Time to Shop Until Inflation Drops: The Effect of Inflation on Household Shopping Behavior*

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Job Market Paper

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November 14, 2025

Abstract

I study how households adapt their shopping behavior when inflation rises. Using transaction-level panel data from 2021–2023, I construct household-specific inflation rates and estimate their causal effects on shopping intensity and bargain-hunting. Higher inflation leads to more shopping trips, greater retailer diversification, and increased reliance on sales and coupons. Responses vary systematically with household characteristics: higher-income households and those with unemployed members respond more strongly, while households whose wages keep pace with inflation respond less. While these adjustments helped households absorb part of the price shock, they imposed substantial time costs. I estimate the time burden from this increased trip frequency using data from the American Time Use Survey, estimating approximately $600 per household per year for each percentage point of sustained inflation. Despite the prominence of search costs in theoretical models of inflation, causal empirical evidence on inflation-induced search behavior has been limited. I provide this evidence by exploiting household-level variation in inflation exposure and show that these behavioral costs are quantitatively important.

JEL Classification: E31, D12, D83, E21, L81, C23.
Keywords: Inflation; Consumer search; Shopping intensity; Bargain hunting.

*I am deeply grateful to my dissertation chair, Eric Sims, and my committee members, Jane Ryngaert and Christiane Baumeister, for their generous guidance, support, and encouragement throughout every stage of this project. I am also grateful to Daniel Cooper, Slavik Sheremirov, Kurt Lunsford, and participants at the 2023 Midwest Economics Association for valuable feedback. I also received many helpful comments and suggestions from Matthias Hoelzlein and participants of the macroeconomics workshop at Notre Dame, as well as from Virna Vidal Menezes and my other fellow graduate students. Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

Since reaching a four-decade high in 2022, inflation has remained a top concern for policymakers and households. While economists typically measure inflation using aggregate indices such as the CPI or PCE, households experience inflation through the evolving prices of the goods they purchase, as well as the prices they observe but choose not to pay. It is not the representative basket of aggregate indices, but the prices of the specific items in their own baskets and the alternatives they encounter that shape households' consumption decisions. These decisions often occur on the margin: whether to switch to generic products, visit another store to take advantage of a sale, or spend additional time searching for lower prices. Standard macroeconomic models with consumer search predict that inflation should induce households to search more intensively across retailers to exploit the resulting price dispersion. Yet despite these theoretical predictions and widespread concern about inflation's effects on households, little causal evidence exists on the specific mechanisms through which households adapt their shopping behavior in response to inflation.

In this paper, I measure how household-specific inflation affected shopping behavior from 2021 to 2023. Measuring the causal effect of inflation on shopping behavior at the household level presents a fundamental identification challenge: households that search more intensively tend to pay lower prices, mechanically reducing their measured inflation and biasing ordinary least squares estimates downward. This simultaneity means that regressing shopping behavior on paid inflation conflates the causal effect of price exposure with the endogenous dampening effect of search itself.

To isolate the causal effect of inflation on shopping intensity and bargain-hunting, I need a measure of inflation exposure that varies across households but is unrelated to their shopping decisions. Using transaction-level purchase data from the NielsenIQ Homescan Consumer Panel, I employ a Bartik-style shift-share instrument (SSIV) that combines each household's pre-inflation consumption shares with subsequent national price changes. This instrument essentially computes a weighted average of the national category-level CPI inflation shocks, where the weights reflect a household's pre-period inflation exposure based on the share of their expenditure devoted to a given CPI category. Because different product categories experienced different inflation rates over this period, households whose pre-inflation expenditure was concentrated in what later became high-inflation categories

faced higher predicted inflation, even though all households faced the same national price shocks. The SSIV captures variation in potential inflation exposure that is: (1) tied to a household's consumption composition, and (2) realized only through national price shifts that households could not anticipate when forming their pre-inflation consumption shares (and thus are as good as random from the perspective of the household). By isolating variation from predetermined consumption patterns interacted with national price shocks, the IV approach recovers the causal behavioral response to inflation.

My results show that a 1 percentage-point increase in household-level inflation causes households to make 16 percent more shopping trips per month, adding 1.95 trips on average, and to visit 11 percent more distinct retailers, an increase of 0.59 stores. Of the extra trips, roughly 35 percent go to discount stores, dollar stores, and warehouse clubs, retailer types that offer systematically lower prices. On the intensive margin of search, likelihood of coupon usage rises by 6 percent (0.81 percentage points) and buying on sale increases by 3 percent (0.91 percentage points). Households also show evidence of stocking-up behavior: items per trip rise by 1 item, an 8 percent increase, while generic expenditure share increases modestly by 0.29 percentage points. For trip frequency, store diversification, and promotion usage, I find negative or near-zero OLS coefficients but large positive IV estimates, reflecting the fact that households that search more intensively pay lower prices, which mechanically reduces their measured inflation and biases OLS downward.

I also find that responses vary systematically with household characteristics. Households with higher incomes increase trip frequency more than lower-income households, despite higher opportunity costs of time, while households with unemployed members show the strongest responses. This pattern suggests that constraints on liquidity, storage, or work flexibility may prevent some households from fully exploiting cost-saving opportunities. I also find households employed in industries with higher nominal wage growth increase shopping effort relatively less.

The NielsenIQ Consumer Panel covers primarily nondurable goods such as food, beverages, personal care products, and household supplies. As such, the inflation exposure and behavioral responses I measure reflect adjustments within these categories. Nondurables represent a particularly important category for understanding household responses to inflation: unlike durable goods purchases that can be delayed or services

that may be discretionary, nondurables are more likely to be essential purchases that households must make regularly. My focus on nondurables captures the shopping margins where adjustment is most frequent and visible. However, households face inflation across their entire consumption basket and likely make additional adjustments in categories not captured in my data, such as delaying medical appointments, postponing durable goods purchases, or switching service providers. As such, my estimates likely understate the full extent of behavioral responses to inflation.

These behavioral adjustments represent a real cost of inflation beyond the direct erosion of purchasing power. While the search effort households exert is individually rational and helps them maintain consumption in the face of rising prices, from a social perspective this effort is unproductive. While some shopping effort would occur even in a frictionless environment due to taste heterogeneity and real cost differences across retailers, the additional effort induced by inflation-driven price dispersion represents a welfare loss. In the absence of nominal rigidities, households would not need to increase search intensity in response to rising aggregate prices. Economists have long recognized that inflation can impose such costs, captured by the term "shoe-leather costs" from the classical monetary economics work of Bailey (1956), Friedman (1969), and Lucas (2000). In that context, inflation raises nominal interest rates, increasing the opportunity cost of holding cash and inducing households to make more frequent trips to the bank to economize on money holdings. Worn-out shoe soles from trips to and from the bank represent real resource costs in terms of time and energy. Early estimates of these classical monetary shoe-leather costs suggested they were modest.[1] However, in modern economies with ubiquitous ATMs, interest-bearing checking accounts, and electronic payments, the size of these costs has likely diminished substantially.

This paper documents a distinct but conceptually related phenomenon: shoe-leather costs arising from search in goods markets rather than money demand. When inflation increases price dispersion across stores and over time, households respond by intensifying shopping effort, making more trips to different retailers and timing purchases to exploit promotions. These trips represent real time costs analogous to the classical monetary shoe-leather costs, but they arise from a fundamentally different friction of search costs

[1] Fischer (1982) estimated approximately 0.3 percent of GDP for 10 percent inflation, while Lucas (2000) revised his earlier estimates upward to slightly less than 1 percent of GDP. More recent theoretical work by Lagos and Wright (2005) using search models of monetary exchange suggests these costs could range from 1 to 5 percent of GDP.

in goods markets rather than opportunity costs in money holdings. As Lucas (2000) wrote of monetary shoe-leather costs, these resources "are simply thrown away, wasted on a task that should not have been performed at all." In this case, the wasted task is repeatedly searching for deals in an environment where prices are sticky and dispersed. Importantly, while the classical monetary friction has likely been largely eliminated by financial innovation, the search friction documented here remains empirically relevant and quantitatively large. Using data from the American Time Use Survey, I estimate that each percentage point of sustained inflation induces approximately $600 per year in time costs per household. These costs should be incorporated into welfare assessments of inflation, particularly when evaluating the trade-offs between price stability and other macroeconomic objectives.

Related Literature. I make contributions to several strands of literature. First, my study contributes directly to the literature on consumer search, and in particular, bargain-hunting behavior. Prior research has documented this behavior empirically: Lee et al. (2021) show using granular expenditure data that households bargain-hunt for their preferred goods and pay lower prices. Survey evidence confirms this is a primary way households cope with high prices. Data from the Federal Reserve's Survey of Household Economics and Decision-making and the Census Bureau's Household Pulse Survey show that a majority of households in 2022 reported shopping at cheaper stores, looking for sales, using coupons, or switching to lower-priced products in response to inflation. These patterns align with standard sticky-price models of inflation with consumer search: when sellers face costs to update prices, inflation generates price dispersion that households can exploit by searching across retailers for the lowest prices on identical goods (Benabou, 1988). Related work also documents how search and shopping strategies shape price dispersion and household expenditure patterns (e.g., Cox et al., 2020; Cavallo and Kryvtsov, 2024; Petrosky-Nadeau et al., 2016; Lee, 2024; Kaplan, 2017; Gauri et al., 2008; Griffith et al., 2009; Janssen and Kasinger, 2025; Pytka, 2024).

My paper also contributes to research that analyzes household consumption responses to inflation expectations and realizations. Ryngaert (2022) uses the New York Fed's Survey of Consumer Expectations to show that households anticipating inflation "disasters" alter their purchasing decisions even before experiencing higher prices. My findings complement this work by documenting behavioral changes in response to realized

inflation of disaster-magnitude proportions (see also Schnorpfeil, Weber, and Hackethal, Schnorpfeil et al.; D'Acunto et al., 2021; McConnell et al., 2010).

This paper also contributes to the inflation measurement literature. Kaplan and Schulhofer-Wohl (2017) apply traditional price indices to household expenditures and find large heterogeneity in inflation rates across households, mostly due to variation in the prices paid for identical goods. Jaravel and O'Connell (2020) highlight how shopping changes affect inflation measurement, while Pathak Chalise (2025) focus on how shopping strategies reduce observed inflation.

My findings also connect to research on home production as a margin of adjustment during deteriorating macroeconomic conditions. Following canonical models such as Becker (1965), studies show that households increase time allocated to activities like cooking, cleaning, and shopping during recessions (Aguiar and Hurst, 2007; Aguiar et al., 2013; Nevo and Wong, 2019; Cacciatore et al., 2023). Other work emphasizes substitution toward lower-quality goods, changes in consumption bundles, or increased housework in response to various kinds of shocks (Jaimovich et al., 2019; Lester, 2014; Gutiérrez-Daza, Gutiérrez-Daza; Guillochon, 2024; Fang et al., 2020; Rupert et al., 1995; Been et al., 2020). My paper provides new evidence on budget-tightening shopping strategies during the recent inflationary episode.

I also contribute to the large literature that measures the welfare costs of inflation and the role of search. Sara-Zaror (2024) focuses on how inflation affects the relative prices households pay through returns to search, with welfare implications stemming from both the dispersion households exploit and the resources they expend in doing so. Building on hypotheses from models of consumer search and price dispersion (Benabou, 1988; Diamond, 1993; Head and Kumar, 2005; Wang, 2016), my paper emphasizes the behavioral responses of households rather than equilibrium price-setting, showing empirically that inflation prompts costly search and adjustment at scale. This evidence can help discipline models of inflation by quantifying the time and resource costs borne by households.

This paper further relates to work linking inflation, search, and inequality, including various studies concerning heterogeneity in search effort, geospatial differences in inflation, and inequality in product variety or innovation (Boerma and Karabarbounis, 2021; Coibion et al., 2021; Nord, 2022; Navarrete and Kim, 2024; Bui, Bui; Jaravel,

2019; Chen et al., 2024). My results complement this literature by showing how realized inflation exposure induces differential adjustments across households, with potential implications for inequality and welfare.

Lastly, my paper speaks to the long-standing but recently revived literature that asks: why do people dislike inflation? Shiller (1997) posed the question, and more recent work finds that weak wage pass-through and diminished purchasing power force households to undertake costly adjustments (Hajdini et al., 2025; Stantcheva, 2024; Guerreiro, Hazell, Lian, and Patterson, Guerreiro et al.). I provide causal evidence that greater inflation exposure prompts such costly behavioral changes, consistent with both survey evidence and observed household spending decisions.

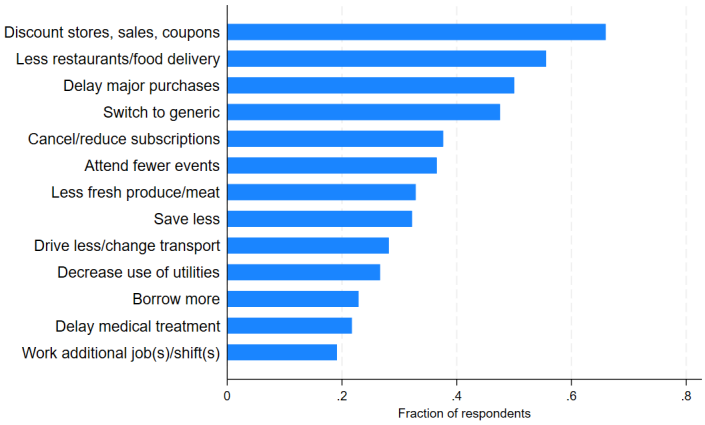
The remainder of this paper proceeds as follows. Section 2 provides additional analysis of self-reported survey responses to identify the range of behaviors households adopted in response to inflation. Section 3 describes a simple consumer choice framework to fix ideas about how households can exert shopping effort as a way to lower their paid prices. Section 4 describes the datasets I use to construct household-specific inflation rates and shopping outcomes for my main empirical analysis. Section 5 outlines my empirical methodology, while Section 6 presents baseline results on how inflation exposure affects shopping effort and bargain-hunting behavior. Section 7 concludes.

2 Survey Evidence on Household Responses to Inflation

In this section, I use survey data from the recent inflationary period to identify what behaviors households employed when facing higher prices. By analyzing self-reported coping behaviors, I provide suggestive evidence regarding along what dimensions inflation is potentially costly for households based on how they adjust.

In 2021 and 2022, surveys began to ask households about their attitudes and actions regarding the increase in prices, including the Household Pulse Survey, conducted by the Census Bureau since the onset of the COVID-19 pandemic. The survey fielded a subset of questions related to inflationary pressures and households' resulting behavior. They are asked the question: *"What changes, if any, have you made to cope with the increase in prices? (Select all that apply)."* Figure 1 shows a subset of the coping strategies the household could select, where shopping at discount stores, buying items on sale, and using coupons was the most commonly selected response.

Figure 1. Household Responses to Higher Prices - Pulse.



Notes: Figure shows a subset of responses to the question "What changes, if any, have you made to cope with the increase in prices? (Select all that apply)" from the Household Pulse Survey. Sample period: September 2022 to June 2023. *Source:* U.S. Census Bureau.

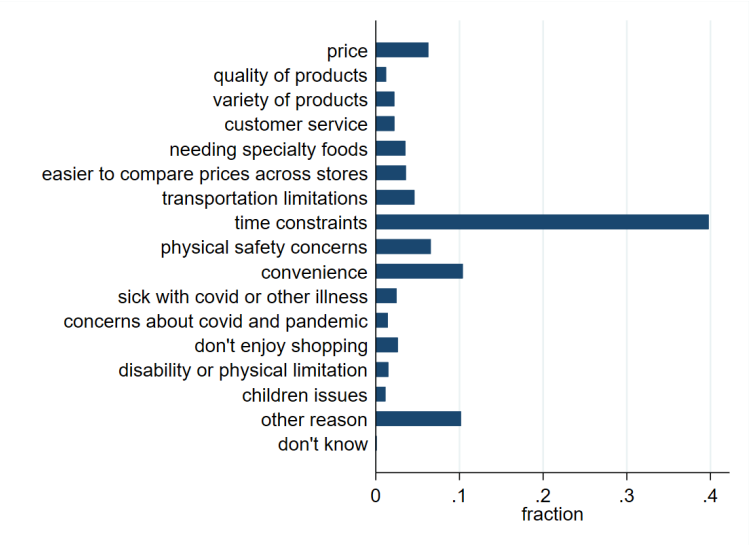
Similarly, the Survey of Household Economics and Decision-making (SHED) from the Federal Reserve Board of Governors asked about inflation coping mechanisms. The SHED is an annual, nationally representative survey, with the 2022 wave considering topics such as price changes' effects on households' budgets and shopping behavior, as well as their online shopping habits.[2] Appendix Figure A1 shows responses to the question: *"Did you take any of the following actions because of increases in prices over the past 12 months?"*. The first and third most commonly-chosen responses out of the SHED survey regarding coping behaviors for inflation were "used less or stopped using," and "switched to cheaper products," indicating that as a result of experiencing higher prices, households were cutting back (or out entirely) or substituting away from certain products that before they were purchasing as part of their consumption bundle.[3]

Data from the American Time Use Survey's 2022-2023 eating and health module provides additional context about household shopping preferences. When asked about online grocery shopping behavior, respondents revealed their primary reason for online shopping at all in the last month was because of time constraints (depicted in Figure 2), while their primary reason for avoiding online shopping was preferring to see and touch the items in the store.

[2]The survey for the 2022 data release was fielded in October 2022 after peak inflation numbers were realized, and so provides insight into the behavior of households who had already experienced peak price increases.

[3]Though I do not focus on substitution as a main outcome, I discuss how substitution can be measured using the price indexes I construct in this paper in Appendix B.

Figure 2. Main Reason for Grocery Shopping Online



Notes: Figure shows responses to the question about the main reason for grocery shopping online in the last month, from the American Time Use Survey's eating and health module, 2022-2023. *Source:* Bureau of Labor Statistics and IPUMS ATUS (Flood et al., 2025).

This evidence highlights the time cost dimension of shopping behavior for some households. I revisit the time use data in Section 6.3 to obtain a back-of-the-envelope cost of inflation in terms of shopping time.

3 Inflation and Consumer Search

I develop a simple model to illustrate the key identification challenge and clarify the economic mechanisms underlying household search responses to inflation. I deliberately keep the model stylized to highlight the core forces at work: how search effort responds to inflation, how this creates a mechanical relationship between search and measured inflation, and how household characteristics like wages might affect search intensity.

3.1 Setup

For a representative nondurable good, let p^H denote the posted high price. The market is characterized by price dispersion: some retailers or purchase opportunities offer discounts of size $\epsilon > 0$ relative to the high price, while others charge the full posted price. By exerting search effort $s \geq 0$ (which can include activities like visiting multiple stores, comparing

prices across retailers, or timing purchases strategically), the household increases the probability of finding these lower prices.

Specifically, let $f(s)$ represent the probability that the household successfully finds and purchases at the low price $p^H - \epsilon$ as a function of search effort. With probability $f(s)$, the household pays $p^H - \epsilon$, and with probability $1 - f(s)$, the household pays the high price p^H.[4] The expected paid price is therefore

$$p(s) = f(s)(p^H - \epsilon) + (1 - f(s))p^H = p^H - \epsilon f(s).$$

Let f have the functional form $f(s) = s/(1+s)$. Under this specification, the expected paid price becomes

$$p(s) = p^H - \epsilon \frac{s}{1+s} = p^H - \epsilon + \frac{\epsilon}{1+s}.$$

Household i earns nominal wage income w_i. The cost of search is modeled as quadratic disutility with a wage-scaled slope parameter:

$$\psi_i(s) = \tfrac{1}{2}\kappa_i s^2,$$

where the household-specific parameter is given by

$$\kappa_i = \kappa_0 \left(\frac{w_i}{\bar{w}}\right)^{\phi}, \qquad \phi > 0.$$

The parameter κ_0 sets the baseline cost level, $\bar{w}$ is a reference wage (normalized to be the economy-wide average), and $\phi > 0$ governs the elasticity of search costs with respect to wages.

The household maximizes utility given by

$$U = u(c) - \psi_i(s),$$

where $u(c) = \log c$ represents standard log utility over consumption. The search disutility

[4]The parameter ϵ represents the maximum possible discount or savings available in the market, while the search technology $f(s)$ maps effort into the probability of realizing these savings, with $f(0) = 0$ (no chance of finding discounts without search) and $f(s) \in [0, 1]$ for all s. I assume that search exhibits positive but diminishing returns: $f'(s) > 0$ ensures that additional search effort always increases the probability of finding low prices, while $f''(s) < 0$ captures diminishing marginal returns to search. The limiting condition $\lim_{s\to\infty} f(s) = 1$ ensures that even infinite search effort cannot guarantee finding the lowest price with certainty (there is always some residual uncertainty). I choose a functional form that satisfies these properties.

$\psi_i(s)$ enters additively, reflecting the fact that shopping effort is costly but distinct from consumption utility. I assume the household takes prices as given.

The household faces a nominal budget constraint:

$$p(s)c = w_i,$$

where the price the household actually pays depends on its endogenous search effort. Substituting the paid price function, the budget constraint becomes

$$\big(p^H - \epsilon f(s)\big)c = w_i.$$

More intensive search lowers $p(s)$, effectively increasing the purchasing power of nominal income.

Inflation definitions. I distinguish between two measures of inflation. Posted inflation is the rate of change in the high price that all households face:

$$\pi^{\text{posted}} = \frac{p^H - p^H_{-1}}{p^H_{-1}}.$$

This represents the common aggregate shock to the price environment. In contrast, household-specific paid inflation depends on the household's search behavior:

$$\pi_i^{\text{paid}} = \frac{p(s_i) - p_{-1}(s_{i,-1})}{p_{-1}(s_{i,-1})} = \frac{(p^H - \epsilon f(s_i)) - (p^H_{-1} - \epsilon_{-1} f(s_{i,-1}))}{p^H_{-1} - \epsilon_{-1} f(s_{i,-1})}.$$

Because search effort is endogenous and varies across households, paid inflation is heterogeneous even when all households face the same posted price path. This distinction between posted and paid inflation is central to understanding the identification challenges I address below.

3.2 Optimality Conditions

The household chooses search effort to balance the marginal benefit of lower prices against the marginal cost of additional shopping effort. Taking consumption c as given from the

budget constraint, the first-order condition for optimal search is:

$$\frac{\partial U}{\partial s} = 0 \quad \Rightarrow \quad c \cdot \frac{\partial p(s)}{\partial s} \cdot \frac{u'(c)}{p(s)} = \kappa_i s. \tag{1}$$

Using $p(s) = p^H - \epsilon f(s)$, we have $\partial p(s)/\partial s = -\epsilon f'(s)$, so the first-order condition becomes

$$c \cdot \epsilon f'(s) \cdot \frac{u'(c)}{p(s)} = \kappa_i s. \tag{2}$$

With log utility, $u'(c) = 1/c$, this simplifies to

$$\frac{\epsilon f'(s)}{p^H - \epsilon f(s)} = \kappa_i s. \tag{FOC-S}$$

The left-hand side represents the marginal benefit of search: an additional unit of effort reduces the paid price by $\epsilon f'(s)$, and this savings applies to the entire consumption bundle c. Dividing by the paid price $p(s) = p^H - \epsilon f(s)$ converts this into proportional terms. The right-hand side is the marginal cost of search effort, which is linear in s due to the quadratic cost function and scaled by the household-specific parameter κ_i.

For the specific functional form $f(s) = s/(1+s)$, we have $f'(s) = 1/(1+s)^2$, so the first-order condition becomes

$$\frac{\epsilon}{(1+s)^2\big(p^H - \epsilon s/(1+s)\big)} = \kappa_i s,$$

which can be rearranged to

$$\frac{\epsilon}{(1+s)\big(p^H(1+s) - \epsilon s\big)} = \kappa_i s.$$

This implicit equation determines optimal search $s^\star$ as a function of the posted price p^H, the dispersion parameter ϵ, and the cost parameter κ_i.

Comparative statics. To characterize how optimal search responds to changes in the economic environment, define the first-order condition implicitly as

$$G(s; p^H, \epsilon, \kappa) \equiv \frac{\epsilon f'(s)}{p^H - \epsilon f(s)} - \kappa s = 0.$$

Taking the total differential with respect to p^H, we have

$$\frac{\partial G}{\partial s} ds^\star + \frac{\partial G}{\partial p^H} dp^H = 0 \quad \Rightarrow \quad \frac{ds^\star}{dp^H} = -\frac{\partial G / \partial p^H}{\partial G / \partial s}.$$

The second-order condition for a maximum requires $\partial G / \partial s < 0$. Computing the partial derivative,

$$\frac{\partial G}{\partial p^H} = \frac{\epsilon f'(s)}{(p^H - \epsilon f(s))^2} > 0,$$

which implies

$$\frac{\partial s^\star}{\partial p^H} = -\frac{\partial G / \partial p^H}{\partial G / \partial s} > 0.$$

Similarly, we can show that

$$\frac{\partial s^\star}{\partial \epsilon} > 0, \qquad \frac{\partial s^\star}{\partial \kappa} < 0.$$

The first result, $\partial s^\star / \partial p^H > 0$, indicates that higher posted prices increase the return to search since potential savings grow in absolute terms. This is the core mechanism that underlies my empirical strategy: exogenous increases in posted inflation should causally increase search intensity. The second result, $\partial s^\star / \partial \epsilon > 0$, shows that greater price dispersion or larger potential discounts also encourage search. The third result, $\partial s^\star / \partial \kappa < 0$, captures the intuitive point that households with higher search costs optimally search less.

Given the wage-scaling $\kappa_i = \kappa_0 (w_i / \bar{w})^\phi$, it follows directly that

$$\frac{\partial s^\star}{\partial w_i} < 0.$$

This captures an opportunity cost channel: higher-wage households face a higher marginal cost of time spent searching, which would tend to reduce their search intensity. However, the overall effect of income on search is theoretically ambiguous because several competing forces are at work. Higher-income households may search less due to higher opportunity costs of time, but they may also search more if the returns to search are convex in consumption levels or if search has fixed costs that are easier for wealthier households to bear. The net effect in the cross-section is therefore an empirical question. Additionally, the opportunity cost mechanism may be more cleanly identified through variation in wage growth over time rather than cross-sectional income differences.

3.3 Identification Challenge

A central challenge in estimating the causal effect of inflation on search behavior is that measured paid inflation is itself an outcome of the household's search decision. Using the definition $p(s) = p^H - \epsilon f(s)$, paid inflation can be decomposed into two components:

$$\pi_i^{\text{paid}} = \frac{p(s_i) - p_{-1}(s_{i,-1})}{p_{-1}(s_{i,-1})} = \frac{(p^H - \epsilon f(s_i)) - (p^H_{-1} - \epsilon_{-1} f(s_{i,-1}))}{p^H_{-1} - \epsilon_{-1} f(s_{i,-1})}.$$

Rearranging, this becomes

$$\pi_i^{\text{paid}} = \underbrace{\frac{p^H - p^H_{-1}}{p^H_{-1} - \epsilon_{-1} f(s_{i,-1})}}_{\text{posted component}} - \underbrace{\frac{\epsilon f(s_i) - \epsilon_{-1} f(s_{i,-1})}{p^H_{-1} - \epsilon_{-1} f(s_{i,-1})}}_{\text{mechanical search component}}.$$

The first term captures changes in the posted price environment that are common across all households (though scaled by the household's initial paid price). The second term, however, reflects the household's own search behavior: if the household increases search from $s_{i,-1}$ to s_i, this mechanically reduces measured paid inflation through the term $-\Delta[\epsilon f(s_i)]$.

This decomposition reveals a fundamental simultaneity problem. Because s_i responds endogenously to the posted price environment (as shown by $\partial s^\star / \partial p^H > 0$), a regression of search on paid inflation confounds two distinct effects. On the one hand, higher posted inflation causally increases search effort, which would generate a positive coefficient. On the other hand, higher search effort mechanically reduces measured paid inflation through the second component, which creates a spurious negative correlation. The net effect of these opposing forces is that OLS estimates of the effect of paid inflation on search are biased toward zero or even negative, despite the underlying causal relationship being positive.

The model helps to fix ideas about several aspects of my empirical analysis. First, it clarifies why instrumented variation in posted inflation is necessary to identify the causal effect of inflation on search. The shift-share instrument I construct provides exactly this type of variation: it captures differential exposure to common category-level price shocks based on predetermined spending patterns, generating variation in the posted price environment that is orthogonal to household-specific search responses.

This framework also highlights several economic mechanisms that may generate heterogeneity in search responses across households. The wage-scaling of search costs suggests an opportunity cost channel where higher-wage households might search less intensively. However, as discussed above, other forces could work in the opposite direction, making the net effect ambiguous. In the empirical analysis, I examine heterogeneity across the income distribution to see which mechanisms appear most important in practice.

Finally, the model predicts that search intensity should generally increase with inflation. In the data, I observe various proxies for search effort including the number of shopping trips, retailer diversity, discount store usage, and promotional purchase frequency. Since these all represent ways to search more intensively, the model is consistent with all margins responding positively to inflation shocks, though the relative magnitudes may depend on household-specific costs and returns to each type of search activity.

4 Data

In this section, I describe how I construct household-level inflation rates and shopping outcomes from transaction-level purchase data. The NielsenIQ Homescan Consumer Panel is uniquely suited for studying household responses to inflation because it combines three essential features: it follows the same households over time, records both prices and quantities for every purchase, and tracks shopping behavior across multiple stores and retail channels. I begin by describing the data source and sample construction, then explain the construction of shopping behavior outcomes, and finally explain my approach to measuring household-specific inflation rates.

4.1 NielsenIQ Homescan Consumer Panel

My analysis relies primarily on household-level purchase data from NielsenIQ's Homescan Consumer Panel Survey. The panel tracks the shopping behavior of randomly recruited households who record all purchases by scanning product barcodes with a handheld device or mobile app. Households receive digital rewards for consistent participation, and must maintain regular scanning activity to remain in the panel. Each year there are roughly 60,000 respondents in the panel, and NielsenIQ retains about 80 percent of the active panel each year. NielsenIQ collects demographic information for households and updates

this information on an annual basis.

For each shopping trip, households record the trip date and store name. For stores covered by NielsenIQ, the price of each scanned good is automatically set to the store's average price during the purchase week. For uncovered retailers, panelists manually enter prices. They also record the number of units purchased, whether they perceived the item to have been on a "deal," whether they used a coupon, and the total discount from that coupon. This level of detail allows me to construct measures of both price changes and shopping strategies.

NielsenIQ organizes purchases hierarchically from individual UPCs to broad departmental categories. The intermediate level consists of approximately 125 "product groups" (eggs, fresh meat, kitchen gadgets, pet care, etc.) that I use to match with CPI subcategory inflation rates for my shift-share instrument construction. I describe this CPI-stratum to NielsenIQ-product-group matching in greater detail in Appendix C. My analysis focuses primarily on non-durables, which constitute the vast majority of scanned purchases in the NielsenIQ data. In 2019, 54 percent of purchases were made at grocery stores, 28 percent at discount stores, 5 percent at warehouse clubs, 4 percent at dollar stores, 2 percent at drug stores, and 1 percent through online shopping, with remaining retailer types accounting for less than 1 percent each. This distribution reflects the composition of routine household shopping and captures the retail channels most relevant for food and household goods purchases.

I use monthly data from 2019 to 2023. The 2019 data serve two purposes: they establish pre-period consumption shares for the shift-share instrument and provide a low-inflation baseline for comparison when analyzing household inflation rates. The 2021 to 2023 period captures household behavior during elevated inflation, when year-over-year food price increases reached levels not seen in decades. This time span provides sufficient variation in inflation exposure to identify behavioral responses.

4.2 Search Effort and Bargain-Hunting Measures

I construct a set of outcomes that capture household responses to inflation across multiple dimensions of shopping behavior. These measures fall into four conceptually distinct categories: search intensity on the extensive margin, search intensity on the intensive margin, retailer type substitution, and basket composition. Together, these measures

provide a granular view of how households adjust shopping behavior in response to inflation.

Search intensity: Extensive margin. I begin my analysis by measuring how households expand search effort by increasing the frequency and scope of their shopping. The first outcome is the number of shopping trips per month, where a trip is defined at the store-date level using unique trip codes provided in the Consumer Panel. Purchases at different stores on the same day count as separate trips, as do purchases at the same store on different days. This measure captures one key margin of adjustment: households may increase trip frequency to better time purchases with temporary sales and promotions, a prediction that emerges naturally from search models where optimal search intensity rises with expected gains from finding lower prices.

The second extensive-margin outcome is the number of distinct retailers visited monthly, which I identify using unique store codes in the data. This retailer diversification measure captures cross-store price comparison shopping. When inflation raises price dispersion across retailers (for instance, because some stores adjust prices more slowly than others), the returns to visiting multiple outlets increase. A related outcome is trips per store, computed as the ratio of total monthly trips to distinct retailers visited. This measure helps distinguish between two forms of diversification: spreading a fixed number of trips across more stores (trips per store falls) versus adding new stores while maintaining trip frequency to existing ones (trips per store remaining stable or rising).

Search intensity: Intensive margin. Beyond expanding the number and scope of trips, households can intensify search within trips by more actively seeking and exploiting deals. I construct two trip-level measures of this intensive-margin bargain hunting. The first is an indicator for whether a household used any coupon during the trip, which I compute from coupon value fields in the purchase data. The second is an indicator for whether the trip included at least one item purchased on sale, identified using deal flags in the data. In my empirical analysis, I compute a household's monthly trip-level propensity to use a coupon or purchase an item on sale. These measures capture how thoroughly households exploit cost-saving opportunities conditional on shopping, complementing the extensive-margin search outcomes.

Retailer type. Households may respond to inflation not only by searching more but also by reallocating trips toward retailers that offer systematically lower prices. I construct trip counts by store type using retailer channel codes in the Consumer Panel, focusing on three categories associated with lower prices: discount retailers, dollar stores, and warehouse clubs. These retailer-type-specific trip measures capture strategic reallocation toward channels known for everyday low pricing, bulk discounts, or having a large amount of generic or private-label goods. In addition to absolute trip counts, I examine the share of total trips allocated to each type to distinguish pure trip expansion from substitution across channels. I also include the level and share of trips to standard grocery stores for comparison.

Basket composition. Finally, I examine how inflation affects what households buy and how much they purchase per trip. The first outcome in this category is generic share, defined as the fraction of a household's monthly expenditure on store-brand or private-label products, identified using brand codes in the data. An increase in generic share indicates quality downgrading, or at the very least, brand substitution away from what are typically considered to be more costly but higher-quality name-brand goods.

I also construct three measures of basket scale and scope. Items per trip is the monthly average number of distinct items purchased per trip, capturing whether households consolidate purchases into fewer, larger trips or break up shopping into smaller baskets. Items per pack measures the average pack size or unit count per purchased item, capturing bulk purchasing or package size substitution. Finally, the number of product groups purchased is the count of distinct NielsenIQ product groups (i.e. categories) that a household buys in a given month, capturing the breadth of a household's consumption basket. This last measure is particularly informative about the scope of a household's search: an increase in product groups suggests broader comparison shopping and more active category-level substitution, consistent with households spreading search effort across a wider range of goods.

4.3 Measuring Household-Level Inflation Rates

Understanding how inflation affects shopping behavior requires measuring the actual price changes that individual households experience, which may differ substantially from

aggregate statistics. In this subsection, I describe how I construct these household-level inflation measures from the Consumer Panel.

Following Kaplan and Schulhofer-Wohl (2017), I start with computing a Laspeyres index which holds the initial-period basket fixed. For each household i, I observe the quantity of each good j (identified by barcode) purchased in month t and its associated price $p_{ij,t}$ in both month t and month $t+12$.[5] The Laspeyres price index compares the cost of the period-t basket at $t+12$ prices to its cost at t prices:

$$P^L_{i,t,t+12} = \frac{\sum_j p_{ij,t+12}\, q_{ij,t}}{\sum_j p_{ij,t}\, q_{ij,t}}. \tag{3}$$

By construction, $P^L_{i,t,t} = 1$, so the associated inflation rate is simply the percent change in the index:

$$\pi^L_{i,t,t+12} = (P^L_{i,t,t+12} - 1) \times 100. \tag{4}$$

The household inflation rates I construct are based on matched barcodes only, i.e. a barcode would have to be present in both January 2021 and January 2022 to be used in the final calculation. I again follow Kaplan and Schulhofer-Wohl (2017) in requiring that a household have at least five matched barcodes in a given month in order to calculate their inflation rate.

This approach holds both the quantities and the product composition fixed at their base period levels. In reality, households may adjust their behavior in response to price changes. They may purchase smaller quantities of goods that have become more expensive, or they may substitute away from expensive products toward cheaper alternatives within the same category (for example, switching from name-brand cereal to store-brand cereal). The Laspeyres index excludes these behavioral responses. It answers the question: "How much more would it cost this household to buy the exact same products in the exact same quantities they bought 12 months ago?"

It is important to clarify what this inflation measure captures and why it is suited to my research question. In principle there is no single "true" measure of inflation, as different inflation concepts serve different purposes. The Bureau of Labor Statistics constructs the CPI to measure changes in the cost of maintaining a constant standard of

[5] If a household buys the same barcode more than once in a month, I follow Kaplan and Schulhofer-Wohl (2017) and set the monthly price equal to the volume-weighted average paid.

living, incorporating quality adjustments and allowing for substitution between goods. My Laspeyres measure serves a different purpose: it quantifies the price shock a household would face given its existing consumption patterns, measuring their exposure to price changes regardless of any adjustments they may have made. This is the relevant concept for studying how inflation induces changes in shopping behavior because it captures the cost pressure households experience, separate from how they respond to that pressure.

I use this fixed-basket approach because alternative indices reflect both price changes and behavioral responses. For example, the Paasche index uses current period quantities rather than base period quantities. Because households may reduce purchases of goods that become more expensive and increase purchases of goods that remain relatively cheaper, the current period basket reflects substitution behavior. A Paasche measure would therefore give less weight to goods experiencing large price increases (because households bought less of them) and more weight to goods with smaller price increases (because households bought more of them). This means changes in a Paasche inflation measure would reflect both price changes and the household's substitution response, mixing the treatment (price exposure) with part of the outcome I aim to study.[6]

However, even with a fixed basket, my inflation measure could still be endogenous to search behavior. If households respond to rising prices by searching more for lower prices on the same goods within their basket, this would create simultaneity bias between measured inflation and search intensity. I address this concern using the instrumental variable strategy described in Section 5.1.

The Laspeyres index is also the natural analog to the Consumer Price Index, which holds basket weights fixed between periodic updates. This comparability is important both for interpreting magnitudes and for relating my findings to familiar inflation concepts used in policy discussions. It also facilitates the construction of my shift-share instrument, which uses national CPI category inflation as the common shock component.

I focus on household-level inflation rates (specifically, year-over-year percent changes

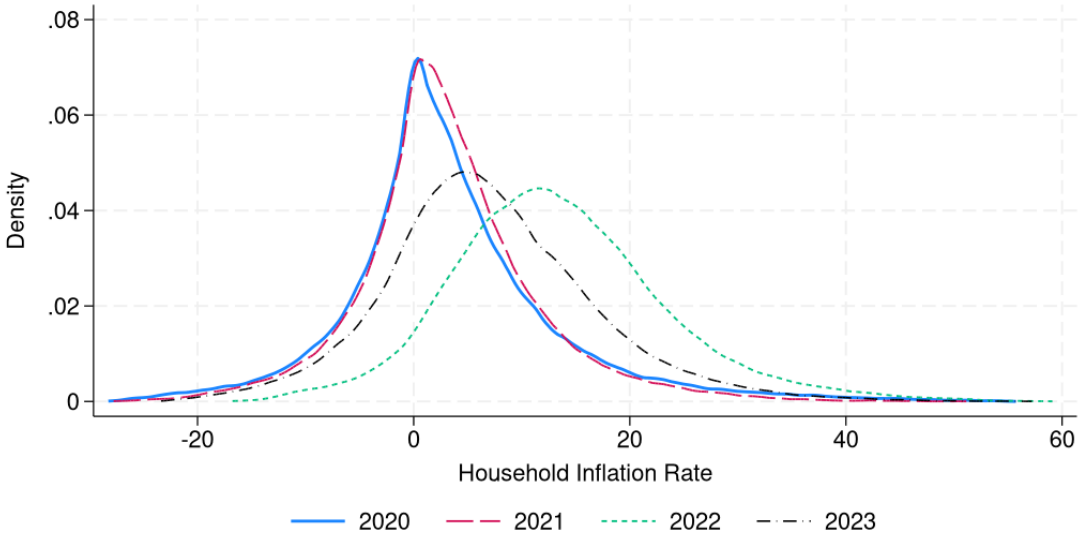
[6]Because the Laspeyres index weights goods by their pre-substitution quantities, it tends to overstate the true cost of living relative to a Paasche index, which weights by post-substitution quantities. This pattern is confirmed in my data, where the Laspeyres inflation rates I calculate are higher than the corresponding Paasche rates (see Appendix Figure A3). The Fisher index, which takes the geometric mean of the Laspeyres and Paasche indices, is often considered a better approximation to a true cost-of-living index. However, for my purposes, the Laspeyres approach is preferable because it captures the full cost pressure households face before adjusting their consumption, which is the relevant treatment for studying how inflation induces behavioral change. Using a Fisher index would again incorporate part of the substitution response I am trying to measure as an outcome. I relegate additional discussion of the Laspeyres index compared to alternative indices in Appendix B.

in a household's price index) rather than absolute price levels. The central question in my analysis is how changes in the cost of living influence household shopping behavior. It is these changes, rather than the absolute cost of the basket, that plausibly trigger adjustments in shopping effort and consumption patterns. While a month-over-month change could in principle capture the most immediate price pressures faced by households, it poses a seasonality issue. Prices for many goods display strong seasonal patterns (e.g., produce, holiday items, school supplies), which can create spurious inflation signals unrelated to underlying cost-of-living changes. A year-over-year comparison naturally differences out this seasonal component by comparing the same month across years.

Year-over-year inflation also aligns with how inflation is commonly reported and discussed in public discourse. Headline CPI statistics are typically presented as 12-month changes, and households likely form expectations and make spending decisions based on these familiar benchmarks rather than on short-run monthly volatility. Using a 12-month horizon therefore better captures the inflation concept that is salient to consumers and relevant for behavioral adjustment.

Figure 3 shows the distribution of household-level inflation rates in 2020, 2021, and 2022. Several features stand out. First, consistent with other analyses of household inflation heterogeneity, I find substantial cross-sectional dispersion even within the same

Figure 3. Distribution of Household Inflation Rates by Year.



Notes: Figure shows the kernel density distribution of household-level twelve-month inflation rates for 2020, 2021, and 2022, constructed using a Laspeyres price index. The density estimates use an Epanechnikov kernel with optimal bandwidth selected automatically using a Gaussian reference rule. Inflation rates are winsorized at the 1st and 99th percentiles. *Source:* NielsenIQ Consumer Panel and author's calculations.

time period, despite all households facing the same aggregate economic conditions and shopping in overlapping sets of stores. Second, the distribution shifts rightward between 2020 and 2022, consistent with the aggregate increase in food inflation over this period. This confirms that the household-level measures capture the broad inflationary episode, not just idiosyncratic variation in individual shopping patterns. Most importantly for my analysis, the distribution widens considerably in 2022 relative to 2020, indicating that inflation did not affect all households equally; instead, the variance in inflation experiences grew as aggregate inflation rose.

The widening of the household inflation distribution in 2022 has direct implications for the behavioral responses I study. In models of consumer search, the return to shopping effort depends on price dispersion: when prices vary more across products or stores, the potential gains from comparison shopping increase. If inflation raises the variance of price changes across categories, it increases the heterogeneity in effective prices faced by households, raising the returns to search. The widening distribution I document is consistent with this mechanism. It implies that the inflationary period was not simply a uniform scaling up of all prices but rather a period of heightened relative price volatility, which should amplify search incentives.

Additionally, the heterogeneity in household inflation rates provides the identifying variation for my empirical strategy. Because households differ in their 2020 consumption patterns, they experience systematically different inflation rates when national category prices evolve heterogeneously. For example, a household with a high share of eggs in 2020 faces much higher inflation in 2022 (when egg prices surge due to avian flu) than a household with a low egg share, even if both live in the same city and shop at the same stores. This differential exposure, driven by predetermined consumption shares interacted with national price shocks, forms the basis of my shift-share instrument. The widening of the distribution in high-inflation periods amplifies this identifying variation, strengthening the first stage and improving the precision of my estimates.

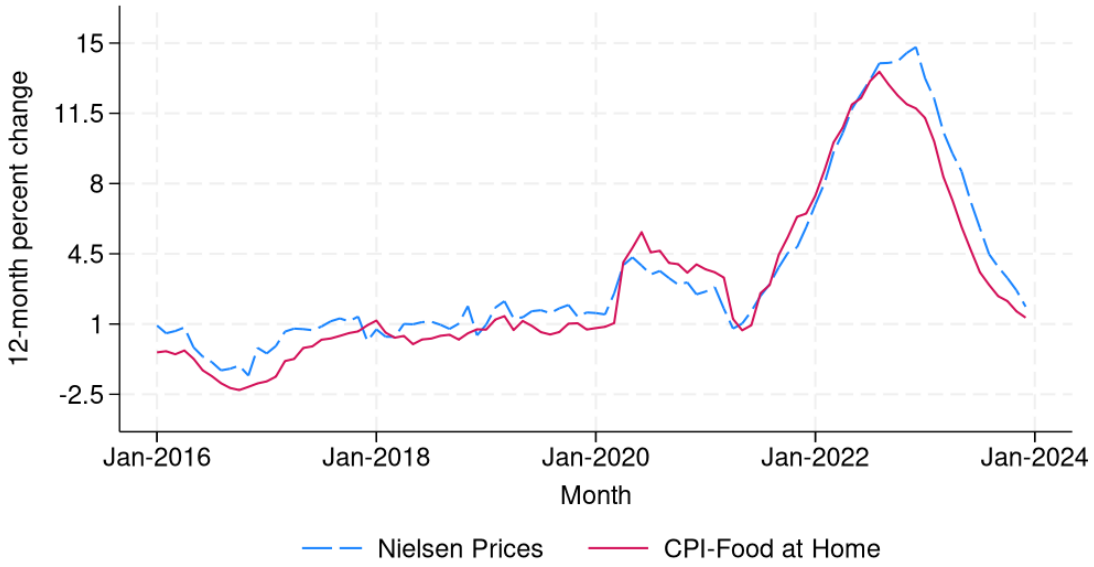
The cross-sectional heterogeneity in inflation experiences may also help explain heterogeneity in behavioral responses. If different households face different magnitudes of inflation shocks, and if the marginal returns to search vary across the inflation distribution (for instance, due to fixed costs of adjusting shopping habits), then households should respond differently in ways that correlate with their inflation exposure. In Section 6.2, I

explore this heterogeneity explicitly by estimating treatment effects across income groups, household size, and other factors. The pattern in Figure 3 motivates this analysis, as the fact that households experience widely varying inflation rates suggests that their behavioral adjustments may also vary, both in magnitude and in the margins along which they adjust. I also report the distribution of household inflation over time in Figure A2, which shows the same increase in the variance of the distribution during times of higher inflation.

A natural concern with any household-level inflation measure constructed from data like the Consumer Panel is whether it accurately captures price movements as measured by official statistics. To validate my approach, I aggregate individual household inflation rates to construct a sample-wide price index and compare it to the published CPI for food at home. Specifically, I construct an expenditure-weighted Laspeyres index across all households in my sample, using the same methodology as for individual households but pooling across the entire panel. This aggregation mimics the structure of the official CPI, which weights category price changes by expenditure shares.

Figure 4 plots both series over the 2016 to 2023 period. The constructed measure

Figure 4. Aggregate Inflation Series.



Notes: Figure shows twelve-month percent change in the Consumer Price Index for food at home (BLS) and a constructed aggregate price index from NielsenIQ Consumer Panel data, 2017-2023. The constructed series is an expenditure-weighted Laspeyres index that aggregates product × county level inflation using annual sales as weights. *Source:* Bureau of Labor Statistics, NielsenIQ Consumer Panel, and author's calculations

tracks headline CPI for food at home closely throughout the sample period, both in levels

and in the timing of inflections. Importantly, the constructed index captures the sharp acceleration in food inflation during 2021 and 2022, the peak in mid-2022, and the subsequent deceleration in 2023. This close correspondence provides confidence in the household-level inflation rates I construct from NielsenIQ data as measuring the same underlying price dynamics as the official statistics.

The similarity between my measure and the CPI is reassuring on several other dimensions. First, it suggests that the UPC matching procedure and quality controls I impose (requiring at least 5 matched UPCs per household-month) are not introducing systematic bias. If my sample were disproportionately capturing price changes for a narrow set of products or missing key categories, the aggregate index would likely diverge from the CPI. Second, it validates the use of national CPI category-level shocks in the shift-share instrument. Because my constructed household inflation measure aggregates to the same dynamics as the official CPI, this suggests that national category-level shocks I use as shifts are indeed the relevant price movements faced by households in the sample. Third, it implies that any remaining measurement error in household-level inflation is likely classical (uncorrelated with true inflation), supporting the interpretation that IV estimation corrects for attenuation bias.[7]

5 Empirical Methodology

To measure the impacts of household inflation on shopping and consumption outcomes, I estimate the following regression model using OLS:

$$y_{it} = \alpha_1 + \beta_1 \pi_{it} + \mu_{i1} + \delta_{t1} + \varepsilon_{it1}, \tag{5}$$

where i indexes households and t indexes time. The variable y_{it} is an outcome, such as the number of shopping trips a household takes or the share of items bought on sale in a given shopping trip, and π_{it} is the year-over-year household-level realized inflation rate

[7] Because of the nature of the data, minor deviations between the two series are expected and do not threaten the validity of my approach. The NielsenIQ Consumer Panel covers a subset of food categories and retail channels, while the CPI Food-at-home potentially includes a broader set of outlets and uses a different quality adjustment methodology. Additionally, to compute the various CPI measures, the BLS uses a fixed basket updated periodically, while my household-level measures allow the comparison set of UPCs to vary as products enter and exit the market. These differences allow me to construct household-specific inflation rates that reflect actual shopping behavior while still tracking aggregate price movements closely enough to ensure comparability with national statistics.

computed from its actual prices paid. The variables μ_i and δ_t represent household and time (month-by-year) fixed effects, respectively, so β_1 is identified by changes in an individual household's inflation rate over time. I include household fixed effects to control for unobserved time-invariant characteristics at the household-level. The time effects control for common shocks to all households at a given month. I also include county-by-month fixed effects to control for regional, time-specific shocks, so that I compare individuals in the same market at the same time. I cluster standard errors at the household level. The error term is ε_{it1}.

Equation 5 provides a natural starting point for measuring how household inflation affects shopping behavior. However, interpreting β_1 as a causal effect requires that variation in π_{it} be uncorrelated with the error term ε_{it1}. This assumption is unlikely to hold in practice. The OLS estimates, reported in Panel A of Table 1, are small and negative, suggesting that households experiencing higher inflation shop less. This pattern runs counter to both theoretical predictions and survey evidence. The negative relationship likely reflects the proposed simultaneity bias, where households who search more in response to rising prices pay lower prices for goods in their basket, mechanically reducing their measured inflation rate π_{it}.

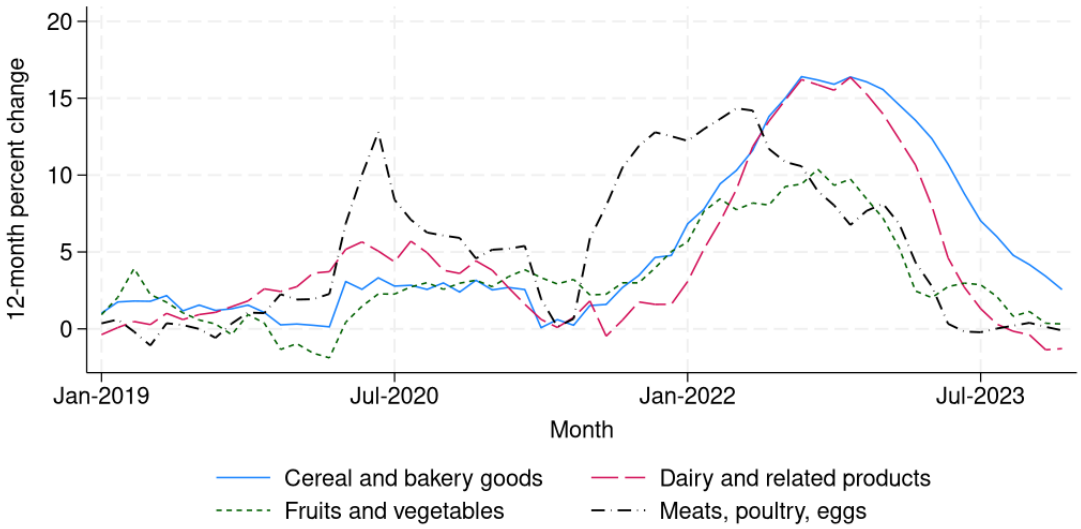
5.1 Instrumenting for Household Inflation

As I describe in Section 3, when estimating the impact of household inflation on shopping and consumption outcomes, the problem resembles a system of linear simultaneous equations where the OLS estimate of β_1 will yield biased results. The ideal experiment would provide variation that moves individual inflation rates without directly affecting shopping behavior through channels other than prices.

To address this endogeneity concern, I construct an instrumental variable that provides plausibly exogenous variation in individual exposure to inflation. The insight motivating my identification strategy is the substantial heterogeneity in price dynamics across product categories, both in the timing and magnitude of price changes. Figure 5 illustrates this variation by showing price growth for major nondurable categories during the recent inflationary period. This heterogeneity means that households with different consumption patterns experience systematically different inflation even when subject to the same aggregate economic conditions. A household whose 2019 basket emphasized eggs, for

example, was exposed to much higher inflation than a neighbor who consumed more bread and fewer poultry products, due to variation in price dynamics of these categories.

Figure 5. Variation in Inflation Across CPI Components.



Notes: Figure shows twelve-month percent change in the Consumer Price Index for major nondurable goods categories, 2020-2023. *Source:* Bureau of Labor Statistics.

I exploit this heterogeneity using a Bartik-style shift–share instrument (SSIV) that combines temporal variation in inflation at the CPI-stratum level with cross-sectional variation in predetermined expenditure shares:

$$\text{SSIV}_{it} = \sum_{k=1}^{N} s_{ik}^{2019} \times \pi_{kt}^{CPI}, \tag{6}$$

where i indexes households, k indexes product groups (matched to NielsenIQ Consumer Panel categories), and t indexes time periods. This instrument predicts household i's inflation in period t as a weighted average of national product-group inflation rates, using pre-pandemic (2019) household expenditure shares as weights. Following the shift–share literature (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), identification comes from heterogeneity in these predetermined exposure shares interacting with common national shocks: the shocks are CPI category inflation rates π_{kt}^{CPI}, which vary over time but are common across households, while the exposure weights s_{ik}^{2019} are household-specific but fixed over time.[8]

[8]Appendix C provides the formal decomposition of household Laspeyres inflation into category-level

It is important to distinguish two distinct forms of endogeneity in this setting. First, households with different 2019 consumption shares may systematically differ in observables (income, location, preferences) or persistent unobservables (patience, risk aversion). This type of endogeneity is permitted and absorbed by household fixed effects. The instrument does not require that households with high egg shares are otherwise identical to households with high bread shares; it only requires that the differential inflation experienced by these two types of households (due to divergent price paths for eggs versus bread) is not itself correlated with differential trends in their shopping behavior for reasons unrelated to inflation.

The exclusion restriction rules out a different type of endogeneity: that national price shocks systematically target specific households at specific times in ways that affect outcomes beyond the price channel. For example, if egg prices rise nationally because of avian flu, the exclusion restriction requires that this shock affects households with high egg shares only because they face higher inflation, not because the shock independently alters their shopping patterns through some other mechanism (such as heightened food safety concerns that lead them to shop more carefully regardless of prices). Several factors could potentially violate this restriction, which I address in Appendix C.5.

6 Effects of Household Inflation on Shopping Outcomes

The first stage is given by

$$\pi_{it} = \gamma_0 + \gamma_1 SSIV_{it} + \theta_{i1} + \lambda_{t1} + \nu_{it1} \tag{7}$$

where γ_1 represents the percentage point increase in actual household inflation rates associated with a 1pp increase in SSIV-predicted household inflation rates[9]

components and shows how this motivates the shift–share instrument in equation (6), along with details on the CPI–Nielsen mapping and summary statistics for the predicted inflation measure.

[9]Note that I do not include time-varying household controls in my main specifications. With household fixed effects already absorbing all time-invariant characteristics, the key remaining controls, household income and household size, vary only at the annual level in the NielsenIQ data, as households update this information at most once per year. Including both household fixed effects and these annual controls creates collinearity issues that substantially weaken the first stage and dramatically increase computational time. While I use demographic information to split the sample for heterogeneity analysis, I do not include these variables as controls. All of my estimations use NielsenIQ's projection factors, which are household-level survey weights that correct for differential sampling probabilities. These weights are constructed to balance the panel to Census population estimates across multiple household characteristics and geographic areas, ensuring my estimates are

The reduced form equation directly regresses outcomes on the instrument:

$$y_{it} = \alpha_2 + \beta_2 SSIV_{it} + \mu_{i2} + \delta_{t2} + \varepsilon_{it2} \tag{8}$$

where β_2 represents the change in shopping or consumption behavior associated with a 1 percentage point increase in predicted household inflation rates. The reduced form is informative on its own, as it captures the total effect of inflation exposure (as predicted by pre-period shares and national shocks) on outcomes, without requiring assumptions about the exclusion restriction. A positive and significant β_2 indicates that households exposed to higher predicted inflation adjust their behavior accordingly.

6.1 Baseline Results

Table 1 reports the effects of household inflation on shopping frequency and diversification. The IV coefficient of interest is $\beta_{IV} = \frac{\beta_2}{\gamma_1}$, which scales the reduced-form effect of the shift-share instrument on outcomes (β_2) by the first-stage effect on paid inflation (γ_1). This coefficient recovers the causal effect of a 1 percentage point increase in realized household inflation on outcomes, purged of simultaneity bias and measurement error. Intuitively, β_{IV} answers the question: when a household experiences higher inflation (as induced by differential exposure to national price shocks), how does its shopping behavior respond?

The IV estimate is a Local Average Treatment Effect (LATE) for compliers, the subset of households whose paid inflation responds strongly to the instrument. In this context, compliers are households whose 2019 consumption patterns exposed them more heavily to categories that experienced large national price shocks. My baseline specification pools observations across the entire 2021-2023 period, so the estimated coefficient should be interpreted as an average treatment effect over this time period.

Shopping Frequency and Retailer Diversification. In the IV specification, a 1 percentage point increase in paid inflation raises monthly shopping trips by 1.95 relative to the baseline mean of 12.15, a 16 percent increase. The same increase in inflation expands the number of distinct retailers visited by 0.59 relative to a mean of 5.41, an 11 percent increase, and raises trips per store by 0.076, a 4 percent increase relative to the mean

representative of the U.S. population.

of 1.91. Together, these patterns indicate that households respond to inflation by both intensifying visits on existing margins and diversifying across more retailers. The large and precise first-stage F-statistics indicate strong instruments across outcomes.

Table 1. Effects of Higher Inflation: Shopping Frequency and Retailer Diversification.

Dependent variable:	Trips	Distinct Retailers	Trips Per Store
	(1)	(2)	(3)
Panel A: OLS			
$\pi_{i,t}$	-0.005***	-0.002***	0.000
	(0.001)	(0.000)	(0.000)
Panel B: Reduced Form			
Predicted π_{it}	0.459***	0.139***	0.018***
	(0.007)	(0.003)	(0.002)
Panel C: IV			
$\pi_{i,t}$	1.951***	0.591***	0.076***
	(0.133)	(0.041)	(0.010)
First-stage F stat.	228.71	228.71	228.71
Base Dep. Var. Mean	12.15	5.41	1.91
Observations	734,132	734,132	734,132

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

Coupon Usage and Sale Items. Table 2 shows similar responses in bargain-hunting within trips. The IV estimates imply that a 1 percentage point rise in paid inflation increases the trip-level propensity for coupon usage by 0.812 percentage points relative to a mean of 12.8 percent, a 6.3 percent increase, and propensity buying on-sale/deal items by 0.914 percentage points relative to a mean of 30.4 percent, a 3.0 percent increase. These results point to within-trip shifting toward promotions, consistent with models where higher expected gains from search during inflation raise optimal search intensity. As an additional specification, I examine monthly totals of bargain-hunting items in Appendix Table **??**, which shows similar patterns of increased coupon and sale item purchases in response to inflation.

Table 2. Effects of Higher Inflation: Propensity for Bargain-Hunting During Shopping Trips.

Dependent variable:	Used Coupon	Bought an On-Sale Item
	(1)	(2)
Panel A: OLS		
$\pi_{i,t}$	-0.046***	-0.021***
	(0.002)	(0.003)
Panel B: Reduced Form		
Predicted π_{it}	0.195***	0.220***
	(0.016)	(0.021)
Panel C: IV		
$\pi_{i,t}$	0.812***	0.914***
	(0.086)	(0.107)
First-stage F stat.	243.56	243.56
Base Dep. Var. Mean	12.80	30.38
Observations	748,378	748,378

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

Shopping Trips to Low-Cost Retailers. Table 3 documents substitution toward lower-cost retailers. A 1 percentage point increase in paid inflation raises monthly trips to discount, dollar, and warehouse retailers by 0.419, 0.121, and 0.149, respectively. Relative to means of 2.25, 0.67, and 0.67, these represent increases of roughly 18.7 percent, 18.2 percent, and 22.4 percent. These shifts are also consistent with rational search behavior under inflation. Discount grocers, dollar stores, and warehouse clubs offer lower everyday prices and emphasize private-label goods, making them attractive destinations for reducing expenditures without cutting quantities. Warehouse clubs additionally enable bulk purchasing for households with storage capacity and liquidity. The fact that all three retail types see significant increases suggests households diversify their store mix rather than simply switching to the cheapest option, taking advantage of low prices at discount grocers, small packages at dollar stores, and bulk discounts at warehouses.

Retailer Substitution. A useful benchmark for interpreting the magnitude of retailer substitution is to ask, of the 1.95 additional trips induced by a 1 percentage point increase

Table 3. Effects of Higher Inflation: Shopping Trips to Lower-Cost Retailers.

Dependent variable:	Discount Store	Dollar Store	Warehouse Club	Grocery
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\pi_{i,t}$	-0.003***	-0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Reduced Form				
Predicted π_{it}	0.101***	0.029***	0.036***	0.177***
	(0.002)	(0.001)	(0.001)	(0.003)
Panel C: IV				
$\pi_{i,t}$	0.419***	0.121***	0.149***	0.736***
	(0.030)	(0.010)	(0.011)	(0.051)
First-stage F-stat.	232.66	232.66	232.66	232.66
Base Dep. Var. Mean	2.24	0.66	0.67	5.20
Observations	723,120	723,120	723,120	723,120

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

in paid inflation, how many are directed to low-cost retailers? The point estimates imply roughly 0.69 trips to discount, dollar, and warehouse retailers combined, representing approximately 35 percent of the total increase in trip frequency. This is substantially higher than the baseline share of trips to value formats in the sample, confirming that the marginal trips are disproportionately allocated to channels where price savings are likely to be greatest. The remaining trips potentially include both additional visits to conventional grocers and exploratory trips to broaden the household's retailer set, both of which are consistent with heightened search intensity.

This reallocation does not come at the expense of conventional grocery stores in absolute terms, even though it does in relative terms. Table 3 shows that trips to conventional grocers increase by 0.736 per month, representing approximately 14 percent growth relative to the mean of 5.20. However, Table 4 reveals that the share of trips allocated to conventional grocers declines by 0.96 percentage points from a mean of 46.39 percent, a 2 percent reduction. These results are not necessarily contradictory. Total trip frequency rises by 1.95 trips per month, and while conventional grocers capture a declining share of this expanded activity, they still receive more trips in absolute terms. This pattern is consistent with a model in which households maintain relationships with

their primary grocer in line with concepts of retailer loyalty but becoming less of a captive shopper the higher inflation becomes. The net effect is an expansion of the retailer set, with disproportionate growth directed toward discount, dollar, and warehouse stores.

Table 4. Effects of Higher Inflation: Share of Shopping Trips to Lower-Cost Retailers.

Dependent variable:	Discount Store	Dollar Store	Warehouse Club	Grocery
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\pi_{i,t}$	-0.024***	-0.000	-0.008***	0.035***
	(0.003)	(0.001)	(0.001)	(0.004)
Panel B: Reduced Form				
Predicted π_{it}	0.006	0.062***	0.103***	-0.231***
	(0.021)	(0.009)	(0.010)	(0.025)
Panel C: IV				
$\pi_{i,t}$	0.025	0.260***	0.429***	-0.960***
	(0.089)	(0.041)	(0.050)	(0.122)
First-stage F-stat.	236.46	236.46	236.46	
Base Dep. Var. Mean	21.92	4.74	5.63	46.39
Observations	745,226	745,226	745,226	745,226

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

Basket Composition. Table 5 shows compositional changes in households' basket induced by higher inflation. The IV coefficient on the generic or store-brand share of expenditure is 0.29 percentage points relative to a mean of 17.47 percent, a 1.7 percent increase. This modest shift toward private-label products is consistent with quality downgrading as a strategy to preserve real consumption, but the magnitude is notably smaller than the effects on search-intensive margins like trip frequency and store diversification. This pattern suggests that households prioritize adjusting where and how they shop before making substantial changes to what they buy. The limited role of generic substitution may reflect either strong brand preferences or the fact that store brands are already a significant share of the basket for many households, limiting the scope for further substitution. Moreover, the shift toward discount stores, dollar stores, and warehouse clubs documented in Table 3 may provide an alternative channel for accessing lower prices

without compromising on branded goods, as these retailers often carry national brands at discounted prices alongside their private-label options.

Table 5. Effects of Higher Inflation: Generic Item Expenditure Share.

Dependent variable:	Generic Items (% of Expenditure)
	(1)
Panel A: OLS	
$\pi_{i,t}$	0.004**
	(0.001)
Panel B: Reduced Form	
Predicted π_{it}	0.069***
	(0.010)
Panel C: IV	
$\pi_{i,t}$	0.290***
	(0.046)
First-stage F-stat.	239.62
Base Dep. Var. Mean	17.47
Observations	749,588

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

Table 6 shows that the number of distinct product groups purchased rises by 15.7 relative to a mean of 64.3, an approximate 24.4 percent increase. This is the largest percentage effect across all outcomes, indicating that households substantially broaden the scope of their consumption baskets when exposed to higher inflation. The increase in product categories purchased suggests that households are not simply buying more of the same goods but are actively exploring and purchasing across a wider range of product types.

Table 6. Effects of Higher Inflation: Basket Variety.

Dependent variable:	Number of Product Groups
	(1)
Panel A: OLS	
$\pi_{i,t}$	-0.021***
	(0.004)
Panel B: Reduced Form	
Predicted π_{it}	3.759***
	(0.034)
Panel C: IV	
$\pi_{i,t}$	15.693***
	(1.039)
First-stage F stat.	237.29
Base Dep. Var. Mean	64.31
Observations	744,226

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

This pattern is consistent with several complementary mechanisms. Broader category coverage may reflect increased search effort as households compare prices and identify deals across more segments of the store. When inflation raises price dispersion, the returns to searching across categories increase, inducing households to expand the range of products they consider and purchase. The increase in product groups may also capture substitution across categories as households shift expenditure away from categories experiencing the sharpest price increases toward those with more moderate inflation. For example, a household facing high meat price inflation might purchase more pasta, beans, or eggs to maintain protein intake at lower cost. The expansion in category coverage complements the other behavioral adjustments that I documented previously. Households that visit more stores and make more trips naturally encounter deals and promotions across a wider range of categories, potentially leading to baskets with more product variety.

Bulk-buying and stocking-up. Finally, Table 7 indicates increased stocking-up behavior. A 1 percentage point increase in paid inflation raises items per trip by 1 item relative to a

mean of 12.82 items, a 7.8 percent increase, and increases items per pack by 0.021 relative to a mean of 1.57, a 1.3 percent increase.

Table 7. Effects of Higher Inflation: Stocking Up and Bulk-Buying.

Dependent variable:	Items Per Trip	Items Per Pack
	(1)	(2)
Panel A: OLS		
$\pi_{i,t}$	0.000	-0.000
	(0.001)	(0.000)
Panel B: Reduced Form		
Predicted π_{it}	0.236***	0.005***
	(0.008)	(0.001)
Panel C: IV		
$\pi_{i,t}$	1.002***	0.021***
	(0.074)	(0.004)
First-stage F stat.	228.16	228.16
Base Dep. Var. Mean	12.82	1.57
Observations	740,651	740,651

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

The simultaneous rise in trips per month and items per trip may initially appear contradictory. If households simply made more trips of the same type, one might expect baskets to shrink as total purchases spread across more shopping trips. Instead, both margins increase. This is suggestive of strategic trip timing, where households may be concentrating larger stock-up trips around bigger promotional events while interspersing smaller trips throughout the month. What I measure as items per trip may then reflect an average that increases because promotion-timed trips become substantially larger.

Several features of the data help rule out alternative explanations for this and the other behavioral changes described above. The strong responses on effort-intensive margins such as trips, store diversification, and shifts toward discount stores, dollar stores, and warehouse clubs are difficult to attribute purely to supply-side changes in promotion availability. If retailers simply offered more deals during high-inflation periods, I might observe higher coupon and sale usage, but the expansion in trips and cross-store shopping points to points to deliberate household decisions to search for better prices.

The combination of more trips with larger baskets and broader category coverage argues against an explanation based on product availability, where households make extra trips because items are frequently out of stock. If supply disruptions were forcing households to make extra trips to find unavailable goods, I would expect smaller baskets and fewer categories per trip.

The baseline specifications assume linear effects, but models of consumer search with price adjustment costs predict nonlinear responses to inflation. In line with Benabou (1988) and Diamond (1993), moderate inflation can increase consumer welfare by raising price dispersion and diluting firm market power, as search costs induce competition among retailers. However, Head and Kumar (2005) show that while inflation increases search incentives through greater dispersion, this effect is strongest at low to moderate inflation levels, potentially diminishing at higher rates. Wang (2016) further demonstrates that when search is endogenized, it can raise retailer competition and drive prices down, though the real balance channel may create offsetting costs at high inflation. My empirical results provide large-scale evidence of such search responses using nationally representative data, documenting behavioral adjustments that generate time costs not captured in standard expenditure or inflation measures. These adjustments may also persist as households update their knowledge about store prices and promotions.

6.2 Heterogeneity in Shopping Responses

The magnitude and nature of shopping responses to inflation vary across household types. Different households face different constraints on time, financial resources, and retail access, which shape both the incentives to search and the ability to exploit various strategies. Understanding this heterogeneity reveals which households bear the largest adjustment costs during inflationary periods and provides insight into the mechanisms driving the behavioral responses documented in Section 6.

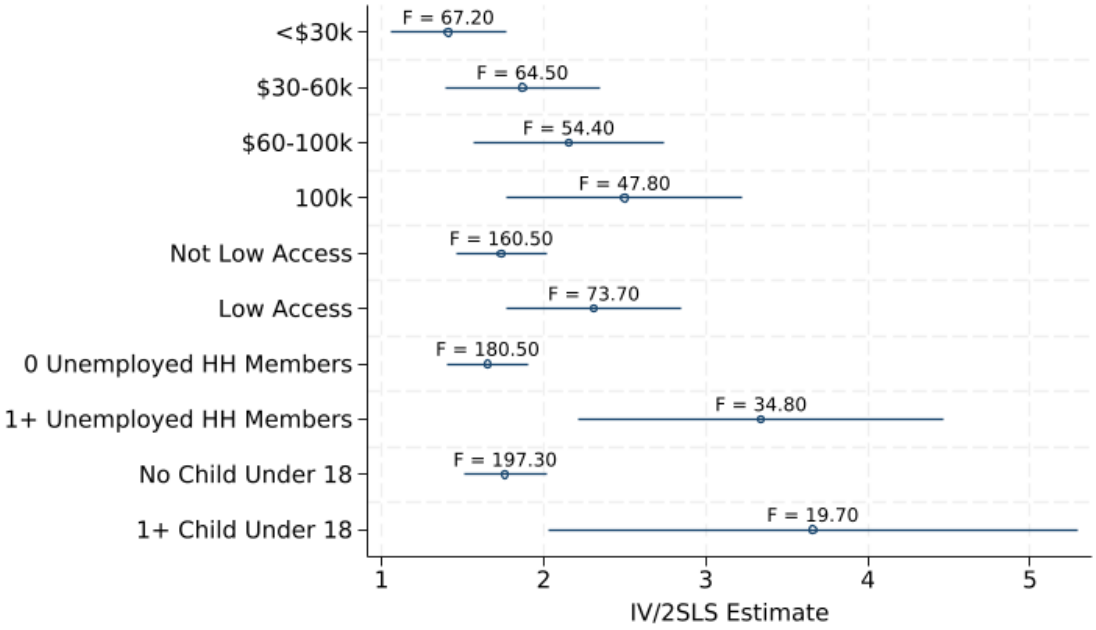
I examine heterogeneity along four dimensions: household income (split into terciles), retail access (low-access vs. higher-access based on USDA Food Access Research Atlas classifications), employment status (whether the household has at least one unemployed member), and household composition (whether the household has at least one child under 18). I classify households as low access if their census tract is designated low access by the USDA, meaning that at least 500 people or 33 percent of tract residents live farther than 1

mile in urban areas or 10 miles in rural areas from the nearest supermarket, supercenter, or large grocery store. For each dimension, I estimate separate IV specifications by group.

6.2.1 Trip Frequency

Figure 6 presents IV estimates of the effect of a 1 percentage point increase in household inflation on monthly shopping trips across all four heterogeneity dimensions. Several patterns emerge that shed light on the underlying mechanisms driving search responses.

Figure 6. Heterogeneity in Trip Responses to Inflation.



Notes: This figure presents IV estimates of the effect of a 1 percentage point increase in household inflation on monthly shopping trips, estimated separately by household characteristics. Income terciles are constructed based on annual household income reported in the Consumer Panel. Low-access households are those in census tracts designated low-access by the USDA Food Access Research Atlas. Unemployed households are those reporting at least one household member as unemployed. Children households are those with at least one child under 18. Error bars represent 95 percent confidence intervals with standard errors clustered at the household level.

First, I find the trip response increases monotonically with income. This runs counter to a simple opportunity cost story, where higher-wage households should search less due to more valuable time. Several mechanisms could explain this pattern. First, higher-income households have larger grocery budgets, so the absolute dollar savings from an additional trip may justify the time cost even at higher wage rates. Second, higher-income households may face lower effective search costs despite higher wages if they have flexible work schedules, better access to technology for price comparison, or

live in denser retail environments with lower travel costs between stores. Third, liquidity and storage constraints may bind for lower-income households, limiting their ability to exploit deals even when they find them through additional search effort. A household that cannot afford to stock up on bulk discounts or lacks storage space gains less from visiting warehouse clubs, potentially dampening the observed trip response.

Interestingly, I find that low-access households exhibit larger trip responses compared to higher-access households. This pattern suggests that households in low-access areas may compensate for limited retail options by making more frequent trips to the stores they can reach, timing visits with different promotions.

Households with at least one unemployed member show larger trip responses than fully employed households. This aligns with the prediction that unemployed individuals face lower opportunity costs of time, making search effort relatively cheaper. The lower shadow wage increases the net benefit of additional trips, inducing stronger responses. Standard errors are relatively large, reflecting the smaller sample of households with unemployed members. Households with at least one child under 18 take more trips than those without children, though the standard errors of the estimates are substantially larger, again due to a smaller sample size for this subgroup. This potentially reflects the competing effects of larger grocery bills versus tighter time constraints from childcare responsibilities.

6.2.2 Substitution Toward Value Retailers

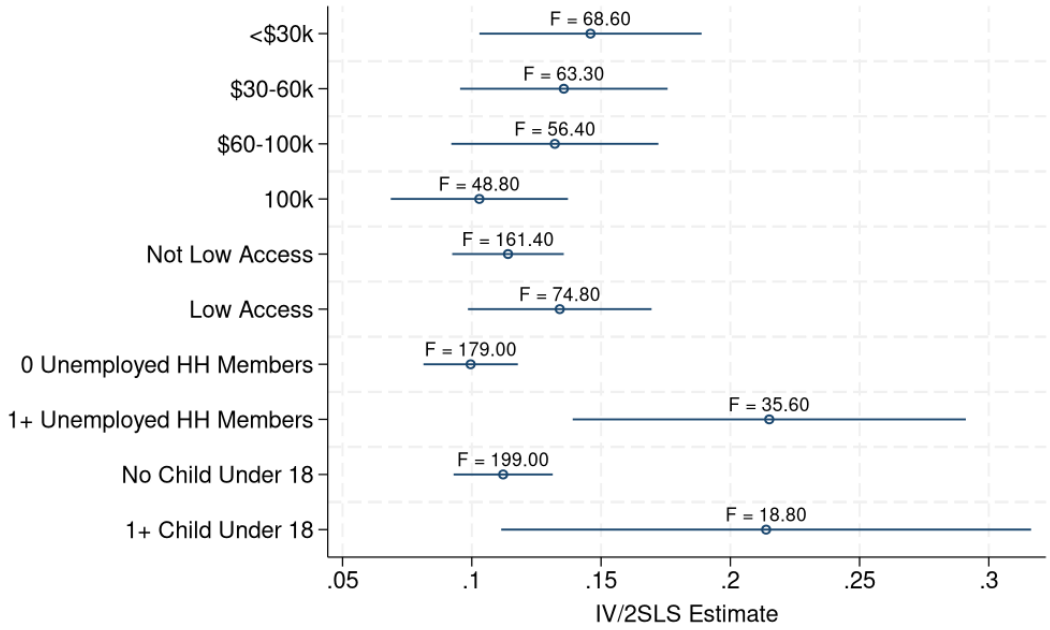
To further understand how households adjust shopping in response to inflation, I examine heterogeneity in trips to specific retailer types. Figures 7 and 8 present IV estimates for trips to dollar stores and warehouse clubs, respectively. These retailer types represent different strategies for reducing expenditure: dollar stores offer low prices on small package sizes (even if they are sometimes at a higher per-unit cost, as other studies have found), while warehouse clubs provide bulk discounts that require upfront liquidity and storage capacity.

The concentration of dollar store responses among lower-income households suggests that dollar stores serve as an accessible cost-saving channel for households facing tighter budget constraints. The small package sizes and low absolute prices make dollar stores compatible with liquidity constraints, unlike warehouse clubs that require larger purchases up front even at lower per-unit costs. The response among low-access households may

reflect the fact that dollar stores are often located in areas with limited traditional grocery options, making them a convenient alternative.

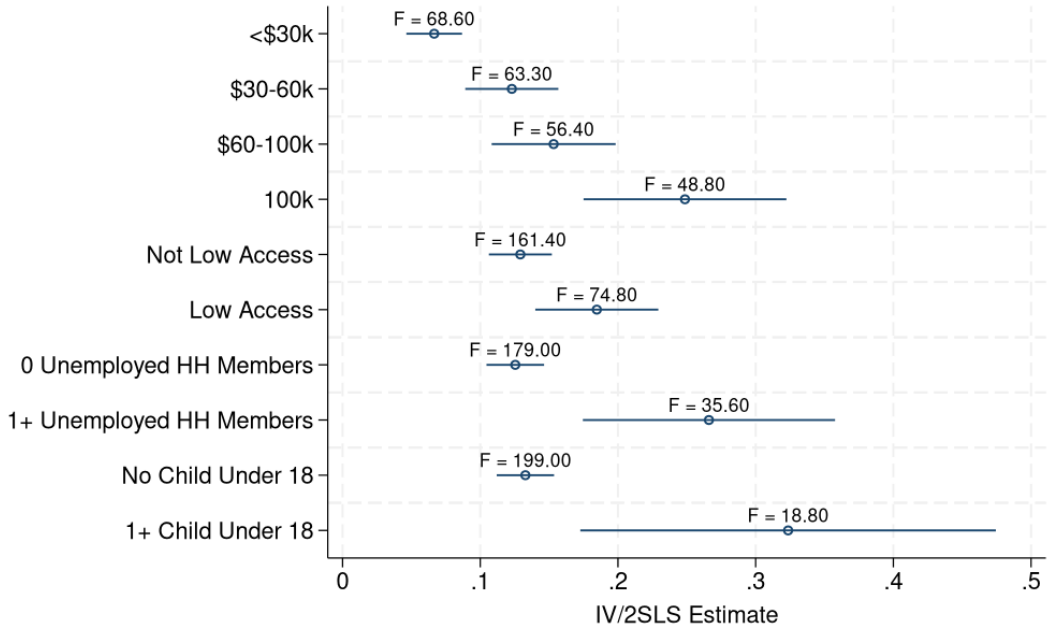
Figure 7 shows that higher-income households show substantially larger increases in warehouse club trips, consistent with binding liquidity and storage constraints for lower-income households. Warehouse clubs require households to have both the upfront cash to purchase in bulk and adequate storage space, conditions that higher-income households are more likely to satisfy. This pattern reinforces the interpretation that lower-income households face constraints beyond time costs that limit their ability to fully exploit all cost-saving strategies.

Figure 7. Heterogeneity in Dollar Store Trip Responses to Inflation.



Notes: Figure presents IV estimates of the effect of a 1 percentage point increase in household inflation on monthly trips to dollar stores, estimated separately by household characteristics. See Figure 6 for definitions of each category.

Figure 8. Heterogeneity in Warehouse Club Trip Responses to Inflation.



Notes: Figure presents IV estimates of the effect of a 1 percentage point increase in household inflation on monthly trips to warehouse clubs, estimated separately by household characteristics. See Figure 6 for definitions of each category.

6.2.3 Employment Status and Nominal Wage Growth

Households experience inflation as a reduction in purchasing power, but the magnitude of this shock depends on how their nominal income evolves relative to prices. If a household's wages keep pace with inflation, the real income effect is muted, potentially reducing the incentive to adjust shopping behavior. Conversely, households whose wages lag behind inflation face larger real income declines and stronger incentives to offset purchasing power losses through search effort.

Nominal wages adjusted slowly and unevenly across industries and occupations during 2022 and 2023. I examine whether households whose wages grew more slowly relative to their inflation exposure exhibited stronger behavioral responses. I construct household-specific wage growth measures by mapping industry-level nominal wage growth from the Atlanta Fed Wage Growth Tracker to household heads in the Consumer Panel. Because the Consumer Panel does not report detailed industry of employment for all households, I predict industry using a multinomial logit model based on broad occupation categories and demographic characteristics, then assign each household the

wage growth rate for their predicted industry.[10] To test whether real income changes mediate the shopping response, I estimate an IV specification that interacts household inflation with nominal wage growth:

$$y_{it} = \alpha + \beta_1 \pi_{it} + \beta_2(\text{Wage Growth}_i \times \pi_{it}) + \mu_i + \delta_t + \varepsilon_{it}, \tag{9}$$

where both π_{it} and the interaction term are instrumented using the shift-share IV and its interaction with wage growth.

Table 8 presents the results. The coefficient on the interaction term is negative and statistically significant for trips and distinct retailers, indicating that households whose wages grew faster responded less strongly to inflation. Specifically, a household experiencing 5 percentage points of annual wage growth increases trips by 0.36 fewer per percentage point of inflation compared to a household with zero wage growth. Relative to the baseline effect of 2.405 trips, this represents a 15 percent reduction in the trip response.

Table 8. Effects of Inflation by Nominal Wage Growth: Shopping Frequency and Retailer Diversification.

Dependent variable:	Trips	Stores	Trips Per Store
	(1)	(2)	(3)
Wage Growth (%) $\times \pi_{i,t}$	-0.072**	-0.018**	-0.002
	(0.022)	(0.007)	(0.001)
$\pi_{i,t}$	2.405***	0.700***	0.084***
	(0.154)	(0.047)	(0.010)
First-stage F Stat.	452.09	452.09	452.09
Base Dep. Var. Mean	12.13	5.42	1.91
Observations	683,386	683,386	683,386

Notes: This table presents IV estimates from specifications that interact household inflation with industry-level nominal wage growth. Both π_{it} and the interaction term are instrumented using the shift-share IV and its interaction with wage growth. Nominal wage growth is measured as the annual percentage change in industry-level wages from the Atlanta Fed Wage Growth Tracker, mapped to households based on predicted industry of employment. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county by month. Standard errors are clustered at the household level. * significant at 10%, ** significant at 5%, *** significant at 1%.

During the 2021 to 2023 period, industry-level wage growth ranged from approximately 2 to 8 percent annually. A household in an industry with 8 percent wage growth experiencing

[10] Appendix D provides details on the method I use to map nominal wage growth to each household head in the panel.

6 percent inflation would respond very differently than a household with 2 percent wage growth experiencing the same 6 percent inflation. The estimates suggest the latter household would increase trips by approximately 0.43 more per month, accumulating to about 5 additional trips per year.

The wage growth interaction and employment status results together highlight that both the level and growth rate of income shape behavioral responses to inflation. Households facing real income declines, whether through stagnant wages or unemployment, adjust shopping behavior more intensively to maintain consumption.

The heterogeneity in shopping effort that I document here reveals important differences in how households respond to inflation and what constraints they face. The positive income gradient in trip responses, combined with the concentration of warehouse club usage among higher-income households and dollar store usage among lower-income households, suggests that different household types pursue different search strategies shaped by their constraints. Higher-income households appear to exploit bulk purchasing and have greater flexibility to expand search across multiple dimensions, while lower-income households face liquidity and storage constraints that may limit their use of this type of retailer. These findings also have distributional implications for the welfare costs of inflation. While all households bear time costs from increased shopping effort, lower-income households may face additional costs from being unable to access the most efficient cost-saving strategies. The fact that they respond less on the trip margin despite facing tighter budget constraints suggests that binding constraints may limit their behavioral responses. This implies that the shoe-leather costs documented in Section 6.3 may understate the true burden on lower-income households if I account for foregone savings from strategies they cannot pursue.

6.3 Time Costs

The shopping adjustments documented in previous sections represent real resource costs to households. While these behavioral responses help maintain purchasing power in the face of rising prices, they require time that could otherwise be allocated to market work, home production, or leisure. In this section, I translate the increase in trip frequency into time costs using data from the American Time Use Survey and discuss how these costs vary across household types. To estimate the time burden of inflation-induced

shopping, I draw on the American Time Use Survey (ATUS). As part of the survey, respondents provide a diary of activities for one day, capturing both the type and duration of activities including time spent grocery shopping. From this, I compute the average grocery shopping trip recorded by 41,793 respondents on their diary days from 2003 to 2024 to last approximately 43 minutes.

Using my baseline IV estimate, a 1 percentage point increase in household inflation raises the number of shopping trips by about 1.95 trips per month. Given an average trip length of 43 minutes, this translates into roughly 1.4 additional hours of shopping per month for each percentage point of inflation. To value this time, I consider a range of wage rates from the Bureau of Labor Statistics. Using median hourly earnings for all workers of approximately 29 dollars per hour and the mean of 36 dollars per hour, the monthly time cost ranges from about 40 to 50 dollars per 1 percentage point of inflation. Sustaining 1 percentage point of inflation for a full year imposes a time cost worth approximately 480 to 600 dollars per household. For larger inflation episodes, the burden scales proportionally: 5 percentage points of sustained inflation implies an annual cost of about 2,400 to 3,000 dollars, while 8 percentage points implies a cost of 3,840 to 4,800 dollars.

These calculations provide a useful benchmark for the shoe-leather costs of inflation beyond direct price increases. However, they likely obscure substantial heterogeneity across household types. The opportunity cost of time varies systematically with wage rates, which differ across income groups, employment status, and occupation. Higher-income households face higher wage rates, potentially raising the dollar value of time costs, while lower-income households face lower wages. At the same time, the trip responses documented in Section 6.2 show that higher-income households actually increase trips more than lower-income households, amplifying their time costs in both hours and dollars. The net effect depends on whether the wage effect or the behavioral response effect dominates.

Households in low-access areas may face longer trip durations due to greater distances to stores, raising the time cost per trip even if trip frequency responses are similar to higher-access households. Employment status also matters: unemployed individuals may face lower shadow wages than their market wages would suggest, as the marginal hour of search does not displace paid work. However, unemployment may proxy for financial distress, making even modest time costs more burdensome relative to available resources.

Household composition introduces additional complexity: households with children may face higher effective time costs if children must accompany adults on trips or if shopping with children increases trip duration, though multi-adult households may have more flexibility to allocate tasks.

The patterns documented in Section 6.2 suggest that time costs vary substantially across households, with potentially important distributional implications. Higher-income households may bear larger dollar costs due to both higher wages and larger trip responses, while lower-income households may bear larger costs relative to their income and face additional constraints that prevent them from accessing the most efficient cost-saving strategies. These time costs represent a welfare loss attributable to price rigidities and dispersion that should be incorporated into assessments of inflation's burden alongside more traditional measures of purchasing power erosion.

7 Conclusion

In this paper, I examine how household-level inflation exposure drives specific behavioral responses during the post-pandemic inflationary episode. Using granular household shopping data, I focus on bargain-hunting behaviors that households reported as primary coping mechanisms, such seeking sales and using coupons, as well as behaviors that are associated with intense product search, such as taking more trips and shopping at a greater variety of retailers. Taken together, these measures capture key behavioral margins that households can adjust when facing inflationary pressures without necessarily needing to fundamentally alter the composition of their basket. With these, rather than immediately substituting away from preferred goods, households can first intensify their search efforts and deal-seeking behaviors to maintain original consumption while still minimizing expenditure increases. This behavioral response that I find is consistent with models where households face search costs but can benefit from increased search when the payoffs to finding lower prices rise with inflation.

The simple theoretical framework I develop serves primarily to illustrate the identification challenge and clarify the key economic forces at work. A potential direction for future work would be to develop a richer structural model that could be taken seriously for quantitative welfare analysis and counterfactual policy evaluation. Several extensions would be valuable. First, moving to a multi-period dynamic setting

would allow for explicit modeling of intertemporal substitution and consumption timing decisions. In such a framework, households that search more effectively would face higher household-specific real interest rates (since they achieve lower paid inflation), creating an additional channel through which inflation affects both the level and timing of consumption. This would provide a way to quantify welfare costs beyond just the direct disutility of search effort, including the utility losses from distorted consumption timing.

It is also the case that in reality, households form expectations about future inflation when making current consumption and search decisions. In a dynamic setting, expected future price increases would affect both whether households stock up on goods today and how much search effort they invest in different periods. For simplicity, the static model abstracts from these intertemporal considerations and treats households as responding to current realized prices. This is another dimension where a multi-period extension would add realism, but for the purposes of illustrating the identification challenge and core mechanisms, the static framework is sufficient. In the empirical implementation, I focus on realized posted inflation rather than expected inflation, which is appropriate given that much of the category-level inflation variation I exploit (through the shift-share instrument) likely reflects shocks that were at least partially unexpected by households.

A structural model could also incorporate the rich heterogeneity I observe in the data more explicitly. This would include modeling how search costs and search returns vary across households with different incomes, family structures, employment situations, and geographic locations. It would also be valuable to model multiple product categories explicitly, allowing households to reallocate spending across categories in response to category-specific inflation shocks. The current model treats consumption as an aggregate, but the data reveal substantial reallocation across product categories during inflationary periods. Incorporating liquidity constraints or credit market frictions would also help rationalize some of the income heterogeneity I find in the empirical results. While the simple opportunity cost mechanism suggests that higher-wage households should search less, I find the opposite in the data. A richer model with borrowing constraints could explain this if lower-income households face binding constraints that limit their ability to act on search incentives (for example, by preventing them from stocking up on goods when prices are low or traveling to distant discount retailers).

Finally, a more realistic model would allow for learning and habit formation in search

behavior. Households may gradually learn which retailers offer better prices or develop shopping routines that persist even after inflation subsides. Modeling these dynamics would provide insights into how temporary inflation shocks can have persistent effects on shopping behavior and market structure.

I will also note that in my simple illustrative model, naturally I take a partial equilibrium approach, treating posted prices as exogenous from the household's perspective. It is possible that if many households intensify search in response to inflation, this could feed back into retailer pricing strategies and affect the equilibrium distribution of prices. Exploring these general equilibrium effects would be valuable, but it is not the primary focus of this paper. My goal is to document and causally identify the household behavioral response to inflation, taking the price environment as given. Understanding this partial equilibrium response is a necessary first step before building richer models that incorporate strategic interactions between searching consumers and price-setting firms.

My findings also raise broader questions about the implications for monetary policy and inflation measurement. If households respond to inflation by increasing search effort, then measured inflation rates (which are based on actual transaction prices) understate the true welfare costs because they do not capture the increased time and effort spent shopping. This suggests that traditional cost-of-living adjustments may be insufficient to compensate households for the full burden of inflation. Additionally, if different demographic groups have different search capacities or face different search costs, then the welfare costs of inflation may be unevenly distributed in ways that are not captured by standard inflation measures. Understanding these heterogeneous effects is crucial for designing policies that protect the most vulnerable households from the costs of inflation.

By documenting these causal responses during a unique and highly salient inflationary period, I provide evidence of how households experience and react to realized inflation, and my results demonstrate that consumer behavior is more dynamic and costly than solely substituting to cheaper, lower quality goods. These behavioral responses involve real resource costs, particularly in terms of time spent searching across retailers and monitoring prices, and survey evidence indicates that many households are indeed partaking in these shopping strategies. Future work should explore how long such adaptations can be sustained, and how ongoing shocks, such as tariffs or supply disruptions, may interact with these behaviors. Taken together, these findings show the consequences of inflation,

in that it affects households not only via prices paid but also in the hidden costs of search, effort, and time.

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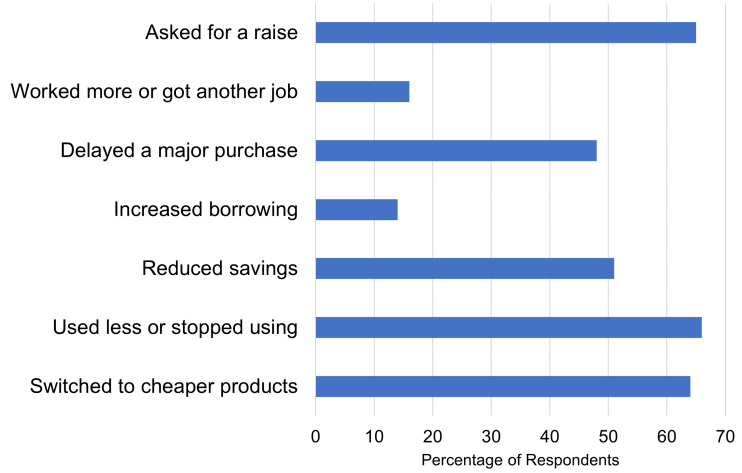
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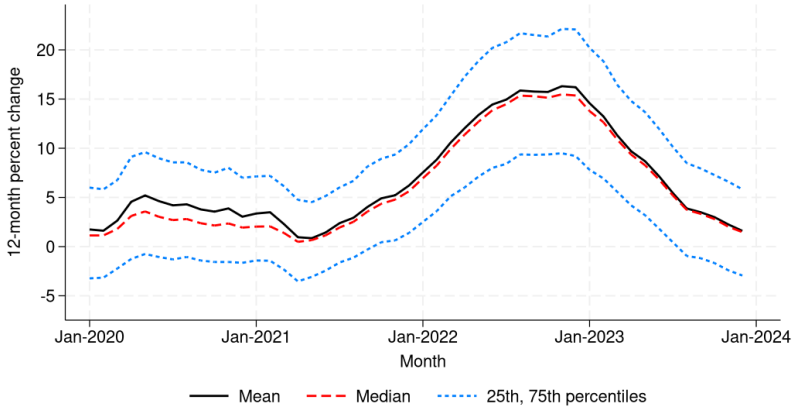
A Additional Tables and Figures

Figure A1. Household Responses to Higher Prices - SHED



Notes: Figure shows responses to the question "Did you take any of the following actions because of increases in prices over the past 12 months?" from the 2022 Survey of Household Economics and Decision-making (SHED), fielded in October 2022. *Source:* Board of Governors of the Federal Reserve System.

Figure A2. Distribution of Household-Level Inflation Rates



Notes: Figure shows the median and mean of household-level twelve-month inflation rates over time, constructed using a Laspeyres price index. The widening gap between measures reflects increasing dispersion in household inflation experiences during periods of higher aggregate inflation. *Source:* NielsenIQ Consumer Panel and author's calculations.

Table A1. Monthly Bargain-Hunting Item Totals.

Dependent variable:	Coupon Items	Sale Items
	(1)	(2)
Panel A: OLS		
$\pi_{i,t}$	-0.029***	-0.033***
	(0.003)	(0.001)
Panel B: Reduced Form		
Predicted π_{it}	0.957***	0.255***
	(0.022)	(0.009)
Panel C: IV		
$\pi_{i,t}$	3.980***	1.060***
	(0.275)	(0.079)
First-stage F-stat.	240.23	240.23
Base Dep. Var. Mean	21.25	5.36
Observations	733,431	733,431

Notes: Each column reports estimates from separate regressions of shopping outcomes on the specified independent variable. The sample includes data from 2021 to 2023. Fixed effects include individual, month, and county x month. Standard errors are clustered at the household level and are in parentheses. * - significant at 10%, ** - significant at 5%, *** - significant at 1%.

B Household Inflation Rates - Alternative Indices

Below I explain alternative ways to construct household inflation rates. The Laspeyres index, which I use in my baseline analysis, is defined as follows:

$$P^{L}_{i,t,t+12} = \frac{\sum_j p_{ij,t+12}\, q_{ij,t}}{\sum_j p_{ij,t}\, q_{ij,t}}. \tag{10}$$

By construction, $P^{L}_{i,t,t} = 1$, so the associated inflation rate is simply the percent change in the index:

$$\pi^{L}_{i,t,t+12} = (P^{L}_{i,t,t+12} - 1) * 100. \tag{11}$$

The Paasche index instead reweights prices by the final-period quantities:

$$P^{P}_{i,t,t+12} = \frac{\sum_j p_{ij,t+12}\, q_{ij,t+12}}{\sum_j p_{ij,t}\, q_{ij,t+12}}, \tag{12}$$

with the corresponding inflation rate

$$\pi^{P}_{i,t,t+12} = (P^{P}_{i,t,t+12} - 1) * 100. \tag{13}$$

Finally, the Fisher index takes the geometric mean of the Laspeyres and Paasche indexes:

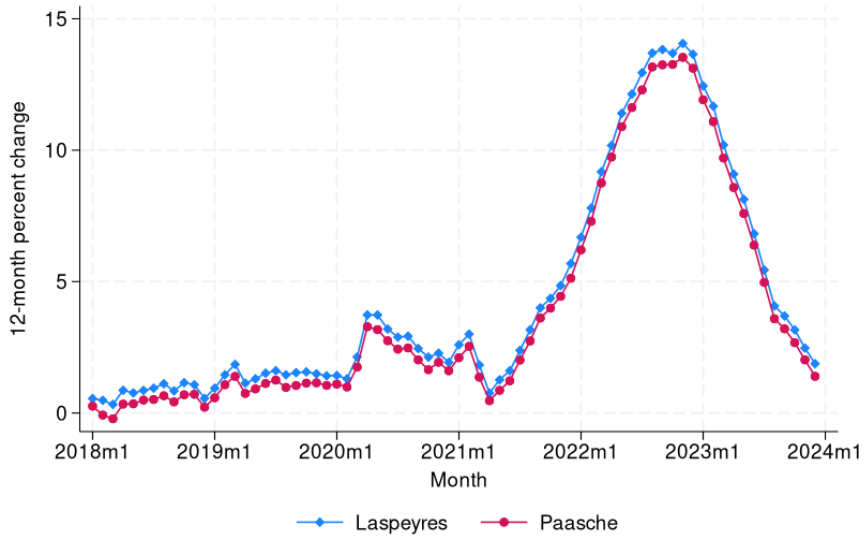
$$P^{F}_{i,t,t+12} = \sqrt{P^{L}_{i,t,t+12}\, P^{P}_{i,t,t+12}}, \tag{14}$$

and its inflation rate is

$$\pi^{F}_{i,t,t+12} = (P^{F}_{i,t,t+12} - 1) * 100. \tag{15}$$

When relative prices shift, more expensive goods receive greater weight in the Laspeyres index (since weights come from the pre-substitution period), while cheaper goods receive greater weight in the Paasche index (since weights come from the post-substitution period). As a result, the Laspeyres measure is typically higher than the Paasche. Figure A3 show this is the case for the household inflation rates I calculate in equations 11 and 13.

Figure A3. Aggregate Household-Level Inflation Rates.

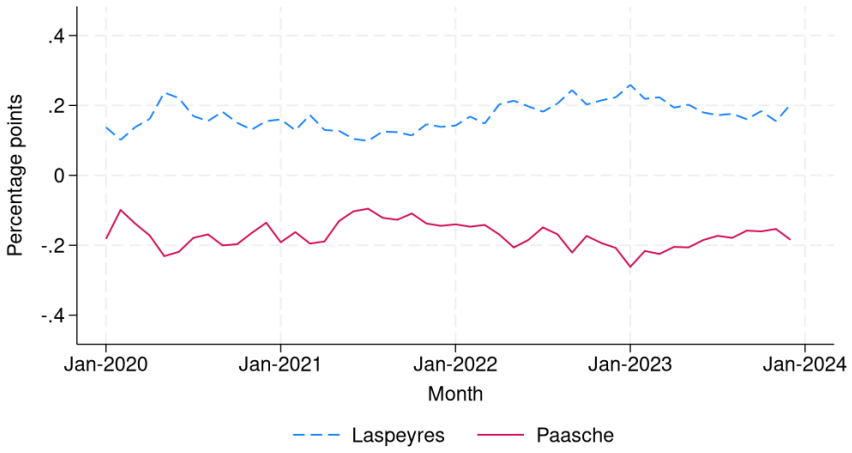


Notes: Figure shows aggregate household-level twelve-month inflation rates constructed using Laspeyres and Paasche price indices. The aggregate series are constructed by first aggregating product-level measures at the county level, then aggregating to the national level using annual sales as weights. The Laspeyres measure is consistently higher than the Paasche measure, reflecting the typical relationship between these indices. *Source:* NielsenIQ Consumer Panel and author's calculations.

This is because the Laspeyres index holds the initial-period basket fixed, implicitly assuming that households continue to purchase the same bundle of goods even after

relative prices change. Because consumers typically substitute away from items that become more expensive, this assumption tends to overstate the true cost of living. In contrast, the Paasche index holds the final-period basket fixed, weighting price changes by the quantities actually consumed after substitution has taken place. This produces the opposite bias: it tends to understate the true cost of living, because it assumes households could have purchased the cheaper, substitution-adjusted bundle from the start. The Fisher index, defined as the geometric mean of the two, balances these opposing biases. It is often considered the best approximation to a true cost-of-living index, and the gap between the Laspeyres and the Fisher provides a measure of the substitution bias inherent in the Laspeyres. I present a time series of the mean difference from the Fisher index for both the Laspeyres and the Paasche in Figure A4.

Figure A4. Mean Differences in Laspeyres and Paasche Indices from Fisher Index.



Notes: Figure shows the time series of mean differences between Laspeyres and Paasche indices and the Fisher index (the geometric mean of the two). The Laspeyres index, which holds the initial-period basket fixed, consistently overstates inflation relative to the Fisher index, while the Paasche index, which holds the final-period basket fixed, consistently understates it. These gaps reflect the substitution bias inherent in each measure. *Source:* NielsenIQ Consumer Panel and author's calculation.

C Shift-Share Instrument Construction

In this section, I describe the data and sources used to construct the shift-share instrument introduced in Section 5.1, and show how it follows from a decomposition of household-level inflation into expenditure-weighted product-group inflation rates.

C.1 CPI Component Data for Instrument Construction

To construct the SSIV, I use disaggregated CPI data published monthly by the Bureau of Labor Statistics (BLS). The CPI measures aggregate price changes using a representative basket methodology that combines household expenditure surveys with extensive price collection from retail establishments.

I match NielsenIQ's product group classifications to corresponding CPI subcategories to construct household-specific inflation exposure measures. Table A2 shows the mapping. This matching allows me to combine the detailed household consumption patterns from NielsenIQ with the national price trend data from CPI to predict individual household inflation rates using the shift-share approach described in Section 5.1.

CPI Series	NielsenIQ Product Group	CPI Series	NielsenIQ Product Group
Apparel	Hosiery, socks; Shoe Care; Sunglasses	Hair, dental, shaving, and miscellaneous personal care products	Personal soap and bath additives; Deodorant; Feminine hygiene; Grooming aids; Hair care; Men's toiletries; Oral hygiene; Sanitary protection; Shaving needs; Skin care preparations
Appliances	Kitchen gadgets	Household furnishings and supplies	Batteries and flashlights; Electronics, records, tapes; Housewares, appliances; Light bulbs, electric goods
Baby food and formula	Baby food; Disposable diapers; Baby needs	Housekeeping supplies	Household supplies
Bacon, breakfast sausage, and related products	Breakfast food	Ice cream and related products	Ice cream, novelties
Beer, ale, and other malt beverages at home	Beer	Juices and nonalcoholic drinks	Juice, drinks - canned, bottled
Recreational books	Books and magazines	Laundry equipment	Laundry supplies
Bread	Bread and baked goods; Dough products	Meats	Packaged meats - deli; Fresh meat
Butter and margarine	Butter and margarine	Medicinal drugs	Cough and cold remedies; Diet aids; Medications/remedies/health aids; Vitamins
Candy and chewing gum	Candy; Gum	Medical equipment and supplies	First aid
Shelf stable fish and seafood	Seafood - canned	Milk	Packaged milk and modifiers; Milk
Canned fruits and vegetables	Fruit - canned; Jams, jellies, spreads; Vegetables - canned	Olives, pickles, relishes	Pickles, olives, and relish
Carbonated drinks	Carbonated beverages; Soft drinks - non-carbonated	Other beverage materials including tea	Tea
Cereals and cereal products	Cereal	Other condiments	Table syrups, molasses
Cheese and related products	Cheese	Household paper products	Paper products; Greeting cards/party needs/novelties
Household cleaning products	Detergents; Fresheners and deodorizers; Household cleaners	Rice, pasta, cornmeal	Pasta
Coffee	Coffee	Pet food and treats	Pet food; Pet care
Cookies	Cookies	Prepared salads	Dressings/salads/prepared foods - deli
Nonelectric cookware and tableware	Baking supplies; Canning, freezing supplies; Cookware; Glassware, tableware	Other processed fruits and vegetables including dried	Fruit - dried; Vegetables and grains - dried; Desserts/fruits/toppings - frozen; Vegetables - frozen
Cosmetics, perfume, bath, nail preparations and implements	Cosmetics; Fragrances - women	Spices, seasonings, condiments, sauces	Spices, seasoning, extracts
Crackers, bread, and cracker products	Crackers	Sauces and gravies	Condiments, gravies, and sauces
Dairy and related products	Cottage cheese, sour cream, toppings; Yogurt	Sewing machines, fabric and supplies	Sewing notions
Salad dressing	Salad dressings, mayo, toppings	Snacks	Nuts; Snacks; Pizza, snacks, hor d'oeurves - frozen; Snacks, spreads, dips - dairy
Eggs	Eggs	Soups	Soup
Fats and oils	Shortening, oil	Distilled spirits at home	Liquor
Film and photographic supplies	Photographic supplies	Stationary, stationary supplies, gift wrap	Wrapping materials and bags; Stationary, school supplies
Flour and prepared mixes	Baking mixes; Flour; Yeast	Sugar and sugar substitutes	Sugar, sweeteners
Fresh fruit and vegetables	Fresh produce	Sugar and sweets	Pudding, desserts - dairy
Frozen and refrigerated bakery products, pies, tarts, turnovers	Baked goods - frozen	Tobacco and smoking products	Tobacco & accessories
Frozen and freeze dried prepared foods	Breakfast foods - frozen; Prepared foods - frozen	Tools, hardware and supplies	Automotive; Hardware, tools
Frozen fish and seafood	Unprepared meat/poultry/seafood - frozen	Toys	Toys & sporting goods
Frozen noncarbonated juices and drinks	Juices, drinks - frozen	Wine at home	Wine

Table A2

C.2 Product Category Shares

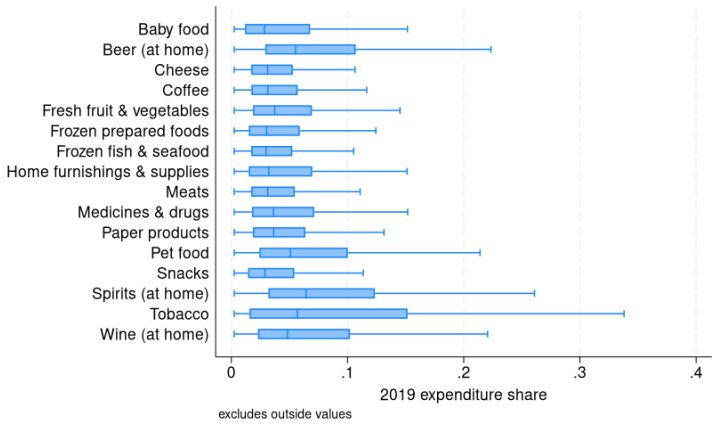
In addition to the national-level CPI data that I use for the shifts in the SSIV, I construct shares that measure each household's exposure to the inflation shocks in each category using the following formula:

$$s_{ik,t} \equiv \frac{\sum_{j \in \mathcal{G}_k} p_{ij,t}\, q_{ij,t}}{E_{i,t}}, \qquad E_{i,t} \equiv \sum_{j \in \mathcal{J}_i(t)} p_{ij,t}\, q_{ij,t},$$

where $\mathcal{G}_k$ is the set of goods (barcodes) in category k, $\mathcal{J}_i(t)$ is the set of all goods purchased by household i in period t, $p_{ij,t}$ is the price paid by i for good j in t, and $q_{ij,t}$ is the quantity of good j purchased by i in t. I construct these shares using expenditure data from 2019, as prices were already rising toward the end of 2020, and I want to ensure that the shares I use are effectively lagged to before the inflationary episode began. Though one might expect household consumption shares to have been altered considerably due to the pandemic in 2020, and therefore the 2019 shares would not be representative of households' true inflation exposure in 2021 and onward, I find that shares in the product groups that I use for my SSIV remain fairly stable since 2019.

In Figure A5 I plot a subset of the expenditure shares (by their corresponding CPI stratum category) that I use in my instrument in order to show some of the variation within and across groups.

Figure A5. Distribution of 2019 Household Expenditure Shares.



Notes: Figure shows the distribution of household expenditure shares in 2019 for a subset of product categories, grouped by their corresponding CPI stratum. Box plots illustrate variation in expenditure shares both within and across product categories.
Source: NielsenIQ Consumer Panel and author's calculations.

C.3 From household inflation to a shift–share representation

This subsection shows how the household-level inflation measure used in the main analysis can be written as a shift–share object, which in turn motivates the SSIV in equation (6).

For each household i and month t, I measure 12-month inflation using a household-specific Laspeyres price index at the barcode level. Let $p_{ij,t}$ and $q_{ij,t}$ denote the price and quantity of barcode j purchased by household i in period t. The 12-month Laspeyres index between t and $t+12$ months is

$$P^{L}_{i,t,t+12} = \frac{\sum_{j\in\mathcal{J}_i(t)} p_{ij,t+12}\, q_{ij,t}}{\sum_{j\in\mathcal{J}_i(t)} p_{ij,t}\, q_{ij,t}}, \tag{A.1}$$

and the associated 12-month inflation rate is

$$\pi^{L}_{i,t,t+12} = \left(P^{L}_{i,t,t+12} - 1\right) \times 100. \tag{A.2}$$

This chained 12-month Laspeyres measure is the endogenous household-level inflation regressor in the main text.

To connect this barcode-level index to the product category shares $s_{ik,t}$ defined above, group barcodes into product categories k (matched to CPI strata), and let $\mathcal{G}_k$ denote the set of barcodes in category k. Define household i's nominal expenditure in category k at time t as

$$E_{ik,t} = \sum_{j\in\mathcal{G}_k} p_{ij,t} q_{ij,t}, \qquad E_{i,t} = \sum_{k} E_{ik,t} = \sum_{j\in\mathcal{J}_i(t)} p_{ij,t} q_{ij,t}, \tag{A.3}$$

so that $s_{ik,t} = E_{ik,t}/E_{i,t}$.

Next, define a household–category Laspeyres index that holds barcode quantities fixed at t:

$$P^{L}_{ik,t,t+12} = \frac{\sum_{j\in\mathcal{G}_k} p_{ij,t+12} q_{ij,t}}{\sum_{j\in\mathcal{G}_k} p_{ij,t} q_{ij,t}}, \qquad \pi^{L}_{ik,t,t+12} = P^{L}_{ik,t,t+12} - 1. \tag{A.4}$$

Using this notation, the numerator and denominator of equation (A.1) can be written as sums over product categories:

$$\sum_{j\in\mathcal{J}_i(t)} p_{ij,t+12} q_{ij,t} = \sum_{k}\sum_{j\in\mathcal{G}_k} p_{ij,t+12} q_{ij,t} = \sum_{k} P^{L}_{ik,t,t+12} \sum_{j\in\mathcal{G}_k} p_{ij,t} q_{ij,t} \tag{A.5}$$

$$= \sum_{k} P^{L}_{ik,t,t+12} E_{ik,t}, \tag{A.6}$$

and $\sum_{j\in\mathcal{J}_i(t)} p_{ij,t}q_{ij,t} = E_{i,t}$. Substituting into equation (A.1) gives

$$P^L_{i,t,t+12} = \frac{\sum_k P^L_{ik,t,t+12}E_{ik,t}}{E_{i,t}} = \sum_k \frac{E_{ik,t}}{E_{i,t}} P^L_{ik,t,t+12} = \sum_k s_{ik,t} P^L_{ik,t,t+12}. \tag{A.7}$$

Because $\sum_k s_{ik,t} = 1$, the household's 12-month inflation rate can equivalently be written as

$$\pi^L_{i,t,t+12} = P^L_{i,t,t+12} - 1 = \sum_k s_{ik,t} P^L_{ik,t,t+12} - 1 \tag{A.8}$$

$$= \sum_k s_{ik,t}\left(P^L_{ik,t,t+12} - 1\right) = \sum_k s_{ik,t}\, \pi^L_{ik,t,t+12}. \tag{A.9}$$

Equation (A.9) shows that, for each 12-month window $(t, t+12)$, the household's overall inflation is exactly an expenditure-weighted average of product-category inflation rates:

$$\pi^L_{i,t,t+12} = \sum_k \underbrace{s_{ik,t}}_{\text{exposure weight}} \times \underbrace{\pi^L_{ik,t,t+12}}_{\text{household–category shift}}.$$

This then has the usual shift–share form: the shares or exposure weights $s_{ik,t}$ loading on the local (household-level) shifts $\pi^L_{ik,t,t+12}$.

However, the household–category inflation terms $\pi^L_{ij,t,t+12}$ are constructed from the prices that household i actually pays for items in category j. These prices embed not only underlying market prices but also endogenous shopping behavior: store choice, brand and size switching, coupon use, and the timing of purchases. As a result, the treatment $\pi^L_{i,t,t+12}$ in equation (A.9) is endogenous, as households that adjust their shopping effort in response to shocks will mechanically change both $\pi^L_{ij,t,t+12}$ and the outcome variables of interest.

C.4 Constructed instrument

To obtain variation in household-level inflation that is driven only by exogenous price movements, I construct a shift–share (Bartik-style) instrument by modifying the components of equation (A.9) in two ways. First, I replace the exposure weights with

predetermined pre-pandemic expenditure shares,

$$s_{ik}^{2019} = \frac{E_{ik,2019}}{E_{i,2019}},$$

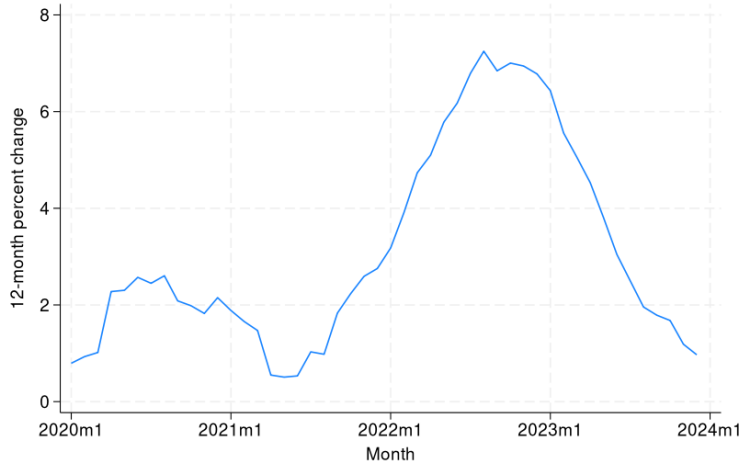
computed using 2019 expenditure data as described above, where $E_{ik,2019}$ is household i's 2019 expenditure in product category k and $E_{i,2019}$ is total 2019 expenditure. Second, I replace the household-specific category inflation terms $\pi_{ik,t,t+12}^{L}$ with common national CPI inflation rates for the corresponding CPI strata, denoted π_{kt}^{CPI}. Combining these two steps yields the shift–share instrument introduced in Section 5.1:

$$\text{SSIV}_{it} = \sum_{k=1}^{N} s_{ik}^{2019} \times \pi_{kt}^{CPI},$$

which is equation (6) in the main text. In this expression, the national CPI inflation rates π_{kt}^{CPI} are the "shifts," which vary over time but are common to all households, while the pre-pandemic expenditure shares s_{ik}^{2019} are the household-specific "shares" that vary across households but are fixed over time and not permitted to respond endogenously to inflation.

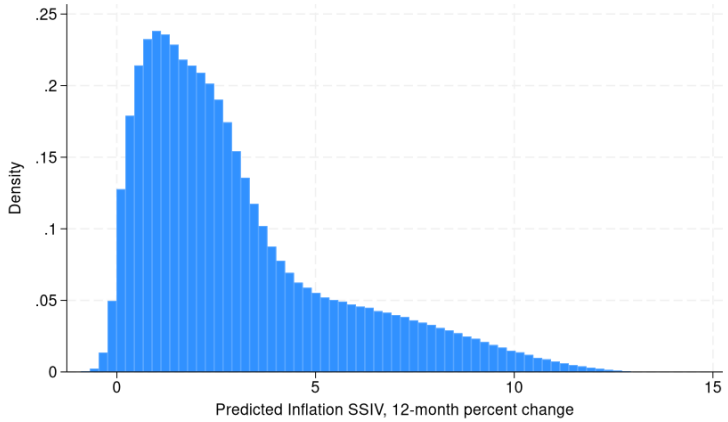
Figures A6 and A7 characterize the resulting shift–share predicted inflation instrument. Figure A6 plots the time series, which closely tracks the aggregate food inflation pattern: relatively stable through 2020, accelerating sharply in 2021–2022, peaking in mid-2022, and then declining in 2023. This validates that the instrument captures the broad inflationary episode. Figure A7 shows the distribution of predicted inflation across household-month observations, revealing substantial cross-sectional variation that stems from differences in households' 2019 consumption baskets interacted with differential price movements across product categories.

Figure A6. Predicted Inflation Instrument.



Notes: Figure shows the time series of the shift-share predicted inflation instrument, constructed using household-specific 2019 expenditure shares and national CPI inflation rates by product category. *Source:* NielsenIQ Consumer Panel, Bureau of Labor Statistics, and author's calculations.

Figure A7. Distribution of Predicted Inflation Instrument.



Notes: Figure shows the distribution of the shift-share predicted inflation instrument across household-month observations. The instrument is constructed using household-specific 2019 expenditure shares and national CPI inflation rates by product category. *Source:* NielsenIQ Consumer Panel, Bureau of Labor Statistics, and author's calculations.

C.5 Potential identification threats

Supply-side disruptions. First, national price shocks may be accompanied by supply-side disruptions that directly affect shopping behavior. For instance, if a category experiences both price increases and inventory issues/shortages, households might make additional trips to find substitute products, confounding the price effect with an availability effect. To

address this concern, I include county by month fixed effects, which absorb any regional supply shocks, retailer-level promotional strategies, or local economic conditions that correlate with national price movements. Identification therefore comes from comparing households within the same local market at the same time who differ in their exposure to national price shocks based on predetermined consumption patterns.

Retailer responses. Another identification concern is that national inflation shocks could correlate with changes in retailer behavior that directly facilitate or hinder search. For example, if categories with high inflation see retailers respond by increasing promotional intensity or reducing product variety, the instrument might capture these supply responses rather than pure demand-side search adjustments. Two features of my research design mitigate this concern. First, I argue the outcomes I examine (trips, store diversification, coupon usage) are primarily demand-driven and reflect household effort rather than retailer supply. Second, to the extent that retailer responses are common within a market, the county by month fixed effects absorb them. Any remaining variation comes from differential household exposure to national shocks, which is determined by pre-period shares that retailers cannot observe or target.

Feedback from Shopping to National CPI. One might worry that national CPI shocks are themselves endogenous to aggregate shopping behavior. If many households simultaneously reduce consumption of a category, this could both lower demand and raise relative prices (through general equilibrium effects), generating reverse causality issues. However, this concern is mitigated by the fact that the CPI category-level shocks I use are driven by national and often global factors (commodity prices, supply chain disruptions, weather shocks) that are plausibly orthogonal to the shopping behavior of any individual household in the NielsenIQ Consumer Panel. The share of national aggregate consumption represented by NielsenIQ panelists is small, so realistically their behavior cannot meaningfully influence national price dynamics.

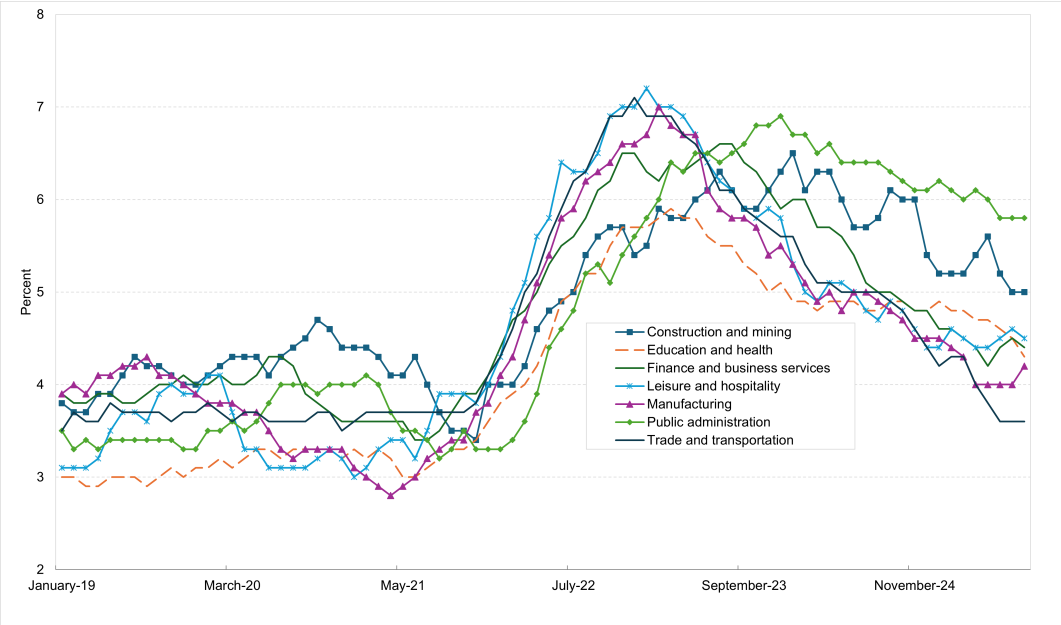
Differential search effort within categories. The exclusion restriction implicitly assumes that category-level inflation does not vary systematically for households exerting higher or lower shopping effort within a category. If households that search more intensively within a category also systematically face lower inflation in that category (because they

find better deals), and if this search intensity is itself correlated with the instrument, then the IV estimates could be biased. However, this concern is attenuated by the structure of the instrument. Because the shifts are at the national CPI level, they do not reflect individual household search effort. A household with a high egg share in 2019 faces the same national egg price shock as one with a low egg share, regardless of how much either household searches. The instrument generates variation in inflation exposure through the interaction of national shocks with predetermined shares, not through endogenous within-category search.

D Constructing Industry Matches and Monthly Nominal Wage Growth

This appendix describes how I infer each household's industry and attach monthly nominal wage growth from the Atlanta Fed Wage Growth Tracker (AFWGT) at the industry level. The Consumer Panel contains household-level broad occupation groups responses for the male and/or female head, some of which can be classified into an industry directly but the remainder contain too many unrelated occupations to do so. To translate those coarse occupation groups into an industry classification that is compatible with AFWGT, I target the industries used by AFWGT (Mining and logging; Construction; Manufacturing; Trade, transportation, and utilities; Information; Financial activities; Professional and business services; Education and health services; Leisure and hospitality; Other services; Government). AFWGT's Industry data reports month-over-month samples of year-over-year nominal wage growth for each of these industries (Figure A8). I ultimately assign to each household-month the growth rate for its predicted industry.

Figure A8. Atlanta Fed Nominal Wage Growth Across Industries.



Notes: Figure shows year-over-year nominal wage growth by industry from the Atlanta Fed Wage Growth Tracker.
Source: Federal Reserve Bank of Atlanta.

Using the American Community Survey (ACS) as labeled data, I estimate a simple multinomial logit that predicts a person's industry (the 11 used by AFWGT) from observables that also exist in my panel: age band, sex, education, employment intensity (hours), and the survey's broad occupation group. ACS NAICS codes are mapped to these industries to form the outcome. For each panel household and year, I run the model on the male and/or female head (when present), keep the head with the higher predicted probability, and record (i) the assigned industry and (ii) its predicted probability as a confidence measure. This yields one industry per household–year. AFWGT's "Industry" series reports monthly year-over-year nominal wage growth for each industry, which I assign to each household in each month.