Food Retail Configuration and Markups[*]

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Abstract

Supermarkets control over 60 percent of the grocery market share followed by warehouse clubs, which accounted for over 25 percent of the US market. This paper documents the trends of firm-level markups in the US food grocery sector using TDLinx data for the establishments located nationally over the period 2004-2020. The objectives in this study are twofold. First, this study traces the development of market power in the food grocery sector using the production function approach by De Loecker and Warzynski (2020). Second, it examines the distribution of markups by quality (high or low), size, and different formats. The main finding is that there is a pattern of rising markups up to 20 percent between 2015-2020 but the level of markup has not rebounded enough as in early 2000s. Empirical results also find that grocery stores have 2.5 times lower markups compared to the supercenters on average. Average markups for grocery stores are about 4-7 percent, while supercenters' markups exceed 16 percent.

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1. Introduction

Food retail businesses operate as oligopolies with the emergence of Wal-Mart, Costco, and Target. An oligopoly exists when a small number of businesses dominate a significant percentage of a market, which results in high entry barriers for competitors. Not surprisingly, Wal-Mart ranked as the biggest retailer of food and consumables in 2021, with sales of more than 393 billion dollars. Supermarkets, which are in direct competition with other food retailers, currently control over 60% of the US grocery market, followed by warehouse clubs (such as Costco) and hypermarkets (such as Kroger and Trader Joe's), which account for over 25 percent of the country's total market (Ozbun, 2022)[1].

Given this situation, there is growing empirical evidence that markups are increasing in the US (Ganapati, 2021a; De Loecker and Eeckhout, 2021; De Loecker et al., 2020; Doraszelski and Jaumandreu, 2019; Chidmi and Lopez, 2007). Markups are crucial to research in empirical industrial organization because they reveal information on the level of production efficiency and the technology employed by businesses. Recently, De Loecker & Eeckhout, (2021) quantify market power by developing a general equilibrium model and find that the cause rising market power is due to a decrease in employment reallocation rate and changes in the cost-structure of firms[2]. From a macroeconomic perspective to understand industrial markups overall, De Loecker et al. (2020) document the evolution of market power using firm-level data over the period of 1955-1980. They find that the markups increased from 21 percent to 61 percent, which is driven by only a few firms in the upper tail of the distribution while most firms have no change in markups. In agricultural sectors, Chidmi & Lopez (2007) are one of the few studies estimating markups for the US grocery stores and find 28 percent of markups over the retail price on average using BLP framework. More recently, Chenarides et al (2021) show that the entry by discount-stores (Aldi) decreases similar retail stores' markups about 7.3 percent compared to stores in non-entry markets. However, there are no studies found to analyze trends in markups in the US food retail sectors.

[1] For the first time ever, the United States' total retail and food service revenues reached $7.44 trillion in 2021

[2] Basu (2019) discusses three different ways of markup estimation and indicates that studies are limited to explain the connections between higher markups and a lower labor share of income and a lower investment rate.

On the other hand, there are several studies found related to the markup using production function approach in the EU retailing. For example, Caselli et al. (2018) investigate the incidence of French manufacturing firms displaying negative markups. Koppenberg & Hirsch (2021) find a strong positive relationship between markups and profitability while firm size and markups are negatively related, indicating that small firms in the EU dairy processing industry can charge higher markups in a differentiated niche market. However, little is known about a long-term and systematic trend for the US food retail sector[3].

This study uses 57,592 establishments (500K+ observations) located nationwide between 2004 and 2020 to analyze the patterns of firm-level markups in the US food grocery sector. Our main objectives are twofold. First, this study documents the development of firm-level markups in the food grocery sector using a production function approach (PFA). Secondly, this paper analyzes the distribution of markups by quality (high or low), size, and different formats. This study follows the most recent approach by De Loecker (2020) who has made new contributions to the literature on markup estimates that build on Hall (1988) and De Loecker and Warzynski (2012). The approach does not need to estimate demand with this method, as opposed to the new empirical IO method (Bresnahan 1989). Rather, this approach proposes cost minimization by producers and relies on data on the output and input of each establishment. As the difference between a variable input's spending share in observed revenue and that input's output elasticity, a measure of the markup is generated for each producer at a specific point in time. By estimating the related production function, we can estimate the markups at the firm-level. In the following section, we describe data sources with advantages and disadvantages followed by an empirical model with markup estimation. Then, we discuss our empirical results and conclusions.

2. Data

The data comes from two sources: store information from Nielsen's TDLinx and the Quarterly Census of Employment and Wages (QCEW). This paper chooses Nielsen's TDLinx data for two

[3] Recent work using production function approach (PFA) includes Lee and Cayseele (2022) (Italian cooperatives); Chenarides et al., (2021) (cross-sectional markups for US supermarkets); Lowrey et al., (2020) (cross-sectional markups for US food bank retailers); Koppenberg and Hirsch, (2021) (EU dairy processing); Hirsch and Koppenberg, (2020) (French food retailing).

reasons. First, TDLinx provides reliable and contains unique retail store's data at the establishment level across the US that is not obtainable in Census data. Second, it is better for this study to use TDLinx over National Establishment Time-Series (NETS) since NETS only provides a number of employees, which is not feasible for economists to estimate production function requiring at least two inputs (labor and capital). Thus, this paper uses the establishment-level of store data including annual estimated revenues from 2004 to 2020 and our sample observes all establishments located in the U.S.

As a measure of labor and capital input, this study uses the number of employees as labor input and store's square footage as capital input. To identify store-level characteristics, we use a unique subchannel code indicated by retail formats under the grocery channel (supermarket limited assortment, natural/gourmet foods, warehouse grocery, superette, conventional, supercenter, and military commissary); categorical number of stores owned by the same brand (1 store, 2-3 stores, 4-5 stores and so forth) ; chain indicator to define whether it is independent or chain; scope of services whether the store provides non-food services (gas, pharmacy, beer, and wine).

Even though its uniqueness of providing store characteristics, it has some limitations. One of the limitations of TDLinx data[4] is that it does not include either total variable cost or input expenditures (i.e., capital and material costs[5]) for measuring markups. Instead, it is able to observe the number of employees at the establishment level. Moreover, there is no information about other input data like material and energy usage while those are provided by Census Bureau at the industry or sectoral level. Therefore, we obtain data from QCEW[6], which includes total annual wages and number of establishments in all counties and periods from 2004 to 2020. Then next step is to compute the annual labor expenditure at the establishment-level by dividing total annual wages over total number of establishments in each county, which is then multiplied by number of employees at the establishment to have a total wage bill by the store annually. Since the two inputs (labor and capital) are only observables in the data, it is not feasible to estimate production functions with different inputs (material) in this study. The descriptive statistics to show key variables estimating the production functions are reported in Table 1 below.

[4] See Cho et al., (2019) and Levin et al. (2018) for the comparison of retail store data over the TDLinx database
[5] Studies using material input to estimate markups include Jafari et al. (2022) for French food processing; Lee & Cayseele (2021) for agricultural cooperatives in Italy; Doraszelski & Jaumandreu (2019) estimated markups based on labor, material, and variable cost.
[6] We use 6-digit NAICS code (Grocery-445110 and Supercenters-452910) to identify industry and county specific data.

[Table 1 around here]

3. Empirical Model

In this session, the empirical model of markups is introduced followed by the estimation process of firm-level markups using a single input elasticity recovered from the production function. Then, the retail production function is followed to illustrate how to recover input elasticity.

3.1. A Model of Retail Markups

Following De Loecker[7](2020), this study uses the PFA to recover markups of price over marginal cost. Based on the assumption of the cost minimization of the retail stores given the production function:

$$Q_{itc} = Q_{itc}(L_{itc}, K_{itc}, \Omega_{itc}) \quad (1)$$

where L_{itc} is a labor input of production, K_{itc} is the capital stock and Ω_{itc} is productivity. The cost-minimizing firm's first-order condition for L_{itc} becomes:

$$\frac{1}{\lambda_{itc}} = \frac{\partial Q(\cdot)}{\partial L_{itc}} \frac{1}{W_{itc}}, \quad (2)$$

where λ_{itc} is a Lagrange multiplier measuring marginal costs. By multiplying both sides by the firm's price P_{itc}, the right-hand side equation can be rewritten in terms of the output elasticity of $\hat{\theta}^{l}_{itc}$, multiplied by its inverse revenue share:

$$\hat{\mu}_{itc} = \hat{\theta}^{l}_{itc} \frac{P_{itc} Q_{itc}}{P^{l}_{itc} V_{itc}} \quad (3)$$

[7] The markup estimation using PFA is introduced by Hall (1988) and further developed by De Loecker and Warzynski (2012) that find exporting firms have higher markups than non-exporting firms.

where output elasticity on labor input l is denoted by θ_{it}^{l} and $\frac{P_{it}Q_{it}}{P_{it}^{V}V_{it}}$[8] is the revenue share of the labor expenditure for each establishment *i* in year t. To measure markups, it is necessary to estimate input elasticity from the previous production function and need to compute the inverse share of labor expenditure on total sales that are directly observed in our data. To this end, the following production function is estimated.

3.2. Retail Production Function

We adopt the following production function to estimate input elasticities following Ackerberg et al. (2015):

$$y_{itc} = \beta_c + \beta_l l_{itc} + \beta_k k_{itc} + \beta_t time_t + \beta_{ll} l_{itc}^2 + \beta_{kk} k_{itc}^2 + \beta_{lk} l_{itc} k_{itc} + \beta_{lt} l_{itc} time_t + \beta_{kt} k_{itc} time_t + \beta_z z_{itc} + \omega_{itc} + \varepsilon_{itc} \tag{4}$$

where all output and input variables are expressed in logs, y_{itc} denotes revenue deflated by a retail price index at the establishment level, l_{itc} is the number of employees (labor) in the establishment *i* in year t, k_{itc} is capital for the establishment in square footage, z_{itc} are instrumental variables, ω_{itc} is a unobserved Hicks-neutral productivity following an AR(1) process, that is, $\omega_{itc} = \rho\omega_{itc-1} + \xi_{itc}$, and ε_{itc} is i.i.d. over time and uncorrelated with l_{itc}. Here, the first stage purges of the measurement error and unobserved productivity shocks in the equation (1). Then, we substitute this expression for the productivity shock into the production function to have:

$$y_{itc} - \rho y_{itc-1} = \beta_c + \beta_l l_{itc} + \beta_k k_{itc} + \beta_t time_t + \beta_{ll} l_{itc}^2 + \beta_{kk} k_{itc}^2 + \beta_{lk} l_{itc} k_{itc} + \beta_{lt} l_{itc} time_t + \beta_{kt} k_{itc} time_t + \beta_z z_{itc} + \xi_{itc} + \varepsilon_{itc} \tag{5}$$

[8] The corrected expenditure share $\frac{\frac{P_{it}\widetilde{Q_{it}}}{exp(\hat{\varepsilon}_{it})}}{P_{it}^{V}V_{it}}$ is used to measure markups suggested in De loecker & Warzynski (2012).

In the second stage, the two-step generalized method of moments (GMM) methodology by Ackerberg et al. (2015) (ACF) and De Loecker (2013) is applied for parameter identification (see the Appendix for details). This allows us to estimate the output elasticity with respect to any of the inputs after identifying the GMM estimations.

4. Empirical Results

Table 2 reports the estimated translog production function results using two-stage GMM technique. All parameters of inputs show the positive signs as expected and highly significant at 1 percent level. We find that all supermarkets show positive productivity in terms of their revenues ranging from 28.2 percent to 75.7 percent using "superette" as a benchmark, which can be considered as a low-quality supermarket. This finding represents that small scale supermarkets have a lower advantage to increase their markups compared to the high-quality supermarkets. These high-quality supermarkets provide a wider product choice with cheaper prices along with pickup/delivery services to increase online sales. Furthermore, they could utilize a more efficient distribution network to reduce operating costs while maintaining product quality for perishable items. We also find that economies of scale effect on stores' productivity by using store's size.[9] We use a single owned store as a benchmark and find that the productivity increases 32.8 percent at most for those stores operating more than 500 stores. Interestingly, the productivity increases almost linearly by the increase in store's size. Lastly, we include scope of nonfood services measured in numbers by stores including whether the store provides beer/wine, pharmacy, and gas station. The services increase the stores' productivity overall about 1.1 percent with a higher significance level.

Table 3 shows the labor and capital elasticities estimated by OLS, two-stage least squares (2SLS), and two-stage GMM regression. We obtain a comparable estimate for labor input ranging from 0.594 to 0.662 and use the elasticity obtained from the two-stage GMM regression to calculate markups following the best practice in this field (ACF et al., 2015; De Loecker &

[9] The store size refers to the number of stores operating in different locations.

Warzynski 2012; De Loecker, 2020). In the result of returns to scale (RTS) under different regressions, and we find that there is an increasing pattern of returns to scale[10] (1.036), which is the sum of labor and capital input elasticity. The similar pattern of returns to scale can be also found in Keh & Chu (2003).

[Table 3 around here]

Table 4 shows estimated markups at the subcategory-level under the same grocery channel[11]. This is necessary because supercenters are included in the same grocery channel code, even though these store formats do not share the same NAICS code provided by census data. By separating the supercenters out, it is more reasonable to compare the markups between grocery stores and supercenters showing that the higher markups are driven by supercenters. It is also found that there exists heterogeneity between nearly zero to 60 percent markups among different supermarket formats. Given the high market share of large supermarket chains, it is not surprising that conventional supermarkets(superette/conventional) have lower markups than high quality supermarkets (natural/gourmet stores) by providing a more limited variety of product category but with higher prices and quality to attract high-income consumers. Therefore, this result suggests the presence of asymmetrical power in the food grocery sectors that could decrease consumer's welfare in the market as Hirsch & Koppenberg (2020) demonstrate the relationship between small and large firms.

[Table 4 around here]

Lastly, Table 5 summarizes the comparison of markups for two panels. The panel A shows that grocery stores and supercenters on average generate 6.3 percent and 16.2 percent[12] of markups respectively. Statista (2022) reports Wal-Mart's gross profit margin ranging from 23.1 percent to 24.9 percent for 2006-2022. It should be noted that profit margin is calculated from revenues minus cost of goods sold (COGS) which must be differentiated when interpreting the magnitude of markups. As indicated by Yuan et al. (2017), Wal-Mart exhibits a higher economy of scale compared to other grocery chains, implying that they invest lower input (labor and

[10] Bhuyan & Lopez (1997) find the increasing returns to scale for twenty food manufacturing sectors including fluid milk (1.058) and meat packing (1.585).
[11] Under the same grocery channel, we observe 7 different subchannel that includes supermarket limited assortment, natural/gourmet foods, warehouse grocery, superette, conventional, supercenters, and military commissary.

capital) costs to increase their profit margins[13]. Panel B compares the markups of independent grocery stores and chain stores. The result shows that chain stores have 27 percent higher markups than independent grocery stores as chain stores would have better supply networks, category killers as well as technology to improve stores' productivity.

[Table 5 around here]

Figure 1 presents the Kernel density estimates of the markups by different supermarket formats under the same grocery store channel. The estimates show that grocery stores charge markups around 4-8 percent above the marginal cost, whereas Supercenters have 17 percent of markups. This finding supports the previous literature (Richards et al., 2018 and Food Marketing Institute, 2017), suggesting that the food retail industry is highly competitive and net margins are far lower than other industries due to the high level of competition among the largest retailers (e.g., Walmart, Target, and Amazon) in the U.S. Most of the low-quality (Superette) and high-quality supermarkets (Natural/Gourmet) have between 3.8 and 7.5 percent of markups, and the distribution is quite overlapped and highly skewed on the left. As we already showed by the previous results, supercenters (Wal-Mart) have 17 percent of markups. Next, the markup distribution by the scope of services is plotted in Figure 2 to compare stores providing a full line of non-food services with the stores that are not providing any services. The plot shows that there is a lower markup distribution for the stores providing no service as expected.

[Figure 1 around here]

[Figure 2 around here]

In Figure 3, the average markups trend shows a decreasing pattern for high- and low-quality supermarkets, whereas markups for supercenters have been stable between 14 and 17 percent. In Figure 3, the increasing pattern of markups in 2020 represents the fact that food grocery retailers were the COVID-19 winner which drove a 57 percent increase in grocery sales due to the dramatic shift in home-related consumption (Ralston, 2022). Our finding is robust when we check the size of the establishment. We show that there exist economies of scale in the

[13] Average profit margin for supermarket is reported between 1 and 3 percent.

grocery sectors as markups increase in the size of the stores and the trends have decreased over the periods.

[Figure 3 around here]

In Figure 4, markups trend by independent and chain stores are compared to check how the markups have changed between 2004 and 2020. The early 2000s has shown the rising markup trend in 2015 for both independent and chain grocery stores until 2010. However, the markups have consistently decreased from 2010 to 2016, which represents the periods of growth of dollar stores and new retail chains. Then the markups increased again even though they are not bounced back.

[Figure 4 around here]

Figure 5 corroborates the previous finding by showing the markups (revenue weighted) by store size for the same period. There is a clear decreasing trend starting in 2010. Then, there has been a “rising” markup trend since 2015. However, the average markup has not been fully recovered yet as the values in the early 2000s show higher markups. This result reflects the intensified competition among retailers in downstream markets (Hirsch & Koppenberg, 2020). Additionally, if the retail market is saturated, deploying buyer power to pressure processors could result in lower upstream market costs being passed on to consumers, lowering oligopoly markups (Dobson et al., 2001; ECN, 2012). Finally, we document state-level markups trend in Figure 6-Figure 9 and county-level markups using geographical maps for the period of 2004, 2010, and 2020, which can be found in Figure 10-Figure 12. The legend indicates the average markups at the county level each year, showing that there is 28.7 percent of all counties had at least 10 percent markups in 2004. Similar findings can also be compared to Figure 5 and Figure 6-Figure 9.

[Figure 5 around here]

[Figure 10 around here]

5. Conclusion

This study estimates the firm-level markups using a richer data set of all grocery stores located nationwide over the period 2004-2020. There is a concern about the higher competition and lower margin rates in food retailing as the growth of supercenters like Walmart and Target and the emergence of online retailers like Amazon. However, there is limited evidence to understand systematic trends of markups for the grocery sector in the U.S.

This paper uses the production function approach by applying a two-step GMM technique to obtain output elasticity and recover markups afterward. Our main finding is that there is a pattern of rising markups between 2015-2020 even though the level of markups is not fully recovered as in the early 2000s. This finding suggests the intensified competition among the retailers in downstream markets that lower markups for supermarkets. Our results also show that grocery stores have 2.5 times lower markups compared to the supercenters on average. Average markups for grocery stores show 4-8 percent over marginal costs and the distribution of markup values for the low- and high-quality supermarkets under the grocery retail format exhibits positive skewness. In our production function estimates, there exists the scale effect in grocery retailing since the store's productivity increases in its size. We find that the large grocery chain stores owning more than 500 stores nationally are much more efficient at least three times higher compared to the independent grocery stores.

The contributions are twofold in this study. First, it fills a gap in the retail and production literature by providing estimated markup trends for the US food grocery sectors that have not been addressed yet. Second, this paper provides evidence of a highly competitive environment having lower markups in the food retail industry associated with high competition amongst retail chains and supercenters.

Future studies should consider exploring different datasets providing more evidence of retail markups using production or stochastic frontier analysis (SFA) with different input variables. Moreover, it is worthwhile to address current macroeconomic issues of labor shortage, inflation, and supply chain shock, which are crucial factors that affect productivity in retailing.

References

Chidmi, B., & Lopez, R. A. (2007). Brand-supermarket demand for breakfast cereals and retail competition. *American Journal of Agricultural Economics*, 89(2), 324-337.

Chenarides, L., Gomez, M. I., Richards, T. J., & Yonezawa, K. (2021). Retail Markups and Discount-Store Entry. The SC Johnson College of Business Applied Economics and Policy Working Paper Series.

Cho, Clare & W. McLaughlin, Patrick & Zeballos, Eliana & Kent, Jessica & Dicken, Chris. (2019). Capturing the Complete Food Environment with Commercial Data: A Comparison of TDLinx, ReCount, and NETS Databases. Technical Bulletins 288291, United States Department of Agriculture, Economic Research Service.

De Loecker, J., & Warzynski, F. (2012). Markups and firm-level export status. *American Economic Review*, 102(6), 2437-71.

De Loecker, J., Eeckhout, J., & Mongey, S. (2021). Quantifying market power and business dynamism in the macroeconomy (No. w28761). *National Bureau of Economic Research*.

De Loecker, J., Eeckhout, J., & Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2), 561-644.

Doraszelski, U., & Jaumandreu, J. (2019). Using cost minimization to estimate markups. Available at SSRN 3496603.

Ganapati, S. (2021). Growing oligopolies, prices, output, and productivity. *American Economic Journal: Microeconomics*, 13(3), 309-27.

Hall, R. E. (1988). The relation between price and marginal cost in US industry. *Journal of political Economy*, 96(5), 921-947.

Hirsch, S., & Koppenberg, M. (2020). Power imbalances in French food retailing: Evidence from a production function approach to estimate market power. *Economics Letters*, 194, 109387.

Lee, H., & Van Cayseele, P. (2022). Market power, markup volatility and the role of cooperatives in the food value chain: Evidence from Italy. *European Review of Agricultural Economics*

Levin, D., Noriega, D., Dicken, C., Okrent, A. M., Harding, M., & Lovenheim, M. (2018). Examining food store scanner data: A comparison of the IRI InfoScan data with other data sets, 2008–2012 (No. 1488-2019-435).

Lowrey, J., Richards, T. J., & Hamilton, S. F. (2020). Food Bank Donations and Retail Pricing. Available at SSRN 3743633.

Jafari, Y., Koppenberg, M., Hirsch, S., & Heckelei, T. (2022). Markups and export behavior: Firm-level evidence from the French food processing industry. *American Journal of Agricultural Economics*.

Keh, H. T., & Chu, S. (2003). Retail productivity and scale economies at the firm level: a DEA approach. *Omega*, 31(2), 75-82.

Koppenberg, M., & Hirsch, S. (2022). Output market power and firm characteristics in dairy processing: Evidence from three EU countries. *Journal of Agricultural Economics*, 73(2), 490-517.

Ralston, K. (2022). COVID-19 Economic Implications for Agriculture, Food, and Rural America. USDA ERS Webpage. Accessed at https://www.ers.usda.gov/covid-19/food-and-consumers/.

Table 1. Descriptive Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Output					
lnY	Revenue deflated in 1,000$	9.309	1.186	5.982	12.577
Inputs					
lnL	Number of employees	3.502	1.138	0.693	6.901
lnK	Square footage in 1,000	2.726	1.093	0.693	5.303
Time	Dummy (2004=1)	9.105	4.853	1	17
Retail configurations					
Retail formats	Dummy	4.388	1.263	1	7
Size	Dummy	5.358	4.049	1	10
Services	Number of services	1.664	1.099	0	4
Observations	540,444				

Note: Retail formats used in the sample include superette (benchmark), supermarket limited assortment, natural/gourmet foods, warehouse grocery, conventional, supercenters, and military commissary. Size (single store is a benchmark) is the number of stores operating in different location. Services provided by each establishment are the sum of the number of non-food services whether the store has wine, beer, gas station, and pharmacy.

Table 2. Production function estimation results

	(1)
Inputs	
lnL	3.873***
	(0.164)
lnK	3.996***
	(0.214)
Time	-0.009***
	(0.001)
$(\mathrm{lnL})^2$	-0.018***
	(0.003)
$(\mathrm{lnK})^2$	-0.068***
	(0.011)
lnL* lnK	-3.043***
	(0.143)
lnL*Time	-0.015***
	(0.000)
lnK*Time	0.015***
	(0.000)
Retail Configuration	
Supermarket-Limited Assortment (high)	0.427***
	(0.009)
Supermarket-Natural/Gourmet Foods (high)	0.757***
	(0.012)
Warehouse Grocery	0.395***
	(0.022)
Supermarket-Conventional	0.498***
	(0.009)
Supercenters	0.282***
	(0.015)
Military Commissary	0.715***
	(0.046)
Scope of services	0.011***
	(0.002)
Chain Economies	
Number of stores (2-3)	-0.032***
	(0.009)
Number of stores (4-5)	0.004
	(0.012)
Number of stores (6-10)	0.021**
	(0.011)
Number of stores (11-25)	0.060***
	(0.011)

Number of stores (26-50)	0.109***
	(0.012)
Number of stores (51-100)	0.162***
	(0.012)
Number of stores (101-200)	0.170***
	(0.010)
Number of stores (201-500)	0.319***
	(0.011)
Number of stores (501+)	0.328***
	(0.008)
Observations	486,102
R-squared	0.9072
Year FE	Yes
County FE	Yes

Note: Output is log of sales deflated by PPI for 6-digit NAICS code level. Benchmark for retail formats is Superette and for economies of scale is the single independent store that is not owned by stores located in other states. Standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Alternatives of input elasticity and returns to scale

Estimates	Obs	Mean	Std. Dev.	Min	Max
Input elasticities					
OLS: β_L	540,444	0.594	0	0.594	0.594
IV: β_L	540,444	0.600	0	0.600	0.600
GMM: β_L	467,704	0.662	0	0.662	0.662
OLS: β_K	540,444	0.435	0	0.435	0.435
IV: β_K	540,444	0.425	0	0.425	0.425
GMM: β_K	467,704	0.374	0	0.374	0.374
Returns to Scale					
OLS: $\beta_L + \beta_K$	540,444	1.029	0	1.029	1.029
IV: $\beta_L + \beta_K$	540,444	1.025	0	1.025	1.025
GMM: $\beta_L + \beta_K$	467,704	1.036	0	1.036	1.036

Note: The estimates are obtained from OLS, two-stage least square (2SLS), and two-stage GMM. The lag of labor is used as an instrument variable for 2SLS.

Table 4. Markups comparison by subchannel within grocery store category

Estimates	Obs	Mean	Std. Dev.	Min	Max
1 - Supermarket-Limited Assortment					
μ_{OLS}	38,743	0.042	0.021	0.008	0.402
μ_{IV}	38,743	0.042	0.021	0.008	0.398
μ_{GMM}	38,743	0.047	0.023	0.009	0.443
2 - Supermarket-Natural/Gourmet Foods					
μ_{OLS}	28,041	0.075	0.034	0.008	0.421
μ_{IV}	28,041	0.074	0.033	0.008	0.417
μ_{GMM}	28,041	0.083	0.037	0.009	0.465
3 - Warehouse Grocery					
μ_{OLS}	4,404	0.040	0.018	0.008	0.238
μ_{IV}	4,404	0.039	0.018	0.008	0.236
μ_{GMM}	4,404	0.044	0.020	0.009	0.263
4 - Superette					
μ_{OLS}	126,861	0.038	0.013	0.005	0.417
μ_{IV}	126,861	0.038	0.013	0.005	0.413
μ_{GMM}	126,861	0.042	0.015	0.006	0.460
5 - Supermarket-Conventional					
μ_{OLS}	300,259	0.065	0.026	0.005	0.595
μ_{IV}	300,259	0.064	0.026	0.005	0.589
μ_{GMM}	300,259	0.072	0.029	0.006	0.656
6 - Supercenter					
μ_{OLS}	40,336	0.147	0.044	0.009	0.581
μ_{IV}	40,336	0.145	0.044	0.009	0.575
μ_{GMM}	40,336	0.162	0.049	0.010	0.641
7 - Military Commissary					
μ_{OLS}	1,800	0.069	0.034	0.021	0.265
μ_{IV}	1,800	0.068	0.034	0.021	0.262
μ_{GMM}	1,800	0.076	0.038	0.023	0.292

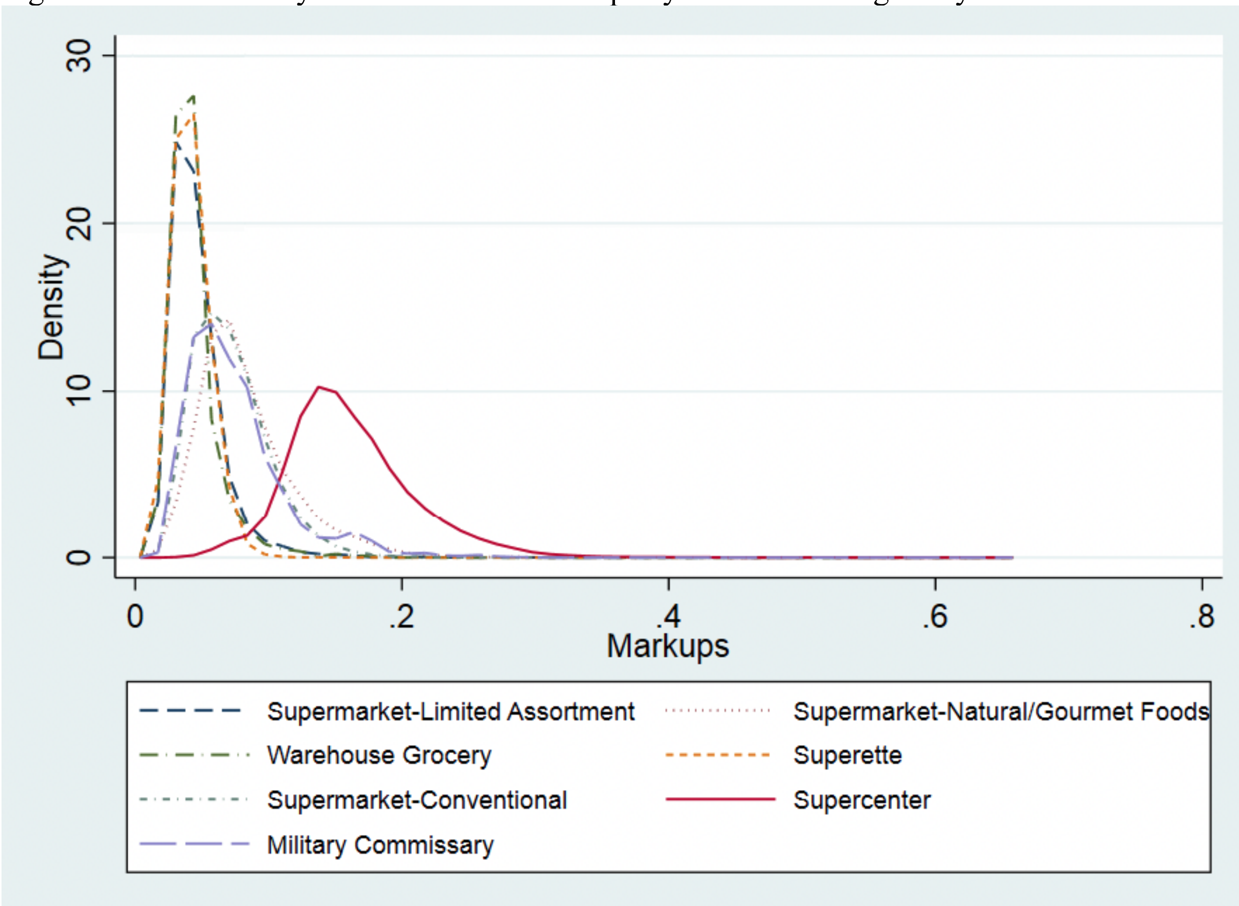
Note: All data samples are defined as grocery category including supercenters based on the TDLinx data definition. The markups are estimated in equation (3). To compare the markups at a disaggregated level within the same grocery channel, a unique store-level subchannel code is applied to identify each store type. Estimates are obtained from OLS, two-stage least square (2SLS), and two-stage GMM. The lag of labor is used as an instrument variable for 2SLS.

Table 5. Markups comparison within grocery store category

Estimates	Obs	Mean	Std. Dev.	Min	Max
Panel A					
Grocery Stores (except supercenters)					
μ_{OLS}	500,108	0.056	0.027	0.005	0.589
μ_{IV}	500,108	0.057	0.027	0.005	0.595
μ_{GMM}	500,108	0.063	0.030	0.006	0.656
Supercenters					
μ_{OLS}	40,336	0.145	0.044	0.009	0.575
μ_{IV}	40,336	0.147	0.044	0.009	0.581
μ_{GMM}	40,336	0.162	0.049	0.010	0.641
Observations	540,444				
Panel B					
Independent stores					
μ_{OLS}	196,423	0.048	0.025	0.005	0.561
μ_{IV}	196,423	0.048	0.025	0.005	0.566
μ_{GMM}	196,423	0.063	0.030	0.006	0.656
Chain stores					
μ_{OLS}	344,021	0.071	0.040	0.007	0.589
μ_{IV}	344,021	0.072	0.040	0.007	0.595
μ_{GMM}	344,021	0.080	0.044	0.008	0.656
Observations	540,444				

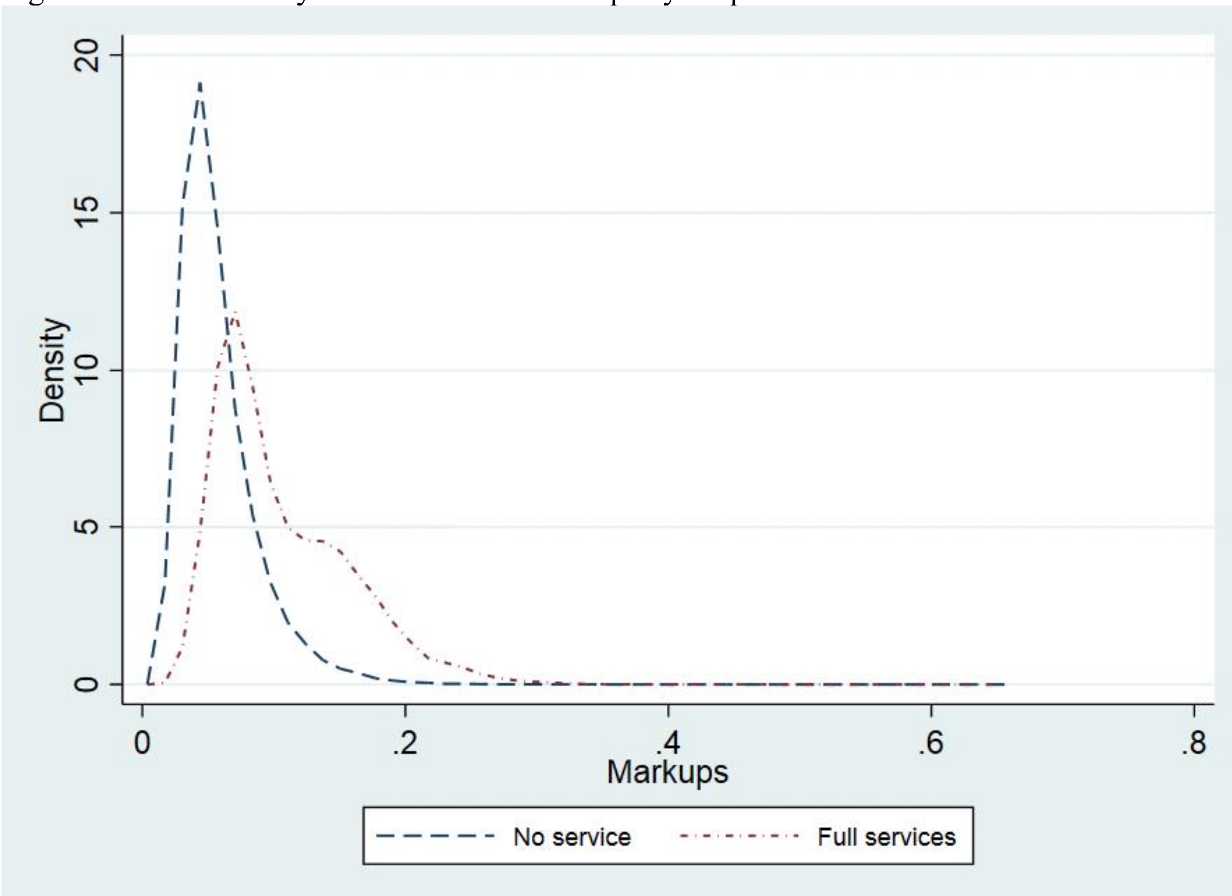
Note: All data samples are defined as grocery category including supercenters based on the TDLinx data definition. To compare the markups of supercenters with other grocery stores, a unique subchannel code is used to identify them separately. Another unique code (if the store is an independent store) is applied to identify the independent and chain stores. Estimates are obtained from OLS, two-stage least square (2SLS), and two-stage GMM. The lag of labor is used as an instrument variable for 2SLS.

Figure 1. Kernel density estimates of the markups by formats under grocery stores



Note: The density is the proportion of cases per unit of markups. The revenue weighted average markups are used from this figure to the end.

Figure 2. Kernel density estimates of the markups by scope of services



Note: The scope of services is measured in numbers from 0 to 4 at the establishment level whether the store provides non-food services (gas, pharmacy, beer, and wine).

Figure 3. Average markups (revenue weighted) trend by formats from 2004-2020

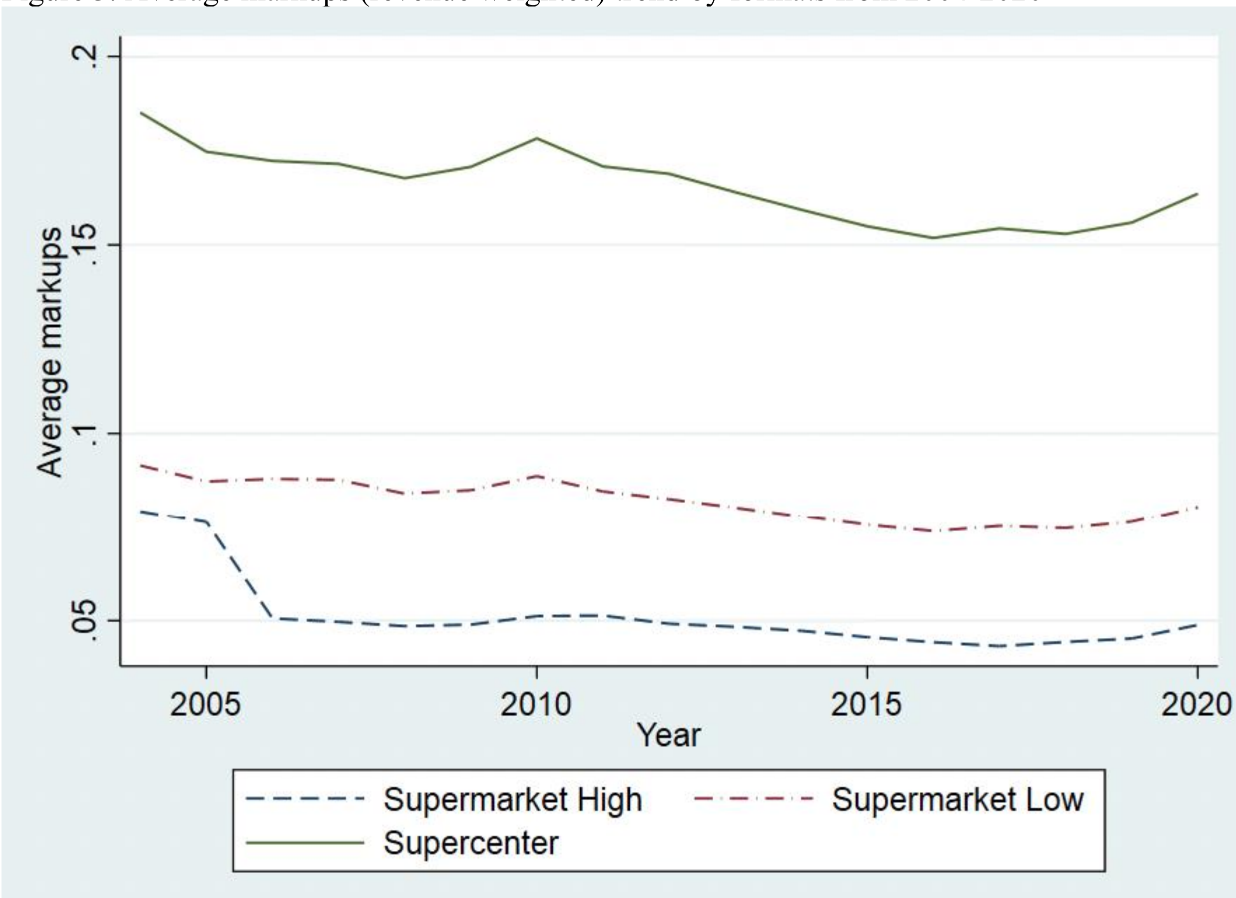


Figure 4. Average markups trend by chain from 2004-2020

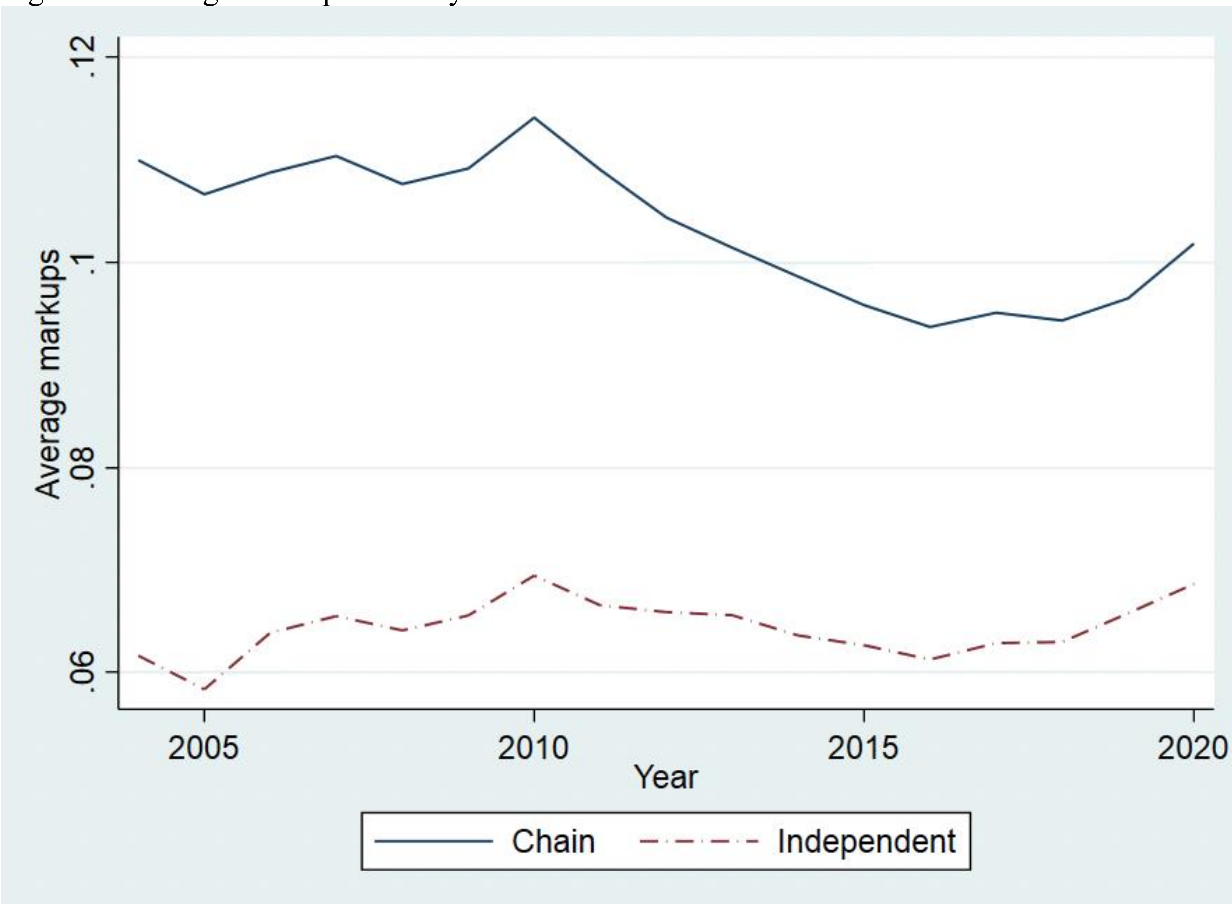


Figure 5. Average markups trend by size from 2004-2020

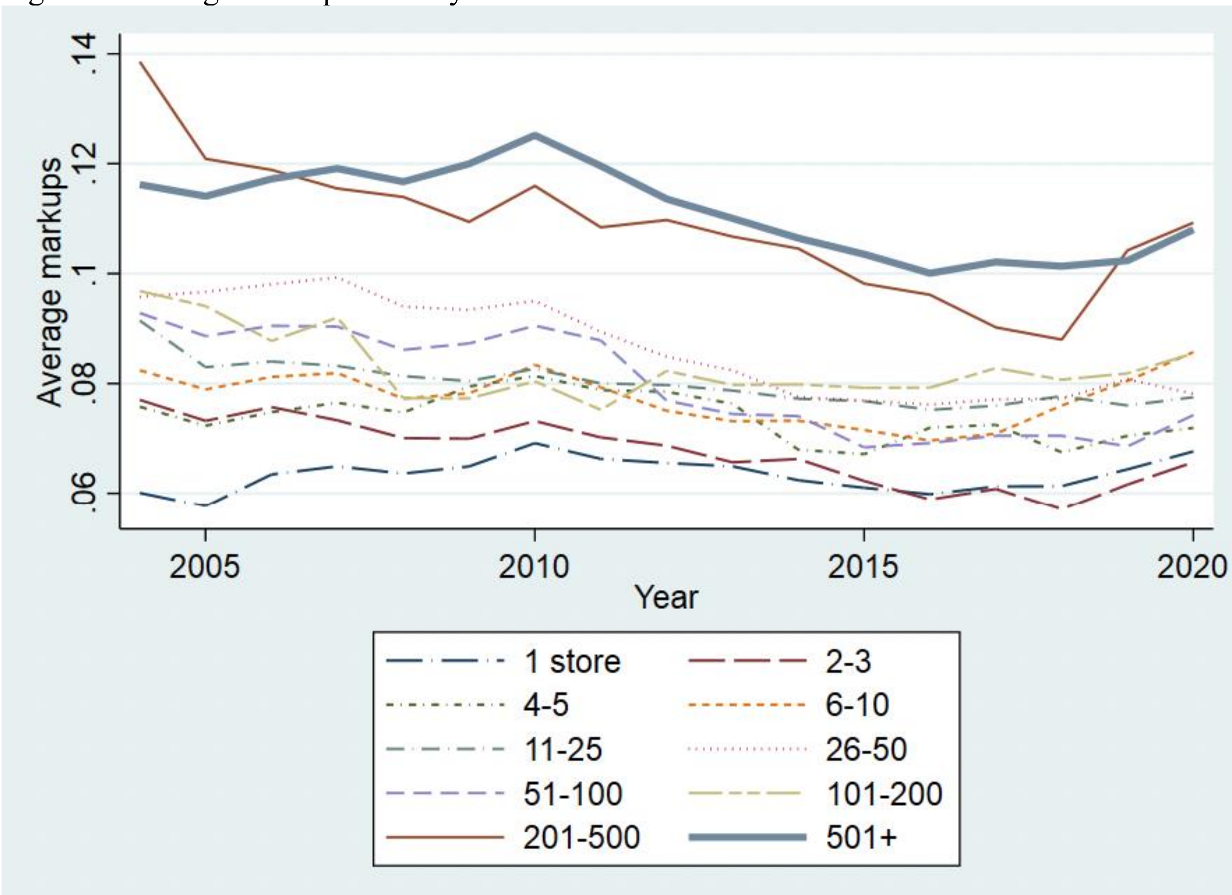


Figure 6. Average markups trend by states from 2004-2020

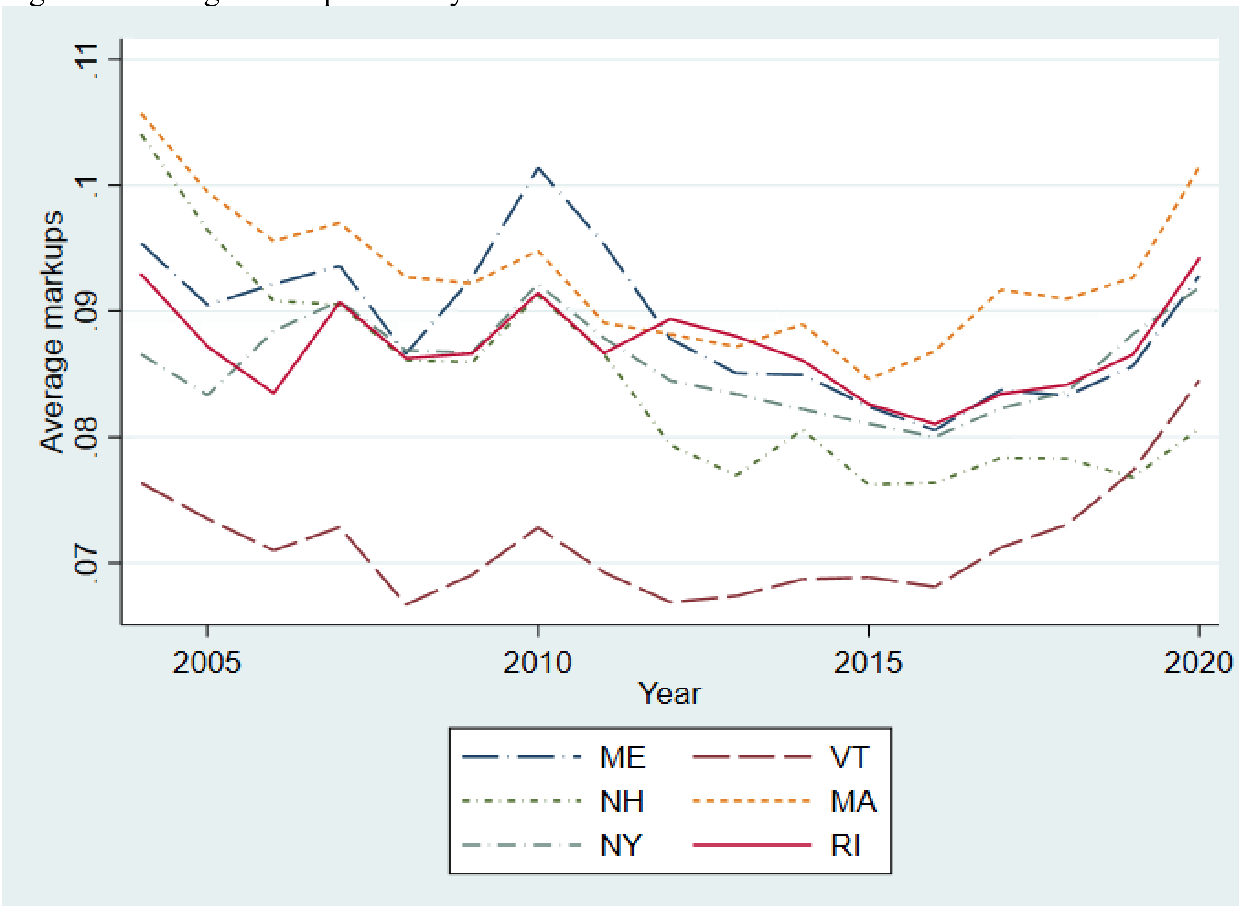
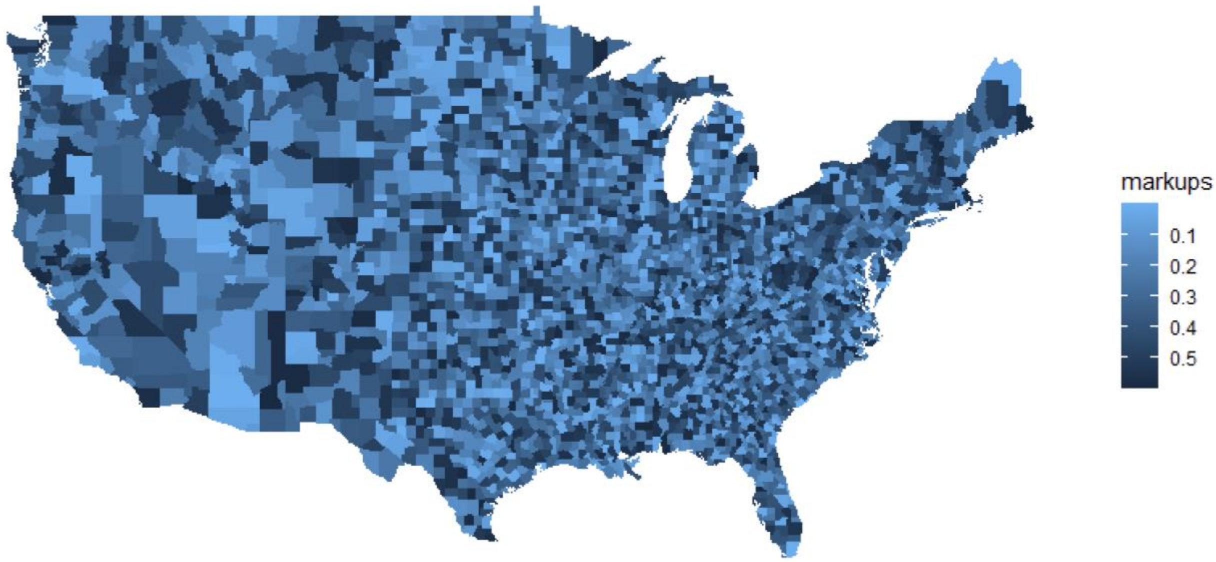


Figure 7. Average markups trend by states from 2004-2020

Figure 8. Average markups trend by states from 2004-2020

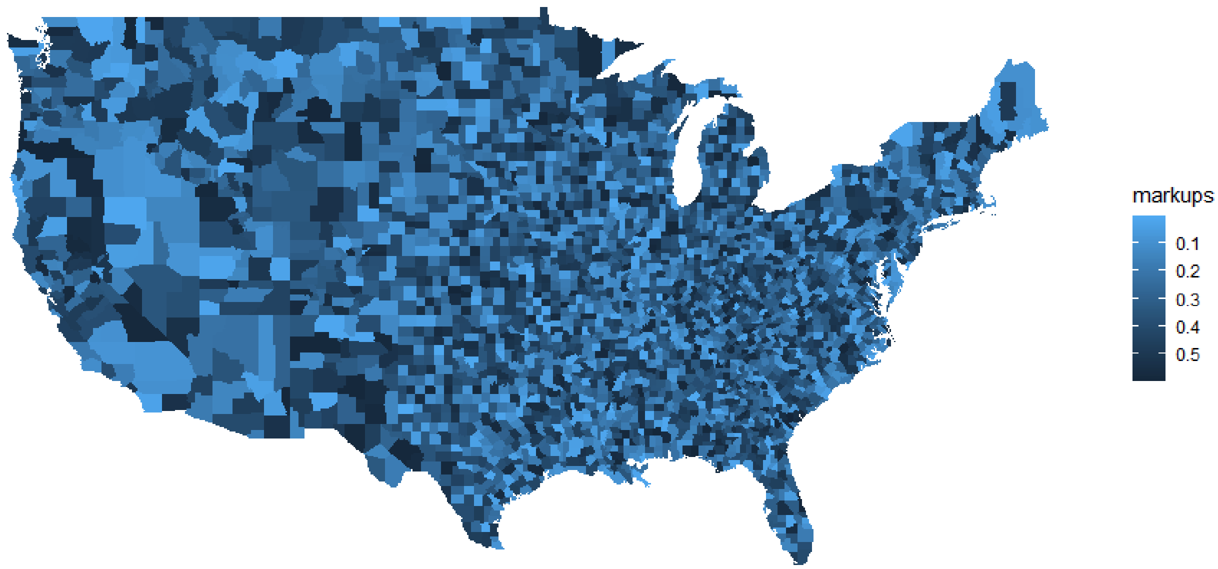
Figure 9. Average markups trend by states from 2004-2020

Figure 10. Average markups by county in 2004.



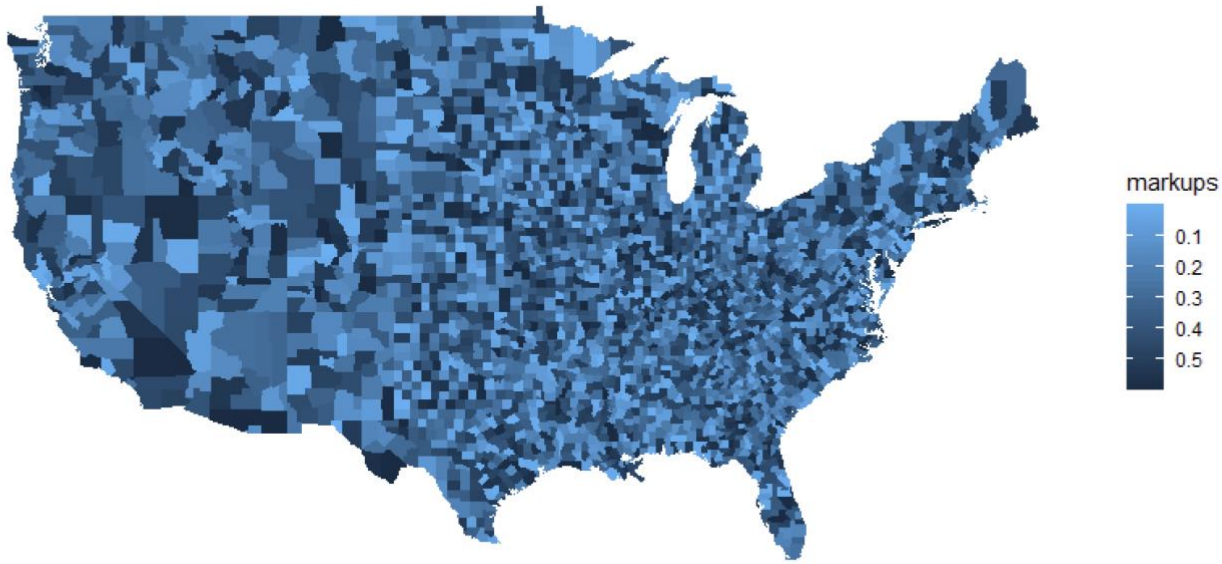
Note: There are 904 counties (28.7% of all counties) having over 10 percentage markups in 2004.

Figure 11. Average markups by county in 2010.



Note: There are 703 counties (22.3%) having over 10 percentage markups in 2010.

Figure 12. Average markups by county in 2020.



Note: There are 814 counties (25.9%) having over 10 percentage markups in 2020.

Appendix

Table A1. Labor expenditure share over revenues of grocery stores

Year	Obs	Mean	Std. Dev.	Min	Max
2004	29,907	0.108	0.065	0.010	0.669
2005	30,550	0.103	0.062	0.011	0.633
2006	30,464	0.108	0.061	0.011	0.641
2007	31,113	0.109	0.062	0.011	0.966
2008	30,874	0.107	0.060	0.010	0.862
2009	30,876	0.108	0.061	0.011	0.652
2010	31,726	0.114	0.065	0.014	0.763
2011	32,227	0.109	0.063	0.014	0.991
2012	32,498	0.107	0.064	0.014	0.914
2013	32,805	0.105	0.063	0.012	0.899
2014	32,884	0.103	0.061	0.010	0.827
2015	33,019	0.101	0.060	0.009	0.836
2016	33,124	0.099	0.058	0.009	0.855
2017	33,394	0.101	0.059	0.009	0.881
2018	32,651	0.102	0.060	0.009	0.898
2019	31,701	0.105	0.062	0.009	0.943
2020	30,631	0.111	0.065	0.011	0.929

Note: Labor expenditure share over revenues at the establishment-level is used to calculate markups in equation (3). We report annual average of the estimates.

Table A2. Markups trend for grocery stores (2004-2020)

2004	Obs	Mean	Std. Dev.	Min	Max
μ_{OLS}	29,907	0.064	0.039	0.006	0.398
μ_{IV}	29,907	0.065	0.039	0.006	0.402
μ_{GMM}	29,907	0.071	0.043	0.007	0.443
2005					
μ_{OLS}	30,550	0.061	0.037	0.006	0.376
μ_{IV}	30,550	0.062	0.037	0.006	0.380
μ_{GMM}	30,550	0.068	0.041	0.007	0.419
2006					
μ_{OLS}	30,464	0.064	0.036	0.007	0.381
μ_{IV}	30,464	0.065	0.037	0.007	0.385
μ_{GMM}	30,464	0.071	0.040	0.008	0.424
2007					
μ_{OLS}	31,113	0.065	0.037	0.006	0.574
μ_{IV}	31,113	0.066	0.037	0.006	0.580
μ_{GMM}	31,113	0.072	0.041	0.007	0.640
2008					
μ_{OLS}	30,874	0.063	0.036	0.006	0.512
μ_{IV}	30,874	0.064	0.036	0.006	0.517
μ_{GMM}	30,874	0.071	0.040	0.006	0.571
2009					
μ_{OLS}	30,876	0.064	0.036	0.006	0.387
μ_{IV}	30,876	0.065	0.036	0.006	0.391
μ_{GMM}	30,876	0.072	0.040	0.007	0.431
2010					
μ_{OLS}	31,726	0.067	0.039	0.009	0.453
μ_{IV}	31,726	0.068	0.039	0.009	0.458
μ_{GMM}	31,726	0.075	0.043	0.009	0.505
2011					
μ_{OLS}	32,227	0.065	0.037	0.008	0.589
μ_{IV}	32,227	0.066	0.038	0.008	0.595
μ_{GMM}	32,227	0.072	0.042	0.009	0.656
2012					
μ_{OLS}	32,498	0.064	0.038	0.008	0.543
μ_{IV}	32,498	0.064	0.038	0.008	0.549
μ_{GMM}	32,498	0.071	0.042	0.009	0.605

2013					
μ_{OLS}	32,805	0.062	0.037	0.007	0.534
μ_{IV}	32,805	0.063	0.038	0.007	0.540
μ_{GMM}	32,805	0.070	0.042	0.008	0.595
2014					
μ_{OLS}	32,884	0.061	0.036	0.006	0.491
μ_{IV}	32,884	0.062	0.036	0.006	0.496
μ_{GMM}	32,884	0.068	0.040	0.007	0.547
2015					
μ_{OLS}	33,019	0.060	0.035	0.005	0.497
μ_{IV}	33,019	0.061	0.036	0.005	0.502
μ_{GMM}	33,019	0.067	0.040	0.006	0.554
2016					
μ_{OLS}	33,124	0.059	0.035	0.005	0.508
μ_{IV}	33,124	0.059	0.035	0.005	0.513
μ_{GMM}	33,124	0.065	0.039	0.006	0.566
2017					
μ_{OLS}	33,394	0.060	0.035	0.005	0.524
μ_{IV}	33,394	0.061	0.036	0.005	0.529
μ_{GMM}	33,394	0.067	0.039	0.006	0.584
2018					
μ_{OLS}	32,651	0.060	0.036	0.005	0.534
μ_{IV}	32,651	0.061	0.036	0.005	0.539
μ_{GMM}	32,651	0.067	0.040	0.006	0.595
2019					
μ_{OLS}	31,701	0.062	0.037	0.005	0.561
μ_{IV}	31,701	0.063	0.037	0.005	0.566
μ_{GMM}	31,701	0.069	0.041	0.006	0.625
2020					
μ_{OLS}	30,631	0.066	0.039	0.006	0.552
μ_{IV}	30,631	0.067	0.039	0.007	0.558
μ_{GMM}	30,631	0.074	0.043	0.007	0.615

Note: Annual average markups are calculated, and the average is weighted by revenues.