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 granular NielsenIQ Retail Scanner data 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.

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 between the bottom and top income deciles. This pattern holds across both disaggregated and

[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 expenditure on food, compared to 13% for middle-income households and an even smaller share for high-income households, based on the Consumer Expenditure Survey.

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—measured by the sales-based Herfindahl–Hirschman Index (HHI)—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 market concentration, we exploit the 2014–2015 bird flu (avian influenza) 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 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 to 2015Q3), while prices adjusted downward less during the subsequent deflationary phase (after

[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. We define large retailers as those with 500 or more employees and small retailers as those with 19 or fewer employees.

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. These patterns are not driven by differences in consumption baskets, retailer composition, or local cost factors. Analogous pass-through patterns in the coffee market provide further support for the role of market concentration.

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 charge higher markups. Consequently, sufficiently large firms pass through cost shocks more aggressively, as the marginal loss of customer capital is smaller 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, so policies that shape local retailer market structure can affect both cost pass-through 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 expenditure to food and face limited access to alternative retailers and substitute goods.[6] As a result, the interaction between local market segmentation and concentrated retail market structures disproportionately burdens consumers in poorer regions.

Moreover, when real income is evaluated using locally constructed food price indexes, real income inequality widens relative to measures based on national price indexes.[7] 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

[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 indexes arising from non-homothetic preferences and heterogeneous inflation across households.

both inflation and market structure when evaluating welfare and designing policies.

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) emphasizes the role of product innovation and segmented consumption goods. Argente and Lee (2021) find that high-income households face lower inflation during recessions by substituting toward lower-quality goods, while Becker (2024) shows that such demand shifts raise markups on cheaper goods purchased by poor households. Handbury (2021) and Molloy (2024) further highlight the roles of income-specific tastes and housing, 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 place-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 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 (Brand, 2021), household search behavior (Sangani, 2022), changes in marginal costs and price sensitivity (Döpper et al., 2025), and the 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

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

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

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 from this literature by exploiting the 2014–2015 avian influenza outbreak, which generated a sharp, temporary, and exogenous supply shock in the US egg market with 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 indexes in capturing true cost-of-living changes (Handbury et al., 2013). Related efforts include Beck and Jaravel (2020), who correct biases in standard cross-country price indexes 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 het-

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

erogeneity in consumption baskets and inflation; and Jaravel (2024), who constructs Distributional Consumer Price Indexes (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 indexes at the MSA level to better capture spatial heterogeneity in inflation.[11] In contrast, official indexes 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 indexes 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; Section 6 discusses potential policy implications; and Section 7 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 using data on food sales, prices, and store locations.[14]

[11] Our index construction is closely related to that in 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 indexes 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.

[14] As a secondary dataset, we use the Business Dynamics Statistics (BDS) from the U.S. Census Bureau, which covers the universe of firms in the retail sector.

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 into 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.

The weekly price data are first aggregated into months according to the National Retail Federation (NRF) calendar and then into quarters by grouping three consecutive NRF months.[18] Using the concordance between product modules and PCE food categories, we identify the food sector in

[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.

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

Table 1: Examples of MSAs by Decile

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.

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, the log geometric Laspeyres price index, which is calculated as follows:

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

where ω_{mkt} represents the weight assigned to product k in quarter t for MSA (or income decile) m, and we use lagged expenditure shares as weights, e.g., $\omega_{mkt} = s_{mkt-1}$. The set $\mathbb{C}_{m,t-1,t}$ includes all "continuing" goods, defined as products sold in both periods t and $t-1$ in MSA (or income decile) m.[19]

We also construct two alternative price indexes: i) one by restricting the sample to UPCs that

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

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 price indexes to address potential biases associated with our baseline measure, such as substitution bias or chain drift.[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.

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

[20] Fixed-basket price indexes do not fully account for demand responses arising from consumers substituting across differentiated goods, and chained price indexes may be subject to chain drift.

[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 Decile by Sales)	0.357 (0.11)
Sales ($ millions)	207.23 (366.62)	Share of Small Chains (Bottom Decile by Sales)	0.016 (0.04)
Population Share	0.005 (0.01)	Share of Large Chains (Top Decile by Store #)	0.619 (0.16)
Sales Share of Chains	0.117 (0.04)	Share of Small Chains (Bottom Decile by Store #)	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.

(richest) income deciles, alongside the official PCE food price index for comparison. The base quarter is set to 2006Q2.[22]

The general trend in Figure 1 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 the bottom income decile compared to 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.

[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.

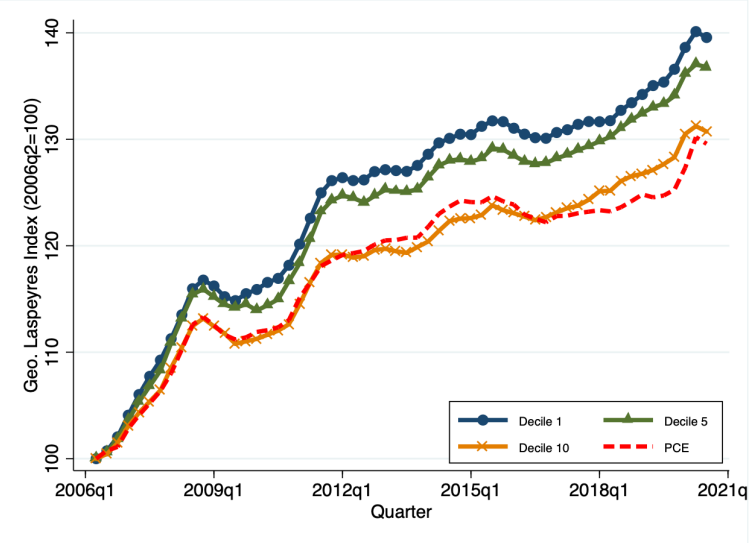


Figure 1: Price Index for Aggregated Food

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.

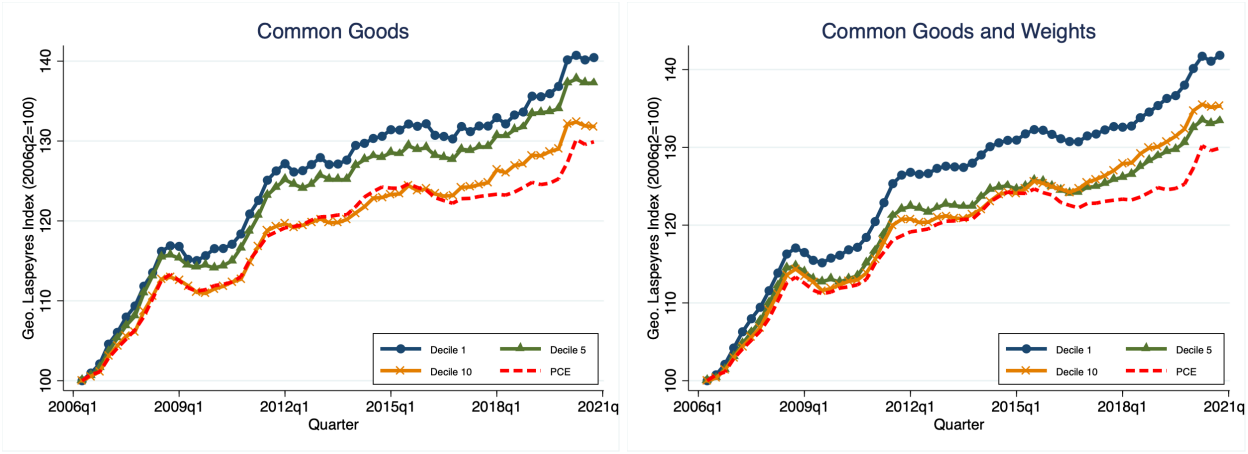


Figure 2: Price Index for Aggregated Food (Common Goods and Weights)

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.

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 indexes, including a chained and direct (bilateral) Tornqvist index, a weighted time-product dummy (WTPD) index, a demand-system-consistent Sato-Vartia index, and an MSA-level index (Online Appendix C.1). These patterns also hold across disaggregated PCE food categories (Online Appendix C.2).

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 indexes more closely track inflation in higher-income areas and understate inflation in lower-income areas.[23]

These differences in food inflation are consistent with several findings in the literature. First, DellaVigna and Gentzkow (2019) show that retailers set nearly uniform prices across locations for a given product, which does not exclude spatial inflation differences arising from differences in the set of retailers and products available across markets.[24] Consistent with this mechanism, Kim and Navarrete (2026) document systematic differences in the composition of products and retailers across MSAs along the income distribution. Finally, our findings relate to Butters et al. (2022), who show that local cost shocks are passed through locally rather than uniformly at the national level, suggesting that local market conditions can contribute to spatial differences in price dynamics.

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 decile of income per capita. 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 expenditure—to the set of common goods:

[23] In Section 6, we discuss the policy implications of this spatial heterogeneity for measuring real income inequality.

[24] Note that DellaVigna and Gentzkow (2019) find lower prices in poorer areas, but the differences are economically small.

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.

common goods account for 31 percent of aggregate food consumption in the richest decile, 45 percent in the median decile, and 61 percent in the poorest decile.

We next run the following regression to examine the cross-sectional variation in retailer market 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 in Table 4 reinforce the finding 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, poorer

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

areas have more concentrated retail markets, with large firms accounting for a greater share of sales.

We show that the results are robust to alternative measures of market concentration: the sales share of the largest retailer (CR1) and the combined sales share of the three largest retailers (CR3) within each MSA. 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. The long-run patterns are consistent with the baseline findings, as presented in Online Appendix D.2. We also repeat the analysis using the U.S. Census Bureau's Business Dynamics Statistics (BDS), defining retailer size based on employment rather than sales. The resulting estimates are similar to our baseline findings, providing external validation of the relationship documented in the NielsenIQ data (Online Appendix D.3).

Finally, a potential concern is that measured market concentration in NielsenIQ may be affected by differential sample coverage across MSAs. For example, if NielsenIQ systematically provides more comprehensive retailer coverage in higher-income MSAs, differences in measured market concentration across regions could partly reflect sampling rather than underlying market structure. In Online Appendix E, we compare NielsenIQ retailer coverage with County Business Patterns (CBP) data from the U.S. Census Bureau and examine whether NielsenIQ coverage varies systematically with MSA income. We find no evidence that NielsenIQ coverage relative to CBP is systematically higher in higher-income MSAs.

3.3 Relationship between Inflation and Market Concentration

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

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

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

Table 5 reports the baseline results in Columns 1–3. Columns 1 and 2 show that inflation is higher in MSAs with greater market concentration and lower income per capita. Column 3 provides suggestive evidence that market concentration is the primary driver of inflation differentials, as its coefficient remains large and significant while the coefficient on income per capita attenuates and becomes statistically insignificant at the 10 percent level when both variables are included. Column 4 adds MSA annual population as a control and Column 5 additionally adds the total number of retail chains as a control. Across these specifications with HHI, the relationship between market concentration and inflation remains positive and statistically significant. In contrast, the relationship between income per capita and inflation is only statistically significant in Column 2 when market concentration, population, and total retail chain count are excluded.

We conduct additional robustness checks using alternative measures of market concentration 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 F.1, F.2, and F.3, and are consistent with the baseline findings. Finally, we show that the same pattern holds in the egg market in Online Appendix F.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

Table 5: Food Inflation across Regions

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.328***		0.302***	0.253**	0.316**
	(0.107)		(0.110)	(0.107)	(0.123)
Income		-0.005**	-0.003	0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Population				-0.004***	-0.005***
				(0.001)	(0.001)
Chain #					0.020**
					(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 column. The last two columns include the MSA population (in 100,000s) as a control variable, measured annually using the BEA data. 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

influenza outbreak and implement a triple-difference design to estimate heterogeneous pass-through across MSAs with different levels of concentration.

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 prices 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

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

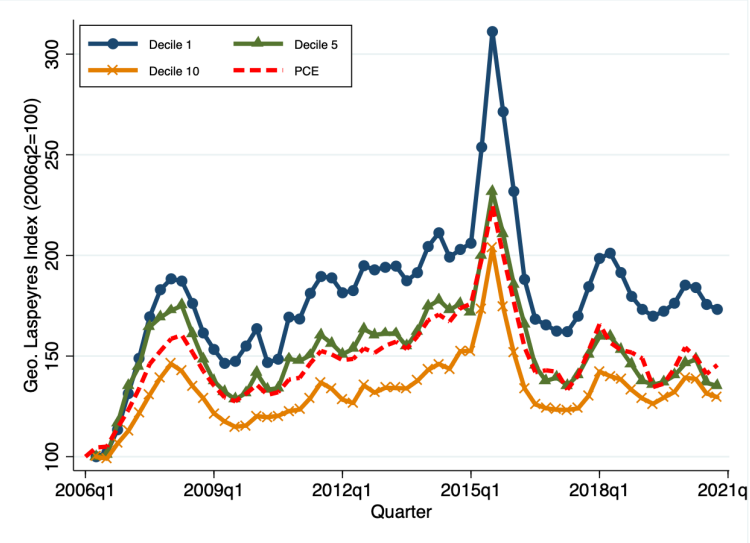


Figure 3: Price Index for Eggs

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.

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, which may have experienced higher inflation in egg prices early in the outbreak.[27,28]

4.1.1 Difference-in-Differences Estimation

Using this information, we first implement a difference-in-differences design that compares egg-price inflation in treated and control MSAs before and after the bird flu outbreak.

To measure whether exposure of local farmers to culling affected local egg prices, we use a four-year window around the start of the bird flu episode in 2014Q4, and run the following

[26] See details from the following Congressional report: https://www.congress.gov/crs-product/R44114?hl=R44114&s=5&r=3.

[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 G).

Table 6: Difference-in-Differences Estimator

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

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

traditional two-way fixed effects regression from 2012Q4 to 2016Q4:

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

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 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

[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.

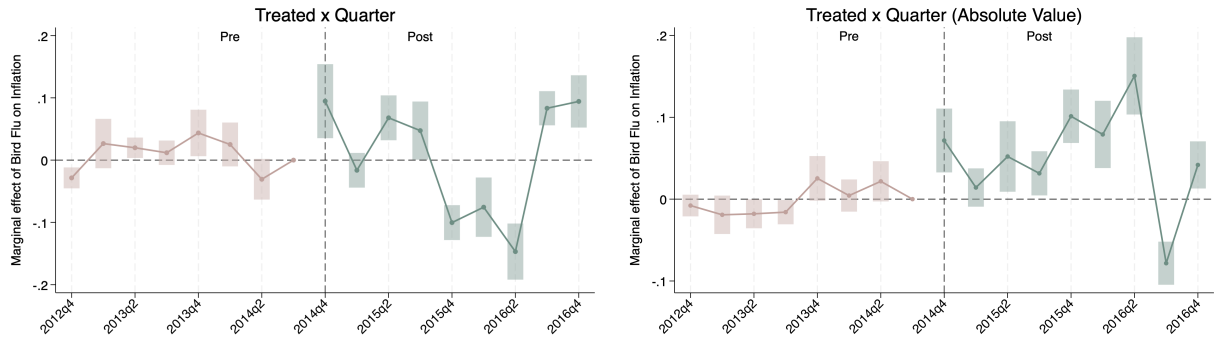


Figure 4: Event Study Difference-in-Differences (Bird Flu)

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.

Flu and Post, which corresponds to 3.9 percentage points higher egg inflation rate in MSAs affected by the bird flu after 2014Q4 during the inflationary period. This 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 3.5 percentage points lower inflation (higher deflation) rate after 2014Q4 during the deflationary period. This 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 points 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 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 the inflationary period and larger price declines during the 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:

$$P_{mt} = \beta_0 + \beta_1 HHI_{mt} + \beta_2(Treated_m \times Post_t) + \beta_3(Treated_m \times HHI_{mt}) + \beta_4(Post_t \times HHI_{mt}) + \beta_5(Treated_m \times Post_t \times HHI_{mt}) + \delta_m + \delta_t + \varepsilon_{mt}, \quad (5)$$

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 equal to 1 if quarter t is after 2014Q4 and zero otherwise. HHI_{mt} is the retailer-sales HHI for eggs 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 four-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 5 percentage points among treated MSAs. This effect is statistically significant at the 1% level. Columns 2 and 3 decompose this effect into the inflationary and deflationary periods, respectively. In Column 2, restricting the sample to the inflationary period, we find that treated MSAs with higher market concentration experienced faster initial price increases in the egg market following the bird flu episode. This coefficient is also significant at the 1% level. In contrast, Column 3 shows that these MSAs did not

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

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 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 chains' 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

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 H.1), alternative measures of market concentration such as CR1 and CR3 (Online Appendix H.2), and the inclusion of neighboring MSAs around treated markets (Online Appendix H.3). Additionally, in Online Appendix H.4, we conduct a placebo test by replacing market concentration with income per capita in the triple-difference specification. The resulting

triple-interaction coefficient shows no robust association with inflation, suggesting that our main results are unlikely to reflect differential responses between higher- and lower-income MSAs. Relatedly, the estimates remain stable in two additional specifications: one adds a triple interaction involving income per capita to the baseline specification, while the other controls for cross-MSA differences in pre-shock price levels (Online Appendix H.5).[31]

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, as follows:

$$\begin{aligned}\Delta \ln price_{umt} = \beta_0 + \beta_1 HHI_{mt} + \beta_2(Treated_m \times Post_t) + \beta_3(Treated_m \times HHI_{mt}) \\ + \beta_4(Post_t \times HHI_{mt}) + \beta_5(Treated_m \times Post_t \times HHI_{mt}) + \delta_m + \delta_t + \delta_u + \varepsilon_{umt},\end{aligned} \tag{6}$$

where $\Delta \ln price_{umt}$ denotes the log change in the price of UPC u in MSA m between quarters $t-1$ and t. We include the UPC fixed effects, δ_u, to ensure that identification comes from price changes within identical products. 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 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.

An alternative explanation is variation in retailer composition across MSAs, as different types of

[31] Sangani (2026) documents lower price levels in lower-income areas; these differences can generate systematic heterogeneity in pass-through.

Table 8: Triple Difference Estimator (UPC-level)

	Δ ln Price	Δ ln Price	Δ ln Price
Bird Flu $\times$ Post $\times$ HHI	0.016***	0.034***	-0.010
	(0.006)	(0.010)	(0.015)
Bird Flu $\times$ Post	-0.009**	-0.005	-0.014
	(0.004)	(0.006)	(0.010)
HHI $\times$ Post	-0.007**	-0.009	-0.004
	(0.003)	(0.006)	(0.007)
Bird Flu $\times$ 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

retailers may exhibit different degrees of cost pass-through. In Online Appendix H.6, we show that our results are not driven by retailer composition differences. In addition, we also provide consistent evidence using fluctuations in commodity prices in the coffee market, following Sangani (2024) (Online Appendix H.7). Lastly, we provide evidence that helps rule out other cost-side channels, such as differential wage growth in the retail sector (Online Appendix H.8).

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.

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.[32] 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 our 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.

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

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

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

where σ denotes the elasticity of substitution across sectors. Within each sector s, there is a discrete number of retailers $\mathcal{N}_s$ supplying differentiated varieties. Consumption at the sectoral level is

$$Y_{st} = \left(\sum_{i \in \mathcal{N}_s} N_{it}^{\frac{\eta}{\rho}} y_{it}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \qquad \rho > 1, \tag{9}$$

where ρ denotes the elasticity of substitution across retailers within a sector, with $\rho > \sigma$, and N_{it} denotes firm i's stock of customer capital, which acts as a demand shifter.

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.

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.[33]

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

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 indexes are

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

[33] 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 decreasing in productivity z_{it}.[34] 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

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

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, varying across firms.[35]

5.3 Steady-State Equilibrium

A steady-state equilibrium is a set of prices, quantities, customer capital, and value functions, $\Big\{ \{p_i, y_i, s_i, N_i, V_i\}_{i \in \mathcal{N}_s}, P_{st}, P \Big\}$, such that the demand system, the customer-capital accumulation, and the associated price-index (10)–(13), together with the firm optimality conditions (15)–(16), are satisfied, with normalized output $Y = 1$.

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

[35] This dynamic channel disappears if $\delta = 1$ or if $\eta = 0$, where customer capital fully depreciates or does not shift demand, respectively. In either case, the problem collapses to the static environment in Atkeson and Burstein (2008).

5.4 Markups and Cost Pass-through

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 A.1.

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

$$\mu_t = \frac{\sum_i p_{it} y_{it}}{\sum_i c_{it} y_{it}}. \tag{17}$$

The next proposition shows that aggregate markups depend on the distribution of firm market shares and increase with market concentration.[36]

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

We next characterize the relationship between firm market share and pass-through of cost shocks.

Proposition 3. *Firm pass-through is incomplete and increases with firm market share once market share is sufficiently high.*
Proof: See Appendix A.3.

Suppose a firm faces an increase in marginal cost. The price response reflects both a direct effect of higher cost and an indirect effect operating through endogenous markups. The magnitude of the indirect effect is heterogeneous across firms and endogenously determined by the market share and customer capital of firms. When a firm is a monopolist ($s_{it} = 1$), pass-through is complete since a price increase does not affect market share and therefore leaves customer capital and markups unchanged. Here, only the direct cost effect remains. More generally, when $0 < s_{it} < 1$, a higher price reduces market share and customer capital by increasing the firm's relative price. The resulting

[36] We provide supporting evidence of this prediction in Online Appendix I.1.

decline in the optimal markup partially offsets the increase in marginal cost, generating incomplete pass-through.

This markup adjustment becomes weaker for firms with sufficiently large market shares. Large firms face a smaller decline in market share following a price increase because their importance in the aggregate price index dampens changes in relative prices. Moreover, their larger customer base makes customer capital less sensitive to marginal changes in market share. As a result, these firms adjust markups less in response to cost shocks, leading to higher pass-through. Consequently, firms with sufficiently high market shares exhibit higher pass-through than smaller firms, suggesting that market concentration can influence aggregate pass-through.[37]

5.5 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 parameterization is as follows. 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 $\sigma = 1.61$ and $\eta = 0.31$ 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 0.44 and 0.01, respectively.

We assume firms are hit by a common aggregate shock x_t, such as the bird flu outbreak, that raises marginal costs additively to $x_t + c_{it}$.[38] We assume the following aggregate shock process:

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

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.

[37] We provide supporting evidence of this prediction in Online Appendix I.2.

[38] Note that the common additive cost shock induces reallocation across firms within each economy as its proportional magnitude varies with firms' initial marginal costs. In our cross-economy comparison, we hold each focal firm's productivity—and hence its initial marginal cost and proportional cost change—fixed across economies with different levels of concentration. The comparison therefore isolates how market structure shapes pass-through, holding the firm's cost level and cost change fixed.

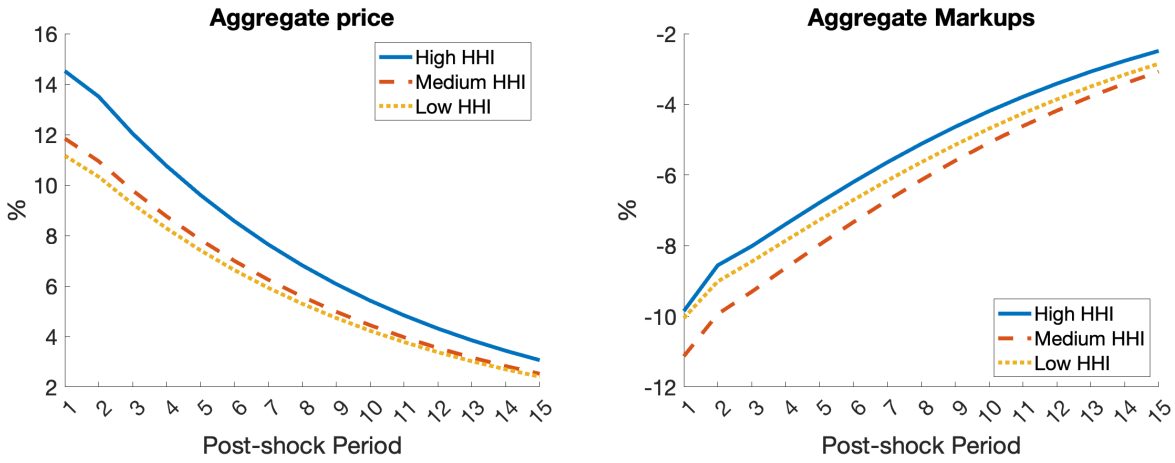


Figure 5: Response of Aggregate Price and Markups to a Cost Shock

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 $\mathcal{N}_s = 10$ 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).

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.[39] 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.[40] 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

[39] 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).

[40] This figure is based on a single simulation. The results are robust to Monte Carlo averaging across repeated simulations and to alternative numbers of simulation draws.

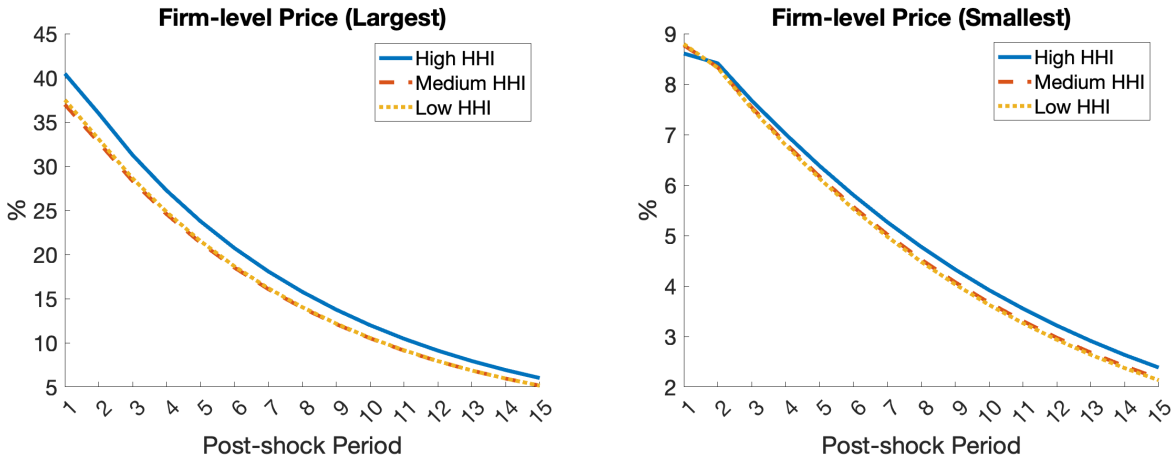


Figure 6: Response of Firm-Level Prices (Large vs. Small) to a Cost Shock

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 $\mathcal{N}_s = 10$ and $\mathcal{N}_s = 17$, respectively.

counterparts with the same productivity (and hence the same initial marginal cost and cost shock) 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). 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. Consequently, it exhibits higher pass-through, as characterized in Proposition 3. Consistent with this mechanism, the declines in its sales share, markups, and customer capital are more muted than those in less concentrated economies, as shown in Figure 7.

By contrast, the responses of the smallest firms vary less across economies. Their sales shares are relatively similar, and their price and markup responses exhibit little variation across concentration levels. This suggests that aggregate dynamics are driven disproportionately by the behavior of large firms, whose responses vary more systematically with market concentration through the interaction of market share, demand sensitivity, and the value of customer capital.[41]

[41] Customer capital shapes such cross-sectional heterogeneity in pass-through importantly through the feedback between pricing and future customer accumulation. This channel is particularly important for large firms, whose equilibrium market share compounds through this channel and becomes more sensitive to market structure than under static pricing (Atkeson and Burstein, 2008). This pattern is largely absent under static pricing and is consistent with our

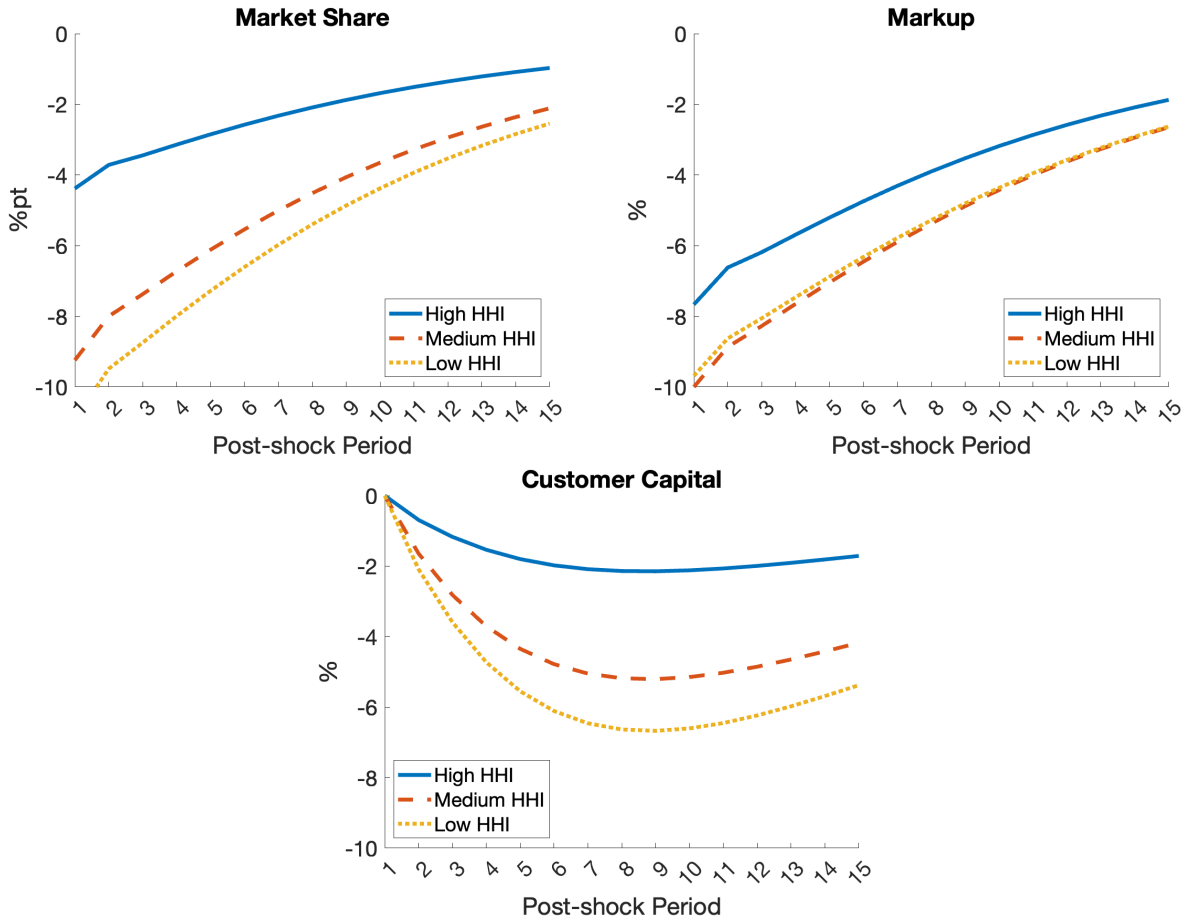


Figure 7: Response of the Largest Firm's Sales Share, Markup and Customer Capital to a Cost Shock

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 $\mathcal{N}_s = 10$ and $\mathcal{N}_s = 17$, respectively.

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. This is an avenue we leave for future work.

empirical evidence in Online Appendix I.2. This also gives a more pronounced aggregate price response to cost shocks in concentrated markets than the static setup.

6 Policy Implications

Our findings have implications for how policymakers evaluate the incidence of food supply shocks and measure real purchasing power across regions. First, our results show that food affordability depends not only on the size of food supply shocks, but also on local market structure. Food affordability has become one of the most salient economic issues in the U.S.[42] Although we study the 2014–2015 avian influenza episode, food products have continued to experience recurring cost shocks. Subsequent bird flu outbreaks have again driven up egg prices; the spread of the New World screwworm has raised beef prices by reducing cattle herds; and broader supply disruptions, including the 2026 oil price shock, have placed additional upward pressure on food prices. Our findings therefore have implications that extend beyond this particular episode.

In particular, our results imply that the same aggregate food supply shock can have different inflationary effects across local markets because of differences in local market structure. While localized supply disruptions can generate larger price increases than national statistics suggest (Butters et al., 2022), we show that even identical cost shocks are transmitted differently across markets. Pass-through is systematically higher in more concentrated grocery markets, so repeated food supply shocks can generate persistent spatial differences in food inflation. Because grocery market concentration is greater in many lower-income areas, these shocks may disproportionately erode food affordability in places where households are least able to absorb higher prices.

Second, our findings have implications for measuring real income inequality. Official price indexes are typically available only at the national level or for relatively wealthy MSAs.[43] Our results show that food cost shocks are transmitted unevenly across local markets because pass-through depends on local grocery market structure. As a result, households in more concentrated markets—which are typically lower-income areas—experience systematically higher food inflation following supply shocks. Yet national price indexes are expenditure-weighted averages across regions, which primarily reflect higher-income areas.[44] Relying on national price indexes can therefore overstate purchasing power in lower-income regions and bias measures of real income inequality and regional cost-of-living differences.[45] Appendix B documents this implication by

[42] Food prices featured prominently in both the 2024 presidential debates and the 2026 State of the Union address.
[43] See details at https://www.bls.gov/cpi/regional-resources.htm.
[44] Figure 1 illustrates this pattern.
[45] For example, if nominal wage growth were identical across regions, national price indexes would overstate real

comparing regional real income gaps measured using national and MSA-specific food price indexes.

Lastly, our results suggest that market power can amplify consumer welfare losses following cost shocks, highlighting a role for competition policy beyond its effects on static markups. The substantial spatial heterogeneity in market concentration further implies that the incidence of cost shocks may differ systematically across regions, particularly between low- and high-income regions. This provides a rationale for incorporating local market conditions more explicitly into competition policy, through geographically targeted merger scrutiny, entry-promoting policies, or other place-based interventions. More broadly, place-based transfers or market regulation may help mitigate the unequal burden of cost shocks when disparities in local competitive conditions cannot be readily addressed through conventional antitrust policy.[46]

7 Concluding Remarks

In this paper, we investigate spatial variation in food inflation and the role of retailer market structure. Using NielsenIQ 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, thereby contributing to narrower price-level gaps while widening real-income gaps between poorer and richer regions. We provide a model 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, and provide policy-relevant insights for the design of antitrust and place-based policies.

wage growth in poorer areas because they fail to account for their systematically higher food inflation.

[46] National concentration measures can obscure local effects: a merger with only modest effects on national concentration may substantially increase concentration in particular local markets.

Appendix

A Analytical Results and Proofs

A.1 Proof of Proposition 1

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

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

Then, the elasticity ϵ_{it} is

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

With (13), it follows that $\frac{\partial P_{st}}{\partial p_{it}} = N_{it}^{\eta}(\frac{p_{it}}{P_{st}})^{-\rho}$, and therefore

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

Thus, the effect of a firm's price on the sectoral price index depends on its market share. The larger the firm's share, the greater its influence on the sectoral price index.

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

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

showing that the elasticity is a linear function of firm market share. Since $\rho > \sigma$, the demand elasticity declines with the firm's market share.

Combining the pricing condition (15) and the envelope condition (16) at the steady state yields

$$\frac{p_{it} - c_{it}}{p_{it}} = \frac{1}{\hat{\epsilon}_{it}}, \tag{A.5}$$

where

$$\hat{\epsilon}_{it} \equiv \epsilon_{it} + \frac{\beta\delta\eta(\rho - 1)(1 - s_{it})\left(1 - \frac{\rho-\sigma}{\rho-1}s_{it}\right)}{1 - \beta\left[(1 - \delta) + \eta\delta(1 - s_{it})\right]}. \tag{A.6}$$

Hence the firm's markup is

$$\mu_{it} = \frac{p_{it}}{c_{it}} = \frac{\hat{\epsilon}_{it}}{\hat{\epsilon}_{it} - 1}. \tag{A.7}$$

Note that $\hat{\epsilon}_{it}$ denotes the effective elasticity faced by the firm. The second term in $\hat{\epsilon}_{it}$ captures the additional dynamic effect arising from customer capital accumulation, which is decreasing in the firm's market share.[47] For expositional convenience, let $A \equiv 1 - \beta(1-\delta)$ and $B \equiv \beta\eta\delta$, then we obtain

$$\frac{d\hat{\epsilon}_{it}}{ds_{it}} = \frac{-A((\rho-\sigma)A + B(\sigma-1))}{(A - B(1-s_{it}))^2} < 0.$$

This along with equation (A.6) proves that firm markups are increasing in firm market share as follows:

$$\frac{d\mu_i}{ds_{it}} = \frac{d\mu_{it}}{d\hat{\epsilon}_{it}} \frac{d\hat{\epsilon}_{it}}{ds_{it}} = -\frac{1}{(\hat{\epsilon}_{it} - 1)^2} \frac{d\hat{\epsilon}_{it}}{ds_{it}} > 0. \tag{A.8}$$

□

A.2 Proof of Proposition 2

Proof. First, at the stationary equilibrium, markup follows (A.7). We can rewrite it as:

$$\mu_{it} = \frac{1}{1 - \frac{1}{\hat{\epsilon}(s_{it})}}, \text{ where } \hat{\epsilon}(s_{it}) \equiv \rho - (\rho-\sigma)s_{it} + \frac{\beta\delta\eta(\rho-1)(1-s_{it})\left(1 - \frac{\rho-\sigma}{\rho-1}s_{it}\right)}{1 - \beta\left[(1-\delta) + \eta\delta(1-s_{it})\right]}. \tag{A.9}$$

Recall that aggregate markup is

$$\mu_t = \left(\sum_i \frac{s_{it}}{\mu_{it}}\right)^{-1} = \left(\sum_i s_{it}\left(1 - \frac{1}{\hat{\epsilon}(s_{it})}\right)\right)^{-1}. \tag{A.10}$$

Following Alviarez et al. (2025) and Grassi et al. (2017), we approximate the relationship around $s_{it} = 0$. Then

$$\frac{1}{\hat{\epsilon}(s_{it})} \simeq \frac{1}{\hat{\epsilon}(0)} + \kappa s_{it},$$

[47] Intuitively, customer capital increases effective demand elasticity more (less) strongly for low(high)-market-share firms. Thus, low-market-share firms have a stronger incentive to restrain current prices in order to preserve and accumulate future customers, whereas this incentive is weaker for high-market-share firms.

where $\kappa \equiv -\frac{\hat{\epsilon}'(0)}{\hat{\epsilon}(0)^2}$, so that

$$\frac{s_{it}}{\mu_{it}} \simeq s_{it}\left(1 - \frac{1}{\hat{\epsilon}(0)} - \kappa s_{it}\right). \tag{A.11}$$

Summing across firms and using $\sum_i s_{it} = 1$ gives

$$\sum_i \frac{s_{it}}{\mu_{it}} \simeq 1 - \frac{1}{\hat{\epsilon}(0)} - \kappa \sum_i s_{it}^2 = 1 - \frac{1}{\hat{\epsilon}(0)} - \kappa HHI_t. \tag{A.12}$$

Hence aggregate markup is approximately

$$\mu_t \simeq \frac{1}{1 - \frac{1}{\hat{\epsilon}(0)} - \kappa HHI_t}. \tag{A.13}$$

As $\kappa \equiv -\frac{\hat{\epsilon}'(0)}{\hat{\epsilon}(0)^2} > 0$, this confirms that aggregate markup increases with the HHI. □

A.3 Proof of Proposition 3

Proof. Let $\lambda_{it} \equiv \dfrac{d\ln p_{it}}{d\ln c_{it}}$. Differentiate $p_{it} = \mu_{it} c_{it}$ gives

$$\lambda_{it} = \frac{d\ln p_{it}}{d\ln c_{it}} = 1 + \frac{d\ln \mu_{it}}{d\ln c_{it}}. \tag{A.14}$$

Note that with no markup, there will be a perfect pass-through

$$\frac{d\ln p_{it}}{d\ln c_{it}} = 1.$$

If not, $\frac{d\ln \mu_{it}}{d\ln c_{it}} \neq 0$, and this becomes

$$\frac{d\ln \mu_{it}}{d\ln c_{it}} = \frac{d\ln \mu_{it}}{ds_{it}} \cdot \frac{ds_{it}}{d\ln c_{it}} = \underbrace{\frac{d\ln \mu_{it}}{d\hat{\epsilon}_{it}}}_{-\frac{1}{\hat{\epsilon}_{it}(\hat{\epsilon}_{it}-1)}<0} \cdot \underbrace{\frac{d\hat{\epsilon}_{it}}{ds_{it}}}_{<0} \cdot \frac{ds_{it}}{d\ln c_{it}} = \underbrace{\frac{-\hat{\epsilon}'(s_{it})}{\hat{\epsilon}_{it}(\hat{\epsilon}_{it}-1)}}_{>0} \cdot \frac{ds_{it}}{d\ln c_{it}}. \tag{A.15}$$

This implies that the sign depends on $\frac{ds_{it}}{d\ln c_{it}}$. Further expanding this term

$$\frac{ds_{it}}{d\ln c_{it}} = \frac{ds_{it}}{d\ln p_{it}} \frac{d\ln p_{it}}{d\ln c_{it}}.$$

With (12), we know that

$$\ln s_{it} = (1-\rho)\ln p_{it} - (1-\rho)\ln P_{st}$$

and

$$\frac{d\ln s_{it}}{d\ln p_{it}} = (1-\rho) - (1-\rho)s_{it} = (1-\rho)(1-s_{it}),$$

as $\frac{d\ln P_{st}}{d\ln p_{it}} = s_{it}$. Substituting this expression above,

$$\frac{ds_{it}}{d\ln c_{it}} = \frac{ds_{it}}{d\ln p_{it}}\frac{d\ln p_{it}}{d\ln c_{it}} = s_{it}(1-\rho)(1-s_{it})\frac{d\ln p_{it}}{d\ln c_{it}}.$$

Then combining it with (A.15) and plugging them into (A.14), we have the pass-through of a cost-shock to prices as follows:

$$\lambda_{it} = \frac{d\ln p_{it}}{d\ln c_{it}} = \frac{1}{1+(\rho-1)s_{it}(1-s_{it})\frac{-\hat{\epsilon}'(s_{it})}{\hat{\epsilon}_{it}(\hat{\epsilon}_{it}-1)}}, \tag{A.16}$$

where $\hat{\epsilon} = \hat{\epsilon}(s_{it})$ following (A.6). Given that $\rho > 1$, $0 < s_{it} < 1$, and $\hat{\epsilon}'(s_{it}) < 0$,

$$0 < \lambda_{it} = \frac{d\ln p_{it}}{d\ln c_{it}} < 1,$$

establishing positive but incomplete pass-through.

Next, we prove how pass-through depends on firms' market share. Let $\Phi_{it} \equiv (\rho-1)s_{it}(1-s_{it})\frac{-\hat{\epsilon}'(s_{it})}{\hat{\epsilon}_{it}(\hat{\epsilon}_{it}-1)}$ so that

$$\lambda_{it} = \frac{1}{1+\Phi_{it}},$$

then we want to verify the sign of $\frac{\partial\Phi_{it}}{\partial s_{it}}$, and thus, the sign of $\frac{\partial\lambda_{it}}{\partial s_{it}} = -\frac{1}{(1+\Phi_{it})^2}\frac{\partial\Phi_{it}}{\partial s_{it}}$.

For expositional convenience, let $A \equiv 1-\beta(1-\delta)$, $B \equiv \beta\eta\delta$, $\Gamma \equiv A\left((\rho-\sigma)A + B(\sigma-1)\right)$, $U(s_{it}) \equiv (\rho A - B - ((\rho-\sigma)A - B)\, s_{it})$, and $V(s_{it}) \equiv (\rho A - B - ((\rho-\sigma)A - B)\, s_{it} - A + B(1-s_{it}))$. Then, we can simplify Φ_{it} as follows,

$$\Phi_{it} = (\rho-1)s_{it}(1-s_{it})\frac{\Gamma}{U(s_{it})V(s_{it})},$$

which gives

$$\begin{aligned}\frac{\partial \Phi(s_{it})}{\partial s_{it}} =& \frac{(\rho-1)\Gamma}{U(s_{it})^2 V(s_{it})^2}\Big((\rho A - B)(\rho-1)A(1-s_{it})^2 - \sigma(\sigma-1)A^2 s_{it}^2\Big) \\ =& \frac{(\rho-1)\Gamma}{U(s_{it})^2 V(s_{it})^2}\Big(\sqrt{(\rho A - B)(\rho-1)A}(1-s_{it}) + \sqrt{\sigma(\sigma-1)A^2}s_{it}\Big) \\ & \cdot \Big(\sqrt{(\rho A - B)(\rho-1)A}(1-s_{it}) - \sqrt{\sigma(\sigma-1)A^2}s_{it}\Big).\end{aligned}$$

Note that the first two terms are strictly positive, so the sign of $\frac{\partial \Phi(s_{it})}{\partial s_{it}}$ (and thus of $\frac{\partial \lambda_{it}}{\partial s_{it}}$) is determined by the last term. This implies that, for a sufficiently high market-share above the threshold $s^* = \frac{\sqrt{(\rho A-B)(\rho-1)A}}{\sqrt{(\rho A-B)(\rho-1)A}+\sqrt{\sigma(\sigma-1)A^2}}$,

$$\frac{\partial \Phi(s_{it})}{\partial s_{it}} < 0 \qquad \text{for sufficiently large } s_{it} > s^*.$$

Consequently,

$$\frac{\partial \lambda_{it}}{\partial s_{it}} > 0 \qquad \text{for sufficiently large } s_{it} > s^*.$$

Therefore, pass-through is positive and incomplete for firms with $0 < s_{it} < 1$, and increases with firm market share once market share is sufficiently high. □

B Real Income Inequality

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

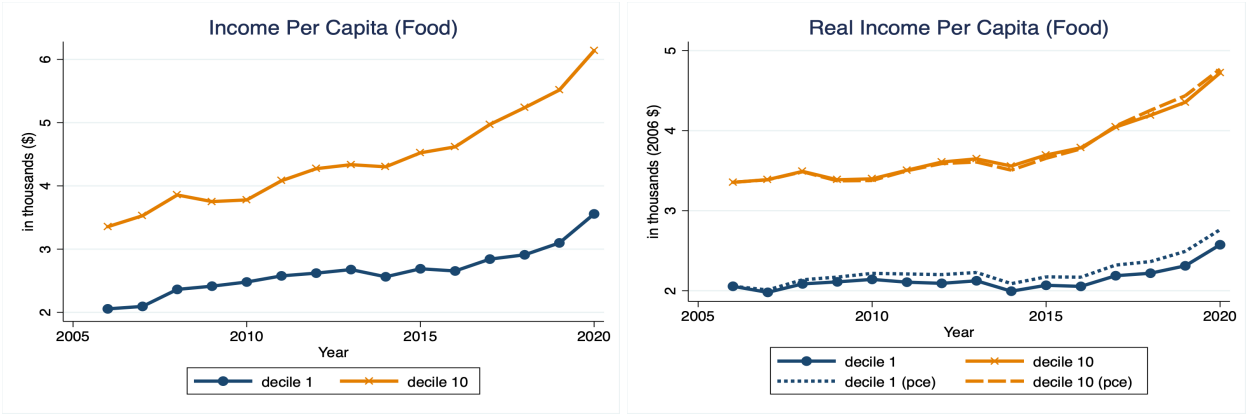


Figure B.1: Nominal and Real Income per Capita

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.

deflate the nominal series using the food price index constructed from the NielsenIQ Retail Scanner.

The two solid lines in Figure B.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 B.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.

References

Allcott, Hunt, Rebecca Diamond, Jean-Pierre Dubé, Jessie Handbury, Ilya Rahkovsky, and Molly Schnell, "Food deserts and the causes of nutritional inequality," *The Quarterly Journal of Economics*, 2019, *134* (4), 1793–1844.

Alviarez, Vanessa I, Michele Fioretti, Ken Kikkawa, and Monica Morlacco, "Concentration and markups in international trade," Technical Report, National Bureau of Economic Research 2025.

Arcidiacono, Peter, Paul B Ellickson, Carl F Mela, and John D Singleton, "The competitive effects of entry: Evidence from supercenter expansion," *American Economic Journal: Applied Economics*, 2020, *12* (3), 175–206.

Argente, David and Munseob Lee, "Cost of living inequality during the great recession," *Journal of the European Economic Association*, 2021, *19* (2), 913–952.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Baker, Scott R, Stephen Teng Sun, and Constantine Yannelis, "Corporate taxes and retail prices," Technical Report, National Bureau of Economic Research Cambridge, MA 2020.

Beck, Günter W and Xavier Jaravel, "Prices and global inequality: new evidence from worldwide scanner data," *Available at SSRN 3671980*, 2020.

Becker, Jonathan, "Do Poor Households Pay Higher Markups in Recessions?," Technical Report, Working paper 2024.

Benkard, C Lanier, Ali Yurukoglu, and Anthony Lee Zhang, "Concentration in product markets," Technical Report, National Bureau of Economic Research 2021.

Bitler, Marianne and Steven J Haider, "An economic view of food deserts in the United States," *Journal of Policy Analysis and Management*, 2011, *30* (1), 153–176.

Brand, James, "Differences in differentiation: Rising variety and markups in retail food stores," *Available at SSRN 3712513*, 2021.

Butters, R. Andrew, Daniel W. Sacks, and Boyoung Seo, "How Do National Firms Respond to Local Cost Shocks?," *American Economic Review*, May 2022, *112* (5), 1737–72.

Cao, Yue, Judith A Chevalier, Jessie Handbury, Hayden Parsley, and Kevin R Williams, "Distributional Impacts of the Changing Retail Landscape," Working Paper 33307, National

Bureau of Economic Research December 2024.

Carvalho, Vasco M and Basile Grassi, "Large firm dynamics and the business cycle," *American Economic Review*, 2019, *109* (4), 1375–1425.

Cawley, John, Chelsea Crain, David Frisvold, and David Jones, "The pass-through of the largest tax on sugar-sweetened beverages: the case of Boulder, Colorado," Technical Report, National Bureau of Economic Research 2018.

_ , David Frisvold, Anna Hill, and David Jones, "The Impact of the Philadelphia Beverage Tax on Prices and Product Availability," *Journal of Policy Analysis and Management*, 2020, *39* (3), 605–628.

Covarrubias, Matias, Germán Gutiérrez, and Thomas Philippon, "From Good to Bad Concentration? US Industries over the Past 30 Years," *NBER Macroeconomics Annual*, 2020, *34*, 1–46.

DellaVigna, Stefano and Matthew Gentzkow, "Uniform Pricing in U.S. Retail Chains," *Quarterly Journal of Economics*, 06 2019, *134* (4), 2011–2084.

Diamond, Rebecca and Enrico Moretti, "Where is standard of living the highest? Local prices and the geography of consumption," Technical Report, National Bureau of Economic Research 2021.

Döpper, Hendrik, Alexander MacKay, Nathan H Miller, and Joel Stiebale, "Rising markups and the role of consumer preferences," *Journal of Political Economy*, 2025, *133* (8), 000–000.

Ehrlich, Gabriel, John C Haltiwanger, Ron S Jarmin, David Johnson, Ed Olivares, Luke W Pardue, Matthew D Shapiro, and Laura Zhao, "Quality Adjustment at Scale: Hedonic vs. Exact Demand-Based Price Indices," Working Paper 31309, National Bureau of Economic Research June 2023.

Foster, Lucia, John Haltiwanger, and Chad Syverson, "The slow growth of new plants: Learning about demand?," *Economica*, 2016, *83* (329), 91–129.

_ , _ , Shawn Klimek, Cornell J Krizan, and Scott Ohlmacher, "The evolution of national retail chains: How we got here," in "Handbook on the Economics of Retailing and Distribution," Edward Elgar Publishing, 2016, pp. 7–37.

Franco, Santiago, *Output market power and spatial misallocation*, The University of Chicago, 2024.

Gagnon, Etienne and David López-Salido, "Small price responses to large demand shocks," *Journal of the European Economic Association*, 2020, *18* (2), 792–828.

Gourio, Francois and Leena Rudanko, "Customer capital," *Review of Economic Studies*, 2014, *81* (3), 1102–1136.

Grassi, Basile et al., "IO in IO: Competition and volatility in input-output networks," *Unpublished Manuscript, Bocconi University*, 2017, pp. 638–677.

Haltiwanger, John, "Job Creation and Firm Dynamics in the United States," *Innovation Policy and the Economy*, 2012, *12*, 17–38.

Handbury, Jessie, "Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities," *Econometrica*, 2021, *89* (6), 2679–2715.

_ **and David E. Weinstein**, "Goods Prices and Availability in Cities," *The Review of Economic Studies*, 09 2014, *82* (1), 258–296.

_ **and Sarah Moshary**, "School food policy affects everyone: Retail responses to the national school lunch program," Technical Report, National Bureau of Economic Research 2021.

_ **, Tsutomu Watanabe, and David E Weinstein**, "How Much Do Official Price Indexes Tell Us About Inflation?," Technical Report, National Bureau of Economic Research 2013.

Hobijn, Bart and David Lagakos, "Inflation inequality in the United States," *review of income and Wealth*, 2005, *51* (4), 581–606.

_ **, Kristin Mayer, Carter Stennis, and Giorgio Topa**, "Household inflation experiences in the US: a comprehensive approach," in "in" Federal Reserve Bank of San Francisco 2009.

Hortaçsu, Ali and Chad Syverson, "The ongoing evolution of US retail: A format tug-of-war," *Journal of Economic Perspectives*, 2015, *29* (4), 89–112.

Hottman, Colin J, "Retail markups, misallocation, and store variety across US cities," *Board of Governors of the Federal Reserve System, Working Paper*, 2017, *63*.

_ **, Stephen J Redding, and David E Weinstein**, "Quantifying the sources of firm heterogeneity," *The Quarterly Journal of Economics*, 2016, *131* (3), 1291–1364.

Jaravel, Xavier, "The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector," *Quarterly Journal of Economics*, 12 2018, *134* (2), 715–783.

_ , "Inflation inequality: Measurement, causes, and policy implications," *Annual Review of Economics*, 2021, *13*, 599–629.

_ , "Distributional consumer price indices," *Available at SSRN 5072082*, 2024.

_ **and Danial Lashkari**, "Measuring growth in consumer welfare with income-dependent preferences: Nonparametric methods and estimates for the United States," *The Quarterly Journal of Economics*, 2024, *139* (1), 477–532.

Jarmin, Ronald S, Shawn D Klimek, and Javier Miranda, "The role of retail chains: National, regional and industry results," in "Producer dynamics: New evidence from micro data," University of Chicago Press, 2009, pp. 237–262.

Kaplan, Greg and Guido Menzio, "The morphology of price dispersion," *International Economic Review*, 2015, *56* (4), 1165–1206.

_ **and Sam Schulhofer-Wohl**, "Inflation at the Household Level," *Journal of Monetary Economics*, 2017, *91*, 19–38.

Kerns-D'Amore, Kristin, Joey Marshall, and Brian McKenzie, "United States Migration Continued to Decline from 2020 to 2021," Technical Report, U.S. Census Bureau 2022. Accessed: 2024-10-30.

Kim, Seula and Michael A. Navarrete, "Lack of Uniform Prices or Lack of Uniform Retailers?," *AEA Papers and Proceedings*, May 2026, *116*, 568–572.

Kleshchelski, Isaac and Nicolas Vincent, "Market share and price rigidity," *Journal of Monetary Economics*, 2009, *56* (3), 344–352.

Leung, Justin H and Zhonglin Li, "Rising Concentration of Household Shopping, Superstar Firms, and Implications for Retail Markups," *American Economic Journal: Applied Economics*, 2026, *18* (1), 160–194.

Martin, Robert S., "Democratic Aggregation: Issues and Implications for Consumer Price Indexes," *Review of Income and Wealth*, 2024, *n/a* (n/a).

Molloy, Raven, "JUE insight: Differences in rent growth by income from 1985 to 2021 and implications for inflation," *Journal of Urban Economics*, 2024, *142*, 103669.

Moretti, Enrico, "Real Wage Inequality," *American Economic Journal: Applied Economics*, January 2013, *5* (1), 65–103.

Nakamura, Emi and Dawit Zerom, "Accounting for incomplete pass-through," *The review of economic studies*, 2010, *77* (3), 1192–1230.

O'Flaherty, Kelsey, "A New Reason to Hate Grocery Inflation: Measuring and Interpreting Inflation

Heterogeneity," Finance and Economics Discussion Series 2026-001, Board of Governors of the Federal Reserve System January 2026.

Paciello, Luigi, Andrea Pozzi, and Nicholas Trachter, "Price dynamics with customer markets," *International Economic Review*, 2019, *60* (1), 413–446.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Nicholas Trachter, "Diverging trends in national and local concentration," *NBER Macroeconomics Annual*, 2021, *35* (1), 115–150.

Sangani, Kunal, "Markups across the income distribution: Measurement and implications," *Available at SSRN 4092068*, 2022.

_ , "Pass-Through in Levels and the Incidence of Commodity Shocks," 2024. Working paper, Stanford University.

_ , "Complete pass-through in levels," *The Quarterly Journal of Economics*, 2026, *141* (2), 1077–1135.

Schanzenbach, Diane Whitmore, Ryan Nunn, Lauren Bauer, and Megan Mumford, "Where does all the money go: Shifts in household spending over the past 30 years," *Brookings Institution, The Hamilton Project*, 2016, *31*.

Smith, Dominic A and Sergio Ocampo, "The evolution of US retail concentration," *American Economic Journal: Macroeconomics*, 2025, *17* (1), 71–101.

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

Syverson, Chad, "Macroeconomics and Market Power: Context, Implications, and Open Questions," *Journal of Economic Perspectives*, August 2019, *33* (3), 23–43.

Online Appendix for "Geospatial Heterogeneity in Inflation: A Market Concentration Story" (NOT FOR PUBLICATION)

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August 18, 2026

A Robustness: NielsenIQ Consumer Panel

As a robustness check, we use the NielsenIQ Consumer Panel to examine the extent to which households make purchases outside their residential MSA. We construct a household-year-level sample from 2006 to 2020 and identify households that make purchases within and outside their residential MSA in each year. Table A.1 shows that 92% of households made purchases exclusively within their residential MSA.

Furthermore, Table A.2 shows that household characteristics and shopping patterns, including income, the number of stores visited, and total spending, are similar across groups. For households that shop outside of their MSA, they visit an average of 1.75 stores, spend approximately 50% of their total expenditure outside their residential MSA, and the average number of these outside MSAs they purchase from is 1.05.

In addition, we compute income deciles using two different MSA definitions in NielsenIQ. One

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

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

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

Table A.2: Characteristics of Households by Shopping Types

Variable	Mean (SD)	Mean (SD)
Indicator	1	0
Income	20.46	19.94
	(5.98)	(5.87)
Store #	3.32	3.77
	(1.90)	(2.08)
Spending Amount	1812.05	1659.12
	(1985.68)	(1811.08)
Store # (out)		1.75
		(1.26)
Spending Amount (out)		714.78
		(1226.29)
MSA # (out)		1.05
		(0.23)
Obs	780,500	64,932

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

is based on the MSA information of households in the NielsenIQ Consumer Panel, and the other is based on the MSA information of consumers, derived by linking the locations of stores from which households make purchases in the Scanner data with household income data in the NielsenIQ

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

Gap	Observation	Percent
-3	1	0.54
-1	20	10.81
0	140	75.68
1	24	12.97
Total	185	100

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

Consumer Panel. Table A.3 shows the gap between these two definitions, revealing that most MSAs (75.68%) align with the same income decile definitions, and only a very small fraction (0.54%) exhibit a gap of three deciles. This finding is consistent with our baseline measures of income deciles based on store locations and BEA income per capita data not being mismeasured.

B MSA-level Price Indices: BLS vs. NielsenIQ

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

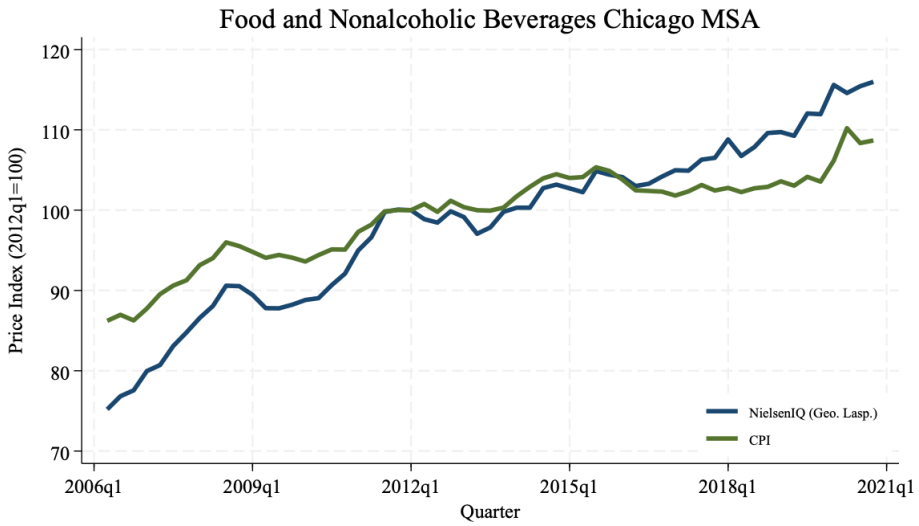


Figure B.1: Price Index for Aggregated Food: CPI vs. NielsenIQ (Chicago MSA)

Notes: This figure compares the CPI provided by the U.S. Bureau of Labor Statistics with the chained geometric Laspeyres price index constructed from NielsenIQ Scanner data for the Chicago MSA.

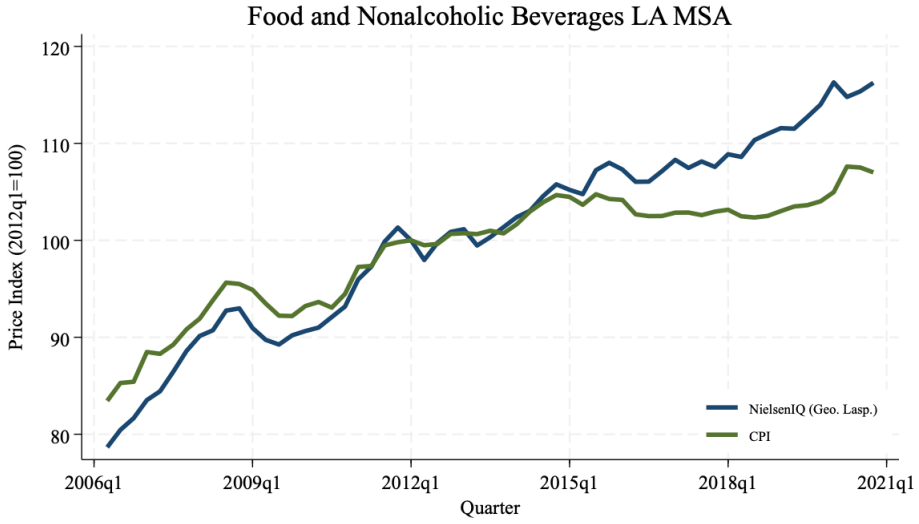


Figure B.2: Price Index for Aggregated Food: CPI vs. NielsenIQ (LA MSA)

Notes: This figure compares the CPI provided by the U.S. Bureau of Labor Statistics with the chained geometric Laspeyres price index constructed from NielsenIQ Scanner data for the Los Angeles MSA.

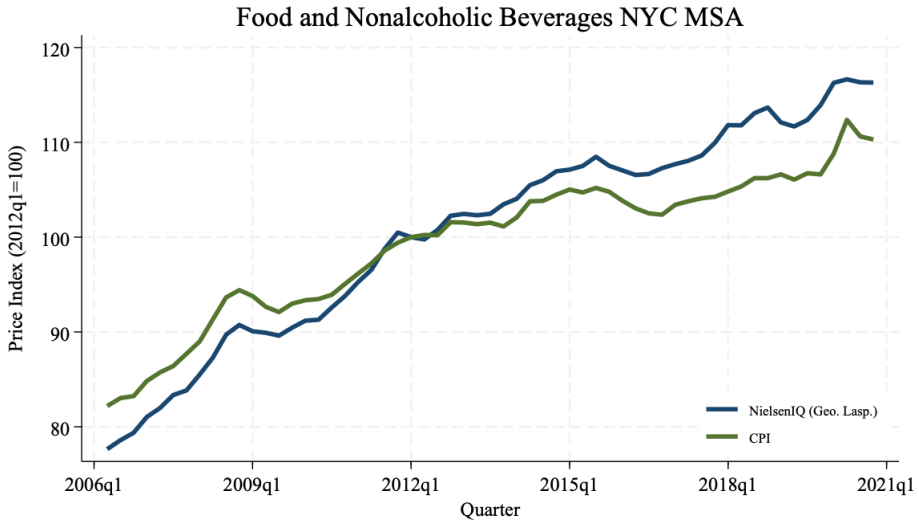


Figure B.3: Price Index for Aggregated Food: CPI vs. NielsenIQ (New York MSA)

Notes: This figure compares the CPI provided by the U.S. Bureau of Labor Statistics with the chained geometric Laspeyres price index constructed from NielsenIQ Scanner data for the New York MSA.

C Robustness: Price and Inflation Patterns

C.1 Alternative Price Indexes

A natural concern with Figure 1 is that our central finding, that the poorest decile experiences higher food inflation, may reflect some properties of the geometric Laspeyres formula rather than differences in underlying price changes. Because a Laspeyres index holds expenditure shares fixed at their base-period values, it does not accommodate substitution toward goods whose relative prices fall and may therefore overstate changes in the cost of living (Diewert, 1976). In addition, when constructed as a chained index, it may be subject to chain drift. We therefore rebuild the aggregate food index using three alternative approaches that relax different assumptions: a Tornqvist index (Figure C.1), a weighted time-product dummy (WTPD) index (Figure C.2), and a Sato-Vartia index (Figure C.3).

Figure C.1 reports two Tornqvist series for the bottom and top income deciles: a chained index and a direct (bilateral) index. The Tornqvist index is a superlative price index that incorporates substitution behavior of consumers by using expenditure-share information from both comparison periods (Diewert, 1976). Under the chained index, the gap between deciles persists at 3 index points by the end of the sample. Chained superlative indexes constructed from scanner data are, however, vulnerable to chain drift: high-frequency promotional cycles combined with asymmetric quantity responses can cause the index to ratchet away from its true level as successive links accumulate (Ivancic et al., 2011; de Haan and van der Grient, 2011). Comparing each quarter directly with the base period avoids this issue by construction, since the resulting index no longer depends on the sequence of intermediate-period links. Doing so raises measured inflation for both deciles and widens the gap slightly, to about 3.5 index points.

One limitation of a bilateral (direct) price index is that each comparison is restricted to goods present in both the base quarter and the comparison quarter, so the matched sample erodes as the two move apart. An alternative method to deal with chain drift is to use a multilateral price index such as the WTPD index. The WTPD avoids chain drift by construction while exploiting all available observations, including goods that enter and exit the sample (Diewert, 2005; de Haan and Krsinich, 2014). Figure C.2 plots the WTPD index for the bottom, median, and top deciles. The gap remains at approximately 3.9 index points.

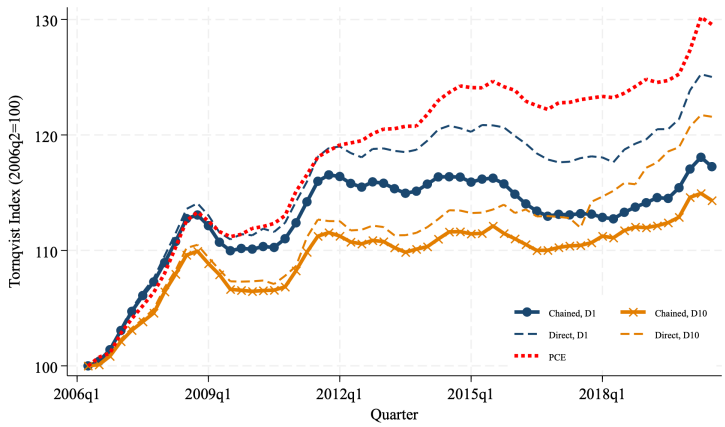


Figure C.1: Tornqvist for Aggregated Food (Chain Drift)

Notes: This figure represents the chained Tornqvist price index and bilateral Tornqvist price index constructed using NielsenIQ Retail Scanner data as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed red line) for aggregate food and beverages. The blue series represent decile 1 corresponds to the poorerest decile of MSAs in our sample and the gold series represent decile 10 corresponds to the richest MSAs in our sample. Among these four series, the dashed lines represent direct (bilateral) price indexes and the solid lines represent chained price indexes.

Taken together, the sign and ordering of the inter-decile gap are robust to the choice of price index, though its magnitude varies: the superlative and multilateral indexes yield gaps roughly half as large as that implied by the geometric Laspeyres index. Since the difference largely reflects the substitution margin that these alternative indexes are designed to capture, we treat the multilateral estimate as our conservative benchmark and report the geometric Laspeyres as a fixed-basket comparison.

As a further robustness check, we construct the Sato-Vartia price index, which is exact for a CES cost function (Sato, 1976; Vartia, 1976). Specifically, we replace the weights in equation (1), ω_{mkt}, with

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

where $\mathbb{C}_{m,t-1,t}$ denotes the set of goods sold in MSA m in both periods. Each price relative is weighted by the logarithmic mean of its expenditure shares in the two periods, normalized to sum to one. Thus, the Sato-Vartia index responds to demand shifts across periods rather than holding the basket fixed at base-period values. Figure C.3 shows that our baseline result remains robust under this substitution-sensitive index.

Lastly, we construct the decile-level price index by aggregating the MSA-level indexes using an

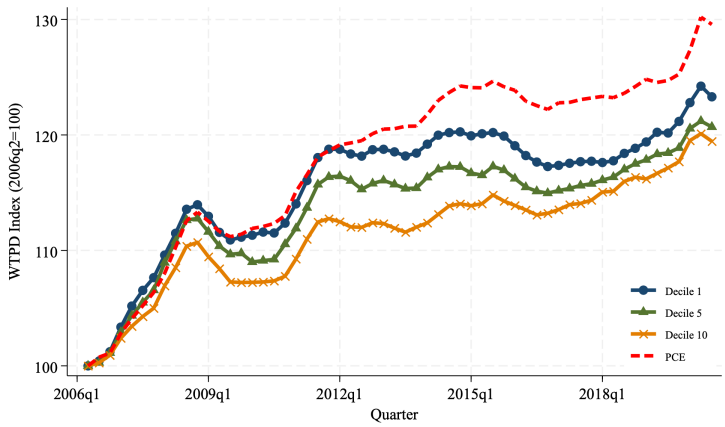


Figure C.2: Weighted Time-Product Dummy (WTPD, Multilateral Index) for Aggregated Food

Notes: This figure represents the weighted time-product dummy (WTPD) index constructed using NielsenIQ Retail 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. Decile 1 corresponds to the poorerest decile of MSAs in our sample and decile 10 corresponds to the richest MSAs in our sample.

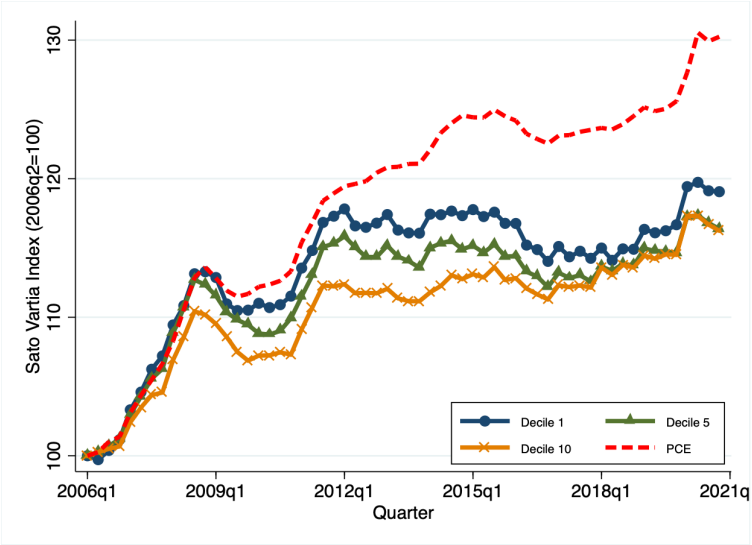


Figure C.3: Demand-based Price Index (Sato-Vartia) for Aggregated Food

Notes: This figure represents the chained Sato-Vartia price index constructed using NielsenIQ Retail 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. All descriptions remain the same as before.

unweighted average. As shown in Figure C.4, the results based on this approach are consistent with our main findings.

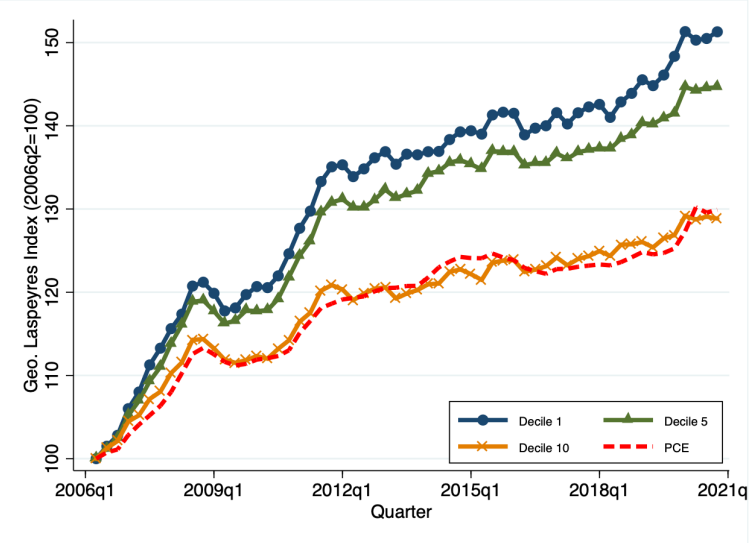


Figure C.4: Price Index for Aggregate Foods (MSA-level)

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

C.2 Other Food Items

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

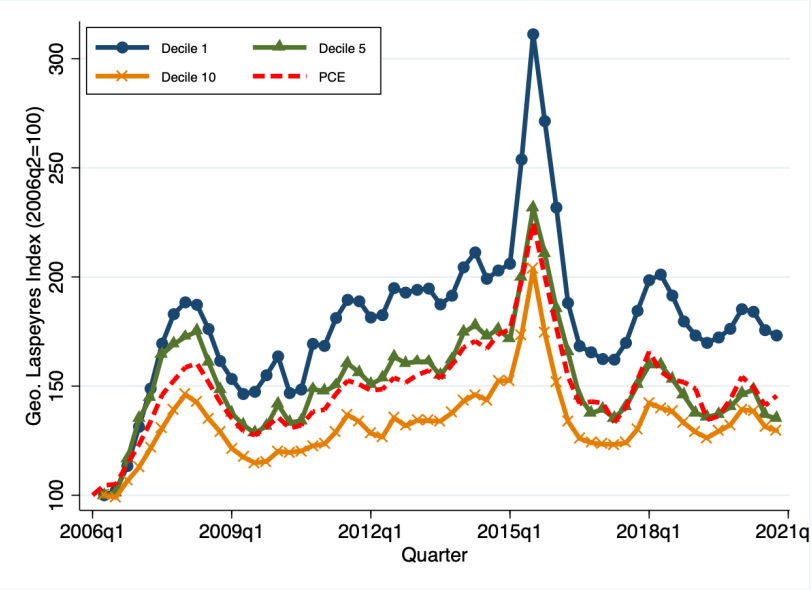


Figure C.5: Price Index for Eggs

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

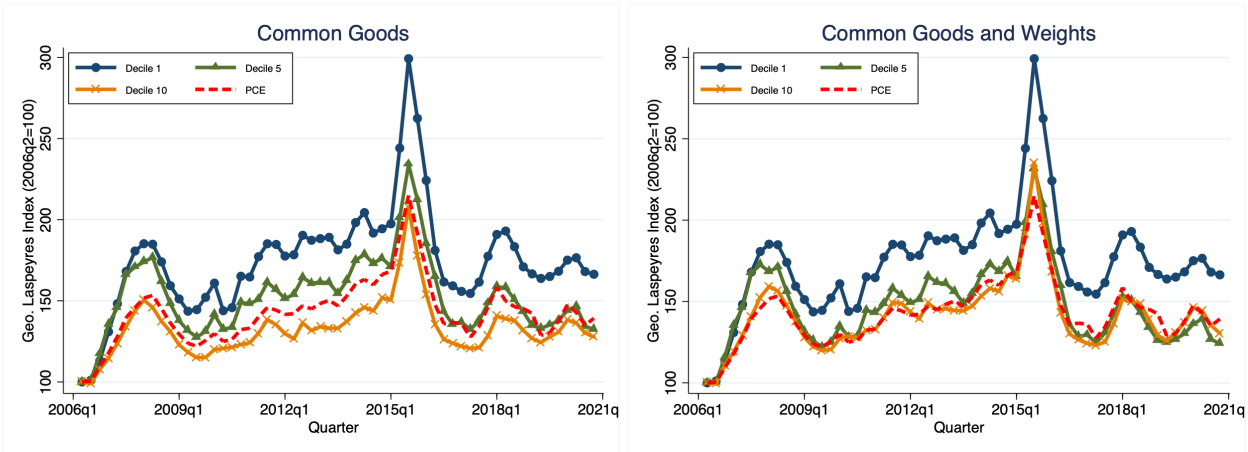


Figure C.6: Price Index for Eggs (Common Goods and Weights)

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

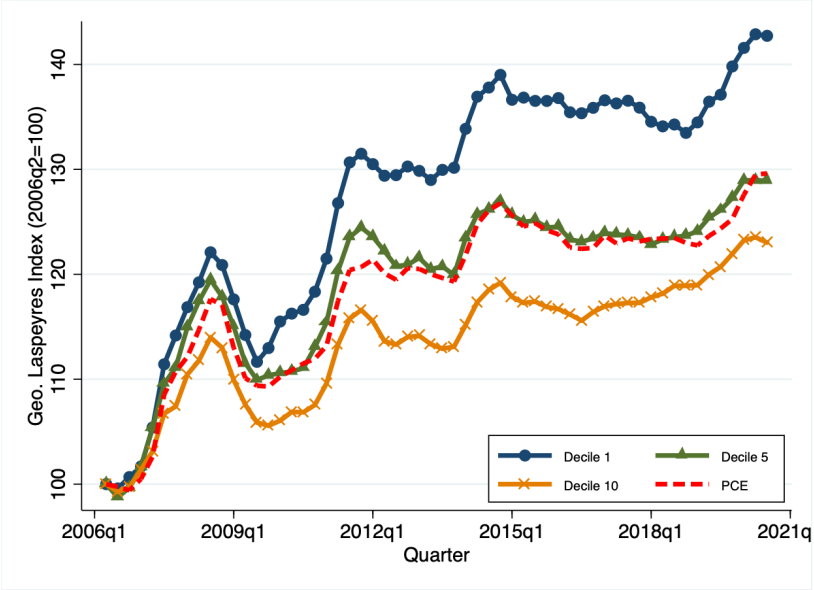


Figure C.7: Price Index for Dairy

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

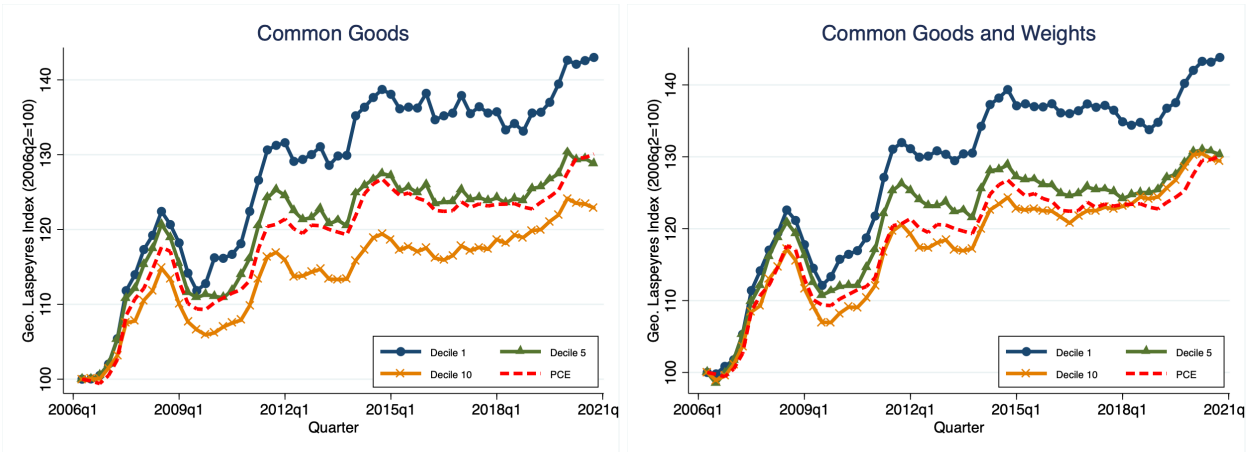


Figure C.8: Price Index for Dairy (Common Goods and Weights)

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

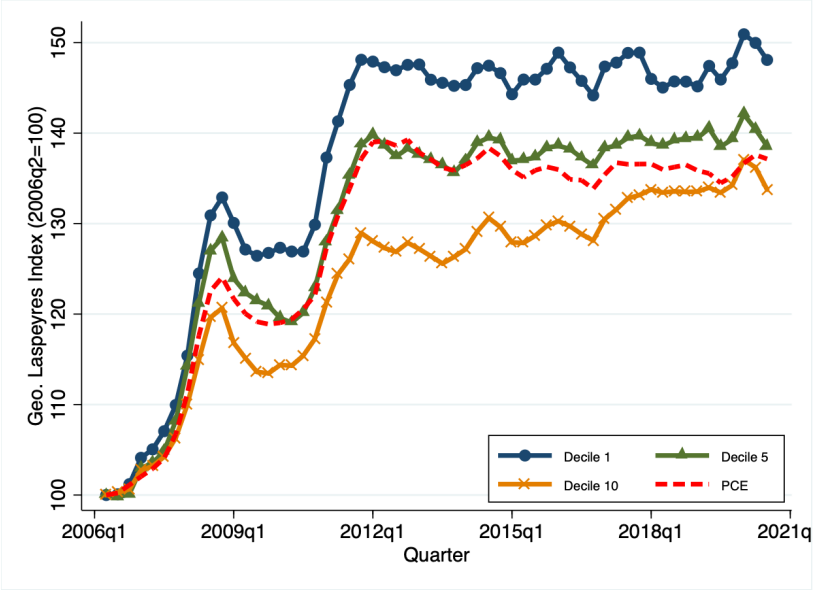


Figure C.9: Price Index for Fats and Oil

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

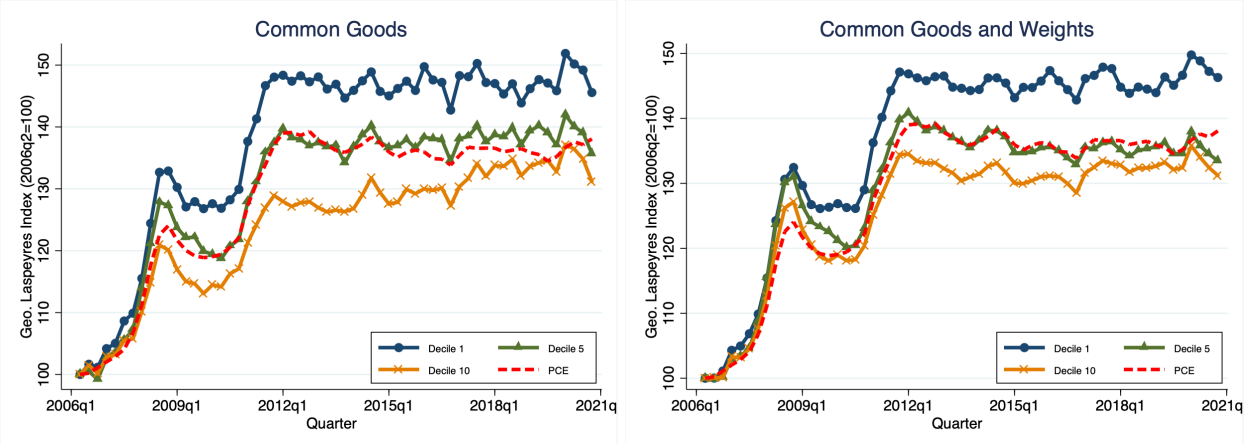


Figure C.10: Price Index for Fats and Oil (Common Goods and Weights)

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

D Robustness: Retailer Market Structure

D.1 Other Measures and Controls

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

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

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

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

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

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

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

D.2 Long-run Relationship

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

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

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

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

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

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

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

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

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

D.3 Business Dynamics Statistics (BDS)

The Business Dynamics Statistics (BDS) is a public version of administrative Census firm-level data. The data provide annual measures of business dynamics in the U.S., such as job creation and destruction, establishment births and deaths, and firm entry and exit. These data are provided for the economy overall as well as for aggregates defined by establishment or firm characteristics such as firm size and age. Furthermore, the data provide sectoral- and geographic-level information, which allows us to track business dynamics at the sector, state, county, and MSA levels.[1]

In BDS, we focus on the retail trade sector (NAICS 44–45) and measure retailer size by employment.[2] For each MSA, the Census Bureau reports the number of firms, establishments, total employment, and job creation and destruction, categorized by three firm-size bins: (i) 1–19 employees, (ii) 20–499 employees, and (iii) 500 or more employees. We define large retailers as those in the third category and, for each MSA, count the number of firms and establishments associated with them. To be consistent with the NielsenIQ, we focus on the period of 2006-2020 in BDS.

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

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

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

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

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

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

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

Table D.5: Retailer Market Structure (BDS)

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

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

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

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

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

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

E MSA-level Coverage: CBP vs. NielsenIQ

One potential concern is that the measured market concentration in NielsenIQ may be affected by differential retailer coverage across MSAs. For example, if NielsenIQ retailer coverage is systematically more comprehensive in higher-income MSAs, differences in measured market concentration across regions could partly reflect sampling rather than underlying market structure.

To address this concern, we compare NielsenIQ retailer coverage with County Business Patterns (CBP) data from the U.S. Census Bureau and examine whether NielsenIQ coverage varies system-

atically with MSA income. In the CBP, we use establishments as the unit of analysis, while in NielsenIQ, we use stores as the baseline retail unit and chains as a robustness measure. Throughout this exercise, we use the term "retailers" to refer interchangeably to the relevant unit of analysis in each dataset. We restrict the CBP sample to the Food and Beverage Stores subsector (NAICS 445) and compare it with retailers in the aggregate food and beverages market in NielsenIQ over 2006-2020. As a robustness check, we further restrict the CBP sample to the "Supermarkets and Other Grocery Retailers" industry (NAICS 445110).

First, using CBP, we calculate the share of retailers located in the 185 MSAs covered by NielsenIQ. These MSAs account for 82.13% of all retailers and 80.80% of total employment in the Food and Beverages Stores sector in CBP on average. Second, among these 185 MSAs, we compute each MSA's share of retailers in NielsenIQ and CBP separately and construct the ratio of the NielsenIQ share to the corresponding CBP share. Next, we regress this ratio on MSA-level income per capita to examine whether NielsenIQ is systematically more representative in higher-income MSAs. We estimate the following regression:

$$\left(\frac{RetailerShare_{mt}^{NielsenIQ}}{RetailerShare_{mt}^{CBP}}\right) = \beta IncomePerCapita_{mt} + \delta_m + \delta_t + \varepsilon_{mt}, \tag{E.1}$$

where $\left(\frac{RetailerShare^{NielsenIQ}{}_{mt}}{RetailerShare^{CBP}{}_{mt}}\right)$ denotes the relative coverage of retailers in NielsenIQ compared with CBP in MSA m and quarter t, $IncomePerCapita_{mt}$ denotes MSA-level income per capita (in thousands of dollars), and δ_m and δ_t denote MSA and quarter fixed effects, respectively.

Tables E.1 and E.2 report the results, with the former based on NAICS 445 and the latter restricted to NAICS 445110. In each table, we consider several specifications. The first three columns measure NielsenIQ coverage using store shares, while the last three columns use retail chain shares, with alternative combinations of quarter and MSA fixed effects. Across all specifications, NielsenIQ coverage is not relatively higher in higher-income MSAs compared with CBP.[3] These results alleviate the concern that the higher retailer concentration we measure in lower-income MSAs is mechanically driven by NielsenIQ providing systematically better coverage in richer areas.

[3]If anything, when exploiting cross-sectional variation across MSAs without MSA fixed effects, higher-income MSAs exhibit relatively lower coverage in NielsenIQ.

Table E.1: NielsenIQ Retailer Coverage Relative to CBP (NAICS 445)

	NielsenIQ/CBP retailer share					
Income	-0.016*	-0.033**	-0.016*	-0.084***	-0.136***	0.006
	(0.009)	(0.014)	(0.009)	(0.027)	(0.042)	(0.029)
Quarter FE	No	Yes	Yes	No	Yes	Yes
MSA FE	No	No	Yes	No	No	Yes
Observations	2,742	2,742	2,742	2,742	2,742	2,742

Note: The table reports MSA-level regressions of NielsenIQ retailer coverage relative to County Business Patterns (CBP). The dependent variable is the ratio of the MSA-level share of retailers observed in NielsenIQ to that in CBP. In CBP, we restrict the sample to the Food and Beverage Stores subsector (NAICS 445). The independent variable is MSA-level income per capita (in thousands of dollars). Columns 1,2, and 3 use the share of stores in an MSA, and Columns 4,5, and 6 use the share of retail chains in an MSA in NielsenIQ. Columns 1 and 4 include no fixed effects, Columns 2 and 5 include quarter fixed effects only, and Columns 4 and 6 include quarter and MSA fixed effects. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.2: NielsenIQ Retailer Coverage Relative to CBP (NAICS 445110)

	NielsenIQ/CBP retailer share					
Income	-0.014	-0.031**	-0.026**	-0.069**	-0.115**	-0.003
	(0.009)	(0.013)	(0.011)	(0.034)	(0.051)	(0.046)
Quarter FE	No	Yes	Yes	No	Yes	Yes
MSA FE	No	No	Yes	No	No	Yes
Observations	2,742	2,742	2,742	2,742	2,742	2,742

Note: The table reports MSA-level regressions of NielsenIQ retailer coverage relative to County Business Patterns (CBP). The dependent variable is the ratio of the MSA-level share of retailers observed in NielsenIQ to that in CBP. In CBP, we restrict the sample to the Supermarkets and Other Grocery Stores subsector (NAICS 445110). The independent variable is MSA-level income per capita (in thousands of dollars). Columns 1,2, and 3 use the share of stores in an MSA, and Columns 4,5, and 6 use the share of retail chains in an MSA in NielsenIQ. Columns 1 and 4 include no fixed effects, Columns 2 and 5 include quarter fixed effects only, and Columns 4 and 6 include quarter and MSA fixed effects. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1.

F Robustness: Inflation and Market Concentration

F.1 Other Measures and Controls

In the main regression (3), we replace HHI with CR1 and CR3 measures for market concentration and report the results in Table F.1. The results are robust to both measures.

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

	Inflation	Inflation	Inflation	Inflation	Inflation
CR1	0.415***		0.395***	0.362***	0.391***
	(0.114)		(0.118)	(0.116)	(0.122)
Income		-0.005**	-0.003	0.001	-0.000
		(0.002)	(0.002)	(0.002)	(0.002)
Population				-0.004***	-0.005***
				(0.001)	(0.001)
Chain #					0.019**
					(0.008)
	Inflation	Inflation	Inflation	Inflation	Inflation
CR3	0.680***		0.646***	0.538***	0.620***
	(0.153)		(0.158)	(0.159)	(0.171)
Income		-0.005**	-0.003	0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Population				-0.003***	-0.004***
				(0.001)	(0.001)
Chain #					0.021***
					(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). The coefficients of interest are on the CR measure (CR1 in the top panel and CR3 in the bottom panel) and income per capita (in thousands of $) in an MSA for a given quarter. The dependent variable is the geometric Laspeyres inflation rate (%) of aggregate food in an MSA for a given quarter. The last two columns include MSA population (in 100,000s) as a control, and the last column additionally controls for the total number of chains in the MSA. 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

F.2 Long-run Relationship

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

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

where $\bar{P}_m$ is the long-run average of inflation, and $\bar{X}_m$ is the long-run average of HHI and income level in MSA m. The results are presented in Table F.2, showing a negative association between food inflation and income and a positive association between food inflation and market concentration across MSAs in the long run. Also, the long-run patterns also hold for both CR1 and CR3 measures

Table F.2: Food Inflation across Regions (Long Run)

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.304**		0.261**	0.202	0.267*
	(0.123)		(0.129)	(0.124)	(0.143)
Income		-0.005**	-0.004	0.001	-0.002
		(0.003)	(0.003)	(0.003)	(0.002)
Population				-0.004***	-0.005***
				(0.001)	(0.001)
Chain #					0.024*
					(0.013)
Observations	185	185	185	185	185

Note: The table presents regression results from equation (F.1) for the cross-sectional association between MSA-level inflation, income, and market concentration in the long run. Each variable is measured as its long-run average across quarters within an MSA, leaving one observation per MSA. The dependent variable is the long-run average of the geometric Laspeyres inflation rate (%) for aggregate food. The coefficients of interest are on the long-run averages of the HHI of retail chain sales and income per capita (in $1000) in an MSA. The last two columns include MSA population (in 100,000s) as a control, and the last column additionally controls for the number of retail chains in an MSA. Standard errors are heteroskedasticity robust. *** p<0.01, ** p<0.05, * p<0.1

as shown in Table F.3.

F.3 Price Indexes

In the main regression (3), we replace the dependent variable with the geometric Laspeyres price index at the MSA level to capture cumulative price differences across MSAs. The results are similar and reflected in Table F.4. Furthermore, we replace HHI with CR1 and CR3 for market concentration, and the results remain robust, as presented in Table F.5.

F.4 Eggs Inflation

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

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

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

The results are presented in Table F.6, which reveal a similar association between HHI, income,

Table F.3: Food Inflation across Regions (Long Run, CRs)

	Inflation	Inflation	Inflation	Inflation	Inflation
CR1	0.393***		0.360***	0.320**	0.345**
	(0.131)		(0.138)	(0.133)	(0.140)
Income		-0.005**	-0.004	0.001	-0.001
		(0.003)	(0.003)	(0.003)	(0.002)
Population				-0.004***	-0.005***
				(0.001)	(0.001)
Chain #					0.023*
					(0.012)
	Inflation	Inflation	Inflation	Inflation	Inflation
CR3	0.838***		0.784***	0.633***	0.708***
	(0.196)		(0.206)	(0.208)	(0.217)
Income		-0.005**	-0.003	0.001	-0.001
		(0.003)	(0.002)	(0.002)	(0.002)
Population				-0.003***	-0.005***
				(0.001)	(0.001)
Chain #					0.025**
					(0.012)
Observations	185	185	185	185	185

Note: The table reports estimates of equation (F.1), examining the long-run cross-sectional relationship between MSA-level food inflation and retailer market concentration. Each variable is measured as its long-run average across quarters within an MSA, leaving one observation per MSA. The dependent variable is the long-run average geometric Laspeyres food inflation rate (%). CR1 is the sales share of the largest retailer within an MSA, and CR3 is the combined sales share of the three largest retailers; the top and bottom panels use CR1 and CR3, respectively. Income denotes long-run average income per capita, measured in thousands of dollars. The fourth and fifth columns control for MSA population (in 100,000s), and the fifth column additionally controls for the long-run average number of chains in the MSA. Heteroskedasticity-robust standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

and egg inflation as in our main analysis for aggregate food. In particular, we find a positive and statistically significant relationship between market concentration and inflation in Columns 1 and 3, and this relationship remains robust even after controlling for the MSA-level population and the number of chains in Columns 4 and 5. We also replace HHI with CR1 and CR3 measures for market concentration in eggs market. The results are shown in Table F.7 and are robust to both measures.

While these results shed light on the link between inflation and market concentration, they do not establish causality. The OLS estimate of β_1 may be subject to endogeneity bias. For instance, the observed relationship could be demand-driven: consumers in MSAs with higher HHI may disproportionately purchase goods experiencing higher inflation. Alternatively, income-related

Table F.4: Food Price Indices across Regions

	Price Index	Price Index	Price Index	Price Index	Price Index
HHI	14.467***		12.778***	10.823***	12.061***
	(3.720)		(3.738)	(3.559)	(3.946)
Income		-0.274***	-0.221**	-0.043	-0.080
		(0.104)	(0.103)	(0.104)	(0.093)
Population				-0.139***	-0.164***
				(0.037)	(0.043)
Chain #					0.400
					(0.320)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	10,915	10,915	10,915	10,915	10,915

Note: The table presents regression results from equation (3) with the dependent variable replaced by the geometric Laspeyres price index. The coefficients of interest are on the HHI of retail chain sales and income per capita (in $1000) in an MSA for a given quarter. The last two columns include MSA population (in 100,000s) as a control, and the last column additionally controls for the total number of chains in the MSA. 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

differences in consumer behavior could play a role: richer MSAs may have consumers who are more sensitive to price changes. Such heterogeneity in consumer behavior may have led retailers in wealthier areas to raise prices at slower rates. Another potential explanation is a supply-side story, where poorer MSAs have fewer stores and varieties, which weakens competition and allows retailers to raise prices more aggressively. There may also be a potential sorting of certain types of retailers into poorer MSAs, those that are more flexible in increasing prices, compared to retailers operating in richer areas. To determine whether the effect we observe is driven by supply-side or demand-side forces, we exploit the 2014–2015 bird flu outbreak as an exogenous supply shock in Section 4 of the main text.

Table F.5: Food Price Indices across Regions (CRs)

	Price Index	Price Index	Price Index	Price Index	Price Index
CR1	14.885***		13.514***	12.186***	12.670***
	(3.560)		(3.622)	(3.420)	(3.586)
Income		-0.274***	-0.225**	-0.041	-0.072
		(0.104)	(0.101)	(0.102)	(0.091)
Population				-0.141***	-0.162***
				(0.037)	(0.043)
Chain #					0.320
					(0.303)
	Price Index	Price Index	Price Index	Price Index	Price Index
CR3	19.923***		17.119***	12.513***	13.758***
	(4.919)		(4.629)	(4.372)	(4.358)
Income		-0.274***	-0.221**	-0.053	-0.085
		(0.104)	(0.098)	(0.101)	(0.092)
Population				-0.136***	-0.156***
				(0.036)	(0.042)
Chain #					0.327
					(0.302)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	10,915	10,915	10,915	10,915	10,915

Note: The table presents regression results from equation (3) with the dependent variable replaced by the geometric Laspeyres price index. The coefficients of interest are on the CR measure (CR1 in the top panel and CR3 in the bottom panel) and income per capita (in $1000) in an MSA for a given quarter. The last two columns include MSA population (in 100,000s) as a control, and the last column additionally controls for the total number of chains in the MSA. 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

Table F.6: Eggs Inflation across Regions

	Inflation	Inflation	Inflation	Inflation	Inflation
HHI	0.514***		0.440***	0.411**	0.483***
	(0.150)		(0.159)	(0.162)	(0.184)
Income		-0.015***	-0.011***	-0.008*	-0.010**
		(0.004)	(0.004)	(0.004)	(0.005)
Population				-0.002**	-0.003**
				(0.001)	(0.001)
Chain #					0.023
					(0.020)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	8,743	8,743	8,743	8,743	8,743

Note: The table represents regression results from (F.2) for the cross-sectional association between MSA-level inflation, income, and market concentration for eggs. The coefficient of interest is on HHI of retail chain's egg sales and income per capita (in $1000) in an MSA for a given quarter. The dependent variable is the geometric Laspeyres inflation rate (%) of eggs in an MSA for a given quarter. The last two columns include the MSA population (in 100,000s) as a control variable, measured annually using the BEA data. Total number of chains is included as a control in the last column. 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

Table F.7: Eggs Inflation across Regions (CRs)

	Inflation	Inflation	Inflation	Inflation	Inflation
	(1)	(2)	(3)	(4)	(5)
CR1	0.633***		0.571***	0.545***	0.587***
	(0.180)		(0.190)	(0.193)	(0.206)
Income		-0.015***	-0.012***	-0.008*	-0.010**
		(0.004)	(0.004)	(0.005)	(0.005)
Population				-0.002**	-0.003**
				(0.001)	(0.001)
Chain #					0.019
					(0.019)
	Inflation	Inflation	Inflation	Inflation	Inflation
CR3	1.083***		0.956**	0.894**	0.918**
	(0.353)		(0.385)	(0.413)	(0.415)
Income		-0.015***	-0.011**	-0.009*	-0.010**
		(0.004)	(0.004)	(0.005)	(0.005)
Population				-0.002	-0.002*
				(0.001)	(0.001)
Chain #					0.012
					(0.017)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	8,743	8,743	8,743	8,743	8,743

Note: The table represents regression results from equation (F.2) by replacing HHI with CR1 (in the top panel) and CR3 (in the bottom panel) for eggs. The coefficient of interest is on CR1 and CR3 of retail chain's eggs sales, as well as income per capita (in thousands of $) in an MSA. The dependent variable is the geometric Laspeyres inflation rate (%) of eggs in an MSA for a given quarter. The last two columns include the MSA population (in 100,000s) as a control variable, measured annually using the BEA data. Total number of chains in the eggs market is included as a control in the last column. 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

G Eggs Market

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

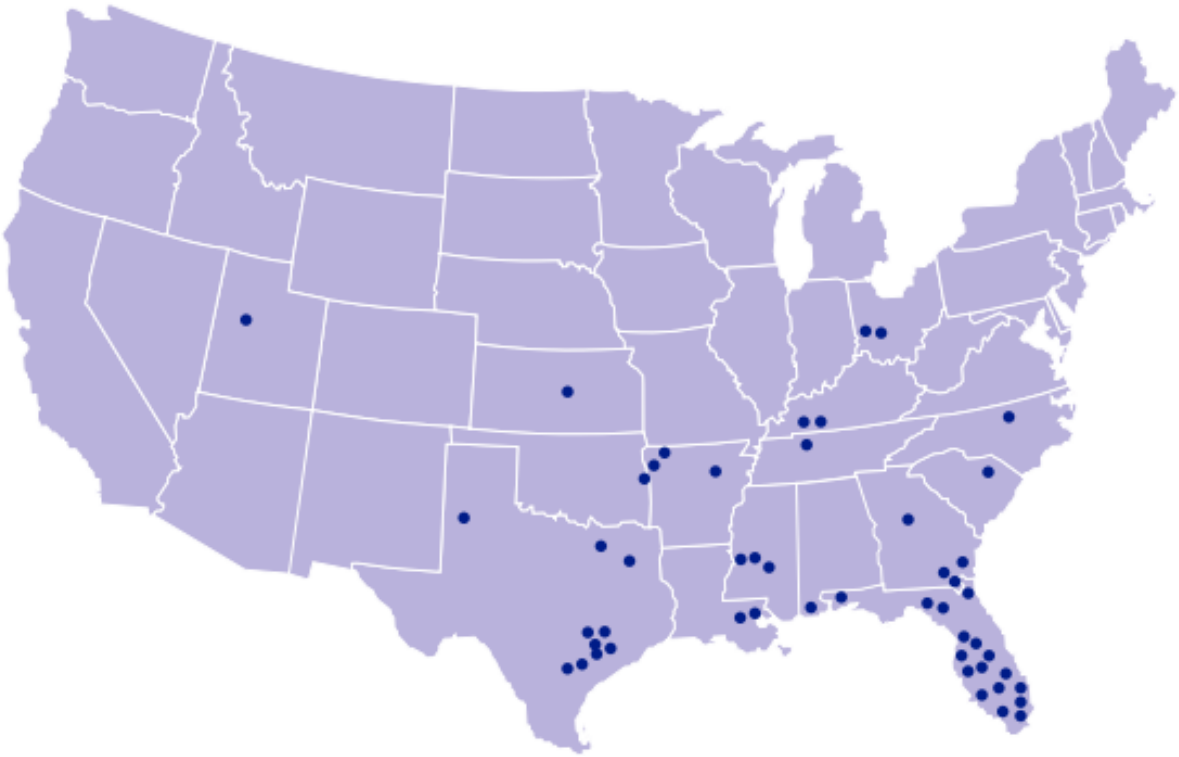


Figure G.1: Location of Cal-Maine Foods

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

H Robustness: Triple-Difference Estimation

H.1 Terciles of HHI

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

$$P_{mt} = \beta_0 + \beta_1(Post_t \times HighHHI_m) + \beta_2(Post_t \times MidHHI_m)$$

$$+ \beta_3(BirdFlu_m \times Post_t) + \beta_4(BirdFlu_m \times Post_t \times MidHHI_m)$$
$$+ \beta_5(BirdFlu_m \times Post_t \times HighHHI_m) + \delta_m + \delta_t + \varepsilon_{mt}, \quad \text{(H.1)}$$

where subscript m indexes MSAs and t indexes quarters. $BirdFlu_m$ and $Post_t$ are defined the same as before. We classify MSAs into terciles based on the distribution of egg-market sales concentration (HHI) in 2014Q3. The bottom tercile ($LowHHI$) comprises the one-third of MSAs with the lowest HHI and serves as the reference group.[4] $HighHHI_m$ is an indicator for the MSAs in the top tercile, and $MidHHI_m$ is an indicator for those in the middle tercile. P_{mt} denotes the geometric Laspeyres quarterly inflation rate for eggs in MSA m in quarter t. MSA and quarter fixed effects, δ_m and δ_t, are included as before, and ε_{mt} is the error term.

The results are presented in Table H.1. Column 1 pools all quarters within the two-year window and shows that, among treated MSAs, those in the top tercile of retail market concentration experience 2.3 percentage points higher inflation, on average, than those in the bottom tercile. This effect is statistically significant at the 1% level. Columns 2 and 3 decompose this effect into the inflationary and deflationary periods, respectively. Restricting the sample to the inflationary period, Column 2 shows that treated MSAs in the top tercile exhibit 4.7 percentage points higher inflation, on average, than treated MSAs in the bottom tercile, significant at the 1% level. In contrast, Column 3 shows no evidence that highly concentrated treated MSAs experience larger price declines during the deflationary period. The estimated effect is positive but statistically insignificant, suggesting persistence in the initial inflationary response. These results are consistent with our main findings.

Furthermore, we use HHI terciles to assess the robustness of our UPC-MSA-quarter-level results. We estimate the following regression, where the dependent variable is the log change in UPC-level prices within the egg market:

$$\Delta \ln price_{umt} = \beta_0 + \beta_1(Post_t \times HighHHI_m) + \beta_2(Post_t \times MidHHI_m)$$
$$+ \beta_3(BirdFlu_m \times Post_t) + \beta_4(BirdFlu_m \times Post_t \times MidHHI_m)$$
$$+ \beta_5(BirdFlu_m \times Post_t \times HighHHI_m) + \delta_u + \delta_m + \delta_t + \varepsilon_{umt}, \quad \text{(H.2)}$$

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

Table H.1: Triple Difference Estimator (Eggs)

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

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

where $\Delta \ln price_{umt}$ denotes the log difference in the price of UPC u in MSA m between quarters $t-1$ and t. The UPC fixed effects, δ_u, account for regional variation in consumption baskets by ensuring that price changes are identified within identical products. All other terms are defined as in equation (H.1).

Table H.2 reports the UPC-level results. In Column 1, pooling all quarters, we find that following the bird flu shock, egg prices in exposed MSAs in the highest concentration tercile increased by an additional 1 percentage point relative to exposed MSAs in the bottom tercile within the same UPCs. This estimate is statistically significant at the 1 percent level. Restricting the sample to the inflationary period, Column 2 shows that the triple interaction for the highest HHI tercile remains positive and significant at the 1 percent level. Quantitatively, prices rose by an additional 2 percentage points in highly concentrated exposed MSAs relative to less concentrated exposed

Table H.2: Triple Difference Estimator (Eggs, UPC-level)

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

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

MSAs for identical egg products. In Column 3, focusing on the deflationary period, the estimated effect is statistically insignificant, suggesting persistence in the inflationary response rather than symmetric price reversals.

H.2 CR Measures

To test the robustness of the triple-difference regression in equation (5), we replace HHI with CR1 and CR3 in the egg market. The results are robust, as displayed in Table H.3.

H.3 Neighboring Treated MSAs

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

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

Table H.3: Triple Difference Estimator (CRs)

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

Note: The table represents regression results from equation (5) by replacing HHI with CR1 or CR3. The coefficient of interest is the interaction of Bird Flu, Post, and CR1 (in the top panel) or CR3 (in the bottom panel). CR1 (CR3) is the concentration ratio of the top 1 (top 3) retail chain's sales of eggs within an MSA, of which value is fixed to 2014Q3 for all quarters in the post period. All else descriptions remain the same as in Table 7. Standard errors are clustered at the MSA-level. *** p<0.01, ** p<0.05, * p<0.1

H.4 Placebo Test

One limitation of our identification strategy is that the triple-difference design identifies whether MSAs with higher market concentration experienced larger inflation responses to the bird flu shock, but it does not by itself prove that market concentration is the underlying mechanism. In other words, the estimates show that inflation rose more in bird-flu-exposed, high-HHI MSAs than in bird-flu-exposed, low-HHI MSAs, relative to unaffected MSAs. However, high-HHI MSAs may

Table H.4: Neigboring MSAs around the Impacted MSAs

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

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

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

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

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

differ from low-HHI MSAs along other dimensions that also affect pass-through from cost shocks to prices. If those characteristics are correlated with HHI, the triple interaction could partly reflect these other local differences rather than market concentration itself.

To assess this concern, we conduct a placebo test using income per capita, a local characteristic that is correlated with market concentration, as shown in Section 3. Specifically, we replace HHI with income per capita and estimate the same triple-difference specification in equation (5). Table H.7 shows that the placebo results differ from the baseline HHI results in three ways. First, the triple-interaction coefficient is statistically insignificant in two of the three specifications. Second, in the inflationary-period specification (column 2), the coefficient is negative and only marginally significant at the 10 percent level. Third, the sign and pattern of the estimates do not resemble the baseline results, where higher HHI consistently predicts stronger inflation responses to the bird flu shock. These results suggest that the baseline findings are unlikely to be driven simply by broad differences between higher- and lower-income MSAs, although they do not rule out all possible correlated local mechanisms.

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

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

Note: The table represents regression results from equation (5), where the treated MSAs include five additional neighboring MSAs around the impacted areas. All else descriptions remain the same as in Table 7. *** p<0.01, ** p<0.05, * p<0.1

H.5 Additional Income and Price Level Controls

Section H.4 shows that income per capita does not drive our main triple-difference results. A remaining concern, however, is that the estimated effect of market concentration may be sensitive to controlling more flexibly for income differences across MSAs. As an additional robustness check, we augment the baseline specification by adding the triple interaction of Bird Flu, Post, and income per capita, along with the corresponding lower-order interaction terms. Table H.8 reports the results.

The coefficient on Bird Flu × Post × HHI remains positive in all three specifications. It is statistically significant at the 1 percent level in the pooled sample and during the inflationary period, with estimates of 0.084 and 0.110, respectively. In the deflationary period, the coefficient is smaller and statistically insignificant. This positive estimate is nevertheless consistent with the baseline results, where retailers in more concentrated markets reduce prices more slowly when aggregate prices are falling. Moreover, the coefficient on Bird Flu × Post × income per capita is statistically insignificant in two of the three specifications and only marginally significant in the pooled sample. Taken together, these results further indicate that the main triple-difference findings are not driven by income differences across MSAs.

Table H.7: Placebo Triple Difference Estimator (Eggs, Income)

	Inflation	Inflation	Inflation
Bird Flu × Post × Income	-0.006	-0.031*	0.001
	(0.011)	(0.018)	(0.011)
Bird Flu × Post	0.066	0.232**	-0.066
	(0.060)	(0.096)	(0.052)
Income × Post	0.002*	-0.001	0.006*
	(0.001)	(0.003)	(0.003)
Bird Flu × Income	-0.126***	-0.117***	0.057*
	(0.035)	(0.033)	(0.030)
Income	0.005	-0.055***	0.021*
	(0.009)	(0.013)	(0.013)
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 Income. 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. Income is income per capita (in $10,000), which is measured annually at the MSA level from BEA data. 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

A related concern is that the estimated effect of market concentration may instead reflect differences in price levels across MSAs, rather than market power per se (Sangani, 2026). As an additional robustness check, we augment the baseline specification by adding the triple interaction of Bird Flu, Post, and Initial Price, along with the corresponding lower-order interaction terms. Initial price is defined as the mean price of a product-MSA pairing over the pre-shock quarters, 2012Q4–2014Q3. Table H.9 reports the results.

The coefficient on Bird Flu × Post × HHI remains positive and statistically significant at the 1 percent level in the pooled sample and during the inflationary period, with estimates of 0.020 and 0.036, respectively. In the deflationary period, the coefficient is smaller in magnitude, changes sign, and is statistically insignificant. These results are consistent with our baseline results in equation (6): we continue to find higher pass-through of costs in MSAs with higher market

Table H.8: Triple Difference Estimator (Eggs, Income Controls)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.084***	0.110***	0.032
	(0.026)	(0.027)	(0.025)
Bird Flu × Post	-0.107*	0.028	-0.181**
	(0.064)	(0.075)	(0.076)
HHI × Post	-0.008	-0.015**	-0.000
	(0.005)	(0.008)	(0.011)
Bird Flu × HHI	-0.222	-0.222	-0.377***
	(0.189)	(0.225)	(0.124)
HHI	0.036	0.061**	0.028
	(0.025)	(0.027)	(0.046)
Bird Flu × Post × Income	0.022*	0.000	0.022
	(0.012)	(0.015)	(0.014)
Income × Post	0.002	-0.001	0.006*
	(0.001)	(0.003)	(0.003)
Bird Flu × Income	-0.163***	-0.150***	0.038
	(0.048)	(0.047)	(0.028)
Income	0.004	-0.057***	0.021*
	(0.009)	(0.013)	(0.013)
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 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. We add additional controls where we replace HHI with Income in the triple interaction and the corresponding interaction terms. Income is income per capita (in $10,000), which is measured annually at the MSA level from BEA data. 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

concentration. Moreover, the coefficient on Bird Flu × Post × Initial Price is small in magnitude and statistically insignificant in all three specifications. Taken together, these results suggest that our main triple-difference findings are not driven by differences in initial price levels across MSAs.

Table H.9: Triple Difference Estimator (Eggs, UPC Level, and Initial Price Controls)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.020***	0.036***	-0.014
	(0.006)	(0.010)	(0.016)
Bird Flu × Post	-0.012***	-0.007	-0.010
	(0.004)	(0.006)	(0.011)
HHI × Post	-0.010***	-0.014**	0.003
	(0.003)	(0.007)	(0.007)
Bird Flu × HHI	-0.014	-0.043	-0.081
	(0.060)	(0.084)	(0.081)
HHI	0.028*	0.054**	-0.021
	(0.015)	(0.024)	(0.025)
Bird Flu × Post × Initial Price	0.006	0.003	-0.001
	(0.006)	(0.007)	(0.019)
Post × Initial Price	-0.009***	-0.067***	0.106***
	(0.003)	(0.004)	(0.009)
Bird Flu × Initial Price	0.010**	0.004	0.027***
	(0.005)	(0.005)	(0.007)
Initial Price	0.031***	0.035***	0.005
	(0.007)	(0.010)	(0.024)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Observations	133,653	81,687	51,878

Note: The table reports estimates from equation (6) augmented with a second triple interaction, and presents two coefficients of interest. The first triple interaction is the interaction of Bird Flu, Post, and HHI, as in equation (6). The second triple interaction is the interaction of Bird Flu, Post, and Initial Price, which tests whether the bird-flu shock's pass-through into prices depends on the initial, pre-shock price level of a given product–MSA pair. Bird Flu is a binary variable equal to one for MSAs in which egg farmers culled their layers during the 2014–2015 bird flu episode, and Post is a binary variable equal to one in the post-shock period beginning 2014Q4. HHI is the Herfindahl-Hirschman index of retail chains' egg sales within an MSA, fixed at its 2014Q3 value for all subsequent quarters. Initial Price is each product-MSA pair's mean price in the quarters before the bird-flu episode; because it requires pre-shock observations, the sample is restricted to product-MSA pairs present before 2014Q4, a modestly smaller sample than in equation (6). Both triple interactions are estimated jointly, together with their constituent lower-order interactions and level terms. 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 restricts to the inflationary period, and Column 3 restricts to the deflationary period. MSA, quarter, and product (UPC) fixed effects are included in all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

H.6 Retailer Composition

An alternative explanation for the observed differences in inflation across MSAs is variation in retailer composition, as retailers may differ in the extent to which they pass through shocks to prices. In particular, pass-through may differ between national, regional, and local chains for several 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.[6] On the other hand, national chains may charge prices closer to marginal costs, which could impact the local level of prices, markups, and pass-through.[7] 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.[8] 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, $(Treated_m \times Post_t \times RegionalShare_{mt})$ and $(Treated_m \times Post_t \times NationalShare_{mt})$, together with the full set of lower-order interactions implied by the inclusion of $RegionalShare_{mt}$ and $NationalShare_{mt}$. Note that the share of local retailers is omitted as the baseline group.

The results are presented in Table H.10.[9] The main results remain stable across all three inflationary regimes: pooled, inflationary, and deflationary. The triple interactions in the pooled period

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

[7] 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.

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

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

Table H.10: 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

(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.

Relatedly, a remaining concern is that the retail chains operating in high- and low-concentration MSAs differ systematically along dimensions beyond whether they are a local, regional, or national retailer. Specifically, retailers may differ along unobserved dimensions beyond the characteristics we observe, and such compositional differences could still drive our results rather than market concentration itself.[10] Table H.10 partially addresses this concern by controlling for whether retailers

[10] Kim and Navarrete (2026) find that the differences in retailer composition can account for some of the variation in price levels across markets, even for the same product.

Table H.11: Triple Difference Estimator (Eggs, UPC-Retailer Level)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.020***	0.025**	0.006
	(0.007)	(0.011)	(0.016)
Bird Flu × Post	-0.015***	-0.004	-0.026**
	(0.004)	(0.006)	(0.011)
HHI × Post	-0.011***	-0.005	-0.018**
	(0.003)	(0.008)	(0.009)
Bird Flu × HHI	-0.035	-0.053	-0.043
	(0.035)	(0.068)	(0.121)
HHI	0.029***	0.050***	0.002
	(0.011)	(0.018)	(0.031)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Retailer FE	Yes	Yes	Yes
Observations	258,553	148,728	109,729

Note: The table reports estimates from equation (6) augmented with retailer fixed effects. The unit of observation changes from UPC-MSA-quarter to UPC-retailer-MSA-quarter. The coefficient of interest is the triple interaction of Bird Flu, Post, and HHI, as in equation (6). Bird Flu is a binary variable equal to one for MSAs in which egg farmers culled their layers during the 2014–2015 bird flu episode, and Post is a binary variable equal to one in the post-shock period beginning 2014Q4. HHI is the Herfindahl-Hirschman index of retail chains' egg sales within an MSA, fixed at its 2014Q3 value for all subsequent quarters. 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 restricts to the inflationary period, and Column 3 restricts to the deflationary period. MSA, quarter, retailer, and product (UPC) fixed effects are included in all specifications. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1

are regional, national, or local retailers. To further isolate differences in pricing across low- and high-concentration markets from differences across retailers, we augment our baseline specification in equation (6) by including retailer fixed effects in the product-retailer-MSA-quarter-level analysis.

Table H.11 reports estimates from specifications that include retailer fixed effects. The results are similar in magnitude and statistical significance to our baseline estimates in Table 8, which do not include retailer fixed effects. In the pooled period, We find that retailers in more concentrated markets increased relative prices by about 2 percent more, significant at 1 percent level. The effect is larger during the inflationary period, when relative prices increase by 2.5 percent more in more concentrated markets, significant at the 5 percent level. We find no statistically significant

differential response during the deflationary period. This suggests that the baseline patterns remain robust even after controlling for differences in retailer composition.

H.7 Commodity Cost Shocks in Coffee Market

We provide consistent evidence in the coffee market by exploiting fluctuations in commodity prices, following Sangani (2024). Given that the United States does not produce a meaningful amount of coffee, we treat changes in the commodity price of Arabica coffee as exogenous to U.S. retail conditions. We measure the global price of coffee (Arabica) using the IMF Commodity Database.[11] Our identification strategy exploits time-series variation in global coffee prices. To control for differences in basket composition, we conduct analysis at the UPC-quarter-MSA level and include UPC and MSA fixed effects. Specifically, we estimate the following regression:

$$\begin{aligned}\Delta \log p_{umt} = {} & \beta_0 \, \Delta \log c_t + \beta_1 \, MidHHI_{mt} + \beta_2 \, HighHHI_{mt} \\ & + \beta_3 \left(\Delta \log c_t \times MidHHI_{mt}\right) + \beta_4 \left(\Delta \log c_t \times HighHHI_{mt}\right) \\ & + \delta_m + \delta_u + \varepsilon_{umt}, \end{aligned} \tag{H.3}$$

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

In Table H.12, we report estimates of pass-through from global Arabica coffee prices to U.S. retail coffee prices. For the baseline group ($LowHHI$), a 1 percent increase in the global coffee price raises retail prices by 0.072 percent (Column 1). The estimated pass-through is 0.068 during positive cost shocks (Column 2) and declines to 0.052 during negative cost shocks (Column 3).

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

Table H.12: Coffee Price Pass-through and Retail Market Concentration across MSAs

	$\Delta \ln$ Price	$\Delta \ln$ Price	$\Delta \ln$ Price
$\Delta \log c_t \times$ HighHHI	0.013***	0.028***	-0.010*
	(0.003)	(0.006)	(0.006)
$\Delta \log c_t \times$ MidHHI	0.006	0.021***	-0.012*
	(0.004)	(0.007)	(0.007)
$\Delta \log c_t$	0.072***	0.068***	0.052***
	(0.002)	(0.004)	(0.004)
HighHHI	-0.005*	-0.012***	-0.002
	(0.003)	(0.003)	(0.003)
MidHHI	-0.001	-0.005**	-0.002
	(0.002)	(0.002)	(0.002)
Sample Periods	All	Positive Cost	Negative Cost
MSA FE	Yes	Yes	Yes
UPC FE	Yes	Yes	Yes
Observations	4,696,457	2,724,256	1,971,691

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

Even in the least concentrated markets, retailers transmit cost declines less completely than cost increases.

We then examine heterogeneity by local concentration through the interaction terms $\Delta \log c_t \times MidHHI_{mt}$ and $\Delta \log c_t \times HighHHI_{mt}$. The coefficient on $\Delta \log c_t \times MidHHI_{mt}$ is statistically insignificant in the pooled sample. This masks offsetting effects across the cost cycle: the coefficient is positive during periods of rising costs (0.021, significant at the 1 percent level) and negative during periods of falling costs (-0.012, significant at the 10 percent level). By contrast, the interaction with $HighHHI_{mt}$ is positive and significant in the pooled sample (Column 1): a 1 percent increase in the global coffee price raises retail prices by an additional 0.013 percent in MSAs in the top tercile of concentration relative to those in the bottom tercile. The same pattern of offsetting effects appears for the top tercile, with larger magnitudes, at 0.028 during rising costs (Column 2, significant at the 1 percent level) and -0.010 during falling costs (Column 3, significant at the 10 percent level).

Taken together, pass-through is stronger in more concentrated retail markets when costs rise, and weaker when costs fall.[12] Because the two interactions carry opposite signs, they compound over a complete cost cycle rather than offset: a 1 percent cost increase followed by a 1 percent cost decrease leaves retail prices in the top tercile 0.038 percent higher relative to the bottom tercile.[13] This provides complementary evidence that transitory cost shocks can generate persistent differences in local price levels, consistent with the pattern we document in the egg market.

H.8 Cost-related Hypothesis

An alternative hypothesis for spatial disparities in inflation revolves around cost differentials. If marginal costs in lower-income areas rise faster than in higher-income areas, this can contribute to higher inflation in those regions, irrespective of the market structure of retailers. To test this hypothesis, we use wage data for retail workers from the American Community Survey (ACS) and compare wage levels and growth across MSAs with varying income levels from 2006 to 2020.[14] We combine the ACS wage data with BDS data at the MSA level to control for differences in firm composition across regions.

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

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

$$\Delta \ln w_{mt} = \beta_0 + \beta_1 Income_{mt} + X'_{mt}\gamma + \delta_t + \varepsilon_{mt}, \tag{H.5}$$

where w_{mt} ($\Delta \ln w_{mt}$) is the average wage level (or growth) in the retail sector in MSA m and year t, $Income_{mt}$ is the income per capita of MSA m in year t, and X_{mt} is a vector of MSA-level

[12] Note here that the cost shock enters with its sign rather than as a treatment indicator. Thus, in the falling-cost sample, a negative interaction coefficient indicates that higher concentration attenuates the response of prices to cost declines. The analogous prediction in the binary bird-flu specification is a positive coefficient on the triple interaction during the deflationary period.

[13] For example, consider a 1 percent cost increase followed by a 1 percent cost decrease. During the rising-cost period, the differential pass-through in the top relative to the bottom HHI tercile raises relative prices by 0.028 percent. During the falling-cost period, the interaction coefficient is -0.010; because the cost change is -1 percent, this implies an additional relative price increase of 0.010 percent. The cumulative difference is therefore $0.028 + 0.010 = 0.038$ percent.

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

Table H.13: Average Wage Levels and Growth in Retail Sector across MSAs

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

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

characteristics, including the share (or growth of the share) of college workers in the retail sector, and the share of large retailers (with 500 or more employees) or establishments associated with large retailers, and δ_t is a year fixed effect.

In Table H.13, the top and bottom panels present the results for the average wage levels and growth, respectively. These results reveal that the average wage level is generally lower in lower-income areas, even after controlling for the composition of skills and the share of large firms or establishments in retail sector. However, the second panel suggests there are no significant patterns in wage growth across MSAs by income level. While the data are aggregated, they provide

suggestive evidence that retailer wages are neither higher nor growing faster in lower-income areas or areas with a higher share of large retailers, making differential retail labor costs an unlikely explanation for the observed inflation patterns.

I Model Validation

I.1 Market Concentration and Markup

The model predicts that markups are higher in markets with greater concentration. We test this prediction by constructing MSA-level average markups for food products using PriceTrak PromoData provided by Nielsen IQ. Specifically, using UPC-level wholesale costs and retail prices, we construct the markup for each UPC as the ratio of its retail price to wholesale cost. We then aggregate these UPC-level markups to the MSA level using quantity weights.

Next, we estimate the following regression to examine the MSA-level association between aggregate markups and market concentration:

$$Markup_{mt} = \beta HHI_{mt} + \delta_m + \delta_t + \varepsilon_{mt}, \tag{I.1}$$

where $Markup_{mt}$ denotes the MSA-level average markup constructed as described above, HHI_{mt} is the average quarterly market concentration, measured by the sales-based HHI, in MSA m during year t, and δ_m and δ_t denote MSA and year fixed effects, respectively. The regression sample is annual and spans 2006–2012.[15]

Table I.1 shows a positive association between MSA-level average markups and market concentration, consistent with the model prediction. The results are also robust when both markups and market concentration are constructed using the NielsenIQ Consumer Panel data.

[15]Note that PromoData only spans 2006-2012. Also, PromoData contains market-level location information for each UPC sold, which we use to map wholesale cost information to each UPC–MSA pair in the NielsenIQ Retail Scanner data. The resulting matched sample includes only a subset of the MSAs in our baseline sample, reflecting some gaps in geographic coverage and product-location overlap across the two datasets.

Table I.1: MSA-level Markups and Market Concentration

	Markup
HHI	0.054**
	(0.025)
Observations	233
Year FE	Yes
MSA FE	Yes

Note: The table presents the MSA-level relationship between average markup and market concentration in 2006-2012. The regression includes year and MSA fixed effects. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1.

I.2 Retailer Market Share and Pass-through

The model predicts that firms with sufficiently large market shares exhibit stronger pass-through of cost shocks. We test this prediction using a triple-difference specification that interacts the treatment variables with retailer-level market share.

Specifically, we partition retailers (r) into four groups based on their market share (within MSA m at quarter t) and define indicator variables, $\mathbb{I}_{mrt} = 1, 2, 3, 4$, for each group. We consider two types of classifications. The first is based on market-share quartiles. The second is based on absolute market-share thresholds: $\mathbb{I}_{mrt} = 1$ if market share is below 0.1, $\mathbb{I}_{mrt} = 2$ if market share is between 0.1 and 0.5, $\mathbb{I}_{mrt} = 3$ if market share is between 0.5 and 0.9, and $\mathbb{I}_{mrt} = 4$ if market share exceeds 0.9. Note that we fix it to 2014Q3 value for the post-shock period.

With this, we run the following regression:

$$\Delta \ln price_{umrt} = \beta_0 + \beta_1(Treated_m \times Post_t) + \sum_{i=1}^{4} \Big[\beta_{i+1}\mathcal{I}(\mathbb{I}_{mrt} = i) + \beta_{i+5}(Treated_m \times \mathcal{I}(\mathbb{I}_{mrt} = i)) + \beta_{i+9}(Post_t \times \mathcal{I}(\mathbb{I}_{mrt} = i)) + \beta_{i+13}(Treated_m \times Post_t \times \mathcal{I}(\mathbb{I}_{mrt} = i))\Big] + \delta_m + \delta_r + \delta_t + \delta_u + \varepsilon_{umrt}, \tag{I.2}$$

where $\mathcal{I}(\cdot)$ is an indicator function, and δ_r is a retailer fixed effect.

Tables I.2 and I.3 report the results using the market-share quartile and absolute market-share classifications, respectively. Across both specifications, the estimated differential pass-through is positive and statistically significant only for retailers with sufficiently large market shares. This finding is consistent with the model's prediction that pass-through is incomplete and increases

Table I.2: Triple Difference Estimator by Market Share Quintiles

	$\Delta \ln$ Price All	$\Delta \ln$ Price Inflation	$\Delta \ln$ Price Deflation
Bird Flu $\times$ Post $\times$ $\mathbb{I}_{mrt} = 2$	-0.006*	-0.003	-0.004
	(0.003)	(0.004)	(0.012)
Bird Flu $\times$ Post $\times$ $\mathbb{I}_{mrt} = 3$	-0.001	-0.002	0.000
	(0.007)	(0.007)	(0.012)
Bird Flu $\times$ Post $\times$ $\mathbb{I}_{mrt} = 4$	0.014***	0.015***	0.010
	(0.004)	(0.005)	(0.015)
Bird Flu $\times$ Post	-0.009***	0.005	-0.028**
	(0.003)	(0.004)	(0.011)
$\mathbb{I}_{mrt} = 2 \times$ Post	0.004**	-0.010***	0.023***
	(0.002)	(0.002)	(0.004)
$\mathbb{I}_{mrt} = 3 \times$ Post	0.006***	-0.020***	0.036***
	(0.002)	(0.003)	(0.004)
$\mathbb{I}_{mrt} = 4 \times$ Post	0.003*	-0.025***	0.037***
	(0.002)	(0.003)	(0.005)
Bird Flu $\times$ $\mathbb{I}_{mrt} = 2$	0.001	-0.002	-0.002
	(0.005)	(0.004)	(0.009)
Bird Flu $\times$ $\mathbb{I}_{mrt} = 3$	-0.001	-0.002	-0.001
	(0.005)	(0.006)	(0.007)
Bird Flu $\times$ $\mathbb{I}_{mrt} = 4$	-0.013***	-0.014***	-0.009
	(0.003)	(0.003)	(0.009)
$\mathbb{I}_{mrt} = 2$	-0.003**	0.001	-0.014***
	(0.001)	(0.002)	(0.003)
$\mathbb{I}_{mrt} = 3$	-0.004***	0.006***	-0.023***
	(0.001)	(0.002)	(0.003)
$\mathbb{I}_{mrt} = 4$	-0.001	0.010***	-0.024***
	(0.001)	(0.001)	(0.004)
Sample Period	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Product FE	Yes	Yes	Yes
Retailer FE	Yes	Yes	Yes
Observations	231,582	142,845	88,649

Note: The table reports estimates from a triple difference-in-differences specification interacting the bird flu shock, the post period, and retailer market share quintiles (fixed to 2014Q3 values for all quarters in the post period with $\mathbb{I}_{mrt} = 1$ as the base group). All regressions include quarter, MSA, product, and retailer fixed effects. Standard errors, reported in parentheses, are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

among firms with sufficiently large market shares.

Table I.3: Triple Difference Estimator by Market Share Ranges

	$\Delta \ln$ Price All	$\Delta \ln$ Price Inflation	$\Delta \ln$ Price Deflation
Bird Flu $\times$ Post $\times$ $\mathbb{I}_{mrt} = 2$	0.006	-0.001	0.009
	(0.005)	(0.005)	(0.009)
Bird Flu $\times$ Post $\times$ $\mathbb{I}_{mrt} = 3$	0.015***	0.020**	-0.001
	(0.005)	(0.008)	(0.015)
Bird Flu $\times$ Post $\times$ $\mathbb{I}_{mrt} = 4$	0.016***	0.021***	0.003
	(0.005)	(0.006)	(0.014)
Bird Flu $\times$ Post	-0.013***	0.004	-0.030***
	(0.003)	(0.004)	(0.007)
$\mathbb{I}_{mrt} = 2 \times$ Post	0.003**	-0.013***	0.022***
	(0.001)	(0.002)	(0.003)
$\mathbb{I}_{mrt} = 3 \times$ Post	0.001	-0.021***	0.026***
	(0.002)	(0.003)	(0.004)
$\mathbb{I}_{mrt} = 4 \times$ Post	0.004	-0.025***	0.038***
	(0.002)	(0.005)	(0.006)
Bird Flu $\times$ $\mathbb{I}_{mrt} = 2$	-0.004*	-0.003	-0.003
	(0.002)	(0.004)	(0.006)
Bird Flu $\times$ $\mathbb{I}_{mrt} = 3$	-0.015***	-0.017***	0.005
	(0.003)	(0.003)	(0.011)
Bird Flu $\times$ $\mathbb{I}_{mrt} = 4$	-0.010***	-0.008***	-0.007
	(0.003)	(0.003)	(0.009)
$\mathbb{I}_{mrt} = 2$	-0.002*	0.006***	-0.015***
	(0.001)	(0.001)	(0.002)
$\mathbb{I}_{mrt} = 3$	0.001	0.011***	-0.018***
	(0.001)	(0.001)	(0.003)
$\mathbb{I}_{mrt} = 4$	-0.003*	0.007***	-0.025***
	(0.002)	(0.003)	(0.004)
Sample Period	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Product FE	Yes	Yes	Yes
Retailer FE	Yes	Yes	Yes
Observations	231,582	142,845	88,649

Note: The table reports estimates from a triple difference-in-differences specification interacting the bird flu shock, the post period, and retailer group dummies based on market share ranges (fixed to 2014Q3 values for all quarters in the post period with $\mathbb{I}_{mrt} = 1$ as the base group). All regressions include quarter, MSA, product, and retailer fixed effects. Standard errors, reported in parentheses, are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

References

Basker, E., Noel, M., 2009. The evolving food chain: competitive effects of wal-mart's entry into the supermarket industry. Journal of Economics & Management Strategy 18, 977–1009.

Chenarides, L., Gomez, M.I., Richards, T.J., Yonezawa, K., 2024. Retail markups and discount-store entry. Review of Industrial Organization 64, 147–181.

Daruich, D., Kozlowski, J., 2023. Macroeconomic implications of uniform pricing. American Economic Journal: Macroeconomics 15, 64–108.

de Haan, J., van der Grient, H.A., 2011. Eliminating chain drift in price indexes based on scanner data. Journal of Econometrics 161, 36–46. URL: https://www.sciencedirect.com/science/article/pii/S0304407610001843, doi:https://doi.org/10.1016/j.jeconom.2010.09.004. measurement with Theory.

DellaVigna, S., Gentzkow, M., 2019. Uniform Pricing in U.S. Retail Chains. Quarterly Journal of Economics 134, 2011–2084.

Diewert, W., 1976. Exact and superlative index numbers. Journal of Econometrics 4, 115–145. URL: https://www.sciencedirect.com/science/article/pii/0304407676900099, doi:https://doi.org/10.1016/0304-4076(76)90009-9.

Diewert, W., 2005. Weighted country product dummy variable regressions and index number formulae. Review of Income and Wealth 51, 561–570. doi:10.1111/j.1475-4991.2005.00168.x.

de Haan, J., Krsinich, F., 2014. Scanner data and the treatment of quality change in nonrevisable price indexes. Journal of Business & Economic Statistics 32, 341–358. URL: https://doi.org/10.1080/07350015.2014.880059, doi:10.1080/07350015.2014.880059, arXiv:https://doi.org/10.1080/07350015.2014.880059.

Ivancic, L., Erwin Diewert, W., Fox, K.J., 2011. Scanner data, time aggregation and the construction of price indexes. Journal of Econometrics 161, 24–35. URL: https://www.sciencedirect.com/science/article/pii/S0304407610001831, doi:https://doi.org/10.1016/j.jeconom.2010.09.003. measurement with Theory.

Jarmin, R.S., Klimek, S.D., Miranda, J., 2009. The role of retail chains: National, regional and industry results, in: Producer dynamics: New evidence from micro data. University of Chicago Press, pp. 237–262.

Kim, S., Navarrete, M.A., 2026. Lack of uniform prices or lack of uniform retailers? AEA Papers and Proceedings 116, 568–572. URL: https://www.aeaweb.org/articles?id=10.1257/pandp.20261063, doi:10.1257/pandp.20261063.

Sangani, K., 2024. Pass-through in levels and the incidence of commodity shocks. Working paper, Stanford University.

Sangani, K., 2026. Complete pass-through in levels. The Quarterly Journal of Economics 141, 1077–1135.

Sato, K., 1976. The ideal log-change index number. The Review of Economics and Statistics 58, 223–228. URL: https://ideas.repec.org/a/tpr/restat/v58y1976i2p223-28.html, doi:None.

Vartia, Y.O., 1976. Ideal log-change index numbers. Scandinavian Journal of Statistics 3, 121–126. URL: http://www.jstor.org/stable/4615624.