Geospatial Heterogeneity in Inflation: The Role of Retailer Dynamics*

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Abstract

Inflation is an important economic indicator that is typically measured and reported at the national level. However, we find systematic geographical variation in inflation within food across metropolitan statistical areas within the United States, which affects spatial inequality. This paper studies how spatial variation in inflation rates affects real income inequality and examines the role of retailer dynamics in driving these differences. Using NielsenIQ Retail Scanner dataset and the Business Dynamic Statistics, we document several stylized facts about the spatial heterogeneity in inflation and retailer dynamics. We find that the poorest MSAs experienced higher inflation rates than the richest MSAs on average from 2006 to 2020, accumulated to 10 p.p. higher inflation. This difference is equivalent to an annual inflation difference of 0.46 percentage points. The poorer MSAs have fewer retailers and fewer varieties of goods with a larger (smaller) fraction of large (small) retailers; these poorer MSAs have higher 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 2014-2015 bird flu episode. Our analysis suggests that retailers' market concentration is a contributing factor to the spatial divergence in inflation. This channel can act as a potential catalyst for amplifying inequality among regions with varying income levels.

JEL Code: E31, I31, J60

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

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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 as well as policymakers often assume uniform inflation within a nation and overlook the potential heterogeneity in inflation rates across different subnational 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 retailer dynamics affect inflation and consequently real income levels differently.

Our analysis is based on NielsenIQ Retail Scanner data and the Business Dynamic Statistics, which is the public version of the Census firm-level data. The two datasets allow us to look at how geographic variation in retailer market structure contributes to inflation rates across different regions in food product markets. Leveraging this database, we construct price indexes, the Herfindahl-Hirschman index (HHI) of retailers' sales, and other statistics associated with market power for each pair of MSA income decile and PCE food category.

Our findings show that food inflation rates vary across regions with different income levels. In particular, on average, the poorest decile of MSAs exhibit higher inflation rates than richer MSAs over the period from 2006 to 2020.[1] The cumulative difference between the bottom and top dcile over this period amounts to 10 p.p. higher inflation. Furthermore, we show that within poorer areas, the fraction of large retailers (with 500 or more employees) is higher while the fraction of small retailers (with 19 or less employees) is lower. The opposite pattern is observed within richer areas. Related to it, we find that higher market concentration of retailers' sales is observed in poorer areas. The market concentration is also associated with higher inflation rate within a MSA-

[1] Note that the largest differences in inflation rates between the top and bottom decile is more pronounced prior to 2016.

PCE disaggregated food category, and 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 and also the MSAs wth the highest degree of market concentration.

These patterns are robust at both disaggregated and aggregate food items, as well as 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.

Although not required for heterogeneous inflation rates across regions, we find heterogeneous pricing for the same goods across regions within food items. Even though poorer regions are experiencing relatively higher inflation rates than richer areas, we find that poorer regions have a relatively lower level of prices than richer MSAs. Our results are partially in contrast with the uniform pricing literature. Despite these lower prices, higher inflation in poorer regions should still be a concern and a source to amplify real income inequality. Specifically, this convergence in prices is not followed by a convergence in incomes. Furthermore, these poorer regions are more likely to be more sensitive to inflation within food than richer regions given that a higher share of their expenditures are allocated to food expenditures.

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 of the country (population weighted). This disconnect between aggregate and disaggregate measures 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.

Furthermore, the differences in prices compounds the unrepresentativeness of price indices. We find that uniform pricing doesn't hold in our sample. Specifically, the poorer MSAs face lower prices than the richer MSAs. This pricing difference leads poorer MSAs to contribute less to official price indices through lower expenditure weights. This difference in prices leads to the higher inflation in poorer MSAs contributing less to official price indices. These differences leave the potential of official price indices to mask large variation in inflation rates across areas.

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.

In addition, our paper contributes to previous studies exploring potential sources of market concentration at a local market level. This is a new channel through which inflation rates could vary. Previous differences in inflation rates across groups were ascribed to differences in consumption baskets Jaravel (2018). By incorporating market power and concentration as sources explaining part of the variation in heterogeneous inflation rates, we are able to engage with the markups literature (Hottman (2017), Autor et al. (2020), and De Loecker et al. (2020). 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. These trends could amplify the difference in inflation rates across high income and low income areas. We aim to analyze retailer dynamics in these segmented local markets to see its correlation with the inflation dispersion across regions.

Lastly, our study is in line with a broad set studies the association between income inequality and price indices. There has previous work (Martin, 2024) investigating using alternative price indices that are not expenditure weighted. Once concern with expenditure weight could be that the price indices could be unrepresentative. Specifically, poor areas may contribute relatively less than rich areas to official price indices given that poor areas consume less (even after adjusting for population). The poor areas further get down-weighted since we find that uniform pricing does not hold. The poorer areas are experiencing higher inflation, but the price of a given UPC is lower. This runs contrary to some previous work by DellaVigna and Gentzkow (2019) that found uniform pricing within certain narrow categories, product modules, in food.

3 Data and Measures

We use two main sources of data to analyze heterogenous inflation rates across regions: NielsenIQ 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 NielsenIQ 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 NielsenIQ 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, 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 BLS that maps NielsenIQ 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 2006Q1-2020Q4. See the 21 categories in Table 1. The concordance between the PCE categories (based on the ELIs) and NielsenIQ product modules is based on a concordance mapping ELIs to NielsenIQ product modules provided by the BLS.

To construct our main dataset from NielsenIQ, 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 NielsenIQ. We further define income deciles by the cross-time average of the MSA-level income per capita.[2] 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 NielsenIQ. 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

[2]See the examples of the income deciles in Table 2.

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

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 with market power and structure for each pairing of MSA income decile-food category-quarter. The summary statistics of the main sample is displayed in Table 3.

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 NielsenIQ. As a starting point, we have used traditional price indexes, where our main focus is on the log geometric Lapeyres price index as follows:

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

where w_{kt} is a weight assigned to product k in quarter t, and we take lagged expenditure shares as weights ($w_{kt} = s_{kt-1}$) for the Laspeyres index. The set $\mathbb{C}_{t-1,t}$ is the set of all

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

"continuing" goods that are sold both in period t and in period $t-1$.

Although our default measure is based on the Laspeyres index, we also use the Paasche index, where we replace the weights with current expenditure shares ($w_{kt} = s_{kt}$). We also do a robustness test using alternative demand-based indexes based on the CES preference assumption due to potential substitution bias associated with the traditional indexes.[5] 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 $\lambda_{t,t-1} = \frac{\sum_{k\in\mathbb{C}_{t-1,t}} p_{k,t}q_{k,t}}{\sum_{k\in\Omega_t} p_{k,t}q_{k,t}}$, $\lambda_{t-1,t} = \frac{\sum_{k\in\mathbb{C}_{t-1,t}} p_{k,t-1}q_{k,t-1}}{\sum_{k\in\Omega_{t-1}} p_{k,t-1}q_{k,t-1}}$.

Laslty, we also construct the price indexes by restricting our sample to UPCs sold in all ten income deciles in a given quarter. This is because consumption baskets vary across different income groups, as indicated in Jaravel (2018), and potentially across regions with different income level. In order to see if the spatial dispersion of price level and growth comes from the differene in consumption basekets, we additionally use the price index constructed with the set of common goods only.

3.3.2 Retailer Dynamics

In Nielsen IQ, we define large and small chains based on the size distribution of the number of stores. 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 count the number of stores owned by retailers at the national level to proxy retailer size. We define large chains by

[5] The traditional indexes do not take into account demand effects that may be generated from consumers' substitution across differentiated goods.

the top decile of chains based on the number of stores and small chains by the bottom decile of it. We calculate the number and share of large and small chains located in each MSA.

Alternatively, 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 within each MSA and compare across different regions (MSAs).

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.

4 Spatial Heterogeneity in Inflation and Retailer Dynamics

4.1 Price and Inflation Patterns

Figure 1 presents the geometric Laspeyres index constructed from the NielsenIQ 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 and 3 for Soda and Juices, each of 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 4

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

In order to see the retailer dynamics across different regions, we compute the summary statistics of the main sample by income-per-capita decile in NielsenIQ. Table 4 displays them, where we see a larger number of retailers and stores and higher sales of retailers in richer income areas. The table shows the share of large chains is higher but the share of small chains is lower in poorer income areas. Also, there is a higher degree of sales market concentration in poorer income areas.

This set of patterns is supported by the following analyses. Figure 5 exhibits the distribution of retailers' store numbers in NielsenIQ 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.

Moreover, we run the following regressions to see the cross-sectional retailer dynamics across MSAs with different income levels:

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

where Y_{mt} is either the sales, total counts of chains or stores, or the share of large retailers in MSA m, quarter t, $Income_{mt}$ is income per capita in MSA m, and δ_m, δ_t are MSA, quarter fixed effects, respectively. The results are presented in Table 5 and confirm the cross-sectional patterns that richer areas have higher sales, more number of retailers and stores, and a lower fraction of large retailers.

We also find this pattern consistently in BDS data. Figure 6 shows that more retailers are located in richer areas, and Figure 7 shows that these retailers create more jobs in those areas. Furthermore, we find there is a clear pattern between firm size and the income deciles. Figure 8 presents the share of large retailers, and Figure 9 displays the share of small retailers, within each of the income deciles. These figures indicate that there is more fraction of large retailers within poorer income areas, while less share of large retailers is observed within richer areas. The reverse pattern is observed for the fraction of small retailers.[6]

In BDS, we also run the following regression to confirm the cross-sectional pattern:

$$LargeFirm_{mt} = \beta_0 + \beta_1 Income_{mt} + \delta_m + \delta_t + \varepsilon_{mt},$$

where $LargeFirm_{mt}$ is the (employment) share of large firms in MSA m, year t, $Income_{mt}$ is income per capita in MSA m, and δ_m, δ_t are MSA, year fixed effects, respectively. The result is displayed in Table 6, where larger firms are more prevalent and have a higher share of employment within lower income deciles.

Furthermore, we 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

[6] Note that the size of retailers is measured by firm-level employment size, and the share is calculated based on the number of firms that operate retail stores in each MSA. This is robust to using the number of establishments. Also, note that these patterns are robust across the whole sample period.

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 7 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 consumption behavior is correlated with the retailer market dynamics and the pricing dispersion observed across different regions. Table 8 presents the cross-time average of the HHI and the elasticity of substitution for a subset of the 21 food items and aggregated food.[7] 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.

[7] We are currently making more progress to estimate the elasticity of substitution based on the nested CES structure as in Hottman (2017). This helps estimate the elasticity of substitution for each of the following different tiers: i) across UPCs within each pair of product group-retailer-MSA, ii) across product groups within each pair of retailer-MSA, and iii) across retailers in each MSA. Furthermore, we would like to back out the MSA-level markups based on this structure to tease out where the effect of market concentration comes from the retailers' markups.

5 Potential Mechanism through Retailers' Market Concentration

To investigate a potential mechanism behind relatively higher inflation in poorer MSAs than richer MSAs, we perform additional analysis using HHI as our measure of market concentration. First we look at the relationship between inflation rates and HHI. Then to determine a causal relationship between the two, we exploit a quasi-experiment using triple difference estimator.

5.1 Standard OLS Estimator

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

$$P_{mt} = \beta_0 + \beta_1 HHI_{mt} + \delta_m + \delta_t + \varepsilon_{mt}, \tag{5.2}$$

where P_{mt} is the (geometric) Laspeyres inflation rate of eggs in MSA m, quarter t, HHI_{mt} is the HHI of retailer sales in MSA m, quarter t. δ_m and δ_t are the MSA and quarter fixed effects, respectively.

To measure whether there is an association between market concentration and inflation, we use the standard OLS estimator described in (5.2). The result is presented in Table 9. In column 1, we exclude any fixed effects and a positive relationship between HHI and inflation. This effect is significant at the 1 percent level. The positive significant association persists once we include MSA and quarter fixed effects in columns 2 and 3.[8] However, we cannot speak to any causal relationships here as this may contain an endogeneity bias. For example, potentially consumers in MSAs with higher HHI values prefer to consume goods that are experiencing relatively higher inflation.

We show the stylized fact that the poorer MSAs experienced higher inflation in food

[8]In this specification and all specifications with MSA level data, we cluster our standard errors at the MSA level.

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 the 2014-2105 bird flu as a quasi-experiment with a triple difference estimator 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, as found in the eggs price Figure 2 around 2014Q4-2015Q1. Based on the USDA report, 36 million layers (birds that lay eggs) were lost due to the bird flu by June 2015.[9]

Importantly, the USDA and GAO reports state that the impact of the bird flu shock exhibits geospatial variations, where the central and western parts of the U.S. were predominantly affected. We have the official confirmed premises of infection detailing when, where, and how many layers were culled from the USDA.[10] These MSAs where layers were culled would be disproportionately affected by the bird flu. Specifically, these MSAs might have higher inflation in eggs early in the bird flu during the inflationary period.

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

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

Leveraging this information, we can construct a diff-in-diff identification strategy by grouping treated and controlled MSAs and compare the effect of the bird flu on them. Furthermore, we can use a triple diff-in-diff estimator by further interacting the MSA-level market concentration with the standard diff-in-diff term to see how the effect varies by the degree of retailer market concentration.

First, to measure whether there these MSAs where farmers culled their layers were disproportionately affected by the bird flu, we use a two-year window around the treatment in 2014q4 and run the following traditional TWFE regression over the sample 2012q4 to 2016q4:

$$P_{mt} = \beta_0 + \beta_1(Treated_m \times Post_t) + \delta_m + \delta_t + \varepsilon_{st}, \tag{5.3}$$

where P_{mt} is the (geometric) Laspeyres inflation rate for eggs in MSA m and quarter t. $Treated_m$ corresponds to a binary variable that indicates whether farmers in MSA m had to cull their layers during the 2014-2015 bird flu according to the USDA. $Post_t$ corresponds to a binary variable that takes the value one after 2014q4. As before, δ_m and δ_t are the MSA fixed effects and quarter fixed effects, respectively. The coefficient on β_1 should be positive at least during the inflationary period of the bird flu given that theses MSAs experienced a relatively larger cost shock.

The result is shown in Table 10. In column 1, we estimate an effect of zero, which may suggest that these MSAs were not disproportionately affected by the 2014-2015 bird flu. However, this null effect is masking heterogeneity in effects during this period. If we separate the sample into inflationary and deflationary periods, we see opposing effects in the MSAs where layers were culled. In column 2, we restrict our sample to inflation period as measure when the national eggs inflation rate was above zero and estimate a 0.04 coefficient on the interaction of Bird Flu and Post. This corresponds to a 4 percentage point higher inflation rate in MSAs affected by the bird flu after 2014q4. This point estimate is significant at the 1 percent level. In column 3, we restrict to the deflationary period and see that MSAs that culled their layers experienced a 4 ppt.

lower inflation rate after 2014q4. This point estimate is significant at the 1 percent level. In column 4, we pool all quarters and take the absolute value of the dependent variable, inflation rate. We find that MSAs that culled their layers experienced larger changes in the inflation rate after 2014q4.

These heterogeneous inflation effects during the bird flu are reflected in Figure 10. In the left panel, the standard event study difference-in-differences coefficients are plotted. The dashed vertical line corresponds to 2014q4, which is the start of the post period. There is no systematic difference in inflation rates between MSAs that culled their layers (the treated MSAs) and MSAs that did not cull their layers (the controlled MSAs) prior to 2014q4.[11] However, after 2014q4, we see some quarters in which the treated MSAs experienced relatively higher inflation and others where they experienced less inflation.

This heterogeneity can be explained by heterogeneous effects depending on whether there is an inflationary or deflationary period of eggs as suggested by the right panel of the figure, 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. There continues to be no significant difference between these two groups of MSAs prior to 2014q4.

Next, we use a triple difference estimator to measure how the impact varies across the treated MSAs (where farmers culled their layers) with different degree of market concentration (HHI). The following regression shows the identification:

$$\begin{aligned} P_{mt} = \beta_0 &+ \beta_1 HHI_{mt} + \beta_2(\text{Treated}_m \times \text{Post}_t) \\ &+ \beta_3(\text{Treated}_m \times HHI_{mt}) + \beta_4(\text{Post}_t \times HHI_{mt}) \\ &+ \beta_5(\text{Treated}_m \times \text{Post}_t \times HHI_{mt}) + \delta_m + \delta_t + \varepsilon_{mt}, \end{aligned} \tag{5.4}$$

where the subscript m corresponds to MSA m and t is quarter t. $Treated_s$ is a binary variable indicating whether MSA s is near to where layers were culled during the 2014-

[11] This satisfies the parallel trends assumption.

2015 bird flu episode according to the USDA report. $Post_t$ is a binary variable that takes the value 1 if quarter t is after 2014q4. HHI_{mt} is HHI of retailer concentration of sales in MSA m for quarter t. P_{mt} is the geometric Laspeyres inflation rate in MSA m in quarter t. The fixed effect terms, δ_m andδ_t, are the same as before, and ε_{st} is the error term.

The result is described in Table 10. In the column 1, we restrict our sample to the inflationary period and find that the MSAs with higher market concentration increased prices at faster rates in the eggs market after the bird flu episode. This point estimate is significant at the 1 percent level. One concern one may have is that potentially, these MSAs with higher market concentration will lower prices by higher amounts during the deflationary period. In column 2, we restrict our sample to the deflationary period and find that the MSAs with higher concentration are not lowering their prices at faster rates during the deflationary period. We find some suggestive evidence that these MSAs are slower to decrease prices in deflationary period as evidenced by our positive coeffieint on the triple interaction term in column 2. This coefficient is significant at the 10 percent level. In column 3, we pool all quarters in the two year window together and we continue to find that MSAs with higher market concentration exhibit higher inflation than the MSAs with lower market concentration.

Our results show a potential mechanism explaining the heterogeneous inflation rates between poor and rich MSAs in the eggs market through the market concentration of retailers. In particular, the triple difference-in-differences results are suggestive that these differences may occur through markups rather than marginal cost with high cost pass-through.[12] Testing this hypothesis and disentangling where the effect comes from still remain as our to-do list.[13]

[12]If differences in marginal costs are the main driving factor behind the heterogeneous inflation rates, we would expect to see higher deflation in the deflationary period in MSAs with higher market concentration.

[13]We are currently in the process of estimating the MSA-level markups and marginal costs based on the nested CES structure following Hottman (2017).

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 2020. This finding is also robust to different types of price indexes and to the set of common goods consumed across all MSA deciles. 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 how this pattern is linked to different retailer dynamics across poor and rich MSAs, we find that the composition and market concentration of retailers vary across different regions. In particular, we find a positive association between the retailer sales concentration and inflation rates. To develop a more causal link between market concentration and inflation, we exploit the 2014-2015 bird flu episode and employ a triple difference estimator. We find that the MSAs affected by the bird flu with higher HHI values experience higher inflation rates than the MSAs affected by the bird flu with lower HHI values. This suggests that retailer market concentration plays a role in pronouncing the impact of the cost shock by charging higher prices.

This work is still preliminary, and there are several remaining future work. We would like to investigate further whether this is linked to retailers' market power by estimating markups in the data. Furthermore, we would like to build a structural model to quantify the channel and derive more testable and policy implications. Lastly, we will continue to analyze the unrepresentativeness of official price indexes.

References

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms*," *The Quarterly Journal of Economics*, 02 2020, *135* (2), 645–709.

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

Feenstra, Robert C., "New Product Varieties and the Measurement of International Prices," *The American Economic Review*, 1994, *84* (1), 157–177.

Feenstra, Robert C, Luca Macedoni, and Mingzhi Xu, "Large Firms, Consumer Heterogeneity and the Rising Share of Profits," Working Paper 29646, National Bureau of Economic Research January 2022.

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.

Hottman, Colin J., "Retail Markups , Misallocation , and Store Variety Across U . S . Cities," in "in" 2017.

_ , **Stephen J. Redding, and David E. Weinstein**, " Quantifying the Sources of Firm Heterogeneity *," *The Quarterly Journal of Economics*, 03 2016, *131* (3), 1291–1364.

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

Kaplan, Greg 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.

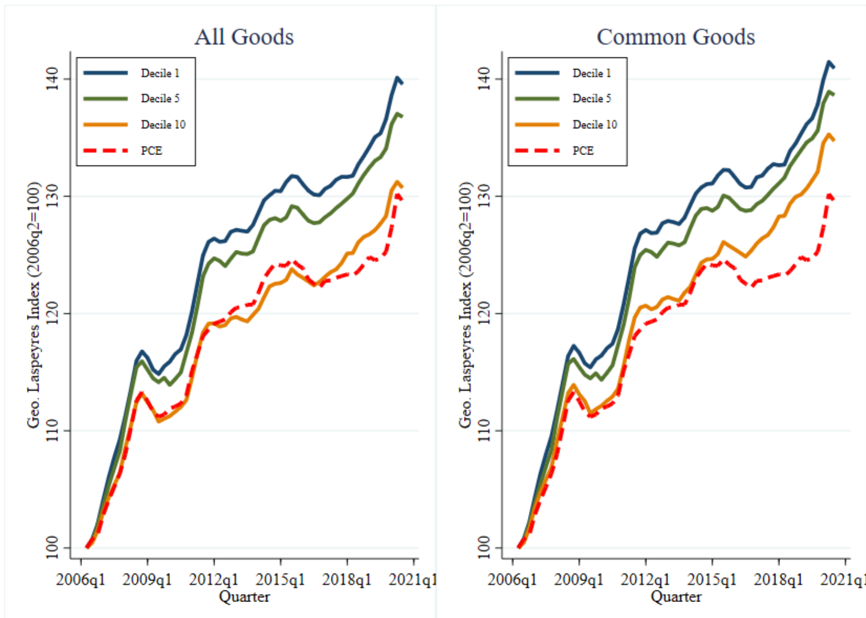
Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, “The Rise of Market Power and the Macroeconomic Implications*,” *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

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

Nevo, Aviv, “Measuring Market Power in the Ready-to-Eat Cereal Industry,” *Econometrica*, 2001, *69* (2), 307–342.

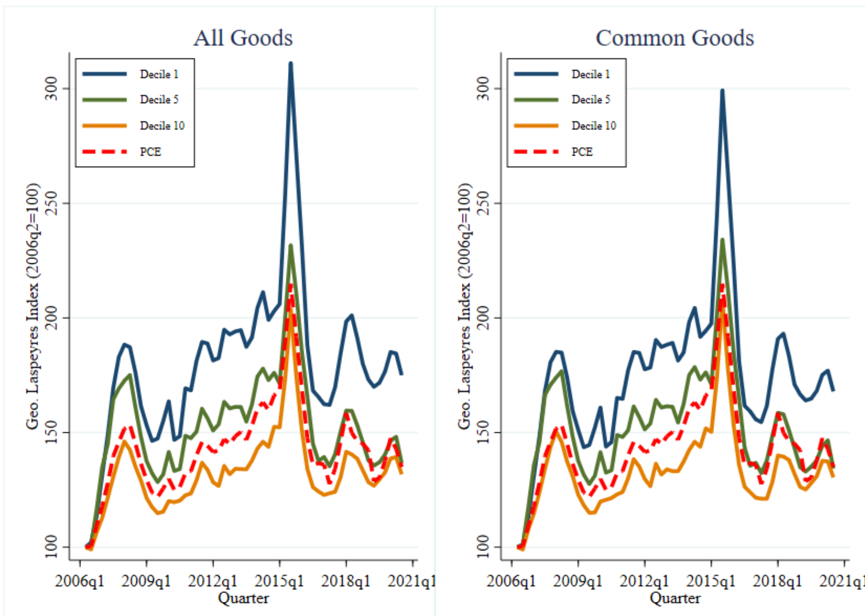
A Figures

Figure 1: Price Index for Aggregated Food



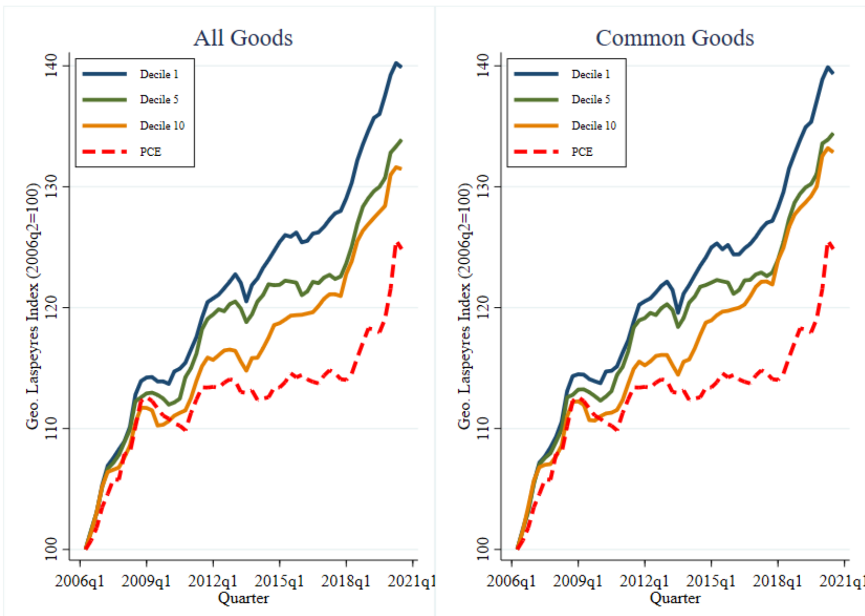
Note: The figure represents the price relatives for the aggregated food market with four series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2020Q4. The data for the three solid lines comes from NielsenIQ Retail Scanner dataset represented 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 NielsenIQ 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



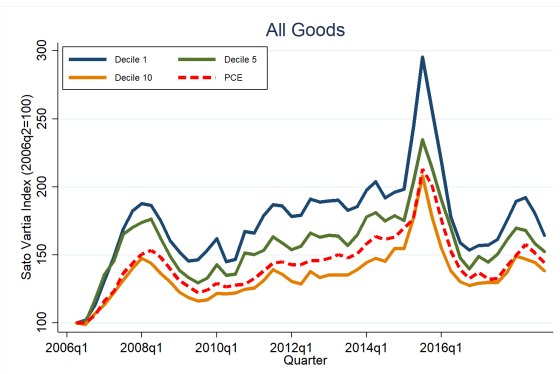
Note: The figure represents the price relatives for the aggregated egg market with five series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2020Q4. The data comes from NielsenIQ Retail Scanner dataset represented by geometric Laspeyres 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 NielsenIQ UPCs to the PCE definition of eggs by using a product module concordance provided by the BLS.

Figure 3: Laspeyres Price Index for Soda and Juices

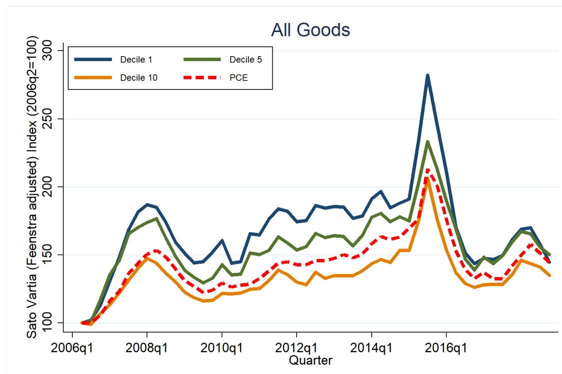


Note: The figure represents the price relatives for soda and juices market with five series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2020Q4. The data comes from NielsenIQ Retail Scanner dataset represented by geometric Laspeyres 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 NielsenIQ UPCs to the PCE definition of eggs by using a product module concordance provided by the BLS.

Figure 4: Demand-based Price Indexes for Eggs



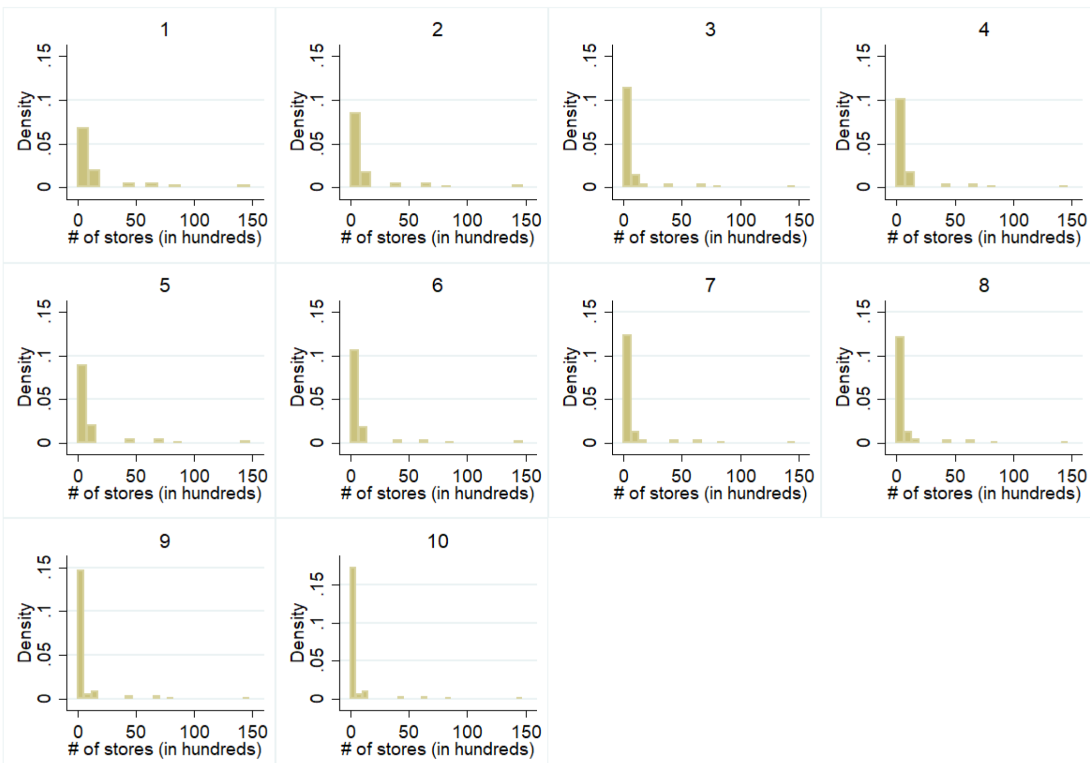
Sato Vartia



Feenstra-adjusted Sato Vartia

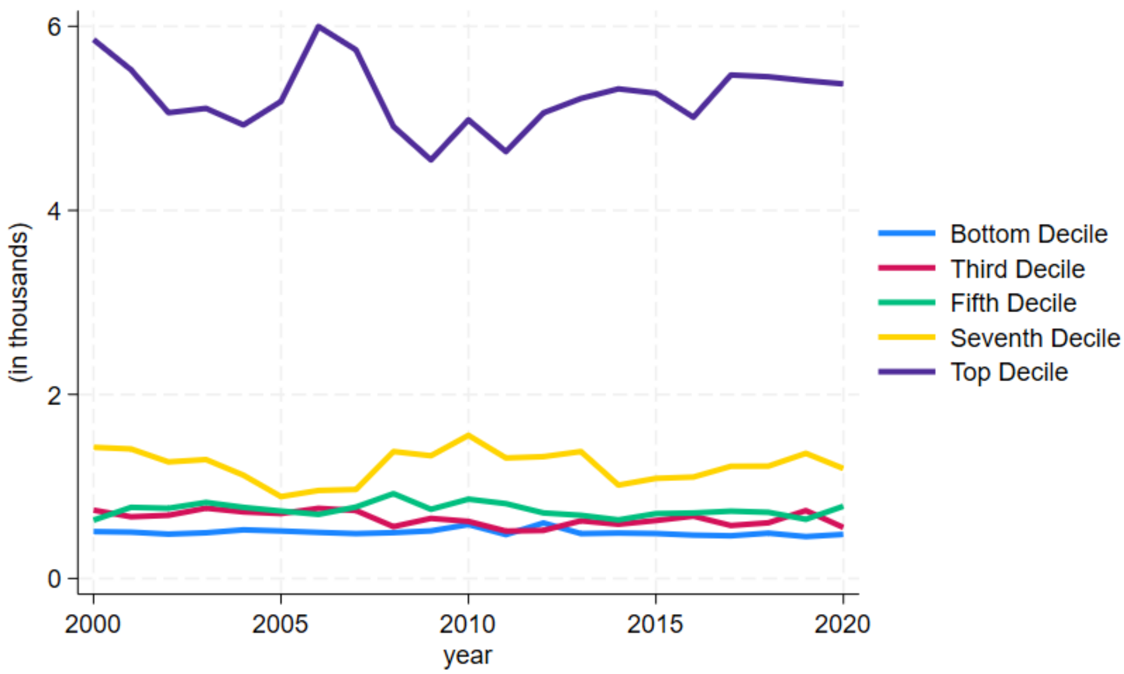
Note: The figure represents the price relatives for the aggregated egg market with five series where each series is normalized to 100 at the start of the sample. The sample period starts in 2006Q2 and ends in 2016Q4. The data comes from NielsenIQ Retail Scanner dataset represented by Sato-Vartia and 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 NielsenIQ UPCs to the PCE definition of eggs by using a product module concordance provided by the BLS.

Figure 5: Distribution of Retailer Size by Income Decile



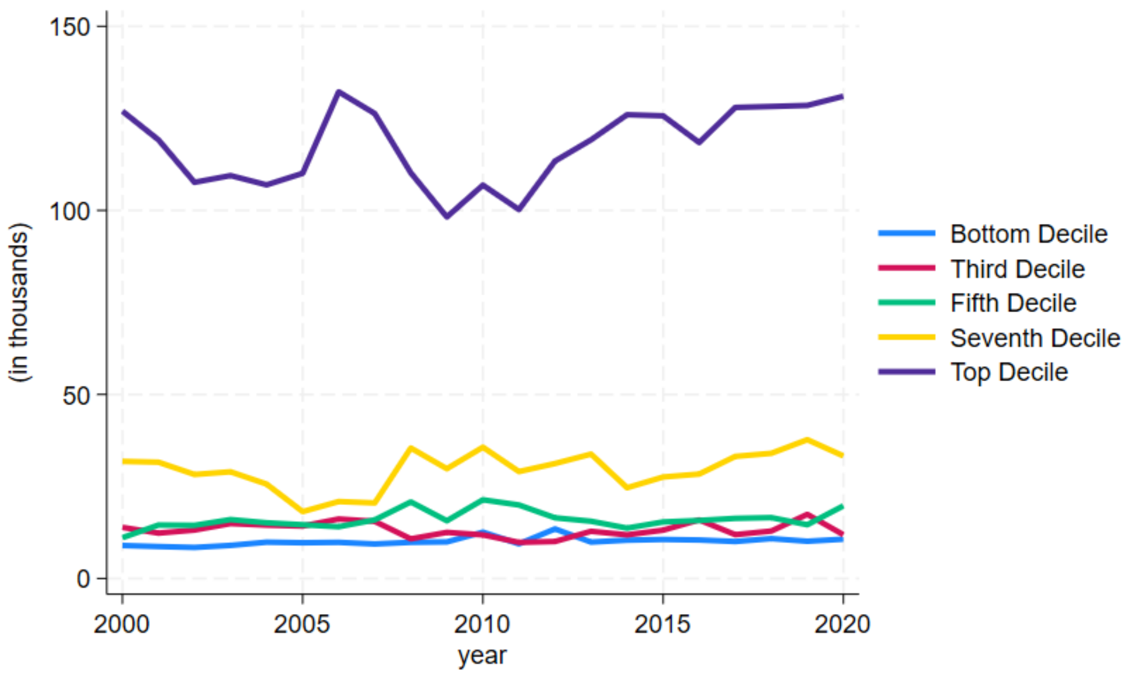
Note: The figure represents the distribution of the number of stores (at the national level) of chains located in each income decile. The data is from NielsenIQ for the aggregate food and beverages.

Figure 6: Number of Retail Chains by Income Decile



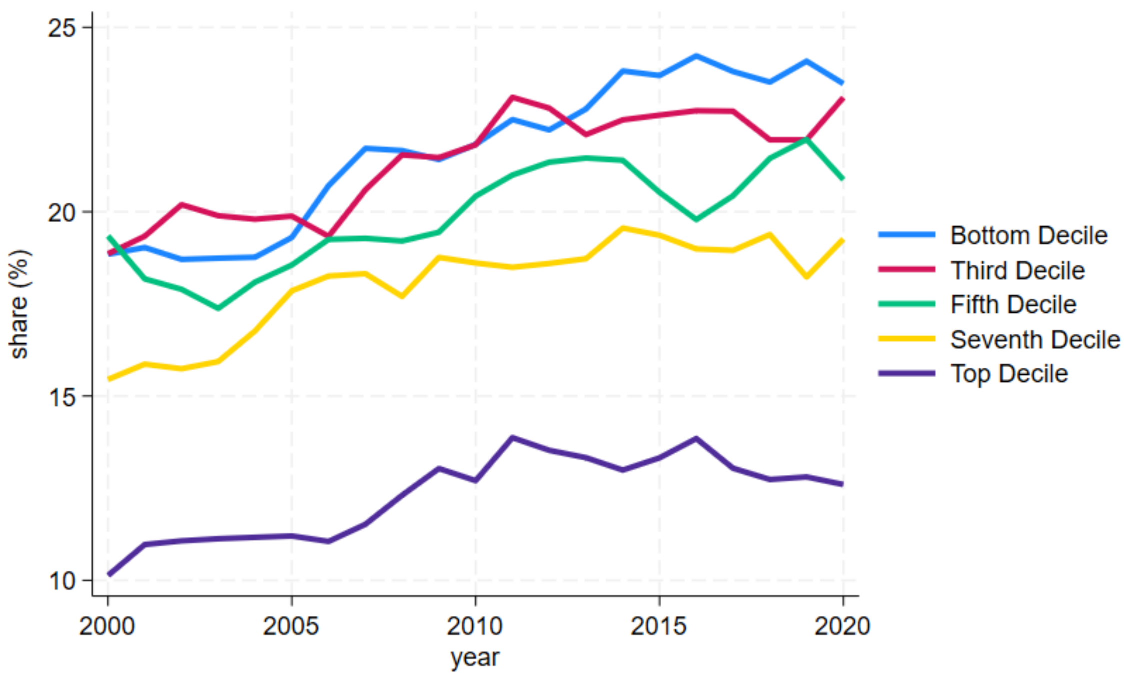
Note: The figure represents the number of retail chains present from 2000 to 2020 in decile 1, 3, 5, 7, and 10. The data on the number of retail chains comes from the Business Dynamics Statistics (BDS). We specifically only use data on chains from the BDS for the retail trade sector (NAICS 44-45).

Figure 7: Employment of Retail Chains by Income Decile



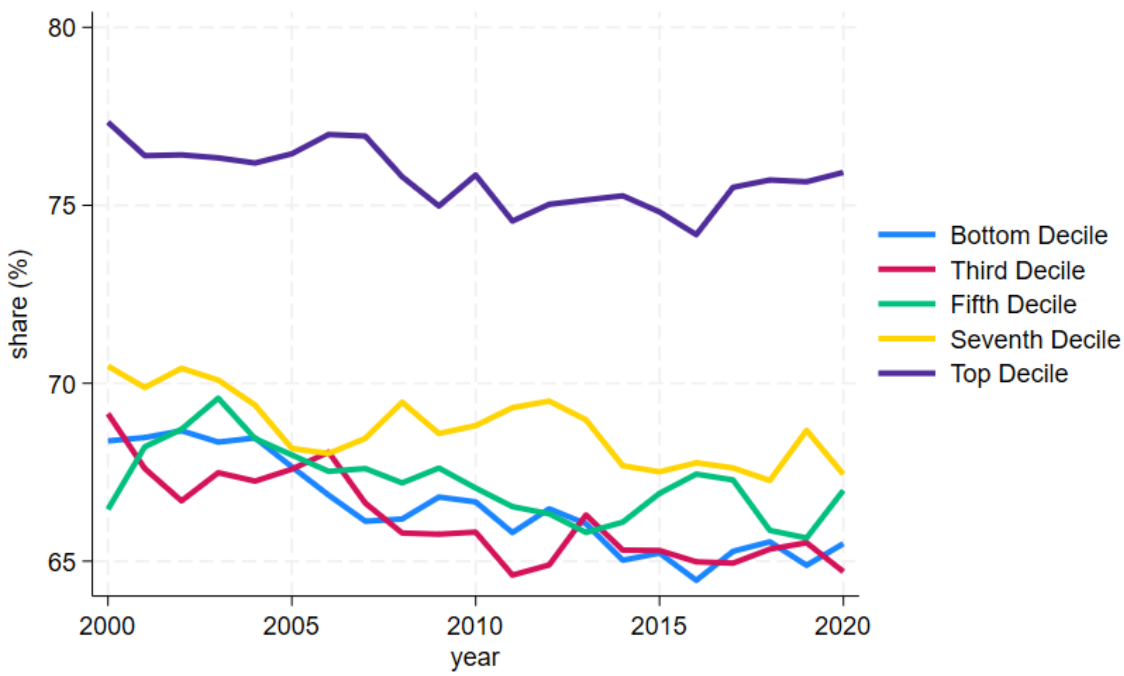
Note: The figure represents the employment of retail chains present from 2000 to 2020 in decile 1, 3, 5, 7, and 10. The data on the number of retail chains comes from the Business Dynamics Statistics (BDS). We specifically only use data on chains from the BDS for the retail trade sector (NAICS 44-45).

Figure 8: Share of Large Retailers



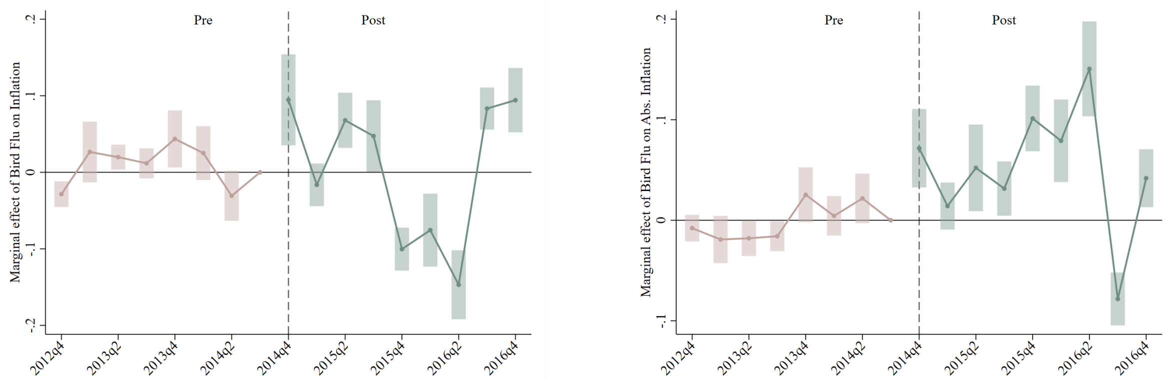
Note: The figure represents the share of establishments from large retail chains present from 2006 to 2019 in decile 1, 3, 5, 7, and 10. A large retail chain is defined as a retail chain (firm level) that has more than 500 employees. The data on the number of retail chains comes from the Business Dynamics Statistics (BDS). We specifically only use data on chains from the BDS for the retail trade sector (NAICS 44-45).

Figure 9: Share of Small Retailers



Note: The figure represents the share of establishments from small retail chains present from 2006 to 2019 in decile 1, 3, 5, 7, and 10. A small retail chain is defined as a retail chain (firm level) that has less than 20 employees. The data on the number of retail chains comes from the Business Dynamics Statistics (BDS). We specifically only use data on chains from the BDS for the retail trade sector (NAICS 44-45).

Figure 10: Event Study Difference-in-Differences (Bird Flu)



(a) Treated $\times$ Quarter

(b) Treated $\times$ Quarter (Absolute Value)

Note: The figure represents the event study difference-in-differences where I look at the dynamic effect of MSAs disproportionately affected by the 2014-2015 bird flu episode on inflation. The panel on the left has the inflation rate as the outcome variable and the panel on the right has absolute value of the inflation rate as the outcome variable. MSAs are assigned treatment, based on a USDA report detailing which farms culled their layers. The Post period starts in 2012q4 and 2012q3 is the reference quarter. Effects are measured from 2012q4 to 2016q4. Standard errors are clustered at the MSA level.

B Tables

Table 1: 21 PCE Food Categories

1	Bakery	12	Milk
2	Beef and Veal	13	Other Foods
3	Beer	14	Other Meats
4	Cereal	15	Pork
5	Coffee	16	Poultry
6	Dairy	17	Processed Fruits and Vegetables
7	Eggs	18	Soda
8	Fats and Oil	19	Spirits
9	Fish	20	Sugar and Sweets
10	Fruits	21	Vegetables
11	Wine		

Note: The table represents the 21 PCE disaggregated Food categories. These disaggregated categories are mutually exclusive. The PCE category Food and Beverages is composed of these 21 categories.

Table 2: Examples of MSA Deciles

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

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

Table 3: Summary Statistics of MSA-quarter level Sample

	Mean (SD)
Income per capita ($1,000)	42.45
	(9.30)
Sales ($1mil.)	206.67
	(365.60)
Number of chains	9.75
	(3.72)
Number of stores	193.20
	(250.78)
Share of large chains	0.11
	(0.06)
Share of small chains	0.09
	(0.10)
Market concentration	0.31
	(0.15)
Observations	11,168
Number of MSAs	188
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 the count of stores of that chain at the national level within an MSA-quarter. Market concentration is measured by the HHI (Herfindahl-Hirschman Index) of chain-level sales.

Table 4: Summary Statistics of MSA-quarter level Sample by Income Deciles

	Decile 1	Decile 3	Decile 5	Decile 7	Decile 10
	Mean	Mean	Mean	Mean	Mean
	(SD)	(SD)	(SD)	(SD)	(SD)
Income per capita ($1,000)	31.37	36.24	38.93	42.18	57.14
	(5.28)	(4.40)	(4.92)	(5.19)	(11.48)
Sales ($1mil.)	26.427	60.86	79.54	136.22	730.63
	(25.37)	(59.57)	(113.72)	(203.59)	(745.44)
Number of chains	7.76	8.72	8.80	9.42	13.16
	(3.06)	(2.76)	(2.96)	(3.37)	(4.96)
Number of stores	61.76	84.91	99.74	164.79	511
	(50.44)	(63.25)	(97.72)	(171.85)	(479.69)
Share of large chains	0.14	0.12	0.11	0.11	0.07
	(0.07)	(0.06)	(0.06)	(0.06)	(0.04)
Share of small chains	0.05	0.07	0.06	0.06	0.16
	(0.07)	(0.09)	(0.09)	(0.07)	(0.13)
Market concentration	0.37	0.36	0.35	0.32	0.20
	(0.16)	(0.16)	(0.14)	(0.13)	(0.11)

Note: The table provides the summary statistics of the main MSA-level sample for the aggregate food and beverages for the five income-per-capita deciles 1, 3, 5, 7, 10. Large (small) chains are defined by those in the top (bottom) decile based on the count of stores of that chain at the national level within an MSA-quarter. Market concentration is measured by the HHI (Herfindahl-Hirschman Index) of chain-level sales.

Table 5: Retailer Dynamics in NielsenIQ

	Sales (in $1mil.)	Chain counts	Store counts	Large firm share
Income	14.01***	0.108***	2.770***	-0.049**
	(0.422)	(0.007)	(0.192)	(0.021)
Quarter FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Observations	11,168	11,168	11,168	11,168

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

Note: The table represents regression results from our two-way fixed effects estimator. The coefficient of interest is the coefficient on income per capita (in $1000) in an MSA for a given quarter. The dependent variable is total sales in in Column 1, total counts of chains and stores in in Column 2, 3, and an unweighted share (%) of large firms in Column 4, where large retailers are defined by the top decile of the number of store counted at the national level in NielsenIQ.

Table 6: The Share of Large Firms (BDS)

	Large firm share	Large firm emp. share
Income	-0.044***	-0.049***
	(0.006)	(0.009)
Year FE	Yes	Yes
MSA FE	Yes	Yes
Observations	8,001	8,001

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

Note: The table represents regression results from our two-way fixed effects estimator. The coefficient of interest is the coefficient on income per capita (in $1000) in an MSA for a given year. The dependent variable is an unweighted share (%) of large retailers in column 1 and an employment weighted large share (%) of large retailers in column 2. Data is collected from the Business Dynamics Statistics and retailers are gathered from retail trade sector (NAICS 44-45) for 2000-2020.

Table 7: HHI across Different Income Deciles

	HHI
Decile	-0.004***
	(0.000)
Year FE	Yes
Item FE	Yes
Observations	10,920
*** p<0.01, ** p<0.05, * p<0.1	

Note: The table represents regression results from our two-way fixed effects estimator. The coefficient of interest is the coefficient on income per capita decile. This independent variable is a discrete categorical variable that takes the value 1 (poorest) to 10 (richest). The outcome variable is HHI. HHI is the Herfindahl-Hirschman index (HHI) of retail chain's sales of a given PCE disaggregated category within an MSA. HHI is a continuous variable than can range from 0 to 1. Column 1 is an unweighted share of large firms. Column 2 is an employment weighted large share of retailers. Data is collected from the Business Dynamics Statistics and retailers are gathered from retail trade sector (NAICS 44-45).

Table 8: 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 NielseIQ 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 9: HHI across Different Income Deciles

	HHI
Decile	-0.004***
	[0.000]
Year FE	Yes
Item FE	Yes
Observations	10,920
*** p<0.01, ** p<0.05, * p<0.1	

Note: The table represents regression results from our two-way fixed effects estimator. The coefficient of interest is the coefficient on income per capita decile. This independent variable is a discrete categorical variable that takes the value 1 (poorest) to 10 (richest). The outcome variable is HHI. HHI is the Herfindahl-Hirschman index (HHI) of retail chain's sales of a given PCE disaggregated category within an MSA. HHI is a continuous variable than can range from 0 to 1. Column 1 is an unweighted share of large firms. Column 2 is an employment weighted large share of retailers. Data is collected from the Business Dynamics Statistics and retailers are gathered from retail trade sector (NAICS 44-45).

Table 10: TWFE Estimator (Bird Flu Episode)

	Inflation	Inflation	Inflation	Abs. Inflation
Bird Flu $\times$ Post	-0.003	0.039***	-0.035***	0.053***
	(0.004)	(0.008)	(0.007)	(0.006)
Sample	All	Inflation	Deflation	All
Quarter FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Quarters	17	10	7	17
MSAs	187	187	187	187
Observations	3,160	1,859	1,301	3,160

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

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 us a binary variable that takes the value 1 after 2014q4. Bird Flu is a binary variable that takes the value 1 if an MSA culled its layers during the 2014-2105 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 20164. MSA and quarter fixed effects are included. Standard errors are clustered at the state-level.

Table 11: Triple Difference Estimator (Market Concentration)

	Inflation	Inflation	Inflation
Bird Flu × Post × HHI	0.078***	0.065*	0.052***
	(0.021)	(0.038)	(0.018)
Bird Flu × Post	-0.002	-0.078***	-0.034**
	(0.012)	(0.026)	(0.014)
HHI × Post	-0.003	-0.006	-0.006
	(0.008)	(0.012)	(0.005)
Bird Flu × HHI	-0.180	1.246*	0.389
	(0.137)	(0.656)	(0.297)
HHI	0.073***	0.022	0.050***
	(0.019)	(0.037)	(0.018)
Sample	Inflation	Deflation	All
Quarter FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Quarters	10	7	17
MSAs	187	187	187
Observations	1,859	1,301	3,160

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

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 us 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. HHI is a continuous variable than can range from 0 to 1. Bird Flu is a binary variable that takes the value 1 if an MSA culled its layers during the 2014-2105 bird flu episode. Column 1 only looks at the inflationary period. Column 2 only looks at 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 20164. MSA and quarter fixed effects are included. Standard errors are clustered at the state-level.