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Geospatial Heterogeneity in Inflation: A Market Concentration Story

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Abstract: We study spatial heterogeneity in inflation across regions with different income levels and the role of retailer market structure. Using NielsenIQ Retail Scanner and Business Dynamics Statistics data, we document new stylized facts on food inflation and local retail concentration. From 2006 to 2020, poorer MSAs experienced annualized food inflation that was 0.46 percentage points higher than richer MSAs, implying a cumulative gap of 8.8 percentage points. Poorer areas also exhibit fewer products, fewer retailers, and higher market concentration. To identify causal effects, we exploit two exogenous cost shocks. We use the 2014–15 avian influenza outbreak in a triple-difference design and global coffee price fluctuations in a difference-in-pass-through design that interact cost shocks with local retail concentration. We develop a heterogeneous-firm model with customer capital accumulation that rationalizes these patterns. Firms with larger market shares accumulate more customer capital and market power, which leads to higher pass-through of cost shocks.

JEL classification: E31, I31, L11, L81, R12

Key words: inflation, retailer market structure, market concentration, market power, passthrough of cost shocks, spatial inequality

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1 Introduction

Inflation is a key economic indicator with broad implications for economic growth, stability, and household well-being. However, it is typically measured and analyzed at the national level.[1] As a result, both the literature and policy discussions often overlook heterogeneity in inflation rates across regions, potentially masking important local disparities.

Understanding local variation in food inflation is crucial for several reasons. Households across regions face different price changes and adjust their consumption accordingly.[2] Food markets are also more localized and segmented than many other sectors, with local market structures playing an important role in price variation.[3] Moreover, food is a necessity and accounts for a disproportionately large share of spending for low-income and vulnerable households.[4] Taken together, these factors suggest that spatial variation in food inflation can have meaningful implications for consumer welfare and spatial inequality, yet this dimension remains underexplored in the literature.

In this paper, we address this gap by documenting spatial heterogeneity in food inflation and examining the role of retailer market structure in driving this variation and its aggregate implications. Using NielsenIQ Retail Scanner data with granular detail at the 12-digit universal product code (UPC) level, we construct price indexes for disaggregated personal consumption expenditure (PCE) food items at the metropolitan statistical area (MSA) level and document novel facts on spatial heterogeneity in food inflation and retailer market structure. We then develop a novel identification strategy to establish the causal relationship between retailer market concentration and inflation, and build a model of heterogeneous retailers with customer capital to account for the mechanism underlying these findings.

We document several new stylized facts. First, we find that food inflation rates vary systematically across regions by income level: poorer MSAs experienced higher inflation than wealthier

[1] The Bureau of Labor Statistics (BLS) provides regional price indexes, but only for a limited subset of large metropolitan areas. They are restricted to 23 Core Based Statistical Areas (CBSA), which are mostly rich areas, including New York–Newark–Jersey City, Los Angeles–Long Beach–Anaheim, Chicago–Naperville–Elgin, San Francisco, Boston, Washington, etc. See more details from https://www.bls.gov/cpi/regional-resources.htm.

[2] In part, this reflects limited geographic mobility, as migration rates have declined since the 1980s (Kerns-D'Amore et al., 2022).

[3] In the NielsenIQ Consumer Panel, we find that 92% of households purchase food exclusively within their home MSAs. See Appendix A for details.

[4] Schanzenbach et al. (2016) report that low-income households spend nearly 20% of their total expenditures on food, compared to 13% for middle-income households and an even smaller share for high-income households, based on the Consumer Expenditure Survey.

MSAs between 2006 and 2020, with a cumulative gap of approximately 8.8 percentage points between the bottom and top income deciles. This pattern holds across both disaggregated and aggregated food categories and remains robust to two key restrictions: i) imposing a "common goods rule" that limits the sample to UPCs sold in all ten income deciles, and ii) applying uniform expenditure weights across deciles when constructing the index. Together, these results indicate that the documented inflation gap does not merely reflect differences in consumption baskets or product expenditure weights across regions.

Second, we find substantial regional variation in product varieties and retailer market structure. Richer areas offer more varieties of goods (UPCs) and have more stores and retail chains.[5] We also find systematic differences in retailer market structure across regions by income level. In NielsenIQ Retail Scanner data, we classify retailers as large or small based on total sales or national store counts—defining large (small) retailers as those in the top (bottom) decile. Poorer MSAs have a higher share of large retailers and a lower share of small ones, while the opposite holds in richer MSAs. These patterns are robust when using the Business Dynamics Statistics (BDS), where retailer size is defined by employment.[6] We also find that retail sales are lower and more concentrated in poorer areas.

We next investigate the relationship between inflation and retailer market structure. Baseline OLS estimates indicate that MSAs with higher market concentration are associated with higher inflation rates. However, this association does not necessarily imply causality. To identify a causal channel, we exploit two exogenous supply shocks in two distinct product markets: i) the 2014–2015 bird flu episode in the egg market with varying exposure across regions, and ii) variation in the commodity price of Arabica coffee, following Sangani (2024). In particular, the bird flu episode exhibits regional variation in exposure that can be leveraged for identification. Using a triple-difference framework, we compare inflation across MSAs with varying levels of market concentration. We find that MSAs with higher concentration—measured by sales-based Herfindahl–Hirschman Index (HHI)—experienced significantly higher inflation following the shock. Using a back-of-the-envelope calculation, we find that the egg inflation gap between the bottom and top income deciles from 2014Q4 to 2015Q3 was 14.5 percentage points, with approximately 64%

[5] Typically, the set of UPCs available in poorer regions is a subset of those found in richer areas. As a result, imposing the common goods rule across income deciles disproportionately reduces the set of UPCs in richer areas.

[6] Large retailers have 500 or more employees, while small retailers have 19 or fewer.

of this gap explained by differences in market concentration.

Furthermore, we find persistent pass-through of shocks over time. In MSAs with higher market concentration, inflation rose more during the inflationary phase of the shock (from 2014Q4 to 2015Q3), while prices adjust downward less during the subsequent deflationary phase (after 2015Q3). This suggests that temporary shocks can have lasting effects on regional inflation, contributing to long-run spatial disparities in inflation and thus potentially amplifying real income inequality. We also rule out alternative explanations based on differences in consumption baskets, retailer composition, and other cost factors. In addition, we find consistent evidence of greater cost pass-through in more concentrated MSAs in the coffee market.

Lastly, to account for the empirical findings, we develop a model of heterogeneous firms with customer capital by extending Atkeson and Burstein (2008) and incorporating customer capital accumulation as in Foster et al. (2016a). In the model, firms with larger sales shares obtain a higher level of customer capital and markups. Consequently, sufficiently large firms pass-through cost shocks more aggressively, as the marginal loss of customer capital is small and demand becomes less elastic with respect to own-price changes. Markets with higher concentration have higher aggregate markups, exhibit larger increases in aggregate prices following a cost shock, and sustain elevated price levels afterward. This mechanism implies that market concentration amplifies welfare losses from market power in the presence of cost shocks and highlights a role for policies governing retailer market structure—such as competition and antitrust policy—in shaping the transmission of shocks to prices, markups, and consumer welfare.

These findings have important distributional and policy implications as retail food markets are highly local. Because food markets are highly localized and more segmented in poorer regions, higher food inflation has a direct and disproportionate effect on local consumer welfare. This effect is particularly pronounced for vulnerable and less mobile households in low-income communities, which devote a larger share of expenditures to food and face more limited access to alternative retailers and substitute goods. As a result, localized market segmentation combined with concentrated retail structures disproportionately burdens consumers in poorer regions.

Moreover, when real income is evaluated using locally constructed food price indexes, real income inequality widens substantially relative to measures based on national price indexes. National price indexes understate inflation in poorer regions. This highlights a key limitation of national inflation measures and underscores the importance of accounting for regional variation in both inflation and market structure when evaluating welfare and designing policies to mitigate the unequal effects of inflation.

Related Literature. This paper contributes to several strands of literature. First, our work relates to the literature on inflation heterogeneity across different groups. Hobijn and Lagakos (2005) and Hobijn et al. (2009) document inflation differences across demographic groups in Consumption Expenditure Survey (CEX) data. Kaplan and Menzio (2015) and Kaplan and Schulhofer-Wohl (2017) show that low-income and old households face higher inflation even for the same bundle of goods in NielsenIQ data.[7] Jaravel (2018) finds similar results with emphasis on the role of product innovation and segmented consumption goods. Argente and Lee (2021) find lower inflation faced by high-income households during the recession with greater substitution toward lower-quality goods. Handbury (2021) documents that products and prices vary by local income-specific tastes, and Molloy (2024) documents lower shelter inflation for poorer households but similar overall inflation with a higher housing expenditure share. This literature focuses primarily on household-level heterogeneity and consumer-side mechanisms, such as basket composition, preferences, and search behavior. In contrast, we document regional heterogeneity in inflation across MSAs with different income levels and identify retailer market structure as a novel source of inflation variation.

Another closely related strand of literature examines retailer market concentration and market power. A large body of work documents rising retailer concentration and the growing role of national chains (Jarmin et al., 2009; Haltiwanger, 2012; Hortaçsu and Syverson, 2015; Foster et al., 2016b; Cao et al., 2024; Smith and Ocampo, 2025). In contrast, Rossi-Hansberg et al. (2021) and Benkard et al. (2021) find declining concentration in either local markets and narrowly defined product markets, respectively. Other papers estimate retailer markups and their heterogeneity, linking them to city size (Hottman, 2017), local housing prices (Stroebel and Vavra, 2019), household search behavior (Sangani, 2022), and changes in marginal costs and price sensitivity (Döpper et al., 2025). Mongey and Waugh (2025) develop a model in which sorting of households with heterogeneous elasticities generates cross-firm variation in market power and markups. Our paper contributes to this literature by documenting systematic variation in retailer market concentration across MSAs

[7] O'Flaherty (2026) documents how large the dispersion in relative price changes are between households even for the same product.

with different income levels and by establishing a causal link between concentration and inflation.

Our paper also contributes to the literature on pass-through of shocks to prices and inflation. Prior work studies pass-through of demand shocks (Arcidiacono et al., 2020; Gagnon and López-Salido, 2020; Handbury and Moshary, 2021) and supply shocks, including tax changes (Cawley et al., 2018, 2020; Baker et al., 2020; Butters et al., 2022), wholesale cost fluctuations (Nakamura and Zerom, 2010), and commodity price changes in coffee (Sangani, 2024). We differ by exploiting a sharp and temporary exogenous supply shock—the 2014–2015 avian influenza (bird flu) outbreak in the U.S. egg market—which exhibits substantial regional variation in exposure. This setting allows us to identify heterogeneous pass-through across MSAs with different levels of market concentration. We are among the first to provide causal evidence on inflation heterogeneity by linking regional differences in market concentration to differential pass-through of shocks. We further propose a customer-capital mechanism underlying this pattern: larger firms in concentrated markets hold greater market power and internalize the dynamic value of their customer base differently, which alters their incentives to pass through cost shocks.[8]

Lastly, our study contributes to the literature using item-level data to construct more accurate inflation measures (Ehrlich et al., 2023), which can outperform official indices in capturing true cost-of-living changes (Handbury et al., 2013). We construct regional price indices at the MSA level, similar to Handbury and Weinstein (2014) and Diamond and Moretti (2022), to better capture spatial heterogeneity in inflation.[9] In contrast, official indices are typically national and expenditure-weighted, or regional but limited to larger and wealthier areas. As a result, poorer regions tend to be underrepresented due to lower aggregate spending and more limited coverage. This concern echoes Martin (2024), who highlights that expenditure-weighted indices may systematically understate inflation in poorer areas—especially when price dynamics vary across regions. Our regional indices provide a more representative measure of local inflation and, therefore, real income inequality. We find that poorer areas experience higher food inflation, which widens real income disparities relative to nominal differences.[10]

[8]This mechanism is closely related to Kleshchelski and Vincent (2009), Foster et al. (2016a), and Paciello et al. (2019).

[9]Unlike Handbury and Weinstein (2014), we do not remove heterogeneity bias nor variety bias to best reflect the consumption basket of households.

[10]This contrasts with Moretti (2013), who finds that real wage inequality is lower than nominal inequality, likely reflecting differences in goods coverage and geographic scope. Our analysis focuses on food prices using highly granular UPC-level data.

The rest of the paper is organized as follows. Section 2 describes the data and key measures. Section 3 presents stylized facts on spatial heterogeneity in food inflation and retailer market structure. Section 4 outlines the empirical strategy for causal inference and presents the main empirical results, Section 5 provides a theoretical framework and the underlying mechanism, and Section 6 concludes.

2 Data and Measures

The primary dataset we use to analyze heterogeneous inflation rates across regions is the NielsenIQ Retail Scanner dataset. The NielsenIQ dataset enables us to measure inflation rates and retailer market structure across regions by analyzing sales, price, and store distribution data from retailers for food products. As a secondary dataset, we use the Business Dynamics Statistics (BDS) and test the robustness of our findings by using alternative definitions of retailer size based on employment.

2.1 NielsenIQ Retail Scanner

Our analysis uses the Retail Measurement Services (RMS) dataset provided by the Kilts Center at Chicago Booth. This dataset includes weekly pricing, volume, and store merchandising data from over 100 retail chains across U.S. markets, covering more than 40,000 individual stores. Total sales in the NielsenIQ RMS sample exceed $200 billion annually, representing 50% of grocery store sales, 55% of drug store sales, 32% of mass merchandiser sales, and 2% of convenience store sales.

A key advantage of this dataset is that it contains detailed information at the finest product level, 12-digit universal product codes (UPCs) that uniquely identify specific goods.[11] The dataset contains over 2.6 million UPCs. Furthermore, NielsenIQ classifies UPC-level goods by 10 departments, 110 product groups, and over 1,000 product modules.

We further use a concordance provided by the U.S. Bureau of Labor Statistics (BLS) that maps NielsenIQ product modules to BLS entry level items (ELIs).[12] These ELIs then map to Personal Consumption Expenditure (PCE) disaggregated categories. Our analysis focuses on the food sector,

[11] For example, two cans of Campbell's tomato soup in different sizes would be classified as two different UPCs.

[12] ELIs are the most granular complete mutually exclusive classification of CPI items produced by the BLS. We were provided this concordance as part of the Re-Engineering Statistics using Economic Transactions (RESET) project.

Table 1: Examples of MSA Deciles

Decile	MSA
1 (lowest)	El Paso (TX), Albany (GA), Yuma (AZ), etc.
5	Knoxville (TN), Panama City (FL), Binghamton (NY), etc.
10 (highest)	New York (NY), Washington (DC), Boston (MA), etc.

Note: The table provides some examples of MSAs located in the deciles 1, 5, and 10. These deciles are time invariant in our setting and are based on income per capita data from the BEA, averaged over the period 2006-2020.

which is identified as the aggregation of 21 PCE food categories, spanning from 2006Q1 to 2020Q3. The following lists these 21 categories: Bakery, Beef and Veal, Beer, Cereal, Coffee, Dairy, Eggs, Fats and Oil, Fish, Fruits, Milk, Other Foods, Other Meats, Pork, Poultry, Processed Fruits and Vegetables, Soda, Spirits, Sugar and Sweets, Vegetables, and Wine.

To construct our main dataset from NielsenIQ, we start with the raw data at the weekly-store-UPC level and link it to personal income data at the MSA level from the U.S. Bureau of Economic Analysis (BEA) based on store location information in NielsenIQ.[13] We then define income deciles by the cross-time average of MSA-level income per capita. Table 1 reports examples of cities in the top, median, and bottom income deciles.

The price data is aggregated to the monthly frequency using the National Retail Federation (NRF) calendar and then aggregated to the quarterly frequency.[14] Using the concordance between product modules and PCE food categories, we identify the food sector in NielsenIQ. Finally, to measure retailer market structure and the degree of competition, we link store identifiers to retail chain identifiers using a crosswalk provided by NielsenIQ.

Our main analysis is at the MSA (or income decile)-food category-quarter level. We generate price indexes, the Herfindahl-Hirschman Index (HHI) of sales concentration, the share of top retailers, and other statistics associated with market structure for each MSA (or income decile)–food category–quarter combination.

[13]Note that our baseline analysis relies on the MSA location of retailer stores in NielsenIQ. Potential concerns about this measure arise if an MSA is broad enough to encompass consumers who move across MSAs, potentially creating a gap between consumer income and that of residents. To address this, we leverage the NielsenIQ Consumer Panel data to examine the fraction of households shopping outside their residential MSAs and explore their characteristics. Additionally, we compare two definitions of income deciles, one based on consumer MSAs and the other based on household MSAs. More details are provided in Appendix A, which help address potential concerns.

[14]The NRF calendar typically starts in early February and ends around the end of January of the following year.

2.2 Business Dynamics Statistics (BDS)

The Business Dynamics Statistics (BDS) is a public version of administrative Census firm-level data. The data provide annual measures of business dynamics in the U.S., such as job creation and destruction, establishment births and deaths, and firm entry and exit. These data are provided for the economy overall as well as for aggregates defined by establishment or firm characteristics such as firm size and age. Furthermore, the data provide sectoral- and geographic-level information, which allows us to track business dynamics at the sector, state, county, and MSA levels.[15] In the BDS, we focus on the retail trade sector (NAICS 44-45) and construct alternative measures for retailer size and market structure at the MSA level.[16] To be consistent with the NielsenIQ, we focus on the period of 2006-2020 in the BDS.

2.3 Main Measures

2.3.1 Price Indexes

To measure and compare food inflation rates across regions with different income levels, we construct price indexes either at the MSA level or by income deciles, using UPC-level data from NielsenIQ. As a starting point, we adopt a traditional price index to measure inflation based, the log geometric Laspeyres price index, which is calculated as follows:

$$\ln \Psi_{mt}^{G} = \sum_{k \in \mathbb{C}_{m,t-1,t}} \omega_{mkt} \ln \frac{p_{mkt}}{p_{mkt-1}}, \tag{1}$$

where ω_{mkt} represents the weight assigned to product k in quarter t for MSA (or income decile) m, and we use lagged expenditure shares as weights, e.g., $\omega_{mkt} = s_{mkt-1}$. The set $\mathbb{C}_{m,t-1,t}$ includes all "continuing" goods, defined as products sold in both periods t and $t-1$ in MSA (or income decile) m.[17]

We also construct two alternative price indexes: i) one by restricting the sample to UPCs that are sold in all ten income deciles in both consecutive quarters $t-1$ and t, referred to as "common

[15]See more details at https://www.census.gov/programs-surveys/bds.html.

[16]Note that NAICS code 44–45 is more aggregated than ideal for our purposes, but it is the most disaggregated level available in the BDS.

[17]To assess the representativeness of NielsenIQ, we compare our price indices with the official CPI series for the MSAs available in the CPI data. See more details in Appendix B.

goods," and ii) another restricting the sample to common goods and applying common weights across deciles. Specifically, we impose $\omega_{mkt} = \omega_{kt}$ for all deciles m, where the weights are fixed to the lagged expenditure shares in the bottom income decile. This approach accounts for the fact that consumption baskets can differ systematically between income groups, as documented in Jaravel (2018), and consequently between regions with different income levels. By focusing on a common set of goods and applying common weights, we move closer to isolating regional inflation differences that are not driven by variation in the composition of consumption baskets.

In addition, we conduct a robustness test using alternative demand-based indexes based on the constant elasticity of substitution (CES) preference assumption, to account for potential substitution bias inherent in traditional indexes.[18] See more details in Appendix C.1.

2.3.2 Retailer Market Structure

In NielsenIQ data, we use store and retailer codes along with geographic information for each store, and identify stores, retailers, and their ownership structures across regions and time. We define the size of retailers based on either total sales or the number of stores they own at the national level. We classify large chains as those in the top decile and small chains as those in the bottom decile of the national size distribution.

Alternatively, using the BDS, we define large and small retailers based on their number of employees at the national level. Large retailers are those with 500 or more employees, while small retailers have 19 or fewer employees. We then calculate the share of large and small firms within each MSA and compare these shares across different income deciles.

Finally, we use the local HHI of retailer sales as our main measure of market concentration in each MSA.[19] Alternatively, we use the sales share of the top one or three retailers within an MSA. Table 2 provides summary statistics for the main sample.

[18] The traditional indexes do not account for demand effects that may arise from consumers substituting between differentiated goods.

[19] As emphasized by Covarrubias et al. (2020) and Syverson (2019), market concentration remains an imperfect proxy for market power. This consideration motivates our reliance on natural experiments for causal identification (Section 4) and on a theoretical framework (Section 5) to discipline the interpretation of our results.

Table 2: Summary Statistics of the Main Sample (MSA-Quarter Level)

	Mean (SD)		Mean (SD)
Income per capita ($ thousands)	42.49 (9.29)	Share of Large Chains (top sales decile)	0.357 (0.11)
Sales ($ millions)	207.23 (366.62)	Share of Small Chains (bottom sales decile)	0.016 (0.04)
Population Share	0.005 (0.01)	Share of Large Chains (top store# decile)	0.619 (0.16)
Sales Share of Chains	0.117 (0.04)	Share of Small Chains (bottom store# decile)	0.008 (0.03)
Number of Chains	9.74 (3.71)	Market Concentration (HHI)	0.416 (0.18)
Number of Stores	193.84 (251.38)	Market Concentration (CR1)	0.534 (0.19)
Number of UPCs	49180.16 (18954.19)	Market Concentration (CR3)	0.817 (0.12)
Observations	11,100	Observations	11,100
Number of MSAs	185	Number of MSAs	185
Number of Quarters	60	Number of Quarters	60

Note: The table provides the summary statistics of the main MSA-level sample for the aggregate food and beverages in NielsenIQ. The population share is defined as the fraction of total population in an MSA. The sales share of chains is the average retailer-level sales share within an MSA, and the number of chains, stores, and UPCs is defined as the average number of chains, stores, and UPCs within an MSA. Large (small) chains are defined as those in the top (bottom) decile of the national distribution of total sales or store counts in a given quarter, and we compute the share of large or small chains within an MSA. Market concentration is measured using either the HHI of chain-level sales or the sales share of the top one or three retailers (CR1 or CR3) within an MSA.

3 Spatial Heterogeneity in Inflation and Market Structure

3.1 Price and Inflation Patterns

Figure 1 presents the geometric Laspeyres price index for aggregated food, constructed from the NielsenIQ Scanner data by income decile. We report results for the first (poorest), fifth, and tenth (richest) income deciles, alongside the official PCE food price index for comparison. The base quarter is set to 2006Q2.[20]

[20] Price indexes are constructed using price and expenditure information from both periods t and $t-1$. Therefore, 2006Q2 is the first quarter for which we are able to estimate a price index.

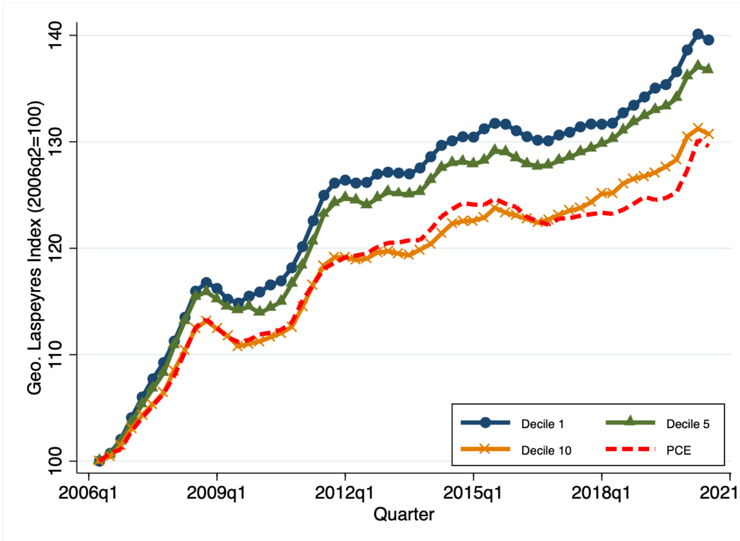

Figure 1: Price Index for Aggregated Food

Notes: This figure represents the chained geometric Laspeyres price index constructed using NielsenIQ Scanner data (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for aggregate food and beverages. The sample period runs from 2006Q2 to 2020Q3, and all series are normalized to the initial quarter. Each solid line corresponds to an income-per-capita decile of MSAs, where decile 1 includes MSAs with the lowest income per capita and decile 10 includes those with the highest income per capita. NielsenIQ UPCs are mapped to the PCE definition of food purchased for off-premises consumption using a product module concordance provided by the U.S. Bureau of Labor Statistics.

The general trend in the figure indicates that the poorest decile ("Decile 1") experiences consistently higher food price growth than the richer deciles ("Decile 5" and "Decile 10"). On average, annualized food inflation is approximately 0.46 percentage points higher in MSAs in the bottom income decile compared to MSAs in the top income decile. Over the sample period, this corresponds to a cumulative inflation gap of nearly 8.8 percentage points between the poorest and richest deciles.

This pattern continues to hold even when we restrict the sample to the set of common goods sold across all income deciles in consecutive quarters $t-1$ and t, and when we apply uniform sales weights. The result is shown in the left and right panels in Figure 2, respectively. These results suggest that the observed variation in price growth across income deciles is not primarily driven by differences in consumption baskets, their composition, or consumer preferences across regions.

These patterns are also robust to alternative price measurement approaches, including those based on demand-based price index and MSA-level price index, and to other disaggregated PCE food categories. More details are provided in Appendix C.1 and C.2.

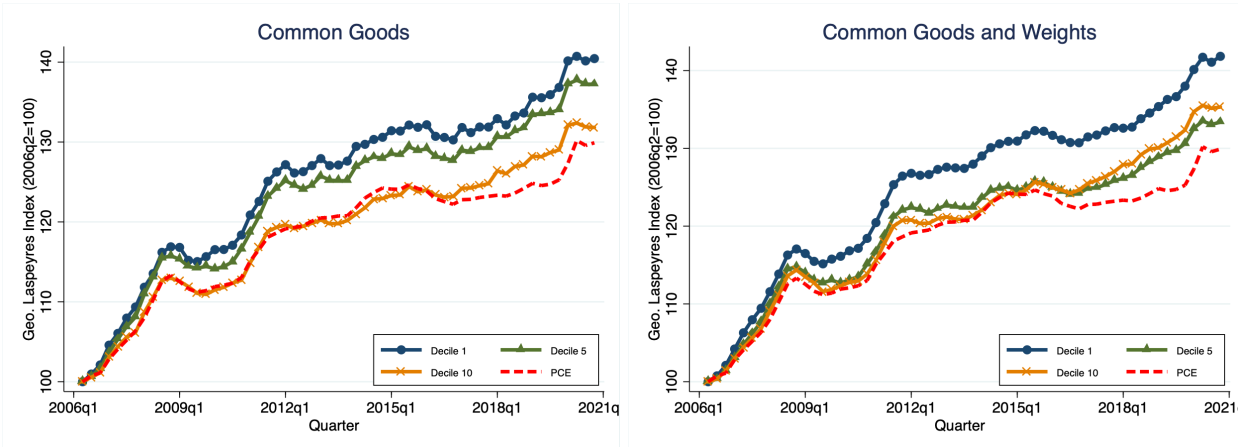

Figure 2: Price Index for Aggregated Food (Common Goods and Weights)

Notes: This figure represents the chained geometric Laspeyres price index constructed using NielsenIQ Retail data (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for aggregate food and beverages. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are restricted to the set of goods present across all ten deciles in quarters $t-1$ and t (named "common goods") in the left panel, and are restricted to these common goods and further based on the same sales weights in decile 1 in the right panel.

Lastly, the official PCE series aligns more closely with the NielsenIQ series for the highest income decile than for any other decile. This suggests that the official PCE price index series understates inflation to the largest extent for individuals living in the poorest areas. This discrepancy in inflation has significant macroeconomic implications. For example, if we assume uniform nominal wage growth across the United States, official national real wage growth would be systematically higher than real wage growth experienced in the poorest areas.

3.2 Retailer Market Structure

We examine retailer market structure across regions with different income levels. Using the MSA-level NielsenIQ sample, we compute summary statistics by income-per-capita decile. Table 3 reports the results, showing that richer areas have more retailers and stores, higher total sales, but lower retailer-level sales shares. In contrast, poorer areas offer fewer UPCs and allocate a larger share of total consumption—both in quantities and expenditures—to the set of common goods: common goods account for 31 percent of aggregate food consumption in the richest decile, 45 percent in the median decile, and 61 percent in the poorest decile.

We next run the following regression to examine the cross-sectional variation in retailer market

Table 3: Summary Statistics of the Main Sample (MSA-Quarter Level) by Income Deciles

	Decile 1	Decile 5	Decile 10
	Mean (SD)	Mean (SD)	Mean (SD)
Income per capita	31.615	39.010	56.733
($ thousands)	(4.876)	(4.994)	(11.793)
Sales	24.639	73.501	773.676
($ millions)	(18.431)	(74.623)	(748.232)
Population Share	0.001	0.002	0.019
	(0.001)	(0.001)	(0.022)
Sales Share of Chains	0.152	0.132	0.084
	(0.049)	(0.040)	(0.027)
Number of Chains	7.267	8.261	13.291
	(2.440)	(2.447)	(4.901)
Number of Stores	58.788	91.243	535.664
	(41.002)	(75.342)	(490.807)
Number of UPCs	32.368	40.419	70.980
(thousands)	(12.131)	(13.292)	(22.167)

Note: The table provides the summary statistics of the main MSA-level sample for the aggregate food and beverages for three income-per-capita deciles: 1, 5, and 10. The population share is defined as the fraction of total population in an MSA. The sales share of chains is the average retailer-level sales share within an MSA, and the number of chains, stores, and UPCs is defined as the average number of chains, stores, and UPCs within an MSA.

structure across MSAs with different income levels:

$$Y_{mt} = \beta_0 + \beta_1 Income_{mt} + \delta_t + \varepsilon_{mt}, \tag{2}$$

where Y_{mt} is either sales, total count of chains or stores, the share of large retailers (defined by the top decile of total sales or store counts at the national level), or market concentration (measured by the HHI of retail chain sales) in MSA m in quarter t. $Income_{mt}$ is income per capita in MSA m, and δ_t is a quarter fixed effect.

The results, presented in Table 4, confirm the cross-sectional patterns that poorer areas have lower sales, fewer retailers and stores, a higher fraction of large retailers, and higher market concentration. These results suggest that retailer market structure varies across regions with different income levels. In particular, retailer market concentration is higher in poorer areas, where a larger share of sales is dominated by larger firms.

We confirm robustness by using alternative measures of market concentration based on the sales

Table 4: Retailer Market Structure across Regions with Different Income Levels

	Sales (in \$1mil.)	Chain#	Store#	Large Firm% (Sales)	Large Firm% (Store)	HHI
Income	26.37***	0.192***	16.43***	-0.002***	-0.009***	-0.004***
	(5.876)	(0.039)	(3.928)	(0.001)	(0.002)	(0.001)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,100	11,100	11,100	11,100	11,100	11,100

Note: The table presents regression results from equation (2), using the main sample in NielsenIQ. The coefficient of interest is on income per capita (in \$1000) in an MSA for a given quarter. The dependent variable is total sales in Column 1, the total count of chains in Column 2, the total count of stores in Column 3, the share of large retailers in Columns 4-5, where large firms are defined as the top decile of the national distribution of either total sales (Column 4) or the number of stores (Column 5), and the sales HHI in Column 6. Quarter fixed effects are included. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

shares of the top firms (CR1 and CR3) and by controlling for MSA-level population. The results are reported in Appendix D.1. We further examine the long-run cross-sectional relationship using MSA-level averages over the sample period.[21] The long-run patterns are consistent with the baseline findings, as presented in Appendix D.2. We also obtain consistent results using the BDS dataset, as shown in Appendix D.3.

3.3 Relationship between Inflation and Market Concentration

To explore spatial heterogeneity in inflation across regions with different income levels and degrees of market concentration, we run the following regression:

$$P_{mt} = \beta_0 + \beta_1 X_{mt} + \delta_t + \varepsilon_{mt}, \tag{3}$$

where P_{mt} is the geometric Laspeyres inflation rate of aggregate food in MSA m in quarter t. X_{mt} is either the HHI of retailer sales or income per capita in MSA m in quarter t, and δ_t is a quarter fixed effect.

Table 5 reports the baseline results in Columns 1–3. Columns 1 and 2 show that inflation is higher in MSAs with greater market concentration and lower income. Column 3 indicates that market concentration is the primary driver of inflation differentials, as its coefficient remains large

[21] Using MSA fixed-effect estimates yields the same results.

Table 5: Food Inflation across Regions

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.328***		0.302***	0.331**	0.323**
	(0.107)		(0.110)	(0.131)	(0.002)
Income		-0.005**	-0.003		-0.004**
		(0.002)	(0.002)		(0.002)
Chain #				0.000	0.005
				(0.009)	(0.008)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	10,730	10,730	10,730	10,730	10,730

Note: The table presents regression results from equation (3), using the main sample in NielsenIQ. The coefficient of interest is on HHI and income per capita (in $1000) in an MSA for a given quarter. The dependent variable is the geometric Laspeyres inflation rate (%) of aggregate food in an MSA for a given quarter. Total number of chains is included as a control in the last two columns. Quarter fixed effects are included in all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

and significant while the income effect attenuates when both variables are included. Columns 4 and 5 add controls for the total number of retail chains in an MSA, which may mechanically affect concentration, and the results remain robust.

We conduct additional robustness checks using alternative measures of market concentration, adding population controls, and examining the long-run relationships among these variables. We also employ the geometric Laspeyres price index as an alternative measure of cumulative price differences. The corresponding results are reported in Appendix E.1, E.2, and E.3, all of which confirm robustness. Finally, we show that the same pattern holds in the egg market in Appendix E.4, which motivates the causal analysis in Section 4.

4 Causal Link between Inflation and Market Concentration

To study the causal relationship between inflation and retail market concentration, we focus on the egg and coffee markets. In the egg market, we exploit a novel quasi-experiment based on the 2014–2015 avian influenza outbreak and implement a triple-difference design to estimate heterogeneous pass-through across MSAs with different levels of concentration. In the coffee market, we estimate the pass-through of Arabica coffee commodity price changes to U.S. retail coffee prices, following Sangani (2024), and examine how it varies with the degree of local retail market concentration.

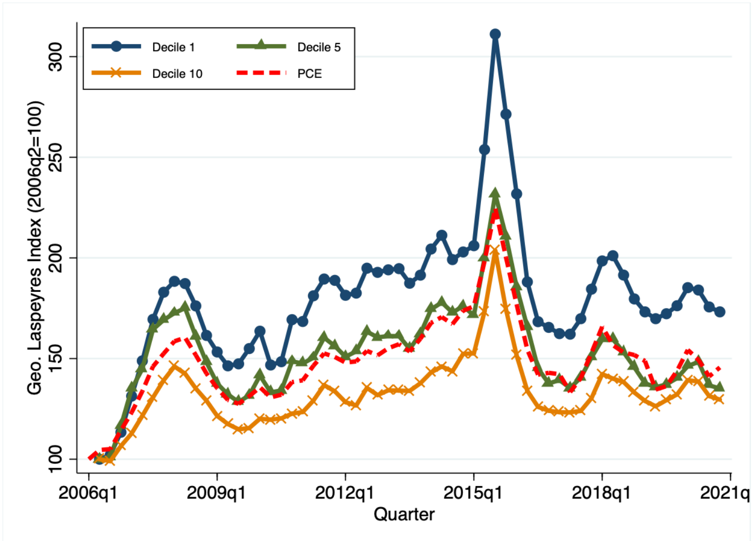

Figure 3: Price Index for Eggs

Notes: This figure represents the chained geometric Laspeyres price index constructed in NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for eggs. The sample period runs from 2006Q2 to 2020Q3, and all series are normalized to the initial quarter. Each solid line corresponds to an income-per-capita decile of MSAs, where decile 1 includes MSAs with the lowest income per capita and decile 10 includes those with the highest income per capita. NielsenIQ UPCs are mapped to the PCE definition of food purchased for off-premises consumption using a product module concordance provided by the U.S. Bureau of Labor Statistics.

4.1 Pass-through of Bird Flu Shock in Egg Market

We use the 2014-2015 highly pathogenic avian influenza (bird flu) outbreak as an exogenous supply shock to the egg market. The 2014-2015 bird flu episode started in 2014Q4 and affected the price and quantities of eggs sold in this period. Based on U.S. Department of Agriculture (USDA) reports, 36 million layers (birds that lay eggs) were lost due to the bird flu by June 2015.[22] This reduction in egg supply caused a sharp spike in egg prices, as shown in Figure 3.

Importantly, reports from the USDA and the Government Accountability Office (GAO) indicate that the impact of the bird flu shock varied geospatially, primarily affecting the central and western U.S. Farmers in these parts of the country were more affected than farmers in other parts of the country in terms of their layers' vulnerability to the disease. We have access to official data from the USDA on the timing, location, and number of bird layers that were culled.[23] By identifying MSAs where layers were culled, we can pinpoint areas disproportionately affected by the bird flu,

[22]The USDA also compensated producers that had to cull their layers. Payment was based on "fair market" values as determined by USDA appraisers.

[23]See details from the following Congressional report: https://crsreports.congress.gov/product/pdf/R/R44114t.

which may have experienced higher inflation in egg prices early in the outbreak.[24,25]

4.1.1 Difference-in-Differences Estimation

Leveraging this information, we first pursue a difference-in-differences identification strategy, grouping treated and control MSAs and comparing the effect of the bird flu outbreak on egg inflation.

To measure whether exposure of local farmers to culling affected local egg prices, we use a two-year window around the start of the bird flu episode in 2014Q4, and run the following traditional two-way fixed effects regression from 2012Q4 to 2016Q4:

$$P_{mt} = \beta_0 + \beta_1(BirdFlu_m \times Post_t) + \delta_m + \delta_t + \varepsilon_{st}, \tag{4}$$

where P_{mt} is the geometric Laspeyres inflation rate for eggs in MSA m in quarter t, $BirdFlu_m$ is an indicator variable equal to one for MSAs in which farmers culled their layers during the 2014-2015 bird flu outbreak, according to the USDA data, and $Post_t$ is a binary variable equal to one in the post-shock period (after 2014Q4). δ_m and δ_t are MSA and quarter fixed effects, respectively. The coefficient on β_1 is expected to be positive during the inflationary phase of the bird flu episode, as these MSAs experienced a relatively larger cost shock.

The results are shown in Table 6. In Column 1, we estimate a statistically insignificant (i.e., null) effect, which suggests that these MSAs affected by the bird flu did not experience more aggregate egg price inflation. However, this null average effect masks substantial heterogeneity over time. When we separate the sample into inflationary and deflationary periods, when the national egg inflation rate is above or below zero, respectively, we observe opposing effects in the MSAs where layers were culled.[26] In Column 2, we restrict the sample to the inflationary period when the national egg inflation rate was above zero. Here, we estimate a coefficient of 0.039 on the interaction of Bird

[24] Based on the report, we identify the following list of impacted MSAs: Des Moines-Ames, Fargo-Valley City, Madison, Mankato, Minneapolis-St Paul, Omaha, Rochester-Madison City-Austin, Sioux City, Sioux Falls (Mitchell).

[25] Egg markets are generally local or regional in nature. For example, Cal-Maine Foods, the largest producer and marketer of eggs in the U.S., primarily operates in the Southern region and had no facilities near the affected MSAs in 2015 (Appendix F). We also check the robustness of our main findings by including additional neighboring MSAs around the impacted areas (Appendix G.3).

[26] The inflationary period includes the following ten quarters: 2012Q4, 2013Q1, 2013Q2, 2013Q4, 2014Q1, 2014Q2, 2014Q4, and 2015Q1–Q3. The deflationary period includes the following seven quarters: 2013Q3, 2014Q3, 2015Q4, and 2016Q1–Q4.

Table 6: Difference-in-Differences Estimator

	Inflation	Inflation	Inflation	Abs. Inflation
Bird Flu × Post	-0.003	0.039***	-0.035***	0.053***
	(0.004)	(0.008)	(0.007)	(0.006)
Sample Periods	All	Inflation	Deflation	All
Quarter FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Observations	3,145	1,850	1,295	3,145

Note: The table represents regression results from equation (4). The coefficient of interest is the interaction of Bird Flu and Post. Bird Flu is a binary variable that takes the value of one for MSAs in which egg farmers culled their layers during the 2014-2015 bird flu episode, and Post is a binary variable that takes the value of one in the post-shock period after 2014Q4. The sample period ranges from 2012Q4 to 2016Q4. Inflationary and deflationary periods are determined by the national price index of eggs. Inflation rate is the main outcome variable for Columns 1-3. Column 1 pools all periods together, Column 2 uses the inflationary period only, and Column 3 focuses on the deflationary period only. Column 4 pools all periods together and has the absolute value of the inflation rate as the outcome variable. MSA and quarter fixed effects are included. Standard errors are clustered at the MSA level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Flu and Post, which corresponds to a 3.9 percentage point higher egg inflation rate in MSAs affected by the bird flu after 2014Q4 during the inflationary period. This point estimate is significant at the 1% level. In Column 3, we restrict the sample to the deflationary period and find that MSAs that culled their layers experienced a 3.5 percentage point lower inflation (higher deflation) rate after 2014Q4 during the deflationary period. This point estimate is also significant at the 1% level. In Column 4, we pool all quarters and take the absolute value of inflation rate as the main dependent variable. We find that MSAs that culled their layers experienced 5.3 percentage point larger absolute changes in the inflation rate after 2014Q4. This coefficient is significant at the 1 percent level.

These heterogeneous inflation effects during the bird flu outbreak are illustrated in Figure 4. The left panel presents the standard event-study difference-in-differences estimates, with the dashed vertical line marking 2014Q4 as the start of the post period. Prior to 2014Q4, there is no systematic difference in inflation between treated MSAs (those that culled layers) and control MSAs, indicating no evidence of differential pre-trends. After 2014Q4, treated MSAs exhibit higher inflation in the initial quarters and then lower inflation in subsequent quarters, yielding an average effect close to zero over the full post period.

These opposing inflation effects reflect heterogeneity across inflationary and deflationary regimes

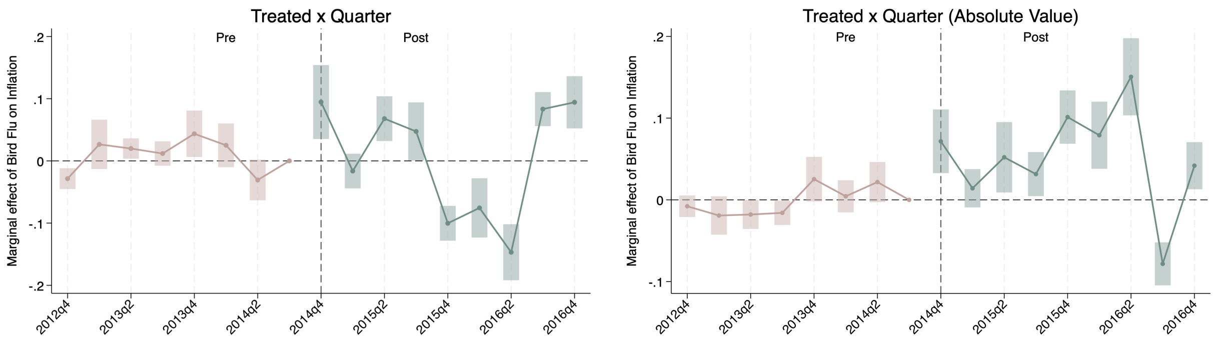

Figure 4: Event Study Difference-in-Differences (Bird Flu)

Notes: The figure presents the event-study difference-in-differences analysis of the differential effect of the 2014–2015 bird flu episode on egg inflation in MSAs whose farmers were directly affected. The outcome variable is egg price inflation in the left panel and its absolute value in the right panel. MSAs are assigned to the treatment group based on USDA reports identifying farms that culled layers. The post period begins in 2014Q4, with 2014Q3 as the reference quarter. Effects are estimated over the period 2012Q4–2016Q4. Standard errors are clustered at the MSA level.

in the egg market. The right panel of Figure 4 illustrates this pattern by using the absolute value of inflation as the outcome variable. Treated MSAs are consistently more affected after 2014Q4, while no significant differences are observed prior to the shock, further supporting the absence of differential pre-trends. The evidence indicates that the bird flu shock generated larger price increases in treated MSAs during inflationary period and larger price declines during deflationary period. This pattern holds in all post-period quarters except 2016Q3.

4.1.2 Triple-Difference Estimation

Next, we implement a triple-difference estimator to examine how the impact of the bird flu on egg inflation varies across treated MSAs with different degrees of market concentration (HHI). The following regression formalizes the identification strategy:

$$
\begin{aligned}
P_{mt} = \beta_0 &+ \beta_1(\text{Post}_t \times \text{HighHHI}_m) + \beta_2(\text{Post}_t \times \text{MidHHI}_m) \\
&+ \beta_3(\text{Bird Flu}_m \times Post_t) + \beta_4(\text{Bird Flu}_m \times \text{Post}_t \times \text{MidHHI}_m) \\
&+ \beta_5(\text{Bird Flu}_m \times \text{Post}_t \times \text{HighHHI}_m) + \delta_m + \delta_t + \varepsilon_{mt}, \qquad (5)
\end{aligned}
$$

where subscript m indexes MSAs and t indexes quarters. BirdFlu$_m$ and Post$_t$ are defined the same as before. We classify MSAs into terciles based on the distribution of egg-market sales concentration

Table 7: Triple Difference Estimator (Eggs)

	Inflation	Inflation	Inflation
Bird Flu × Post × HighHHI	0.023***	0.047***	0.015
	(0.006)	(0.014)	(0.012)
Bird Flu × Post × MidHHI	0.003	0.023**	-0.005
	(0.009)	(0.010)	(0.016)
Bird Flu × Post	-0.012**	0.016**	-0.038***
	(0.005)	(0.008)	(0.005)
Post × HighHHI	-0.003	-0.002	-0.002
	(0.002)	(0.004)	(0.006)
Post × MidHHI	0.000	0.000	0.002
	(0.002)	(0.004)	(0.006)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	3,145	1,850	1,295

Note: The table represents regression results from equation (5). The coefficient of interest is the interaction of Bird Flu, Post, and High HHI. Bird Flu is a binary variable that takes the value of one for MSAs in which egg farmers culled their layers during the 2014-2015 bird flu episode, and Post is a binary variable that takes the value of one in the post-shock period after 2014Q4. High HHI is an indicator for the top tercile MSAs, and Mid HHI is an indicator for the mid tercile MSAs in the distribution of sales HHI in 2014Q3. The sample period ranges from 2012Q4 to 2016Q4. Inflationary and deflationary periods are determined by the national price index of eggs. Column 1 pools all periods together, Column 2 only considers the inflationary period, and Column 3 only considers the deflationary period. MSA and quarter fixed effects are included across all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

(HHI) in 2014Q3. The bottom tercile (LowHHI) comprises the one-third of MSAs with the lowest HHI and serves as the reference group.[27] HighHHI_m is an indicator for the MSAs in the top tercile, and MidHHI_m is an indicator for those in the middle tercile. P_{mt} denotes the geometric Laspeyres quarterly inflation rate for eggs in MSA m in quarter t. MSA and quarter fixed effects, δ_m and δ_t, are included as before, and ε_{mt} is the error term.

The results are presented in Table 7. Column 1 pools all quarters within the two-year window and shows that, among treated MSAs, those in the top tercile of retail market concentration experience 2.3 percentage points higher inflation, on average, than those in the bottom tercile. This effect is statistically significant at the 1% level. Columns 2 and 3 decompose this effect into the inflationary

[27] We fix HHI to its 2014Q3 value, the quarter preceding the outbreak, to mitigate endogeneity concerns and isolate the effect of the supply shock on price dynamics. Results are robust to fixing HHI to its two-year average over 2012Q4–2014Q3.

and deflationary periods, respectively. Restricting the sample to the inflationary period, Column 2 shows that treated MSAs in the top tercile exhibit 4.7 percentage points higher inflation, on average, than treated MSAs in the bottom tercile, significant at the 1% level. In contrast, Column 3 shows no evidence that highly concentrated treated MSAs experience larger price declines during the deflationary period. The estimated effect is positive but statistically insignificant, suggesting persistence in the initial inflationary response. These results are robust to using a continuous measure of HHI (Appendix G.1), to alternative measures of market concentration such as CR1 and CR3 (Appendix G.2), and to including neighboring MSAs around treated markets (Appendix G.3).

Furthermore, to assess whether these results are economically meaningful, we conduct a back-of-the-envelope calculation to quantify how much of the inflation gap between the poorest and richest deciles can be attributed to differences in market concentration (Appendix H.1). We also examine aggregate implications for real income inequality (Appendix H.2).

4.1.3 Robustness Checks

A potential concern is that the higher inflation observed in poorer regions with greater market concentration may be partially driven by differences in consumption baskets. As discussed in Section 2, poorer areas have access to fewer products than richer ones. To address this issue, we re-estimate the triple-difference specification at a more granular level, using UPC–MSA–quarter observations. The dependent variable is the log change in UPC-level egg prices, and we estimate the following regression:

$$\begin{aligned}\Delta \ln price_{umt} = \beta_0 &+ \beta_1(\text{Post}_t \times \text{HighHHI}_m) + \beta_2(\text{Post}_t \times \text{MidHHI}_m) \\ &+ \beta_3(\text{Bird Flu}_m \times Post_t) + \beta_4(\text{Bird Flu}_m \times \text{Post}_t \times \text{MidHHI}_m) \\ &+ \beta_5(\text{Bird Flu}_m \times \text{Post}_t \times \text{HighHHI}_m) + \delta_u + \delta_m + \delta_t + \varepsilon_{umt},\end{aligned} \tag{6}$$

where $\Delta \ln price_{umt}$ denotes the log change in the price of UPC u in MSA m between quarters $t-1$ and t. The UPC fixed effects, δ_u, ensure that identification comes from price changes within identical products across MSAs. All other variables are defined as in the baseline specification.

Table 8 reports the UPC-level results. In Column 1, pooling all quarters, we find that following the bird flu shock, egg prices in exposed MSAs in the highest concentration tercile increased by

Table 8: Triple Difference Estimator (Eggs, UPC-level)

	$\Delta \ln$ Price	$\Delta \ln$ Price	$\Delta \ln$ Price
Bird Flu × Post × HighHHI	0.010***	0.020***	-0.007
	(0.004)	(0.006)	(0.008)
Bird Flu × Post × MidHHI	0.005	0.019***	-0.012
	(0.004)	(0.005)	(0.008)
Bird Flu × Post	-0.006*	0.000	-0.013*
	(0.003)	(0.005)	(0.007)
Post × HighHHI	-0.004***	-0.005	-0.002
	(0.002)	(0.003)	(0.003)
Post × MidHHI	-0.001	-0.003	0.002
	(0.002)	(0.003)	(0.004)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
UPC FE	Yes	Yes	Yes
Observations	145,989	84,418	61,470

Note: The table represents regression results from equation (6). The dependent variable is the log price difference of product u in MSA m between quarters $t-1$ and t. All descriptions remain the same as before, except that MSA, UPC, and quarter fixed effects are included across all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

an additional 1 percentage point relative to exposed MSAs in the bottom tercile within the same UPCs. This estimate is statistically significant at the 1 percent level. Restricting the sample to the inflationary period, Column 2 shows that the triple interaction for the highest HHI tercile remains positive and significant at the 1 percent level. Quantitatively, prices rose by an additional 2 percentage points in highly concentrated exposed MSAs relative to less concentrated exposed MSAs for identical egg products. In Column 3, focusing on the deflationary period, the estimated effect is statistically insignificant, suggesting persistence in the inflationary response rather than symmetric price reversals.

The UPC-level results are consistent with the main MSA-level findings in Table 7. The UPC-level evidence further strengthens the argument that the inflationary effects are driven by retailer market concentration rather than differences in consumption baskets. These results are also robust to using a continuous measure of HHI (Appendix G.1).

We also rule out additional alternative explanations for our main findings. In particular, we show that the results are not driven by differences in the composition of different retailer types

Table 9: Coffee price pass-through and retail market concentration across MSAs

	$\Delta \ln$ Price	$\Delta \ln$ Price	$\Delta \ln$ Price
$\Delta \log c_t$	0.073***	0.073***	0.050***
	(0.003)	(0.006)	(0.005)
MidHHI $\times \Delta \log c_t$	0.002	0.009	-0.008
	(0.005)	(0.009)	(0.009)
HighHHI $\times \Delta \log c_t$	0.013***	0.026***	-0.009
	(0.005)	(0.008)	(0.008)
MidHHI	0.001	-0.002	0.000
	(0.001)	(0.002)	(0.002)
HighHHI	-0.000	-0.005**	0.000
	(0.001)	(0.002)	(0.002)
Sample Periods	All	Positive Cost	Negative Cost
MSA FE	Yes	Yes	Yes
UPC FE	Yes	Yes	Yes
Observations	4,394,667	2,557,907	1,836,250

Notes: The table reports regression results from equation (7). The coefficient of interest is the interaction of High HHI and $\Delta \log c_t$. High HHI is an indicator for the top tercile MSAs, and Mid HHI is an indicator for the mid tercile MSAs in the distribution of sales HHI each quarter. The dependent variable is the log price difference of product u in MSA m between quarters t and $t+4$. Positive cost shock period contains quarters with positive log price changes, and negative cost shock period includes those with zero or negative log price changes. Column 1 pools all periods together, Column 2 only considers the positive-shock period, and Column 3 only considers the negative-shock period. The sample period ranges from 2006Q1 to 2020Q3. All specifications include UPC and MSA fixed effects. Standard errors are clustered at the MSA level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

(local versus regional versus national chains) or by differential wage growth in the retail sector; see Appendix G.4 and G.5, respectively.

4.2 Pass-through of Commodity Cost Shocks in Coffee Market

We provide consistent evidence in the coffee market by exploiting fluctuations in commodity prices, following Sangani (2024). Given that the United States does not produce a meaningful amount of coffee, we treat changes in the commodity price of Arabica coffee as exogenous to U.S. retail conditions. We measure the global price of coffee (Arabica) using the IMF Commodity Database.[28] Our identification strategy exploits time-series variation in global coffee prices. To control for differences in basket composition, we conduct analysis at the UPC-quarter-MSA level and include

[28] The IMF Series ID for coffee is PCOFFOTMUSDM.

UPC and MSA fixed effects. Specifically, we estimate the following regression:

$$\begin{aligned}\Delta \log p_{umt} = \beta_0 \, \Delta \log c_t + \beta_1 \, \text{MidHHI}_{mt} + \beta_2 \, \text{HighHHI}_{mt} \\ + \beta_3 \left(\Delta \log c_t \times \text{MidHHI}_{mt}\right) + \beta_4 \left(\Delta \log c_t \times \text{HighHHI}_{mt}\right) \\ + \alpha_u + \gamma_m + \varepsilon_{umt}, \end{aligned} \tag{7}$$

where $\Delta \log p_{umt}$ denotes the change in the log price of UPC u in MSA m between quarters t and $t+4$. We classify MSAs into terciles based on the distribution of coffee-market HHI in each quarter. As before, the bottom tercile (LowHHI) comprises the one-third of MSAs with the lowest HHI and serves as the reference group. $\Delta \log c_t$ corresponds to the log change in the global Arabica coffee price between quarters t and $t+4$. We estimate the regression with our pooled sample, for periods of positive cost shocks (quarters in which the global coffee price increases between t and $t+4$, with positive log price changes), and for periods of negative cost shocks (quarters in which the global coffee price weakly decreases over the same horizon, with zero or negative log price changes).

In Table 9, we report estimates of pass-through from global Arabica coffee prices to U.S. retail coffee prices. For the baseline group (LowHHI), a 1 percent increase in the global coffee price raises retail prices by 0.073 percent (Column 1). The estimated pass-through is 0.073 during positive cost shocks (Column 2) and declines to 0.05 during negative cost shocks (Column 3).

We then examine heterogeneity by local concentration through the interaction terms $\Delta \log c_t \times \text{MidHHI}_{mt}$ and $\Delta \log c_t \times \text{HighHHI}_{mt}$. The coefficients on $\Delta \log c_t \times \text{MidHHI}_{mt}$ are statistically insignificant across specifications. In contrast, the interaction with HighHHI_{mt} is positive and significant in the pooled sample (Column 1) and during positive cost shocks (Column 2). In Column 1, a 1 percent increase in the global coffee price leads to an additional 0.013 percent increase in retail prices in MSAs in the top tercile of concentration relative to those in the bottom tercile. In Column 2, positive cost shock periods, a 1 percent increase in the global coffee price leads to an additional 0.026 percent increase in retail prices in MSAs in the top tercile of concentration relative to those in the bottom tercile.

Overall, these results indicate stronger pass-through in more concentrated retail markets. Also, the higher pass-through is only observed during periods of rising costs and not during subsequent cost declines. This implies that even temporary cost shocks can generate persistent differences in local price levels. These patterns are consistent with our findings in the egg market.

5 Theoretical Framework

5.1 Environments

In this section, we develop a theoretical framework to find a mechanism for the empirical findings. Following Atkeson and Burstein (2008), we model an economy for food sectors in an MSA with by assuming a two-level nested CES demand system. Within each sector, a finite number of retailers compete in prices under Bertrand competition.

At the top level, aggregate consumption across sectors s is given by

$$Y = \left(\int_s Y_s^{\frac{\sigma-1}{\sigma}} ds \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1, \tag{8}$$

where σ denotes the elasticity of substitution across sectors. Within each sector s, there are discrete number of retailers $\mathcal{N}_s$ supplying differentiated varieties. Sectoral consumption aggregates according to

$$Y_s = \left(\sum_{i \in \mathcal{N}_s} y_i^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \qquad \rho > 1, \tag{9}$$

where ρ is the elasticity of substitution across retailers within a sector, assuming $\rho > \sigma$.

Given this demand structure, firm $i \in \mathcal{N}_s$ faces the following demand function:

$$y_{it} = Y_t \left(\frac{P_{st}}{P_t} \right)^{-\sigma} \left(\frac{p_{it}}{P_{st}} \right)^{-\rho} N_{it}^{\eta}, \tag{10}$$

where P_t and P_{st} denote the aggregate price index and the sectoral price index. N_{it} represents firm i's stock of customer capital, which shifts firm demand with elasticity η.

Customer capital evolves over time as follows. At the beginning of period t, firm i inherits an undepreciated stock $(1-\delta)N_{it}$. After production and sales take place, customer capital accumulates as a function of the firm's within-sector market share and depreciates at rate δ.[29]

[29] This formulation follows Foster et al. (2016a), who model customer capital as accumulating with firm revenue. Also, it aligns with Kleshchelski and Vincent (2009), where customer acquisition is proportional to past market share.

The law of motion for customer capital is

$$N_{it+1} = (1-\delta)N_{it} + (1-\delta)s_{it}, \tag{11}$$

where s_{it} is firm i's within-sector market share, defined as

$$s_{it} = \frac{p_{it}y_{it}}{P_{st}Y_{st}} = \frac{N_{it}^{\eta}p_{it}^{1-\rho}}{\sum_{j\in\mathcal{N}_s} N_{jt}^{\eta}p_{jt}^{1-\rho}}. \tag{12}$$

The corresponding sectoral and aggregate price indices are

$$P_{st} = \left(\sum_{i\in\mathcal{N}_s} N_{it}^{\eta}p_{it}^{1-\rho}\right)^{\frac{1}{1-\rho}}, \qquad P_t = \left(\int_s P_{st}^{1-\sigma}ds\right)^{\frac{1}{1-\sigma}}. \tag{13}$$

5.2 Firms

Each firm produces with marginal cost c_{it} which is determined by its productivity z_{it} (as a decreasing function of productivity).[30] Firm productivity is drawn from a Pareto distribution with scale and shape parameters, z_{min} and γ, respectively.

Firm i chooses its price to maximize the present discounted value of profits,

$$V(c_{it}, N_{it}) = \max_{p_{it}} \big(p_{it} - c_{it}\big) y_{it} + \beta \mathbb{E}_t V(c_{it+1}, N_{it+1}), \tag{14}$$

subject to the customer-capital accumulation process (11). The optimal pricing policy is characterized by the following first-order condition:

$$y_{it} + (p_{it} - c_{it})\frac{\partial y_{it}}{\partial p_{it}} + \beta(1-\delta)\,\mathbb{E}_t\left[\frac{\partial V_{it+1}}{\partial N_{it+1}}\right]\frac{\partial s_{it}}{\partial p_{it}} = 0, \tag{15}$$

which reflects a dynamic trade-off between higher current markups and the effect of current pricing on future customer capital through market share. The envelope condition with respect to customer capital is

$$\frac{\partial V_{it}}{\partial N_{it}} = (p_{it} - c_{it})\,\eta\,\frac{y_{it}}{N_{it}} + \beta(1-\delta)\,\mathbb{E}_t\left[\frac{\partial V_{it+1}}{\partial N_{it+1}}\right], \tag{16}$$

[30] For example, under constant-returns-to-scale production with labor as the only input and wage w, marginal cost is $c_{it} = \frac{w}{z_{it}}$.

which captures the marginal value of customer capital.

Equation (15) highlights that pricing decisions are forward-looking: firms internalize how higher prices reduce current market share and, in turn, future customer capital. The strength of this intertemporal trade-off depends on the marginal value of customer capital, which varies across firms. This dynamic channel disappears if $\delta = 1$, so that customer capital fully depreciates each period, or if $\eta = 0$, where customer capital does not shift demand. In either case, the problem collapses to the static pricing environment as in Atkeson and Burstein (2008).

5.3 Steady-State Equilibrium

A steady-state equilibrium is a collection of prices, quantities, customer capital, and value functions, $\Big\{\{p_i, y_i, s_i, N_i, V_i\}_{i\in\mathcal{N}_s}, P_s, P\Big\}$, such that the demand system and the law of motion for customer capital (10)-(13), as well as the firm optimality conditions (15)-(16) hold, with normalized aggregate output $Y = 1$.

5.4 Markups

In equilibrium, firms with larger market shares set higher markups, as shown in Proposition 1. This result is consistent with Atkeson and Burstein (2008), while we additionally incorporate customer capital dynamics.

Proposition 1. *Firm markups are increasing in firm market share.*
Proof: See Appendix I.1.

The intuition is straightforward. Firms with larger market shares face a lower marginal value of customer capital, which makes the cost of losing customers lower with higher price and markups.

We define the aggregate markup in a sector as the ratio of total revenue to total variable cost:

$$\mu = \frac{\sum_i p_i q_i}{\sum_i c_i q_i}. \tag{17}$$

The next proposition presents that aggregate markups depend on the distribution of firm market shares and increase with market concentration.

Proposition 2. *Aggregate markups are increasing in market concentration. Proof: See Appendix I.2.*

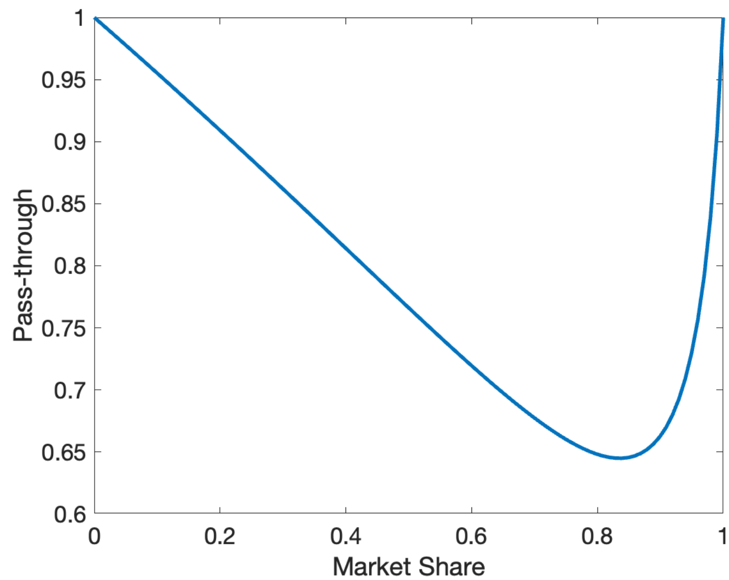

Figure 5: Market Share and Pass-through

Notes: The figure plots the relationship between retailer pass-through of cost shock and market share at the equilibrium.

5.5 Cost Pass-Through

Firm-level pass-through of cost shocks is incomplete and non-monotonic in market share. Proposition 3 shows that pass-through is U-shaped in firm market share, with a cutoff share above (below) which pass-through increases (decreases) with market share. Figure 5 presents this pattern.

Proposition 3. *Firm pass-through is incomplete and exhibits a U-shaped relationship with firm market share. Proof: See Appendix I.3.*

Suppose a firm experiences an increase in marginal cost. The price response reflects both a direct effect of higher cost and an indirect effect operating through endogenous markups. In extreme cases, where the firm is infinitesimal with zero markups ($s_{it} \to 0$) or the firm is a monopolist ($s_{it} \to 1$), pass-through is complete. This is because price adjustment does not affect market share and therefore leaves customer capital investment and markups unchanged. In both cases, the indirect markup channel is absent, so only the direct cost effect remains.

For firms with an interior market share, a price increase reduces market share and customer capital, holding all else fixed, because the firm's relative price rises. This induces a decline in the optimal markup, which partially offsets the direct effect of higher costs and generates incomplete pass-through. The strength of this channel depends on firm size. As firms become very large, market share is less elastic with respect to own-price changes because their dominance in the aggregate price index attenuates relative price movements. At the same time, these firms have a larger customer base, so the marginal loss of customer capital following a price increase is relatively small.

As firms become medium-sized or smaller, market share becomes more sensitive to price changes and the cost of losing customer capital increases. These firms therefore respond to cost shocks primarily through markup reductions, which lowers pass-through. As market share declines further, however, markups become sufficiently low that they constrain the scope for additional adjustment. Beyond this threshold, firms increase pass-through toward completeness, despite facing a higher elasticity of market share and customer capital. The interaction of these forces implies a U-shaped relationship between firm market share and pass-through.

The U-shaped relationship implies that sufficiently large or small firms exhibit higher pass-through than firms with intermediate market shares. Consequently, the distribution of market shares across firms determines the aggregate degree of pass-through and the overall price response to cost shocks.

5.6 Pricing Dynamics and Market Concentration

Next, we simulate the model to study how aggregate price responses and pass-through to a common cost shock vary with market concentration.

The benchmark parameterization follows standard values in the literature. We set $\beta = 0.99$ to match a quarterly interest rate of 1.2%; $\rho = 3.85$, consistent with the median cross-firm elasticity estimates in Hottman et al. (2016); and $\delta = 0.15$ as in Gourio and Rudanko (2014). We normalize the Pareto scale parameter to $z_{min} = 1$ and set the shape parameter to $\gamma = 5.49$ following Carvalho and Grassi (2019). We jointly calibrate $\sigma = 1.65$ and $\eta = 0.33$ to match the top and bottom deciles of the retailer-level sales share distribution within an MSA in the data. The corresponding moments are 0.43 and 0.01 in the data, which the model closely matches by generating 0.45 and 0.01, respectively.

We assume firms are hit by a common aggregate shock x_t that raises marginal costs additively to $x_t + c_{it}$. This captures an exogenous supply disruption, such as the bird flu outbreak. We assume the following aggregate shock process:

$$x_1 > 0, \quad x_t = \phi^{t-1} x_{t-1} \text{ (for } t \geq 2), \quad 0 < \phi < 1,$$

where we set $x_1 = 0.1$ and $\phi = 0.875$. For simplicity, firm productivity is assumed to be time-invariant, z_i, implying that the idiosyncratic component of marginal cost, c_i, is also time-invariant.

In the baseline economy, the number of retailers is set to $\mathcal{N}_s = 10$, which corresponds to the average number of chains per MSA in the data. To discipline differences in market concentration, we vary $\mathcal{N}_s$ while holding all other structural parameters fixed.[31] We compare the baseline economy to counterfactuals with $\mathcal{N}_s = 3$ and $\mathcal{N}_s = 17$, which correspond to two standard deviations below and above the mean, respectively. We find that market concentration declines with the number of retailers, even when the underlying productivity distribution is held fixed.

For each economy, we present the impulse response functions of aggregate prices and markups following a cost increase in Figure 6. Prices rise after the shock, and the increase is more pronounced in the high-HHI ($\mathcal{N}_s = 3$) economy. Along the transition path, price changes remain higher in the high-HHI economy. These patterns are consistent with the empirical evidence on pass-through following cost shocks. Furthermore, aggregate markups decline on impact, but the magnitude of the decline is smaller in the high-HHI economy.

To examine these results more closely, we investigate the impulse response functions of firm-level prices for the largest and smallest firms in the baseline economy and compare them with the counterparts (with the same productivity) in the other two economies. Figure 7 presents the results, where the largest firm raises its price on impact, with the strongest response occurring in the high-HHI economy ($\mathcal{N}_s = 3$). This firm has the highest market share and the largest stock of customer capital relative to otherwise identical firms in lower-HHI economies ($\mathcal{N}_s = 10$ or 17). As a result, when the shock hits, the large firm in the high-HHI economy can raise prices more aggressively because it faces lower sensitivity of sales share to price changes and a lower marginal value of customer capital. This firm lies on the upward-sloping range of the U-shaped relationship characterized in Proposition 3. Consistent with this mechanism, the declines in its sales share,

[31] In each economy, firms are drawn from the same productivity distribution with identical parameters. This ensures that firms share the same fundamentals across economies, while their pricing decisions and outcomes may still vary with different market structure (the number of competitors).

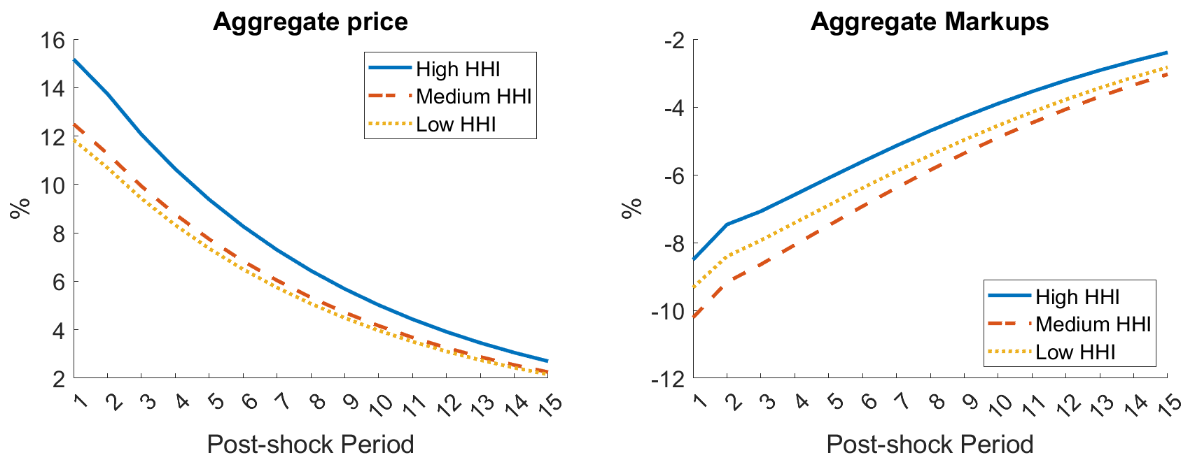

Figure 6: Response of Aggregate Price and Markups to a Cost Shock

Notes: The figure plots the impulse responses of the aggregate price level (left panel) and markups (right panel) to a positive common cost shock. "High HHI" corresponds to the economy with $\mathcal{N}_s = 3$, and "Medium HHI" and "Low HHI" denote the economies with $\mathcal{N}_s = 7$ and $\mathcal{N}_s = 17$, respectively. Aggregate prices are measured as the average of firm-level prices within each economy, and aggregate markups are constructed using equation (17).

markups, and customer capital are more muted than those of its counterparts in less concentrated economies, as shown in Figure 8.

By contrast, the responses of the smallest firms are similar across economies. Their sales shares are comparable, and their price and markup responses exhibit little variation across concentration levels. This implies that aggregate dynamics are largely driven by the behavior of large firms, whose responses vary systematically with market concentration through the interaction of market share, demand sensitivity, and the value of customer capital.

These results provide potential policy implications. High-HHI economies exhibit higher pass-through, which is accompanied by higher equilibrium markups (Proposition 2). As a result, consumers in high-HHI economies face both higher average prices and a stronger transmission of cost shocks, suggesting that market concentration can exacerbate welfare losses associated with market power in the presence of cost shocks. In the current framework, the number of firms is taken as given and determines the degree of market concentration. Endogenizing firm entry and market structure would allow an explicit analysis of optimal policy and may reveal welfare gains from policies that promote entry and competition. Building on this framework, the model could also be extended to a multi-region setting to study place-based policies that shape retailer location choices and market structure and improve allocations across regions. This is an avenue we leave for future

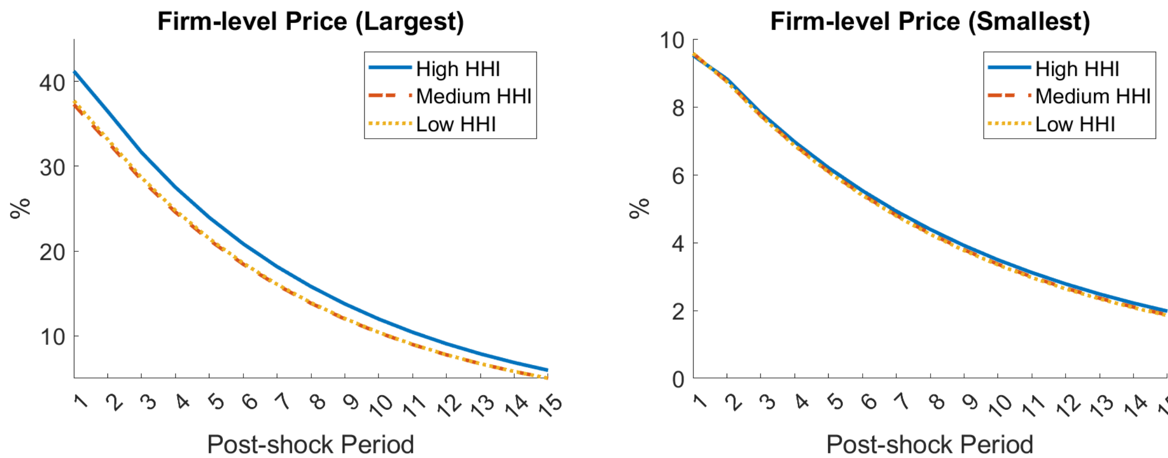

Figure 7: Response of Firm-Level Prices (Large vs. Small) to a Cost Shock

Notes: The figure plots the impulse responses of firm-level prices for the largest retailer (left panel) and the smallest retailer (right panel) in the baseline economy to a positive common cost shock. In the counterfactual economies, we use the corresponding firms with the same fundamentals as these two baseline firms. "High HHI" corresponds to the economy with $\mathcal{N}_s = 3$, and "Medium HHI" and "Low HHI" denote the economies with $\mathcal{N}_s = 7$ and $\mathcal{N}_s = 17$, respectively.

work.

6 Concluding Remarks

In this paper, we investigate spatial variation in food inflation and the role of retailer market structure. Using NielsenIQ Retail Scanner data, we document that lower-income MSAs experience systematically higher food inflation than wealthier areas. Poorer MSAs also exhibit fewer product varieties and retailers, a higher share of large chains, and greater market concentration. Exploiting exogenous cost shocks—the 2014–2015 bird flu outbreak and fluctuations in Arabica coffee prices—we show that MSAs with higher retail concentration experience larger inflation spikes following cost shocks and slower price declines thereafter. This implies that temporary shocks generate persistent differences in local inflation and real income. We provide a theoretical framework in which large retailers' market power and customer capital amplify cost pass-through in more concentrated markets. Our findings highlight the central role of local market structure in shaping inflation dynamics, consumer welfare, and real income inequality. They also underscore the limitations of national inflation measures, which can mask economically meaningful local price variation.

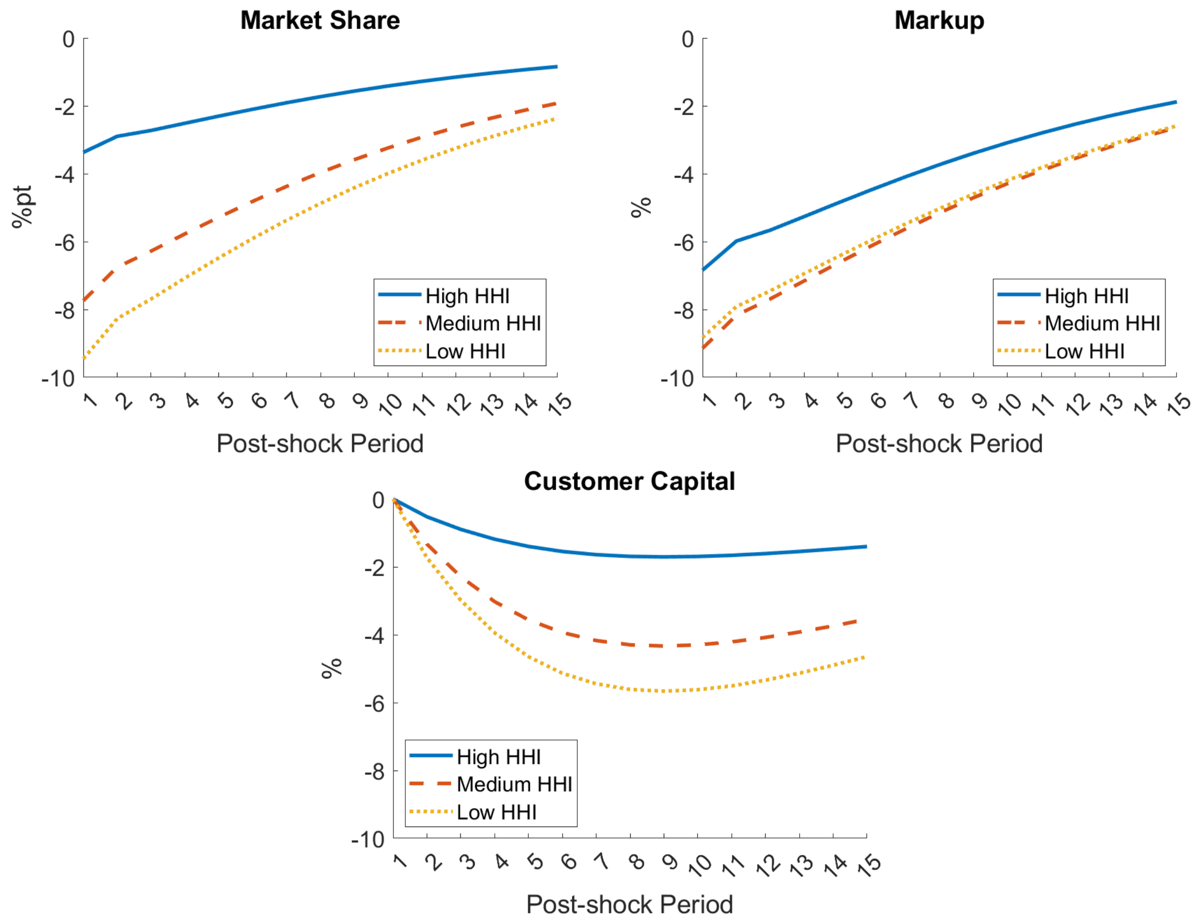

Figure 8: Response of the Largest Firm's Sales Share, Markup and Customer Capital to a Cost Shock

Notes: The figure plots the impulse responses of firm-level market share (top left), markups (top right), and customer capital (bottom panel) for the largest retailer in the baseline economy following a positive common cost shock. In the counterfactual economies, we consider the corresponding firm with the same fundamentals as the focal firm. "High HHI" corresponds to the economy with $\mathcal{N}_s = 3$, and "Medium HHI" and "Low HHI" denote the economies with $\mathcal{N}_s = 7$ and $\mathcal{N}_s = 17$, respectively.

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Appendix

A Robustness: NielsenIQ Consumer Panel

We use the household-year level sample from 2006 to 2020 in the NielsenIQ Consumer Panel data and identify households that make purchases within and outside their residential MSA in a given year. Table A.1 shows that 92% of households made purchases exclusively within their residential MSA.

Table A.1: Fraction of Households Shopping within their Residential MSA

Indicator	Observation	Percent
1	780,500	92.32
0	64,932	7.68
Total	845,432	100

Notes: The table shows the fraction of households that consume within their residential MSA (with an indicator value of 1) in each given year. The data covers household-year observations from 2006 to 2020.

Furthermore, when examining household characteristics and shopping patterns by each category, Table A.2 shows that their properties (such as income levels, the average number of stores households purchase from, and total amount of spending) are similar across groups. For households that shop outside of their MSA, they visit an average of 1.75 stores, spend approximately 50% of their total expenditure outside their residential MSA, and the average number of these outside MSAs they purchase from is 1.05.

In addition, we compute income deciles using two different MSA definitions in NielsenIQ. One is based on the MSA information of households in the NielsenIQ Consumer Panel, and the other is based on the MSA information of consumers, derived by linking the locations of stores from which households make purchases in the Scanner data with household income data in the NielsenIQ Consumer Panel. Table A.3 shows the gap between these two definitions, revealing that most MSAs (75.27%) align with the same income decile definitions, and only a very small fraction (0.54%) exhibit a gap of three deciles. This finding is consistent with our baseline measures of income deciles based on store locations and BEA income per capita data not being mismeasured.

Table A.2: Characteristics of Households by Shopping Types

Variable	Mean (SD)	Mean (SD)
Indicator	1	0
Income	20.46	19.94
	(5.98)	(5.87)
Store #	3.32	3.77
	(1.90)	(2.08)
Spending Amount	1812.05	1659.12
	(1985.68)	(1811.08)
Store # (out)		3.77
		(2.08)
Spending Amount (out)		714.78
		(1226.29)
MSA # (out)		1.05
		(0.23)
Obs	780,500	64,932

Notes: The table provides the shopping characteristics of households by their types based on whether they shop within their residential MSA (indicator=1) or not (indicator=0). The second column indicates the households only shopping inside their MSA, and the last column shows those shopping outside of their MSA. Store # is the number of stores the households purchase from, Spending Amount is the total amount of spending, Store # (out) is the number of stores outside of the household's living MSA, Spending Amount (out) is the amount of spending made outside of their living MSA, and MSA # (out) is the number of MSAs the household shop, outside of their residential MSA. This is the household-year level sample over 2006-2020.

Table A.3: Gaps in Two Income Decile Definitions: Household vs. Consumer MSAs

Gap	Observation	Percent
-3	1	0.54
-1	20	10.75
0	140	75.27
1	25	13.44
Total	186	100

Notes: The table computes the gap in income deciles when defined by consumer income and household income, using the MSA-level sample.

B MSA-level Price Indices: BLS vs. NielsenIQ

To assess the representativeness of NielsenIQ, we compare NielsenIQ food price indices with the official CPI series provided by the U.S. Bureau of Labor Statistics for the MSAs available in the CPI data. In particular, we use three MSAs—Chicago, Los Angeles, and New York. NielsenIQ tracks the official series well across all three markets, as shown in Figures B.1, B.2, and B.3.

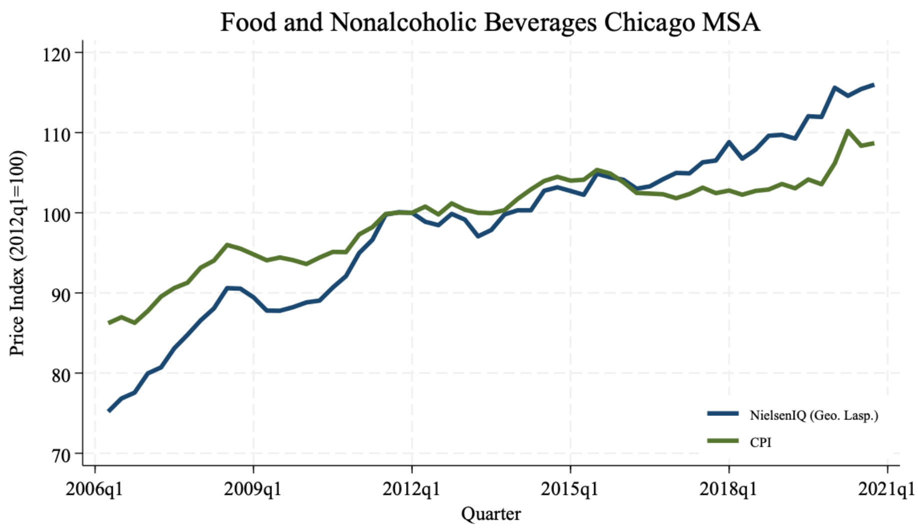

Figure B.1: Price Index for Aggregated Food: CPI vs. NielsenIQ (Chicago MSA)
Notes: This figure compares the CPI provided by the U.S. Bureau of Labor Statistics with the chained geometric Laspeyres price index constructed from NielsenIQ Scanner data for the Chicago MSA.

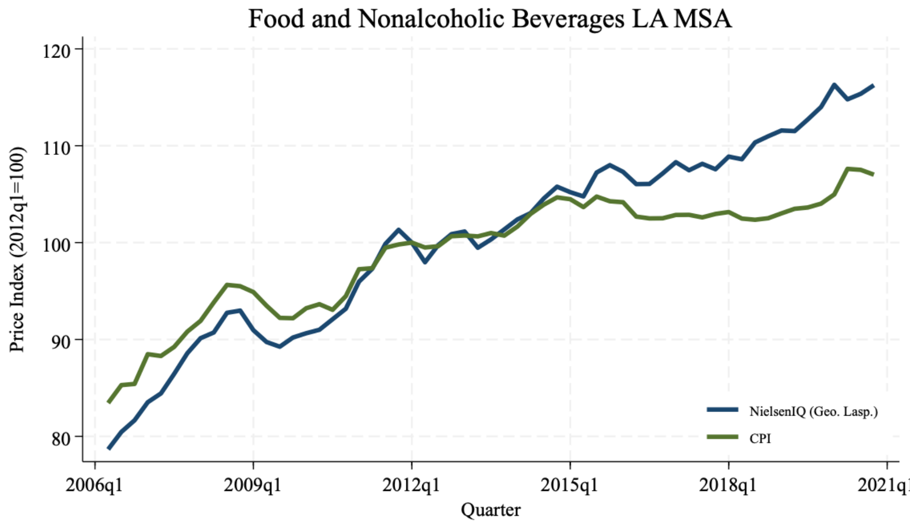

Figure B.2: Price Index for Aggregated Food: CPI vs. NielsenIQ (LA MSA)
Notes: This figure compares the CPI provided by the U.S. Bureau of Labor Statistics with the chained geometric Laspeyres price index constructed from NielsenIQ Scanner data for the Los Angeles MSA.

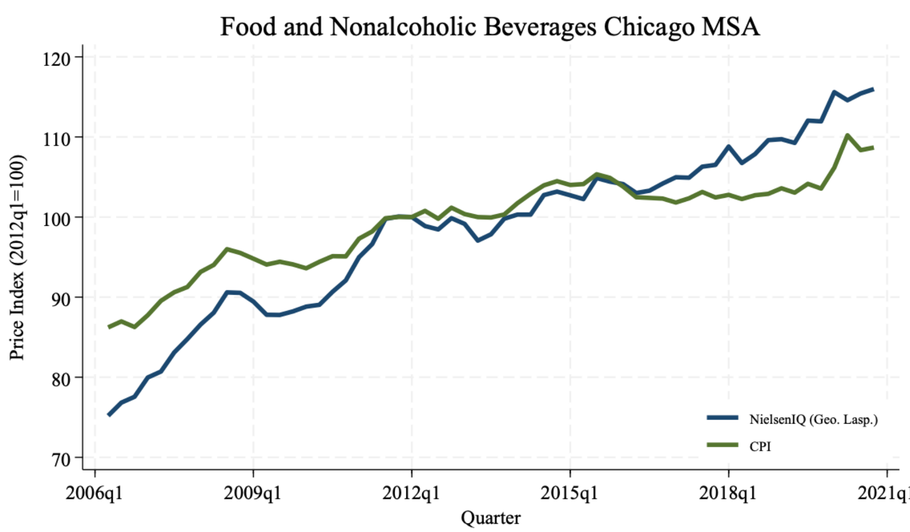

Figure B.3: Price Index for Aggregated Food: CPI vs. NielsenIQ (New York MSA)
Notes: This figure compares the CPI provided by the U.S. Bureau of Labor Statistics with the chained geometric Laspeyres price index constructed from NielsenIQ Scanner data for the New York MSA.

C Robustness: Price and Inflation Patterns

C.1 Other Price Indexes

Alternatively, we use Sato-Vartia index, one of the demand-based indexes, to check robustness. To create the index, we replace the weights in equation (1), ω_{mkt}, with the following:

$$\omega_{mkt} = \frac{\frac{(s_{mkt} - s_{kt-1})}{(\ln s_{mkt} - \ln s_{mkt-1})}}{\sum_{k \in \mathbb{C}_{m,t-1,t}} \frac{(s_{mkt} - s_{mkt-1})}{(\ln s_{mkt} - \ln s_{mkt-1})}},$$

which accounts for product entry and exit, in addition to the demand effects for common goods appearing between periods $(t-1)$ and t. Figure C.1 shows that the baseline result still holds with the demand-based index.

In addition, we construct the decile-level price index by aggregating the MSA-level indexes using an unweighted average. As shown in Figure C.2, the results based on this approach are consistent with our main findings.

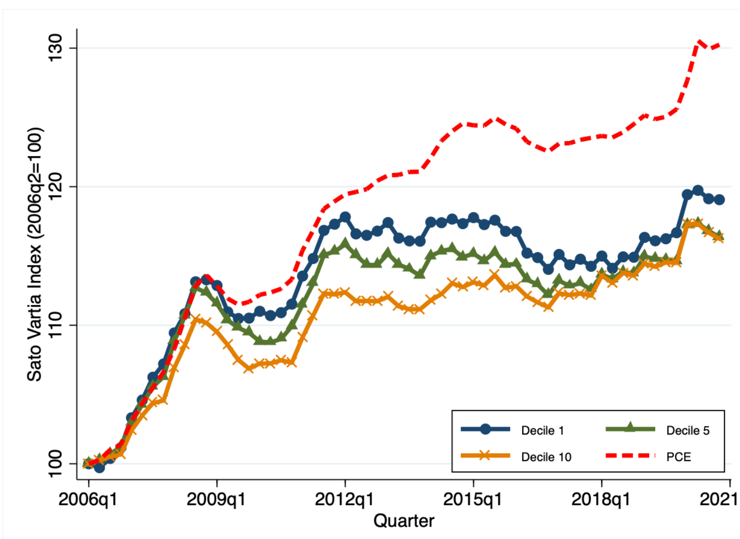

Figure C.1: Demand-based Price Index (Sato-Vartia) for Aggregated Food

Notes: This figure represents the chained Sato-Vartia price index constructed using NielsenIQ Retail data (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for aggregate food and beverages. All descriptions remain the same as before.

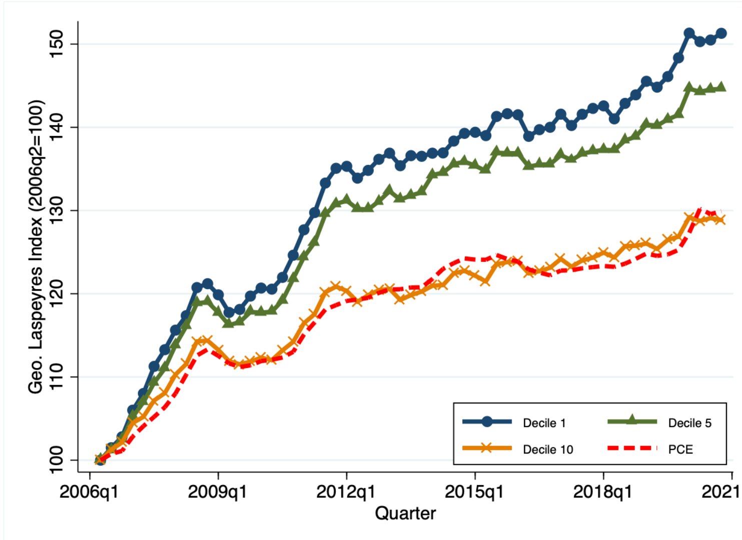

Figure C.2: Price Index for Aggregate Foods (MSA-level)

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for aggregate food and beverages. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are the unweighted average of the MSA-level indexes.

C.2 Other Food Items

We also construct these price indexes for more disaggregated food categories and find consistent results across them. For illustrative purposes, we present results for the following three representative categories: eggs, dairy, and fats and oils.

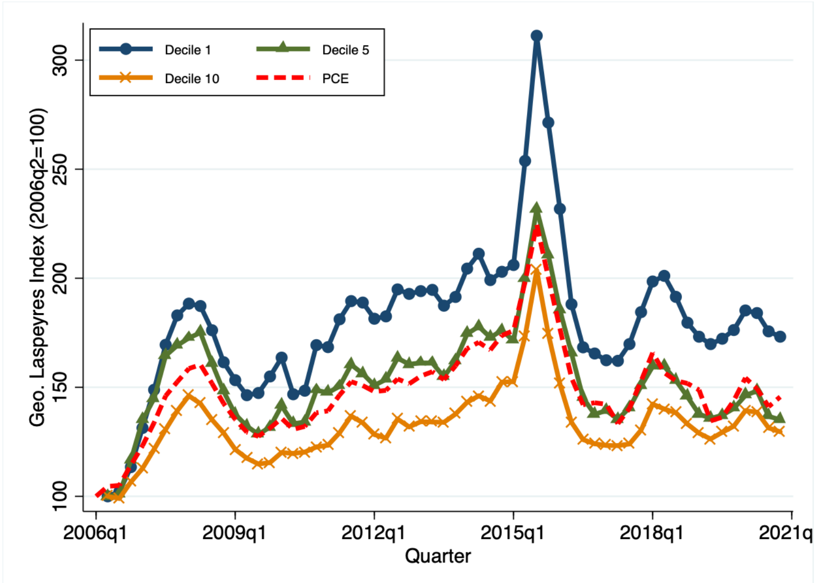

Figure C.3: Price Index for Eggs

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for eggs. All else remains the same as before.

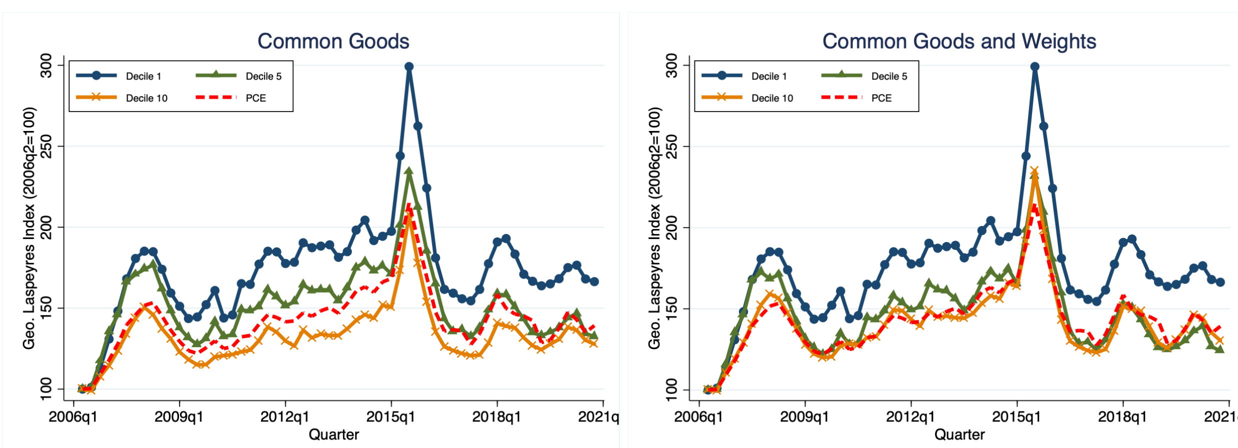

Figure C.4: Price Index for Eggs (Common Goods and Weights)

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for eggs. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are restricted to the set of goods present across all ten deciles in quarters $t-1$ and t (named "common goods") in the left panel, and are restricted to these common goods and further based on the same sales weights in decile 1 in the right panel.

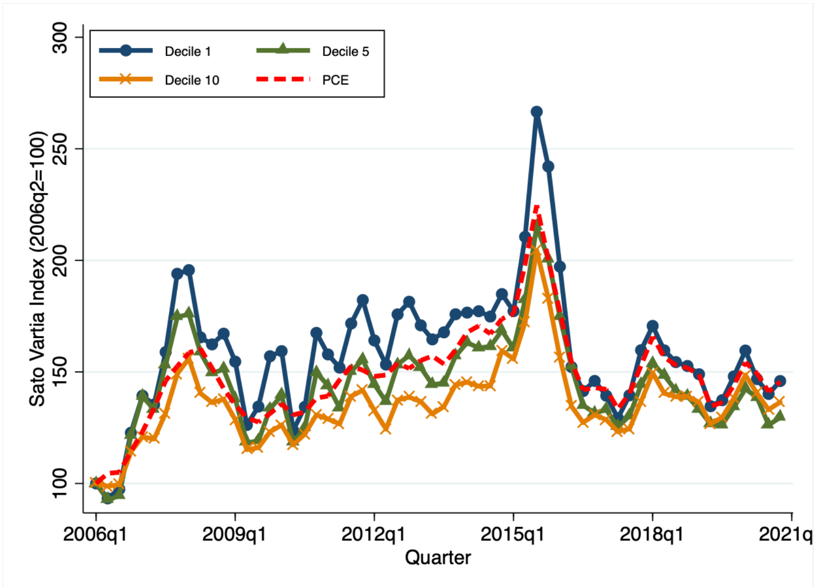

Figure C.5: Demand-based Price Index (Sato-Vartia) for Eggs

Notes: This figure represents the chained Sato-Vartia price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for eggs. All descriptions remain the same as before.

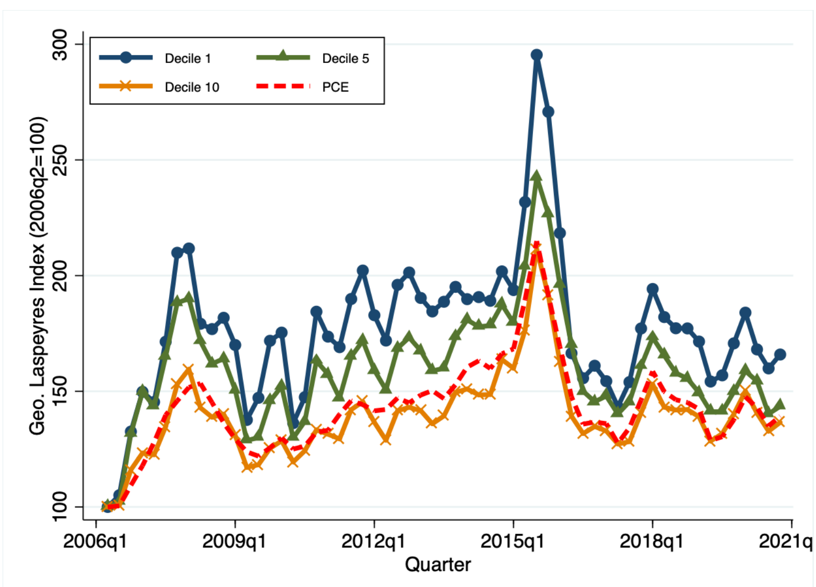

Figure C.6: Price Index for Eggs (MSA-level)

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for eggs. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are the average of the MSA-level indexes.

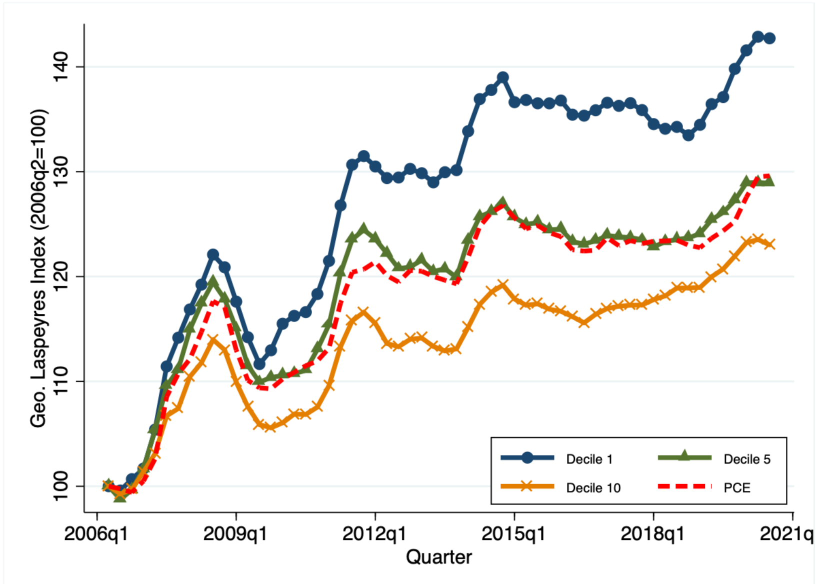

Figure C.7: Price Index for Dairy

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for dairy. All else remains the same as before.

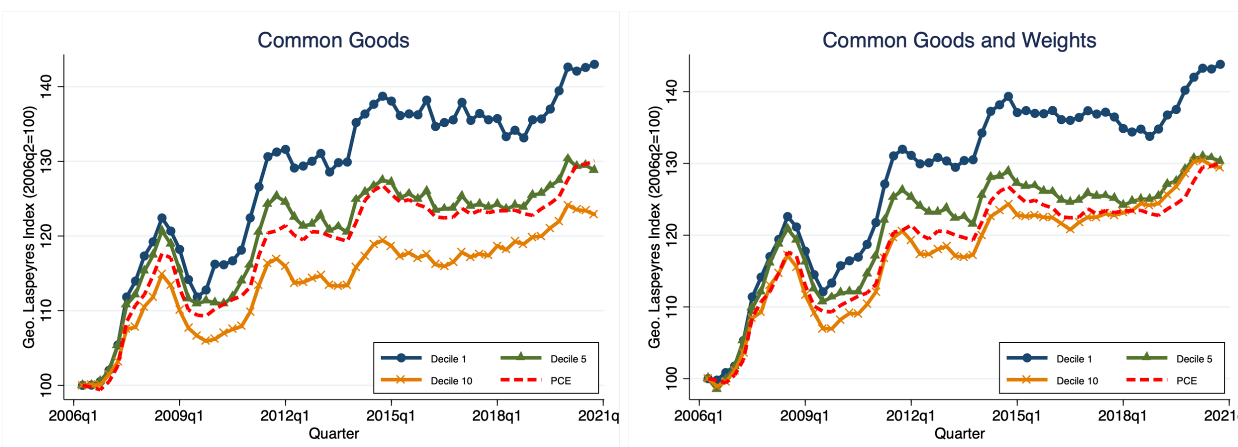

Figure C.8: Price Index for Dairy (Common Goods and Weights)

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for dairy. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are restricted to the set of goods present across all ten deciles in quarters $t-1$ and t (named "common goods") in the left panel, and are restricted to these common goods and further based on the same sales weights in decile 1 in the right panel.

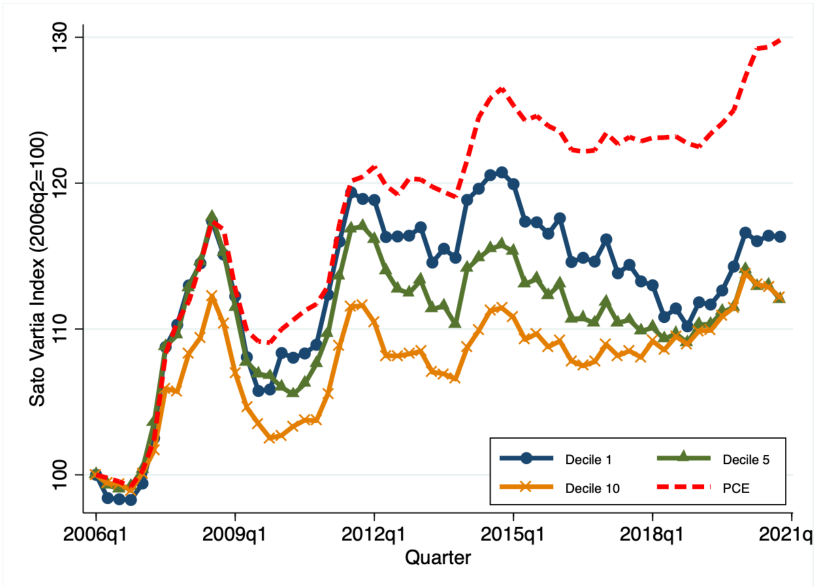

Figure C.9: Demand-based Price Index (Sato-Vartia) for Dairy

Notes: This figure represents the chained Sato-Vartia price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for dairy. All descriptions remain the same as before.

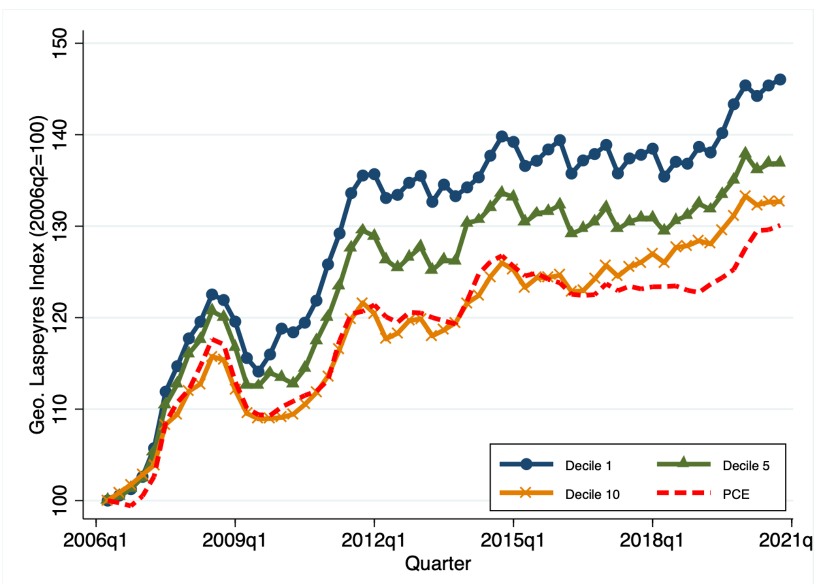

Figure C.10: Price Index for Dairy (MSA-level)

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for dairy. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are the average of the MSA-level indexes.

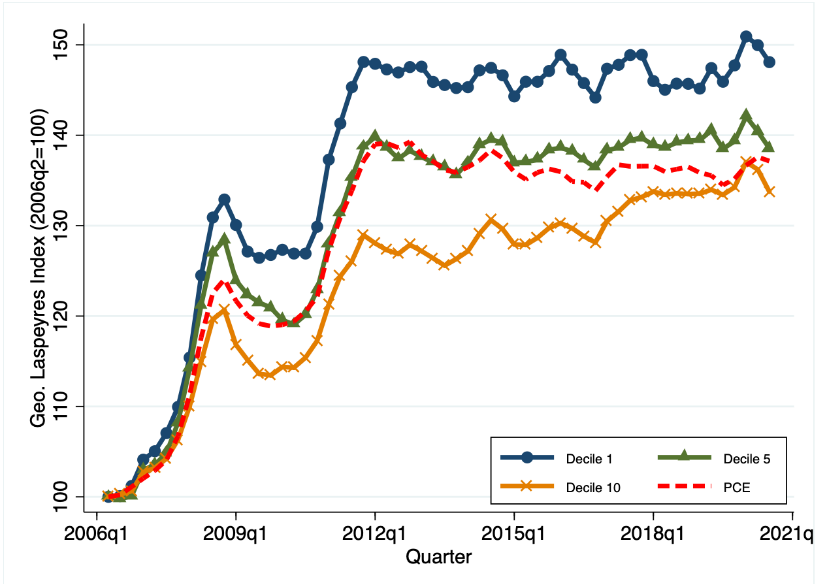

Figure C.11: Price Index for Fats and Oil
Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for fats and oil. All else remains the same as before.

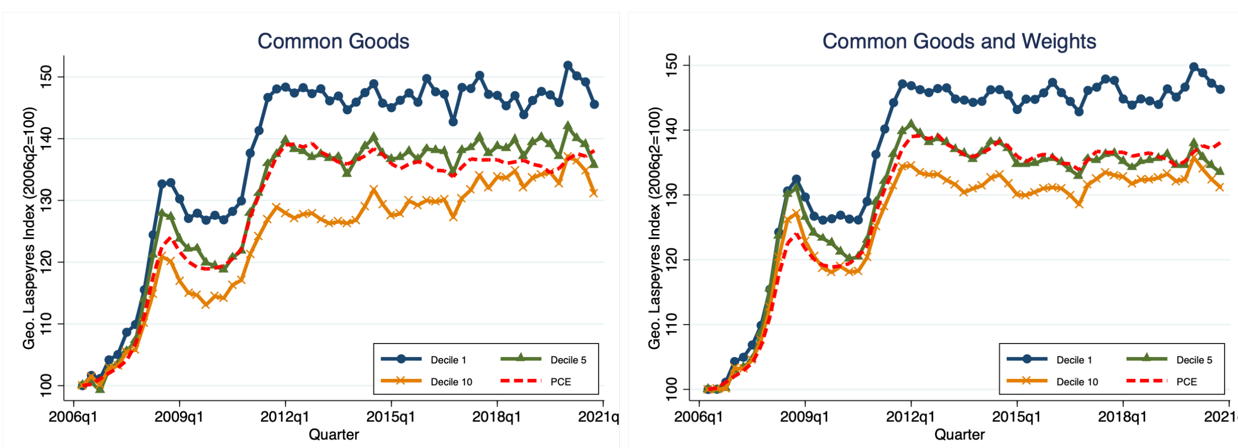

Figure C.12: Price Index for Fats and Oil (Common Goods and Weights)
Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for fats and oil. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are restricted to the set of goods present across all ten deciles in quarters $t-1$ and t (named "common goods") in the left panel, and are restricted to these common goods and further based on the same sales weights in decile 1 in the right panel.

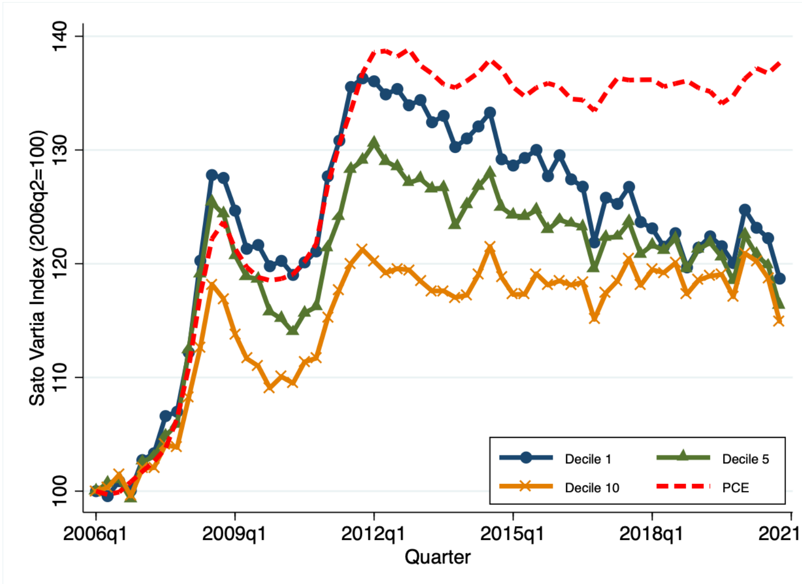

Figure C.13: Demand-based Price Index (Sato-Vartia) for Fats and Oil

Notes: This figure represents the chained Sato-Vartia price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for fats and oil. All descriptions remain the same as before.

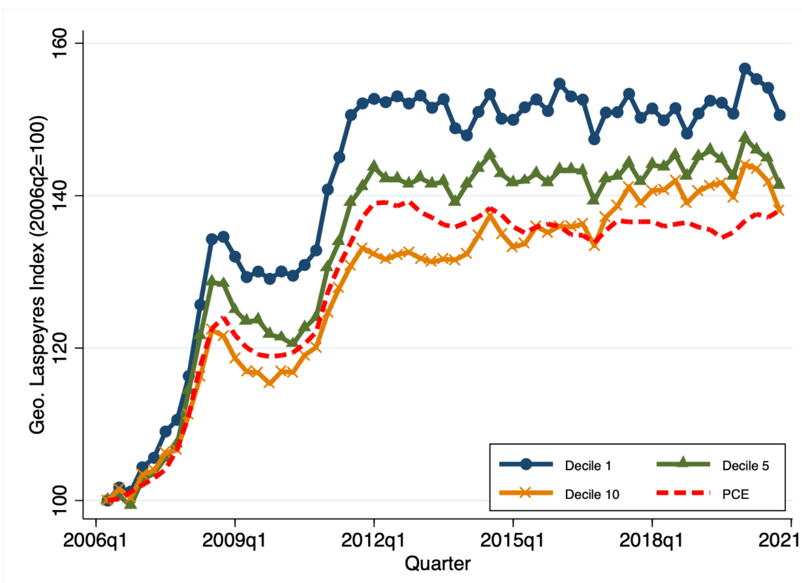

Figure C.14: Price Index for Fats and Oil (MSA-level)

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for fats and oil. All descriptions remain the same as before except that the solid lines constructed in NielsenIQ are the average of the MSA-level indexes.

D Robustness: Retailer Market Structure

D.1 Other Measures and Controls

We assess the robustness of the regression results in Table 4 by using alternative measures of market concentration (CR1 and CR3) and controlling for MSA-level population. The corresponding results are reported in Tables D.1 and D.2, respectively, which are consistent with our findings.

Table D.1: Retailer Market Structure across Regions with Different Income Levels (CRs)

	CR1	CR3
Income	-0.004***	-0.003***
	(0.001)	(0.001)
Quarter FE	Yes	Yes
Observations	11,100	11,100

Note: The table presents regression results from equation (2) by replacing the main dependent variable with the sales share of the top one and three retailers in an MSA for a given quarter in Columns 1 and 2, respectively. The coefficient of interest is on income per capita (in \$1000) in an MSA. All else remains the same as in Table 4. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

Table D.2: Retailer Market Structure across Regions with Different Income Levels (Population Control)

	Sales (in \$1mil.)	Chain#	Store#	Large Firm% (Store)	HHI
Income	8.482***	0.103***	2.651**	-0.007***	-0.003*
	(2.979)	(0.027)	(1.059)	(0.002)	(0.001)
Population	13.27***	0.066***	10.22***	-0.001***	-0.001***
	(2.034)	(0.009)	(0.768)	(0.000)	(0.000)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	11,100	11,100	11,100	11,100	11,100

Note: The table presents regression results from equation (2) by controlling for MSA-level population additionally. The coefficient of interest is on income per capita (in \$1000) in an MSA. All else remains the same as in Table 4. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

D.2 Long-run Relationship

We estimate the following regression relating income levels to retailer market structure in the long run:

$$\bar{Y}_m = \beta_0 + \boldsymbol{\beta_1} In\bar{c}ome_m + \varepsilon_m, \tag{D.1}$$

where $\bar{Y}_m$ is the long-run average of sales, total count of chains or stores, the share of large retailers (defined as the top decile of total sales or the number of store counts at the national level), or market concentration (HHI), and $In\bar{c}ome_m$ is the long-run average per capita income in msa m. The results are shown in Table D.3, which support the robustness of the main findings. Furthermore, we observe consistent patterns with CR measures, presented in Tables D.4.

Table D.3: Retailer Market Structure across Regions with Different Income Levels (Long Run)

	Sales (in $1mil.)	Chain#	Store#	Large Firm% (Sales)	Large Firm% (Store)	HHI
Income	27.32***	0.198***	17.48***	-0.003***	-0.009***	-0.005***
	(2.921)	(0.023)	(2.135)	(0.008)	(0.001)	(0.002)
Observations	185	185	185	185	185	185

Note: The table presents regression results from equation (D.1). The coefficient of interest is on the long-run average of income per capita (in $1000) in an MSA. The variable definitions remain the same as in Table 4, but based on long-run averages. Standard errors are clustered at the MSA level.*** p<0.01, ** p<0.05, * p<0.1

Table D.4: Retailer Market Structure across Regions with Different Income Levels (Long Run, CRs)

	CR1	CR3
Income	-0.004***	-0.003***
	(0.001)	(0.001)
Observations	185	185

Note: The table presents regression results from equation (D.1). The coefficient of interest is on the long-run average of income per capita (in $1000) in an MSA. The variable definitions remain the same as in Table 4, but based on long-run averages. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

D.3 BDS

In the BDS, we focus on the retail trade sector (NAICS 44–45) and measure retailer size by employment. For each MSA, the Census Bureau reports the number of firms, establishments, total employment, and job creation and destruction, categorized by three firm-size bins: (i) 1–19 employees, (ii) 20–499 employees, and (iii) 500 or more employees. We define large retailers as those in the third category and, for each MSA, count the number of firms and establishments associated with them.

We estimate the following regression to examine cross-sectional patterns in BDS:

$$Y_{mt} = \beta_0 + \beta_1 Income_{mt} + \delta_t + \varepsilon_{mt}, \tag{D.2}$$

where Y_{mt} is the number of firms, establishments, total employment (in thousands), the share of large retailers, and the share of establishments owned by large retailers in MSA m in year t. As before, $Income_{mt}$ represents the income per capita in MSA m in year t, and δ_t denotes a year fixed effect. The results are presented in Table D.5 and are consistent with the baseline findings from NielsenIQ. They also confirm that poorer areas tend to have fewer firms and establishments, as well as a higher share of large firms and establishments.

Table D.5: Retailer Market Structure (BDS)

	Firm Counts	Estab Counts	Employment	Large Firm Share	Large Estab Share
Income	128.02***	188.96***	3.002***	-0.003***	-0.001***
	(45.02)	(62.18)	(0.891)	(0.001)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	5,715	5,715	5,715	5,715	5,715

Notes: The table represents regression results from equation (D.2). The coefficient of interest is the coefficient on income per capita (in \$1000) in an MSA for a given year. The dependent variable is the total number of firms in Column 1, total number of establishments in Column 2, total employment size (in thousands) in Column 3, the unweighted share of large firms in Column 4, and the unweighted share of establishments associated with large firms in Column 5 in an MSA for a given year. Large firms are defined by those with 500 or more employees. Data is collected from the Business Dynamics Statistics and retailers are gathered from retail trade sector (NAICS 44-45) for 2006-2020. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

As in the previous analysis, we examine the long-run cross-sectional relationship across MSAs using the following regression:

$$\bar{Y}_m = \beta_0 + \boldsymbol{\beta_1} \bar{Income}_m + \varepsilon_m, \tag{D.3}$$

where $\bar{Y}_m$ is the long-run average of the number of firms, establishments, total employment (in thousands), the share of large retailers, and the share of establishments owned by large retailers, and $\bar{Income}_m$ is the long-run average for the income per capita in MSA m. Table D.6 shows results that reinforce the consistency of patterns in the BDS data.

Table D.6: Retailer Market Structure (BDS, Long Run)

	Firm Counts	Estab Counts	Employment	Large Firm Share	Large Estab Share
Income	137.92***	203.61***	3.210***	-0.003***	-0.001***
	(20.71)	(29.15)	(0.427)	(0.000)	(0.000)
Observations	381	381	381	381	381

Notes: The table represents regression results from equation (D.3). The variable definitions remain the same as in Table D.5, but based on long-run averages over 2006-2020 in the BDS. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

E Robustness: Inflation and Market Concentration

E.1 Other Measures and Controls

In the main regression (3), we replace HHI with CR1 and CR3 measures for market concentration and report the results in Table E.1. The results are robust to both measures. Furthermore, we control for MSA-level population in Table E.2 and find consistent results.

E.2 Long-run Relationship

Furthermore, we explore the long-run association between inflation, income level, and market concentration across MSAs with the following regression:

$$\bar{P}_m = \beta_0 + \boldsymbol{\beta_1} \bar{X}_m + \varepsilon_m, \tag{E.1}$$

Table E.1: Food Inflation across Regions (CRs)

	Inflation	Inflation	Inflation	Inflation
CR1	0.415***	0.395***	0.413***	0.404***
	(0.114)	(0.118)	(0.128)	(0.128)
Income		-0.003		-0.004**
		(0.002)		(0.002)
Chain #			-0.000	0.004
			(0.008)	(0.008)
	Inflation	Inflation	Inflation	Inflation
CR3	0.680***	0.646***	0.705***	0.690***
	(0.153)	(0.158)	(0.180)	(0.180)
Income		-0.003		-0.004**
		(0.002)		(0.002)
Chain #			0.003	0.007
			(0.008)	(0.008)
Quarter FE	Yes	Yes	Yes	Yes
Observations	10,730	10,730	10,730	10,730

Note: The table presents regression results from equation (3). The coefficient of interest is on income per capita (in thousands of $) and CR (CR1 in the top panel and CR3 in the bottom panel) in an MSA for a given quarter. The dependent variable is the geometric Laspeyres inflation rate (%) of aggregate food in an MSA for a given quarter. The last two columns additionally control for the total number of chains in the MSA. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

Table E.2: Food Inflation across Regions (Population Control)

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.248**		0.253**	0.318**	0.316**
	(0.105)		(0.107)	(0.123)	(0.123)
Income		0.001	0.001		-0.001
		(0.002)	(0.002)		(0.002)
Chain #				0.020**	0.021**
				(0.009)	(0.008)
Population	-0.003***	-0.004***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	10,730	10,730	10,730	10,730	10,730

Note: The table presents regression results from equation (3). The coefficient of interest is on HHI and income per capita (in $1000) in an MSA for a given quarter. All specifications include the long-run average population (in 100,000s) as a control variable, measured annually using the BEA data. The dependent variable is the geometric Laspeyres inflation rate (%) of aggregate food in an MSA for a given quarter. Total number of chains is included as a control in the last two columns. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

where $\bar{P}_m$ is the long-run average of inflation, and $\bar{X}_m$ is the long-run average of HHI and income level in msa m. The results are shown in Table E.3, which confirms the negative association between food inflation and income as well as the positive association between food inflation and market concentration across MSAs in the long run. Also, the long-run patterns also hold for both CR1 and CR3 measures. These are shown in Table E.4.

Table E.3: Food Inflation across Regions (Long Run)

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.304**		0.261**	0.279**	0.267**
	(0.125)		(0.128)	(0.132)	(0.132)
Income		-0.005**	-0.004		-0.004
		(0.003)	(0.003)		(0.003)
Chain #				-0.005	0.002
				(0.008)	(0.009)
Observations	185	185	185	185	185

Note: The table presents regression results from equation (E.1) for the cross-sectional association between MSA-level inflation, income, and market concentration in the long run. The coefficient of interest is on HHI and income per capita (in $1000) in an MSA. The dependent variable is the long-run average of the food Laspeyres inflation rate. The last two columns control for the long-run average number of chains in an MSA. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

E.3 Price Indices

In the main regression (3), we replace the dependent variable with the Laspeyres price index at the MSA level to capture cumulative price differences across MSAs. The results are similar in Table E.5. Furthermore, we replace HHI with CR1 and CR3 for market concentration, and the results remain robust, as presented in Table E.6.

E.4 Eggs Inflation

We estimate the following OLS regression as before, focusing specifically on egg prices:

$$P_{mt} = \beta_0 + \beta_1 X_{mt} + \delta_t + \varepsilon_{mt}, \tag{E.2}$$

where P_{mt} is the geometric Laspeyres inflation rate of eggs, X_{mt} denotes the HHI of retailer sales or income per capita in MSA m in quarter t, and δ_t represents quarter fixed effects. The results are

Table E.4: Food Inflation across Regions (Long Run, CRs)

	Inflation	Inflation	Inflation	Inflation
CR1	0.393***	0.360**	0.375**	0.361***
	(0.120)	(0.122)	(0.123)	(0.123)
Income		-0.004		-0.004
		(0.003)		(0.003)
Chain #			-0.005	0.000
			(0.007)	(0.009)
Observations	185	185	185	185
	Inflation	Inflation	Inflation	Inflation
CR3	0.838***	0.784***	0.841***	0.818***
	(0.199)	(0.205)	(0.212)	(0.212)
Income		-0.003		-0.004
		(0.003)		(0.003)
Chain #			0.000	0.006
			(0.008)	(0.009)
Observations	185	185	185	185

Note: The table presents regression results from equation (E.1) for the cross-sectional association between MSA-level inflation, income, and market concentration in the long run. The coefficient of interest is on CR1 (in the top panel) and CR3 (in the bottom panel), as well as income per capita (in \$1000) in an MSA. The dependent variable is the long-run average of the food Laspeyres inflation rate. The last two columns control for the long-run measure of the average of chains in the MSA. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

Table E.5: Food Price Indices across Regions

	Price Index	Price Index	Price Index	Price Index	Price Index
HHI	14.47***		12.78***	12.65***	12.30***
	(3.720)		(3.737)	(4.217)	(4.206)
Income		-0.274***	-0.221**		-0.200**
		(0.104)	(0.103)		(0.087)
Chain #				-0.341	-0.120
				(0.325)	(0.309)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	10,915	10,915	10,915	10,915	10,915

Note: The table presents regression results from equation (3) with the dependent variable replaced by the Laspeyres price index. The coefficient of interest is on income per capita (in \$1000) and HHI in an MSA for a given quarter. The last two columns additionally control for the number of chains in the MSA. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

presented in Table E.7, which reveal a similar association between HHI, income, and egg inflation as in our main analysis for aggregate food. In particular, we find a positive and statistically significant

Table E.6: Food Price Indices across Regions (CRs)

	Price Index	Price Index	Price Index	Price Index
CR1	14.88***	13.51***	13.58***	13.11***
	(3.560)	(3.622)	(3.809)	(3.834)
Income		-0.225**		-0.190**
		(0.101)		(0.087)
Chain #			-0.402	-0.192
			(0.305)	(0.290)
Quarter FE	Yes	Yes	Yes	Yes
Observations	10,915	10,915	10,915	10,915
	Price Index	Price Index	Price Index	Price Index
CR3	19.92***	17.12***	17.02***	16.26***
	(4.919)	(4.629)	(4.648)	(4.652)
Income		-0.221**		-0.196**
		(0.098)		(0.087)
Chain #			-0.359	-0.145
			(0.299)	(0.285)
Quarter FE	Yes	Yes	Yes	Yes
Observations	10,915	10,915	10,915	10,915

Note: The table presents regression results from (3) with the dependent variable replaced by the Laspeyres price index. The coefficient of interest is on income per capita (in $1000) and CR1 (in the top panel) and CR3 (in the bottom panel) in an MSA for a given quarter. The last two columns additionally control for the total number of chains in the MSA. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

Table E.7: Eggs Inflation across Regions

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.514***		0.440***	0.488**	0.483**
	(0.150)		(0.159)	(0.185)	(0.185)
Income		-0.015***	-0.011**		-0.014**
		(0.004)	(0.004)		(0.005)
Chain #				-0.005	0.011
				(0.014)	(0.017)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	8,743	8,743	8,743	8,743	8,743

Note: The table represents regression results from (E.2) for the cross-sectional association between MSA-level inflation, income, and market concentration for eggs. The coefficient of interest is on HHI of retail chain's eggs sales and income per capita (in $1000) in an MSA. The dependent variable is the Laspeyres inflation rate (%) of eggs in an MSA for a given quarter. Total number of chains in eggs market is controlled in the last two columns. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

relationship between market concentration and inflation in Columns 1 and 3, and this relationship remains robust even after controlling for the MSA-level income per capita and the number of chains in Columns 4 and 5. We also replace HHI with CR1 and CR3 measures for market concentration in eggs market. The results are shown in Table E.8 and are robust to both measures.

Table E.8: Eggs Inflation across Regions (CRs)

	Inflation	Inflation	Inflation	Inflation
CR1	0.633***	0.571***	0.604***	0.594***
	(0.180)	(0.190)	(0.208)	(0.207)
Income		-0.012***		-0.013***
		(0.004)		(0.005)
Chain #			-0.008	0.008
			(0.014)	(0.017)
	Inflation	Inflation	Inflation	Inflation
CR3	1.083***	0.956**	1.027**	0.975**
	(0.353)	(0.385)	(0.403)	(0.403)
Income		-0.011**		-0.012**
		(0.004)		(0.005)
Chain #			-0.009	0.005
			(0.014)	(0.016)
Quarter FE	Yes	Yes	Yes	Yes
Observations	8,743	8,743	8,743	8,743

Note: The table represents regression results from Equation (E.2) by replacing HHI with CR1 (in the top panel) and CR3 (in the bottom panel) for eggs. The coefficient of interest is on CR1 and CR3 of retail chain's eggs sales, as well as income per capita (in thousands of $) in an MSA. The dependent variable is the geometric Laspeyres inflation rate (%) of eggs in an MSA for a given quarter. Total number of chains in eggs market is controlled in the last two columns. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

While these results shed light on the link between inflation and market concentration, they do not establish causality. The OLS estimate of β_1 may be subject to endogeneity bias. For instance, the observed relationship could be demand-driven: consumers in MSAs with higher HHI may disproportionately purchase goods experiencing higher inflation. Alternatively, income-related differences in consumer behavior could play a role: richer MSAs may have consumers who are more sensitive to price changes. Such heterogeneity in consumer behavior may have led retailers in wealthier areas to raise prices at slower rates. Another potential explanation is a supply-side story, where poorer MSAs have fewer stores and varieties, which weakens competition and allows retailers to raise prices more aggressively. There may also be a potential sorting of certain types of retailers into poorer MSAs, those that are more flexible in increasing prices, compared to retailers operating in richer areas. To isolate whether the effect we observe is driven by supply-side or demand-side forces, we exploit the 2014–2015 bird flu outbreak as an exogenous supply shock in Section 4 in the main text.

F Eggs Market

Note that eggs markets in general tend to be local and regional. For instance, Cal-Maine Foods, which is the largest producer and marketer of eggs in the U.S., primarily operates in regional markets. See Figure F.1 that plots the locations of Cal-Maine Foods, which are mainly concentrated in Southern areas.

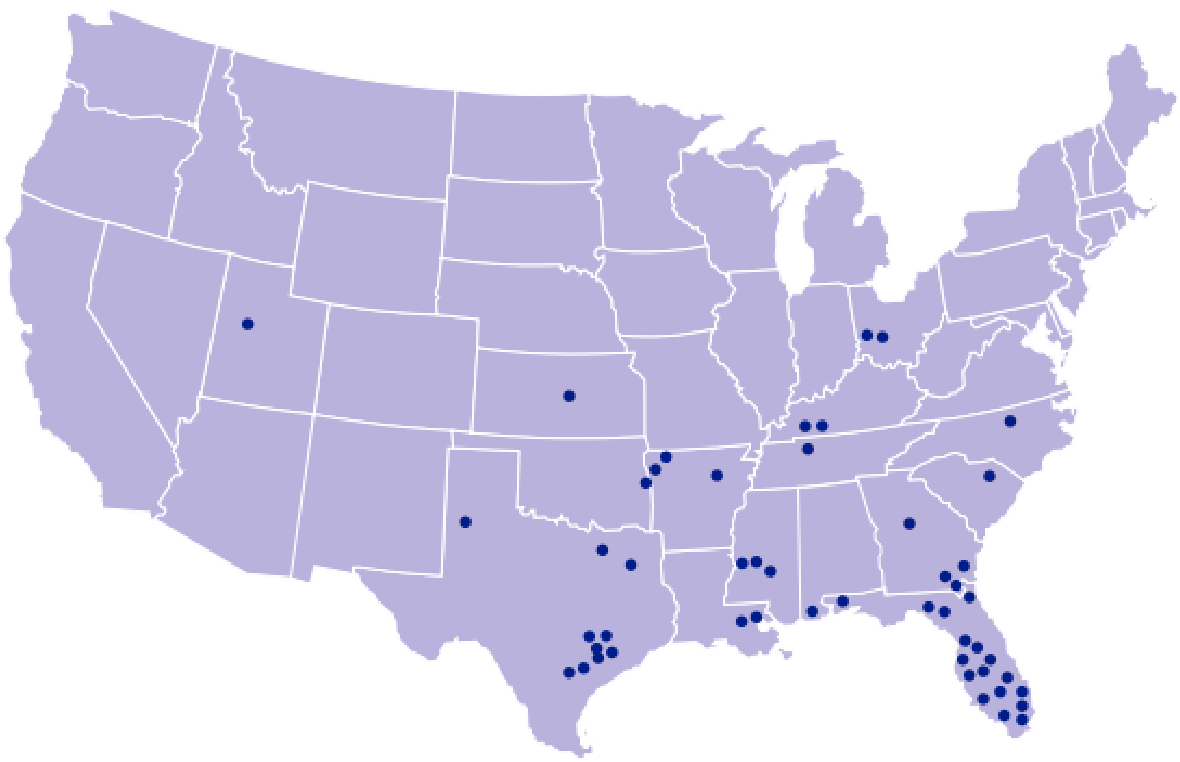

Figure F.1: Location of Cal-Maine Foods

Notes: The figure represents the local locations of Cal-Maine Foods, which is the largest national eggs producing company in the United States.

G Robustness: Triple-Difference Estimation

G.1 Continuous HHI

We use continuous measure of HHI to confirm robustness of our main triple-difference regression results. Specifically, we estimate the following regression:

$$\begin{aligned} P_{mt} = \beta_0 &+ \beta_1 HHI_{mt} + \beta_2(\text{Treated}_m \times \text{Post}_t) \\ &+ \beta_3(\text{Treated}_m \times HHI_{mt}) + \beta_4(\text{Post}_t \times HHI_{mt}) \\ &+ \beta_5(\text{Treated}_m \times \text{Post}_t \times HHI_{mt}) + \delta_m + \delta_t + \varepsilon_{mt}, \end{aligned} \tag{G.1}$$

where the subscript m corresponds to MSA m and subscript t corresponds to quarter t. $Treated_m$ is a binary variable indicating whether layers in MSA m were culled during the 2014-2015 bird flu episode according to the USDA report. $Post_t$ is a binary variable that takes value 1 if quarter t is after 2014Q4, and zero otherwise. HHI_{mt} is the HHI of retailer concentration of sales in MSA m in quarter t. For the post-treatment period, we fix it to the value in 2014Q3.[32] P_{mt} is the geometric Laspeyres inflation rate for eggs in MSA m in quarter t. The fixed effect terms, δ_m and δ_t, are the same as before, and ε_{mt} is the error term.

The results are presented in Table G.1. Column 1 pools all quarters within the two-year window and shows that treated MSAs with higher market concentration exhibit significantly higher inflation, on average, than those with lower concentration. The coefficient of 0.5 on the triple interaction implies that, for a one-unit increase in HHI, quarterly egg inflation rises by 0.5 percentage points among treated MSAs. This effect is statistically significant at the 1% level. Columns 2 and 3 decompose this effect into the inflationary and deflationary periods, respectively. In Column 2, restricting the sample to the inflationary period, we find that treated MSAs with higher market concentration experienced faster initial price increases in the egg market following the bird flu episode. This coefficient is also significant at the 1% level. In contrast, Column 3 shows that these MSAs did not reduce prices by larger amounts during the deflationary period. We find that MSAs with higher concentration were slower to decrease prices, as indicated by a positive coefficient on the triple interaction term. This coefficient is statistically significant at the 10% level. These results

[32] This is to avoid endogeneity concerns and to isolate the effect of supply shocks on local market concentration. The result is also robust to fixing it to the two-year average value over 2012Q4-2014Q3.

Table G.1: Triple Difference Estimator (Eggs)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.050***	0.084***	0.040*
	(0.010)	(0.019)	(0.023)
Bird Flu × Post	-0.030***	-0.006	-0.056***
	(0.007)	(0.010)	(0.012)
HHI × Post	-0.010**	-0.008	-0.008
	(0.005)	(0.008)	(0.011)
Bird Flu × HHI	-0.165	-0.254	-0.075
	(0.107)	(0.156)	(0.074)
HHI	0.037	0.056*	0.026
	(0.025)	(0.030)	(0.041)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	3,145	1,850	1,295

Note: The table represents regression results from equation (G.1). The coefficient of interest is the interaction of Bird Flu, Post, and High HHI. Bird Flu is a binary variable that takes the value of one for MSAs in which egg farmers culled their layers during the 2014-2015 bird flu episode, and Post is a binary variable that takes the value of one in the post-shock period after 2014Q4. HHI is the Herfindahl-Hirschman index (HHI) of retail chain's sales of eggs within an MSA, fixed to 2014Q3 values for all quarters in the post period. The sample period ranges from 2012Q4 to 2016Q4. Inflationary and deflationary periods are determined by the national price index of eggs. Column 1 pools all periods together, Column 2 only considers the inflationary period, and Column 3 only considers the deflationary period. MSA and quarter fixed effects are included across all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

are consistent with our main findings.

Furthermore, we confirm robustness for the UPC-MSA-quarter level analysis by using continuous HHI measures. We estimate the following regression, where the dependent variable is the log change in UPC-level prices within egg market:

$$\begin{aligned}\Delta \ln price_{umt} = {} & \beta_0 + \beta_2 HHI_{mt} + \beta_4(Treated_m \times Post_t) \\ & + \beta_5(Treated_m \times HHI_{mt}) + \beta_6(Post_t \times HHI_{mt}) \\ & + \beta_7(Treated_m \times Post_t \times HHI_{mt}) + \delta_m + \delta_t + \delta_u + \varepsilon_{umt},\end{aligned} \tag{G.2}$$

where $\Delta \ln price_{umt}$ denotes the log difference in the price of UPC u in MSA m between quarters $t-1$ and t. The UPC fixed effects, δ_u, account for regional variation in consumption baskets by

Table G.2: Triple Difference Estimator (UPC-level)

	Δ ln Price	Δ ln Price	Δ ln Price
Bird Flu × Post × HHI	0.016***	0.034***	-0.010
	(0.006)	(0.010)	(0.015)
Bird Flu × Post	-0.009**	-0.005	-0.014
	(0.004)	(0.006)	(0.010)
HHI × Post	-0.007**	-0.009	-0.004
	(0.003)	(0.006)	(0.007)
Bird Flu × HHI	0.001	-0.049	-0.076
	(0.061)	(0.085)	(0.088)
HHI	0.024	0.054**	-0.019
	(0.015)	(0.024)	(0.027)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
UPC FE	Yes	Yes	Yes
Observations	145,989	84,418	61,470

Note: The table represents regression results from our triple difference-in-differences at the UPC level. HHI is the Herfindahl-Hirschman index (HHI) of retail chain's sales of eggs within an MSA, fixed to 2014Q3 values for all quarters in the post period. All else remains the same as before, except that MSA, UPC, and quarter fixed effects are included across all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

ensuring that price changes are identified within identical products across regions. All other terms are defined as in equation (G.1).

Table G.2 presents the consistent results. In Column 1, we pool all quarters within the sample period and find that MSAs with higher market concentration saw a 1.6 percent increase in egg product prices relative to those with lower concentration. This estimate is significant at the 1 percent level. In Column 2, we restrict the sample to the inflationary period and find that MSAs affected by the bird flu with higher market concentration experienced a 3.4 percent increase in egg product prices relative to similarly affected MSAs with lower market concentration. This estimate is statistically significant at the 1 percent level. In Column 3, we limit the analysis to the deflationary period and find no statistically significant effect.

G.2 CR Measures

To test the robustness of the triple-difference regression in equation (G.1), we replace HHI with CR1 and CR3 in the egg market. The results are robust, as displayed in Table G.3.

Table G.3: Triple Difference Estimator (CRs)

	Inflation	Inflation	Inflation
Bird Flu × Post × CR1	0.052***	0.093***	0.044*
	(0.010)	(0.022)	(0.024)
Bird Flu × Post	-0.037***	-0.021	-0.064***
	(0.008)	(0.013)	(0.015)
CR1 × Post	-0.010*	-0.008	-0.006
	(0.005)	(0.008)	(0.013)
Bird Flu × CR1	-0.139	-0.204*	-0.092
	(0.090)	(0.110)	(0.056)
CR1	0.046**	0.060**	0.045
	(0.022)	(0.027)	(0.028)
	Inflation	Inflation	Inflation
Bird Flu × Post × CR3	0.098***	0.191***	0.099*
	(0.030)	(0.063)	(0.055)
Bird Flu × Post	-0.092***	-0.134**	-0.125***
	(0.028)	(0.057)	(0.048)
CR3 × Post	-0.023*	-0.021	-0.029
	(0.012)	(0.021)	(0.030)
Bird Flu × CR3	0.003	0.037	-0.194
	(0.120)	(0.232)	(0.150)
CR3	0.049	0.038	0.071
	(0.043)	(0.057)	(0.088)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	3,145	1,850	1,295

Note: The table represents regression results from equation (G.1) by replacing HHI with CR1 or CR3. The coefficient of interest is the interaction of Bird Flu, Post, and CR1 (in the top panel) or CR3 (in the bottom panel). CR1 (CR3) is the concentration ratio of the top 1 (top 3) retail chain's sales of eggs within an MSA, of which value is fixed to 2014Q3 for all quarters in the post period. All else descriptions remain the same as in Table G.1. Standard errors are clustered at the MSA-level. *** p<0.01, ** p<0.05, * p<0.1

G.3 Neighboring Treated MSAs

We incorporate five additional neighboring MSAs around the affected areas using MSA maps provided by the Census Bureau.[33] These MSAs are listed in Table G.4. We then re-estimate regressions based on equation (4) and equation (G.1) including these additional treated MSAs. The results, presented in Tables G.5 and G.6, are consistent with our baseline findings.

Table G.4: Neigboring MSAs around the Impacted MSAs

#	MSA	State
1	CEDAR RAPIDS-WATERLOO & DUBUQUE	IA
2	MILWAUKEE	WI
3	LA CROSSE-EAU CLAIRE	WI
4	LINCOLN & HASTINGS-KEARNY	NE
5	DULUTH-SUPERIOR	MN-WI

Note: The table provides the set of neighboring MSAs around the impacted MSAs.

Table G.5: Difference-in-Differences Estimator (Neighbor MSAs)

	Inflation	Inflation	Inflation	Abs. Inflation
Bird Flu × Post	-0.003	0.037***	-0.033***	0.047***
	(0.004)	(0.006)	(0.007)	(0.005)
Sample Periods	All	Inflation	Deflation	All
Quarter FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Observations	3,145	1,850	1,295	3,145

Note: The table represents regression results from equation (4), where the treated MSAs include five additional neighboring MSAs around the impacted areas. All else descriptions remain the same as in the main Table 6. *** p<0.01, ** p<0.05, * p<0.1

G.4 Retailer Composition

In addition to differences in basket composition, another potential explanation is variation in retailer composition across MSAs, as different types of retailers may exhibit different degrees of pass-through of shocks to prices. Specifically, pass-through can be different between national and local chains for the following reasons. On the one hand, national chains—with a larger number of

[33] See details at https://www.census.gov/geographies/reference-maps/2020/demo/state-maps.html.

Table G.6: Triple Difference Estimator (Neighbor MSAs)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.049***	0.074***	0.056**
	(0.008)	(0.019)	(0.024)
Bird Flu × Post	-0.028***	-0.001	-0.062***
	(0.007)	(0.010)	(0.012)
HHI × Post	-0.011**	-0.008	-0.010
	(0.005)	(0.008)	(0.011)
Bird Flu × HHI	-0.129	-0.198	-0.002
	(0.087)	(0.134)	(0.072)
HHI	0.039	0.054*	0.031
	(0.025)	(0.030)	(0.041)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	3,145	1,850	1,295

Note: The table represents regression results from equation (G.1), where the treated MSAs include five additional neighboring MSAs around the impacted areas. All else descriptions remain the same as in Table G.1. *** p<0.01, ** p<0.05, * p<0.1

stores spread across diverse regions—may be better able to hedge against local shocks and less responsive to them, resulting in lower pass-through in affected areas.[34] On the other hand, national chains may charge prices closer to marginal costs, potentially due to low search costs, market transparency or scale economies, and can potentially impact the local level of prices, markups, as well as pass-through.[35] Following this logic, their pass-through of cost shocks will be higher as the market will operate closer to a competitive market. In either case, the presence of national versus local retail chains can influence the degree of pass-through in affected areas.

Within eggs market during our sample period, we also find a positive correlation between HHI and the share of national retailers. This suggests that variation in the presence of national versus local chains across MSAs may offer an alternative explanation for our results. Under this interpretation, geographic differences in inflation still originate on the retailer side, but are driven

[34] This hypothesis is consistent with Daruich and Kozlowski (2023), finding that prices in stores of multi-region chains respond less to local shocks than those in one-region chains. The hypothesis also aligns with the uniform pricing puzzle documented in DellaVigna and Gentzkow (2019), showing that national chains charge geographically uniform prices and their prices are insensitive to local demand shocks.

[35] Chenarides et al. (2024) find that the entry of hard-discounter reduced markups for incumbent retailers in local markets. Related to it, Basker and Noel (2009) also show that the entry of Walmart reduced the prices of local competitors.

Table G.7: Triple Difference Estimator (Retailer Composition)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.047***	0.082***	0.036
	(0.010)	(0.020)	(0.023)
Bird Flu × Post	-0.028***	-0.006	-0.053***
	(0.007)	(0.010)	(0.012)
HHI × Post	-0.010**	-0.009	-0.005
	(0.005)	(0.008)	(0.011)
Bird Flu × HHI	-0.151	-0.253	-0.018
	(0.113)	(0.163)	(0.098)
HHI	0.033	0.050*	0.025
	(0.025)	(0.029)	(0.040)
Regional Share	0.037	-0.016	0.255***
	(0.034)	(0.034)	(0.071)
National Share	0.078**	0.055	0.205***
	(0.036)	(0.036)	(0.077)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	3,145	1,850	1,295

The table represents regression results from equation (G.1) with the additional controls of the share of national and regional retailers. All other descriptions remain the same as in the main Table G.1. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

by differences in retailer composition rather than market concentration per se. Depending on which of the above mechanisms is at play, our current estimates of the effect of market concentration may be subject to upward or downward bias.

To test this, we follow Jarmin et al. (2009) and classify retailers into three categories based on their geographic footprint: (i) local retailers, operating in only one state; (ii) regional retailers, operating in two to ten states; and (iii) national retailers, operating in more than ten states. We then compute the share of each group within each MSA-quarter. In the regression, we include the shares of national and regional retailers as covariates, using the local share as the omitted baseline.

The results are presented in Table G.7. The main results remain stable across all three inflationary regimes: pooled, inflationary, and deflationary. The triple interactions in the pooled period (Column 1) and the inflationary period (Column 2) reveal a positive and statistically significant association with inflation as before. In the deflationary period (Column 3), the coefficient remains positive, although it loses statistical significance at the 10 percent level. This suggests that the baseline results on the effect of market concentration on the pass-through of shocks are not solely attributable to differences in retailer composition across MSAs.[36]

G.5 Cost-related Hypothesis

An alternative hypothesis for spatial disparities in inflation revolves around cost differentials. If marginal costs in lower-income areas rise faster than in higher-income areas, this can contribute to higher inflation in those regions, irrespective of the market structure of retailers. To test this hypothesis, we use wage data for retail workers from the American Community Survey (ACS) and compare wage levels and growth across MSAs with varying income levels from 2006 to 2020.[37] We link it to BDS data to control for the composition of firms, which may vary across regions.

We estimate the following two regressions to examine wage variation in wage levels and wage growth across MSAs with different income levels:

$$w_{mt} = \beta_0 + \beta_1 Income_{mt} + X'_{mt}\gamma + \delta_t + \varepsilon_{mt} \tag{G.3}$$

$$\Delta \ln w_{mt} = \beta_0 + \beta_1 Income_{mt} + X'_{mt}\gamma + \delta_t + \varepsilon_{mt}, \tag{G.4}$$

where w_{mt} ($\Delta \ln w_{mt}$) is the average wage level (or growth) in the retail sector in MSA m and year t, $Income_{mt}$ is the income per capita of MSA m in year t, and X_{mt} is a vector of MSA-level characteristics, including the share (or growth of the share) of college workers in the retail sector, and the share of large retailers (with 500 or more employees) or establishments associated with large retailers, and δ_t is a year fixed effect.

In Table G.8, the top and bottom panels present the results for the average wage levels and growth, respectively. These results reveal that the average wage level is generally lower in lower-income areas, even after controlling for the composition of skills and the share of large firms or establishments in retail sector. However, the second panel suggests there are no significant patterns in wage growth across MSAs by income level. While the data are aggregated, they provide suggestive evidence that retailer wages are neither higher nor growing faster in areas with lower

[36] Indeed, the magnitude of the coefficients is slightly attenuated relative to our baseline estimates, which may align more closely with the hypothesis of a higher share of national chains leading to higher pass-through.

[37] We restrict our sample to prime-age workers (aged 20-55) that earn more than $5000 and work at least 40 weeks per year in the retail sector.

Table G.8: Average Wage Levels and Growth in Retail Sector across MSAs

	Wage	Wage	Wage	Wage	Wage	Wage
Income	3.785***	2.871***	3.000***	3.770***	2.371***	2.822***
	(0.508)	(0.382)	(0.427)	(0.532)	(0.293)	(0.390)
College Share		2.761***			2.441***	2.780***
		(0.343)			(0.289)	(0.343)
Large Firm Share			-2.437***		-1.883***	
			(0.360)		(0.261)	
Large Estab Share				-0.126		-0.368
				(0.393)		(0.319)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,868	2,868	2,868	2,868	2,868	2,868
	∆Wage	∆Wage	∆Wage	∆Wage	∆Wage	∆Wage
Income	- 0.020	-0.015	-0.023	-0.023	-0.017	-0.018
	(0.014)	(0.013)	(0.014)	(0.014)	(0.082)	(0.014)
∆College Share		0.082***			0.082***	0.082***
		(0.008)			(0.008)	(0.008)
Large Firm Share			-0.008		-0.006	
			(0.021)		(0.020)	
Large Estab Share				-0.025		-0.025
				(0.028)		(0.025)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,580	2,566	2,580	2,580	2,566	2,566

Note: The table presents MSA-level wage regression results from equations (G.3) and (G.4). The dependent variable in the top panel is the average wage (in $1000), while the bottom panel has the log difference in the average wages within retail sector in an MSA in a given a year. The sample period spans from 2006 to 2020 with year fixed effects included. The main independent variable is the MSA-level income per capita (in thousands of $). In Columns 2, 5, 6, the share of college-educated retailer workers is included in the top panel, and its growth is included in the bottom panel as a control. In Columns 3 and 5, the share of large retailers (%, those with 500 employees or more) is controlled, and in Columns 4 and 6, the share of establishments associated with these large retailers is controlled within an MSA in a given year. *** p<0.01, ** p<0.05, * p<0.1

income or a higher share of large retailers, which helps rule out other cost factors.

H Aggregate Implications

H.1 Back-of-the-Envelope

To assess whether the magnitudes estimated in Table G.1 are economically meaningful, we perform a back-of-the-envelope calculation to quantify how much of the inflation gap between the poorest and richest deciles can be explained by our market concentration mechanism.[38] We examine differences in egg inflation between the top and bottom income deciles during the inflationary period of the 2014–2015 bird flu episode. To measure the contribution of market concentration, we compute the following term:

$$\pi_{contribution} = \frac{q \cdot \beta \cdot HHI_{diff}}{\pi_{d1} - \pi_{d10}}. \tag{H.1}$$

Here, $\pi_{contribution}$ denotes the share of the inflation gap attributable to differences in retailer market concentration. The term q denotes the number of quarters in the inflationary period (2014Q4–2015Q3), which equals four. π_{d1} denotes cumulative egg inflation for the poorest decile during this period, and π_{d10} denotes cumulative egg inflation for the richest decile over the same period. Inflation rates are measured in decimal units in the calculation.[39] The coefficient β corresponds to the estimate on the triple interaction Bird Flu $\times$ Post $\times$ HHI from Table G.1, Column 2. Finally, HHI_{diff} denotes the difference in retail market concentration (HHI) between the poorest and richest deciles as of 2014Q3.

Although there was a general surge in egg prices during this period, the cumulative inflation gap in eggs between the poorest and richest deciles from 2014Q4 to 2015Q3 was 14.5 percentage points (0.145 in decimal units), which corresponds to the denominator of equation (H.1). Based on our triple-difference estimates and observed differences in retailer market concentration across deciles, we estimate that 9.3 percentage points of this gap are accounted for by differences in retailer market concentration. Consequently, we obtain a value of 64 percent for $\pi_{contribution}$, suggesting that a substantial portion of the observed inflation gap during the bird flu episode can be explained by variation in local retailer concentration.

H.2 Real Income Inequality

We further examine cumulative growth in nominal and real income per capita across income deciles. Nominal income per capita is sourced from the BEA at the MSA level and averaged within each decile. To construct cumulative real income per capita growth, we deflate nominal income per capita

[38] We focus on estimates from Table G.1 rather than Table G.2 because the former captures differences in inflation across consumption baskets. The smaller magnitudes in Table G.2 imply that basket composition differences also contribute to the observed decile-level inflation gap.

[39] Because inflation is measured quarterly in decimal units, cumulative inflation over the four-quarter period is approximated by summing predicted quarterly effects.

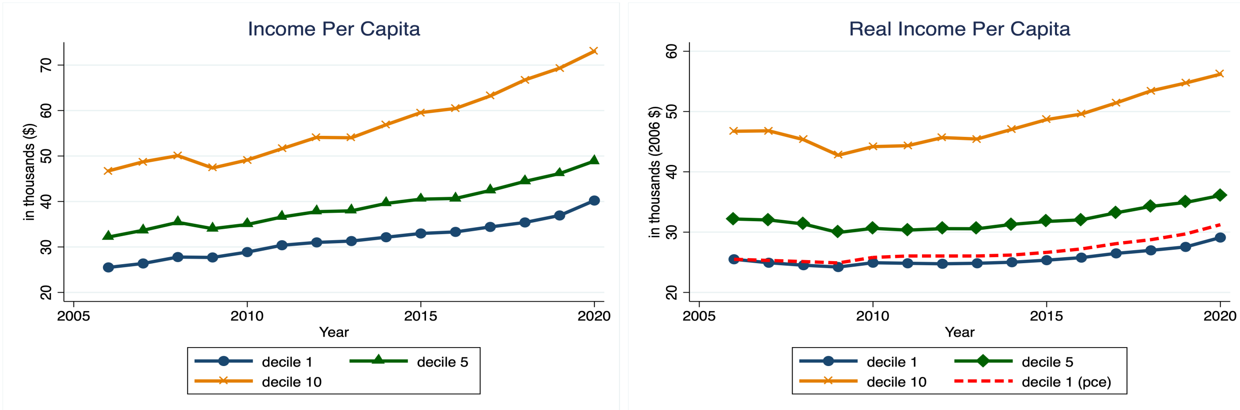

Figure H.1: Nominal and Real Income per Capita

Notes: This figure displays nominal and real income per capita (in thousands of dollars) across income deciles, with the left panel showing nominal values and the right panel showing real values. The nominal income per capita (in thousands) series in the left panel is calculated for each income decile by averaging across MSAs and is sourced from the U.S. Bureau of Economic Analysis (BEA). The right panel presents real income per capita (in thousands), normalized to 2006, by income decile. For the three solid lines, real income is constructed by dividing nominal income per capita by an aggregate food price index derived from NielsenIQ. The dashed line represents real income per capita for decile 1, deflated instead by the official food PCE price index. The sample period begins in 2006Q1 for the nominal series and in 2006Q2 for the real series, ending in 2020Q3. All series are normalized to the initial quarter. Decile 1 represents MSAs in the bottom income decile and decile 10 represents MSAs in the top income decile.

using the food price index derived from the NielsenIQ Retail Scanner data.

The three solid lines in Figure H.1 illustrate the patterns of nominal and real income per capita across three income deciles. The data indicate that both nominal and real income per capita have generally increased across all deciles, except during the Great Recession, when both the top and bottom deciles experienced a temporary decline. However, the gap between the top and bottom deciles has widened over time for both measures. This divergence is particularly pronounced for real income per capita, reflecting persistent regional disparities in inflation.

Building on our earlier findings, accounting for variation in retailer market structure is crucial for understanding regional heterogeneity in inflation and real income inequality. We find that lower-income areas exhibit higher retailer market concentration and, on average, face higher food inflation. Our event study analysis further shows that retailer concentration has a causal impact on local inflation by altering the degree of shock pass-through. This can also contribute to persistent regional inflation disparities, which is important to assess real income inequality across MSAs.

Recognizing regional inflation disparities is also essential for more accurate real income measures. Official price indexes are typically available only at the national level or for wealthier MSAs.[40] Since the national index is an expenditure weighted average across regions, where expenditure weights are disproportionately higher in richer areas, it tends to better reflect the inflation patterns of higher-income regions. As a result, relying on national indexes may misrepresent the real income dynamics of lower-income areas. This is illustrated by the red dashed line in the right panel of Figure H.1, which shows real income per capita for the bottom decile constructed with the official PCE price index for food and beverages. Relying on this national index overstates real income in decile 1 (both in levels and growth), thereby understating the real income gap and consequently real income inequality. Constructing regional price indexes allows for more accurate measurement of real income disparities and offers deeper insights into the dynamics of inequality.

Although our analysis is limited to food and beverage prices due to the availability of reliable data for these items, this focus carries important implications. On one hand, our estimates may understate real income inequality, as poorer households typically allocate a larger share of their consumption to food, making them more vulnerable to food price inflation. On the other hand, if food inflation disparities are uniquely driven by segmentation in retail markets, our results may overstate broader inequality patterns. Understanding the scope and drivers of inflation disparities across consumption categories is therefore important to understanding real income inequality across regions.

I Model Appendix

I.1 Proof of Proposition 1

Proposition 4. *Firm markups are increasing in firm market share.*

Proof. The price elasticity of demand for firm i, ϵ_{it}, can be derived as follows. Using the demand curve (10),

$$\ln y_{it} = \ln Y_t - \sigma \ln \frac{P_{st}}{P_t} - \rho \ln \frac{p_{it}}{P_{st}} + \eta \ln N_{it}. \tag{I.1}$$

[40] See details from https://www.bls.gov/cpi/regional-resources.htm.

Then, the elasticity ϵ_{it} is

$$\epsilon_{it} \equiv -\frac{\partial \ln y_{it}}{\partial \ln p_{it}} = -(\rho - \sigma)\frac{\partial \ln P_{st}}{\partial \ln p_{it}} + \rho. \tag{I.2}$$

With (13), it follows that $\frac{\partial P_{st}}{\partial p_{it}} = (\frac{p_{it}}{P_{st}})^{-\rho}$, and thus, the following can be obtained:

$$\frac{\partial \ln P_{st}}{\partial \ln p_{it}} = \frac{p_{it}}{P_{st}}\frac{\partial P_{st}}{\partial p_{it}} = (\frac{p_{it}}{P_{st}})^{1-\rho} = s_{it}. \tag{I.3}$$

This indicates that the marginal effect of adjusting firm-level price on sectoral price index depends on the firm's market share. The larger share the firm has, it has more influence on sectoral price.

Rephrasing (I.2) with (I.3), we can get the following relationship,

$$\epsilon_{it} \equiv (1 - s_{it})\rho + s_{it}\sigma, \tag{I.4}$$

showing that the elasticity is a linear function of firm market share. In particular, given that $\sigma < \rho$, the elasticity declines in firm market share.

Now, evaluating the firm's Euler equation (15) at the steady state, where we drop time subscript onward, we get the following equation:

$$\frac{p_i - c_i}{p_i} = \frac{1}{\epsilon_i + \frac{\beta\delta\eta(\rho-1)(1-s_i)}{1-\beta(1-\delta)}},$$

which can determine firm markup at the equilibrium as follows:

$$\mu_i = \frac{\hat{\epsilon}_i}{\hat{\epsilon}_i - 1} \quad \text{where } \hat{\epsilon}_i \equiv \epsilon_i + \frac{\beta\delta\eta(\rho-1)(1-s_i)}{1-\beta(1-\delta)}. \tag{I.5}$$

Next, we can prove that markup increases in market share with the following step. First, getting the derivative of $\hat{\epsilon}$ with respect to sales share, we have

$$\frac{d\hat{\epsilon}_i}{ds_i} = \frac{d\epsilon_i}{ds_i} - \frac{\beta\delta\eta(\rho-1)}{1-\beta(1-\delta)} < 0, \tag{I.6}$$

given (I.4). Given this, if we get the derivative of markup with respect to sales share, we have

$$\frac{d\mu_i}{ds_i} = \frac{d\mu_i}{d\hat{\epsilon}_i} = -\frac{1}{(\hat{\epsilon}_i - 1)^2}\frac{d\hat{\epsilon}_i}{ds_i} > 0. \tag{I.7}$$

This completes the proof. □

I.2 Proof of Proposition 2

Proposition 5. *Aggregate markups are increasing in market concentration.*

Proof. First, at the stationary equilibrium, markup follows (I.5). We can rewrite it as:

$$\begin{aligned}\mu_i &= \frac{1}{1-\frac{1}{\hat{\epsilon}_i}} = \frac{1}{1-\frac{1}{\rho-(\rho-\sigma)s_i+\frac{\beta\delta\eta(\rho-1)(1-s_i)}{1-\beta(1-\delta)}}}\\ &= \frac{1}{\rho+\frac{\beta\delta\eta(\rho-1)}{1-\beta(1-\delta)}-\left(\rho-\sigma+\frac{\beta\delta\eta(\rho-1)}{1-\beta(1-\delta)}\right)s_i}.\end{aligned} \tag{I.8}$$

Let $\hat{\rho} \equiv \rho + \frac{\beta\delta\eta(\rho-1)}{1-\beta(1-\delta)}$. Then (I.8) can be rephrased as the following geometric series:

$$\mu_i = \frac{1}{1-\frac{1}{\hat{\rho}}\sum_{m=0}^{\infty}(\frac{\hat{\rho}-\sigma}{\hat{\rho}})^m s_i^m}, \tag{I.9}$$

where the common factor is $\frac{\hat{\rho}-\sigma}{\hat{\rho}} \in (0,1)$. Then, we have

$$\frac{s_i}{\mu_i} = s_i(1-\frac{1}{\hat{\rho}}-\frac{1}{\hat{\rho}}(\frac{\hat{\rho}-\sigma}{\hat{\rho}})s_i-\frac{1}{\hat{\rho}}(\frac{\hat{\rho}-\sigma}{\hat{\rho}})^2 s_i^2-...)$$

Following Alviarez et al. (2025) and Grassi et al. (2017), we approximate the higher-order terms to be zero:

$$\frac{s_i}{\mu_i} \simeq s_i(1-\frac{1}{\rho}-\frac{1}{\rho}(\frac{\rho-\sigma}{\rho})s_i).$$

Summing over i gives

$$\sum_i \frac{s_i}{\mu_i} = (1-\frac{1}{\hat{\rho}}) - \frac{\hat{\rho}-\sigma}{\hat{\rho}^2}\sum_i s_i^2,$$

and plugging it back to (2), we can rewrite the aggregate markup as follows:

$$\mu = \frac{1}{\frac{(\hat{\rho}-1)}{\hat{\rho}} - \frac{(\hat{\rho}-\sigma)}{\hat{\rho}^2}\sum_i s_i^2} = \frac{1}{\frac{(\hat{\rho}-1)}{\hat{\rho}} - \frac{(\hat{\rho}-\sigma)}{\hat{\rho}^2} HHI}.$$

Thus, with higher HHI, aggregate markup rises. $\square$

I.3 Proof of Proposition 3

Let $\lambda_i \equiv \dfrac{d\ln p_i}{d\ln c_i}$. Differentiate $p_i = \mu_i c_i$:

$$\lambda_i = \frac{d\ln p_i}{d\ln c_i} = 1 + \frac{d\ln \mu_i}{d\ln c_i}. \tag{I.10}$$

Note that with no markup, there will be a perfect passthrough

$$\frac{d\ln p_i}{d\ln c_i} = 1.$$

If not, $\frac{d\ln \mu_i}{d\ln c_i} \neq 0$, and this becomes

$$\frac{d\ln \mu_i}{d\ln c_i} = \frac{d\ln \mu_i}{ds_i}\cdot\frac{ds_i}{d\ln c_i} = \underbrace{\frac{d\ln \mu_i}{d\hat{\epsilon}_i}}_{-\frac{1}{\hat{\epsilon}_i(\hat{\epsilon}_i-1)}<0} \cdot \underbrace{\frac{d\hat{\epsilon}_i}{ds_i}}_{\sigma-\hat{\rho}<0} \cdot \frac{ds_i}{d\ln c_i} = \underbrace{\frac{(\hat{\rho}-\sigma)}{\hat{\epsilon}_i(\hat{\epsilon}_i-1)}}_{>0} \cdot \frac{ds_i}{d\ln c_i}, \tag{I.11}$$

where $\hat{\rho} \equiv \rho + \frac{\beta\delta\eta(\rho-1)}{1-\beta(1-\delta)}$. Thus, the sign depends on $\frac{ds_i}{d\ln c_i}$. Getting this term further

$$\frac{ds_i}{d\ln c_i} = \frac{ds_i}{d\ln p_i}\frac{d\ln p_i}{d\ln c_i}.$$

With (12), we know that

$$\ln s_i = (1-\rho)\ln p_i - (1-\rho)\ln P_s$$

and

$$\frac{d\ln s_i}{d\ln p_i} = (1-\rho) - (1-\rho)s_i = (1-\rho)(1-s_i),$$

as $\frac{d \ln P_s}{d \ln p_i} = s_i$. Plugging it back to above,

$$\frac{ds_i}{d \ln c_i} = \frac{ds_i}{d \ln p_i} \frac{d \ln p_i}{d \ln c_i} = s_i(1-\rho)(1-s_i) \frac{d \ln p_i}{d \ln c_i}.$$

Then combining it with (I.11) and plugging them into (I.10), we have the passthrough of cost-shock on prices as follows:

$$\lambda_i = \frac{d \ln p_i}{d \ln c_i} = \frac{1}{1 + \frac{(\hat{\rho}-\sigma)(\rho-1)s_i(1-s_i)}{\hat{\epsilon}_i(\hat{\epsilon}_i-1)}}, \tag{I.12}$$

where $\hat{\epsilon} = \hat{\epsilon}(s_i)$ following (I.4) and (I.5). Given that $\frac{(\hat{\rho}-\sigma)(\rho-1)s_i(1-s_i)}{\hat{\epsilon}_i(\hat{\epsilon}_i-1)} > 0$, this confirms

$$0 < \lambda_i = \frac{d \ln p_i}{d \ln c_i} < 1,$$

confirming incomplete but positive pass-through of cost shock.

Next, we prove how pass-through depends on firms' market share. Let $\Phi_i = \frac{(\hat{\rho}-\sigma)(\rho-1)s_i(1-s_i)}{\hat{\epsilon}_i(\hat{\epsilon}_i-1)}$. Then we want to verify eventually:

$$\frac{\partial \Phi_i}{\partial s_i}, \quad \text{and thus } \frac{\partial \lambda_i}{\partial s_i} = -\frac{1}{(1+\Phi_i)^2} \frac{\partial \Phi_i}{\partial s_i}.$$

$$\frac{\partial \Phi_i}{\partial s_i} = (\hat{\rho}-\sigma)(\rho-1) \frac{(1-2s_i)\hat{\epsilon}_i(\hat{\epsilon}_i-1) - s_i(1-s_i)(2\hat{\epsilon}_i-1)(\sigma-\hat{\rho})}{(\hat{\epsilon}_i(\hat{\epsilon}_i-1))^2},$$

of which sign depends on the sign of

$$(1-2s_i)\hat{\epsilon}_i(\hat{\epsilon}_i-1) - s_i(1-s_i)(2\hat{\epsilon}_i-1)(\sigma-\hat{\rho}). \tag{I.13}$$

Using (I.4) and (I.5), we know $\hat{\epsilon}_i = (1-s_i)\hat{\rho} + s_i\sigma$ and can phrase (I.13) as

$$(1-2s_i)((\sigma-\hat{\rho})s_i + \hat{\rho})((\sigma-\hat{\rho})s_i + \hat{\rho} - 1) - s_i(1-s_i)(2(\sigma-\hat{\rho})s_i + 2\hat{\rho} - 1)(\sigma-\hat{\rho}).$$

Let $X(s_i) \equiv (1-2s_i)((\sigma-\hat{\rho})s_i+\hat{\rho})((\sigma-\hat{\rho})s_i+\hat{\rho}-1) - s_i(1-s_i)(2(\sigma-\hat{\rho})s_i+2\hat{\rho}-1)(\sigma-\hat{\rho})$.

Then we can prove the following:

$$\frac{dX}{ds_i} = -2\Bigg((s_i\sigma + (1-s_i)\hat{\rho})(s_i\sigma + (1-s_i)\hat{\rho} - 1) + (\sigma - \hat{\rho})^2 s_i(1-s_i)\Bigg) < 0,$$

so that X is a monotone decreasing function in s_i, and there will be a cutoff s^* above (below) which $X(s) < 0$ and create more pronounced (mitigated) pass-through of shock. Note that $X(0) = \hat{\rho}(\hat{\rho} - 1) > 0$ and $X(1) = -\sigma(\sigma - 1) < 0$, and given $\frac{dX}{ds_i} < 0$, there will be a cutoff $s^* \in (0, 1)$ such that

$$X(s^*) = 0, \quad X(s) < 0 \text{ if } s > s^* \text{ and } X(s) > 0 \text{ if } s < s^*.$$

Connecting this to the above, we have

$$\text{if } s_i > s^*, \quad \frac{\partial \Phi_i}{\partial s_i}|_{s_i > s^*} < 0 \quad \text{and thus } \frac{\partial \lambda_i}{\partial s_i}|_{s_i > s^*} > 0$$

$$\text{if } s_i < s^*, \quad \frac{\partial \Phi_i}{\partial s_i}|_{s_i < s^*} > 0 \quad \text{and thus } \frac{\partial \lambda_i}{\partial s_i}|_{s_i < s^*} < 0.$$