Geospatial Heterogeneity in Inflation: A Market Concentration Story*

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July 18, 2025

Abstract

We study how inflation varies across regions with different income levels and the role of retailer market structure. Using NielsenIQ Retail Scanner and Business Dynamics Statistics data, we document new stylized facts of spatial heterogeneity in food inflation and retailer market structure. From 2006 to 2020, poorer MSAs experienced annualized food inflation that was 0.46 percentage points higher than that of richer ones—amounting to a cumulative difference of 8.8 percentage points over the period. Poorer areas also had fewer goods, fewer retailers, and higher market concentration. Using a triple-difference estimator during the 2014–2015 bird flu outbreak, we identify a causal link between market concentration and inflation.

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

Keywords: inflation, retailer market structure, market concentration, spatial inequality

*We thank Miguel Ampudia, Boragan Aruoba, Ben Bernanke, Marcus Casey, Thesia Garner, John Haltiwanger, Judith Hellerstein, Colin Hottman, David Johnson, Ethan Kaplan, Munseob Lee, Giacomo Ponzetto, John Shea, Lumi Stevens, Nico Trachter, and participants at seminars at the BLS, University of Maryland, Federal Reserve Board, Federal Reserve Bank of Atlanta, and various conferences including the NBER Competition in the U.S. Agricultural Sector Meeting, BSE Summer Forum, UChicago-SNU Inequality conference, BdE-BOC-ECB-Fed Conference, NASMES Meeting, DC Urban Economics Workshop, Midwest Macro Meeting, and SED for helpful comments. We also thank the RESET team for providing the infrastructure to address our research project. This research is funded by the Washington Center for Equitable Growth. Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. The views expressed here are those of the authors and do not necessarily reflect the views of the Federal Reserve System, Board of Governors, or their staff. Michael Navarrete worked on this paper while a PhD student at the University of Maryland, College Park. All errors are our own.

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1 Introduction

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

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

In this paper, we aim to address this gap in spatial variation by documenting spatial heterogeneity in food inflation rates, examining the role of retailer market structure in shaping this variation and its aggregate implications. We use NielsenIQ Retail Scanner data, which provides granular detail at the 12-digit universal product codes (UPC level), and construct price indexes for disaggregated personal consumption expenditure (PCE) food items at the metropolitan statistical area (MSA) level.[5]

We document several new stylized facts. First, 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 aggregated food categories

[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 the following 23 Core Based Statistical Areas (CBSA), which are mostly rich areas: New York–Newark–Jersey City; Los Angeles–Long Beach–Anaheim; Chicago–Naperville–Elgin; Dallas–Fort Worth–Arlington; Houston; Atlanta; Washington; Miami; Boston; Philadelphia; Phoenix; Detroit; Seattle; San Francisco; Riverside; San Diego; Minneapolis; Denver; St. Louis; Tampa; Baltimore; Honolulu; Anchorage. See more details from https://www.bls.gov/cpi/regional-resources.htm.

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

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

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

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

and remains robust under two key restrictions: i) we apply a "common goods rule" that limits the sample to UPCs sold in all ten income deciles, and ii) we impose uniform expenditure weights across deciles when constructing the index. These adjustments ensure that the observed inflation gap is not driven by differences in consumption composition or weighting schemes across regions.

Second, we find substantial regional variation in product varieties and retailer market structure. Richer areas have more varieties of goods (UPCs) and a greater number of stores and retail chains. Typically, the set of UPCs available in poorer regions is a subset of those found in richer areas.[6] We also find systematic differences in retailer market structure across regions by income. Using NielsenIQ Retail Scanner data, we classify retailers as large or small based on total sales or national store counts—defining large retailers as those in the top decile and small retailers in the bottom decile. Poorer MSAs have a higher share of large retailers and a lower share of small ones, while the opposite holds in richer areas. These patterns are robust when using the Business Dynamics Statistics (BDS), where we define retailer size based on employment—500 or more employees for large retailers and 19 or fewer for small ones. We also find that retail sales are lower and more concentrated in poorer areas.

Next, we investigate the relationship between inflation and retailer market structure. Using OLS, we find that market concentration is associated with higher inflation rates at the MSA level. However, this does not establish a causal relationship. To identify causality, we exploit the 2014–2015 bird flu outbreak as an exogenous supply shock in the egg market. Using a triple-difference framework, we compare inflation across MSAs with varying levels of market concentration. We find that MSAs with higher concentration—measured by sales-based HHI—experienced significantly higher egg 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 66% of this gap explained by differences in market concentration. We also rule out alternative explanations such as differences in consumption baskets, retailer composition, and underlying cost structures.

Furthermore, we find asymmetric pass-through of shocks over time: in MSAs with higher market concentration, inflation rose more during the inflationary phase (from 2014Q4 to 2015Q3),

[6]This suggests that imposing the common goods rule across income deciles limits the UPCs in wealthier areas but has a smaller impact on those in poorer areas.

but prices fell less during the subsequent deflationary phase (after 2015Q3). This suggests that temporary shocks can have lasting effects on regional inflation, contributing to long-run spatial disparities in inflation and thus potentially amplifying real income inequality.

Lastly, to see implications for income inequality, we construct real income per capita by deflating nominal income per capita with the food index we derive from the NielsenIQ Retail Scanner data. We find that both nominal and real income per capita have increased over time, and the gap between the top and bottom deciles has widened for both measures. In particular, the divergence is more pronounced for real income per capita, reflecting persistent regional disparities in inflation. If we use the official national index, the gap is mitigated and the actual extent of real income inequality is understated. This is due to the official indexes are aggregated at the national level using expenditure weights, which are disproportionately accounted for by rich areas. This underscores the need for policymakers to adopt localized approaches to measuring inflation and assessing regional disparities when designing policies to address real income inequality.

The spatial dimension of our analysis yields other important implications for understanding income inequality through the lens of food market segmentation and retailer concentration. Because food markets are highly localized—with most purchases made close to home—higher food inflation can have a significant and direct effect on consumer welfare in local areas. This effect is particularly pronounced for vulnerable and immobile individuals in low-income communities, who spend a larger share of their income on food. In these communities, the impact of inflation is compounded by limited access to alternative retailers and a narrower range of substitute goods. As a result, the interplay of localized market segmentation and concentrated retail structures disproportionately harms consumers in poorer regions. Our findings suggest that policymakers should account for regional variation in both inflation and market structure when designing policies to alleviate the unequal effects of inflation on economically disadvantaged areas.

Related Literature This paper contributes to several major strands of the literature. First, our work relates to the literature on inflation heterogeneity across different groups. Hobijn and Lagakos (2005) and Hobijn et al. (2009) use Consumption Expenditure Survey (CEX) data and document inflation differences by different demographic groups. Kaplan and Menzio (2015) and Kaplan and Schulhofer-Wohl (2017) use NielsenIQ Consumer Panel and Retail Scanner data and find inflation disparities across households with different income levels for the same bundle of goods, with low-income and older households experiencing higher inflation on average. Jaravel (2018) finds similar results with the same data but emphasizes the role of product innovation and segmented consumption goods. Argente and Lee (2021) find lower inflation faced by high-income households during the recession, as they were better able to substitute toward lower-quality goods. Handbury (2021) documents that products and prices offered in markets vary by local income-specific tastes, which can affect welfare differently between low- and high-income households. Molloy (2024) documents lower shelter inflation for poorer households but similar overall inflation due to their higher housing expenditure share. These studies primarily focus on inflation heterogeneity at the household level or attribute differences to consumer-related factors, such as differences in consumption baskets, price sensitivity, preferences, or search efforts. Our paper contributes to this body of work by providing new evidence of inflation heterogeneity across regions that differ in income levels and identifying retailer market structure as a novel source of inflation variation.

Another important strand of literature closely related to our paper is the growing body of work on retailer market concentration and market power. Numerous studies have documented the increasing trends in retailer market concentration and the rising role of national chains (Jarmin et al., 2009; Haltiwanger, 2012; Hortaçsu and Syverson, 2015; Foster et al., 2016; Cao et al., 2024; Smith and Ocampo, 2025). Other studies find a declining trend in concentration in local markets (Rossi-Hansberg et al., 2021) and narrowly defined product markets (Benkard et al., 2021). Others estimate retailer markups and explore their heterogeneity, with some attributing it to city size (Hottman, 2017) and local housing prices (Stroebel and Vavra, 2019). Sangani (2022) finds higher retailer markups faced by rich households due to differences in search behavior; and Döpper et al. (2025) find an increase in markups in NielsenIQ data and attribute it to decreases in marginal costs and price sensitivity. Mongey and Waugh (2025) build a model showing that the sorting of households with different elasticities into high- and low-price varieties accounts for variation in firms' market power and markup. Our paper contributes to this literature by providing new evidence of variation in retailer market concentration across regions with different income levels. In particular, we document a novel finding that retailer market concentration is higher in lower-income areas, and establish a causal relationship between market concentration and inflation across MSAs.

Our paper also contributes to literature on pass-through of shocks to prices and inflation. Prior studies examine the pass-through of demand-based shocks (Arcidiacono et al., 2020; Gagnon and

López-Salido, 2020; Handbury and Moshary, 2021) or supply-based shocks, either tax changes (Cawley et al., 2018, 2020; Baker et al., 2020; Butters et al., 2022) or wholesale prices (Nakamura and Zerom, 2010) to retail prices. We differ in our identification strategy, where we exploit a novel, exogenous supply-side shock: the 2014–2015 avian influenza (bird flu) outbreak that disrupted the U.S. egg market. A key advantage of this episode is its sharp and temporary nature, with a steep increase in egg prices followed by a rapid decline. This dynamic allows us to identify heterogeneous pass-through patterns across metropolitan statistical areas (MSAs) with varying degrees of market concentration. We find that MSAs with higher market concentration exhibit greater pass-through (i.e., more inflation) during the inflationary phase of the shock, but attenuated pass-through (i.e., less deflation) during the subsequent deflationary phase. This implies that even if shocks are temporary, the effects on regional differences are not. This is a novel mechanism that helps explain the stylized fact we document: poorer regions experience higher food inflation. We are among the first to provide a causal explanation for this pattern by linking regional variation in market concentration to differential pass-through during shocks.

Lastly, our study contributes to the literature using item-level data to construct more accurate inflation measures (Ehrlich et al., 2023), which can outperform official indices in capturing true cost-of-living changes (Handbury et al., 2013). We construct regional price indices at the MSA level, similar to Handbury and Weinstein (2014), to better capture spatial heterogeneity in inflation.[7] In contrast, official indices are either national, aggregated using expenditure weights, or regional, but often limited to wealthier areas. As a result, poorer regions are typically underrepresented due to their lower aggregate consumption and limited coverage. This concern echoes Martin (2024), who highlights that expenditure-weighted indices may systematically understate inflation in poorer areas—especially when price and inflation dynamics vary across regions. Our regional indices offer a more representative view of local inflation and, in turn, real income inequality. We find that poorer areas experience higher food inflation, which amplifies real income disparities relative to what nominal measures suggest. This stands in contrast to Moretti (2013), who finds real wage inequality to be lower than nominal, likely due to differences in goods and geographic coverage.[8]

The rest of the paper is organized as follows. Section 2 describes the data and key measures.

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

[8]We focus on food prices using highly granular data.

Section 3 presents stylized facts on spatial heterogeneity in food inflation and retailer market structure. Section 4 outlines the empirical strategy used to identify causality and presents the main findings. Section 5 discusses aggregate implications of this channel. Section 6 explores alternative hypotheses, and Section 7 concludes the paper.

2 Data and Measures

We use two main datasets to analyze heterogeneous inflation rates across regions are the NielsenIQ Retail Scanner dataset and Business Dynamics Statistics (BDS). The NielsenIQ dataset enables us to measure inflation rates and retailer market structure across regions by analyzing sales, price, and store distribution data from retailers for food products. The BDS allows us to test the robustness of our findings by using alternative definitions of retailer size based on the number of employees.

2.1 NielsenIQ Retail Scanner

Our analysis uses the 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. The dataset contains over 2.6 million UPCs. Furthermore, NielsenIQ classifies UPC-level goods by 10 departments, 110 product groups, and over 1,000 product modules. We further use a concordance provided by the U.S. Bureau of Labor Statistics (BLS) that maps NielsenIQ product modules to BLS entry level items (ELIs).[9] 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 (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,

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

Table 1: Examples of MSA Deciles

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

Sugar and Sweets, Vegetables, and Wine), spanning from 2006Q2 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 based on store location information in NielsenIQ.[10] We then define income deciles by the cross-time average of MSA-level income per capita. Table 1 reports examples of cities in particular income deciles. The price data is aggregated to the monthly frequency using the National Retail Federation (NRF) calendar and then aggregated to the quarterly frequency.[11] Using the concordance between product modules and PCE food categories, we identify the food sector in NielsenIQ. Finally, to measure retailer market structure and the degree of competition, we link store identifiers to retail chain identifiers using a crosswalk provided by NielsenIQ.

Our main analysis is at the MSA (or income decile)-food category-quarter level. We generate price indexes, the Herfindahl-Hirschman index 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. We use HHI as our main measure of market concentration, relying on data from the NielsenIQ Retailer Scanner dataset. 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.

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

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

Table 2: Summary Statistics of MSA-quarter level Sample

	Mean (SD)		Mean (SD)
Income per capita ($ thousands)	42.49 (9.29)	Share of Large Chains (top sales decile)	0.357 (0.11)
Sales ($ millions)	207.23 (366.62)	Share of Small Chains (bottom sales decile)	0.016 (0.04)
Population Share	0.005 (0.01)	Share of Large Chains (top store# decile)	0.619 (0.16)
Number of Chains	9.74 (3.71)	Share of Small Chains (bottom store# decile)	0.008 (0.03)
Number of Stores	193.84 (251.38)	Market Concentration (HHI)	0.416 (0.18)
Number of UPCs	49180.16 (18954.19)	Market Concentration (CR1)	0.534 (0.19)
		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. Large (small) chains are defined by those in the top (bottom) decile based on total sales or the count of stores of that chain at the national level in a given quarter. We compute the share of these large or small chains within an MSA-quarter. Market concentration is measured using either the Herfindahl-Hirschman Index (HHI) of chain-level sales or the sales share of the top one or three retailers within an MSA (CR1 or CR3).

2.2 Business Dynamics Statistics (BDS)

The Business Dynamics Statistics (BDS, henceforth) is a public version of administrative Census firm-level data, the Longitudinal Business Dynamics. 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.[12] In the BDS, we use retailers' information (based on NAICS code

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

44-45) and construct alternative measures for retailer size and market structure at the MSA level.[13] We define large firms as those with 500 or more employees nationally. To be consistent with the NielsenIQ, we focus on the period of 2006-2020 in the BDS.

2.3 Main Measures

2.3.1 Price Indexes

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

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

where ω_{mkt} represents the weight assigned to product k in quarter t for MSA m (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 that are sold in both periods t and $t-1$ in MSA m (or income decile m).

We also construct two alternative price indexes: (i) one by restricting the sample to UPCs that are sold in all ten income deciles in both consecutive quarters $t-1$ and t (common goods) and (ii) another which restricts to common goods and applies common weights across deciles. Specifically, we impose $\omega_{mkt} = \omega_{kt}$ for all deciles m, where the weights are fixed to the lagged expenditure shares in the bottom income decile. This approach accounts for the fact that consumption baskets can differ systematically between income groups, as documented in Jaravel (2018), and consequently between regions with different income levels. By focusing on a common set of goods and applying common weights, we move closer to isolating regional inflation differences that are not driven by variation in the composition of consumption baskets.

In addition, we conduct a robustness test using alternative demand-based indexes based on the constant elasticity of substitution (CES) preference assumption, to account for potential substitution

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

bias inherent in traditional indexes.[14] See more details in Appendix B.

2.3.2 Retailer Market Structure

In NielsenIQ data, we define large and small chains based on the distribution of store counts at the national level. Using store and retailer codes along with geographic information for each store, we identify stores, retailers, and their ownership structures across regions and time. We define the size of retailers based on 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 size distribution. We then calculate the number and share of large and small chains in each MSA.

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

Finally, we use the local sales shares of retailers to construct the local Herfindahl-Hirschman index (HHI), to measure the degree of market concentration among retailers in each MSA.

3 Spatial Heterogeneity in Inflation and Market Structure

3.1 Price and Inflation Patterns

Figure 1 presents the geometric Laspeyres price index for aggregated food, constructed from the NielsenIQ Scanner data by income decile. We report results for the first (poorest), fifth, and tenth (richest) income deciles, alongside the official PCE food price index for comparison. The base quarter is set to 2006Q2.[15]

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

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

[15] 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.

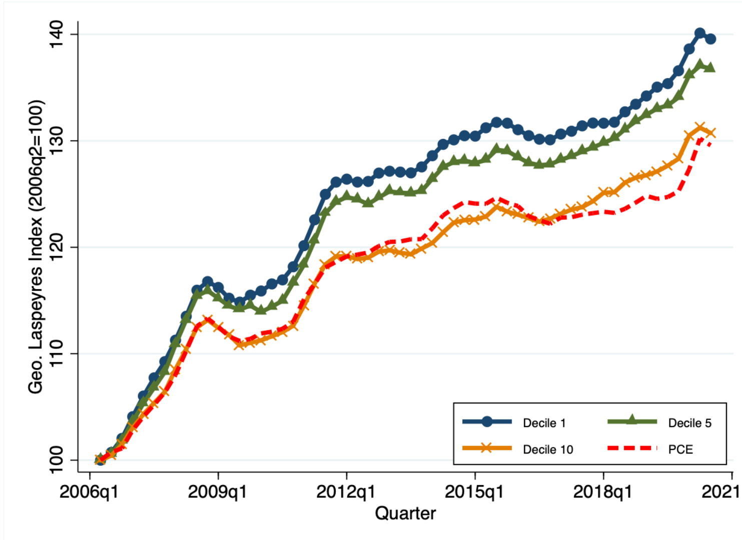

Figure 1: Price Index for Aggregated Food

Notes: This figure represents the chained geometric Laspeyres price index constructed using NielsenIQ 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. The sample period begins in 2006Q2 and ends in 2020Q3, and the series is normalized at the initial quarter. Each solid line corresponds to a decile of the income per capita ranking of MSAs, with decile 1 containing the MSAs with the lowest income per capita and decile 10 containing the MSAs with the highest income per capita. We map the NielsenIQ UPCs 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.

corresponds to a cumulative inflation gap of nearly 8.8 percentage points between the poorest and richest deciles.

This pattern continues to hold even when we restrict the sample to the set of common goods sold across all income deciles in consecutive quarters $t-1$ and t, and when we apply uniform sales weights. The result is shown in the left and right panels in Figure 2, respectively. These results suggest that the observed variation in price growth across income deciles is not primarily driven by differences in consumption baskets, their composition, or consumer preferences across regions. These patterns are also robust to alternative price measurement approaches, including those based on demand-based price index and MSA-level price index. More details are provided in Appendix B. Moreover, the pattern remains consistent for other disaggregated PCE food categories, as shown in Appendix C.

Lastly, note that the official PCE series aligns more closely with the NielsenIQ series for the highest income decile than for any other decile. This suggests that the official PCE price index series understates inflation to the largest extent for individuals living in the poorest areas. This

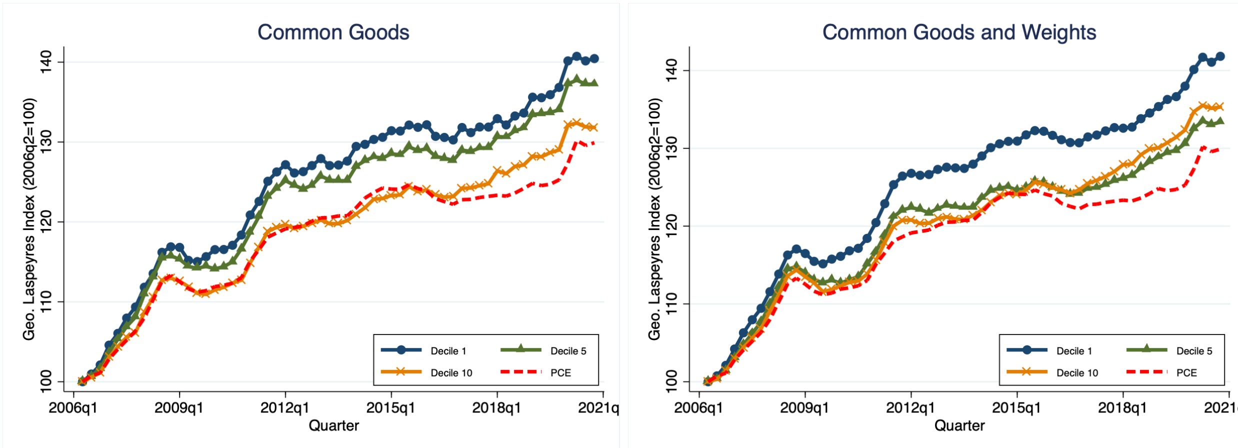

Figure 2: Price Index for Aggregated Food (Common Goods and Weights)

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 and t-1 (which we name "common goods") in the left panel, and are not just restricted to the common goods but also based on the same sales weights in decile 1 in the right panel.

discrepancy in inflation has significant macroeconomic implications. For example, if we assume uniform nominal wage growth across the United States, official national real wage growth would be systematically higher than real wage growth experienced in the poorest areas.

3.2 Retailer Market Structure

We examine retailer market structure across regions by computing market concentration statistics from the NielsenIQ sample, grouped by income-per-capita decile. Table 3 shows that richer areas have a greater number of retailers, greater number of stores, and higher sales. Also, poorer areas have fewer UPCs and have higher total consumption allocated to the set of common goods (both in quantity and in expenditure).

We next run the following regressions 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 the number of store counts at the national level), or market concentration

Table 3: Summary Statistics of MSA-quarter level Sample by Income Deciles

	Decile 1	Decile 5	Decile 10
	Mean (SD)	Mean (SD)	Mean (SD)
Income per capita ($ thousands)	31.615	39.010	56.733
	(4.876)	(4.994)	(11.793)
Sales ($ millions)	24.639	73.501	773.676
	(18.431)	(74.623)	(748.232)
Population Share	0.001	0.002	0.019
	(0.001)	(0.001)	(0.022)
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 (thousands)	32.368	40.419	70.980
	(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. Large (small) chains are defined by those in the top (bottom) decile based on total sales or the count of stores of that chain at the national level in a given quarter. We compute the share of these large or small chains within an MSA-quarter.

in MSA m in quarter t. The market concentration is measured as either the Herfindahl-Hirschman index (HHI) of retail chain sales or the sales share of the top one and three retailers (CR1 and CR3) in an MSA in a given quarter. $Income_{mt}$ is income per capita in MSA m, and δ_t is a quarter fixed effect.

The results, presented in Table 4, confirm the cross-sectional patterns that poorer areas have lower sales, fewer retailers and stores, a higher fraction of large retailers, and higher market concentration, measured in both HHI and the sales share of top firms (CR1 and CR3). These results suggest that retailer market structure varies across regions with different income levels. In particular, retailer market concentration is higher in poorer areas, where a larger share of sales is dominated by larger firms.

Furthermore, we look into this cross-sectional association across MSAs in the long run by using the MSA-level long-run average across the sample period.[16] We run the following regression for the association between income level and retailer market structure:

[16]Using the MSA fixed effect estimates gives the same results.

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

	Sales (in \$1mil.)	Chain #	Store #	Large Firm Share (Sales)	Large Firm Share (Store #)
Income	26.37***	0.192***	16.43***	-0.002***	-0.009***
	(5.876)	(0.039)	(3.928)	(0.001)	(0.002)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	11,100	11,100	11,100	11,100	11,100
	HHI	CR1	CR3		
Income	-0.004***	-0.004***	-0.003***		
	(0.001)	(0.001)	(0.001)		
Quarter FE	Yes	Yes	Yes		
Observations	11,100	11,100	11,100		

Note: The table presents regression results from Equation (2). The coefficient of interest is on income per capita (in \$1000) in an MSA for a given quarter. In the top panel, the dependent variable is total sales in Column 1, the total count of chains and stores in Columns 2 and 3, respectively, the unweighted shares (%) of large firms in Column 4 and Column 5, where large retailers are defined as the top decile of total sales in Column 4 and the top decile of the number of stores in Column 5 (at the national level). In the bottom panel, the dependent variable is the Hirschman-Herfindahl Index (HHI) based on retailer sales in Column 1, and the sales share of the top one and three retailers in an MSA for a given quarter in Columns 2 and 3, respectively. All these variables are constructed in NielsenIQ. *** p<0.01, ** p<0.05, * p<0.1

$$\bar{Y}_m = \beta_0 + \boldsymbol{\beta_1} Inc\bar{o}me_m + \varepsilon_m, \tag{3}$$

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 measures (HHI, CR1 or CR3), and $Inc\bar{o}me_m$ is the long-run average per capita income in msa m. The results are shown in Table 5, which support the robustness of these associations in the long run. We observe consistent patterns in the BDS data as well. See Appendix D for further details.

3.3 Relationship between Inflation and Market Concentration

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

$$P_{mt} = \beta_0 + \beta_1 X_{mt} + \delta_t + \varepsilon_{mt}, \tag{4}$$

Table 5: Retailer Market Structure across Regions with Different Income Levels (Long Run)

	Sales (in \$1mil.)	Chain #	Store #	Large Firm Share (Sales)	Large Firm Share (Store #)
Income	27.32***	0.198***	17.48***	-0.003***	-0.009***
	(2.921)	(0.023)	(2.135)	(0.008)	(0.001)
Observations	185	185	185	185	185
	HHI	CR1	CR3		
Income	-0.005***	-0.004**	-0.003***		
	(0.002)	(0.002)	(0.001)		
Observations	185	185	185		

Note: The table presents regression results from Equation (3). 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. *** p<0.01, ** p<0.05, * p<0.1

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 6 presents the results in the first three columns. Columns 1 and 2 show that inflation tends to be higher in areas with higher market concentration and lower-income areas. Interestingly, Column 3 indicates that higher market concentration is the primary driver of inflation disparities, as its effect dominates that of low income when both variables are included in the regression. Columns 4 and 5 include controls for the total number of retail chains in an MSA, which may mechanically influence the degree of market concentration, and the results remain robust. We also replace HHI with CR measures and confirm its robustness. This is presented in Appendix E.1. In addition, we use the geometric Laspeyres price index as an alternative measure of cumulative price differences; the results are similar and reported in Appendix F.

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

$$\bar{P}_m = \beta_0 + \boldsymbol{\beta_1} \bar{X}_m + \varepsilon_m, \tag{5}$$

where $\bar{P}_m$ is the long-run average of inflation, and $\bar{X}_m$ is the long-run average of HHI and income level in msa m. The results are shown in Table 7, which confirms the negative association between food inflation and income as well as the positive association between food inflation and market

Table 6: Food Inflation across Regions

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

Note: The table presents regression results from Equation (4). The coefficient of interest is on HHI and income per capita (in $1000) in an MSA for a given quarter. The dependent variable is the geometric Laspeyres inflation rate (%) of aggregate food in an MSA for a given quarter. Total number of chains is included as a control in the last two columns. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Food Inflation across Regions (Long Run)

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

Note: The table presents regression results from Equation (5) for the cross-sectional association between MSA-level inflation, income, and market concentration in the long run. The coefficient of interest is on HHI and income per capita (in $1000) in an MSA. The dependent variable is the long-run average of the food Laspeyres inflation rate. The last two columns control for the long-run average number of chains in an MSA. *** p<0.01, ** p<0.05, * p<0.1

concentration across MSAs in the long run. Note that the results are also robust with both CR1 and CR3 measures, which are displayed in Appendix F.

4 Causal Link between Inflation and Market Concentration

To explore causal relationship between inflation and retailer market concentration, we focus our analysis on the egg market in this section. In particular, we exploit a quasi-experiment based on the 2014-2015 bird flu outbreak and apply a triple-difference estimator.

Table 8: Eggs Inflation across Regions

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

Note: The table represents regression results from (6) for the cross-sectional association between MSA-level inflation, income, and market concentration for eggs. The coefficient of interest is on HHI of retail chain's eggs sales and income per capita (in $1000) in an MSA. The dependent variable is the Laspeyres inflation rate (%) of eggs in an MSA for a given quarter. Total number of chains in eggs market is controlled in the last two columns. *** p<0.01, ** p<0.05, * p<0.1

4.1 Standard OLS Estimator

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

$$P_{mt} = \beta_0 + \beta_1 X_{mt} + \delta_t + \varepsilon_{mt}, \tag{6}$$

where P_{mt} is the geometric Laspeyres inflation rate of eggs, X_{mt} denotes the HHI of retailer sales or income per capita in MSA m in quarter t, and δ_t represents quarter fixed effects. The results are presented in Table 8, which reveal a similar association between HHI, income, and egg inflation as in our earlier analysis for aggregate food. In particular, we find a positive and statistically significant relationship between market concentration and inflation in Column 1, and this relationship remains robust even after controlling for the MSA-level income per capita and the number of chains in Columns 4 and 5. These results are robust to CR1 and CR3 measures, as shown in Appendix E.2.

While these results shed light on the link between inflation and market concentration, they do not establish causality. The OLS estimate of β_1 may be subject to endogeneity bias. For instance, the observed relationship could be demand-driven: consumers in MSAs with higher HHI may disproportionately purchase goods experiencing higher inflation. Alternatively, income-related differences in consumer behavior could play a role: richer MSAs may have consumers who are more sensitive to price changes. Such heterogeneity in consumer behavior may have led retailers in

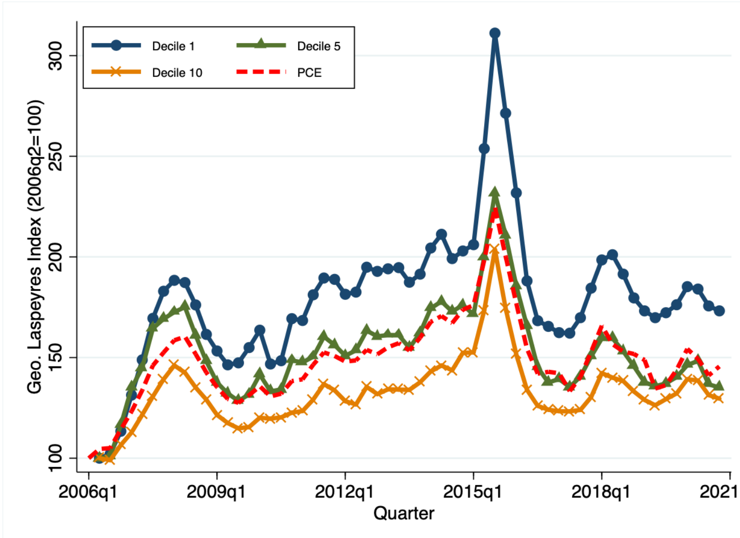

Figure 3: Price Index for Eggs

Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for eggs. The sample period begins in 2006Q2 and ends in 2020Q3, and the series is normalized at the initial quarter. Each solid line corresponds to a decile of the income per capita ranking of MSAs, with decile 1 containing the MSAs with the lowest income per capita and decile 10 containing the MSAs with the highest income per capita. We map the NielsenIQ UPCs 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.

wealthier areas to raise prices at slower rates. Another potential explanation is a supply-side story, where poorer MSAs have fewer stores and varieties, which weakens competition and allows retailers to raise prices more aggressively. There may also be a potential sorting of certain types of retailers into poorer MSAs, those that are more flexible in increasing prices, compared to retailers operating in richer areas. To isolate whether the effect we observe is driven by supply-side or demand-side forces, we exploit the 2014–2015 bird flu outbreak as an exogenous supply shock.

4.2 Triple-Difference Estimator

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 affected the price and quantities of eggs sold, as evidenced in Figure 3 and started in 2014Q4. 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.[17]

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

This reduction in egg supply caused a sharp spike in egg prices, as shown in Figure 3.

Importantly, reports from the USDA and the Government Accountability Office (GAO) indicate that the impact of the bird flu shock varied geospatially, primarily affecting the central and western U.S. Farmers in these parts of the country were more affected than farmers in other parts of the country in terms of their layers' vulnerability to the disease. We have access to official data from the USDA on the timing, location, and number of bird layers that were culled.[18] 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.[19,20,21]

Leveraging this information, we pursue a difference-in-differences identification strategy, grouping treated and control MSAs and comparing the effect of the bird flu outbreak on egg inflation. We then extend this approach by using a triple difference-in-differences estimator, which interacts MSA-level market concentration with the standard diff-in-diff term. This allows us to examine how the effect of the outbreak on egg inflation varies based on the degree of retailer market concentration.

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

$$P_{mt} = \beta_0 + \beta_1(Treated_m \times Post_t) + \delta_m + \delta_t + \varepsilon_{st}, \tag{7}$$

where P_{mt} is the geometric Laspeyres inflation rate for eggs in MSA m in quarter t, $Treated_m$ is an indicator variable that takes the value of one if farmers in MSA m culled their layers during the 2014-2015 bird flu outbreak, according to the USDA, and $Post_t$ is a binary variable that takes the value of one after 2014Q4, and zero otherwise. δ_m and δ_t are MSA and quarter fixed effects, respectively. The coefficient on β_1 should be positive, at least during the inflationary period of the bird flu episode, given that these MSAs experienced a relatively larger cost shock.

[18]See details from https://crsreports.congress.gov/product/pdf/R/R44114.

[19]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).

[20]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. See Appendix G for further details.

[21]Note that as robustness, we also include additional neighboring MSAs around these areas. See more details in Appendix H.1.

Table 9: 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 our two-way fixed effects estimator. The coefficient of interest is the interaction of Post and Bird Flu. Post is a binary variable that takes the value of one after 2014Q4. Bird Flu is a binary variable that takes the value of one if egg farmers in an MSA culled their layers during the 2014-2015 bird flu episode. Column 1 pools all periods together and has the inflation rate as the outcome variable. Column 2 only looks at the inflationary period and has the inflation rate as the outcome variable. Column 3 only looks at the deflationary period and has the inflation rate as the outcome variable. Column 4 pools all periods together and has the absolute value of the inflation rate as the outcome variable. Inflationary and deflationary periods are determined by the national price index of eggs. The sample period ranges from 2012Q4 to 2016Q4. MSA and quarter fixed effects are included. Standard errors are clustered at the MSA-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results are shown in Table 9. In Column 1, we estimate a statistically insignificant (i.e., null) effect, which may suggest that these MSAs affected by bird flu did not experience more aggregate egg price inflation. However, this null effect masks heterogeneity across time in the effects during this period. 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.[22] 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 Flu and Post, which corresponds to a 3.9 percentage point higher egg inflation rate in MSAs affected by the bird flu after 2014Q4 during the inflationary period. This point estimate is significant at the 1% level. In Column 3, we restrict the sample to the deflationary period and find that MSAs that culled their layers experienced a 3.5 percentage point lower inflation (higher deflation) rate after 2014Q4 during the deflationary period. This point estimate is also significant at the 1% level. In Column 4, we pool all quarters and take the absolute value of the dependent variable (the inflation rate). We find that MSAs that culled their layers experienced 5.3 percentage

[22]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.

point larger absolute changes in the inflation rate after 2014Q4. This coefficient is significant at the 1 percent level.

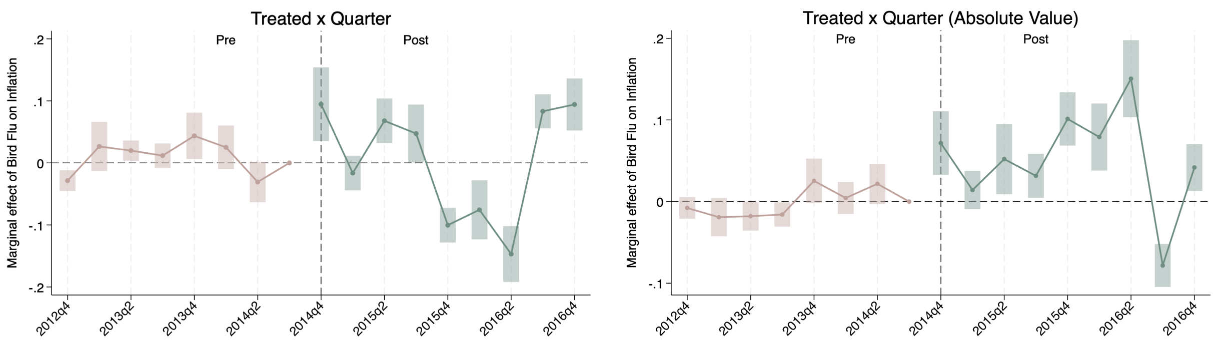

Figure 4: Event Study Difference-in-Differences (Bird Flu)

Notes: The figure represents the event study difference-in-differences analysis examining the differential effect of the 2014-2015 bird flu episode on egg inflation in MSAs whose farmers were directly affected by the bird flu. The outcome variables in the left and right panels are the inflation rate and the absolute value of the inflation rate, respectively. MSAs are assigned to the treatment group based on USDA reports detailing which farms culled their layers. The post-period starts in 2014Q4, and 2014Q3 is the reference quarter. Effects are measured from 2012Q4 to 2016Q4. Standard errors are clustered at the MSA level.

These heterogeneous inflation effects during the bird flu outbreak are reflected in Figure 4. The left panel plots the standard event study difference-in-differences coefficients. The dashed vertical line corresponds to 2014Q4, marking the start of the post-period. We observe no systematic difference in inflation rates between MSAs that culled their layers (the treated MSAs) and MSAs that did not cull their layers (the control MSAs) prior to 2014Q4. There appears to be no pre-trend difference between the treated MSAs and the control MSAs . However, after 2014Q4, the treated MSAs experienced relatively higher inflation initially, then relatively lower inflation in subsequent quarters, with a roughly zero effect on average.

These opposing inflation effects can be explained by heterogeneous impacts depending on whether the egg market is in an inflationary or deflationary period. This dependency on the inflationary or deflationary phase is reflected in the right panel, where we replace the dependent variable with the absolute value of the inflation rate. We find that the impacted MSAs were consistently more affected after 2014Q4. Additionally, we continue to observe no significant difference between these two groups of MSAs prior to 2014Q4, further supporting the notion that the bird flu shock had a heterogeneous effect depending on local egg supply conditions. This pattern of higher inflation in the inflationary period and lower inflation in the deflationary period for treated

MSAs holds for every quarter in the post period except 2016Q3.

Next, we use a triple-difference estimator to measure of how the impact of the bird flu on egg inflation varies across treated MSAs (where farmers culled their layers) with different degrees of market concentration (HHI). The following regression outlines the identification strategy:

$$\begin{aligned} P_{mt} = \beta_0 &+ \beta_1 HHI_{mt} + \beta_2(\text{Treated}_m \times \text{Post}_t) \\ &+ \beta_3(\text{Treated}_m \times HHI_{mt}) + \beta_4(\text{Post}_t \times HHI_{mt}) \\ &+ \beta_5(\text{Treated}_m \times \text{Post}_t \times HHI_{mt}) + \delta_m + \delta_t + \varepsilon_{mt}, \end{aligned} \tag{8}$$

where the subscript m corresponds to MSA m and subscript t corresponds to quarter t. $Treated_m$ is a binary variable indicating whether layers in MSA m were culled during the 2014-2015 bird flu episode according to the USDA report. $Post_t$ is a binary variable that takes value 1 if quarter t is after 2014Q4, and zero otherwise. HHI_{mt} is the HHI of retailer concentration of sales in MSA m in quarter t. For the post-treatment period, we fix it to the value in 2014Q3.[23] 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 from our triple-difference estimator are presented in Table 10. Column 1 pools all quarters within the two-year window and shows that treated MSAs with higher market concentration exhibit significantly higher inflation, on average, than those with lower concentration. The coefficient of 0.5 on the triple interaction implies that, for a one-unit increase in HHI, quarterly egg inflation rises by 0.5 percentage points among treated MSAs. For example, an increase in HHI from 0.25 to 0.75 implies a 0.25 percentage point higher inflation rate per quarter. This effect is statistically significant at the 1% level. Columns 2 and 3 decompose this effect into the inflationary and deflationary periods, respectively. In Column 2, restricting the sample to the inflationary period, we find that treated MSAs with higher market concentration experienced faster initial price increases in the egg market following the bird flu episode. This coefficient is also significant at the 1% level. In contrast, Column 3 shows that these MSAs did not reduce prices by larger amounts during the deflationary period. We find that MSAs with higher concentration were slower to decrease prices, as indicated by a positive coefficient on the triple interaction term. This coefficient is statistically

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

Table 10: Triple Difference Estimator

	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 our triple difference-in-differences. The coefficient of interest is the interaction of Post, HHI, and Bird Flu. Post is a binary variable that takes the value 1 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. Bird Flu is a binary variable that takes the value 1 if an MSA culled its layers during the 2014-2105 bird flu episode. Columns 1 pools all periods together. Column 2 only considers the inflationary period, and Column 3 only considers the deflationary period, where the inflationary and deflationary periods are determined by the national price index of eggs. The sample period ranges from 2012q4 to 20164. 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

significant at the 10% level. These results are robust to including neighboring MSAs around the treated MSAs, as presented in Appendix H.1, and to alternative measures of market concentration, such as CR1 and CR3, as shown in Appendix H.2.

5 Aggregate Implications

5.1 Back-of-the-Envelope

To assess whether the magnitudes estimated in Table 10 are economically meaningful, we perform a back-of-the-envelope calculation to estimate 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 deciles during the inflationary period of the bird flu episode. To measure the contribution of market concentration, we perform the following calculation:

$$\pi_{contribution} = \frac{(1 + \beta * HHI_{diff})^q - 1}{\pi_{d1} - \pi_{d10}}, \tag{9}$$

where $\pi_{contribution}$ denotes the contribution of market concentration to the inflation gap in the egg market between the first and tenth deciles during the inflationary period of the 2014-2015 bird flu episode. Given that we are only considering the inflationary period, this corresponds to the four quarters from 2014Q4 to 2015Q3. π_{d1} denotes inflation in eggs for the poorest decile during this inflationary period, and π_{d10} denotes inflation in eggs for the richest decile during the same inflationary period. β corresponds to the coefficient on the triple interaction of Bird Flu $\times$ Post $\times$ HHI from Table 10 Column 2. HHI_{diff} corresponds to the difference in HHI values in the egg market between the poorest and richest decile, and q refers to the number of quarters in the 2014-2015 bird flu inflationary period, which is equal to 4.

Although there was a general surge in egg prices during this period, the inflation gap in eggs between the poorest and richest deciles from 2014Q4 to 2015Q3 was 14.5 percentage points. This value corresponds to the denominator of Equation (9). Based on our triple-difference estimates, combined with the differences in retailer market concentration between these two deciles as of 2014Q3, we estimate that 9.2 percentage points of this gap can be attributed to market concentration effects. Consequently, we calculate a value of 66 percent for $\pi_{contribution}$. This suggests that a substantial portion of the inflation gap between the poorest and richest deciles during the bird flu episode can be attributed to retailer market concentration.

5.2 Real Income Inequality

We further examine cumulative growth in nominal and real income per capita across income deciles. Nominal income per capita is sourced from the BEA at the MSA level and averaged within each decile. To construct cumulative real income per capita growth, we deflate nominal income per capita using the food price index derived from the NielsenIQ Retail Scanner data.

The three solid lines in Figure 5 illustrate the patterns of nominal and real income per capita across three income deciles. The data indicate that both nominal and real income per capita have

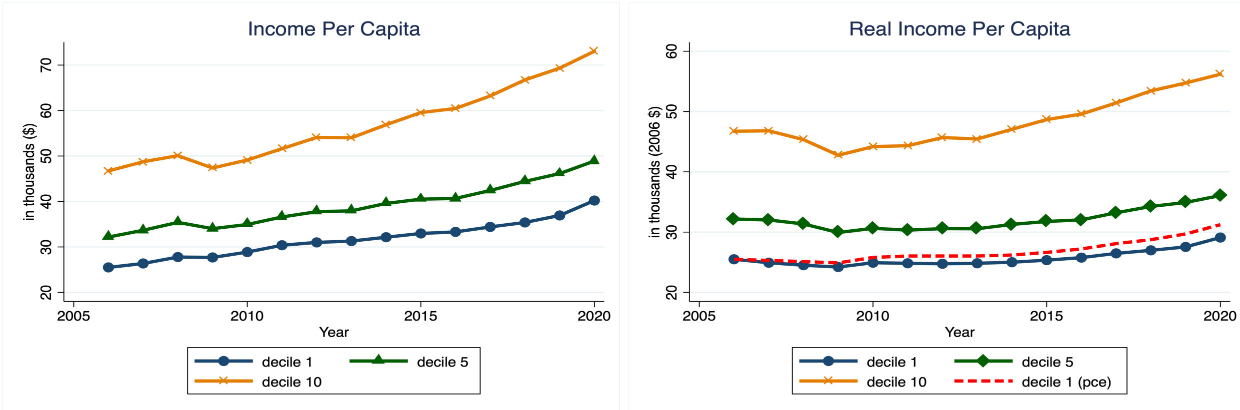

Figure 5: Nominal and Real Income per Capita

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

generally increased across all deciles, except during the Great Recession, when both the top and bottom deciles experienced a temporary decline. However, the gap between the top and bottom deciles has widened over time for both measures. This divergence is particularly pronounced for real income per capita, reflecting persistent regional disparities in inflation.

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

Recognizing regional inflation disparities is also essential for more accurate real income measures. Official price indexes are typically available only at the national level or for wealthier MSAs.[24] Since the national index is an expenditure weighted average across regions, where expenditure weights are disproportionately higher in richer areas, it tends to better reflect the inflation patterns

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

of higher-income regions. As a result, relying on national indexes may misrepresent the real income dynamics of lower-income areas. This is illustrated by the red dashed line in the right panel of Figure 5, which shows real income per capita for the bottom decile constructed with the official PCE price index for food and beverages. Relying on this national index overstates real income in decile 1 (both in levels and growth), thereby understating the real income gap relative and consequently real income inequality. Constructing regional price indexes allows for more accurate measurement of real income disparities and offers deeper insights into the dynamics of inequality.

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

6 Alternative Hypotheses

6.1 Basket Composition

A potential concern is that the observed higher inflation in poorer regions with greater market concentration may be partially driven by differences in consumption baskets. As shown in Section 2, consumption baskets vary across regions, with poorer areas having access to substantially fewer products than richer ones. To address this concern, we test the robustness of our triple-difference results by shifting our unit of observation to a more granular level: UPC-MSA-quarter level. Our dependent variable is the log change in UPC-level prices within egg market, modeled as follows:

$$\begin{aligned}\Delta \ln price_{umt} = \beta_0 &+ \beta_2 HHI_{mt} + \beta_4(Treated_m \times Post_t) \\ &+ \beta_5(Treated_m \times HHI_{mt}) + \beta_6(Post_t \times HHI_{mt}) \\ &+ \beta_7(Treated_m \times Post_t \times HHI_{mt}) + \delta_m + \delta_t + \delta_u + \varepsilon_{umt},\end{aligned} \tag{10}$$

where $\Delta \ln price_{umt}$ denotes the log difference in the price of UPC u in MSA m between quarter t and quarter $t-1$. The UPC fixed effects, δ_u, account for regional variation in consumption baskets by ensuring that price changes are identified within identical products across regions. All other terms are defined as in Equation 8.

Table 11 presents the results. In Column 1, we pool all quarters within the sample period and find that MSAs with higher market concentration saw a 1.8 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 2.7 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.

The disaggregated UPC-level results in Table 11 are consistent with the aggregate findings reported in Table 10. The stronger price increases observed in MSAs with higher market concentration align with the broader inflation patterns in the egg category documented at the regional level. Both analyses also reveal an important asymmetry: while MSAs with greater market concentration exhibit larger price increases during the inflationary period, there is no corresponding relative price decline in the deflationary period. The UPC-level evidence further strengthens the argument that these inflationary effects are driven by retailer market concentration, rather than alternative explanations such as differences in consumption baskets.

6.2 Retailer Composition

In addition to differences in basket composition, another potential explanation is variation in retailer composition across MSAs, as different types of retailers may exhibit different degrees of pass-through of shocks to prices. Specifically, pass-through can be different between national and local chains for the following reasons. On the one hand, national chains—with a larger number of 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.[25] On the other hand, national

[25]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 is also consistent with the uniform

Table 11: Triple Difference Estimator (UPC-level)

	$\Delta \ln$ Price	$\Delta \ln$ Price	$\Delta \ln$ Price
Bird Flu × Post × HHI	0.018***	0.027***	-0.005
	(0.006)	(0.009)	(0.013)
Bird Flu × Post	-0.012***	0.003	-0.016**
	(0.004)	(0.005)	(0.007)
HHI × Post	-0.007**	-0.005	-0.002
	(0.003)	(0.006)	(0.007)
Bird Flu × HHI	0.009	-0.027	-0.027
	(0.065)	(0.080)	(0.064)
HHI	0.026	0.059**	-0.021
	(0.016)	(0.024)	(0.026)
Sample Periods	All	Inflation	Deflation
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
UPC FE	Yes	Yes	Yes
Observations	146,103	84,525	61,578

Note: The table represents regression results from our triple difference-in-differences at the UPC level. 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

chains may charge prices closer to marginal costs, potentially due to low search costs, market transparency or scale economies, and can potentially impact the local level of prices, markups, as well as pass-through.[26] Following this logic, their pass-through of cost shocks will be higher as the market will operate closer to a competitive market. In either case, the presence of national versus local retail chains can influence the degree of pass-through in affected areas.

Within eggs market during our sample period, we also find a positive correlation between HHI and the share of national retailers. This suggests that variation in the presence of national versus local chains across MSAs may offer an alternative explanation for our results. Under this interpretation, geographic differences in inflation still originate on the retailer side, but are driven by differences in retailer composition rather than market concentration per se. Depending on which of the above mechanisms is at play, our current estimates of the effect of market concentration may

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.

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

Table 12: Triple Difference Estimator (Retailer Composition)

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

The table represents regression results from our triple difference-in- differences with the additional controls of the share of national and regional retailers. All other descriptions remain the same as in the main Table 10. *** p<0.01, ** p<0.05, * p<0.1

be subject to upward or downward bias.

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

The results are presented in Table 12 remain stable across all three inflationary regimes: pooled, inflationary, and deflationary. The triple interactions in the pooled period (Column 1) and the inflationary period (Column 2) reveal a positive and statistically significant association with inflation as before. In the deflationary period (Column 3), the coefficient remains positive, although it loses statistical significance at the 10 percent level. Importantly, a null effect during the deflationary period still indicates an asymmetric response across regimes. If the effect were symmetric, we would expect MSAs affected by the bird flu to experience greater deflation during the deflationary period.

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.[27]

6.3 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.[28] We link it to BDS data to control for the composition of firms, which may vary across regions.

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

$$w_{mt} = \beta_0 + \beta_1 Income_{mt} + X'_{mt}\gamma + \delta_t + \varepsilon_{mt} \tag{11}$$

$$\Delta \ln w_{mt} = \beta_0 + \beta_1 Income_{mt} + X'_{mt}\gamma + \delta_t + \varepsilon_{mt}, \tag{12}$$

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

In Table 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 areas with lower

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

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

income or a higher share of large retailers, which helps rule out the cost-based channel.

7 Concluding Remarks

In this paper, we investigate spatial variation in food inflation and the role of retailer market structure. Using NielsenIQ Retail Scanner data, we find that poorer MSAs experienced higher food inflation than wealthier areas. These areas also have fewer varieties and retailers, a higher share of large retailers, as well as greater market concentration. Exploiting the 2014–2015 bird flu outbreak as an exogenous shock, we find that MSAs with higher market concentration experienced larger inflation spikes (in the inflationary period) and weaker price declines afterward (in the deflationary period). This suggests that market concentration plays a key role when retailers face cost shocks, allowing them to pass-through higher prices to consumers. Given the asymmetry of pass-through, temporary shocks can have lasting effects, contributing to persistent differences in inflation and real income. These findings underscore the importance of local market structure in shaping inflation dynamics and real income inequality. They also highlight the limitations of national inflation measures, which can mask meaningful local variation in consumer prices.

A key direction for future research is to understand what drives regional differences in market concentration. One possibility is variation in retailer market power, which may enable firms to exert higher market power in more concentrated markets (Atkeson and Burstein, 2008). This calls for direct measurement—such as markups—and a theoretical framework to explain the observed pass-through asymmetries. Another promising venue is to explore how retailer market structure interacts with local labor markets and further impacts real income inequality.

References

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.

Basker, Emek and Michael Noel, "The evolving food chain: competitive effects of Wal-Mart's entry into the supermarket industry," *Journal of Economics & Management Strategy*, 2009, *18* (4), 977–1009.

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

Butters, R Andrew, Daniel W Sacks, and Boyoung Seo, "How do national firms respond to local cost shocks?," *American Economic Review*, 2022, *112* (5), 1737–1772.

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.

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.

Chenarides, Lauren, Miguel I Gomez, Timothy J Richards, and Koichi Yonezawa, "Retail markups and discount-store entry," *Review of Industrial Organization*, 2024, *64* (1), 147–181.

Daruich, Diego and Julian Kozlowski, "Macroeconomic implications of uniform pricing," *Ameri-*

can Economic Journal: Macroeconomics, 2023, *15* (3), 64–108.

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

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, 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.

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

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 U.S. Cities," in "in" 2017.

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.

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. The Swiss National Bank/Study Center Gerzensee Special Issue: "Modern Macroeconomics: Study Center Gerzensee Conference in Honor of Robert G. King" Sponsored by the Swiss National Bank and the Study Center Gerzensee.

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

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.

Mongey, Simon and Michael E Waugh, "Pricing Inequality," Technical Report, National Bureau of Economic Research 2025.

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.

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.

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.

Appendix

A Robustness with NielsenIQ Consumer Panel

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

Table A.1: Fraction of Households Shopping Outside of their Residential MSAs

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 outside their residential MSA (with an indicator value of 1) in each given year. The data covers household-year observations from 2006 to 2020.

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

In addition, we compute income deciles using two different MSA definitions in NielsenIQ. One is based on the MSA information of households in the 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 Consumer Panel. Table A.3 shows the gap between these two definitions, revealing that most MSAs (75.27%) align with the same income decile definitions, and only a very small fraction (0.54%) exhibit a gap of three deciles. This confirms that our baseline measures of income deciles based on store locations and BEA income per capita data are not mismeasured.

Table A.2: Characteristics of Households by Shopping Types

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

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

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

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

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

B Robustness for Price Indexes

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

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

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

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

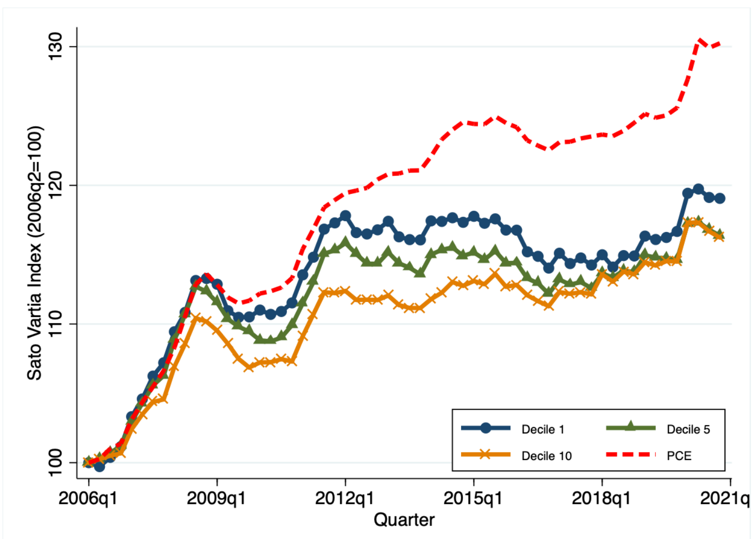

Figure B.1: Demand-based Price Index (Sato-Vartia) for Aggregated Food

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

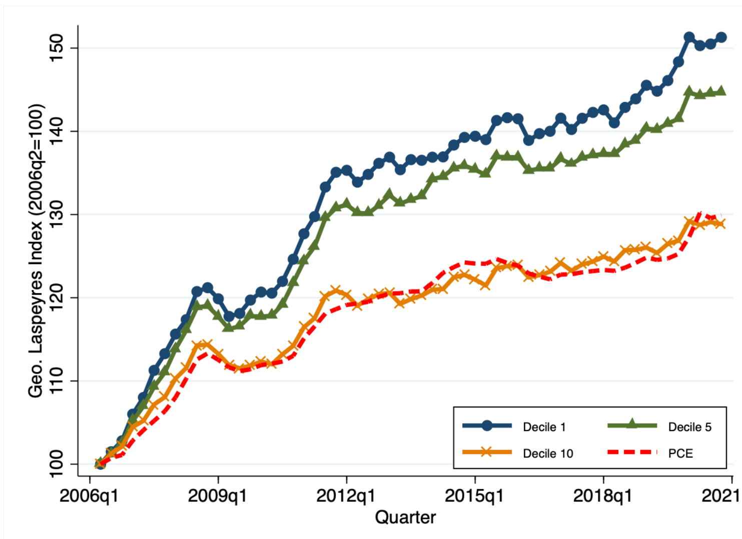

Figure B.2: Price Index for Aggregate Foods (MSA-level)

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

C Robustness with Other Food Items

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

C.1 Eggs

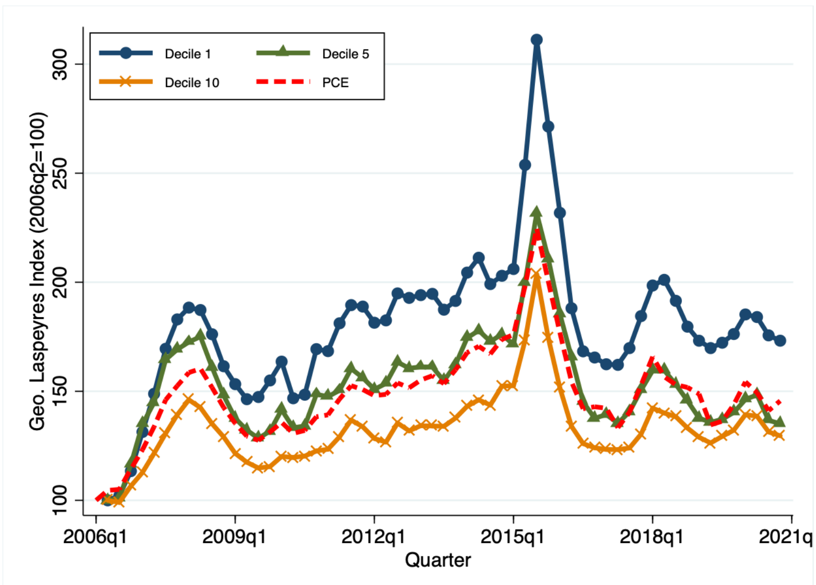

Figure C.1: Price Index for Eggs

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. The sample period begins in 2006Q2 and ends in 2020Q3, and the series is normalized at the initial quarter. Each solid line corresponds to a decile of the income per capita ranking of MSAs, with decile 1 containing the MSAs with the lowest income per capita and decile 10 containing the MSAs with the highest income per capita. We map the NielsenIQ UPCs 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.

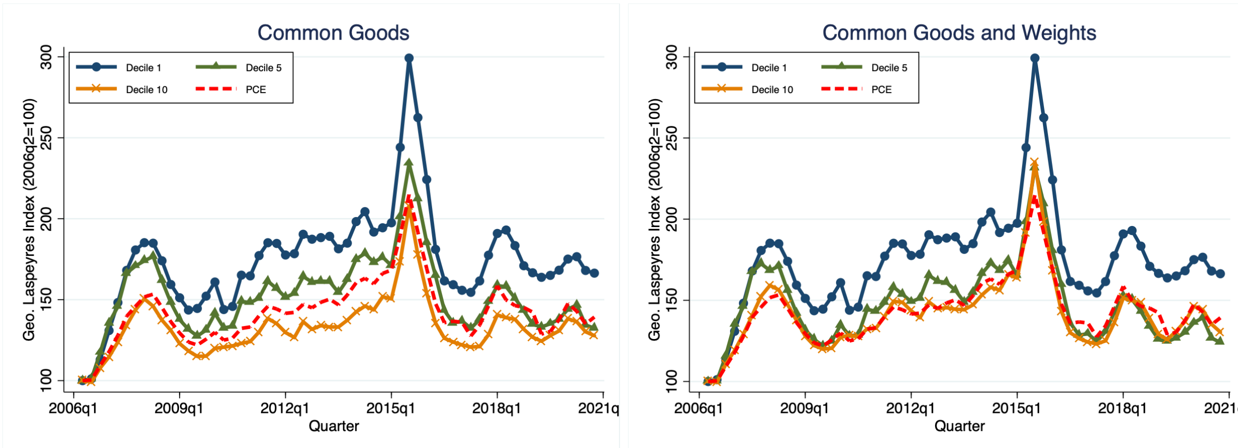

Figure C.2: Price Index for Eggs (Common Goods and Weights)

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 and t-1 (which we name "common goods") in the left panel, and are not just restricted to the common goods but also based on the same sales weights in decile 1 in the right panel.

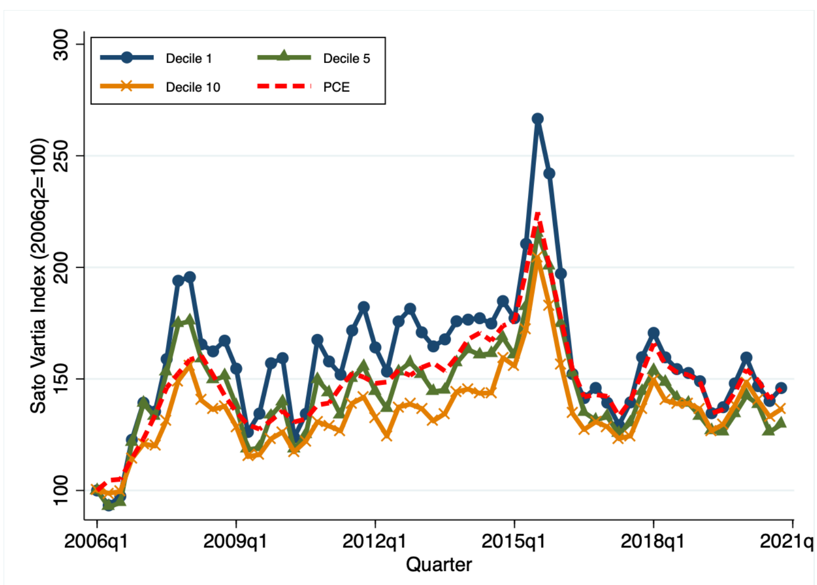

Figure C.3: Demand-based Price Index (Sato-Vartia) for Eggs

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

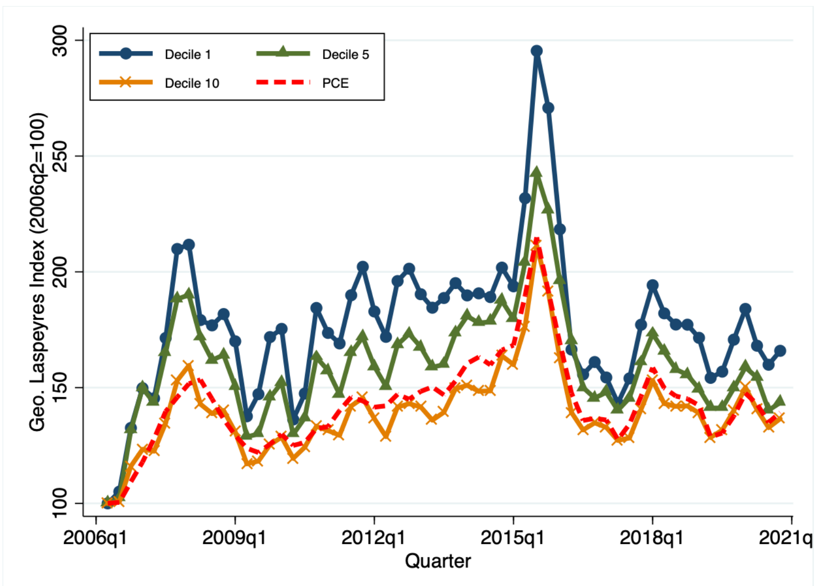

Figure C.4: Price Index for Eggs (MSA-level)

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

C.2 Dairy

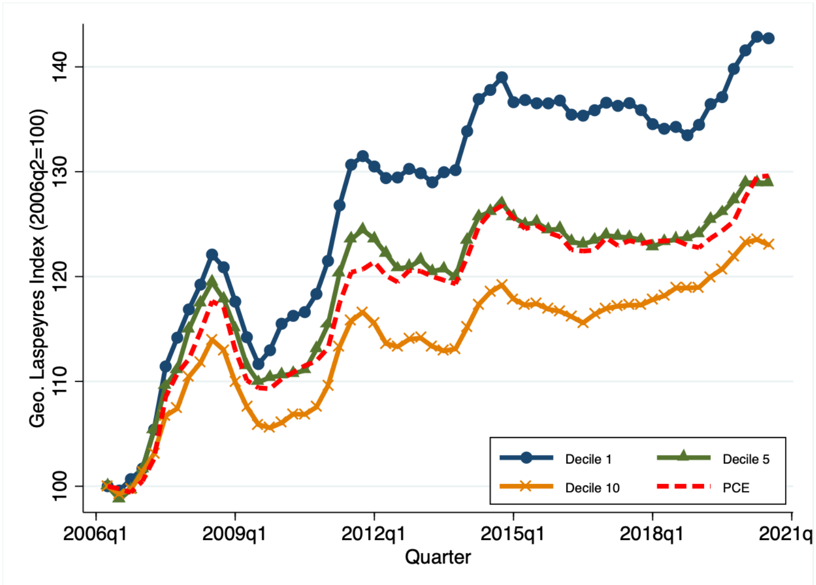

Figure C.5: Price Index for Dairy

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. The sample period begins in 2006Q2 and ends in 2020Q3, and the series is normalized at the initial quarter. Each solid line corresponds to a decile of the income per capita ranking of MSAs, with decile 1 containing the MSAs with the lowest income per capita and decile 10 containing the MSAs with the highest income per capita. We map the NielsenIQ UPCs 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.

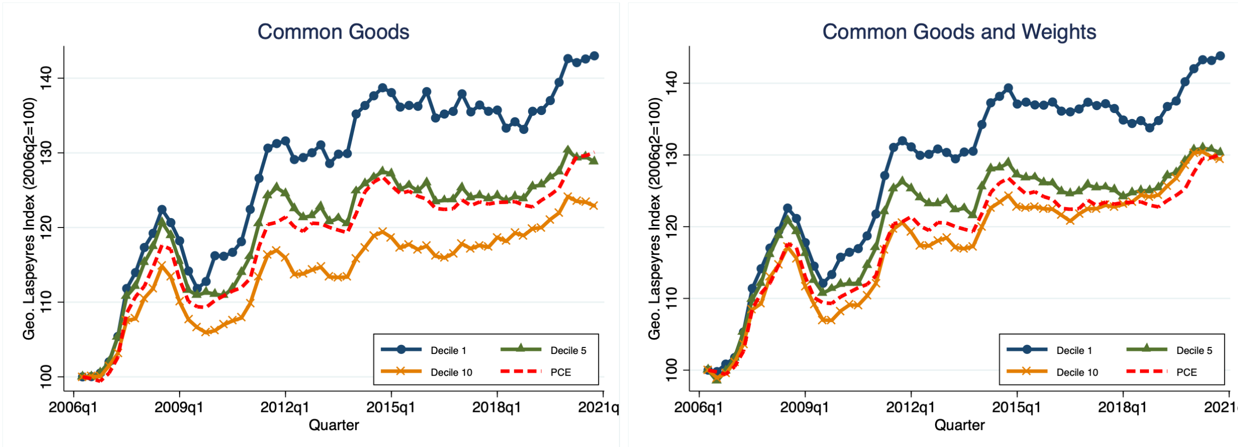

Figure C.6: Price Index for Dairy (Common Goods and Weights)
Notes: This figure represents the chained geometric Laspeyres price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for 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 10 deciles in quarters t and t-1 (which we name "common goods") in the left panel, and are not just restricted to the common goods but also based on the same sales weights in decile 1 in the right panel.

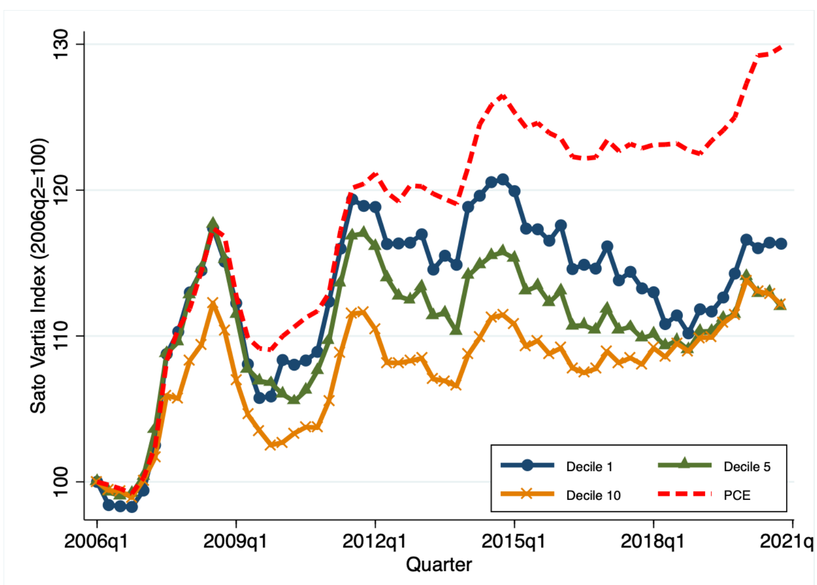

Figure C.7: Demand-based Price Index (Sato-Vartia) for Dairy
Notes: This figure represents the chained Sato-Vartia price index constructed in the NielsenIQ (solid lines) as well as the official personal consumption expenditures (PCE) index from the Bureau of Economic Analysis (dashed line) for dairy. All descriptions remain the same as before.

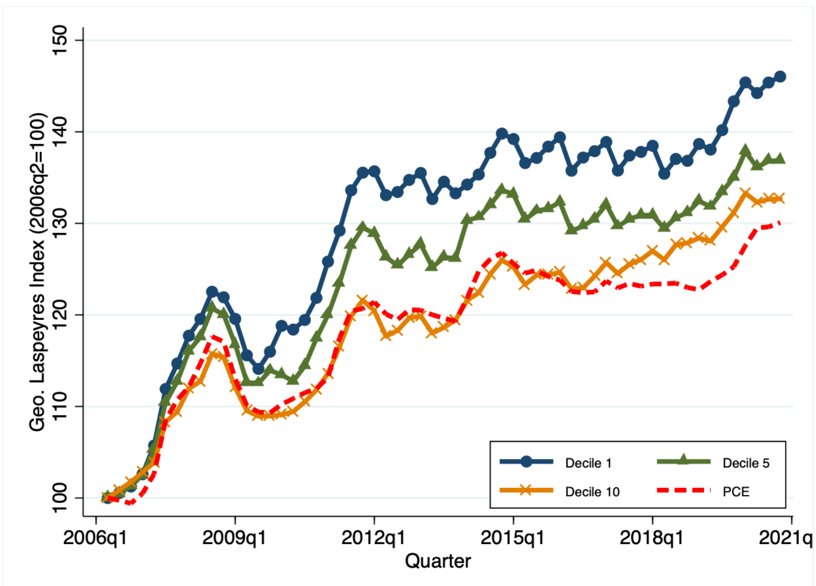

Figure C.8: Price Index for Dairy (MSA-level)

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

C.3 Fats and Oil

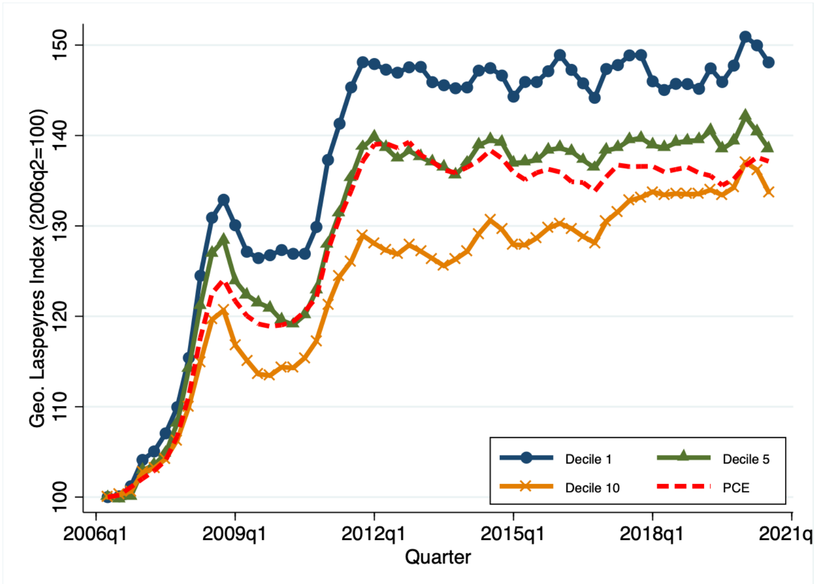

Figure C.9: Price Index for Fats and Oil

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. The sample period begins in 2006Q2 and ends in 2020Q3, and the series is normalized at the initial quarter. Each solid line corresponds to a decile of the income per capita ranking of MSAs, with decile 1 containing the MSAs with the lowest income per capita and decile 10 containing the MSAs with the highest income per capita. We map the NielsenIQ UPCs 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.

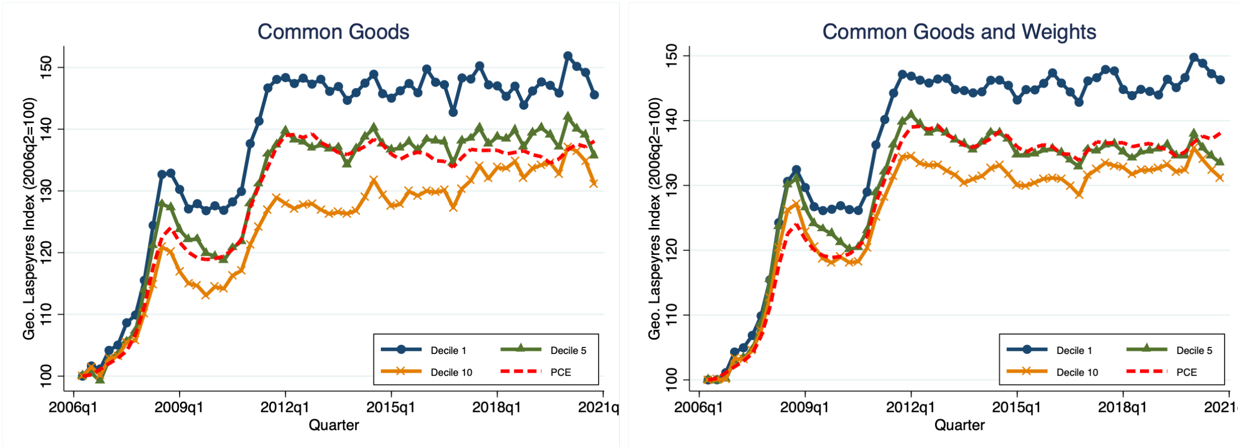

Figure C.10: Price Index for Fats and Oil (Common Goods and Weights)

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 10 deciles in quarters t and t-1 (which we name "common goods") in the left panel, and are not just restricted to the common goods but also based on the same sales weights in decile 1 in the right panel.

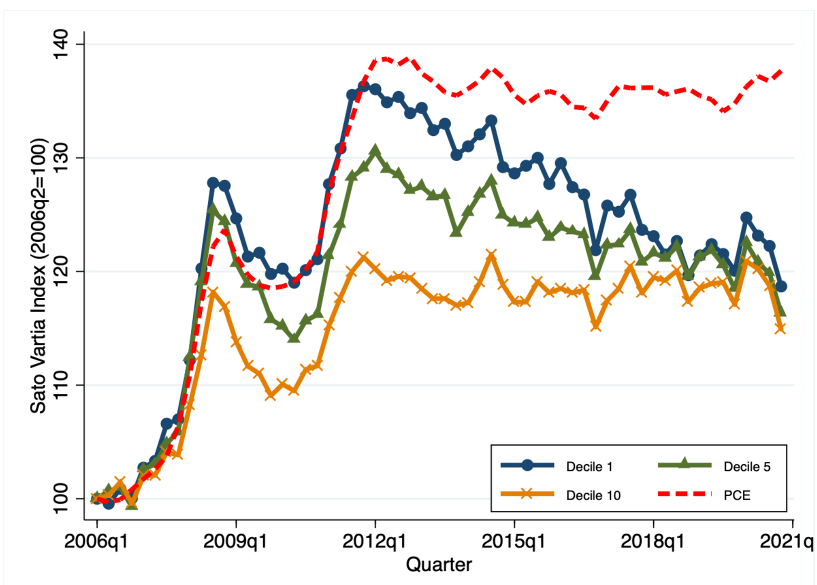

Figure C.11: Demand-based Price Index (Sato-Vartia) for Fats and Oil

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

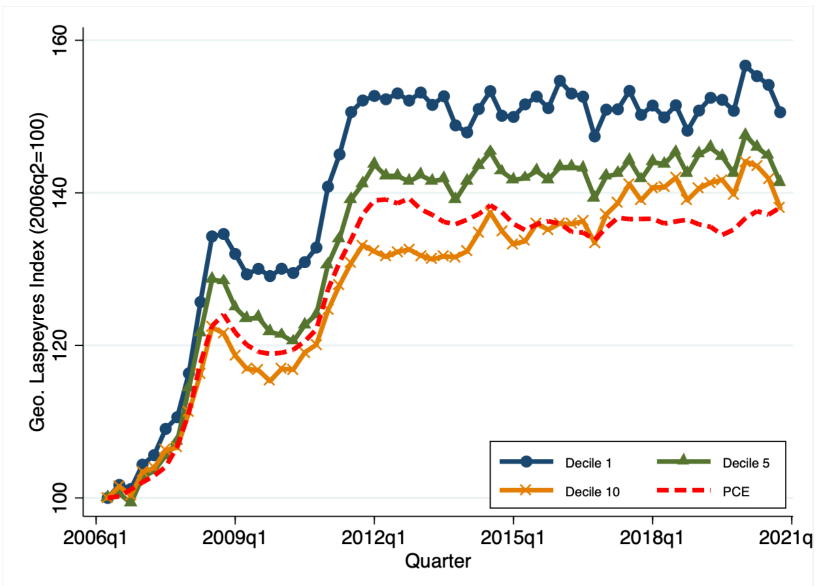

Figure C.12: Price Index for Fats and Oil (MSA-level)

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

D Heterogeneity in Retailer Market Structure in BDS

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

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

$$Y_{mt} = \beta_0 + \beta_1 Income_{mt} + \delta_t + \varepsilon_{mt}, \tag{13}$$

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.1 and are consistent with the baseline findings from NielsenIQ. They also confirm that poorer areas tend to have fewer firms and establishments, as well as a higher share of large firms and establishments.

Table D.1: 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 (13). 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. *** p<0.01, ** p<0.05, * p<0.1

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

$$\bar{Y}_m = \beta_0 + \boldsymbol{\beta_1} In\bar{come}_m + \varepsilon_m, \tag{14}$$

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 $In\bar{come}_m$ is the long-run average for the income per capita in msa m. Table D.2 shows results that reinforce the consistency of patterns in the BDS data.

Table D.2: 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 (14). The variable definitions remain the same as in Table D.1, but based on long-run averages over 2006-2020 in the BDS. *** p<0.01, ** p<0.05, * p<0.1

E Robustness of Heterogeneity in Inflation

E.1 Food Inflation

In the main regression (4), we replace the HHI with the CR1 and CR3 measures for market concentration and the results shown in Table E.1 are robust to both measures.

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

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

Note: The table presents regression results from Equation (4). The coefficient of interest is on income per capita (in thousands of \$) and CR (CR1 in the top panel and CR3 in the bottom panel) in an MSA for a given quarter. The dependent variable is the geometric Laspeyres inflation rate (%) of aggregate food in an MSA for a given quarter. The last two columns additionally control for the total number of chains in the MSA. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

E.2 Egg Inflation

We replace the HHI with the CR1 and CR3 measures for market concentration in eggs market. The results are shown in Table E.2 and are robust to both measures.

Table E.2: Eggs Inflation across Regions (CRs)

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

Note: The table represents regression results from Equation (6) by replacing HHI with CR1 (in the top panel) and CR3 (in the bottom panel) for eggs. The coefficient of interest is on CR1 and CR3 of retail chain's eggs sales, as well as income per capita (in thousands of $) in an MSA. The dependent variable is the geometric Laspeyres inflation rate (%) of eggs in an MSA for a given quarter. Total number of chains in eggs market is controlled in the last two columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

F Robustness of Heterogeneity in Price Index and Long-run Inflation

In the main regression (4), we replace the dependent variable with the Laspeyres price index at the MSA level to capture cumulative price differences across MSAs. The results are similar in Table F.1. Furthermore, we replace the HHI with the CR1 and CR3 measures for market concentration, and the results are also robust in Table F.2. Also, the long-run results also hold for both CR1 and CR3 measures. These are shown in Table F.3.

Table F.1: Food Price Indices across Regions

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

Note: The table presents regression results from (4) with the dependent variable replaced by the Laspeyres price index. The coefficient of interest is on income per capita (in $1000) and HHI in an MSA for a given quarter. The last two columns additionally control for the number of chains in the MSA. *** p<0.01, ** p<0.05, * p<0.1

Table F.2: Food Price Indices across Regions (CRs)

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

Note: The table presents regression results from (4) with the dependent variable replaced by the Laspeyres price index. The coefficient of interest is on income per capita (in $1000) and CR1 (in the top panel) and CR3 (in the bottom panel) in an MSA for a given quarter. The last two columns additionally control for the total number of chains in the MSA. *** p<0.01, ** p<0.05, * p<0.1

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

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

Note: The table presents regression results from (5) for the cross-sectional association between MSA-level inflation, income, and market concentration in the long run. The coefficient of interest is on CR1 (in the top panel) and CR3 (in the bottom panel), as well as income per capita (in $1000) in an MSA. The dependent variable is the long-run average of the food Laspeyres inflation rate. The last two columns control for the long-run measure of the average of chains in the MSA. *** 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.

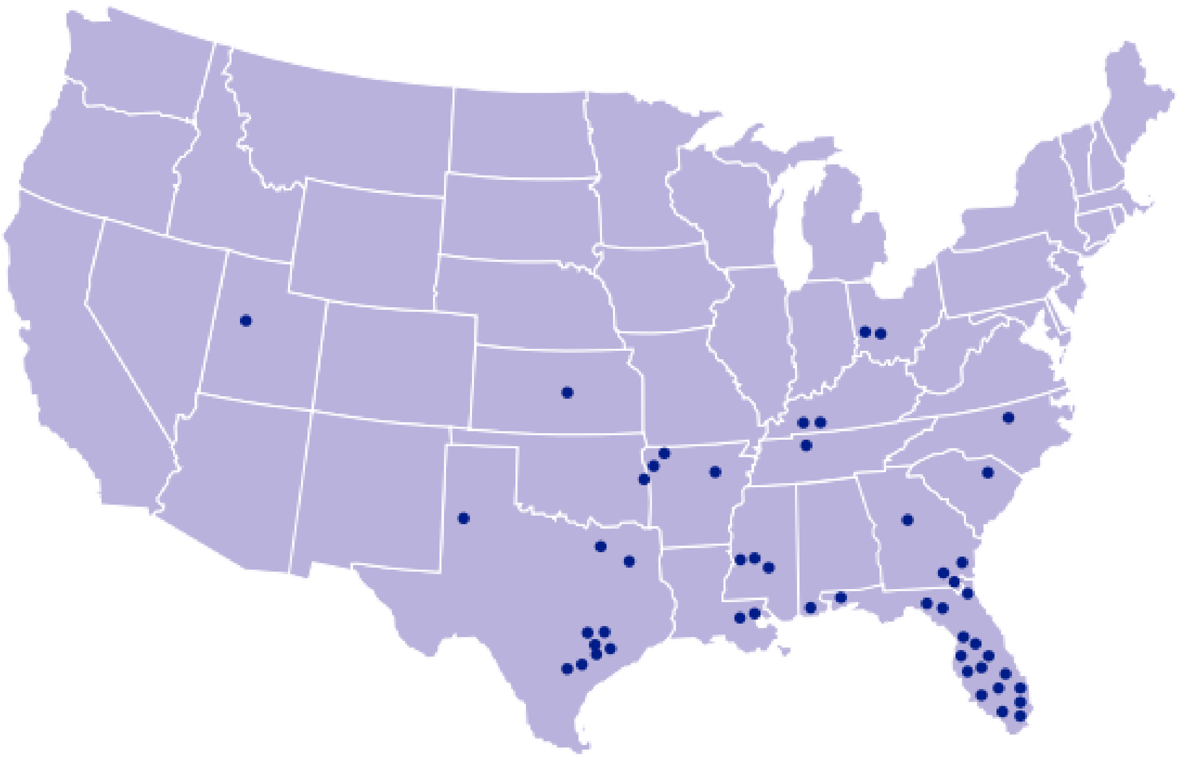

Figure G.1: Location of Cal-Maine Foods
Notes: The figure represents the local locations of Cal-Maine Foods, which is the largest national eggs producing company in the states.

H Robustness of the Triple-Difference Regression

H.1 Neighboring Treated MSAs

We incorporate five additional neighboring MSAs around the affected areas using MSA maps provided by the Census Bureau.[29] These MSAs are listed in Table H.1. We then re-estimate regressions based on Equation (7) and Equation (8) including these additional treated MSAs. The results, presented in Tables H.2 and H.3, are consistent with our baseline findings.

Table H.1: 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.2: 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 our difference-in-differences estimator where the treated MSAs include five additional neighboring MSAs around the impacted areas. All else descriptions remain the same as in the main Table 9. *** p<0.01, ** p<0.05, * p<0.1

H.2 CR Measures

To test the robustness of the triple-difference regression in Equation (8), we replace HHI with an alternative measure of market concentration: the sales share of the top one (CR1) or top three retailers (CR3) in the egg market. The results are robust, as displayed in Table H.4.

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

Table H.3: Triple Difference Estimator (Neighbor MSAs)

	Inflation	Inflation	Inflation
Bird Flu $\times$ Post $\times$ HHI	0.049***	0.074***	0.056**
	(0.008)	(0.019)	(0.024)
Bird Flu $\times$ Post	-0.028***	-0.001	-0.062***
	(0.007)	(0.010)	(0.012)
HHI $\times$ Post	-0.011**	-0.008	-0.010
	(0.005)	(0.008)	(0.011)
Bird Flu $\times$ 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 our triple difference-in-differences where the treated MSAs include five additional neighboring MSAs around the impacted areas. All else descriptions remain the same as in Table 10. *** p<0.01, ** p<0.05, * p<0.1

Table H.4: 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 our triple difference-in-differences. The coefficient of interest is the interaction of Post, CR1 (in the top panel), CR3 (in the bottom panel), and Bird Flu. Post is a binary variable that takes the value 1 after 2014Q4. CR1 (CR3) is the concentration ratio of the top 1 (top 3) retail chain's sales of eggs within an MSA. Both CR1 and CR3 are continuous variables that can range from 0 to 1. Note that we fix CR1 and CR3 values to 2014Q3 values for all quarters in the post period. Bird Flu is a binary variable that takes the value 1 if an MSA culled its layers during the 2014-2015 bird flu episode. Column 1 only considers the inflationary period. Column 2 only considers the deflationary period. Columns 3 pools all periods together. Inflationary and deflationary periods are determined by the national price index of eggs. The sample period ranges from 2012Q4 to 2016Q4. MSA and quarter fixed effects are included across all specifications. Standard errors are clustered at the MSA-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$