, E. R. (2015). Inflation expectations and readiness to spend: Cross-sectional evidence. *American Economic Journal: Economic Policy*, 7(1):1–35.

Bauer, M. D. and Swanson, E. T. (2023). A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual*, 37(1):87–155.

Benabou, R. (1988). Search, price setting and inflation. *The Review of Economic Studies*, 55(3):353–376.

Beraja, M., Hurst, E., and Ospina, J. (2019). The aggregate implications of regional business cycles. *Econometrica*, 87(6):1789–1833.

Bilal, A. (2023). The geography of unemployment. *The Quarterly Journal of Economics*, 138(3):1507–1576.

Binetti, A., Nuzzi, F., and Stantcheva, S. (2024). People's understanding of inflation. Working Paper 32497, National Bureau of Economic Research. Revision Date June 2024.

Blanchard, O. and Galí, J. (2010). Labor markets and monetary policy: A new keynesian model with unemployment. *American Economic Journal: Macroeconomics*, 2(2):1–30.

Blanco, A., Boar, C., Jones, C. J., and Midrigan, V. (2023). Non-linear inflation dynamics in menu cost economies. NBER Working Paper 32094, National Bureau of Economic Research.

Broda, C. and Weinstein, D. E. (2010). Product creation and destruction: Evidence and price implications. *American Economic Review*, 100(3):691–723.

Buettner, T. and Madzharova, B. (2021). Unit sales and price effects of preannounced consumption tax reforms: Micro-level evidence from european vat. *American Economic Journal: Economic Policy*, 13(3):103–134.

Burdett, K. and Judd, K. L. (1983). Equilibrium price dispersion. *Econometrica*, 51(4):955–969.

Burdett, K. and Menzio, G. (2018). The (q,s,s) pricing rule. *The Review of Economic Studies*, 85(2):892–928.

Bénabou, R. and Gertner, R. (1993). Search with learning from prices: Does increased inflationary uncertainty lead to higher markups? *The Review of Economic Studies*, 60(1):69–93.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics*, 12(3):383–398.

Candia, B., Coibion, O., and Gorodnichenko, Y. (2020). Communication and the beliefs of economic agents. Working Paper 27800, National Bureau of Economic Research.

Candia, B., Coibion, O., and Gorodnichenko, Y. (2023). The macroeconomic expectations of firms. In Manski, C. F. and Thomas, F., editors, *Handbook of Economic Expectations*, pages 321–353. Elsevier, Amsterdam.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (1999). Monetary policy shocks: What have we learned and to what end? In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics*, volume 1, Part A of *Handbook of Macroeconomics*, pages 65–148. Elsevier, Amsterdam.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1):1–45.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8):2644–2678.

D'Acunto, F., Fuster, A., and Weber, M. (2021a). Diverse policy committees can reach underrepresented groups. Working Paper 29275, National Bureau of Economic Research.

D'Acunto, F., Malmendier, U., Ospina, J., and Weber, M. (2021b). Exposure to grocery prices and inflation expectations. *Journal of Political Economy*, 129(5):1615–1639.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2020). Changing business dynamism and productivity: Shocks versus responsiveness. *American Economic Review*, 110(12):3952–3990.

DellaVigna, S. and Gentzkow, M. (2019). Uniform pricing in u.s. retail chains. *The Quarterly Journal of Economics*, 134(4):2011–2084.

Diamond, P. A. (1971). A model of price adjustment. *Journal of Economic Theory*, 3(2):156–168.

Duranton, G. and Puga, D. (2020). The economics of urban density. *Journal of Economic Perspectives*, 34(3):3–26.

Duranton, G. and Turner, M. A. (2018). Urban form and driving: Evidence from us cities. *Journal of Urban Economics*, 108:170–191.

Eckert, F., Fort, T. C., Schott, P. K., and Yang, N. J. (2020). Imputing missing values in the us census bureau's county business patterns. NBER Working Paper 26632, National Bureau of Economic Research, Cambridge, MA.

Farhi, E. and Werning, I. (2019). Monetary policy, bounded rationality, and incomplete markets. *American Economic Review*, 109(11):3887–3928.

Gabaix, X. and Graeber, T. (2024). The complexity of economic decisions. Working Paper 33109, National Bureau of Economic Research.

Gaballo, G. and Paciello, L. (2021). Spending allocation under nominal uncertainty: a model of effective price rigidity. CEPR Discussion Paper DP16101, Centre for Economic Policy Research (CEPR).

García-Schmidt, M. and Woodford, M. (2019). Are low interest rates deflationary? a paradox of perfect-foresight analysis. *American Economic Review*, 109(1):86–120.

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Goldberg, P. K. and Hellerstein, R. (2013). A structural approach to identifying the sources of local currency price stability. *The Review of Economic Studies*, 80(1):175–210.

Golosov, M. and Lucas, R. E. (2007). Menu costs and phillips curves. *Journal of Political Economy*, 115(2):171–199.

Gopinath, G., Gourinchas, P.-O., Hsieh, C.-T., and Li, N. (2011). International prices, costs, and markup differences. *American Economic Review*, 101(6):2450–2486. †.

Han, Z., Tan, F., and Wu, J. (2022). Analytic policy function iteration. *Journal of Economic Theory*, 200:105395.

Handbury, J. and Weinstein, D. E. (2015). Goods prices and availability in cities. *The Review of Economic Studies*, 82(1):258–296.

Hazell, J., Herreño, J., Nakamura, E., and Steinsson, J. (2022). The slope of the phillips curve: Evidence from u.s. states. *Quarterly Journal of Economics*, 137(3):1299–1344.

Head, A., Liu, L. Q., Menzio, G., and Wright, R. (2012). Sticky prices: A new monetarist approach. *Journal of the European Economic Association*, 10(5):939–973.

Hulten, C. R. (1973). Divisia index numbers. *Econometrica*, 41(6):1017–1025.

Hulten, C. R. (1978). Growth accounting with intermediate inputs. *The Review of Economic Studies*, 45(3):511–518.

Huo, Z. and Takayama, N. (2023). Rational expectations models with higher-order beliefs. *Available at SSRN 3873663*.

Ivancic, L., Diewert, W. E., and Fox, K. J. (2011). Scanner data, time aggregation and the construction of price indexes. *Journal of Econometrics*, 161(1):24–35.

Jaimovich, N., Rebelo, S., and Wong, A. (2019). Trading down and the business cycle. *Journal of Monetary Economics*, 102:96–121.

Janssen, M. C., Parakhonyak, A., and Parakhonyak, A. (2017). Non-reservation price equilibria and consumer search. *Journal of Economic Theory*, 172:120–162. Journal of Economic Theory, Volume 172, November 2017, Pages 120-162.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news. *American Economic Review*, 111(4):1092–1125.

Kaplan, G. and Menzio, G. (2015). The morphology of price dispersion. *International Economic Review*, 56(4):1207–1238.

Kaplan, G., Menzio, G., Rudanko, L., and Trachter, N. (2019). Relative price dispersion: Evidence and theory. *American Economic Journal: Microeconomics*, 11(3):68–124.

Klenow, P. J. and Willis, J. L. (2016). Real rigidities and nominal price changes. *Economica*, 83(331):443–472.

Kumar, S., Afrouzi, H., Coibion, O., and Gorodnichenko, Y. (2015). Inflation targeting does not anchor inflation expectations: Evidence from firms in new zealand. NBER Working Paper 21814, National Bureau of Economic Research.

L'Huillier, J.-P. (2020). Consumer imperfect information and endogenous price rigidity. *American Economic Journal: Macroeconomics*, 12(2):94–123.

Lorenzoni, G. (2009). A theory of demand shocks. *American Economic Review*, 99(5):2050–2084.

Lucas, R. E. (1972). Expectations and the neutrality of money. *Journal of economic theory*, 4(2):103–124.

Mankiw, N. G. (1985). Small menu costs and large business cycles: A macroeconomic model of monopoly. *Quarterly Journal of Economics*, 100(2):529–537.

Matsuyama, K. and Ushchev, P. (2017). Beyond ces: Three alternative classes of flexible homothetic demand systems. Research Paper WP BRP 172/EC/2017, Higher School of Economics. Available at SSRN: `https://ssrn.com/abstract=3015279` or `http://dx.doi.org/10.2139/ssrn.3015279`.

Matějka, F. (2015). Rigid pricing and rationally inattentive consumer. *Journal of Economic Theory*, 158:656–678. Part B.

Midrigan, V. (2011). Menu costs, multiproduct firms, and aggregate fluctuations. *Econometrica*, 79(4):1139–1180.

Mongey, S. and Waugh, M. E. (2024). Discrete choice, complete markets, and equilibrium. Staff Report 656, Federal Reserve Bank of Minneapolis.

Morris, S. and Shin, H. S. (2002). Social value of public information. *American Economic Review*, 92(5):1521–1534.

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

Nakamura, E. and Zerom, D. (2010). Accounting for incomplete pass-through. *The Review of Economic Studies*, 77(3):1192–1230.

Phelps, E. S. (1969). The new microeconomics in inflation and employment theory. *American Economic Review*, 59(2):147–160.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. In Taylor, J. B. and Uhlig, H., editors, *Handbook of Macroeconomics*, volume 2 of *Handbook of Macroeconomics*, pages 71–162. Elsevier, Amsterdam.

Rebelo, S., Santana, M., and Teles, P. (2024). Behavioral sticky prices. Working Paper 32214, National Bureau of Economic Research. Revised October 2024.

Reis, R. (2006). Inattentive producers. *The Review of Economic Studies*, 73(3):793–821. Published: 01 July 2006.

Rondina, G. and Walker, T. B. (2021). Confounding dynamics. *Journal of Economic Theory*, 196:105251. Available at: `https://doi.org/10.1016/j.jet.2021.105251`.

Rotemberg, J. J. (1982). Sticky prices in the united states. *Journal of Political Economy*, 90(6):1187–1211.

Rothschild, M. (1974). Searching for the lowest price when the distribution of prices is unknown. *Journal of Political Economy*, 82(4):689–711.

Rubbo, E. (2023). Networks, phillips curves, and monetary policy. *Econometrica*, 91(4):1417–1455.

Sara-Zaror, F. (2024). Inflation, price dispersion, and welfare: The role of consumer search. FEDS Working Paper 2024-47, Federal Reserve Board of Governors.

Smets, F. and Wouters, R. (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American Economic Review*, 97(3):586–606.

Stroebel, J. and Vavra, J. (2019). House prices, local demand, and retail prices. *Journal of Political Economy*, 127(3):1391–1436.

Taylor, J. B. (1980). Aggregate dynamics and staggered contracts. *Journal of Political Economy*, 88(1):1–23.

Venkateswaran, V. (2014). Heterogeneous information and labor market fluctuations. Available at SSRN: https://ssrn.com/abstract=2687561 or http://dx.doi.org/10.2139/ssrn.2687561.

Weitzman, M. L. (1979). Optimal search for the best alternative. *Econometrica*, 47(3):641–654.

Wolinsky, A. (1986). True monopolistic competition as a result of imperfect information. *The Quarterly Journal of Economics*, 101(3):493–511.

Woodford, M. (2003). Imperfect common knowledge and the effects of monetary policy. In Aghion, P., Frydman, R., Stiglitz, J., and Woodford, M., editors, *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, pages 25–58. Princeton University Press, Princeton, NJ.