Geospatial Heterogeneity in Inflation: A Market Concentration Story*

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April 27, 2024

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Preliminary Draft

Abstract

Inflation is an important economic indicator that is typically measured and reported at the national level. However, there is systematic geographical variation in inflation across metropolitan statistical areas (MSAs) within the United States, which can affect spatial inequality. This paper studies how spatial variation in inflation rates affects income inequality and examines the role of retailer market power in driving these differences. Using Nielsen Retail Scanner dataset, we uncover that the poorest MSAs experienced higher inflation rates than the richest MSAs from 2006 to 2016 at both disaggregated and aggregated levels of food. Accumulating the differences in inflation rates over this decade, the poorest decile experiences an approximately 10 percentage points higher inflation rate than the richest decile. Furthermore, we observe variations in retailer dynamics across MSAs with different income levels: poorer MSAs have fewer retailers and varieties of goods, but exhibit a higher fraction of larger retailers and a greater degree of retailer market concentration relative to richer MSAs. To explore the causal link between inflation and market concentration, we use a triple difference estimator, with a particular focus on the egg market during the 2015 bird flu episode. Our analysis underscores that retailers' market concentration and power can be a contributing factor to higher inflation rates and lead to spatial divergence in price inflation. This channel can act as a potential catalyst for amplifying inequality among regions with varying income levels and create important policy implications.

JEL Code: E31, I31, J60
Keywords: inflation, spatial inequality, mobility, market power, concentration

*This research is funded by the Washington Center for Equitable Growth. All results are calculated based on data from The Nielsen Company (US), LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the Brookings Institution, NielsenIQ or the Washington Center for Equitable Growth. All errors are our own.

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1 Introduction

Inflation is an important economic indicator that can have significant implications for economic growth and stability. However, the literature on inflation and policymakers often assume uniform inflation within a nation and overlook the potential heterogeneity in inflation rates across different regions and disaggregated food categories. Our research seeks to address this gap by first documenting the heterogeneity in inflation rates across metropolitan statistical areas (MSAs) for each Personal Consumption Expenditure (PCE) food item and then investigating the relationship between inflation and market concentration to understand a mechanism through which the market power of retailers (or product producers) affects price inflation and consequently real income levels differently.

By measuring inflation rates across regions with different income levels, we shed light on how the inflation rate in poorer areas has changed over time relative to richer areas. And we aim to understand how the trend impacts spatial inequality by affecting real income levels. If inflation rates are persistently higher in poorer areas than richer areas, then they can widen real income gaps between these regions and exacerbate spatial inequality. Furthermore, this increased inequality can also dampen spatial mobility preventing residents from poorer MSAs moving to richer MSAs. This can amplify the negative relationship between inequality and social mobility as illustrated by previous studies (Kearney and Levine, 2014; Chetty et al., 2014).

Our analysis is based on Nielsen Retail Scanner data, which allows us to look at how geographic variation in demand and market structure contributes to differential inflation rates in food products. Leveraging this database, we construct price indexes, the Herfindahl-Hirschman index (HHI), and other statistics associated with market power for each pair of MSA income decile and PCE food category. Our findings show that poorer MSAs exhibit higher inflation rates than richer MSAs over the period from 2006 to 2016. In particular, this trend is robust at both disaggregated food item and aggregate food levels. Furthermore, we show that higher market concentration within a

MSA-PCE disaggregated food category is associated with higher inflation rates, and that this effect is more pronounced in poorer MSAs. In other words, the MSAs in the bottom decile in terms of income per capita are the MSAs with the largest price change over the decade, which have also experienced the highest degree of market concentration. These patterns are robust to imposing a common goods rule to control for differences in consumption baskets across MSAs and also robust to different food categories. These findings suggest that higher market concentration in poorer areas is associated with higher inflation rates, even after controlling for the variety of consumption baskets.

These findings have important implications for policymakers in multiple dimensions. First, understanding the underlying reason for heterogeneity in inflation rates can inform monetary policy and consumer protection. Official government price indexes are aggregated to the national level, which can misrepresent inflation in the poorest regions of the country. These price indexes are aggregated using expenditure weights and the rich areas account for a disproportionate share of expenditures. Thus, relying on aggregate indexes may underrepresent the poorest regions and overrepresent the richest areas. By focusing exclusively on aggregate measures, the central bank could make monetary policy decisions that are not reflective of most country (population weighted). Related to this, this highlights the need for policymakers to consider market concentration at the regional level instead of only considering market concentration at the national level, in particular, when antitrust cases are brought relating to food products.

In addition, this analysis also provides an important guidance on reducing income inequality and promoting mobility across different income groups. As spatial inequality gets more pronounced, it will reduce economic mobility by reducing mobility from low to high income areas. This can further amplify the original geographic differences, such as the market power of retailers or (good producers) in poorer areas, behind the dispersed trends of inflation rates and increase real income inequality. Our study adds a new dimension, geospatial heterogenity, that policymakers should consider when designing policies that could mitigate the adverse effects of inflation on vulnerable populations.

2 Literature Review

Previous work has shown that higher income households face lower inflation rates than poorer households (Jaravel (2018); Kaplan and Schulhofer-Wohl (2017)). On the other hand, poor households and rich households are commingled by living in the same geographic region. Handbury (2021) documents that the welfare difference between rich and poor households could depend on the set of goods available in each region, which gets the most exacerbated in wealthy cities that have the largest amenities. Our research can contribute to this line of studies by shedding light on how much of the variation in inflation rates can be attributed to basket composition and to regional variation. Our contribution to this literature will be identifying a new source of heterogeneity in inflation: regional. We find another mechanism other than a demand based one, typically love of variety, that can account for these differences: market concentration.

Our work is also related to another strand of research on the sorting of individuals and firms across geographic regions. Behrens et al. (2014) find that there is sorting occurring in the United States where talented and high-skilled individuals choose to live in large cities. Leonardi and Moretti (2022) also emphasize sorting between retailers and cities, which can increase the degree of competition. These agglomeration effects and higher levels of competition could be one of the driving forces for the heterogeneity in inflation rates that we observe across different regions. We are currently focusing our analysis at the MSA level, which is close to the same geographic unit as the sorting literature.[1] We empirically show results that are consistent with sorting to the richest MSAs, where high-skilled workers move, leads to higher competition as shown by lower market concentration in these areas.

In addition, our paper contributes to previous studies exploring potential sources of

[1]We have also done the aggregation across states and found similar patterns with slightly less differences across deciles.

market concentration at a local market level. Nevo (2001) shows that collusion is not necessary for firms to charge high-price cost margins in the cereal market which is characterized by high concentration. Feenstra et al. (2022) find that the profit share of firms has been increasing over time. Neiman and Vavra (2019) exploit the fact that aggregate product concentration is falling over time, but individual product concentration is increasing over time. They analyze this as a result of fewer products purchased by each household, but with increasing variations in consumption baskets across households. These trends could amplify the difference in inflation rates across high income and low income areas. We aim to analyze market concentration at the segmented local markets to see its correlation with the inflation dispersion across different regions. Our findings are consistent with this literature and we are able to contribute by looking at multiple markets across 21 disaggregated PCE categories across the entire U.S.

Lastly, our study is in line with a broad set studies the association between income inequality and mobility. Kearney and Levine (2014) identify a causal relationship between inequality and social mobility by showing places with higher levels of income inequality have lower high school completion rates. Chetty et al. (2014) adopt cross commuting zone analysis and documents that places with higher rates of social mobility tend to be characterized by lower levels of income inequality. Our findings add to the literature another source amplifying the relationship between economic inequality and social mobility by shedding light on a new mechanism through spatial heterogeneity in market structure and inflation rates.

3 Data and Measures

We use two main sources of data to analyze heterogenous inflation rates across regions: Nielsen Retail Scanner (RMS) dataset and Business Dynamic Statistics (BDS). The RMS dataset lets us measure inflation rates across regions by using sales information sales across retailers for food products. The BDS dataset will allow us to see if market concentration is a driving force in the patterns that we observe.

3.1 Nielsen Retail Scanner

Our analysis is based on the RMS dataset provided by the Kilts Center at Chicago Booth. The data consists of weekly pricing, volume, and store merchandising conditions generated by more than 100 retail chains across all U.S. markets, which includes over 40,000 individual stores. Total sales in the Nielsen RMS are worth over $200 billion per year and represent 50% of total sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, and 2% in convenience stores.

A key advantage of this data is that it contains detailed information at the finest product level, 12-digit universal product codes (UPCs) that uniquely identify specific goods. The data consists of over 2.6 million UPCs. Furthermore, Nielsen classifies UPC-level goods by 10 departments, 110 product groups, and over 1,000 product modules. We further use a concordance provided by the BLS that maps Nielsen product modules to entry level items (ELIs). These ELIs then map to PCE disaggregated categories.

Currently, our analysis focuses on the food sector, identified as the aggregation of 21 PCE food categories, over the period 2006Q1-2016Q4.[2] To construct our main dataset from Nielsen, we start with the weekly-store-UPC level raw data and link it to the MSA-level BEA personal income data by store location information in Nielsen. We further define income deciles by the cross-time average of the MSA-level income per capita. And then, we aggregate the data to the monthly frequency using the National Retail Federation (NRF) calendar and aggregate it up to the quarterly level. Next, using the concordance between the product modules and the PCE food categories, we identify the food sector in Nielsen. Lastly, to measure manufacturer market power and degree of competition, we merge the quarterly data with manufacturer identifiers by UPC codes.[3] We follow the similar steps as Hottman et al. (2016).

Our main analysis is at the MSA income decile, food category, and quarter level. We generate price indexes, the Herfindahl-Hirschman Index, and other statistics associated

[2] The 21 categories are Bakery, Beef and Veal, Beer, Cereal, Coffee and Tea, Dairy, Eggs, Fats and Oils, Fish and Seafood, Fruit, Milk, Other Foods, Other Meats, Pork, Poultry, Processed Fruit and Vegetables, Soda and Juice, Spirits, Sugar, Vegetables, and Wine.

[3] The manufacturer identifiers are provided by GS1, the company in charge of allocating barcodes.

with market power and structure for each pairing of MSA income decile-food category-quarter.

3.2 Business Dynamic Statistics

The Business Dynamic Statistics (BDS, henceforth) is a public version of the administrative Census firm-level data, the Longitudinal Business Dynamics (LBD, henceforth). The data provides the annual measures of business dynamics in the U.S., such as job creation and destruction, establishment births and deaths, and firm entry and exit. This is provided for the economy overall as well as aggregated by establishment or firm characteristics such as firm size and age. Furthermore, the data provides sectoral and geographic level information which allows us to track the business dynamics at the sector, state, county, and MSA levels.[4] In the BDS, we use retailers' information (based on NAICS 44-45) and construct a set of business dynamics measures at the MSA level.

3.3 Main Measures

3.3.1 Price Indexes

To measure and compare the cost of living across the income deciles, we construct price indexes from the UPC-level data in Nielsen. As a starting point, we have used traditional price indexes, such as Laspeyres and Paasche indexes, and our main focus is on the log geometric price index given by:

$$\ln \Psi_t^G = \sum_{k \in \mathbb{C}_{t-1,t}} w_{kt} \ln \frac{p_{kt}}{p_{kt-1}}, \tag{3.1}$$

where w_{kt} is a weight assigned to product k (typically based on the product's market share) in quarter t. The set $\mathbb{C}_{t-1,t}$ is the set of all "continuing" goods that are sold both in period t and in period $t-1$. Note that the Laspeyres index uses lagged expenditure

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

shares as weights ($w_{kt} = s_{kt-1}$), and the Paasche index uses current expenditure shares ($w_{kt} = s_{kt}$).[5]

3.3.2 Business Dynamics

Using the BDS, we define large and small retailers by their employment size. In particular, large retailers are those with 500 or more employees, and small retailers are those with 19 or less employees. Following this, we construct the share and employment share of large and small firms across different regions (MSAs).

Furthermore, in Nielsen, we use store and retailer codes and geographic information to identify stores, retailers, and their ownership structure (i.e. which retailer owns which stores across different regions and time). In particular, we calculate the number of retailers located in each MSA. Also, we construct the number of stores owned by retailers to proxy retailer size. Lastly, we use the sales share of retailers and construct the Herfindahl-Hirschman index (HHI) to indicate the degree of retailers' market concentration in each region.

[5] Note that there are potential issues associated with the traditional indexes as they do not take into account demand effects that may be generated from consumers' substitution across differentiated goods. For the reason, we do a robustness test using alternative demand-based indexes based on the CES preference assumption. One is the Sato-Vartia index, where we replace the above weight with $w_{kt} = \frac{\frac{(s_{k,t} - s_{k,t-1})}{(\ln s_{k,t} - \ln s_{k,t-1})}}{\sum_{k \in \mathbb{C}_{t-1,t}} \frac{(s_{k,t} - s_{k,t-1})}{(\ln s_{k,t} - \ln s_{k,t-1})}}$, which considers the demand effect for common goods appearing between $(t-1)$ and t. Another index is the Feenstra-adjusted Sato-Vartia index, which further considers the effect of product entry and exit. It is constructed by the following formula,

$$\ln \Psi_t^{Feenstra-SV} = \ln \Psi_t^{SV} + \frac{1}{\sigma - 1} \ln \frac{\lambda_{t,t-1}}{\lambda_{t-1,t}},$$

where $\lambda_{t,t-1} = \frac{\sum_{k \in \mathbb{C}_{t-1,t}} p_{k,t} q_{k,t}}{\sum_{k \in \Omega_t} p_{k,t} q_{k,t}}$, $\lambda_{t-1,t} = \frac{\sum_{k \in \mathbb{C}_{t-1,t}} p_{k,t-1} q_{k,t-1}}{\sum_{k \in \Omega_{t-1}} p_{k,t-1} q_{k,t-1}}$.

4 Spatial Heterogeneity in Inflation and Retailer Dyanmics

4.1 Trend of Price Inflation

Figure 1 presents the geometric Laspeyres index constructed from the Nielsen Scanner along with the official PCE price index across the 1st (poorest), 5th, and 10th (richest) income deciles. We focus on aggregated food, where the left panel shows the price index including all UPCs, and the right panel only includes common goods: the UPCs that are present across all deciles. We set the base quarter to 2006Q2.

The general trend captured by the subfigures is that the poorest decile ("Decile 1") exhibits higher price growth than the richer deciles ("Decile 5" and "Decile 10"). This pattern still holds even after we restrict to the set of common goods when constructing the price indexes. This implies that the dispersion of price growth across deciles is not necessarily driven by different consumption baskets nor by different preferences amongst consumers across different regions. These findings are generally preserved for the 21 PCE food categories as well as other aggregated food series. See Figure 2 for Eggs, which is one of the PCE food categories. Furthermore, the patterns stay robust even after using the demand-based price indexes, which is presented in Figure 3

Lastly, the official PCE series is closest to the series for the highest income decile than it is to any other decile. This implies that the official PCE series does a poorer job of capturing the pricing pattern in poor areas, and thus cannot properly track the pricing dispersion across different income deciles over time. Specifically, the official PCE price index series is understating inflation for individuals living in the poorest areas. This has macroeconomic implications. For example, if we assumed uniform wage growth across the United States, then official real wage growth over this period is is higher than actual real wage growth in the poorest areas.

4.2 Retailer Dynamics

Figure 6 shows that more retailers are located in richer areas. Furthermore, we find there is a clear pattern between firm size and the income deciles. Figure 4 presents the share of large retailers across different income deciles, and Figure 5 displays the share of small retailers across different income deciles. These figures indicate that there is more fraction of large retailers, while less fraction of small retailers is observed in poorer areas relative to richer areas. The retailer size in the figures is measured by employment size. Note that these patterns are robust across the whole sample period.

In addition, we find another consistent result in Nielsen, where we define retailer size by the number of stores it owns. Figure 7 exhibits the distribution of retailers' store numbers across income deciles. This shows that the poorer deciles have the smallest mass of small retailers (with less number of stores) relative to the richer deciles.

We also find that poorer decile experiences a higher degree of retailer market concentration from the following regression:

$$HHI_{idt} = \beta_0 + \beta_1 Decile_{dt} + \delta_i + \delta_t + \varepsilon_{idt},$$

where HHI_{idt} is the Herfindahl–Hirschman index of retailer sales for PCE food category i, MSAs in income decile d in quarter t, $Decile_{dt}$ is an indicator for income decile, and δ_i, δ_t are the fixed effects for PCE food category and time, respectively. Table A1 shows the result, where the HHI is higher in lower income deciles.

Related to it, we construct the HHI with a version for all goods and another version for common goods only for each decile. We also estimate consumers' elasticity of substitution between products, following Feenstra (1994), to understand how individuals' consumption behavior is correlated with market power and the pricing dispersion observed across different regions. Table A2 displays the cross-time average of the HHI and the elasticity of substitution for a subset of the 21 food items and aggregated food. The table broadly suggests that market concentration varies across different markets, but within each market, the market is more skewed in the poorest areas towards larger firms. In addition, higher income areas tend to have higher elasticity of substitution in most markets, where the higher estimates imply consumers are more willing to substitute different goods into their baskets.

Lastly, we also tabulate the total number of UPCs sold, common goods sales as a fraction of total sales, and quantity of common goods as a fraction of total UPCs. We perform this analysis for each food category across income deciles. Consistent with our intuition, we find that poorer areas have fewer UPCs and have higher quantity and expenditure shares of total consumption allocated to the set of common goods.

5 Potential Mechanism through Retailers' Market Concentration

To investigate a potential mechanism behind the widening pattern of price indexes, we estimate further regressions.

5.1 Standard OLS Estimator

First, to see how the price level is associated with the degree of market concentration, we run the following simple OLS regression:

$$P_{st} = \beta_0 + \beta_1 HHI_{st} + \delta_s + \delta_t^{yr} + \delta_t^{qtr} + \varepsilon_{st},$$

where P_{st} is the (geometric) Laspeyres index of eggs in MSA s, quarter t, HHI_{st} is the HHI of retailer sales in MSA s, quarter t, and δ_s, δ_t^{yr}, δ_t^{qtr} are the MSA, year, quarter fixed effects, respectively. Table A3 displays the result, showing that the positive association between price level and the HHI. However, we cannot speak to any causal relationships here as this may contain an endogeneity bias.

We show the stylized fact that the poorer MSAs experienced higher inflation in food and beverages than the richest MSAs. However, we are not able to conclusively show what is driving this difference in inflation rates. One potential explanation is a supply side story where poorer MSAs have fewer stores available for consumers and this weakened competition allows retailers to increase prices. An alternative explanation could be a demand story where even after we restrict to same set of goods across MSAs, the consumers in rich MSAs are different than the consumers in poor MSAs. One potential difference in consumers would be if consumers living in MSAs in the top decile were more sensitive to price changes such that this increased sensitivity to price would lead firms to increase prices at slower rates.

In order to isolate whether the effect that we find is coming from the supply side or demand side, we use an instrumental variable approach as described in the next section.

5.2 Triple Difference Estimator

We use the 2014-2015 highly pathogenic avian influenza effect, the as an exogenous supply shock to the egg market. The 2015 bird flu episode affected the price and quantities of eggs sold. We also know that the USDA compensated producers for birds that had to euthanized. Payment was based on "fair market" values as determined by USDA appraisers.[6] We have the official confirmed premises of infection detailing when, where, and how many egg layer birds were culled from the USDA. These producers were being compensated for culling their birds, so the MSAs where they are located should see a smaller increase in prices for eggs during the bird flu episode.

In order to have a valid triple difference estimator and have a causal interpretation we need to satisfy the parallel trends assumption. This means that for the MSAs affected by the bird flu shock where producers received compensation for culling their birds that the MSAs with higher HHI values would have similar inflation trends as MSAs with lower HHI values in the absence of the bird flu shock.

[6] https://crsreports.congress.gov/product/pdf/R/R44114

For the traditional TWFE,

$$P_{st} = \beta_0 + \beta_1(Treated_s \times Post_t) + \delta_s + \delta_t^{yr} + \delta_t^{qtr} + \varepsilon_{st} \tag{5.2}$$

where P_{st} is the geometric Laspeyres price index for eggs in MSA s and quarter t. $Treated_s$ corresponds to a binary variable that indicates the MSAs closest to the premises identified by the USDA for culling their egg layers. $Post_t$ corresponds to a binary variable that takes the value one after 2015q1. As before, δ_s, δ_t^{yr}, δ_t^{qtr} are fixed effects for MSA s, year and quarter in t. The coefficient on β_1 should be positive given that these were the producers that were compensated for culling their birds and some of that compensation should be passed through to consumers.

However, what we are interested in is whether there is a differential response between MSAs with high market concentrations and MSAs with low market concentrations.

$$\begin{aligned} P_{st} = {} & \beta_0 + \beta_1 Treated_s + \beta_2 HHI_{st} + \beta_3 Post_t + \beta_4(Treated_s \times HHI_{st}) \\ & + \beta_5(Treated_s \times HHI_{st}) + \beta_6(Post_t \times HHI_{st}) \\ & + \beta_7(Treated_s \times HHI_{st} \times Post_t) + \delta_s + \delta_t^{yr} + \delta_t^{qtr} + \varepsilon_{st} \end{aligned} \tag{5.3}$$

In Equation 5.3 the subscript s corresponds to MSA s and t corresponds to quarter t. $Treated_s$ is a binary variable indicating whether MSA s is near to where egg layers were culled during the 2015 Bird Flu according to the USDA report. $Post_t$ is a binary variable that takes the value 1 if quarter t is after 2015q1. HHI_{st} is HHI of retailer concentration of sales in MSA s for quarter t. P_{st} is the geometric Laspeyres price index in MSA s in quarter t. The fixed effect terms, δ_s, δ_t^{yr}, δ_t^{qtr}, are the same as before, and ε_{st} is the error term.

Table A4 shows the regression results of the triple difference estimator in Equation 5.3. In the first column, we run a difference-in-differences estimator where we find that areas affected by the bird flu, which received government subsidies experienced less inflation. In the second column, we run the traditional triple difference estimator without fixed effects and we find that that for the MSAs affected by the bird flu that the MSAs with higher HHI values experienced higher inflation after the bird flu shock than the MSAs affected by the bird flu with lower HHI values. In the third column we include the fixed effects. The coefficient on the interaction term remains positive and significant, but falls in magnitude from 0.03 to 0.02 and the significance falls from the 1 percent level to the 5 percent level.

6 Concluding Remarks

We document that poorer MSAs in the US were experiencing higher inflation rates than the richest MSAs in the US for both aggregated food and disaggregated food categories between 2006 and 2016. We show this using a geometric Laspeyres price index in order to closely match the PCE approach for calculating price indexes. However, this finding is robust to other traditional price indexes such as Paasche and even demand based price indexes such as the Sato-Vartia Feenstra-adjusted price index. Furthermore we document that official price indexes PCE systematically understate the inflation that poorer areas experience by having price indexes closer to the richest decile.

To investigate what is driving these systematic inflation rate differences across poor and rich MSAs we look at retailer market concentration. We find a positive association between retailer market power as measure by HHI and inflation rates. We find similar patterns when we look at associations between share of firms within the retail sector where poorer MSAs have a larger share of large firms and smaller share of small firms. To develop a more causal link between market concentration and inflation, we exploit the bird flu episode using a triple difference estimator and find that MSAs with higher HHI values do experience higher inflation rates.

This is a preliminary draft where we still want to expound our analysis of the bird flu episode both in the analysis and documentation of the event. We also want to expand our dataset to the end of 2021 to cover the pandemic period where the US experienced high inflation for the first time in decades. Finally, we want to investigate turnover across MSAs where entering and exiting goods may churning at different rates and playing different roles across MSAs.

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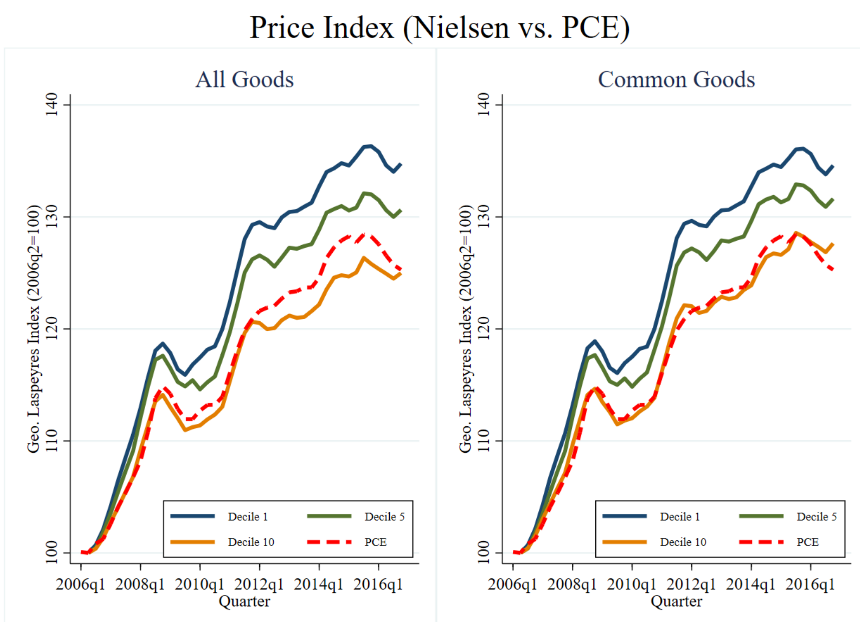
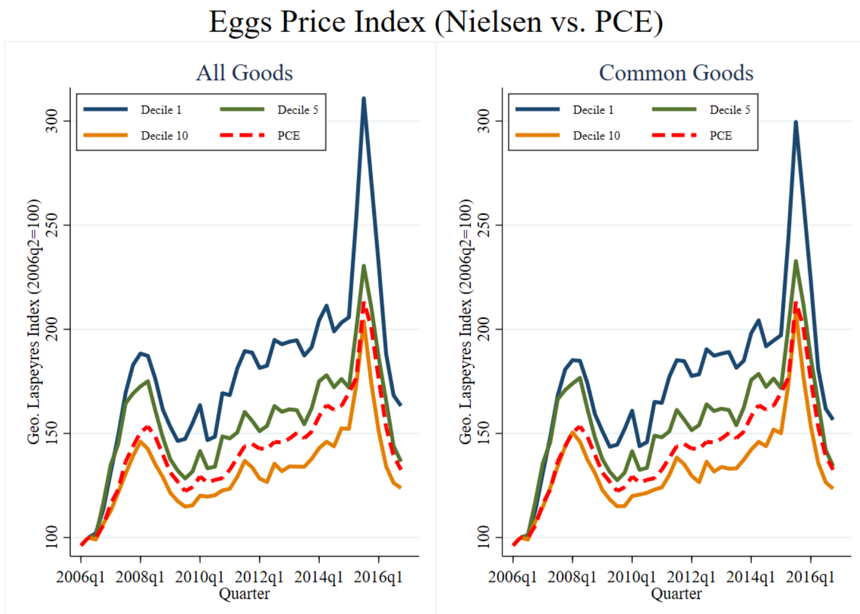
A Figures

Figure 1: Price Index for Aggregated Food



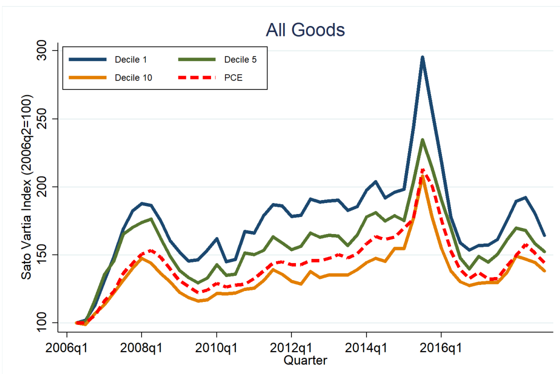
Note: The figure represents the price relatives for the aggregated food market with four series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2016Q4. The data for the three solid lines comes from Nielsen Retail Scanner dataset represented by geometric Laspeyres price indexes, while the dashed line comes from the BEA (official measure). Each solid line corresponds to a decile of the income per capita ranking of MSAs with decile 1 containing the states with the lowest income per capita and decile 10 containing the states with the highest income per capita. The left panel is the set of goods that individuals face at retailers in quarter t and t-1. The right panel corresponds to the set of goods that are present across all 10 deciles in quarter t and t-1. We map the Nielsen UPCs to the PCE definition of food purchased for off-premises consumption by using a product module concordance provided by the BLS.

Figure 2: Laspeyres Price Index for Eggs

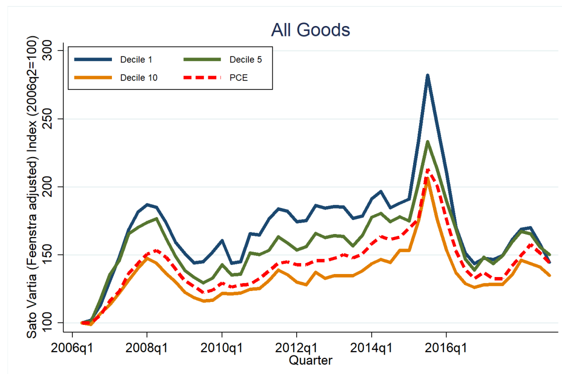


Note: The figure represents the price relatives for the aggregated egg market with five series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2016Q4. The data comes from Nielsen Retail Scanner dataset represented by geometric Laspeyres price indexes. 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 states with the highest income per capita. The red dashed line corresponds to the PCE price index. The left panel is the set of goods that individuals face at retailers in quarter t and t-1. The right panel corresponds to the set of goods that are present across all 10 deciles in quarter t and t-1. We map the Nielsen UPCs to the PCE definition of eggs by using a product module concordance provided by the BLS.

Figure 3: Demand-based Price Indexes for Eggs



Sato Vartia



Feenstra-adjusted Sato Vartia

Note: The figure represents the price relatives for the aggregated egg market with five series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2016Q4. The data comes from Nielsen Retail Scanner dataset represented by Sato-Vartia and Feenstra-adjusted Sato-Vartia price indexes. 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 states with the highest income per capita. The red dashed line corresponds to the PCE price index. We map the Nielsen UPCs to the PCE definition of eggs by using a product module concordance provided by the BLS.

Figure 4: Share of Large Retailers

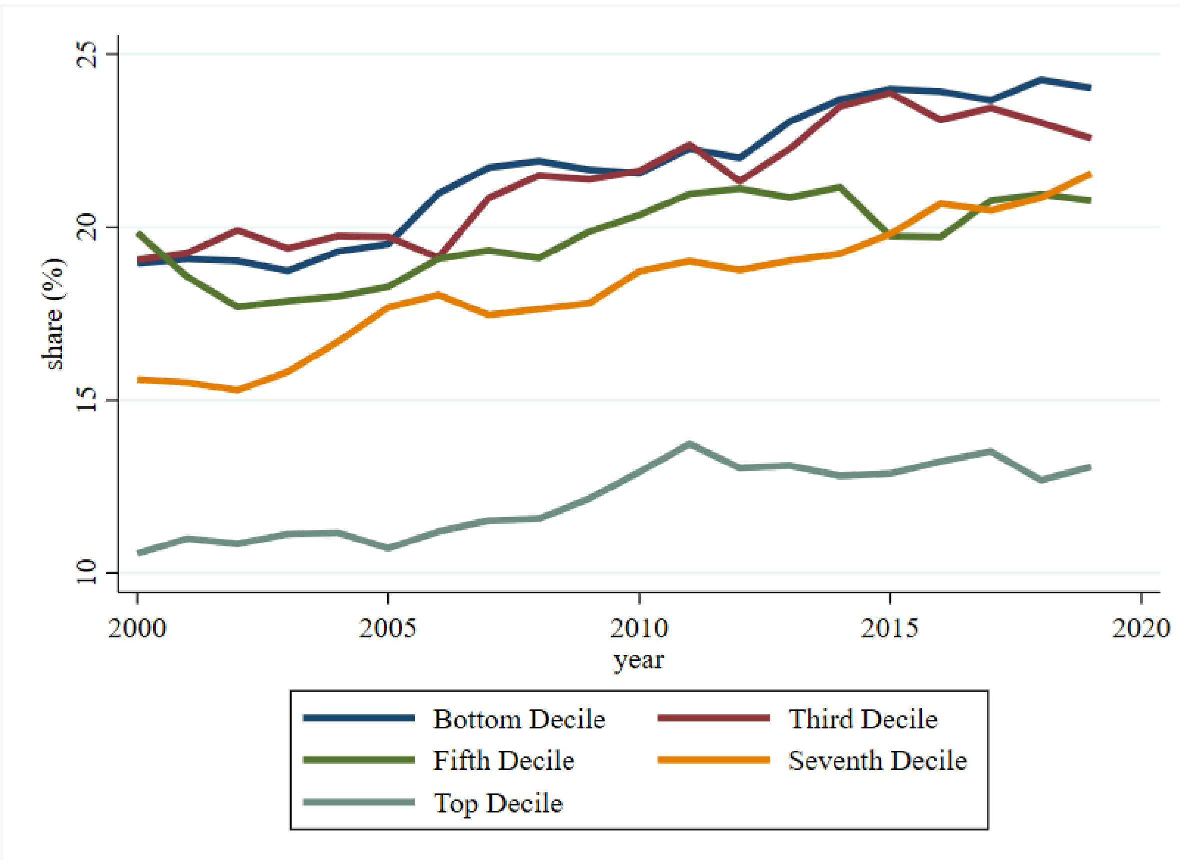


Figure 5: Share of Small Retailers

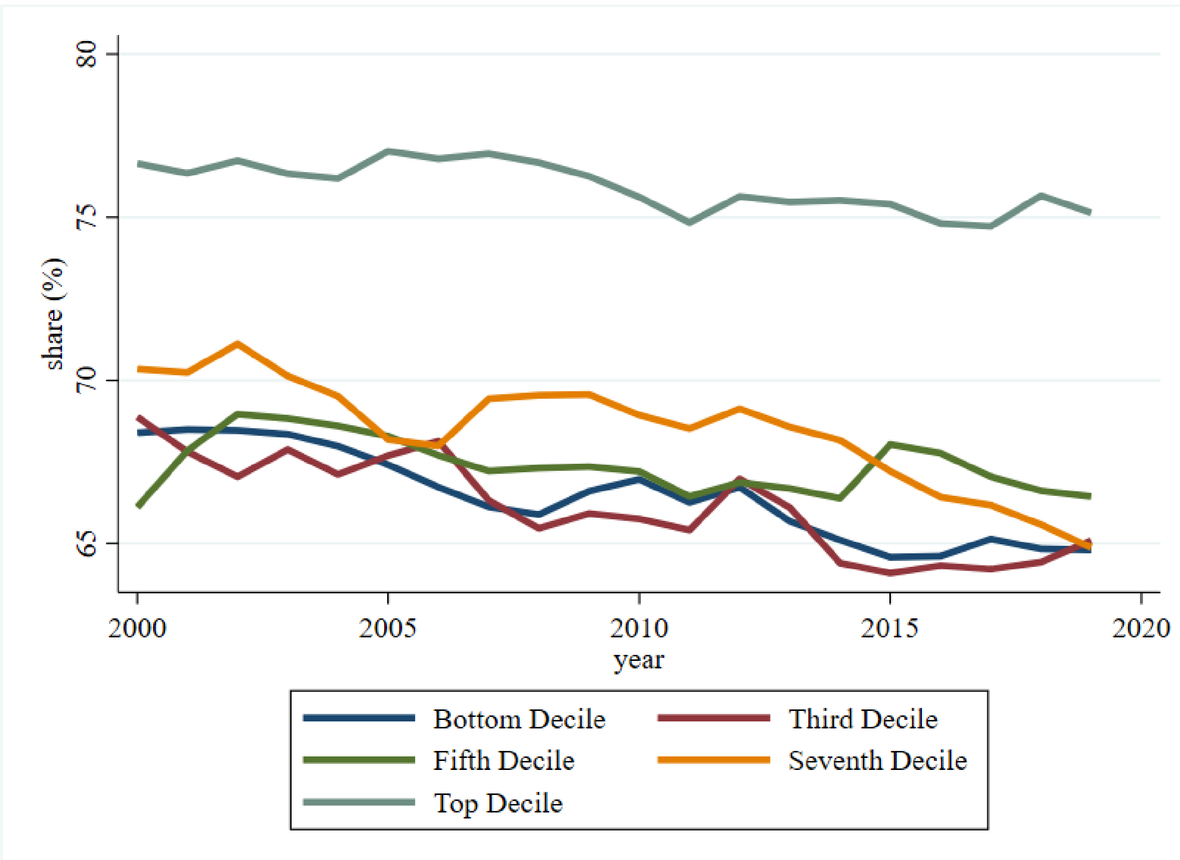


Figure 6: Number of Retailers

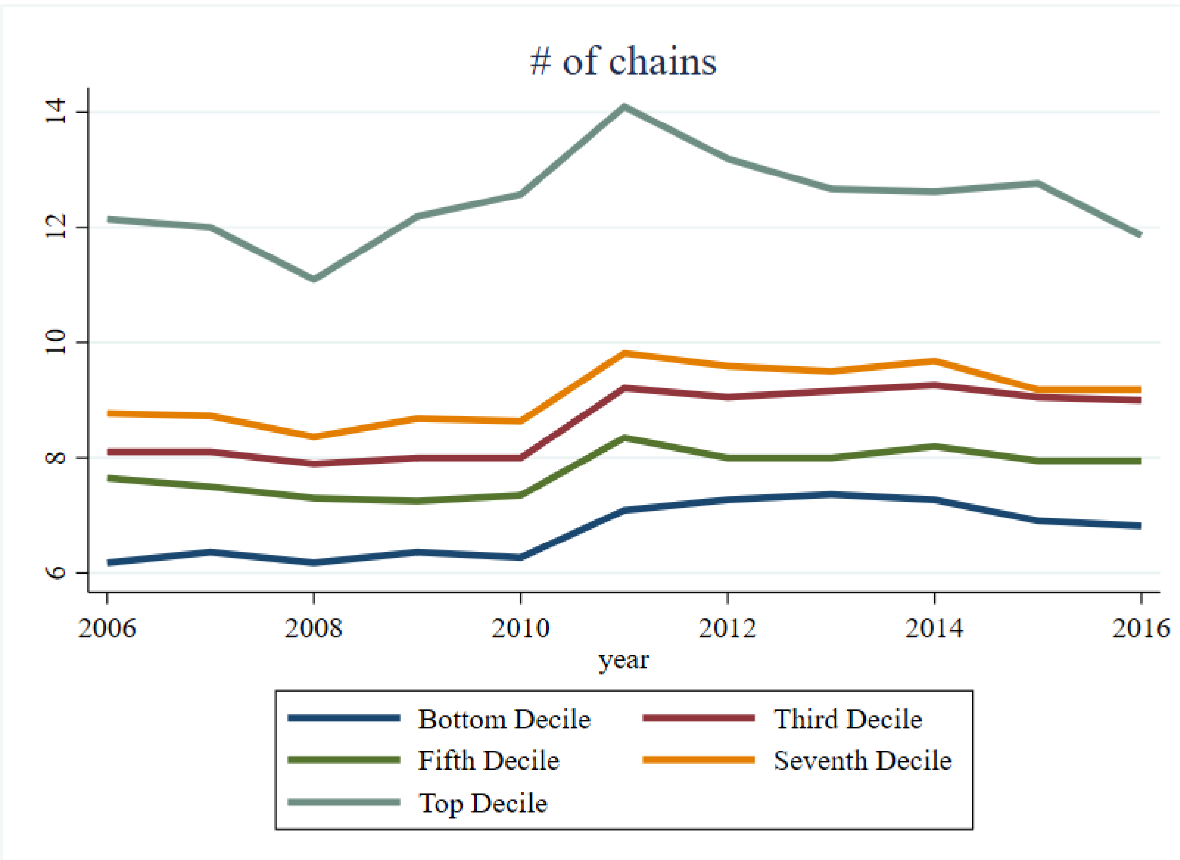
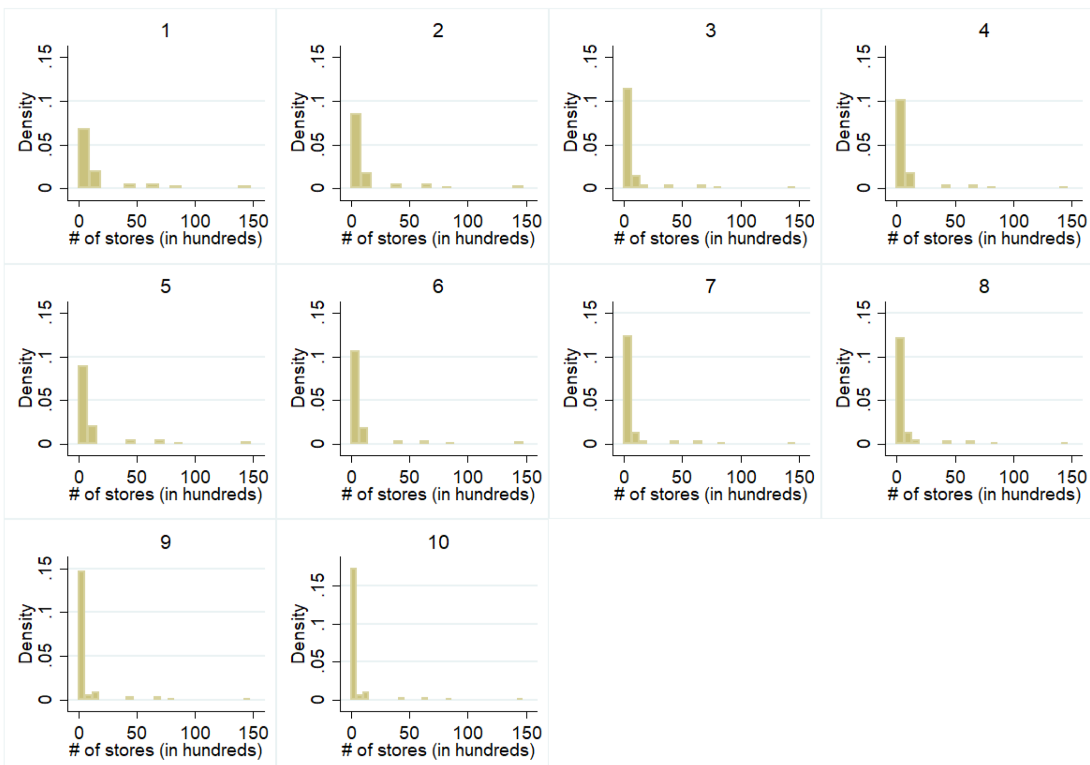


Figure 7: Distribution of Retailer Size (in number of nationwide stores) across Different Income Deciles



B Tables

Table A1: HHI across Different Income Deciles

	HHI
Decile	-0.004***
	[0.000]
Fixed Effects	Yes
Observations	10,920
*** p<0.01, ** p<0.05, * p<0.1	

Table A2: HHI and the Elasticity of Substitution

Item	Decile	HHI	Elasticity of substitution
Cereal	1-3	0.1337	4.3106
Cereal	4-7	0.1343	4.3289
Cereal	8-10	0.1361	5.4731
Eggs	1-3	0.3324	3.5803
Eggs	4-7	0.3104	7.6531
Eggs	8-10	0.2892	8.1946
Fats and Oil	1-3	0.0639	4.0299
Fats and Oil	4-7	0.0610	4.1235
Fats and Oil	8-10	0.0580	4.6153
(Alcoholic Beverages)			
Beer	1-3	0.2798	6.2084
Beer	4-7	0.2311	6.5024
Beer	8-10	0.1740	8.1054
Spirits	1-3	0.0515	5.3730
Spirits	4-7	0.0492	6.2725
Spirits	8-10	0.0474	7.0815

Note: Each subpanel represents one of the 21 PCE-items with statistics on HHI when calculated using all goods. We show the average of three subgroups based on deciles of the income per capital ranking of MSAs: the average of deciles 1-3 (three lowest income per capita deciles), the average of deciles 4-7 (median income per capita deciles), and the average of deciles 8-10 (three richest income per capita deciles). The HHI measures levels of market concentration with a range of 0 to 1 where values closer to 1 represent higher levels of market concentration. All of the statistics are produced using the Nielsen Retail Scanner dataset, averaged over 2006Q1-2016Q4. The elasticity of substitution is constructed following the method in Feenstra (1994). The elasticity of substitution measures how easy it is for individuals in those deciles to substitute across goods in the corresponding local market where higher values correspond to higher ease of substitution. Note that the last two items are alcoholic beverages, which belong to the broadest aggregate foods category named “Food and Beverages".

Table A3: Association between HHI and Price Level

	Price
HHI	0.011*
	[0.006]
Fixed Effects	Yes
Observations	9,484

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Triple Difference Estimator (Retailer Market Power)

	Price	Price	Price
Bird Flu × HHI × Post		0.033***	0.018**
		[0.011]	[0.008]
Bird Flu × Post	-0.006***	-0.023***	-0.017***
	[0.002]	[0.007]	[0.005]
HHI × Post		-0.014**	-0.008*
		[0.006]	[0.005]
Bird Flu × HHI		-0.003	-0.030**
		[0.009]	[0.015]
HHI		0.013***	0.014***
		[0.002]	[0.005]
Fixed Effects	Yes	No	Yes
Observations	9,484	9,484	9,484

*** p<0.01, ** p<0.05, * p<0.1