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

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Abstract

This paper develops a model of monetary non-neutrality driven by information asymmetry about 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. Information asymmetry causes demand for individual good to depend on perceived relative price. As a result, the passthrough of aggregate shocks to prices is incomplete. The key mechanism is that, following a monetary shock, consumers attribute some of the resulting price changes to firm idiosyncratic shocks, inducing them to search for alternatives. To dissuade search, firms limit the extent to which they pass the shock through to prices. Consistent with the mechanism, higher inflation is associated empirically with measures of more active consumer search. Additionally, I develop a measure for county-level search frictions and show that regions with higher search frictions exhibit lower passthrough of shocks. Calibration of the model further demonstrates substantial monetary non-neutrality.

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

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Monetary policy is known to have large real effects on the economy in the short run. Following an unexpected increase in interest rate, both output and inflation decline. This pattern has been repeatedly uncovered in the empirical literature.[1] On one hand, 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. On the other hand, information asymmetry regarding marginal costs between consumers and firms has significant effects on inflation dynamics. For instance, studies of anticipated VAT reforms reveal a rapid passthrough of VAT-induced cost changes to prices, typically within four months (Buettner and Madzharova, 2021). The extensive public discussion surrounding such reforms likely reduces information asymmetry and accelerates household learning about cost changes, resulting in fast passthrough. In contrast, standard Calvo or menu-cost models calibrated to macro and micro data would predict a much slower passthrough. Similarly, inflation rises substantially after an oil shock (Känzig, 2021). The recent evidence shows that consumers are highly sensitive to gasoline price fluctuations (Kumar et al., 2015), which reduces the information asymmetry of cost changes from oil price shocks.

This paper develops a model of monetary non-neutrality driven solely by consumer-side frictions in a sequential search framework. The model builds on sequential search literature (e.g., Wolinsky, 1986; Anderson and Renault, 1999). By incurring a search cost, consumers can visit a firm to learn both its price and associated match utility. I extend this framework by introducing information asymmetry regarding marginal costs between consumers and firms. In particular, the model incorporates heterogeneous firms which experience firm-specific productivity shocks in each period. Due to incomplete information about monetary shocks, consumers are unable to distinguish between idiosyncratic and aggregate shocks to marginal costs, after observing prices in their visits.

[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.

Consumers' search behavior is characterized by a simple reservation value rule under restrictions on the information sets.[2] The reservation value is derived from taking expectations of price distribution. The position and shape of the price distribution depends on the consumer's belief about average marginal cost, which in turn depends on monetary shocks. As the perceived average marginal cost rises, the reservation value declines. Intuitively, consumers are more inclined to make a purchase when they expect higher average marginal costs, and consequently, higher prices for outside options.

Firm's demand depends on perceived relative price between its own price and average perceived price index on the first order. Following a positive monetary shock, the change in average perceived price index is dampened compared to the actual change due to information frictions about monetary shocks on the consumer side. As a result, individual firms behave as if they are competing against firms that set lower prices on average, prompting consumers to search for alternatives. To deter this search, firms compress their markups, limiting the passthrough of the monetary shock.

I then characterize the Phillips curve. It associates the change in price index with both actual and perceived average marginal costs. It highlights a broader intuition that consumers' inability to track movements in average marginal cost influences their search behavior, which then affects firms' price-setting decisions. Thus, the rate at which consumers learn about average marginal costs is crucial in explaining inflation dynamics over the business cycle. This insight is applied to price dynamics during VAT reforms and post-pandemic episodes. Finally, I extend the analysis to aggregate supply shocks and explore a general setup with flexible preferences and a consistent information structure.

I further present three comparative statics results about passthroughs. First, within an equilibrium, more productive firms pass through less monetary shocks due to their greater sensitivity to consumers' expectations of the price index. Consequently, they contribute most to the incompleteness of aggregate passthrough. Second, passthroughs decrease in equilibria with higher search costs across all productivity levels, as higher search costs correspond to lower reservation values, which uniformly reduce the demand elasticity faced by firms. Third, as consumers gradually learn about the monetary shock, passthrough increases toward one.

[2]The restriction is that I do not allow consumers to learn about monetary shocks over individual prices they observe. I will discuss this assumption later.

My mechanism is consistent with empirical evidence. In particular, I use the 2006-2019 Nielsen 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 1.2 additional trips in the retail sector, about 3% of the average number of trips. Consumers also visit 0.38 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 on search costs. 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 Nielsen Retail Scanner data. The data covers stores from 377 MSAs and 533 MiSAs. Price indices are created for MSAs with at least 20 stores. When aggregated to the state level, these indices strongly correlate with non-tradeable sector price indices (excluding retail) constructed by Hazell et al. (2022) using BLS micro-price data, explaining over 70% of the variation.

To address endogeneity concerns, I first control for county fixed effects and then interact with exogenously identified shocks. I find that a one standard deviation increase in the search index makes a region's inflation approximately 12% more responsive to inflationary shocks. This supports the model's prediction that regions with lower search costs exhibit larger inflation responses. Then, I conduct similar analysis on unemployment rates. In line with predictions of theories on local wage Philipps curve (Blanchard and Galí, 2010), the unemployment rate is about 20% lower for regions with lower search cost.

Finally, I present one calibration of the model. The calibration suggests accumulated consumption response is equivalent to a Calvo model with 32% of firms adjusting prices each quarter. The equivalent duration of price is 8.4 months. This is consistent with the empirical estimates in Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008).

Related Literature. This paper contributes to three strands of literature. The first studies the monetary non-neutrality in models with frictions on the firm side. 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). Recently, Morales-Jiménez and Stevens (2024) combines information frictions and menu cost. This paper contributes to this literature by proposing another important mechanism acting via consumer-side frictions.

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 monetary general equilibrium framework as in Golosov and Lucas (2007). Unlike previous work that incorporates search frictions alongside firm-side pricing frictions, my model assumes firms are frictionless, allowing them to adjust prices flexibly based on complete information about the economic environment.

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 encounter as revealing the information about aggregate shocks. I shut down this learning channel. Instead, consumers form beliefs based on exogenous signals. This facilitates a simple characterization of consumer search behavior. Therefore, it is more compatible with the general equilibrium framework. This paper also broadly contributes to the literature on information frictions and the transmission of monetary policy. 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.

The rest of the paper is organized as follows. Section 1 presents the model. Section 2 shows empirical evidences. Section 3 presents the calibration results. The last section concludes. Appendix A contains some of the proofs omitted from the text. Appendix B contains a general model. Appendix C contains procedure of variable construction and additional empirical evidence. Appendix D contains additional details of calibration.

1 Model

I develop a macroeconomic model with (i) information asymmetry between consumers and firms about average marginal costs and (ii) search frictions on the goods market. The model has four types of agents: workers, shoppers, firms and a monetary authority.

Notation − Time is discrete and infinite $t \in N$. 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., $\hat{y} = \log Y - \log \bar{Y}$. The steady state will be formally defined below.

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

$$Y_{kt} = A_{kt} L_{kt} \tag{1}$$

where L_{kt} is the amount of labor employed. A_{kt} is the firm's productivity, which is i.i.d. across firms. Specifically, I assume $\log A_{kt}$ is subject to IID shocks,

$$\log A_{kt} = \sigma_a \varepsilon_{akt} \tag{2}$$

where the productivity innovations follow $\varepsilon_{akt} \sim \mathcal{N}(0, 1)$. Importantly, firms have full information about all macroeconomic variables and set prices flexibly.

Household − There is a continuum of households indexed by $i \in [0, 1]$. Household consists of a shopper and a worker. Shopper specializes in searching and obtaining goods. Shopper only buys and consumes one good at a time.[3] Therefore, the price shopper pays is uncertain and her consumption depends on the price of a particular good she picks. On the other hand, worker makes decisions on labor supply, money holdings, and consumption expenditures transferred to shopper.

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

There are two stages within a period, which I call morning and afternoon. In the morning, the monetary authority sets money supply, and workers decide on the expenditure allocated for consumption in expectation of price quotes that shoppers will receive. In the afternoon, firms post their prices, and shoppers take the expenditure as given and search for a good that offers a combination of a lower price and higher match utility. Workers have full information about aggregate money supply shocks, but the shopper is not. As I will demonstrate, this assumption ensures that the passthrough of money supply shocks to nominal wage is complete, and that monetary non-neutrality arises solely from information asymmetry between shoppers and firms. I assume that the worker and shopper cannot communicate.

Worker has standard preference (Hellwig and Venkateswaran, 2009; Golosov and Lucas, 2007). Worker maximizes the expected discounted utility with discount factor $\beta \in (0,1)$ and period utility defined over the expected value which shopper will obtain after shopping $E_t^w V(\frac{X_{it}}{P_{it}})$ within period t, holdings of real money balances $\frac{M_{it}}{P_{it}}$, and labor effort L_{it}, where E_t^w is worker's expectation in the morning within this period. Worker can save in either money or risk-free one-period bonds B_{it} (in zero net supply) that pay an interest rate of R_t.

$$\max_{B_{it},Z_{it},L_{it},M_{it}} E_0 \sum_{t=0}^{\infty} \beta^t \big(E_t^w V(\frac{Z_{it}}{P_{it}}) - L_{it} + \psi E_t^w \log \frac{M_{it}}{P_{it}}\big)$$

$$\text{s.t.} \quad Z_{it} + B_{it} + M_{it} = W_t L_{it} + M_{it-1} + R_{t-1} B_{it-1} + \Pi_{it} + T_{it}$$

where W_t is nominal wage, T_{it} is nominal lump-sum transfer and Π_{it} is firm nominal profits allocated to household i. P_{it} is the price quote shopper accepts in the afternoon. The value which shopper will obtain depends on the consumption.

Shopper – Following Wolinsky (1986) and Anderson and Renault (1999), shoppers have imperfect information about prices that firms are charging and match utilities of all goods. Shopper can obtain a price quote through a sequential search process: by incurring a search cost $\kappa \geq 0$, a shopper can visit a firm to learn both its price and associated match utility. If the shopper is not satisfied with current firm, she may continue to visit other firms in search of lower prices and higher match utility. shoppers have free recall, meaning there are no additional costs for purchasing goods from firms they have previously visited.

Before shopping in period t, shopper i receives a signal s_{it} about log aggregate money supply m_t. The signal takes the simple form,

$$s_{it} = m_t + \sigma_s \varepsilon_{sit} \tag{3}$$

where ε_{sit} follows $\varepsilon_{sit} \sim \mathcal{N}(0,1)$. Denote the information set of shopper i as x_{it}. $E_{it}(m_t|x_{it})$ is shopper i's expectation of money supply at time t. It follows $E_{it}(m_t|x_{it}) \sim H_t(x)$. I impose following restriction on shoppers' information set.

Assumption 1 *Shoppers do not treat individual prices as signals about money supply.*

This assumption implies that learning from shopping is not allowed.[4] It makes sense if the idiosyncratic variations in prices are large enough that information content in these prices are negligible. Introducing learning from shopping can be disturbing as it may break down the reservation value property. For example, 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 low price.[5] I also assume that shoppers do not learn from Z_{it} to facilitate learning over time.[6]

Each shopper purchases one good and each household consumes one good in one period. Shopper i maximizes the following utility,

$$V\big(\frac{Z_{it}}{P_{it}};\Omega_{it}\big) = \max\left\{\max_{k\in\Omega_{it}}\big\{\log\frac{Z_{it}}{P_{kt}} + \frac{1}{\lambda}\upsilon_{ikt}\big\}, E^s_{it}\left(V\big(\frac{Z_{it}}{P_{it}};\Omega_{it}\cup\{j\}\big)\Big|x_{it}\right) - \kappa\right\} \tag{4}$$

where Ω_{it} denotes the set of visited firms. $\upsilon_{ikt} \sim G$ is match utility between shopper i and good k. G has continuously differentiable density function g. It captures idiosyncratic consumer preferences for certain goods over others. I assume that the realizations of υ_{ikt} are independent across firms and individuals. 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

[4]In Section 1.5, I relax this assumption by allowing the shopper to receive a signal about the current price index.

[5]Benabou and Gertner (1993), L'Huillier (2020), Gaballo and Paciello (2021) focus on the information role of individual prices. Their analysis is thus restricted to two-firm case. Janssen et al. (2017) investigates the non-reservation property in a search equilibrium.

[6]If one allows shoppers learn from Z_{it} after they pick a firm, shoppers can infer money shock. The model becomes static. To facilitate learning over time, I assume they do not learn from Z_{it}. In Section 1.5, I specify a fully consistent information structure in a more general setup.

match utility. Goods are more substitutable. The inside maximum represents that shopper can choose the firm that gives the largest combination of utility from consumption and match utility in the set of visited firms because they can recall freely. The outside maximum implies an optimal stopping problem that shopper can either stop searching and choose the firm that inside maximum implies or keep searching by incurring a search cost κ and draw a random firm j conditional on shopper i's information set x_{it}.

Monetary Authority – The aggregate money supply follows an exogenous random walk with volatility $\sigma_{m,t}$:

$$\log M_t = \log M_{t-1} + \hat{m}_t \tag{5}$$

where the money innovation is IID and follows $\hat{m}_t \sim \mathcal{N}(0, \sigma_m^2)$.

Equilibrium – The natural equilibrium concept is Perfect Bayesian Nash equilibrium (PBNE). Since productivity is assumed to have unbounded support, as I will show, any positive price is on-equilibrium price. The regulations on the off-equilibrium belief is not strictly needed in this model.[7] Formally, I define the equilibrium as follows:

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

1. *Shoppers' perceived pricing strategy coincides objective pricing strategy.*
2. *Shoppers choose search strategy optimally by forming belief about price distribution according to perceived pricing strategy and their own information set.*
3. *Workers supply labor, choose bond, money holdings and consumption expenditure optimally.*
4. *Firms choose nominal prices to maximize real profits given distribution of reservation values.*
5. *Money supply evolves exogenously.*
6. *All markets clear.*

I further define the steady-state equilibrium.

Definition 2 (Steady-State Equilibrium) *A steady-state equilibrium is the above equilibrium except money supply is constant M^s and shoppers know the money supply.*

[7] 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.

1.1 Equilibrium Characterization

I now characterize equilibrium. I proceed in two steps. First, I solve for equilibrium prices and households' budget allocations. Second, I characterize the reservation value on the first order and derive the elasticity of demand. I then show properties of elasticity of demand.

Equilibrium Prices and Consumption Expenditure – I start by deriving equilibrium wage and interest rates, and household budget allocations. In the spirit of Golosov and Lucas (2007), I study an unanticipated permanent shock to money. I consider a small shock, i.e., $\hat{m} \to 0$. I suppose the economy is initially in a steady state with constant aggregates $\{\bar{P}, \bar{M}^s, \bar{W}, \bar{R}\}$. Consider a permanent monetary shock arriving at t = 0 so that $M_t^s = (1+\hat{m})\bar{M}^s$ for all $t \geq 0$. Let $\psi = 1 - \beta$.

Proposition 1 *Suppose money supply is $M_t^s = (1+\hat{m})\bar{M}^s$, $\forall t \geq 0$, and profit, transfer and labor demand are evenly distributed across households, i.e., $\Pi_{it} = \Pi_t$, $T_{i0} = \hat{m}\bar{M}^s$ and $L_{it} = L_t$, equilibrium prices satisfy,*

$$W_t = M_t^s; \quad R_t = \beta^{-1}$$

Households' choices on bond and money holdings, and consumption expenditure are the same,

$$B_{it} = 0; \quad M_{it} = (1+\hat{m})\bar{M}^s; \quad X_{it} = (1+\hat{m})\bar{M}^s$$

Proof. See Appendix A. ■

This proposition extends results in Golosov and Lucas (2007) to heterogeneous households. These results are exact without resort to first-order approximation. First, the equilibrium wage are determined by exogenous money supply and nominal interest rate remains the same as in the steady state. Shoppers can ignore the transitional dynamics of macroeconomic variables while searching. Second, households have the same consumption expenditure, bond and money holdings. In each period, there is an as-if representative household even though households may accept different price quotes ex post. Conditions in the proposition ensures that each household's budget constraint is identical, i.e., they receive same bump of money and profit share. Additionally, The consumption expenditure is determined solely by money supply because log utility of consumption decouples the worker's and shopper's decisions. Shopper's choice of firm is irrelevant to the worker's problem. Finally, the dynamics of aggregate consumption and price index are jointly restricted by $P_tC_t = (1+\hat{m})\bar{M}^s$. P_t is price index defined below. lower passthrough of money supply shock to price index implies higher monetary non-neutrality, given fixed $\hat{m}$.

Characterization of Firm Demand in Equilibrium – I first show an important lemma that characterizes the search behavior,

Lemma 1 *Under Assumption 1, the search problem has the reservation value property. Let u_{it} be the reservation value for shopper i at period t. It is determined by,*

$$-\kappa + E_p E_\upsilon(\max\{\frac{1}{\lambda}\upsilon - p, u_{it}\}|x_{it}) = u_{it} \tag{6}$$

The left-hand side represents the benefit of search net of search cost. The right-hand side shows the utility that shopper will obtain if she purchases from the current firm. The expectation takes over the distributions of prices and match utility. To understand the intuition, consider a shopper who can stop searching and secure utility u_{it}. If she instead samples another firm k, she will prefer the new good if $\frac{1}{\lambda}\upsilon_{ikt} - p_{kt} > u_{it}$. Since shopper can return without additional cost, the additional utility obtained in this case is $\frac{1}{\lambda}\upsilon_{ikt} - p_{kt} - u_{it}$. The reservation value is defined as the utility level at which shopper is indifferent between continuing her search and purchasing from current firm.

While the distribution of match utility is given exogenously, shopper needs to form a belief about distribution of prices using perceived firm's pricing strategy and her information set. Define $f(p, m_t|x_{it})$ as the density of price distribution conditional on shopper i's information set when the actual money supply is m_t. The above equation can be re-written as the following,

$$\int \int_{\lambda(u(x_{it})+p)}^{\infty} \big(\frac{1}{\lambda}\upsilon - p - u(x_{it})\big) g(\upsilon) d\upsilon f(p, m_t|x_{it}) dp = \kappa \tag{7}$$

The inner integral is expected additional utility compared to the reservation value given the next draw is price p. Integration over price distribution given next draw is random gives the unconditional expected additional utility. Note that the reservation value is determined in equilibrium as price distribution is an endogenous object.

Given the search rule, I turn to the determination of demand and profit for each firm. The probability that a shopper of information set x_{it} purchases from a firm that sets a price p_{kt} is $1 - G\big(\lambda(u(x_{it}) + p_{kt})\big)$. I define $\rho(m_t)$ as the unconditional probability that a shopper purchase from the current firm. Suppose the expected mass of shoppers who visit any firm in the first round is one. A fraction $\rho(m_t)$ of these shoppers settle with the firms they visit. The remaining $1 - \rho(m_t)$ shoppers visit a firm in the second round, a further $(1 - \rho(m_t))^2$ visit in the third round, and so on. Firms take $\rho(m_t)$ as given when making pricing decisions because firms are atomistic, they cannot influence the search outcomes for the population of shoppers. The share of shoppers who purchase from a firm that sets price p_{kt} is:

$$\mu(p_{kt}, m_t) = \frac{1}{\rho(m_t)} \int \big(1 - G(\lambda(u(x) + p_{kt}))\big) h_t(x) dx \tag{8}$$

where $h_t(x)$ is the density distribution of expected money supply at time t. The integral is taken with respect to information set because shoppers with heterogeneous information sets have different reservation value as shown in (6). The unconditional probability $\rho(m_t)$ is given by,

$$\rho(m_t) = \int \int \big(1 - G(\lambda(u(x) + p))\big) h_t(x) dx f(p, m_t) dp$$

where $f(p, m_t)$ is the actual price distribution when money supply is m_t. I can now write profit for firm with productivity A_{kt},

$$\pi_{kt} = \mu(p_{kt}, m_t) \frac{X_t}{P_{kt}} (P_{kt} - \frac{W_t}{A_{kt}}) \tag{9}$$

where $X_t = \int X_{it} dj$ as shopper's information set is independent of expenditure. Therefore, $\mu(p_{kt}, m_t)$ can be interpreted as the average expenditure share spent on good k.

Next, I define price index. Unlike conventional models in which there is a demand curve linking demand for individual goods to aggregate demand, such relationship is missing here. Instead, I define the expenditure share-weighted price index.

$$P_t = \exp\big(\int p\mu(p, m_t) f(p, m_t) dp \big) \tag{10}$$

where $\mu(p, m_t)$ and $f(p, m_t)$ are the expenditure share and price distributions.

Characterization of the Steady-State Equilibrium – Shoppers know the money supply in the steady state. The information sets are therefore $x_{it} = \bar{m}$, $\forall i$. The density distribution of expected money supply is degenerated, i.e., $h(x) = \delta_{\bar{m}}$. I rewrite the reservation value in (6),

$$-\kappa + E_p E_\upsilon(\max\{\frac{1}{\lambda}\upsilon - p, \bar{u}\} | \bar{m}) = \bar{u} \tag{11}$$

$\bar{u}$ is the steady-state reservation value. I also denote $f(p)$ as the steady-state price distribution and $\mu(p)$ as steady-state distribution of expenditure share. The profit for firm with productivity A_{kt} is given by,

$$\pi_{kt} = \frac{1}{\rho} \big(1 - G(\lambda(\bar{u} + \ln P_{kt}))\big) \frac{X_t}{P_{kt}} (P_{kt} - \frac{W_t}{A_{kt}}) \tag{12}$$

The first-order condition with respect to P_{kt} results in,

$$\bar{P}_{kt} = \frac{e_{kt}}{e_{kt}-1}\frac{\bar{W}}{A_{kt}} \tag{13}$$

$$e_{kt} = \lambda \frac{g\big(\lambda(\bar{u}+\bar{p}_{kt})\big)}{1-G\big(\lambda(\bar{u}+\bar{p}_{kt})\big)} + 1 \tag{14}$$

where $\bar{P}_{kt}$ is the optimal price firm k charges in the steady state. The level of the elasticity is controlled by the relative importance of match utility to utility from consumption, λ. Larger λ means goods are more substitutable. The elasticity is determined by a hazard function, where the density g represents the marginal shoppers who are indifferent between staying and searching. The survival function $1-G$ indicates that adjusting the price will impact the profit obtained from all infra-marginal shoppers. One can think of hazard function capturing effective marginal shoppers as determining the elasticity of demand on the extensive margin. Moreover, $\bar{P}_{kt}$ is endogenously determined by (12) and (13). I impose the following assumption on cumulative distribution of match utility G to generate well-defined prices.

Assumption 2 *G is log-concave.*

This assumption is often made in search literature. Note that most of commonly used distribution functions are log-concave, e.g., normal distribution, uniform distribution, Type-I extreme value distribution. I now show the existence of the steady-state equilibrium.

Theorem 1 (Existence of Steady-State Equilibrium) *Under Assumption 1 and 2, there exists a steady-state equilibrium in which consumers search actively.*

Proof. See Appendix A. ■

This theorem is proved in two steps. First, under assumption 2, the elasticity of demand, which depends on the hazard function $\frac{g(x)}{1-G(x)}$, is increasing in its argument. It implies that higher price induces higher elasticity and lower markup. Therefore, the individual prices are uniquely determined by (12) and (13). Also, markup is lower as firms face pickier shoppers, i.e., $\bar{u}$ is larger. Second, I prove that reservation value is uniquely determined by (10) for any given price distribution. 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. I focus on the equilibrium in which shoppers search actively.

Characterization of the Dynamic Equilibrium – After a permanent monetary shock to the steady state, shoppers know that the money supply is not fixed and following random walk process as described in (5). The information set x_{it} is given by,

$$x_{it} = \{\bar{m}, \{s_{it-j}\}_{j=t}^{\infty}\}$$

Shopper i's expected monetary shock is $E_{it}\hat{m}_t = E_{it}m_t - \bar{m}$ as shoppers know $\bar{m}$. Define the average information friction about monetary shock on the shoppers' side as $\theta_t = \frac{\bar{E}_t\hat{m}}{\hat{m}}$. As I show in Proposition 1, money supply controls average marginal cost, i.e., nominal wage in this model. As a result, $1 - \theta_t$ measures the degree of information asymmetry between consumers and firms regarding nominal wage. Information asymmetry affects the search behavior through reservation value as described in (6).

Firms, knowing the shock and information asymmetry, set pricing strategy accordingly. Formally, the price that firm k sets after a monetary shock, on the first order, is given by,

$$p_{kt} = \bar{p}_{kt} + \varphi_t(\bar{p}_{kt})\hat{m} \tag{15}$$

where $\bar{p}_{kt}$ is the log steady-state price. $\varphi_t(\bar{p}_{kt}) = \varphi(\bar{p}_{kt}; \theta_t)$ is the passthrough from monetary shock to price, which depends on average information friction θ_t. Thereafter, I will call $\varphi_t(p)$ the total passthrough since it is related to the sum of two passthroughs which I will show in Section 1.2. The first-order approximation to price index is given by,

$$p_t = \bar{p} + \int \hat{p}_t \mu(p) f(p) dp$$

where $\bar{p}$ is the log price index in the steady state. Plug in the definition of the total passthrough $\hat{p}_{kt} = \varphi_t(\bar{p}_{kt})\hat{m}_t$,

$$p_t = \bar{p} + \Phi_t \hat{m}_t \tag{16}$$

where $\Phi_t = \int \varphi_t(p)\mu(p)f(p)dp$. Φ_t is the aggregate total passthrough, which is the key object in our analysis. It measures the aggregate effect of a small monetary shock on price index. According to the equilibrium definition, shoppers understand firms' pricing strategy and steady-state distributions. They thus know Φ_t. The average expected change in log price index is $\bar{E}_t\hat{p}_t = \theta_t\Phi_t\hat{m}_t$.

The following lemma presents a first-order approximation to the reservation value determined in (6) compared to the steady-state value as determined in (11).

Lemma 2 *Fix the variance ratio* $\frac{\sigma_s^2}{\sigma_m^2}$. *To the first order as* $\sigma_m \to 0$, *the reservation value* $u(x_{it})$ *is given by,*

$$u(x_{it}) = \bar{u} - \Phi_t E_{it}(\hat{w}_t | x_{it})$$

where $\Phi_t = \int \varphi_t(p)\mu(p)f(p)dp$.

Proof. See Appendix A. ■

This lemma shows that Φ_t also governs the passthrough from the nominal wage to reservation value. It shows that higher signals imply a lower reservation value. Intuitively, when a shopper perceives higher nominal marginal costs, it raises their expectation of outside prices and shoppers are more likely to purchase from the current firm. As a result, the reservation value is lower. Moreover, the slope depends on the aggregate passthrough which 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., $\varphi_t(p) = \varphi_0$, then $\Phi_t = \varphi_0$. An increase in perceived nominal marginal costs would shift every point in the distribution to the right by the same amount. 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 reservation value.

Using results in Lemma (2), I present firm's pricing strategy in the dynamic equilibrium.

Proposition 2 *Firm charges a markup over the marginal cost,*

$$P_{kt} = \frac{e_{kt}}{e_{kt} - 1} \frac{W_t}{A_{kt}} \tag{17}$$

e_{rt} *is the elasticity of demand. Let the variance ratio* $\frac{\sigma_m^2}{\sigma_s^2}$ *be fixed. In the limit when* $\sigma_m \to 0$,

$$e_{kt} = \lambda \frac{g\big(\lambda(\bar{u} + \bar{p} + p_{kt} - \bar{E}_t p_t)\big)}{1 - G\big(\lambda(\bar{u} + \bar{p} + \hat{p}_{kt} - \bar{E}_t p_t)\big)} + 1 \tag{18}$$

where $\bar{E}_t p_t = \bar{p} + \theta_t \Phi_t \hat{m}_t$. e_{kt} *increases in* $p_{kt} - \bar{E}_t p_t$.

Proof. See Appendix A. ■

This proposition provides a simple characterization of the elasticity of demand. To reach this result, first note that a firm's demand contains the dispersion of shoppers' expectations, but under first-order approximation, only the average expectation of the price index is retained. It has important implication that the elasticity depends on perceived relative price. To see the intuition, suppose shoppers know the money shock and, therefore, the price index. In that case, elasticity becomes simply a function of actual relative price.[8] This property is commonly observed in preferences used in the literature.[9] When information is noisy, the average perceived movement of the price level is typically dampened. As a result, the perceived relative price becomes larger for given price. Under Assumption 2, the elasticity of demand is increasing in relative price, leading to lower markups. I elaborate this point in Section 1.2.

1.2 Passthroughs

I now characterize passthroughs in equilibrium. I present the main finding: the aggregate passthrough of a money supply shock to the price index is generically incomplete, which is crucial for inducing monetary non-neutrality.

It is useful to define passthroughs in terms of markup elasticities, i.e., the elasticity of markup to price. Following Amiti et al. (2019), I have the following Lemma,

Lemma 3 *Let mu_{kt} denote log markup of firm k at time t. The movements in price is given by,*

$$\hat{p}_{kt} = \gamma_{kt}(\hat{w} - a_{kt}) + \xi_{kt}\hat{p}_t$$

where p_t is log price index, γ_{kt} is own-cost passthrough and ξ_{kt} is competitor-price passthrough.

$$\gamma_{kt} = (1 - \frac{dmu_{kt}}{dp_{kt}}\Big|_{\hat{m}=0})^{-1}; \xi_{kt} = \frac{dmu_{kt}}{dp_t}\Big|_{\hat{m}=0}\gamma_{kt} \tag{19}$$

The total passthrough for each firm is defined as:

$$\varphi_{kt} = \gamma_{kt} + \Phi_t\xi_{kt} \tag{20}$$

The aggregate total passthrough Φ_t is,

$$\Phi_t = \frac{\Gamma}{1 - \Xi_t} \tag{21}$$

where $\Gamma = \int \gamma(p)\mu(p)f(p)dp$, $\Xi_t = \int \xi_t(p)\mu(p)f(p)dp$.

[8] When the shock is fully known, there is no dispersion of expectations, making the result exact.

[9] This property holds in its exact form in models with nested CES. It holds as a first-order approximation for the Kimball demand family as Ill as for the broad homothetic families of demand considered in Matsuyama and Ushchev (2017).

The lemma links passthroughs with elasticity of demand via markup elasticity. As a result, passthroughs also depend on perceived relative prices. The lemma then derive total passthrough in equilibrium. Integrating on both sides, we achieve the aggregate total passthrough. Note that the aggregate own-cost passthrough does not depend on θ_t. It implies that firms pass part of the change in marginal cost to prices regardless of information frictions. As shown in (21), it determines the lower bound of the aggregate total passthrough.

I now state our main results on passthroughs. I start with full-information case.

Theorem 2 (Full-information Benchmark) *If the information about money supply is complete, i.e., $\sigma_s = 0$, the total passthrough follows,*

$$\varphi_{kt} = 1 \ \forall k, t$$

This theorem establishes that the passthrough from money supply shock to individual prices for all firms is one under full information. From Proposition 2, we know that elasticity is a function of actual relative prices if shoppers are aware of the shock. It follows that, in this scenario, the sum of passthroughs, $\gamma_{kt} + \xi_{kt}$, equals one, as the two markup elasticities are always identical. Intuitively, for a given firm, if all other firms fully pass through the monetary shock and all shoppers know this fact, the optimal strategy is to do the same. This constitutes a Nash equilibrium. With relative prices and markups unchanged, the increase in nominal wages is fully reflected in the increase in prices. Money is neutral. The theorem complements Amiti et al. (2019), who show that the total passthrough is one for broad preferences including nested CES and first-order Kimball demand family, by pointing out that the complete information about the price index is necessary for this property to hold. However, the total passthrough becomes incomplete under incomplete information. I now state the results in this case.

Theorem 3 (Passthroughs under Incomplete Information) *If the information about money supply is incomplete, $\sigma_s > 0$. the total passthrough follows,*

$$\varphi_{kt} < 1 \ \forall k, t$$

This is the main theorem of this paper. It establishes that the total passthrough is generically incomplete if there exists any information frictions about the underlying monetary shock. The full-information case is a knife-edge case. The key step to understand the intuition of this result is:

$$1 - (\gamma_{kt} + \xi_{kt}) \propto -\frac{\partial mu_{kt}}{\partial p_{kt}}(1 - \theta_t) > 0$$

It shows that the deviation of sum of the passthroughs, $\gamma_{kt} + \xi_{kt}$, from one can be decomposed into two terms. The first term is the markup elasticity. It captures the role of search frictions. From Proposition 3, the elasticity increases in own price. Markup elasticity is thus positive. The second term shows the information asymmetry about average nominal production cost between consumers and firms. It captures the role of information frictions. Since $\theta_t < 1$, this term is also positive.

The main mechanism is that when the information about money supply shock is incomplete, the perceived relative prices become larger. In other words, shoppers attribute more of the increase in prices to idiosyncratic productivity shocks.[10] From Proposition 2, it motivates more marginal consumers to search for alternatives, which drives down the markup. To dissuade search, firms limit the extent to which they pass the shock to prices, implying monetary non-neutrality.

Furthermore, remember total passthrough as $\varphi_{kt} = \gamma_{kt} + \Phi_t \xi_{kt}$. The individual passthrough depends on aggregate total passthrough. Intuitively, the fact that shoppers understand that aggregate total passthrough is incomplete reduces perceived price index even more and leads to even lower passthrough. This amplification is originated from the strategic complementarities in pricing between firms, which is a type of real rigidities (Klenow and Willis, 2016).

As a final remark, one may think that, if passthroughs from the shock to prices are complete, while shoppers are motivated to search more, mass of shoppers still increases in subsequent rounds of shopping. Firms may end up with same demand as in the steady state under some conditions.[11] However, this argument overlooks the fact that the unconditional probability of purchasing from the current firm is treated as exogenous to the firms. 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.

Aggregate Supply Shocks – I now study the responses of price index and output following an aggregate supply shock. Fix the money supply at the steady state. The firm productivity process is now modified as follows,

$$\log A_{kt} = \log A_t + \sigma_a \varepsilon_{akt} \tag{22}$$

[10]From definition of equilibrium, shoppes know the objective pricing strategy. Given the perceived money supply, they can derive the perceived idiosyncratic productivity shocks.

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

where A_t is the aggregate productivity. Denote $a_t = \log A_t$. It follows an AR(1) process,

$$a_t = \rho_A a_{t-1} + \varepsilon_{At} \tag{23}$$

where ε_{At} is IID shock to aggregate productivity. It follows $\varepsilon_{At} \sim \mathcal{N}(0, \sigma_A^2)$. Shoppers receive Gaussian signals about a_t and they know $\bar{a} = 0$ in the steady state.

Consider the case where an aggregate productivity shock ε_A, hits the economy at time zero and there is no shock thereafter. We can still define $\hat{p}_{kt} = -\varphi_t(\bar{p}_{kt})a_t$ and aggregate total passthrough Φ_t as expenditure share-weighted $\varphi_t(p)$. The measure of average information friction about aggregate supply shock on the shopper side is given by $\theta_t = \frac{\bar{E}a_t}{a_t}$. Also, we can similarly define passthroughs as in Lemma 1 except the movements in price is modified as follows,

$$\hat{p}_{kt} = \gamma_{kt}(-a_t - a_{kt}) + \xi_{kt}\hat{p}_t \tag{24}$$

It is straightforward to show that Theorem 2 and Theorem 3 hold for aggregate productivity shocks.

The underlying mechanism is akin to that of a monetary shock. When there is information asymmetry about a positive aggregate productivity shock, perceived relative prices decline, as consumers attribute the decrease in prices primarily to idiosyncratic shocks. Consequently, they are more likely to purchase from the current firm as they believe outside prices are on average higher, inducing firms to limit the extent to which they pass the shock onto prices. As a result, prices remain higher than the ones that frictionless model would imply, leading to lower demand relative to the natural output, and a contraction in employment. This reflects the typical response of inflation and output following a supply shock in a New-Keynesian model with nominal rigidities (Galí, 1999). Thus far, the model generates properties of both monetary non-neutrality and supply shock that have been substantially documented in the literature.

1.3 Phillips Curve

Philipps curve contains the relationship between changes in price index and aggregate output. I characterize the Phillips curve in this model.

Theorem 4 *The Phillips curve for a monetary shock is a combination of the following two equations,*

$$\hat{p}_t = \Gamma\hat{w}_t + (1-\Gamma)\lambda_t\bar{E}_t\hat{w}_t \tag{25}$$

$$\hat{w}_t = \hat{p}_t + \hat{c}_t \tag{26}$$

where $\lambda_t = \frac{\Gamma}{1-\theta_t+\Gamma\theta_t}$ *and* $\lambda_t \leq 1$. $\lambda_t = 1$ *if* $\theta_t = 1$.

In this theorem, I separate the aggregate supply equation that associates nominal wage with price index and wage determination equation that is derived from the labor market clearing condition. The first equation holds under more general conditions in Section 1.5. The second equation can not apply in setups where labor elasticity is finite. Combining these equations establishes a link between changes in the price index and aggregate output, which is the form usually presented in the New-Keynesian Literature.

This theorem summarizes the mechanisms we emphasized before in a more concise and sharp manner. It shows that price index movements are driven by two parts. First, actual changes in marginal cost are reflected in price index through the aggregate own-cost passthrough. It serves as the lower bound of the total passthrough. Moreover, firms adjust prices based on households' beliefs about nominal wage, which is directly reflected in the second term. Since perceived changes in marginal cost are generally dampened relative to actual changes, the price index does not fully capture shifts in nominal wage, resulting in monetary non-neutrality. Furthermore, because $\lambda_t < 1$, the combined passthrough of actual and perceived nominal wage changes is less than one. λ_t further amplifies the effect of dampened perceptions. This amplification stems from the real rigidity discussed earlier and can be large. For example, suppose $\theta_t = 0.1$ and $\Gamma = 0.5$, then $\lambda_t = 0.53$. The following Corollary shows the Phillips curve applying to aggregate supply shocks.

Corollary 1 *The Phillips curve for an aggregate productivity shock is given by,*

$$\hat{c}_t = \Gamma a_t + (1-\Gamma)\lambda_t \bar{E}_t a_t \tag{27}$$

where $\lambda_t = \frac{\Gamma}{1-\theta_t+\Gamma\theta_t}$ *and* $\lambda_t \leq 1$. $\lambda_t = 1$ *if* $\theta_t = 1$.

Proof. See Appendix A. ■

The intuition is similar. Following a positive aggregate productivity shock, the decline in the price index is moderated by information asymmetry about nominal wage as well as real rigidities. As a result, the increase in aggregate output is dampened.

Remarks − I wrap up the results on Phillips curve with a few additional insights.

First, it is widely accepted that in modern Phillips curve models, firms' expectations play a central role in driving inflation. Recent efforts have been devoted to conducting new surveys of firms' expectations (Candia et al., 2023). However, this model presents an alternative view echoing

Reis (2023). It shows that households' expectations can influence firms' pricing decisions and, consequently, inflation. The model is extreme since firms are assumed to have full information just to show the mechanism. Reality is in between. Both firms' knowledge of macroeconomic variables and their second-order beliefs, i.e., their understanding of consumers' expectations regarding average marginal costs or price levels, are critical.

Second, the Euler equation dictates that inflation, rather than the price level itself, drives household decisions. In models with information frictions on the household side, it is typically sufficient for households to receive signals about underlying shocks (Angeletos and Lian, 2018). However, this model highlights the importance of keeping up with the average marginal cost and, in turn, the price level on household side. As households learn about price level over time, their search behavior converges to the steady state. The average expectation of price level may never be correct if households only receive information about underlying shocks. Recent findings by D'Acunto et al. (2021) show that households learn price level by shopping and update their inflation expectations accordingly. Recently, Lorenzoni and Werning (2023) show that the race between price level and wage level is crucial to think about inflation as conflict.

Third, price stickiness may be influenced by a sequence of public events triggered by underlying shocks. For example, VAT reforms are often extensively discussed in the public sphere, leading to increased consumer awareness of the cost changes faced by firms. The relatively comprehensive knowledge of these shocks, combined with rapid learning through social media, facilitates a faster passthrough to prices. Similarly, the elevated inflation following the pandemic may be partly attributed to the historically high media coverage of supply chain disruptions and labor shortages. Many restaurants and retail establishments have explicitly communicated to their customers the need to raise prices due to escalating labor and material costs, thereby conveying this information about costs directly to consumers.

1.4 Comparative Statics

In this section, I present a set of comparative statics results to distill the role of various forces that affect the distribution of passthroughs. They shed lights on the compositional effect of aggregate total passthrough and how these two frictions impact individual total passthrough. In particular, I establish that, all else equal, (i) total passthrough is lower for high-productivity firms;

(ii) total passthrough is larger when search cost is smaller for any given productivity; (iii) total passthrough is larger when information friction is smaller for any given productivity.

To push the results as far as possible, I impose the functional form on cumulative distribution of match utility, G:

Assumption 3 *G follows the Type-I extreme-value distribution.*

I adopt this assumption to push the results as far as possible. Besides, I also impose this restriction in Section 4 where I calibrate the model. Therefore, the results here can shed lights on calibration.

I start with comparing markups and passthroughs across firms within a given equilibrium. I define passthroughs on primitives: $\varphi(p(a)) = \varphi(a)$, $\gamma(p(a)) = \gamma(a)$ and $\xi(p(a)) = \xi(a)$.

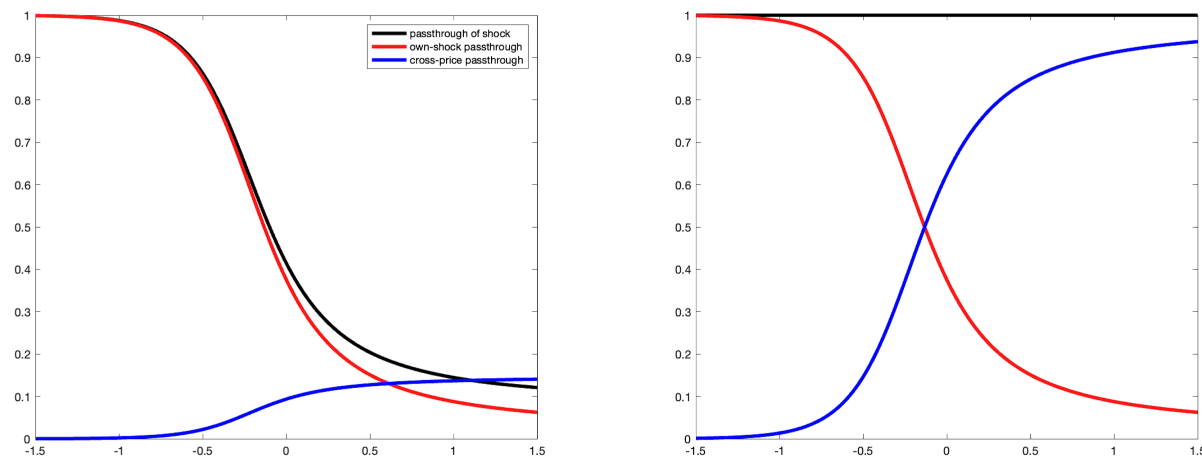
Proposition 3 *In a given equilibrium, $MU(a)$ and $\xi(a)$ increases in productivity; $\gamma(a)$ and $\varphi(a)$ decreases in productivity. Also, the following limiting results hold:*

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 optimal 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. To understand the results on passthroughs, suppose the information about monetary shock is complete. The decrease in own-shock passthrough is exactly offset by the increase in competitor-price passthrough. The resulting total passthrough is always one for firms of any productivity. However, in the incomplete-information case, the competitor-price passthrough rises less ($\theta < 1$). The increase in competitor-price passthrough is not sufficient to cancel out the decrease in own-shock passthrough, leading to total passthroughs less than one. This effect is particularly large for high-productivity firms since most of their responses to aggregate shocks originate from their responses to competitors' prices. The key takeaway is that high-productivity firms contribute more to monetary non-neutrality. Figure 1 illustrates that under full information when the information asymmetry about nominal wage vanishes, the total passthrough is one for any given productivity level. Under incomplete information case, total passthrough is smaller for firms with higher productivity.

This result 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

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 competitor-price passthrough. The black line represents total passthrough. The left and right panels show passthroughs in the incomplete and complete information cases, respectively.

exchange rate shocks (Amiti et al., 2019). The literature reconciles these evidence with oligopolistic CES. The total passthrough in these models is always one. However, our model provides an alternative which behaves more flexible in passthroughs.

I now study the distribution of passthroughs across equilibria with different search cost.

Proposition 4 *Let equilibrium passthrough distributions $\gamma(a;\kappa), \xi(a;\kappa), \varphi(a;\kappa)$ for given κ. Given $\sigma_s > 0$, 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. *Competitor-price passthrough: $\forall a, \xi(a;\kappa_2) > \xi(a;\kappa_1)$; $\lim_{\kappa\to\infty} \xi(a) = 0$; $\lim_{\kappa\to 0} \xi(a) = \theta$*
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. To arrive at this result, notice that higher search cost implies lower reservation value but lower reservation value also implies higher prices. Lemma A.1 shows that the decrease in reservation value dominates. The effect of higher search cost acts like increasing productivity of all firms. According to Proposition 3, this decreases own-cost passthrough and thus total passthrough. Furthermore, the limiting result shows that the monetary non-neutrality can vary from zero to one because the aggregate own-cost passthrough, which serves the lower bound for aggregate total passthrough, approaches zero when search cost is infinite. In Section 3.2, I present empirical evidence on this result.

Proposition 5 *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. *Competitor-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 yet another important dimension along which the information friction about underlying aggregate shock shapes the distribution of passthrough. It shows that competitor-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 does not change because it is calculated by setting aggregate shock is zero. Furthermore, a natural implication of this proposition is that as shoppers learn over time, the average perception of money supply converges to the actual one. The monetary non-neutrality is largest at the beginning and fades out in the long run. The following corollary states this intuition formally.[12]

Corollary 2 *Suppose money supply follows random walk (5) and in each period, shopper receives a signal about money supply (3). Then, Φ_t increases over time and $\lim_{t\to\infty} \Phi_t = 1$. θ_t is given by $\theta_t = \sum_{j=0}^{t} (1-K)^j K$, where K is Kalman gain. $K = \frac{\sigma_m^2}{2\sigma_s^2}(\sqrt{1 + \frac{4\sigma_s^2}{\sigma_m^2}} - 1)$.*

Taken together, our results presented as Propositions 3-5 yield general predictions of monetary non-neutrality in the presence of both search and information frictions. In particular, these propositions establish that, all else equal, monetary non-neutrality is mostly contributed by high-productivity firms (Proposition 3), more significant in the economy of more search frictions (Proposition 4) and more information frictions (Proposition 5).

[12] Appendix A also shows results regarding learning in the case of an aggregate productivity shock.

1.5 Generalization and Extension

I generalize the model to accommodate (i) a single household without division between worker and shopper, (ii) consistent information structure, (iii) general preference with finite labor supply elasticity and no utility for money (iv) monetary authority sets interest rate. The details of setup and equilibrium are delegated to Appendix B. I have the following result.

Proposition 6 *The equilibrium dynamics of $\{\hat{p}_t, \hat{w}_t, c_t, i_t\}$ is described by the following system of equations:*

$$\begin{aligned} \hat{c}_t &= \bar{E}_t \hat{c}_{t+1} - (i_t - \bar{E}_t(\hat{p}_{t+1} - \hat{p}_t)) \\ \hat{p}_t &= \Gamma(\hat{w}_t - a_t) + (1-\Gamma)\lambda_t \bar{E}_t(\hat{w}_t - a_t) \\ \hat{c}_t + \hat{p}_t &= \Psi(\hat{w}_t - a_t) + (1-\Psi)\lambda_t \bar{E}_t(\hat{w}_t - a_t) \\ i_t &= \phi_\pi(\hat{p}_t - \hat{p}_{t-1}) + \varepsilon_{mt} \end{aligned}$$

where $\lambda_{1t} = \frac{\Gamma}{1-\theta_t+\Gamma\theta_t}$, $\Psi = \frac{1+\eta\tilde{\Gamma}}{1+\eta}$; $\theta_t = \frac{\bar{E}\hat{w}_t}{w_t}$; ε_{mt} *is the monetary shock.*

where $\tilde{\Gamma}$ is defined similarly as Γ, which I leave to Appendix B.

The first equation is the Euler equation under incomplete information as described in Angeletos and Lian (2018). The second equation presents the Phillips Curve similar in Theorem 4 by combining aggregate supply shocks. The third equation results from labor market clearing. Since shoppers' average perception of price index influences demand across firms, thereby affecting equilibrium wages and labor demand. The last equation is the monetary policy rule, controlling nominal interest rate.

I further extend the model to allow multiple goods produced by one firm with different productivity for each good.

$$\log A_{kjt} = \log A_t + a_{kt} + a_{kjt}$$

where a_{kjt} is the productivity of producing good j by firm k at time t. It is IID shock following $a_{kjt} \sim \mathcal{N}(0, \tilde{\sigma}_a^2)$. 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. We have the following result.

Proposition 7 *Firm charges same markup over all the products it sells. The passthrough of productivity shocks a_{kjt} 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.[13] 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 store-specific shocks is complete.

2 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 average 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.

2.1 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.

[13] See Gopinath and Itskhoki (2011) for a summary of this literature.

Data – The data source is the Nielsen Consumer Panel Data set.[14] Nielsen 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 Nielsen-defined product modules and covers around 30% of all expenditure on goods in the CPI.[15]

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.

[14] The Nielsen data are made available through the Kilts Center for Marketing Data at the University of Chicago Booth School of Business. Information on data availability and access can be found at http://research.chicagobooth.edu/nielsen/. The conclusions drawn from the Nielsen data are solely ours and do not reflect the views of Nielsen. Nielsen is not responsible for, and had no role in, analyzing or preparing the results reported in this paper.

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

Table 1: Descriptive Statistics of Household Search Behavior

	Mean	Standard Deviation	10th Percentile	90th Percentile	Observations
#Trips	41.49	29.13	12	80	3,353,048
Spending HHI(%)	7.55	6.32	2.69	14.11	3,353,048
# Dist. 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)[16] 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:

$$y_{it+1} = \lambda_i + \beta\hat{\pi}_t + X_{it} + e_{it} \tag{28}$$

where t is time; i represents household. λ_i is the household fixed effect. $\hat{\pi}_t$ 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

[16]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.

causality because inflation and household search behavior are co-determined in theory. Second, it may take time for households to change the shopping habit. 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.

Table 2: Search and Unanticipated Inflation

	#Trips	#Distinct Stores	#Dist. Stores|Trips	Spending HHI
π^s-FD	1.185***	0.381***	0.339***	-0.143***
	(0.033)	(0.009)	(0.008)	(0.011)
π^s-ALL	0.174***	0.056***	0.048***	-0.021**
	(0.019)	(0.006)	(0.005)	(0.007)
Oil News	0.191***	0.134***	0.040***	-0.004
	(0.011)	(0.009)	(0.003)	(0.004)
MPS (BS23)	-0.165***	-2.036***	-0.064***	0.040***
	(0.013)	(0.195)	(0.004)	(0.005)
Observations	3,143,110	3,143,110	3,143,110	3,143,110
HH fixed effects	√	√	√	√
HH time-varying effects	√	√	√	√

Notes: The table reports the estimates in specification (18). #Trips is the number of trips. #Dist. Store is the number of distinct stores. #Dist. Store|Trips is the number of distinct stores and the regression controls the number of trips for a given household 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.

The results are presented in Table 2. The first row shows that A 1 percentage point increase in unanticipated food and drink inflation is associated with: (i) 1.2 additional trips, (ii) a 0.143 decrease in the spending HHI, (iii) a 0.38 increase in the number of different retailers visited, and (iv) a 0.34 increase in the number of different retailers visited conditional on the number of trips. 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 Nielsen 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 1. 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 Nielsen includes. Nielsen 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.[17] Second, there may be substantial substitution happens within one trip, e.g., consumer may trade down quality of goods within the store (Jaimovich et al., 2019). This hurts 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.

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.

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

2.2 Evidence on Search Frictions

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.

2.2.1 MSA-Level Search Index

Search frictions bridges information asymmetry and 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 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. In particular, 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.[18] I then construct county-level search index by aggregating establishment density for each industry within a county,

$$SI_{cy} = \log(\sum_j \text{Share}_{jc\tau} \frac{N_{jcy}}{A_c}) \tag{29}$$

[18] Gopinath and Itskhoki (2011) argue that the tradeable sector is better described as a bargaining environment between a final-good producer and a limited number of intermediate-good suppliers. I include Finance and Insurance, and Educational Services as robustness check in Appendix C.1.

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 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 imputation of missing employment data provided in Eckert et al. (2020). Then, I utilize CBP data at the state level, which has way less 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:

$$Share_{jc\tau} = \frac{\text{annual wage}_{js\tau} \times \text{employment}_{jc\tau}}{\sum_j \text{annual wage}_{js\tau} \times \text{employment}_{jc\tau}} \tag{30}$$

where s is state and τ is period 1998-2000. The permanent heterogeneity of search index across counties may be correlated with local economic conditions, such as local income, product varieties and housing prices.[19] Therefore, I subtract the mean of search index over the period 2006-2019 for each county. Denote this mean as $\overline{SI}_c$.

$$\Delta SI_{cy} = SI_{cy} - \overline{SI}_c \tag{31}$$

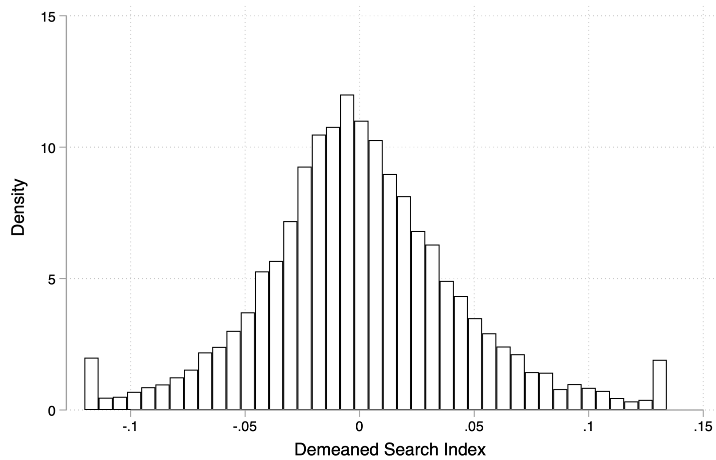
Positive ΔSI_{cy} indicates increase in establishment density above its mean in year y. I take the median of demeaned search indices across counties within a Metropolitan Statistical Area (MSA) and Mitropolitan Statistical Area (MicroSA).[20] Figure 1 shows the density distribution of demeaned

[19]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.

[20]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.

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 represent

Figure 2: Density distribution of demeaned search index



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

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 search index, the demeaned search index is not 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.

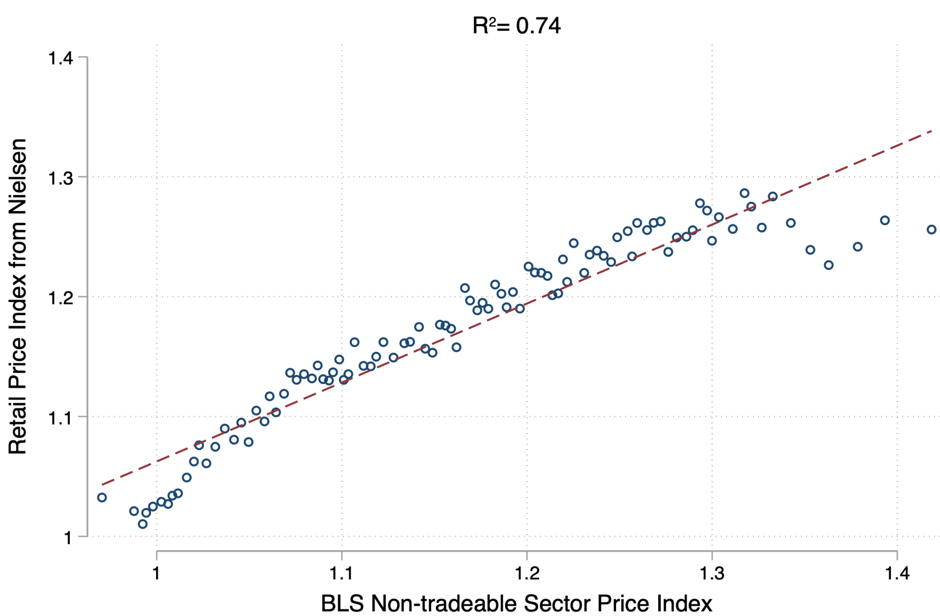
Correlation with local economic conditions can bring following issues. First, higher local wage may affect inflation through other channels. For example, housing prices are usually positively correlated with wages. Stroebel and Vavra (2019) shows that regions with higher housing prices also have higher 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.

2.2.2 MSA-Level Price Index

To construct price indices, I utilize another dataset collected by The Nielsen Company (US), LLC - the Retail Scanner Database.[21] 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. MSAs are larger area and Nielsen has better coverage. I restrict the attention to product modules that (i) have at least 20 stores sell in each MSA and (ii)) exist through out the sample for each MSA. I then eliminate MSAs that have less than 500 modules. Details are delegated to Appendix C.2.[22]

Figure 3: 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.

[21] Again, the conclusions drawn from the Nielsen data are solely ours and do not reflect the views of Nielsen. Nielsen is not responsible for, and had no role in, analyzing or preparing the results reported in this paper.

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

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.[23] 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.[24] 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:

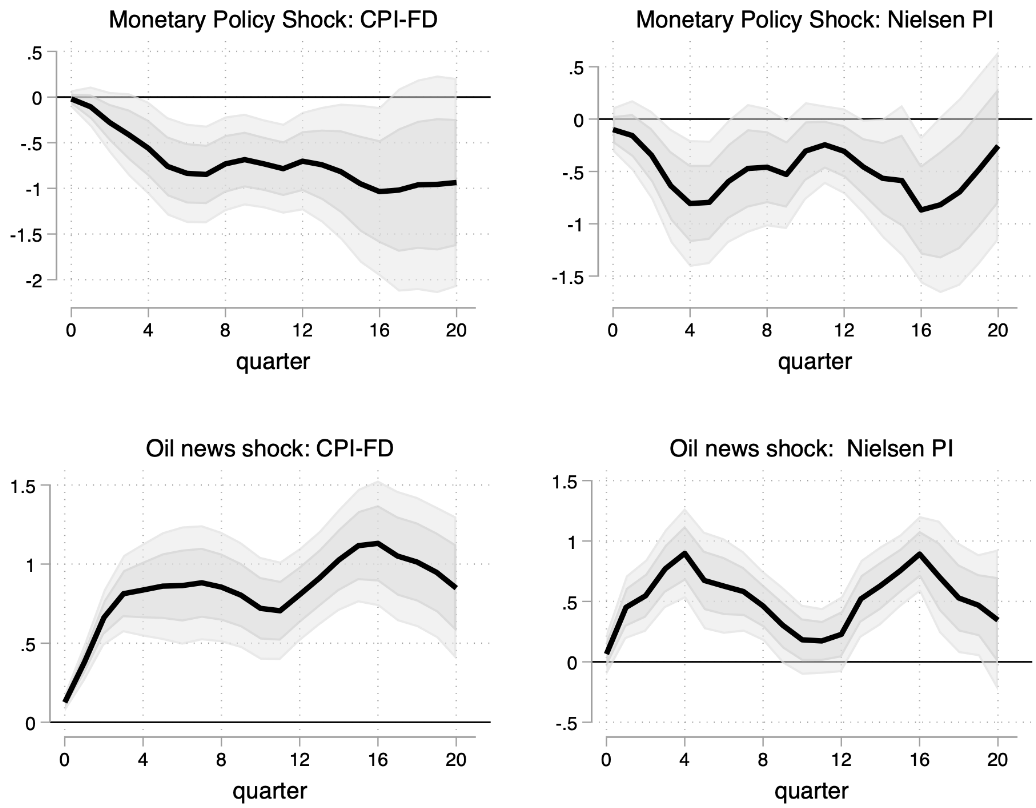
$$P_T = \prod_{i=1}^{n} \left(\frac{p_{i,t}}{p_{i,0}} \right)^{\frac{1}{2}\left[\frac{p_{i,0} \cdot q_{i,0}}{\Sigma\left(p_{i,0} \cdot q_{i,0}\right)} + \frac{p_{i,t} \cdot q_{i,t}}{\Sigma\left(p_{i,t} \cdot q_{i,t}\right)} \right]} \tag{32}$$

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.

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

[24] 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.

Figure 4: 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 3 shows a highly significant correlation between our retail price indices (derived from Nielsen 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.

I calculate the cumulative 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 4 shows the impulse responses of cumulative inflation to monetary policy shocks and oil news shock. It has third implications. First, the responses are similar to both series for both shocks. This indicates that our price indices capture the variations we want. Second, the responses of cumulative inflation to oil new shocks exhibit double-hump shape. This is especially true for the constructed price indices.[25] Details of specification of the regression are delegated to Appendix C.2.

2.2.3 Search Index and Passthroughs to Price Indices

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),

$$\sum_{l=0}^{h} \pi_{kt+l} = \lambda_{kq} + \eta_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=0}^{4} \kappa_{lh} u_{kt-l} + X_{ky} + e_{kth} \tag{33}$$

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 are 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. π_{kt} is quarterly inflation at time t and MSA k. 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. They include ΔSI_{ky-1} and variables that measure local economic conditions defined before, i.e., log annual wage,

[25] I am not interested in the reason underlying this pattern. It may be caused by short time frame.

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. Moreover, I cluster standard errors at MSA level to account for correlation within a MSA.

I use the previous year's demeaned search index to address endogeneity concern that the entry and exit decisions of establishments are influenced by local economic conditions. In the previous year, firms cannot base their decisions on a random shock that had not yet occurred. I also control for time fixed effects to account for the effect of other macroeconomic variables that may affect the effects of shocks on cumulative inflation, such as economy-level unemployment rates, industrial production and interest rates. Hazell et al. (2022) use time fixed effect to absorb changing inflation expectation. I control for lagged inflation rates 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 yearly real local wages and total employment to account for the effects of changing local labor market conditions in response to the shock, as well as the unemployment rate in this period. 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,

$$\sum_{l=0}^{h} \pi_{kt+l} = \lambda_{kq} + \alpha_h \epsilon_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=0}^{4} \kappa_{lh} u_{kt-l} + \sum_{l=0}^{4} \eta_{lh} X_{t-l} + X_{ky} + e_{kth} \tag{34}$$

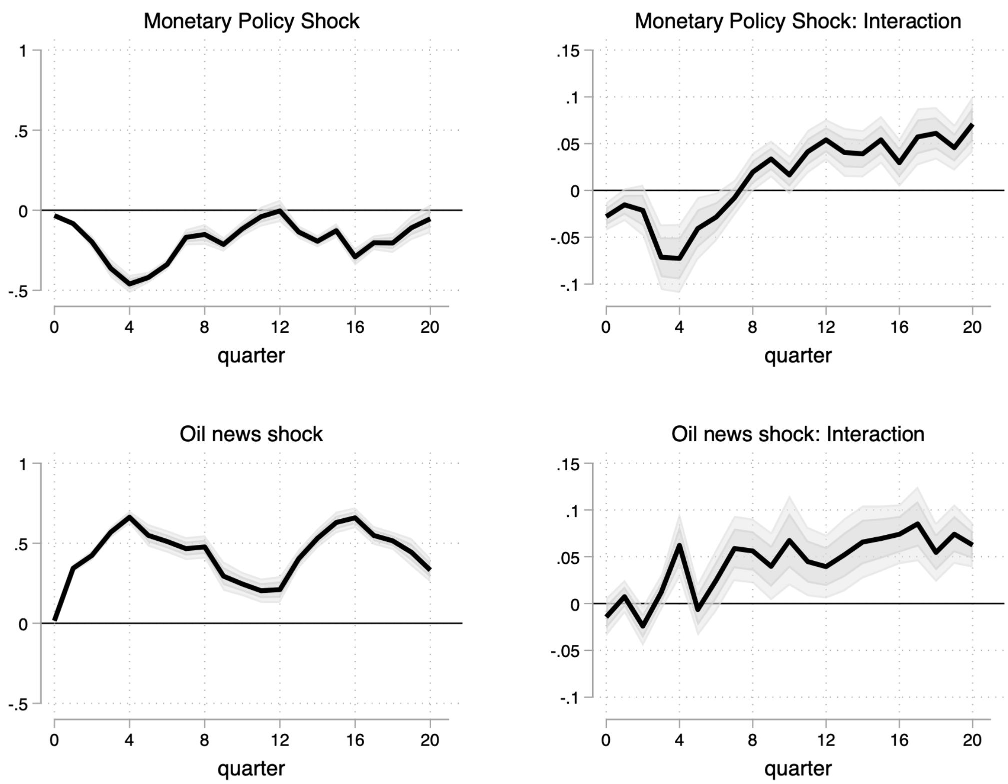
where X_t represents the aggregate control, i.e., inflation calculated from CPI-FD. The main coefficient of interest here is α_h, which measures the passthrough of shocks to inflation at different horizons. The average effect provides a natural benchmark to interpret the magnitude of the interaction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

Results – Figure 5 reports the results from estimating the baseline specification (33) and average effect of shocks in (34). 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 5 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 3. 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.

The right panel illustrates the interaction coefficients at different horizons. In general, MSAs with higher demeaned search indices and lower search frictions experience a greater passthrough of shocks to cumulative inflation. This influence is statistically significant and economically relevant. Following a monetary policy shock, the price index initially decreases. Consumers are more inclined to make purchases because they believe that they have encountered firms with higher productivity, and expect the average prices of outside firms to remain high. Consequently, firms do not reduce prices as much as would be under complete passthrough. However, according to Proposition 6, the effect of information asymmetry on passthroughs is smaller in regions with lower search frictions. Therefore, the interaction efficient is negative, indicating more passthrough to inflation. Over time, consumers learn the monetary shock and start to believe the average prices are actually low. At this point, the price index begins to rise after reaching its trough. the same underlying mechanism leads to positive interaction coefficients. Moreover, the magnitudes of interaction coefficients are large. One standard-deviation increase in the demeaned search index implies 12% additional passthrough of the shock to the cumulative inflation. The interaction coefficients for oil news shocks follow a similar pattern. The decrease in the average effect during the third year is relatively moderate compared to the peak response, and inflation begins to rise again afterward. This could explain why we do not observe negative interaction coefficients, as seen with monetary policy shocks. For oil news shocks, a one standard-deviation increase in the demeaned search index also results in about 12% additional passthrough to cumulative inflation.

Figure 5: 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 (34). The right panel shows dynamics of the interaction coefficient over time estimated in (33). Dark and light shaded area represents 68% and 90% confidence interval respectively.

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.

2.2.4 Search Index and Unemployment Rate

I next show that following the increased passthrough of shocks to price indices, there is less monetary non-neutrality and less impact on unemployment rate after an aggregate supply shock.

Specification – The main specification is the following,

$$u_{kh} = \lambda_{kq} + \eta_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=1}^{4} \kappa_{lh} u_{kt-l} + X_{ky} + e_{kth} \tag{35}$$

Notations are the same as in (33). The coefficient of interest is β_h I estimate the average effect of shocks on unemployment rate as follows,

$$u_{kt+h} = \lambda_{kq} + \alpha_h \epsilon_t + \beta_h \Delta SI_{ky-1} \times \epsilon_t + \sum_{l=1}^{4} \gamma_{lh} \pi_{kt-l} + \sum_{l=1}^{4} \kappa_{lh} u_{kt-l} + X_{ky} + e_{kth} \tag{36}$$

Again, notations are the same as in (24) and I do not add additional controls.

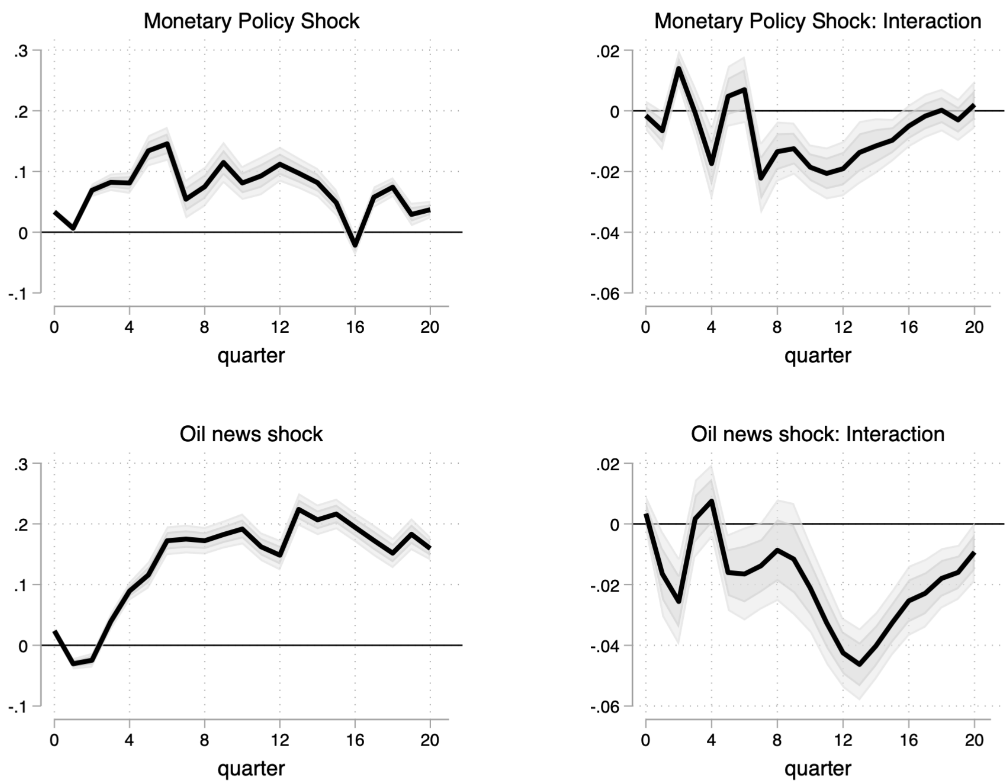
Results – Figure 5 reports the results from estimating (35) and (36).

The left panel in Figure 6 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. In general, MSAs with higher demeaned search indices have less responses in unemployment rate. This influence is statistically significant and economically relevant. Consistent with the theory, following a monetary policy shock, more passthrough of the shock to price indices in regions with lower search frictions as shown in Figure 5 decreases the monetary non-neutrality. the magnitude of such decrease is large. One standard-deviation increase in the demeaned search index implies 20% less responses of unemployment rate.

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 5, the associated downward pressure on unemployment is lower.

Figure 6: 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 (36). The right panel shows dynamics of the interaction coefficient over time estimated in (35). Dark and light shaded area represents 68% and 90% confidence interval respectively.

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.

3 Calibration

In this section, I present a calibration of the model and show the implied price duration and monetary non-neutrality.

I set $\beta = 1.02^{-0.25}$, which implies a steady-state annualized real interest rate of 2 percent. The productivity dispersion σ_a is set to be consistent with Decker et al. (2020), i.e., $\sigma_a = 0.3$.

The parameter that measures the substitutability between goods, λ and search cost κ are jointly pinned down by two empirical moments. First, I use the estimate of elasticity of substitution from DellaVigna and Gentzkow (2019). They use Nielsen Retailer Scanner database and find that prices of identical products, measured by barcode, are similar across stores within the same retail chain. Leveraging this empirical pattern, they use prices from other regions within the same chain as an instrument to estimate the elasticity of substitution across goods. According to Proposition 7, retailers charge the same markup as shown in (17) for all products they sell. The average elasticity of substitution across stores and products is 0.25, implying a markup of 1.67. In the model, lower λ and higher κ imply higher markup.

Second, I use the estimate of average own-cost passthrough from Amiti et al. (2019). With the universe of Belgian manufacturing firms database and credible instruments for marginal costs, they document that the average own-cost passthrough is around 0.5 for larger firms. I match the counterpart in the model to this estimate. Proposition 4 establishes that higher search cost induces lower average own-cost passthrough. Higher λ amplifies this effect. Interestingly, Amiti et al. (2019) also show that the sum of own-cost and competitor-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 prominent in the non-tradeable industries, e.g., retail and broad services, whereas the buyer-seller relationship in tradeable industries is better described as contract which typically involves bargaining between a final-good producer and a limited number of intermediate-good suppliers (Gopinath and Itskhoki, 2011). Therefore, we should interpret the calibration results with caution because the average own-cost passthrough is estimated for the manufacturing sector.

The information asymmetry decreases over time as consumers learn about the monetary shock. I assume that consumers learn as described in Corollary 2. Therefore, the sequence of θ_t is uniquely determined by the Kalman gain K, which is in turn determined by the variance ratio $\frac{\sigma_m^2}{\sigma_s^2}$. Note that $K = \theta_0$. To calibrate K, I use the estimate from Liu (2024). Built on DellaVigna and Gentzkow (2019), Liu (2024) find weaker strategic complementarity than reported in Amiti et al. (2019), with a typical firm adjusting its price with an elasticity of 0.14 in response to competitors' price changes.

Table 3 summarizes the calibrated parameters, and Table 4 presents the fit of the model to data. Despite its parsimonious structure, the model is successful in matching key moments in the data. I now present the implied monetary non-neutrality and price duration by the calibrated model.

Table 3: Baseline calibration of the model

Parameter	Description	Value
κ	Search cost	0.26
λ	Good substitutability	3.73
θ_0	Information friction	0.28

Notes: The table reports the calibrated values for parameters of interest.

Table 4: Model fit

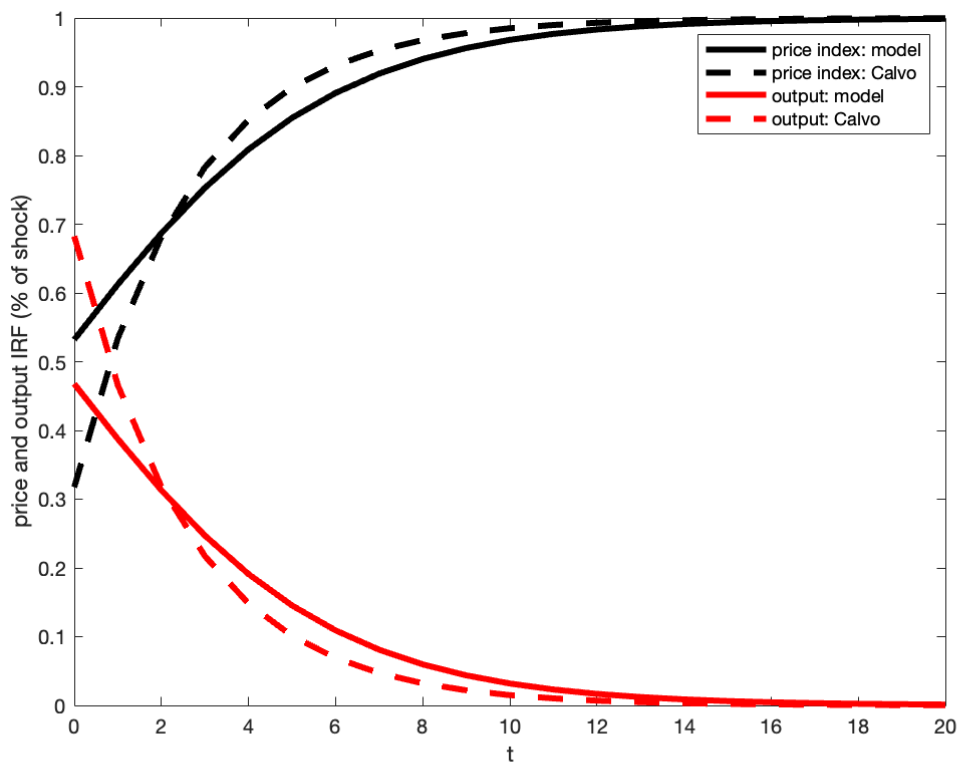
	Moment	Model	Data	Source
M1	Average markup	1.67	1.67	DellaVigna and Gentzkow (2020)
M2	Average own-cost passthrough	0.5	0.5	Amiti et al. (2019)
M3	Average competitor-price passthrough	0.14	0.14	Liu (2024)

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

Properties of the Calibrate Model – The solid black and red line in Figure 7 show the impulse responses of price index and output in the calibrated economy. As predicted by Proposition 5, the aggregate total passthrough is approaching one as learning occurs over time.

Monetary non-neutrality is defined as the sum of discounted change in output as the first-order approximation to the sum of discounted utilities. To understand the magnitude of the monetary non-neutrality implied by the calibrated model, I derive the implied the Calvo parameter θ, which is the probability of not being able to adjust prices for individual firms, such that the discounted change in output is equivalent to the one calculated from the calibrated model. Details are left to Appendix D.

Figure 7: Impulse responses of price index and output in the calibrated economy



Notes: The figure shows the impulse responses of price index and output after a small monetary shock. The solid lines present the impulse responses of the calibrated economy. The dashed lines show the impulse responses of Calvo model that generates same monetary non-neutrality as the calibrated economy.

The calibrated model is equivalent to a Calvo model with $\theta = 0.6825$, implying a price duration of 8.4 months. This is consistent with the findings in Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008), who estimate regular price durations between 7 and 11 months using the BLS micro-price database. It also aligns with Christiano et al. (2005), who calibrate a full-fledged New Keynesian model to match empirical impulse responses and estimate $\theta = 0.6$.

Moreover, the dashed lines in Figure 7 illustrate the impulse responses of the equivalent Calvo model. It shows that the monetary non-neutrality of the calibrated model is more back-loaded compared to the Calvo model and the on-impact effect of the monetary shock on price index is larger, although θ_t also increases exponentially, same as Calvo, as described by Corollary 2. This follows directly from equation (21), where the exponential rise in θ increases the total aggregate passthrough by enhancing aggregate competitor-price passthrough in the denominator. The key difference is that in our model, the mechanism acts through dampening responses to competitors' prices, while firms' responses to own shocks are shut down in the standard Calvo model.

Overall, the calibrated model generates empirically plausible monetary non-neutrality, which is more back-loaded compared to the implications of a standard Calvo model.

4 Conclusion

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