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 data, we document that, from 2006 to 2020, poorer MSAs experienced annual food inflation 0.46 percentage points higher than richer MSAs, implying an 8.8 percentage point cumulative gap. Poorer areas also have fewer products, fewer retailers, and higher market concentration. To identify causal effects, we exploit the 2014–2015 avian influenza outbreak and show that higher local retail concentration amplifies the pass-through of cost shocks. We develop a heterogeneous-firm model with customer capital accumulation that rationalizes these patterns.

Keywords: inflation; retailer market structure; market concentration; market power; pass-through 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. Food markets are also more localized and segmented than many other sectors, with local market structures playing an important role in price variation.[2] Moreover, food is a necessity and accounts for a disproportionately large share of spending for low-income and vulnerable households.[3] 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 new 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 MSAs between 2006 and 2020, with a cumulative gap of approximately 8.8 percentage points

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

[3]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.

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 goods 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.[4] 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.[5] We also find that retail sales are lower and more concentrated in poorer areas.

Finally, descriptive OLS regressions reveal a positive association between retailer market concentration and inflation at the MSA level. Inflation is also negatively related to income, but this relationship disappears once we control for market concentration.

Next, to identify the causal relationship between inflation and retailer market concentration, we exploit the 2014–2015 bird flu episode in the egg market, which provides plausibly exogenous variation in exposure across regions. 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% 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

[4]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.

[5]These patterns are robust when using the Business Dynamics Statistics (BDS), where retailer size is defined by employment. Large retailers have 500 or more employees, while small retailers have 19 or fewer.

to 2015Q3), while prices adjust downward less during the subsequent deflationary phase (after 2015Q3). The absence of offsetting deflation during the deflationary period suggests that temporary shocks can have persistent effects on regional inflation, contributing to long-run spatial disparities in prices and potentially amplifying real income inequality. We rule out alternative explanations related to differences in consumption baskets, retailer composition, and local cost factors; consistent evidence from pass-through in the coffee market further supports this interpretation.

To rationalize the mechanism underlying our empirical findings, we develop a model of heterogeneous firms with customer capital that links market concentration to pass-through. We build on Atkeson and Burstein (2008) and incorporate customer capital accumulation following 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 spatial policy implications because retail food markets are highly localized. In poorer regions, where these markets are more segmented, higher food inflation has a disproportionate effect on 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.[6] As a result, the interaction between local market segmentation and 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.[7]

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

[7] This is consistent with Beck and Jaravel (2020) and Jaravel (2024), who document biases in standard aggregate price indices arising from non-homothetic preferences and heterogeneous inflation across households.

National price indexes systematically 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.[8] Jaravel (2018) finds similar results with emphasis on the role of product innovation and segmented consumption goods. Argente and Lee (2021) find high-income households face lower inflation during recessions due to substitution toward lower-quality goods, and Becker (2024) shows that such demand shifts raise markups on cheaper goods, increasing prices faced by poor households. Handbury (2021) and Molloy (2024) further highlight the role of income-specific tastes and housing in shaping inflation differences, respectively. 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. This spatial variation can provide a tractable margin for policy as differences across locations are observable and align with existing policy frameworks, such as placed-based transfers, competition policy, and local market regulation.

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), rising product variety

[8] O'Flaherty (2026) documents substantial dispersion in relative price changes across products and shows that some within-product dispersion across households also exists.

(Brand, 2021), household search behavior (Sangani, 2022), changes in marginal costs and price sensitivity (Döpper et al., 2025), and rise in concentration of household shopping (Leung and Li, 2026).[9] Jaravel (2018) and Jaravel (2021) show that firms disproportionately innovate in products with higher demand from rich households, leading to greater product entry and stronger competition in markets serving richer consumers. Our paper contributes to this literature by documenting systematic variation in retailer market concentration across MSAs with different income levels and by establishing a causal link between concentration and inflation.

Our paper is also related to the literature on food deserts and local retail access, which emphasizes spatial disparities in the availability of grocery stores and healthy foods (Bitler and Haider, 2011; Allcott et al., 2019). We highlight a complementary mechanism operating through local market structure: retail environments with fewer competitors tend to be more concentrated, which can increase markups and amplify the pass-through of cost shocks, contributing to systematically higher food inflation.

Our paper also contributes to the literature on the pass-through of shocks to retail 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 how pass-through varies systematically 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.[10]

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

[9] Similarly, Franco (2024) finds that markups are lower in larger cities using the Census micro-level data.

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

cost-of-living changes (Handbury et al., 2013). Related efforts include Beck and Jaravel (2020), who correct biases in standard cross-country price indices by constructing a scanner-data-based index that accounts for non-homothetic preferences, product variety, and taste heterogeneity; Jaravel and Lashkari (2024), who derive a correction to real consumption (welfare) that accounts for heterogeneity in consumption baskets and inflation; and Jaravel (2024), who construct Distributional Consumer Price Indices (D-CPIs) based on heterogeneous inflation rates across demographic groups and show that real inequality grows faster under D-CPIs than under official CPIs. In a similar vein, we construct regional price indices at the MSA level to better capture spatial heterogeneity in inflation.[11] 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.[12] 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.[13]

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

[11] This is close to Handbury and Weinstein (2014) and Diamond and Moretti (2021). Unlike Handbury and Weinstein (2014), we do not remove heterogeneity bias nor variety bias to best reflect the consumption basket of households.

[12] 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.

[13] This contrasts with Moretti (2013) and Diamond and Moretti (2021), who document that real inequality is lower than nominal inequality when taking into account variations in goods coverage, geographic scope, or cost-of-living. Our analysis focuses on food prices using highly granular UPC-level data.

for food products.[14]

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.[15] 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).[16] These ELIs then map to Personal Consumption Expenditure (PCE) disaggregated categories. Our analysis focuses on the food sector, 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.[17] We then define income deciles by the cross-time average of MSA-level income per capita. Table 1 reports examples of MSAs in the top, median, and bottom income deciles.

[14] As a secondary dataset, we use the Business Dynamics Statistics (BDS), which covers the universe of firms in the retail sector. In BDS, we use alternative definitions of retailer size based on employment. We confirm the robustness of our findings in BDS, which suggests that our results are not driven by sampling limitations in NielsenIQ. See more details in Online Appendix D.3.

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

[16] 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.

[17] Our baseline uses retailers' MSA locations in NielsenIQ. To address cross-MSA shopping concerns, we use NielsenIQ Consumer Panel data to examine its prevalence and compare income deciles defined by store MSA versus household MSA; see Online Appendix A.

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.

The price data is aggregated to the monthly frequency using the National Retail Federation (NRF) calendar and then aggregated to the quarterly frequency.[18] 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.

2.2 Main Measures

2.2.1 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)

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

m.[19]

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 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.[20] See more details in Online Appendix C.1.

2.2.2 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. We use the local HHI of retailer sales as our main measure of market concentration in each MSA.[21] 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.

[19] 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 Online Appendix B.

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

[21] 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 Descriptive Evidence

3.1 Spatial Heterogeneity in Retail Prices and Inflation

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.[22]

[22] 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.

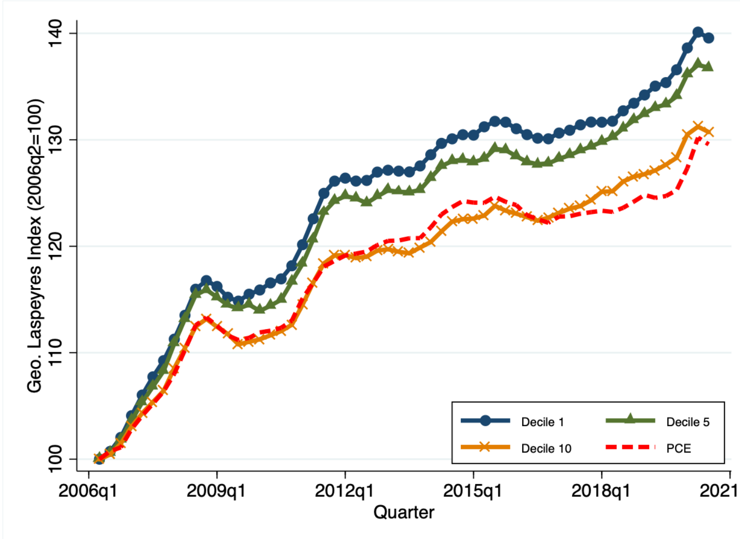

Figure 1: Price Index for Aggregated Food

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 Online Appendix C.1 and C.2.

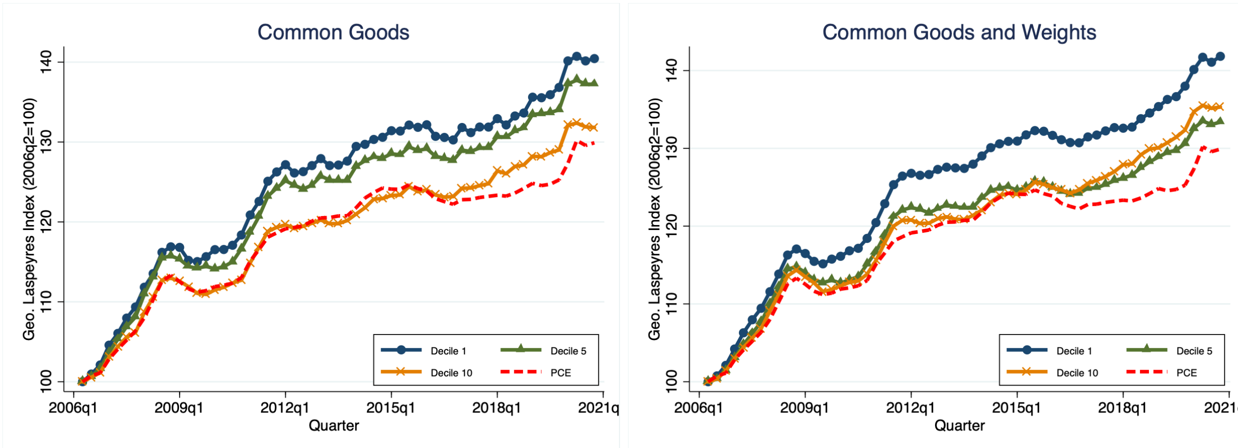

Figure 2: Price Index for Aggregated Food (Common Goods and Weights)
Notes: This figure represents the chained geometric Laspeyres price index constructed using NielsenIQ Retail data (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (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 aggregate price indices more closely track inflation in higher-income areas and understate inflation in lower-income areas. This discrepancy in inflation has important macroeconomic implications, particularly for assessing real income inequality and cost-of-living differences across different regions.[23] In Appendix A, we examine aggregate implications of this spatial heterogeneity for real income inequality.

3.2 Spatial Heterogeneity in 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.

[23]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.

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.

We next run the following regression to examine the cross-sectional variation in retailer market 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 in quarter t, and δ_t denotes quarter fixed effects.

The results, presented in Table 4, reinforce 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.

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

We show that the results are robust to alternative measures of market concentration based on the sales shares of the top firms (CR1 and CR3) and by controlling for MSA-level population. The results are reported in Online Appendix D.1. We further examine the long-run cross-sectional relationship using MSA-level averages over the sample period.[24] The long-run patterns are consistent with the baseline findings, as presented in Online Appendix D.2. We also obtain consistent results using the Business Dynamics Statistics (BDS) dataset from the U.S. Census Bureau, as shown in Online 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

[24]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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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 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 Online 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 Online 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 market. In particular, 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.

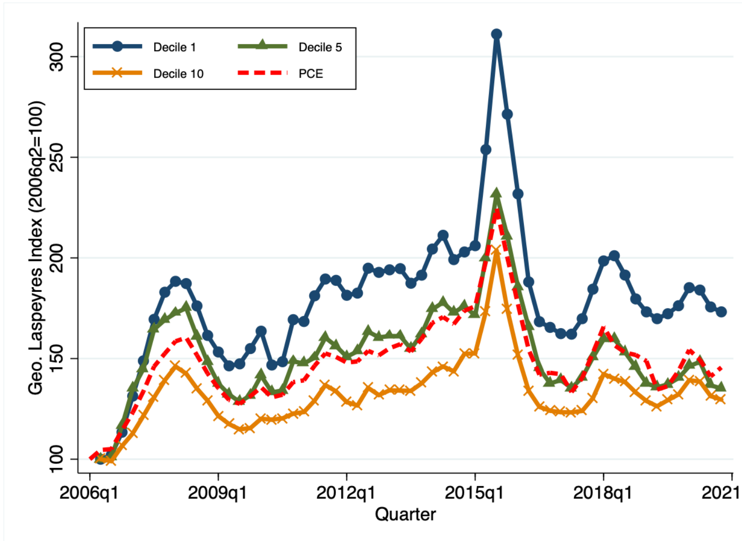

Figure 3: Price Index for Eggs

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.[25] 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.[26] By identifying MSAs where layers were culled, we can pinpoint areas disproportionately affected by the bird flu,

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

[26] 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.[27,28]

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.[29] 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

[27] 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).

[28] 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 (Online Appendix F).

[29] 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 $\times$ 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

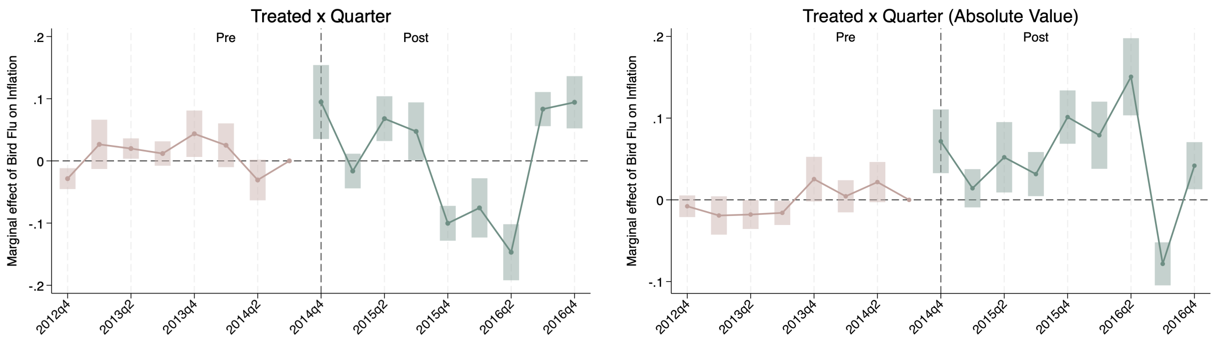

Figure 4: Event Study Difference-in-Differences (Bird Flu)

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:

$$\begin{aligned} P_{mt} = \beta_0 + \beta_1 HHI_{mt} + \beta_2(\text{Treated}_m \times \text{Post}_t) + \beta_3(\text{Treated}_m \times HHI_{mt}) + \beta_4(\text{Post}_t \times HHI_{mt}) \\ + \beta_5(\text{Treated}_m \times \text{Post}_t \times HHI_{mt}) + \delta_m + \delta_t + \varepsilon_{mt}, \end{aligned} \tag{5}$$

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

Table 7: 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 (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. 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

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 pre-shock value in 2014Q3.[30] 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 7. 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 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

[30]This is to avoid endogeneity concerns and to isolate the effect of supply shocks on local market concentration.

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.

4.2 Robustness Checks

We conduct several robustness checks for the main results. The findings are robust to using terciles of HHI (Online Appendix G.1), alternative measures of market concentration such as CR1 and CR3 (Online Appendix G.2), and the inclusion of neighboring MSAs around treated markets (Online Appendix G.3).

Another 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:

$$\begin{aligned}\Delta \ln price_{umt} = {} & \beta_0 + \beta_2 HHI_{mt} + \beta_4(Treated_m \times Post_t) + \beta_5(Treated_m \times HHI_{mt}) \\ & + \beta_6(Post_t \times HHI_{mt}) + \beta_7(Treated_m \times Post_t \times HHI_{mt}) + \delta_m + \delta_t + \delta_u + \varepsilon_{umt},\end{aligned} \tag{6}$$

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 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

Table 8: 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

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, 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.

Furthermore, an alternative explanation is variation in retailer composition across MSAs, since 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 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.[31] On the other hand, national chains may charge prices

[31] 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

closer to marginal costs, which could impact the local level of prices, markups, and pass-through.[32] 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.[33] 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 by differences in retailer composition rather than market concentration.

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. To account for the possibility that differential pass-through reflects retailer geographic scope rather than market concentration, we augment equation (5) with two additional triple interactions, $(\text{Treated}_m \times \text{Post}_t \times \text{RegionalShare}_{mt})$ and $(\text{Treated}_m \times \text{Post}_t \times \text{NationalShare}_{mt})$, together with the full set of lower-order interactions implied by the inclusion of $\text{RegionalShare}_{mt}$ and $\text{NationalShare}_{mt}$. Note that the share of local retailers is omitted as the baseline group.

The results are presented in Table 9.[34] 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.

On top of these, we show that the results are not driven by cost-side channels, such as differential wage growth in the retail sector (Online Appendix G.4). We also provide consistent evidence in the coffee market by exploiting fluctuations in commodity prices, following Sangani (2024), in Online

puzzle documented in DellaVigna and Gentzkow (2019), showing that national chains charge geographically uniform prices and their prices are insensitive to local demand shocks.

[32] 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.

[33] Note that within the eggs market during our sample period, we find a positive correlation between HHI and the share of national retailers.

[34] Given space constraints, we report only the coefficients on the terms of primary interest.

Table 9: Triple Difference Estimator (Retailer Composition)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.070*	0.096**	0.053
	(0.038)	(0.044)	(0.082)
Bird Flu × Post	0.065	-0.043	0.026
	(0.105)	(0.198)	(0.119)
HHI × Post	-0.010*	-0.018**	0.012
	(0.006)	(0.009)	(0.012)
Bird Flu × HHI	-0.164	-0.197	-0.085
	(0.138)	(0.181)	(0.200)
HHI	0.034	0.056*	0.022
	(0.026)	(0.029)	(0.049)
Bird Flu × Post × Regional Share	-0.103	0.072	-0.104
	(0.182)	(0.310)	(0.215)
Bird Flu × Post × National Share	-0.110	0.028	-0.092
	(0.104)	(0.174)	(0.155)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	3145	1850	1295

The table reports regression results from equation (5), including additional triple interactions of Bird Flu × Post with national retailer share and regional retailer share. The coefficients on these triple interactions are reported in the table. Additional interaction controls involving retailer shares are included in the regressions but omitted from the table for brevity. All other descriptions remain the same as in Table 7. *** p<0.01, ** p<0.05, * p<0.1

Appendix G.5.

4.3 Back-of-the-Envelope

To assess whether the magnitudes estimated in Table 7 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. 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:

$$\pi_{contribution} = \frac{q \cdot \beta \cdot HHI_{diff}}{\pi_{d1} - \pi_{d10}}, \tag{7}$$

where $\pi_{contribution}$ 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} and π_{d10} denote cumulative egg inflation for the poorest and the richest decile, respectively, over the same period. Inflation rates are measured in decimal units in the calculation.[35] The coefficient β corresponds to the estimate on the triple interaction Bird Flu $\times$ Post $\times$ HHI from Table 7, Column 2. Finally, HHI_{diff} denotes the difference in retail market concentration (HHI) between the poorest and richest deciles as of 2014Q3.

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 (7). 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.

5 Theoretical Framework

5.1 Environments

In this section, we develop a theoretical framework to identify the mechanisms underlying retail market concentration and pass-through and to guide the interpretation of the empirical findings. Following Atkeson and Burstein (2008), we model an economy for food sectors within an MSA 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 is a discrete

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

number of retailers $\mathcal{N}_s$ supplying differentiated varieties. Consumption at the sectoral level is

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

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 as follows.[36]

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

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

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

[36] 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.

5.2 Firms

Each firm produces with marginal cost c_{it} which is in productivity z_{it}.[37] 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 follows

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

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 is

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

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 set 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), and the firm optimality conditions (15)-(16) hold, with normalized output $Y = 1$.

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

5.4 Markups

In equilibrium, firms with larger market shares set higher markups, as shown in Proposition 1. The intuition is that firms with larger market shares face a lower marginal value of customer capital, which reduces the cost of losing customers and allows them to set higher prices and markups.. This mechanism is consistent with Atkeson and Burstein (2008), while our framework additionally incorporates customer capital dynamics.

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

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 B.2.*

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.

Proposition 3. *Firm pass-through is incomplete and exhibits a U-shaped relationship with firm market share. Proof: See Appendix B.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 large 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 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 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 our data. To discipline differences in market concentration, we vary $\mathcal{N}_s$ while holding all other structural parameters fixed.[38] 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 5. Prices rise after the shock, and this increase is more pronounced in the high-HHI ($\mathcal{N}_s = 3$) economy. This difference persists along the transition path, as price changes remain higher in the high-HHI economy. These patterns are consistent with our 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 6 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).

[38] 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).

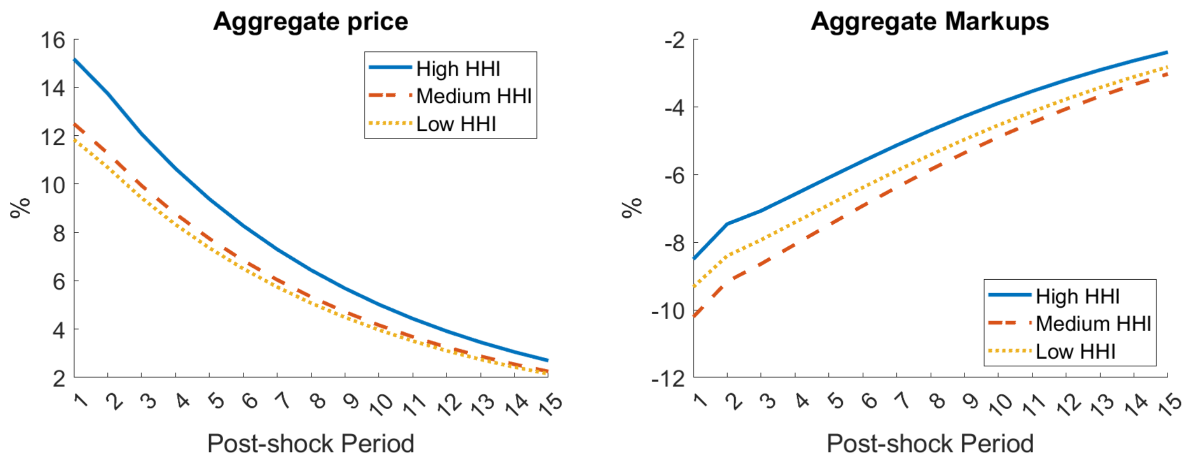

Figure 5: Response of Aggregate Price and Markups to a Cost Shock
Notes: The figure plots the impulse responses of the aggregate price level (left panel) and markups (right panel) to a positive common cost shock. "High HHI" corresponds to the economy with $\mathcal{N}_s = 3$, and "Medium HHI" and "Low 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).

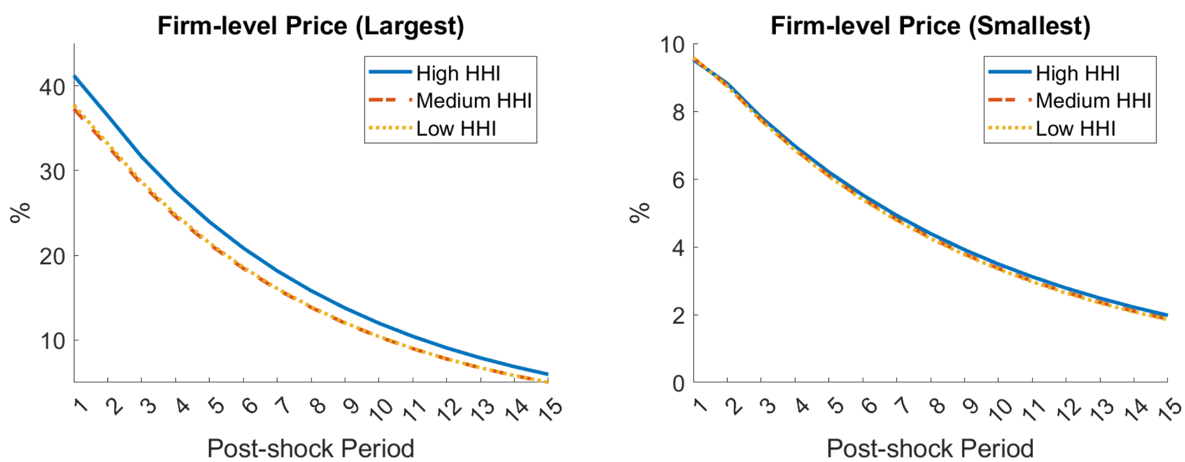

Figure 6: Response of Firm-Level Prices (Large vs. Small) to a Cost Shock
Notes: The figure plots the impulse responses of firm-level prices for the largest retailer (left panel) and the smallest retailer (right panel) in the baseline economy to a positive common cost shock. In the counterfactual economies, 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.

As a result, when the shock hits, the largest 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, markups, and customer capital are more muted than those of its counterparts in less concentrated

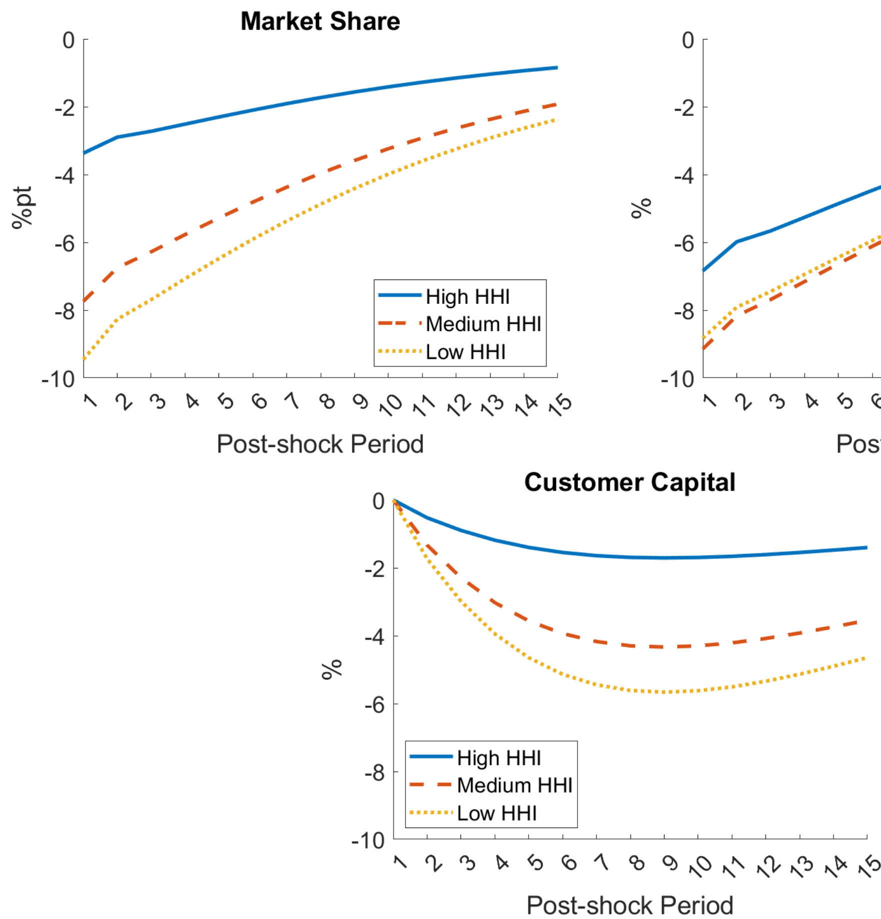

Figure 7: Response of the Largest Firm's Sales Share, Markup and Customer Capital to a Cost Shock

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.

economies, as shown in Figure 7.

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.

The model highlights market structure as a potential amplifier of the welfare costs of cost shocks. High-HHI economies exhibit higher pass-through, which is accompanied by higher equilibrium markups (Proposition 2). As a result, 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 how place-based policies shape retailer location choices, affect market structure, and improve resource allocation across regions. This is an avenue we leave for future 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 from the 2014–2015 bird flu outbreak, we show that MSAs with higher retail concentration experience larger inflation spikes and slower subsequent price declines. 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.

Appendix

A Real Income Inequality

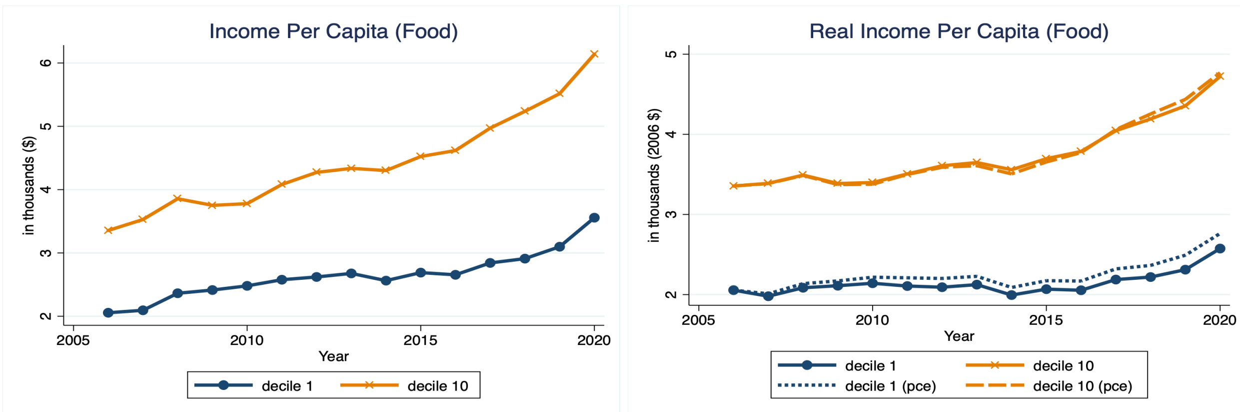

Figure A.1: Nominal and Real Income per Capita

Notes: This figure displays nominal and real income per capita allocated to food (in thousands of dollars) across income deciles, with the left panel showing nominal values and the right panel showing real values (food price deflator). For the two solid lines in the right panel, real income is constructed using decile-level food price indexes derived from NielsenIQ. The two dashed lines use the official PCE food price index for deflation, where the short-dashed line corresponds to decile 1 and the long-dashed line to decile 10. The sample period is 2006 to 2020. Decile 1 represents MSAs in the bottom income decile, and decile 10 represents those in the top income decile.

We examine nominal and real income per capita across income deciles over time. We focus on food-at-home given the coverage of the NielsenIQ data. First, we estimate the share of nominal income per capita allocated to food for each MSA. The Consumer Expenditure Survey (CEX) reports food-at-home expenditure shares by household income ranges, with nine groups defined prior to 2014 and seven groups thereafter. Using NielsenIQ Consumer Panel, we map household income into these groups and compute each group's expenditure weight within an MSA. We then construct the MSA-level food expenditure share as the weighted average of CEX group-level food shares using these weights. Multiplying by MSA-level nominal income per capita from the Bureau of Economic Analysis yields average income allocated to food at the MSA level. Next, we average this measure across MSAs within each decile for the left panel. To obtain real income per capita, we deflate the nominal series using the food price index constructed from the NielsenIQ Retail Scanner.

The two solid lines in Figure A.1 illustrate the patterns of nominal and real income series for the top (decile 10) and bottom (decile 1) income deciles. The data indicate that both nominal and real income per capita have generally increased across all deciles. In particular, the gap between the top and bottom deciles has widened over time for both measures.

Ignoring differences in regional inflation compresses measured real income gaps. This is illustrated by the two dashed lines in the right panel of Figure A.1, which plot real income per capita for the bottom and top deciles constructed using the official PCE food price index. The figure shows that relying on this national index overstates real income in decile 1, both in levels and in growth rates, but has little effect on the decile 10 series relative to the baseline. As a result, it understates the real income gap and, in turn, real income inequality.

This pattern arises because official price indexes are typically available only at the national level or for relatively wealthy MSAs.[39] Since the national index is an expenditure weighted average across regions, where expenditure weights are disproportionately higher in richer areas, it primarily reflects the inflation patterns of higher-income regions. Consequently, relying on national indexes can misrepresent the real income in lower-income areas.

B Analytical Results and Proofs

B.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),

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

Then, the elasticity ϵ_{it} is

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

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:

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

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

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

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

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:

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

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

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

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

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

This completes the proof. □

B.2 Proof of Proposition 2

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

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

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

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

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

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. □

B.3 Proof of Proposition 3

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

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

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

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

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 (B.11) and plugging them into (B.10), we have the passthrough of cost-shock on prices as follows:

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

where $\hat{\epsilon} = \hat{\epsilon}(s_i)$ following (B.4) and (B.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 the sign of $\frac{\partial \Phi_i}{\partial s_i}$, and thus, the sign of $\frac{\partial \lambda_i}{\partial s_i} = -\frac{1}{(1+\Phi_i)^2}\frac{\partial \Phi_i}{\partial s_i}$. Note that

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

of which sign depends on the sign of

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

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

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

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

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