Labor Market Power in Food Retailing*

Ujjwol Paudel†

December 28, 2024

Job Market Paper

[Click here for the latest version]

Abstract

I study the extent and evolution of labor market power in the US food retailing sector by estimating the wedge between workers' marginal productivity and wage. Using data on American food retailers for the period 2004-2022, I first examine how concentration in labor markets moderates effects of county minimum wages on individual store's employment. On two proxies of labor market concentration—population density and number of establishments—I find that highly concentrated markets have more positive employment effects from minimum wages. Based on this model-free result, I hypothesize that labor oligopsony power enables food retailers in concentrated markets to maintain greater productivity-wage gaps, allowing them to absorb minimum wage increases by sacrificing some surplus while still expanding employment. To test this hypothesis, I implement a production function estimation strategy from industrial organization literature which lets me estimate the labor markdowns or wage-productivity gaps, and understand how they differ by concentration levels. I find that the mean markdown is 1.37, meaning that food retail workers get \$0.73 for every \$1 generated on the margin. At the industry-year level, I document that mean markdowns are falling over time which suggests that labor markets are getting competitive over the years. Using two different instrumental variables, I find that a 10% increase in labor market concentration levels leads to a 6–11% increase in labor markdowns. This implies that employers in markets with higher labor concentration have higher labor market power and suppress workers' wages further below their marginal productivity. I then examine how this markdown-measure of market power varies along worker, firm, and market characteristics.

Keywords: monopsony, markdowns, minimum wages, food retail

JEL: D43, L4, L5, M2

*I am grateful to my advisor Timothy J. Richards for his invaluable guidance and encouragement. Thank you to Stephen H. Hamilton and Nicholas Vreugdenhil for their helpful comments and suggestions. All errors are mine. *The author(s) declare no financial relationships, research support, or conflicts of interest related to this research. The views expressed herein are those of the author(s).*

†Arizona State University. Email: upaudel1@asu.edu.

1 Introduction

There is a growing literature that studies causes and consequences of imperfect competition in labor markets, particularly those with many lower-skilled, lower-paid employees. Some show that rising monopsony power accounts for decline in labor's share of income (Karabarbounis and Neiman (2013)), wage stagnation and rising wage inequality (Deb et al. (2022); Deb et al. (2023)), and an income redistribution away from rural households (Rubens (2023)). On the other hand, there is also an extensive evidence for a rise in sales-concentration- and markups-based measures of market power in the US retail sector (De Loecker, Eeckhout, and Unger (2020); Smith and Ocampo (2021); MacDonald, Dong, and Fuglie (2023); Miller (2024)), and a small literature examines how this increase in sales-concentration from mergers impacts labor market outcomes (Prager and Schmitt (2021); Arnold (2021)). In 2021, President Biden issued an executive order to expand antitrust laws to include labor market outcomes on an assumption of increased labor monopsony power from rising consolidation in retail and in other sectors (The White House (2021)).[1] As a result, understanding the channels and dynamics of employer market power remains key from welfare standpoint. In this paper, I study one channel of labor market power and estimate and characterize the labor markdowns in the US food retail sector.

Studying monopsony power in US food retailing is important for at least four reasons. First, there are thousands of store-level merger and acquisitions (henceforth, mergers) every year in my sample period 2004-2022 (Figure 1). Mergers serve as quasi-experimental shocks, altering market structures by elevating market concentration as measured by the Herfindahl–Hirschman Index (HHI), and potentially lead to increased monopsony power across US local markets (Arnold (2021)). Second, the aggregate retail sector, which includes food and beverage retailers, employs about 10 percent of the US workforce (which amounted to 15.5 million employees in October, 2023) according to Bureau of Labor Statistics (2023), so labor

[1] Keeping with the 2021 Excecutive Order (The White House (2021)), Federal Trade Commission announced a complete ban on noncompete clauses in April 2024 to foster workers' job-to-job mobility, increase wages, and promote competitiveness in labor markets (Federal Trade Commission (2024a)).

markdowns can affect a sizeable portion of the country's population.[2] Third, in contrast to other sectors of the economy, fully 25% of employees in the food retailing sector earn at or near the minimum wage, so are more likely to be subject to the exercise of employer market power than workers in other industries. [3] Fourth, very little of the existing literature on labor monopsony power addresses workers in food retailing, despite growing concerns about rising retail concentration and market power (Smith and Ocampo (2021); Claire Kelloway (2022)) coupled with unequal retail wage growth (Hortaçsu and Syverson (2015)).

I define a firm's labor monopsony power or simply labor market power as the ratio of its marginal revenue product of labor and its wage (Manning (2003); Yeh, Macaluso, and Hershbein (2022); Azar and Marinescu (2024)). In a perfectly competitive market, this wage-productivity markdown ratio is 1, and the firm's labor supply is perfectly elastic. Absent enough competition amongst the employers, the dominant ones can leverage buyer power in the labor market as workers have heterogeneous preferences for non-wage amenities (like commuting distance or paid time-off) or have frictions to move between jobs. As workers cannot easily exercise their outside options due to market imperfections, the firms tend to pay wages less than the workers' marginal productivity. Hence, firms face upward sloping labor supply curve, and higher monopsony power reflects as lower wages and higher markdowns (Manning (2003); Manning (2021a); Card (2022)).

My analysis of labor market power proceeds in three steps. First, I examine employment impacts of minimum wage as it provides a critical lens through which to study labor market power, particularly in industries characterized by high employer concentration. A body of evidence on this topic (Card and Krueger (1993); Okudaira, Takizawa, and Yamanouchi (2019); Azar et al. (2024)) suggests that degree of labor market concentration shapes the employment effects of minimum wage increases: in highly concentrated markets where firms can possess significant oligopsony power, increases in minimum wage can lead

[2] According to Textkernel's Jobfeed data from https://www.textkernel.com/jobfeed/us-retail-data-2022/, nearly 7.5 million workers (half of the retail workforce) resigned in 2021, attributing to factors such as low pay, unfavorable working conditions, among others.

[3] Author's calculation based on 2023 data from https://usa.ipums.org/usa/intro.shtml.

to more positive employment outcomes. This occurs because firms in such markets can maintain large productivity-wage gaps, enabling them to absorb higher wage floors without reducing employment and, in some cases, even expanding it. By analyzing how labor market concentration moderates minimum wage effects on employment, I can assess both the extent to which firms can exercise monopsony power and how closely labor market concentration is tied to the actual exercise of that power.

On two proxies of labor market concentration—inverse of total number of county establishments in food retailing sector, and inverse of county population density—I find increasing minimum wages on concentrated labor markets have either null or positive effects on employment at individual stores.[4][5] To this end, I use multiple specifications (with and without fixed effects, controls, and trend variables) to regress log store employment on interaction of log county minimum wage and county-level concentration measure. For every 10% rise in minimum wage in more concentrated market, I find 0.8% to 11% increase in store employment across different specifications. As a placebo test, I use a threshold of HHI < 0.1, following FTC's 2023 Merger Guidelines for unconcentrated markets (Federal Trade Commission (2023)), and find store employment falls when minimum wage increases in such labor markets. Both these results involving null or positive and negative employment effects in concentrated and unconcentrated markets, respectively, are consistent with a hypothesis that firms in concentrated labor markets have market power over workers and are able to supress wages below their marginal productivity (Manning (2021a); Manning (2021b); Azar et al. (2024); Azar and Marinescu (2024)).

In the second step of my analysis, I test whether firms in concentrated labor markets use monopsony power to suppress wages by estimating the labor markdowns, gaps between

[4] Azar et al. (2024) highlight that the two proxies—inverse of the total number of county establishments in the food retailing sector and inverse of county population density—make sense as they effectively capture different dimensions of labor market concentration, a key determinant of monopsony power. The inverse of the number of establishments measures the degree to which hiring opportunities are dominated by fewer employers in a given market, directly reflecting employer concentration. Meanwhile, inverse population density serves as a broader proxy for geographic isolation and limited competition for workers, as less densely populated areas tend to have fewer employers per worker, amplifying monopsony power.

[5] I use Vaghul and Zipperer (2022) to get data on county-level minimum wages from 2004-2022.

workers' wages and their marginal productivity. To this end, I build and estimate a structural model based on the production function estimation approach from the industrial organization (IO) literature (De Loecker and Warzynski (2012); Card (2022); Lamadon, Mogstad, and Setzler (2022)). Under no assumption about a firm's labor supply curve, the wedge between output elasticity and revenue share of labor gives the firm's aggregate market power on the product markets (markups) and on the labor markets (markdowns) (Hall (1988); Yeh, Macaluso, and Hershbein (2022); Rubens (2023)). To separately identify and estimate markups and markdowns, I follow rest of the IO literature and assume the retailers have at least one additional input which is *flexible*, that is without monopsony power and adjustment costs (Yeh, Macaluso, and Hershbein (2022); Rubens (2023)). I use *cost-of-goods-sold* variable as a flexible input. As I show in the empirical section, the assumptions on flexibility of this input are fundamental for identification but are reasonable and let me disentangle markdowns (labor market power) from markups (product market power).

I estimate the production function model by combining multiple data sources of retailers and workers in the US food retailing industry for the period 2004-2022.[6] The primary data on food retailers comes from NielsenIQ's TDLinx. In the dataset, I observe store level information on its identification code, store type, location, size, grocery channel, parental code, age, sales revenue, number of checkout registers, and full-time employment. Similar to Arnold (2021), I define merger activity to affect a store if its individual code does not change from year $t-1$ to t, but its parental code does change reflecting new store ownership. In my production function, CPI-deflated sales revenue, checkouts, and employment enter as output, capital, and labor variables, respectively. For the cost-of-goods-sold (COGS) variable, I first calculate the COGS share of revenue using Compustat's COGS and total revenue variables. I then use this share to impute COGS values for each store in the TDLinx dataset.[7] I

[6]This version of the paper has analysis for the period 2004-2019; I am currently augmenting 3 years of additional data.

[7]By imputing store-level COGS values in this way, I am making two assumptions. First, I assume that the COGS-to-revenue ratio is proportional and applies uniformly across all stores within the same retail chain. Second, I assume that individual stores in TDLinx share similar cost structures to their headquarters in Compustat, ignoring potential differences like size or location. To support my first assumption, I argue that

use store's county location to find its commuting zone, which together with county forms geographic units in my labor market definition.[8] My next data source, The Quarterly Census of Employment and Wages (QCEW), contains industry-county-level information on wages and total number of grocery establishments.[9] The final data source, US Census Bureau, has information on county-level population, income, unemployment rate, and area in square miles, which I use as control variables in my regressions and for heterogeneity analysis of markdown estimates.

I find significant labor market dynamics in the food retailing sector, with a mean markdown estimate of 1.37 (SE = 0.60) in my preferred production function specification. This implies that workers receive \$0.73 in wages for every dollar generated at the margin, which is approximately 27% below their competitive wage. Heterogeneity analysis reveals that grocery store workers face a higher markdown of 1.4, while those in mass merchandisers earn near-competitive wages, which likely reflects structural differences in labor market power across store types. Additionally, older firms exhibit higher markdowns, and thus greater monopsony power or entrenched wage-setting practices. At the aggregate year-industry level, I document that markdowns rose between 2005 and 2007 but have steadily declined since 2007, thus pointing to competitive labor market conditions over time.

In the third and final step of my analysis, I relate the markdowns with labor market concentration defined in terms of inverse establishment count at the county level. I recognize the potential endogeneity of labor market concentration, where factors such as wages, labor demand, or supply may simultaneously influence and be influenced by concentration (Berry, Gaynor, and Scott-Morton (2019); Miller et al. (2022)).[10] To remedy this endogeneity, I

food retailers often operate on slim and consistent margins due to standardized pricing and procurement practices, making the COGS-to-revenue ratio relatively stable across firms and stores. I base my second assumption on the fact that food retailing is characterized by uniform product categories (e.g., groceries), centralized supply chains, and economies of scale, which reduce variability in cost structures across stores within the same chain.

[8] I link county FIPS code with its corresponing commuting-zone (CZ) using the county-CZ cross-walk file available at: https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/.

[9] The Quarterly Census of Employment and Wages (QCEW) data is publicly available at https://www.bls.gov/cew/.

[10] See Berry, Gaynor, and Scott-Morton (2019) and Miller et al. (2022) for a critique of the structure-

employ two instrumental variable (IV) strategies. For each of the two IVs, I regress log store markdown with log county HHI using a set of county fixed effects and control variables. Using leave-one-out-IV (LOOIV), which I define as the inverse of total employers in all counties except the focal one, I find that 10% increase in HHI leads to 6-11% increase in markdowns. I supplement this IV-result with a shift-share-IV (SSIV) defined as follows. First, I identify the national-level trend in food retail mergers (*shift*) and calculate each county's pre-existing exposure to this trend (*share*) using the local share of establishments or employers in the food retail industry from QCEW data. I then construct the SSIV by multiplying the national merger trend by each county's share, creating an instrument that captures exogenous variation in local labor market concentration to address endogeneity when estimating its impact on markdowns. Using SSIV, I find 10% increase in HHI leads to about 10% increase in markdowns. In sum, I conclude that higher labor market concentration is tied to higher labor market power, which enables firms to absorb minimum wage increases and to still expand employment.

Contributions This paper makes four main contributions. First, I contribute to the literature on the interaction between minimum wages and labor market concentration by analyzing how county-level minimum wages affect store employment in the U.S. food retail sector. My findings—null or positive employment effects in concentrated markets and negative effects in unconcentrated markets—align with prior studies on minimum wage impacts (Card and Krueger (1993); Giuliano (2013); Okudaira, Takizawa, and Yamanouchi (2019); Cengiz et al. (2019); Azar et al. (2024)). However, my paper extends this literature in important ways. Most closely related to Azar et al. (2024), which also examines monopsony power and minimum wages, I expand the scope by focusing specifically on publicly traded food retailers rather than limiting the analysis to General Merchandise stores. Additionally, I consider a longer time horizon (2004–2022) to capture long-term trends and structural

conduct-performance (SCP) paradigm for its reliance on simplistic correlations between market structure and performance while neglecting the endogeneity of concentration. The central idea is that failing to account for the endogenous relationship between concentration and outcomes like wages can lead to biased estimates, since changes in labor demand or supply may simultaneously influence both wages and market concentration.

shifts in labor markets that prior studies with shorter timeframes may overlook. Methodologically, while most of current studies and even my existing empirical approach about minimum wage impacts rely on two-way fixed effects regressions, I address the growing concerns about their limitations (Goodman-Bacon (2021); Callaway and Sant'Anna (2021)) by employing a heterogeneity-robust difference-in-differences framework in an ongoing work. Specifically, I adopt stacked DiD approach developed by Cengiz et al. (2019) and DiD approach of de Chaisemartin and D'Haultfœuille (2024), both of which allow for more flexible modeling of treatment effect heterogeneity over time.

The second contribution is to the literature on labor monoposony power. The idea that firms have wage-setting power dates back to Robinson (1933) and is now well-established (Manning (2003); Manning (2011); Dube et al. (2018); Card et al. (2021); Card (2022); Yeh, Macaluso, and Hershbein (2022); Berger, Herkenhoff, and Mongey (2022); Azar, Berry, and Marinescu (2022); Kroft et al. (2022); Deb et al. (2023); Azar and Marinescu (2024)). While all of these papers all agree on existence of non-zero wage-productivity wedge in different sectors of the US economy, none focuses on quantifying the markdowns specifically in the US food retail. Insights from prior analyses of labor monopsony power in other industries might not hold in the food retailing given substantial rise in retail concentration and usage of minimum wage workers in the industry. This is the focus of my work as I estimate the extent and evolution of labor market power in the US food retailing industry. In addition, I also relate the exercise of labor market power (measured as markdowns) with the potential for market power (measured as concentration) by using two instrumental variables, addressing endogeneity of concentration.

Third, my paper contributes to the IO literature on production function estimation approach. My methodology of estimating retail labor markdowns follows the production function approach developed in Hall (1988), De Loecker (2011) and De Loecker and Warzynski (2012), and leverages the econometrics of 'proxy-variable' production function estimation strategy in Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves,

and Frazer (2015). Some of the papers using this approach to estimate markdowns focus on US manufacturing (Yeh, Macaluso, and Hershbein (2022)), Chinese tobacco industry (Rubens (2023)), and Indian manufacturing (Brooks et al. (2021)), and find economically and statistically significant exercise of monopsony power on inputs such as labor. Others use this approach to quantify markups in international trade (De Loecker and Warzynski (2012)), manufacturing industries (Demirer (2022); Raval (2023)), publicly traded US firms (Traina (2018); De Loecker, Eeckhout, and Unger (2020)), and US retail food stores (Chenarides et al. (2023)). This paper focuses on labor markdowns in the US food retail and illustrates a strategy to infer markdowns in an industry which relies heavily on minimum wage workers and raw materials.

Finally, my paper relates to U.S. antitrust policies by highlighting how labor market concentration in the food retail sector exacerbates wage suppression and employment distortions, and adding to the broader discussion on the role of monopsony power in labor markets. These findings align with President Biden's 2021 Executive Order on Promoting Competition, which emphasizes addressing employer concentration to protect workers from suppressed wages and reduced job mobility (The White House (2021)). They also complement the Federal Trade Commission's (FTC) recent challenge to the Kroger-Albertsons proposed merger, where FTC argued that such consolidation would harm not only consumers but also workers by diminishing competition for labor and worsening wages (Federal Trade Commission (2024b)). By documenting how concentrated labor markets allow employers to suppress wages below workers' marginal productivity, my research underscores the importance of incorporating monopsonistic effects into antitrust enforcement, as advocated by recent studies (Marinescu and Hovenkamp (2019); Naidu and Posner (2022)).

Layout The rest of the paper proceeds as follows. Section 2 describes the data and model-free evidence on how labor market concentration moderates minimum wage effects on employment. Section 3 presents the model and discusses identification and estimation strategies. Section 4 discusses markdown estimates. Finally, section 5 concludes.

2 Data and Descriptive Evidence

In this section, I provide details on data and reduced-form evidence on how labor market concentration moderates employment effects of county minimum wages. This forms the first step in my analysis of labor market power. The central question I address in this step is whether increasing minimum wages in concentrated labor markets increases employment; if it does, it gives a suggestive evidence for the presence of labor market power (or labor markdowns) in concentrated markets.

2.1 Data and Summary Statistics

The analysis uses six datasets and spans years 2004-2022.[11] I discuss each of them in detail below and only briefly mention their purpose here. First, I use NielsenIQ's TDLinx, a store-level dataset on US retailers in the food industry. I use this data for inputs and output variables in my production function, and to create merger counts and labor market concentration levels. I also use store employment data in my reduced-form analysis of minimum wage impacts. Second, I use Computstat data on grocery firms to get information on cost-of-goods-sold, which forms a key input in the production function. The third dataset is Consumer Price Index (PPI) data available from the US Bureau of Labor Statistics (BLS), which I use to deflate reveneue measures. Fourth, data on labor market variables—wages, employment, and establishment counts—are from the Quarterly Census of Employment and Wages (QCEW) of the US BLS. Fifth, I use the US Census Bureau to get data on county income, population, and unemployment rate. This serves two purposes: (1) as control variables in regressions; (2) to do heterogeneity analysis of markdowns along labor market characteristics. Last, data on county minimum wages comes from Vaghul and Zipperer (2022).

[11] This version of the paper has analysis for the period 2004-2019; I am currently augmenting 3 years of additional data.

2.1.1 NielsenIQ's TDLinx Data

First, I use the NielsenIQ's TDLinx data which contains information on a near universe of 5 types of food retail stores: convenience, drug, mass merchandiser, grocery, and wholesale club (Cho et al. (2019)).[12] In the dataset, I observe store's unique identification number, banner name, location, parent or owner code, number of stores under the same parent, weekly sales in dollars, area of selling space, number of full time employees, number of checkout registers, and indicators for whether store sells gasoline, pharmacy, liquor, wine and beer.

I follow Arnold (2021) and define that merger and acquisition (or simply, merger) occurs at a store at time t when it changes its parental code but not its individual ID from previous time period $t-1$. Based on this definition, store's parent code sometimes also change when it becomes an independent store (with parent code 99999), which likely reflects the sale of the store, so I do not include such a case as a merger event. In addition, this approach of merger identification doesn't classify buyer chain stores as affected by mergers since their ownership code doesn't change.[13] So the number of merger events at any time is the number of all stores, *not chains*, impacted by mergers. Figure 1 shows the evolution of the number of these consolidation events during the sample period 2004-2019. The existence of a large number of store-level merger events each year suggests that labor market concentration might be rising over time, potential raising labor monopsony power and reduced wage growth (Hortaçsu and Syverson (2015); Arnold (2021)). I test both these hypotheses through the lens of minimum wages.

Of all variables in TDLinx, 3 are key to my analysis: store employment, number of checkouts, and sales revenue. The first two are labor and capital variables, and revenue deflated by annual Consumer Price Index (from the US Bureau of Labor Statistics) forms

[12] TDLinx data is proprietary, and I access it through the Administrative Data Research Facility (ADRF) which is a secured data-access portal operated by the Coleridge Initiative: https://coleridgeinitiative.org/administrative-data-research-facility.

[13] Family code only changes in the TDLinx for the 'acquired' stores, not 'acquiring' stores. For instance, in the Albertsons-Safeway merger in 2015, family code for Albertsons did not change, but it changed for Safeway. So in our merger definition, Safeway stores have merger activity in 2015, but Albertsons stores do not.

'output' variable in the production function. I also use labor variable in my analysis of how labor market concentration moderates minimum wage impacts on store employment. I use store age, location, NAICS code, channel category, and identification codes in analysis of markdown heterogeneity by store and market attributes. Finally, the merger variable forms the core of one of my instrumental variables, shift-share IV, in analysis of markdowns by labor market concentration.

2.1.2 Compustat

The second dataset is Annual Compustat file from Wharton Research Data Services, which provides comprehensive firm-level financial information for publicly traded US firms, in my case food retailers.[14] From this data, I use two variables: cost-of-goods-sold (COGS) and total revenue. Specifically, I use these variables to calculate COGS-to-revenue ratios, with which I then impute store-level COGS values in the TDLinx dataset. Before imputing store-level COGS values, I calculate real measures by deflating store-level sales revenue by annual Consumer Price Index (CPI) from the US Bureau of Labor Statistics.

Two key assumptions underpin my COGS imputation methodology. First, I assume the COGS-to-revenue ratio remains proportional and uniform across all stores within the same retail chain. Second, I assume individual stores in TDLinx to share similar cost structures with their Compustat headquarters, regardless of size or location differences. I argue that the nature of food retail operations supports these assumptions—standardized pricing and procurement practices create slim and consistent margins throughout the stores within the same chain. Additionally, uniform product categories, centralized supply chains, and economies of scale create relatively stable cost structures across stores within the same chain.

Figure 2 shows cost of goods sold (COGS) as a share of total revenue for US food retailers. The graph illustrates variation over time, with a notable peak around 2012-2013 at approximately 76%. In my analysis of markdown estimates, I exploit both this time-series variation and cross-sectional variation (60% to 87%) within chains.

[14] I access Compustat data through https://wrds-www.wharton.upenn.edu.

2.1.3 Quarterly Census of Employment and Wages (QCEW) Data

QCEW data, published by the Bureau of Labor Statistics (BLS), contains detailed quarterly employment and wage information reported by employers and covers over 95 percent of US jobs at county, metropolitan statistical area (MSA), state, and NAICS-classified industry levels. For this study, I use county and MSA level quarterly data on wages, employment, and establishment count for NAICS = 445, which contains the industries in the Food and Beverage Stores subsector within the larger retail sector.

I use number of establishment count from the QCEW data to define a measure of county concentration. Specifically, I follow Azar et al. (2024) and define county HHI_{est} to be inverse of the establishment county in the NAICS = 445 sector. As a result, I get $\text{HHI}_{\text{est}} \in (0, 1]$, where a number closer to 1 (0) reflects higher (lower) concentration or fewer (higher) number of employers in the market. I also use this measure to create two additional binary indicators for concentration: $\chi(\text{HHI}_{\text{est}} \geq 0.18)$ and $\chi(\text{HHI}_{\text{est}} < 0.1)$. The first indicator equals 1 if county's HHI is at least 0.18, and 0 otherwise. Similarly, the second indicator equals 1 if county's HHI is less than 0.1, and 0 otherwise. The thresholds 0.18 and 0.1 are from the FTC 2023 Merger Guidelines for highly concentrated and unconcentrated markets, respectively (Federal Trade Commission (2023)).

I plot across-county variation in labor market concentration (HHI_{est}) in Figures 6 and 7. I report two US maps in Figure 6 for two years 2005 and 2019. In both the years, several counties have high concentration levels as indicated by the dark red color, but there is variation in concentration across counties. Figure 7 plots intensity of concentration changes between 2005 and 2019. The figure shows substantial geographic variation in labor market concentration changes across counties during 2005-2019. Although my final data covers approximately one-third of US counties, the spatial and temporal heterogeneity within those markets provide a natural experiment setting for identifying how local market concentration moderates the employment effects of county-level minimum wage policies in the food retail sector.

Figures 3 and 4 show simple relationship of county concentration HHI_{est} (measured as inverse establishments count) with county wages (measured in dollars per worker per week) and county employment (measured as sum of store employment within the county) in the US food retail sector. Figure 3 reveals a negative relationship with a slope coefficient of -150.12 (SE = 53.45). Most data points cluster around lower concentration levels (0.0-0.1) with weekly wages ranging from $300 to $700 per worker. As concentration increases, there is a clear downward trend in wages, suggesting that workers in more concentrated markets tend to earn lower wages. Similarly, Figure 4 shows a slightly positive relationship of concentration with store employment with a slope coefficient of 125.20 (SE = 63.41). The gray shaded areas around the fitted black line represents the 95% confidence interval. Due to inherent endogeneity of market concentration, I interpret the graphical results as only correlation and not causal. However, observations from both graphs are consistent with hypotheses that higher concentration is associated with higher labor market power (that is, greater markdowns), lower wages, and more positive employment effects from minimum wages. I make these correlations more precise in my reduced-form analysis below.

2.1.4 County Covariates and Minimum Wage Data

I supplement the QCEW data with data on county covariates like population, unemployment, and income from the US Census Bureau.[15] I use these variables as controls in my regressions and for heterogeneity analysis of markdown estimates along market attributes.

My final dataset, county minimum wage series, comes from Vaghul and Zipperer (2022). Figure 5 plots US map of number of state level changes in minimum wages from 2004-2019. Over the sample period, there is a heterogeneity in number of changes across different geographic regions. In my analysis of county minimum wage effects, I assume that all counties within a state have the same minimum wage policy as that of the state.

Table 1 provides summary statistics on all the variables used in my estimation.

[15] I collect this data from https://data.census.gov.

2.2 Model-Free Findings

In this section, I present model-free evidence on how labor market concentration moderates effects of county minimum wages on store employment. I estimate the effects using different specifications involving two-way fixed effects regressions.[16]

I estimate two-way fixed effects (TWFE) regression in equation (1):

$$y_{sct} = \alpha_c + \beta_t + \delta \text{MW}_{ct} + \tau \text{HHI}_c + \gamma \text{MW}_{ct} \times \text{HHI}_c + \mathbf{X}'_{ct}\phi + \Delta_c \times t + \Delta_c \times t^2 + \epsilon_{sct} \quad (1)$$

where y_{sct} denotes log of total full time employment at a store s in county c for time t, α_c are county fixed effects, β_t are time fixed effects, MW_{ct} is the log of county minimum wage, $\mathbf{X}'_{ct}$ is a vector of county-specific control variables (log county income and unemployment rate), $\Delta_c \times t$ and $\Delta_c \times t^2$ denote county-specific linear and quadratic time trends, and ϵ_{sct} is the error term. I cluster standard errors at the county level, since this is where the minimum wage treatment occurs. Here, γ measures the elasticity of store employment with respect to county minimum wage in a concentrated labor market.

In specification (1), HHI_c is the average of county-HHI across years. In my analysis, I use several variations of HHI. For continuous measures, I define HHI in terms of inverse of county establishment and inverse of county population density. I supplement these with binary indicators to classify markets according to FTC's 2023 Merger Guidelines in terms of concentrated (HHI $\geq$ 0.18) and unconcentrated (HHI $<$ 0.1) markets (Federal Trade Commission (2023)).

Using these varying measures of HHI and varying specifications in 1, I report minimum wage employment estimates in concentrated and unconcentrated labor markets.

2.2.1 MW has null or positive employment effects in concentrated markets

The first empirical finding is that increasing minimum wages in concentrated labor markets have either null or positive (never negative) effects on store employment. Table 2 reports

[16] I recognize the potential bias associated with TWFE regressions (Goodman-Bacon (2021)), and hence supplement TWFE results with heterogeneity robust estimators developed in Cengiz et al. (2019) and de Chaisemartin and D'Haultfœuille (2024) in an ongoing work.

estimates where I take HHI as the inverse of total number of county establishments in the QCEW data. Across all specifications with or without fixed effects, controls, and trend variables, increasing minimum wage in concentrated market leads to a positive employment effect at individual stores. However, the estimates are not statistically significant.

When I define HHI as inverse of county population density, I find in Table 3 that minimum wages in concentrated markets have statistically significant effects on store employment. In all specifications, I find that a 10% increase in minimum wages leads to near 11% increase in employment at stores in concentrated counties at 5% significance level.

Next, I take the interaction variable to be binary with 1 if HHI in terms of county establishment is at least 0.18, following FTC's 2023 threshold for concentrated markets (Federal Trade Commission (2023)). I present the results in Table 4. In all specifications with or without fixed effects, controls, and trend variables, I find that in highly concentrated labor markets, 10% increase in minimum wage leads to about 2% increase in store employment. Throughout, the results are significant at 5% level.

These findings about null or positive employment effects are consistent with those in prior literature (Okudaira, Takizawa, and Yamanouchi (2019); Azar et al. (2024)), and provide suggestive evidence that retailers in concentrated markets have some employment surplus (productivity-wage gap or labor markdowns), which they leverage to raise employment following an increase in minimum wage.

2.2.2 MW has negative employment effects in unconcentrated markets

The second empirical finding is that increasing minimum wages in unconcentrated labor markets have negative effects on store employment. The primary purpose of this finding is to provide a placebo test for my first finding above.

Table 5 reports estimates where I take HHI as the binary indicator with value 1 if HHI is less than 0.1, following the FTC's 2023 threshold for unconcentrated markets (Federal Trade Commission (2023)). In all specifications with or without fixed effects, controls, and trend variables, I find that in unconcentrated labor markets, increasing minimum wage leads

to about reduction in store employment. Throughout, the results are significant at the 5% level.

The two sets of results regarding minimum wage employment effects together suggest that concentrated labor markets tend to be associated with labor market power or labor markdowns. In my next set of analysis, I precisely estimate the size of labor markdowns on all markets, and especially on markets with higher concentration. To this end, I develop a structural model based on the production function estimation approach which allows me to identify the markdown estimates in the US food retail sector.

3 Structural Model

In this section, I develop a structural model to estimate labor markdowns in US food retailing. Following a production function approach based on industrial organization literature, the model captures the relationship between key inputs and output in food retailing and generates parameters necessary to infer markdowns.

Firms with labor monopsony power can set wages below the marginal revenue product of labor. Using a production function, I estimate the productivity to measure how it differs from observed wages. In intuitive terms, the model gives output elasticity of labor, and the ratio of this elasticity and labor share of revenue reveals the extent of market power in both product (markups) and labor (markdowns) markets. To separately identify markups and markdowns, I estimate output elasticity of cost-of-goods-sold (COGS) variable. Its wedge with COGS share of revenue captures markups: market power in the product markets. In the final step, I infer labor markdowns—a measure of labor market power—by dividing labor wedge with COGS wedge.

Once I estimate the labor markdowns, I relate them with labor market concentration by employing two instrumental variable strategies. This step aims to rationalize the moderating role of concentration on minimum wage employment effects I document in Section 2.2.

3.1 Model Details

I develop the model by first motivating how markdowns—wedge between marginal productivity of labor and wages—relate to elasticity of labor supply. This is analogous to the relationship of markup (ratio of price and marginal cost) and elasticity of consumer demand, the Lerner index. Although elasticity of labor supply also measures labor monopsony power, its estimation is complicated by simultaneity and endogeneity issues due to the interdependence of wage and price setting, and market power that firms tend to exercise in both product and labor markets simultaneously. To overcome this difficulty, I build on the insight of Hall (1988) and De Loecker and Warzynski (2012) that wedge between labor's output elasticity and its share of revenue measures market power in both labor and product markets. I formalize this insight using *production function* approach implemented in recent literature (De Loecker, Eeckhout, and Unger (2020); Demirer (2022); Yeh, Macaluso, and Hershbein (2022); Raval (2023); Chenarides et al. (2023)).

3.1.1 Markdowns and Labor Supply Elasticity

I relate markdowns—wedge between marginal revenue product of labor and observed wages (Manning (2003))—with elasticity of labor supply. To this end, let $\Pi(L)$ denote firm's revenue in terms of labor L and other inputs which are optimized, and $W(L)$ denote wages paid to labor L. Then the firm solves the following optimization problem to maximize its profit:

$$\max_{L} \left[\Pi(L) - W(L)L\right]. \tag{2}$$

Upon differentiation with respect to L, the first order condition is:

$$\begin{aligned}
\Pi'(L) &= W(L) + W'(L)L \\
&= W(L)\left[1 + \frac{W'(L)L}{W(L)}\right] \\
&= W(L)\left[1 + \frac{1}{\eta}\right],
\end{aligned} \tag{3}$$

where $\Pi'(L)$ denotes the marginal revenue product of labor, and $\eta := \frac{W(L)}{W'(L)L}$ denotes the elasticity of labor supply. Then Equation (3) simplifies to

$$\nu := \frac{\Pi'(L)}{W(L)} = 1 + \frac{1}{\eta}. \tag{4}$$

Equation (4) gives one-to-one relationship between labor markdowns ν and elasticity of labor supply η.

Markdown ν and elasticity of labor supply η are both intuitive measures of labor market power. When $\nu = 1$, it means marginal revenue product of labor $\Pi'(L)$ equals wages $W(L)$, so each worker earns wages equal to the value she provides to her employer. In terms of elasticity of labor supply, $\nu = 1$ corresponds to $\eta = \infty$, hence the labor supply curve is perfectly elastic or flat. The labor market is said to be perfectly competitive in this situation. In imperfectly competitive labor markets, workers earn less than their marginal revenue product, so $\nu > 1$ which corresponds to $\eta < \infty$ or finite elasticity of labor supply. Estimating ν or η is the goal of this chapter.

However, estimating firm-specific elasticity of labor supply is challenging because firms often have market power in both product (markups) and labor (markdowns) markets. These dual forces of market power results in interdependence of price and wage setting, leading to simultaneity and endogeneity issues. The firm's wage decisions affect labor supply, which in turn influences production and pricing strategies. In addition, unobserved factors like productivity shocks and market conditions affect both wages and prices. This intertwined relationship makes it difficult to isolate and accurately measure η and to determine whether changes in wages are due to changes in labor supply elasticity or the result of increased market power.

To overcome this challenge, I adapt production function approach from the industrial organization (IO) literature to get estimates of labor markdowns in the presence of changes in merger-induced concentration levels. I use the insight of Hall (1988) and De Loecker and Warzynski (2012) that gaps between output elasticities and revenue shares gives market power in both product and input markets. To separately identify these two sources of market

power, I follow Yeh, Macaluso, and Hershbein (2022) and use an input—one that is free of monopsony power and adjustment costs—which together with labor input allow me to pin down market level labor markdowns.

3.1.2 Production Function Approach

Consider a food retailing store i operating at time period t. Its output, in terms of weekly sales revenue, is denoted by Q_{it}. The inputs that enter the "production" process are denoted by a vector X_{it} and consist of number of full-time workers (L_{it}), number of check-out registers (C_{it}), and cost-of-goods-sold ($COGS_{it}$).[17] For simplicity, I also denote these three inputs by $(X_{it}^1, X_{it}^2, X_{it}^3)$. Of these three inputs, I take $COGS_{it} \equiv X_{it}^3$ as a *flexible* input: free of adjustment costs and monopsony power.

Let ρ_{it} denote a store's productivity shock, unobserved to the econometrician, and $Q_{it} = F(X_{it}; \rho_{it})$ its production function. With logarithmic transformation on both sides, the function transforms to

$$q_{it} = f(x_{it}; \alpha) + \rho_{it} + \epsilon_{it}. \tag{5}$$

Here, q_{it} is log of output or weekly sales reveneue, x is vector of log of inputs in X_{it}, α is a vector of parameters to be estimated, and ϵ_{it} is the error term, unobserved to both the store and the reseacher. Following the literature on economics of production function (De Loecker and Warzynski (2012); Yeh, Macaluso, and Hershbein (2022)), I consider *translog* specification of $f(x_{it}; \alpha)$. The specification involves logged inputs, and their squares and interactions:

$$q_{it} = \sum_{k=1}^{3} \alpha_k x_{it}^k + \sum_{k=1}^{3} \alpha_{kk} (x_{it}^k)^2 + \sum_{j,k=1}^{3} \alpha_{jk} (x_{it}^j)(x_{it}^k) + \rho_{it} + \epsilon_{it}, \tag{6}$$

where $x_{it}^k = \ln X_{it}^k$. There are at least two reasons for choosing this specification. First, it provides a second-order logarithmic approximation to any differentiable production function and subsumes Cobb-Douglas function as a special case. Second, the translog specification

[17] NielsenIQ's TDLinx has data on store's full-time employees equivalent, defined as the sum of number of full-time employees and half of the number of part-time employees. For store-level analysis, I work with this definition for labor input.

allows output elasticities to vary with input levels and enables both forces of market power—markups and markdowns—to change over time in response to shifts in output elasticities and revenue shares. The goal in estimation of production function (6) is to estimate output elasticities:

$$\left(\alpha_{it}^{k} := \frac{d \ln Q_{it}}{d \ln X_{it}^{k}}\right)_{k=1}^{3}$$

which I do by first recovering elasticity parameters $(\alpha_k, \alpha_{kk}, \alpha_{jk})$, as I describe in Section 3.2 below.

3.1.3 Model Assumptions

Identification and estimation of production function (6) rest upon several prerequisites standard in the production function literature (Hall (1988); Olley and Pakes (1996); Levinsohn and Petrin (2003); De Loecker and Warzynski (2012); Ackerberg, Caves, and Frazer (2015); Yeh, Macaluso, and Hershbein (2022)).

First, I assume that the production function $Q_{it} = F(X_{it}; \rho_{it})$ is continous and twice continuously differentiable with

$$\lim_{X_{it}^3 \to 0} \frac{\partial F(\mathbf{X}_{it}; \rho_{it})}{\partial X_{it}^3} = +\infty \quad \text{and} \quad \lim_{X_{it}^3 \to +\infty} \frac{\partial F(\mathbf{X}_{it}; \rho_{it})}{\partial X_{it}^3} = 0.$$

The continuity and differentiability assumption imply that the marginal product of all inputs can be computed accurately. The first limit condition ensures that as quantity of the flexible input $X_{it}^3 = COGS_{it}$ approaches zero, the marginal product of the input approaches infinity. It reflects the idea that a very small amount of the input is highly productive. Similarly, the second limit condition implies that with large quantities of the flexible input, the marginal product of the input approaches zero. This condition implies diminishing returns, meaning that adding more of the input will eventually lead to very small increases in output. Both limit conditions ensure that the production function behaves in a manner consistent with economic theory, where inputs are productive up to a point, but their marginal productivity decreases as more of the input is used.

Second, I assume that food retail stores are cost minimizing. This assumption permits derivation of firm-level markdowns by comparing output elasticities of inputs to their respective expenditure shares. It does so by taking the Lagrangian of the production function and solving the first order conditions associated with labor and COGS inputs.

Next, I assume that food retailers do not have adjustment costs and monopsony power on the COGS input. The first part of this assumption implies food retailers do not incur costs when they change quantities between two time periods for COGS input, that is

$$\mathcal{A}(COGS_{it-1}, COGS_{it}) = 0$$

given the adjustment cost function $\mathcal{A}(\cdot, \cdot)$. That COGS is free from adjustment costs follows from how environment where food retailers generally operate in: frequent restocking, flexible and established supply-chain contracts, and advanced inventory systems. The perishable nature of food products requires frequent inventory turnover, thus adjusting the store's COGS routinely with minimal costs. Efficient supply chains also tend to facilitate quick and cost-effective stock replacement. Usage of advanced inventory management systems allow food retailers to efficiently optimize their stock levels and adjust COGS with minimal manual effort and cost. These factors enable rapid COGS updates at low cost, unlike in industries with longer production cycles or less flexible inventory management.

The second part of the assumption means food retailers do not have market power in COGS, that is COGS price per unit is independent of the number of units purchased. While large retailers may have higher neotiation power than smaller retailers, absolute monopsony power in generally non-existent for several reasons. First, the US food retailing is highly competitive, with numerous players from large supermarkets to small local stores, so there are limits for an individual buyer power over the COGS input. Second, food suppliers often have multiple sales channels, including direct-to-consumer and restaurants, which restricts retailers' bargaining power. Third, prices of several food products are influenced by global commodity markets and agricultural or other conditions which are beyond retailers' power. Fourth, government regulations also protect suppliers from unfair practices by large retailers.

For instance, Packers and Stockyards Act of 1921 aims to protect farmers and ranchers from unfair practices of retailers in the US meat industry (U.S. Department of Agriculture (2024)).

As materials input is fundamental in COGS, I also borrow the arguments of Yeh, Macaluso, and Hershbein (2022) in favor of materials being free from adjustment costs and monopsony power. Namely, the US Census Bureau regards materials input to be generally traded on "open and global markets", and thus broader market forces, instead of firms with market power, determine the prices of materials (Yeh, Macaluso, and Hershbein (2022); U.S. Census Bureau (2024)). Besides, Atalay (2014) finds no evidence for quantity-dependent pricing for material inputs. Similar to the reasoning in Yeh, Macaluso, and Hershbein (2022), if monopsony power or adjustment costs affect COGS, the estimated labor markdowns would be relative to those for COGS, thus establishing a minimum threshold for labor market power.

My next assumption concerns that food retailers use COGS statically. This condition implies that decisions on COGS input are based solely on current-period conditions and simplifies the analysis to a static optimization problem by excluding dynamic, multi-period considerations.

Given these first four assumptions, Yeh, Macaluso, and Hershbein (2022) show (in their Proposition 1) an explicit expression for labor markdowns:

$$\nu_{it} = (\mu_{it})^{-1} \cdot \frac{\theta_{it}^{L}}{\tau_{it}^{L}}. \tag{7}$$

Here, $\mu_{it} = \frac{\theta_{it}^{M}}{\tau_{it}^{M}}$ is the product markup term as the ratio of output (that is, sales reveneue) elasticity of COGS input and COGS share of total store revenue. Similarly, θ_{it}^{L} is the output elasticity of labor, and τ_{it}^{L} is the labor share of revenue. In other words, labor wedge (ratio of output elasticity of L to its revenue share) equals the product of markdown and markup terms. Without a flexible input, the labor wedge thus gives markdown estimates that form lower bounds for true markdown estimates.

The key goal in this chapter is to estimate the right-hand side in equation (7). To this end, I estimate output elasticities of labor and COGS inputs using the production

function in equation (6) and directly calculate their revenue shares from data. As is standard in the production function proxy-variable literature, this estimation relies on additional assumptions below.

Next, I assume that for flexible input COGS, the productivity shock ρ_{it}, unobserved to the researcher, is scalar and Hicks-neutral. Further, I take the technology parameters α in the production function in equation (5) are constant across food retailers and over time. The scalar unobservable assumption has an interpretation that ρ_{it} is a single latent variable that captures all unobserved factors—for instance, managerial ability, workforce skills, and firm-specific technologies—affecting the production process. Thus, it condenses multiple unobserved productivity factors into a single term, reducing the dimensionality of unobserved components influencing the production (or sales revenue) and simplifying the estimation.

The productivity shock ρ_{it} is Hicks-neutral when the average and marginal products of all inputs factors rise by the same proportion as the shock itself. This contrasts with input-augmenting technology that favors one input over another, thus the marginal rate of technical substitution between any two inputs is not constant. Formally, given a production function $Y = F(\cdot)$, Hicks neutrality occurs when technological progress uniformly increases the productivity of all inputs by a scaling factor $\delta > 1$, changing output to $Y' = \delta F(\cdot) = \delta Y$ without changing relative marginal productivity of inputs or optimal input proportions.

On final part of this assumption, while food retailers are assumed to share common technology parameters, it does not mean that output elasticities of inputs are constant across firms, except in the case of a Cobb-Douglas production function (De Loecker and Warzynski (2012)).

The restrictions in this assumption imply that production function $Q_{it} = F(X_{it}; \rho_{it})$ takes the form

$$Q_{it} = F(X_{it}) \cdot \exp(\rho_{it}). \tag{8}$$

Thus, applying the natural log on both sides of equation (8) results in the production function

in equation (5). Assumption 5 also ensures I can use proxy variable methodologies of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015) to get the output elasticities required for estimating labor markdowns.

Given a flexible input (in my case, COGS) that meets the previous assumption, I also assume that the input demand function of a firm i is strictly increasing in ρ_{it}. Further, such an input demand function needs to be invertible in ρ_{it}. The first part of this assumption implies that the input demand function $COGS_{it} = g(\rho_{it})$ is strictly monotone increasing with respect to the firm's productivity ρ_{it}. That is, if a firm's productivity ρ_{it} increases, the amount of flexible input $COGS_{it}$ also increases. Mathematically, it means $g'(\rho_{it}) > 0, \ \forall \rho_{it}$. This predictable and upward movement permits researchers to understand firm's productivity by following the usage of COGS input. The second part requires the invertibility of flexible input demand function $g(\rho_{it})$. The goal here is to permit nonparametric estimation of output (that is, revenue) where there is no direct observation of productivity shocks.

My next assumption requires that the production function in equation (5) takes the form of *translog* specification in equation (6). There are three main reasons behind my choice of a translog specification. First, it is widely supported in recent production function literature (De Loecker and Warzynski (2012); Ackerberg, Caves, and Frazer (2015)) and subsumes classical specifications such as Cobb-Douglas. In particular, the translog specification (6) reduces to Cobb-Douglas by dropping the second order and interaction terms. Second, the translog function serves as a second-degree Taylor series approximation to a general, differentiable production function, thus it has an advantage of being flexible. Third, it permits recovery of firm-specific output elasticities, which are key to recovering markdown estimates.

Further, I take that the information set $\mathcal{J}_{it}$ of firm i at time t includes its productivity history $\{\rho_{i\tau}\}_{\tau=0}^{t}$ and excludes $\{\rho_{i\tau}\}_{\tau=t+1}^{\infty}$. Further, the transitory shocks ϵ_{it} needs to satisfy that $\mathbb{E}[\epsilon_{it} \mid \mathcal{J}_{it}] = 0$. The first part of this assumption implies that a firm's production decisions are based on information of current and past productivity levels, but not on future

productivity levels. In the second part, transitory shocks refer to any random and short-term deviation in the firm's productivity. The assumption indicates that these transitory shocks are unpredictable and average out to zero over time. That is, these shocks do not systematically impact the firm's production decisions or expectations and only add noise to productivity.

Next, I assume that a firm's future productivity satisfies first order Markov process:

$$\Pr(\rho_{i,t+1} \mid \mathcal{J}_{it}) = \Pr(\rho_{i,t+1} \mid \rho_{it}).$$

Further, the distribution $\Pr(\rho_{i,t+1} \mid \rho_{it})$ is recognized by firms and is stochastically increasing in ρ_{it}. This assumption highlights a key firm behavior. The Markov property of productivity implies that the stochastic process behind the evolution of productivity is memoryless. That is, a firm's future productivity shock given its information set depends only on the current state and not on the historical trajectory of productivity. The second part of this assumption implies that higher current productivity levels tend to result in a higher probability of increased future productivity. Formally, for any two values of current productivity, ρ_{it}^1 and ρ_{it}^2, where $\rho_{it}^1 < \rho_{it}^2$, the future productivity ρ_{it+1} given ρ_{it}^2 is likely to be higher than ρ_{it+1} given ρ_{it}^1. The stochastically increasing property is important as it simplifies the modeling of dynamic behavior by ensuring that the productivity process has a predictable structure. Specially, it helps in constructing valid moment conditions for Generalized Method of Moments (GMM) estimation, as I leverage the positive correlation between current and future productivity to identify the parameters of the production function.

Finally, I require that a firm's capital stock (in this case, number of check-out registers) k_{it} at time t is a function of its lagged capital k_{it-1} and investment ν_{it-1}:

$$k_{it} = \kappa(k_{it-1}, \nu_{it-1}),$$

where ν_{it-1} is dynamic and decided in period $t-1$; labor input L_{it} is non-dynamic, chosen in t, and does not impact future periods. This assumption indicates the distinction between capital and labor timing decisions. Current capital is based on past investment decisions,

that is $k_{it} \in \mathcal{J}_{it-1}$. which allows the model to leverage lagged information to control for unobserved productivity shocks. This signifies that firms face an inherent delay (of typically a full period) in acquiring and fully operating a new capital. In contrast, labor is non-dynamic, that is it's choice in current period does not influence future profits.

Given these ten assumptions, I now describe identification and estimation strategies.

3.2 Identification and Estimation

3.2.1 Identification

The identification of parameters in production function (6) relies on an instrumental variable approach, which addresses endogeneity concerns about unobserved productivity shocks. To this end, I use a vector of instruments, denoted as $\mathbf{z}_{it}$, for a vector of log of endogeneous inputs $\mathbf{X}_{it} = (L_{it}, C_{it}, COGS_{it})$, consisting of number of full-time workers, number of check-out registers, and cost-of-goods-sold (COGS), respectively. Taking the log of each input, the instrument vector $\mathbf{z}_{it}$ thus consists of instrument for log of full-time labor ($l_{it} = \ln L_{it}$), number of check-out registers ($k_{it} = \ln C_{it}$), and cost-of-goods-sold ($m_{it} = \ln COGS_{it}$). To create these instruments, I follow De Loecker and Warzynski (2012) and define $\mathbf{z}_{it}$ to be a vector of lag of corresponding inputs, except for number of check-out registers. Thus, the instrument vector is $\mathbf{z}_{it} = (l_{it-1}, k_{it}, m_{it-1})$.

For above instruments to generate unbiased estimates of production function parameters, I need to verify that the instruments satisfy two key assumptions.

Assumption 1: Exogeneity. First, the instruments in $\mathbf{z}_{it}$ must be exogenous, meaning they are uncorrelated with productivity shocks ρ_{it}. This is achieved through timing assumptions about the choice of inputs. That is, a firm makes decisions on inputs $(l_{it-1}, c_{it}, cogs_{it-1})$ without realizing the productivity shock ρ_{it}, thus validating the exogeneity criterion:

$$\mathbb{E}[\mathbf{z}_{it} \cdot \rho_{it}] = 0.$$

Assumption 2: Rank Condition. Second, the instruments need to be *valid*, that is they should satisfy that the moment conditions associated with lagged inputs explain

parameters associated to current inputs. The validity of the instruments follows from smooth evolution of input demand functions and from the requirement that input prices should not change drastically between two periods. Similar to Yeh, Macaluso, and Hershbein (2022), I rely on the result of Atalay (2014) that prices of materials (in this case, cost-of-goods-sold) are mostly smooth over time, and that COGS does not enter like a perfect substitute or perfect complement in the production process.

3.2.2 Estimation Strategy

In this section, I outline the *modus-operandi* of proxy variable approach to estimate output elasticites for computing labor markdowns. Given a production function, which in this case takes translog specification (6),

$$q_{it} = f(\mathbf{x}_{it}; \alpha) + \rho_{it} + \epsilon_{it}$$

with log output q_{it}; log inputs $\mathbf{x}_{it} = (l_{it}, k_{it}, m_{it})$ of full-time workers, number of check-out registers, and cost-of-goods-sold; (unobserved) productivity shock ρ_{it}; and error term ϵ_{it}, I estimate the vector of parameters α by applying a three-step procedure involving nonparametric methods and the Generalized Method of Moments (GMM) to control for unobserved productivity.

Step 1: Nonparametric Regression for Log Output. Implement an OLS regression of q_{it} on a third-order polynomial in (l_{it}, k_{it}, m_{it}) with interactions to get log output $\hat{\phi}_{it}$ without measurement error ϵ_{it} and residuals $\hat{\epsilon}_{it}$. In this step, I use multiple specifications: with or without year and county fixed effects, and county control variables.

Step 2: Estimation of Productivity and Productivity Shocks. Isolate a firm's productivity ρ_{it} by estimating the productivity as the difference between the estimated log output and the fitted value from the regression,

$$\rho_{it}(\tilde{\alpha}) = \phi_{it} - f(\mathbf{x}_i; \tilde{\alpha}),$$

and implement an OLS regression of $\rho_{it}(\tilde{\alpha})$ on a third-order polynomial in $\rho_{it-1}(\tilde{\alpha})$ to get estimates of productivity shocks $\zeta_{it}(\tilde{\alpha})$.

This step allows differentiation of persistent component of productivity and transitory shocks.

Step 3: Generalized Method of Moments (GMM) Estimation. Apply the GMM using the moment conditions

$$\mathbb{E}\big(\zeta_{it}(\tilde{\alpha}) \cdot \mathbf{z}_{it}\big) = \mathbf{0}$$

to obtain estimates of production parameters $\hat{\alpha}$.

Markdown Estimates. Using the estimates of $\hat{\alpha}$, I then compute output elasticites of labor and COGS inputs in order to infer markdown estimates. To this end, recall that the production function is:

$$q_{it} = f(x_{it}; \alpha) + \rho_{it} + \epsilon_{it}. \tag{9}$$

The function $f(x_{it}; \alpha)$ takes the translog specification:

$$\begin{aligned} f(x_{it}; \alpha) = {} & \alpha_K k_{it} + \alpha_L l_{it} + \alpha_M m_{it} \\ & + \alpha_{KL} k_{it} l_{it} + \alpha_{KM} k_{it} m_{it} + \alpha_{LM} l_{it} m_{it} \\ & + \frac{1}{2}\big(\alpha_{KK} k_{it}^2 + \alpha_{LL} l_{it}^2 + \alpha_{MM} m_{it}^2\big), \end{aligned} \tag{10}$$

where (k_{it}, l_{it}, m_{it}) denotes a vector of logged capital (number of checkout registers), full-time employment (labor), and cost-of-goods-sold (materials).

Step 3 in GMM-IV approach gives estimates $\hat{\alpha} \in \mathbb{R}^9$, a vector of parameters for each store-year (i, t) pair. I use these estimates to compute output elasticities of capital, labor, and cogs variables as follows:

$$\hat{\theta}_{it}^K = \hat{\alpha}_K + \hat{\alpha}_{KM} m_{it} + \hat{\alpha}_{KL} l_{it} + \hat{\alpha}_{KK} k_{it} \tag{11}$$

$$\hat{\theta}_{it}^L = \hat{\alpha}_L + \hat{\alpha}_{KL} k_{it} + \hat{\alpha}_{LM} m_{it} + \hat{\alpha}_{LL} l_{it} \tag{12}$$

$$\hat{\theta}_{it}^M = \hat{\alpha}_M + \hat{\alpha}_{KM} k_{it} + \hat{\alpha}_{LM} l_{it} + \hat{\alpha}_{MM} m_{it} \tag{13}$$

Next, I use cogs elasticities and cogs-share of store revenue, $\hat{\theta}_{it}^{M}$ and τ_{it}^{M}, to compute store-level markups:

$$\mu_{it} = \frac{\hat{\theta}_{it}^{M}}{\tau_{it}^{M}} \exp(-\hat{\epsilon}_{it}) \tag{14}$$

where $\hat{\epsilon}_{it}$ is the residual from the first step in GMM-IV procedure. Finally, I use these markup estimates together with labor elasticities and revenue shares, $\hat{\theta}_{it}^{L}$ and τ_{it}^{L}, to compute labor markdowns:

$$\nu_{it} = \frac{\hat{\theta}_{it}^{L}}{\tau_{it}^{L}} \cdot \mu_{it}^{-1} \tag{15}$$

4 Results

4.1 Markdown Estimates and Heterogeneity

This section presents markdown estimates based on production function approach described in Section 3. In Table 7, I report elasticities and mean markdowns across four different specifications in the first stage OLS estimation in GMM-IV procedure. The translog production function estimates show significant input elasticities across all specifications. Materials (COGS) have the largest output elasticity, ranging from 0.696 to 0.772, followed by labor (0.083 to 0.169) and capital (0.056 to 0.060). All elasticities are statistically significant, with materials and labor showing significance at the 1% level, while capital is significant at the 10% level.

The estimated labor markdowns vary substantially across specifications. Without fixed effects and controls (column (1)), I find mean markdown is 2.218. However, it is reasonable to consider both county and year fixed effects to account for unobserved heterogeneity associated to time and markets. On this specification, which is my preferred specification (column 3), I find a markdown of 1.372, meaning that workers receive about \$0.73 for every dollar of marginal revenue they generate. The returns to scale, measured as the sum of input elasticities, consistently show slight decreasing returns across all specifications, ranging from 0.906 to 0.9251.

Next, I consider the heterogeneity of markdown estimates by channel category of TDLinx stores and report the results in Table 8. In the two categories I observe in the final sample—Grocery Stores and Mass Merchandisers—I find grocery stores have a markdown of close to 1.4 (st. dev. = 0.6). On the other hand, workers in mass merchandisers appear to earn near competitive wages as indicated by the mean markdown of 1.02.

I also analyze how markdown estimates differ by NAICS sectors that my sample stores belong to. Table 9 presents the results. In stores that are in NAICS code 445110 (that is, "Supermarkets and Other Grocery (except Convenience) Stores"), the mean markdown is 1.63 (st. dev. = 0.8). On the other hand, stores in NAICS code 455219 (namely, "All Other General Merchandise Retailers") have mean markdown less than 1, meaning that workers in these stores earn more than their marginal productivity value.

In Table 10, I examine the sources of variation in markdowns. The variance decomposition of labor markdowns shows that labor's share of revenue is the dominant source of variation, accounting for 49% of the total markdown variance. This suggests that differences in how firms allocate their revenue to labor compensation play a crucial role in determining the extent of wage suppression across food retail establishments. The output elasticity of labor and markups contribute relatively less to markdown variation, at 11.6% and 13.6% respectively. Interestingly, I find a negative covariance between output elasticity and labor share (-0.125), which suggests that stores with higher labor productivity tend to have lower labor cost shares. Similarly, the positive covariance between labor share and markups (0.089) suggests that stores with higher product market power tend to share more revenue with workers.

For further heterogeneity analysis, I relate markdowns with store age in simple summary reduced-form regression. Figure 8 shows that store's age is positively correlated with markdowns, that is, older firms tend to have greater wage supression.

In Figures 11 and 12, I plot US counties by estimates of labor markdowns. Specifically, Figure 11 shows how sample counties differ in terms of their markdown estimates, with red

indicating counties with largest markdowns. Figure 7 shows counties according to the largest changes in markdowns between years 2005 and 2019; this figure shows great variation how markdowns have evolved across US markets.

At the aggregate level, I find that yearly markdowns are falling over time. Figure 10 illustrates this evolution of mean markdown of 1.15 in year 2005 to 1.08 in 2019. This finding about falling markdown is robust to a different specification in GMM-IV markdown estimation. Namely, Figure 13, which is based on the first stage OLS without fixed effects and control variables, also shows that markdowns are falling over the sample period. This suggests that labor markets in US food retailing is getting competitive over time. Next, I relate markdowns with labor market concentration.

4.2 Markdown and Labor Market Concentration

In this section, I present the third set of analysis: how labor markdowns (actual exercise of labor market power) relate to labor market concentration (potential exercise of labor market power). The purpose of this section is to provide theoretical support for the null or positive employment effects of minimum wages in concentrated markets, that I document in Section 2.2.

To examine the relationship, I regress log of store markdowns with log of labor market concentration (defined in terms of inverse of total number of county establishments) by accounting for the concentration endogeneity. Specifically, I run the following regression:

$$\ln(\nu_{ict}) = \alpha_c + \beta \ln \text{HHI}_{ct} + \mathbf{X}'_{ct}\phi + \epsilon_{ict} \tag{16}$$

where the left hand side denotes log of markdown at store i in county c at year t, α_c denotes county fixed effects, and $\mathbf{X}$ denotes a vector of control variables. The parameter of interest is β and measure the HHI-markdown elasticity. I cluster the standard errors at the county level. To address the endogeneity of HHI, I employ two instrumental variables.

The first instrumental variable is leave-one-out-IV (LOOIV) and is defined as the inverse of total number of establishments in all other counties except the focal county. Table 11

reports the regression estimates across three different specifications. In column (1) without county fixed effects and control variables, I find that 10% increase in labor market concentration leads to 3.8% increase in markdowns. When I add county fixed effects in column (2), I find this effect slightly reduces to 2.7%. In the preferred specification with county fixed effects and control variables, I find a rise in markdowns by about 5.9%. In Table 15, I run the same analysis but using a different specification of a measure of markdowns, and arrive at the same conclusion. In the context of food retailing, this effect is also economically significant due to a substantial presence (about 25% in 2023) of minimum wage workers.

My second IV, shift-share IV, leverages on merger count, and I construct it as follows. First, I identify the national-level trend in food retail mergers to capture broad industry-wide shifts. Next, I calculated each county's pre-existing exposure to these national shifts by determining their proportion of food retail establishments relative to the national total, using QCEW data. I then create the final SSIV by multiplying these two components—the national merger trend (shift) and each county's establishment share (share). This multiplication generates county-specific variation based on initial market structure rather than contemporaneous conditions, helping me address endogeneity concerns when estimating the impact of local labor market concentration on markdowns.

Using this SSIV, I report the estimates in Table 12. In column (1) without county fixed effects and control variables, I find that a 10% increase in HHI leads to approximately 3% reduction in markdowns. However, when I account for unobserved county confounders by adding county fixed effects and county control variables in my preferred specifition (3), I find that there is a near 1 to 1 correspondense between HHI and markdowns. That is, 10% increase in HHI is associated with 10% increase in store level markdowns. In Table 16, I use an alternative measure of markdowns but arrive at the same conclusion although with a slightly smaller effect on markdowns from concentration. Overall, this effect is economically substantial given a large portion of workers who earn near minimum wages.

In summary, I find that food retailers have statistically and economically significant

labor markdowns, that these markdowns are decreasing over time, but they are higher in concentrated labor markets. It is due to this presence of markdowns that food retailers are able to absorb some of the increases in county minimum wages and still expand employment.

5 Conclusions

I examine labor market dynamics in US food retail. The findings show significant wage suppression through employer market power, with workers receiving \$0.73 for each dollar of marginal productivity. While the trend shows improving market competitiveness over time, there is substantial markdown variation across different market structures, with more concentrated markets enabling greater exploitation of labor market power.

My analysis demonstrates that labor market concentration serves as a key mechanism through which food retailers exercise wage-setting power, with a 10% increase in concentration leading to 6-11% higher markdowns. This relationship helps to explain the counterintuitive positive employment effects of minimum wages in concentrated markets I document in my reduced-form analysis, as firms operating with larger productivity-wage gaps have more flexibility to absorb wage increases while maintaining or expanding employment. Future research could explore how technological change and evolving market structures may further impact these dynamics, particularly in the context of increasing automation and digital transformation in the retail sector. Another line of work could relax some of the assumptions I make in estimating labor market power.

References

Ackerberg, D.A., K. Caves, and G. Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica* 83:2411–2451.

Arnold, D. 2021. "Mergers and Acquisitions, Local Labor Market Concentration, and Worker Outcomes." Unpublished, Working paper, Department of Economics, Princeton University.

Atalay, E. 2014. "Materials Prices and Productivity." *Journal of the European Economic Association* 12:575–611.

Azar, J., E. Huet-Vaughn, I. Marinescu, B. Taska, and T. von Wachter. 2024. "Minimum Wage Employment Effects and Labour Market Concentration." *The Review of Economic Studies* 91:1843–1883.

Azar, J., and I. Marinescu. 2024. "Monopsony Power in the Labor Market: From Theory to Policy." *Annual Review of Economics* 16:491–518.

Azar, J.A., S.T. Berry, and I. Marinescu. 2022. "Estimating Labor Market Power." Working Paper No. 30365, National Bureau of Economic Research, August.

Berger, D., K. Herkenhoff, and S. Mongey. 2022. "Labor Market Power." *American Economic Review* 112:1147–1193.

Berry, S., M. Gaynor, and F. Scott-Morton. 2019. "Do Increasing Markups Matter? Lessons from Empirical Industrial Organization." *Journal of Economic Perspectives* 33(3):44–68.

Brooks, W.J., J.P. Kaboski, Y.A. Li, and W. Qian. 2021. "Exploitation of labor? Classical monopsony power and labor's share." *Journal of Development Economics* 150:102627.

Bureau of Labor Statistics. 2023. "Bureau of Labor Statistics, December 2023."

Callaway, B., and P.H. Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics* 225:200–230.

Card, D. 2022. "Who Set Your Wage?" *American Economic Review* 112:1075–1090.

Card, D., A.R. Cardoso, J. Heining, and P.M. Kline. 2021. "Firms and labor market inequality: Evidence and some theory." *Journal of Labor Economics* 36:S13–S70.

Card, D., and A.B. Krueger. 1993. "Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania." Working paper, National Bureau of Economic Research, October.

Cengiz, D., A. Dube, A. Lindner, and et al. 2019. "The Effect of Minimum Wages on Low-Wage Jobs." *The Quarterly Journal of Economics* 134:1405–1454.

Chenarides, L., M.I. Gómez, T.J. Richards, and K. Yonezawa. 2023. "Retail Markups and Discount-Store Entry." *Review of Industrial Organization*, pp. .

Cho, C., P.W. McLaughlin, E. Zeballos, J. Kent, and C. Dicken. 2019. "Capturing the complete food environment with commercial data: A comparison of TDLinx, ReCount, and NETS databases." Technical Bulletin No. 1953, Economic Research Service, USDA.

Claire Kelloway. 2022. "U.S. Food Prices Are Up. Are the Food Corporations to Blame for Taking Advantage?", pp. . Published on January 14, 2022, at 7:00 AM EST on Time.com.

de Chaisemartin, C., and X. D'Haultfœuille. 2024. "Difference-in-Differences Estimators of Intertemporal Treatment Effects." *The Review of Economics and Statistics*, pp. .

De Loecker, J. 2011. "Recovering markups from production data." *International Journal of Industrial Organization* 29:350–355.

De Loecker, J., J. Eeckhout, and G. Unger. 2020. "The Rise of Market Power and the Macroeconomic Implications." *The Quarterly Journal of Economics* 135:561–644.

De Loecker, J., and F. Warzynski. 2012. "Markups and Firm-Level Export Status." *American Economic Review* 102:2437–71.

Deb, S., J. Eeckhout, A. Patel, and L. Warren. 2023. "Market Power and Wage Inequality.", pp. . Forthcoming at Econometrica.

—. 2022. "What Drives Wage Stagnation: Monopsony or Monopoly?" *Journal of the European Economic Association* 20:2181–2225.

Demirer, M. 2022. "Production Function Estimation with Factor-Augmenting Technology: An Application to Markups." Unpublished, Revise and Resubmit, Econometrica.

Dube, A., J. Jacobs, S. Naidu, and S. Suri. 2018. "Monopsony in Online Labor Markets." Working Paper No. 24416, National Bureau of Economic Research.

Federal Trade Commission. 2010. "2010 Merger Guidelines." https://www.justice.gov/atr/file/810276/dl?inline.

—. 2023. "2023 Merger Guidelines." https://www.ftc.gov/system/files/ftc_gov/pdf/2023_merger_guidelines_final_12.18.2023.pdf.

—. 2024a. "FTC Announces Rule Banning Noncompetes." https://www.ftc.gov/news-events/news/press-releases/2024/04/ftc-announces-rule-banning-noncompetes.

—. 2024b. "Kroger Company/Albertsons Companies, Inc., In the Matter of." https://www.ftc.gov/legal-library/browse/cases-proceedings/kroger-companyalbertsons-companies-inc-matter, Docket Number: 9428. Case Status: Pending. Last Updated: September 30, 2024.

Giuliano, L. 2013. "Minimum Wage Effects on Employment, Substitution, and the Teenage Labor Supply: Evidence from Personnel Data." *Journal of Labor Economics* 31:155–194.

Goodman-Bacon, A. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225:254–277.

Hall, R.E. 1988. "The Relation between Price and Marginal Cost in U.S. Industry." *Journal of Political Economy* 96:921–947.

Hortaçsu, A., and C. Syverson. 2015. "The Ongoing Evolution of US Retail: A Format Tug-of-War." *Journal of Economic Perspectives* 29(4):89–112.

Karabarbounis, L., and B. Neiman. 2013. "The Global Decline of the Labor Share." *Quarterly Journal of Economics* 129:61–103.

Kroft, K., J.W.P. Laliberté, R. Leal-Vizcaíno, and M.J. Notowidigdo. 2022. "Salience and Taxation with Imperfect Competition." Working paper No. w27409, National Bureau of Economic Research.

Lamadon, T., M. Mogstad, and B. Setzler. 2022. "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market." *American Economic Review* 112:169–212.

Levinsohn, J., and A. Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies* 70:317–341.

MacDonald, J.M., X. Dong, and K. Fuglie. 2023. "Concentration and Competition in U.S. Agribusiness." Economic Information Bulletin No. EIB-256, U.S. Department of Agriculture, Economic Research Service.

Manning, A. 2021a. "The Elusive Employment Effect of the Minimum Wage." *Journal of Economic Perspectives* 35(1):3–26.

—. 2011. "Imperfect Competition in the Labor Market." In D. Card and O. Ashenfelter, eds. *Handbook of Labor Economics*. Elsevier, vol. 4, Part B, pp. 973–1041.

—. 2021b. "Monopsony in Labor Markets: A Review." *ILR Review* 74:3–26.

—. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press.

Marinescu, I., and H.J. Hovenkamp. 2019. "Anticompetitive Mergers in Labor Markets." *Indiana Law Journal* 94:Article 5.

Miller, N., S. Berry, F.S. Morton, J. Baker, T. Bresnahan, M. Gaynor, R. Gilbert, G. Hay, G. Jin, B. Kobayashi, F. Lafontaine, J. Levinsohn, L. Marx, J. Mayo, A. Nevo, A. Pakes, N. Rose, D. Rubinfeld, S. Salop, M. Schwartz, K. Seim, C. Shapiro, H. Shelanski, D. Sibley, A. Sweeting, and M. Wosinska. 2022. "On the misuse of regressions of price on the HHI in merger review." *Journal of Antitrust Enforcement* 10:248–259.

Miller, N.H. 2024. "Industrial Organization and The Rise of Market Power." *Unknown*, pp. , http://www.nathanhmiller.org/iomktpower.pdf.

Naidu, S., and E.A. Posner. 2022. "Labor Monopsony and the Limits of the Law." *Journal of Human Resources* 57:S284–S323.

Okudaira, H., M. Takizawa, and K. Yamanouchi. 2019. "Minimum Wage Effects Across Heterogeneous Markets." *Labour Economics* 59:110–122.

Olley, G.S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64:1263–1297.

Prager, E., and M. Schmitt. 2021. "Employer Consolidation and Wages: Evidence from Hospitals." *American Economic Review* 111:397–427.

Raval, D. 2023. "Testing the Production Approach to Markup Estimation." *The Review of Economic Studies* 90:2592–2611.

Robinson, J. 1933. *The Economics of Imperfect Competition*, 2nd ed. Palgrave Macmillan London, DOI: https://doi.org/10.1007/978-1-349-15320-6.

Rubens, M. 2023. "Market Structure, Oligopsony Power, and Productivity." *American Economic Review* 113:2382–2410.

Smith, D., and S. Ocampo. 2021. "The Evolution of U.S. Retail Concentration." Working paper No. Working Paper 526, U.S. Bureau of Labor Statistics.

The White House. 2021. "Executive Order on Promoting Competition in the American Economy." https://www.whitehouse.gov/briefing-room/presidential-actions/2021/07/09, Accessed August 26, 2023.

Traina, J. 2018. "Is Aggregate Market Power Increasing? Production Trends Using Financial Statements." Available at SSRN: https://ssrn.com/abstract=3120849 or http://dx.doi.org/10.2139/ssrn.3120849.

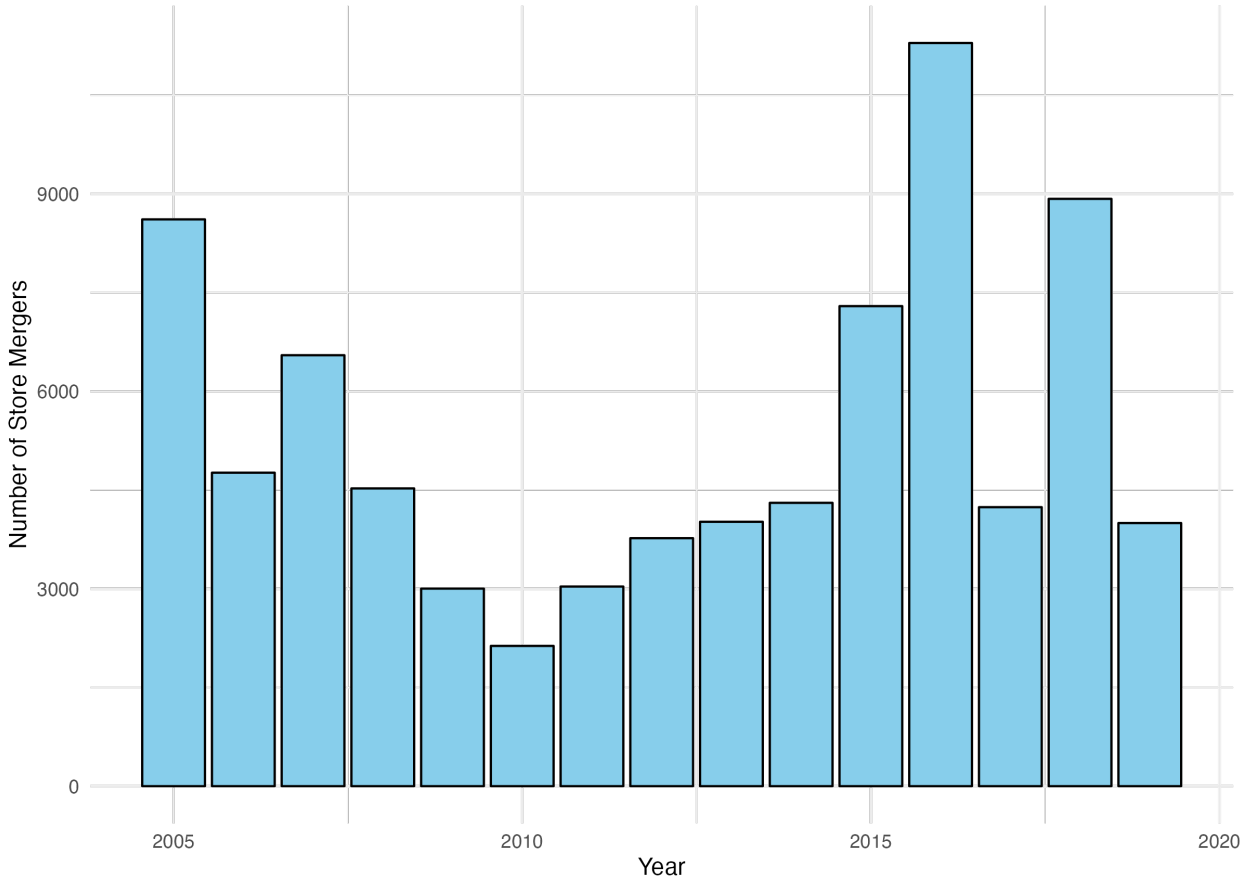
U.S. Census Bureau. 2024. "Annual Survey of Manufactures: 2020 MA-10000 Instructions." https://www2.census.gov/programs-surveys/asm/technical-documentation/questionnaire/2020/instructions/2020-MA-10000-Instructions.pdf, Accessed: 2024-07-13.

U.S. Department of Agriculture. 2024. "Packers and Stockyards Act." https://www.ams.usda.gov/sites/default/files/media/PSAct.pdf, Accessed: 2024-07-13.

Vaghul, K., and B. Zipperer. 2022. "Historical State and Sub-state Minimum Wages." https://github.com/benzipperer/historicalminwage/releases/tag/v1.4.0, Version 1.4.0.

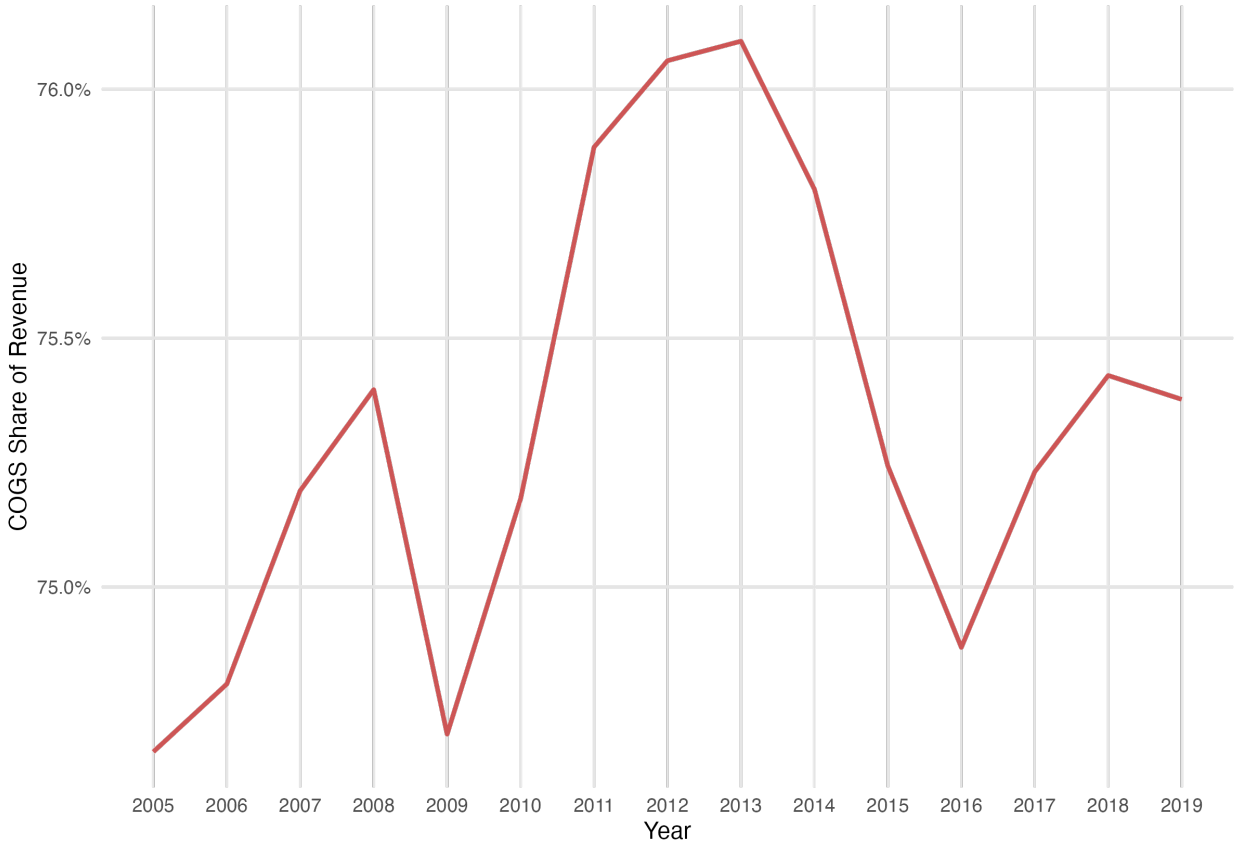
Yeh, C., C. Macaluso, and B. Hershbein. 2022. "Monopsony in the US Labor Market." *American Economic Review* 112:2099–2138.

Figure 1: Number of Store Mergers in US Food Retailing



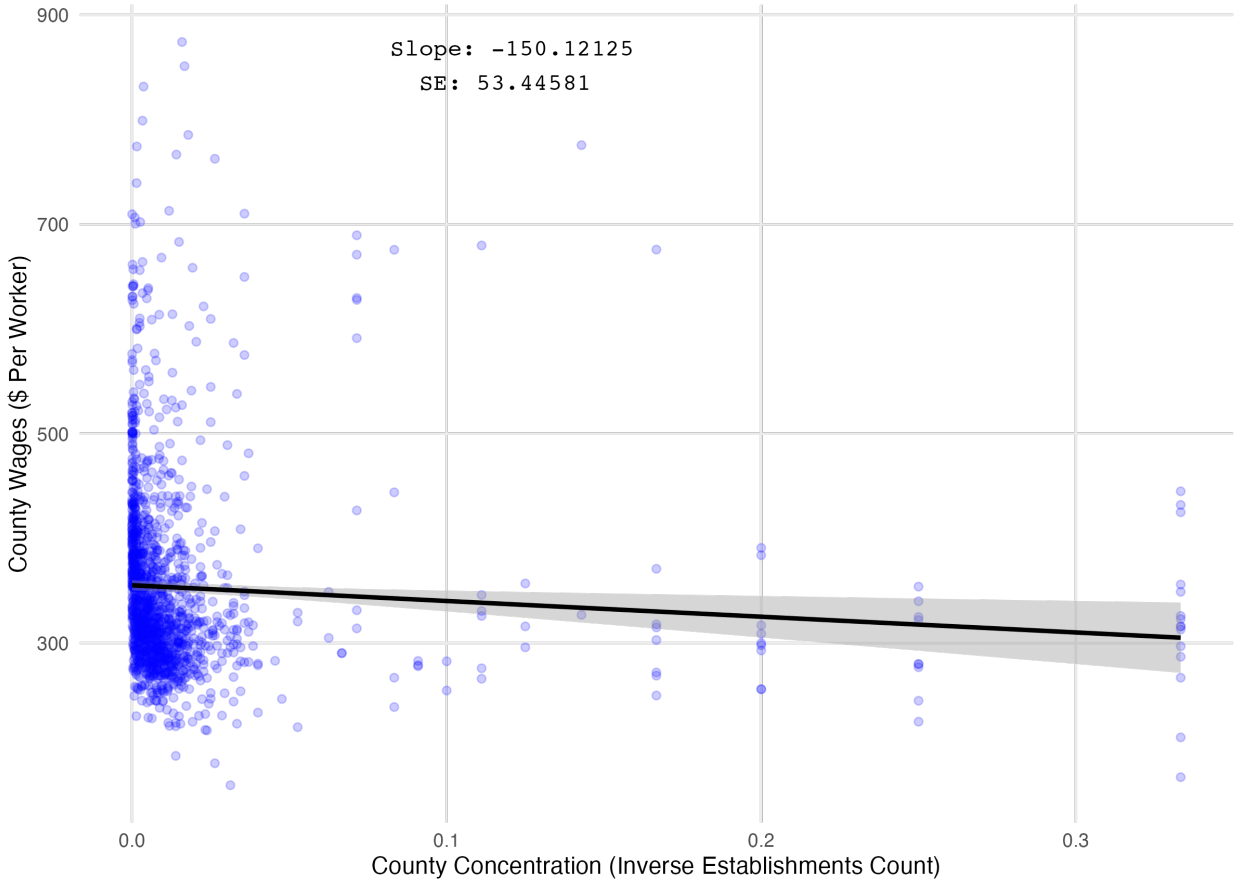
Notes: The graph shows number of food retail stores involved in mergers and acquisitions (M&As) in the US during 2005-2019. I define a store is involved in an M&A in year t if its parent ownership code changes between $t-1$ and t. If a store is sold by a parent owner and becomes an 'independent' store, I do not label the event as a M&A as the event does not reflect a merger activity, although it satisfies the criteria for one. Data source: NielsenIQ TDLinx.

Figure 2: Cost of Goods Sold Share of Revenue Over Time



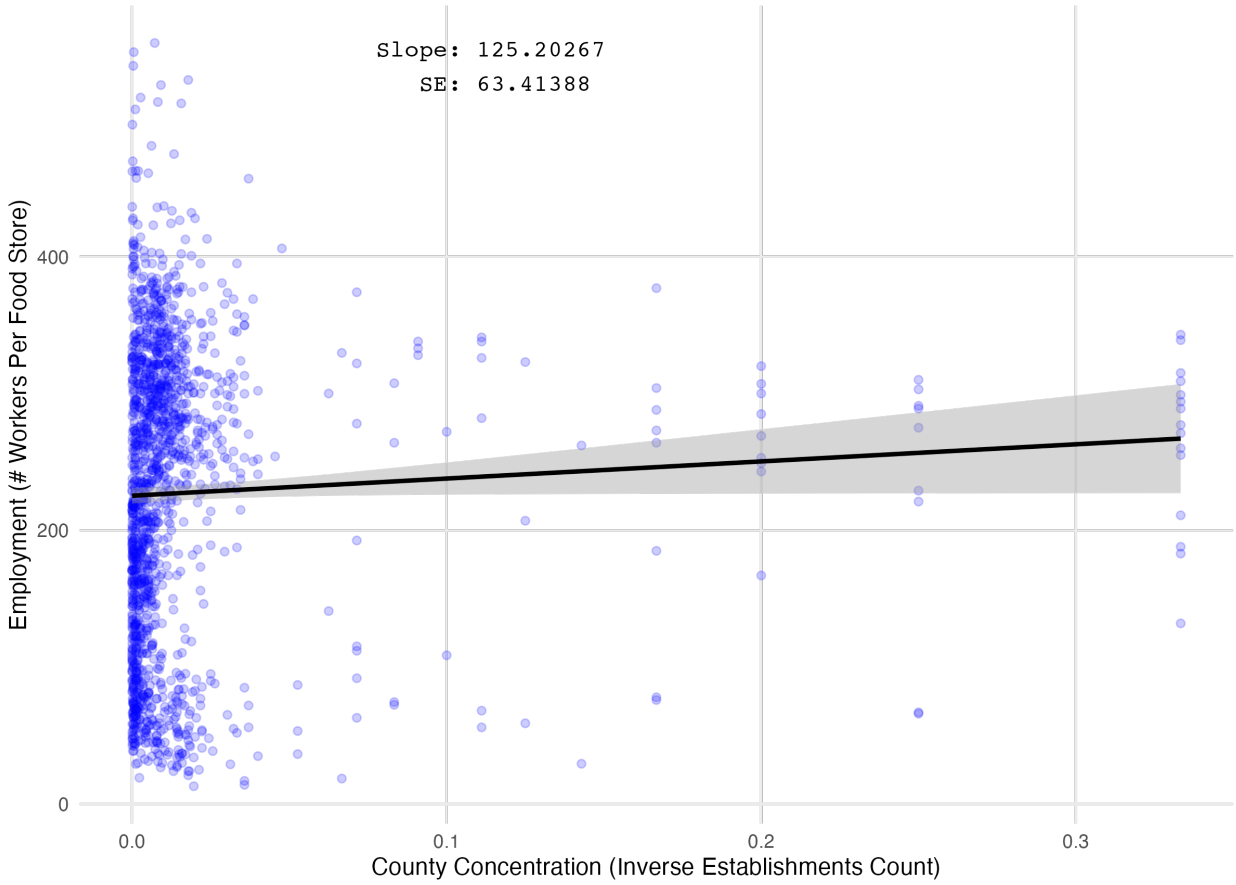
Notes: The figure shows cost of goods sold (COGS) as a share of total revenue for US food retailers. *Data source:* Compustat (https://wrds-www.wharton.upenn.edu).

Figure 3: Relationship Between Concentration and Wages



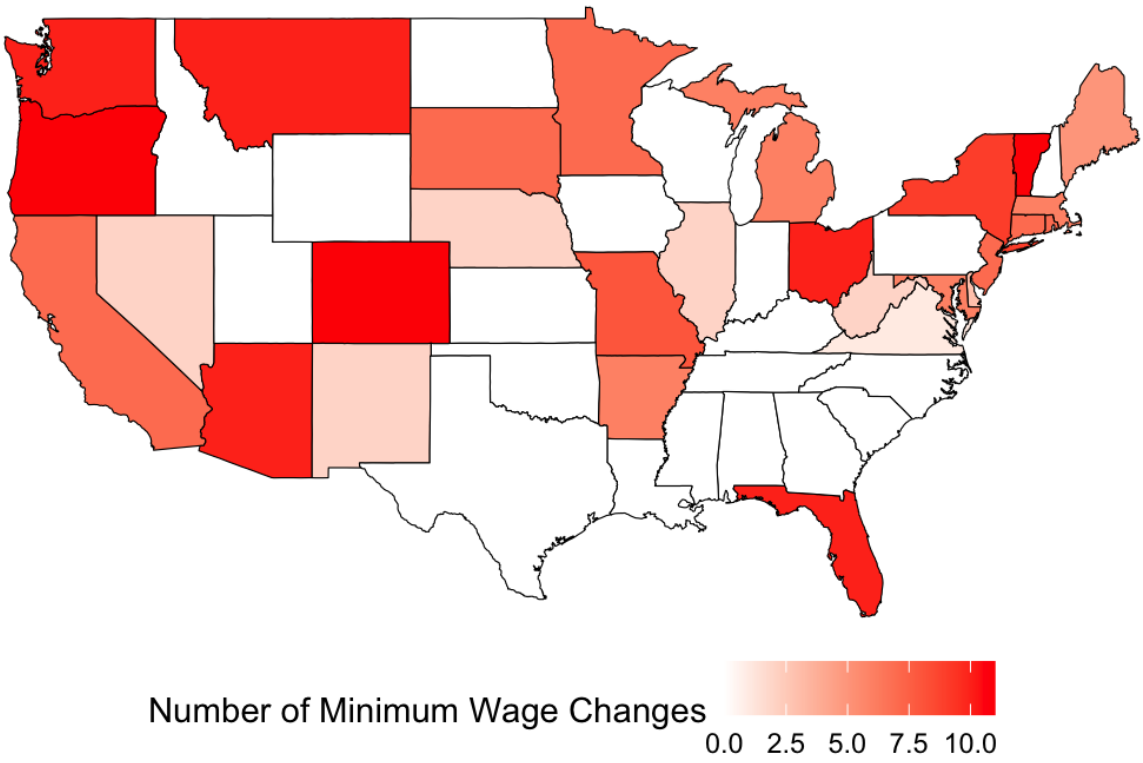
Notes: The figure shows relationship between concentration and wage at county level. I define concentration as inverse number of employers or establishments and wages are per food-retail worker in the county. Data on both establishment count and wages come from the Quarterly Census of Employment and Wages, US BLS for years 2004-2019 (https://www.bls.gov/cew/downloadable-data-files.htm).

Figure 4: Relationship Between Concentration and Employment



Notes: The figure shows relationship between county concentration and store employment in food retailing sector. I define concentration as inverse number of employers or establishments in the county, and employment measures number of full-time workers in the store. Data on establishment count come from the Quarterly Census of Employment and Wages, US BLS (https://www.bls.gov/cew/downloadable-data-files.htm). Data on store full-time employment comes from NielsenIQ TDLinx. The sample period is 2004-2019.

Figure 5: State Level Changes in Minimum Wages



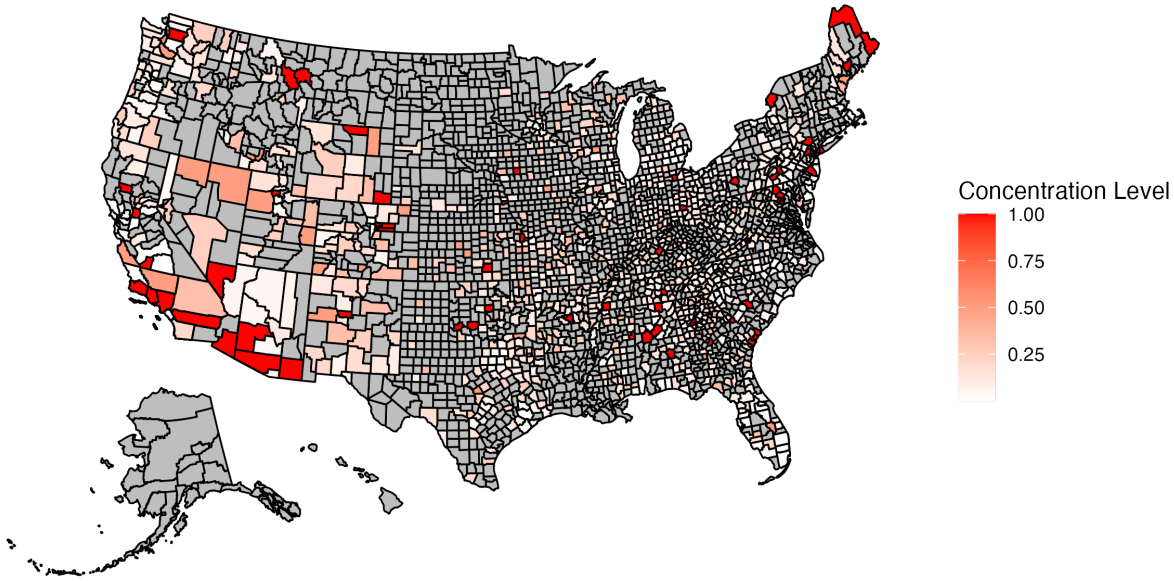
Notes: The figure shows number of changes in state minimum wages from years 2004-2019. *Data Source:* Vaghul and Zipperer (2022).

Table 1: Summary of Variables Used in Estimation

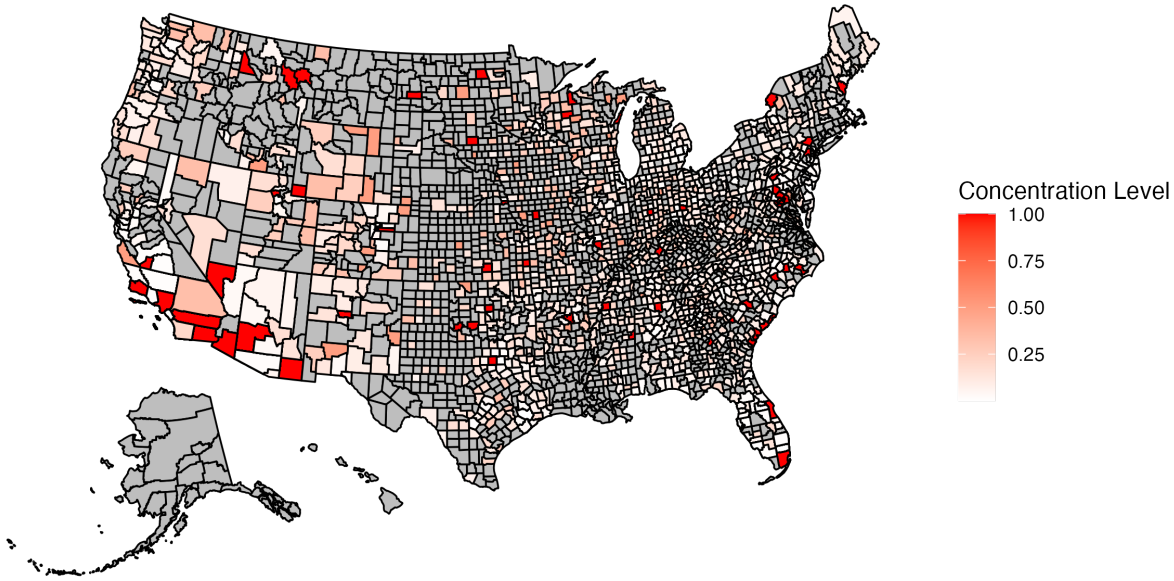
Variables	Unit	Data Source	Mean	St. Dev.	Min	Max
Store Employment	#	TDLinx	191.7	149.3	4	992
Merger	Binary	TDLinx	0.01	0.08	0	1
County Establishments	#	QCEW	76.7	156	1	1,580
County Weekly Wage	$ / worker	QCEW	427.7	151.1	2	2,713
Store Space	Sq Ft '000	TDLinx	51.8	18.5	3	224
County Income	$'000	US Census	55.6	14.7	20.1	151.8
County Population	#'000	US Census	1,150	2,060	3.8	10,095
Capital (Checkout Registers)	#	TDLinx	18	9.8	1	59.92
Store Weekly Materials (COGS)	$'000	Compustat	472	227	9.8	2,456
Store Weekly Labor Cost	$'000	TDLinx-QCEW	71.9	52.6	0.7	1,394
Output (Store Weekly Revenue)	$'000	TDLinx	629	309	15	3,300
Store Age	Years	TDLinx	9.7	5.2	0	20
County Unemployment Rate	%	US Census	6.1	2.7	1.6	29.4
County Minimum Wage	$/Hr.	Vaghul and Zipperer (2022)	7.5	1.2	5.2	13.3
County Area	Sq Mi	US Census	1,593.1	2,581.6	26	20,056.9

Notes: The data is publicly trading food retailers for sample period 2004-2019, and number of firm-year observations is 74,929.

Figure 6: County Level Labor Market Concentration by Inverse Establishment Count



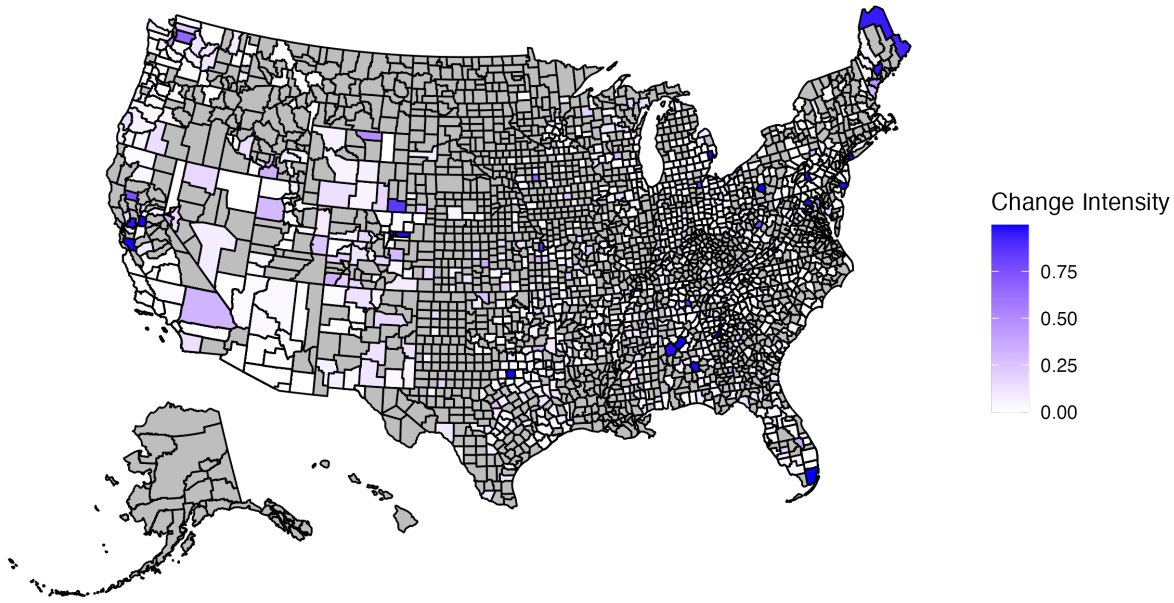
(a) Labor market concentration in year 2005



(b) Labor market concentration in year 2019

Notes: The two figures show labor market concentration at the county level in years 2005 (Panel (a)) and 2019 (Panel (b)). I define concentration as the inverse of total number of county establishments in NAICS 445000 sector. The data source is the Quarterly Census of Employment and Wages, US BLS (https://www.bls.gov/cew/downloadable-data-files.htm). Concentration level ranges from 0 to 1, with 1 being most concentrated (that is, the county has a single employer or establishment), and 0 being the least concentrated. The counties in grey color are not present in my sample.

Figure 7: Intensity of Changes in County Level Labor Market Concentration



Notes: The figure shows intensity of changes in labor market concentration between 2005 and 2019. I define concentration as the inverse of total number of county establishments in NAICS 445000 sector. The data source is the Quarterly Census of Employment and Wages, US BLS (https://www.bls.gov/cew/downloadable-data-files.htm). Intensity of changes in concentration level ranges from 0 to 1, with 1 being the most intense change, and 0 being the least change in concentration. The counties in grey color are not present in my sample.

Table 2: Minimum Wage Employment Effects by Labor Market Concentration: Inverse of Establishment Count.

	Log Store Employment			
	(1)	(2)	(3)	(4)
Log Min Wage	0.1128**	0.1074**	0.0849**	0.0795*
	(0.0499)	(0.0492)	(0.0421)	(0.0412)
Log Min Wage × Average HHI_{est}	0.1245	0.1293	0.1462	0.1454
	(0.1267)	(0.1264)	(0.1266)	(0.1268)
FIPS & Year FEs	Yes	Yes	Yes	Yes
Control Variables		Yes	Yes	Yes
FIPS-Specific Linear Time Trends			Yes	Yes
FIPS-Specific Quadratic Time Trends				Yes
Fit statistics:				
Observations	74,929	74,929	74,929	74,929
R^2	0.45222	0.45224	0.45227	0.45228

Note: Clustered (FIPS) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. I define average HHI_{est} as follows: For each labor market (FIPS), I compute average of number of establishments in food retailing across years using `annual_avg_estabs_count` variable in QCEW, and take inverse of the average. This gives me a measure of labor market concentration in terms of number of employers, with more employers or food retailers indicating lower labor market concentration and hence lower HHI. Control variables include log of FIPS-level median household income and unemployment rate from the US Census Bureau.

Table 3: Minimum Wage Employment Effects by Labor Market Concentration: Inverse of Population Density.

	Log Store Employment			
	(1)	(2)	(3)	(4)
Log Min Wage	0.1134**	0.1078**	0.0868**	0.0818**
	(0.0487)	(0.0480)	(0.0418)	(0.0410)
Log Min Wage × Average HHI_{pop}	0.9365**	0.9941**	1.034**	1.023**
	(0.4379)	(0.4483)	(0.4415)	(0.4394)
FIPS & Year FEs	Yes	Yes	Yes	Yes
Control Variables		Yes	Yes	Yes
FIPS-Specific Linear Time Trends			Yes	Yes
FIPS-Specific Quadratic Time Trends				Yes
Fit statistics:				
Observations	74,929	74,929	74,929	74,929
R^2	0.45223	0.45225	0.45228	0.45229

Note: Clustered (FIPS) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. I define average HHI_{pop} as follows: For each labor market (FIPS), I compute average of population density across years using `population` and `area_sqmiles` variables from the US Census Bureau, and take inverse of the average. This gives me a measure of labor market concentration in terms of population: the idea is that more densely populated regions likely invite more food retailers (employers), leading to lower labor market concentration and lower HHI. Control variables include log of FIPS-level median household income and unemployment rate from the US Census Bureau.

Table 4: Minimum Wage Employment Effects by Labor Market Concentration: Highly Concentrated Markets (per FTC 2023 Merger Guidelines) by Inverse Establishment Count.

	Log Store Employment			
	(1)	(2)	(3)	(4)
Log Min Wage	0.1183**	0.1134**	0.0921**	0.0868**
	(0.0481)	(0.0474)	(0.0411)	(0.0401)
Log Min Wage × $\chi(\text{HHI}_{\text{est}} \geq 0.18)$	0.0922**	0.0942**	0.1019**	0.1010**
	(0.0429)	(0.0426)	(0.0430)	(0.0432)
FIPS & Year FEs	Yes	Yes	Yes	Yes
Control Variables		Yes	Yes	Yes
FIPS-Specific Linear Time Trends			Yes	Yes
FIPS-Specific Quadratic Time Trends				Yes
Fit statistics:				
Observations	74,929	74,929	74,929	74,929
R^2	0.45222	0.45224	0.45228	0.45228

Note: Clustered (FIPS) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. The moderating variable $\chi(\text{HHI}_{\text{est}} \geq 0.18)$ is binary with value 1 if the market's average HHI in terms of inverse number of establishments across years is at least 0.18, and 0 otherwise. The threshold 0.18 is from the FTC 2023 Merger Guidelines for highly concentrated markets (Federal Trade Commission (2023)). When I use the threshold 0.25 from the FTC 2010 Merger Guidelines for highly concentrated markets (Federal Trade Commission (2010)), the moderation effects are exactly the same. Control variables include log of FIPS-level median household income and unemployment rate from the US Census Bureau.

Table 5: Minimum Wage Employment Effects by Labor Market Concentration: Unconcentrated Markets (per FTC 2023 Merger Guidelines) by Inverse Establishment Count.

	Log Store Employment			
	(1)	(2)	(3)	(4)
Log Min Wage	0.2075***	0.2041***	0.1883***	0.1832***
	(0.0570)	(0.0569)	(0.0549)	(0.0538)
Log Min Wage × $\chi(\text{HHI}_{\text{est}} < 0.1)$	-0.1061**	-0.1084**	-0.1178***	-0.1171***
	(0.0461)	(0.0461)	(0.0449)	(0.0448)
FIPS & Year FEs	Yes	Yes	Yes	Yes
Control Variables		Yes	Yes	Yes
FIPS-Specific Linear Time Trends			Yes	Yes
FIPS-Specific Quadratic Time Trends				Yes
Fit statistics:				
Observations	74,929	74,929	74,929	74,929
R^2	0.45227	0.45229	0.45234	0.45234

Note: Clustered (FIPS) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. The moderating variable $\chi(\text{HHI}_{\text{est}} < 0.1)$ is binary with value 1 if the market's average HHI in terms of inverse number of establishments across years is less than 0.1, and 0 otherwise. The threshold 0.1 is from the FTC 2023 Merger Guidelines for unconcentrated markets (Federal Trade Commission (2023)). Control variables include log of FIPS-level median household income and unemployment rate from the US Census Bureau.

Table 6: Minimum Wage Employment Effects by Labor Market Concentration: Unconcentrated Markets (per FTC 2023 Merger Guidelines) by Inverse Population Density.

	Log Store Employment			
	(1)	(2)	(3)	(4)
Log Min Wage	0.1937**	0.1986**	0.1893**	0.1814**
	(0.0793)	(0.0794)	(0.0779)	(0.0768)
Log Min Wage × $\chi(\text{HHI}_{\text{pop}} < 0.1)$	-0.0717	-0.0816	-0.0927	-0.0904
	(0.0693)	(0.0695)	(0.0688)	(0.0688)
FIPS & Year FEs	Yes	Yes	Yes	Yes
Control Variables		Yes	Yes	Yes
FIPS-Specific Linear Time Trends			Yes	Yes
FIPS-Specific Quadratic Time Trends				Yes
Fit statistics:				
Observations	74,929	74,929	74,929	74,929
R^2	0.45221	0.45223	0.45226	0.45226

Note: Clustered (FIPS) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. The moderating variable $\chi(\text{HHI}_{\text{pop}} < 0.1)$ is binary with value 1 if the market's average HHI in terms of inverse of population density across years is less than 0.1, and 0 otherwise. The threshold 0.1 is from the FTC 2023 Merger Guidelines for unconcentrated markets (Federal Trade Commission (2023)). Control variables include log of FIPS-level median household income and unemployment rate from the US Census Bureau.

Table 7: Estimates of Translog Production Function

	Estimation Method			
	(1)	(2)	(3)	(4)
Capital (Checkouts)	0.059*	0.060*	0.056*	0.056*
	(0.035)	(0.034)	(0.031)	(0.032)
Labor	0.169***	0.083***	0.102***	0.089***
	(0.038)	(0.023)	(0.023)	(0.027)
Materials (COGS)	0.696***	0.772***	0.747***	0.768***
	(0.179)	(0.147)	(0.170)	(0.146)
Returns to Scale (Elasticities Sum)	0.925**	0.916**	0.906**	0.915**
	(0.467)	(0.460)	(0.432)	(0.451)
Mean Markdown	2.218	1.067	1.372	1.166
Specifications:				
Year FEs	No	Yes	Yes	Yes
FIPS FEs	No	No	Yes	Yes
Controls	No	No	No	Yes
Observations	74,929	74,929	74,929	74,929

Note: Different specifications correspond to specifications in first stage (OLS) in GMM-IV procedure in production function estimation. Clustered standard errors at the FIPS (county) level are in parentheses. Control variables include a vector of log of county population, income, unemployment rate. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: Summary Statistics of Markdowns by Channel Category

Channel	Mean	Median	Min	Max	IQR	St. Dev.
Grocery	1.392	1.119	0.108	19.019	1.275	0.598
Mass Merchandiser	1.019	0.945	0.037	14.746	0.468	0.609
Entire Sample (Obs. = 74,929)	1.372	1.116	0.037	19.019	0.701	0.599

Note: The table shows summary statistics of store-level markdowns by channel category for 2004-2019. The estimates are based on OLS specification with two-way fixed effects and no controls in the first step of GMM-IV procedure.

Table 9: Summary Statistics of Markdowns by NAICS

NAICS	Mean	Median	Min	Max	IQR	St. Dev.
445110	1.628	1.589	0.008	3.763	1.063	0.799
455219	0.756	0.634	0.039	3.759	0.399	0.518
Entire Sample (Obs. = 74,929)	1.372	1.116	0.037	19.019	0.701	0.599

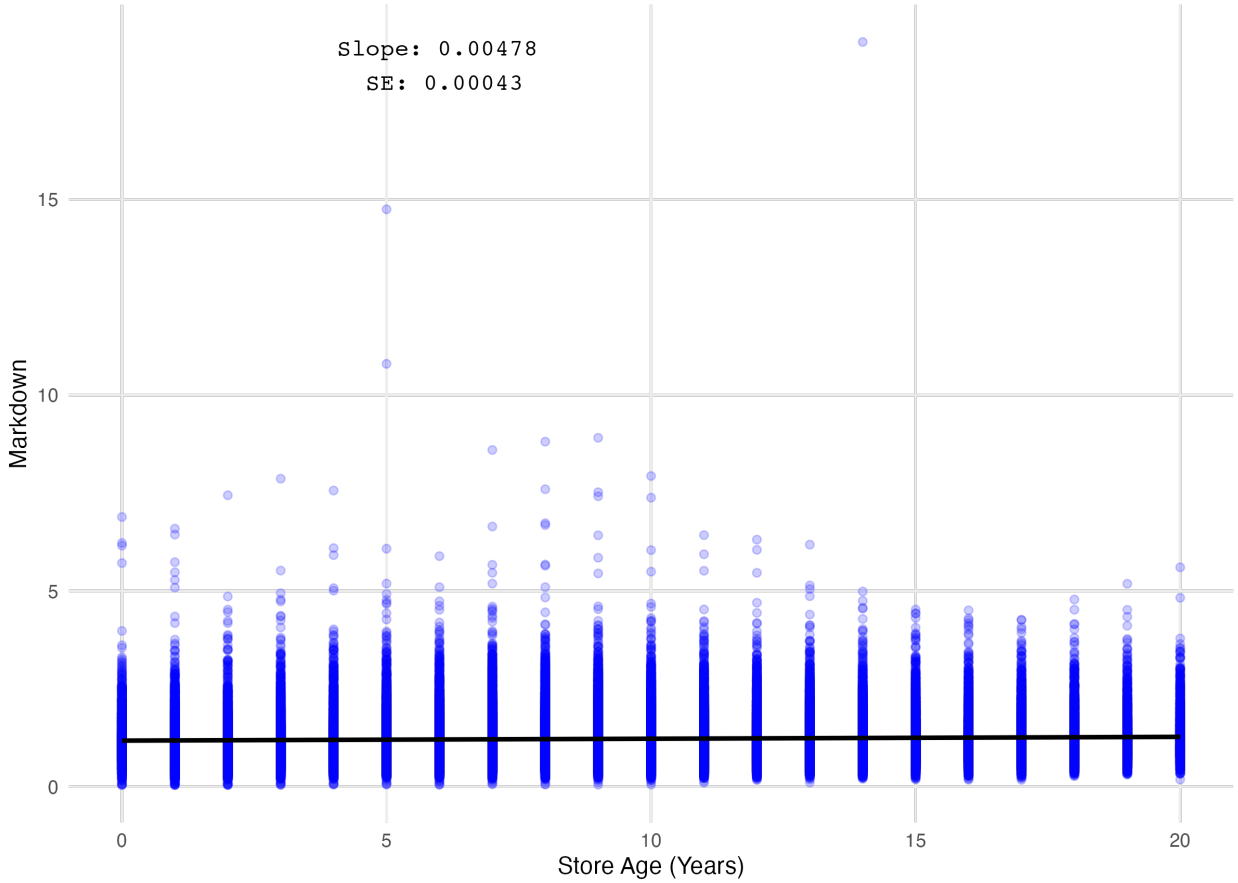
Note: The table shows summary statistics of store-level markdowns by 6-digit NAICS codes for 2004-2019. NAICS 445110 refers to "Supermarkets and Other Grocery Stores, Excluding Convenience Stores", and 455219 refers to "All Other General Merchandise Stores", according to NAICS Association (https://www.naics.com). The estimates are based on OLS specification with two-way fixed effects and no controls in the first step of GMM-IV procedure.

Table 10: Variance Decomposition of ν into θ_l, α_l, and μ

Component	Variance	Relative Contribution
Markdown (ν)	0.598	1.000
Output elasticity of labor (θ_l)	0.070	0.116
Labor share of revenue (α_l)	0.293	0.490
Markup (μ)	0.081	0.136
	Covariance	
$\theta_l,\ \alpha_l$	-0.037	-0.125
$\theta_l,\ \mu$	-0.013	-0.044
$\alpha_l,\ \mu$	0.027	0.089

Note: The table shows the variance decomposition of markdowns into output elasticity of labor, labor share of revenue, and markup, along with their covariances. I calculate relative contributions as a fraction of the total variance of markdowns (ν), and multiply covariance terms by a factor of two as in variance decomposition formula.

Figure 8: Relationship Between Store Age and Markdowns



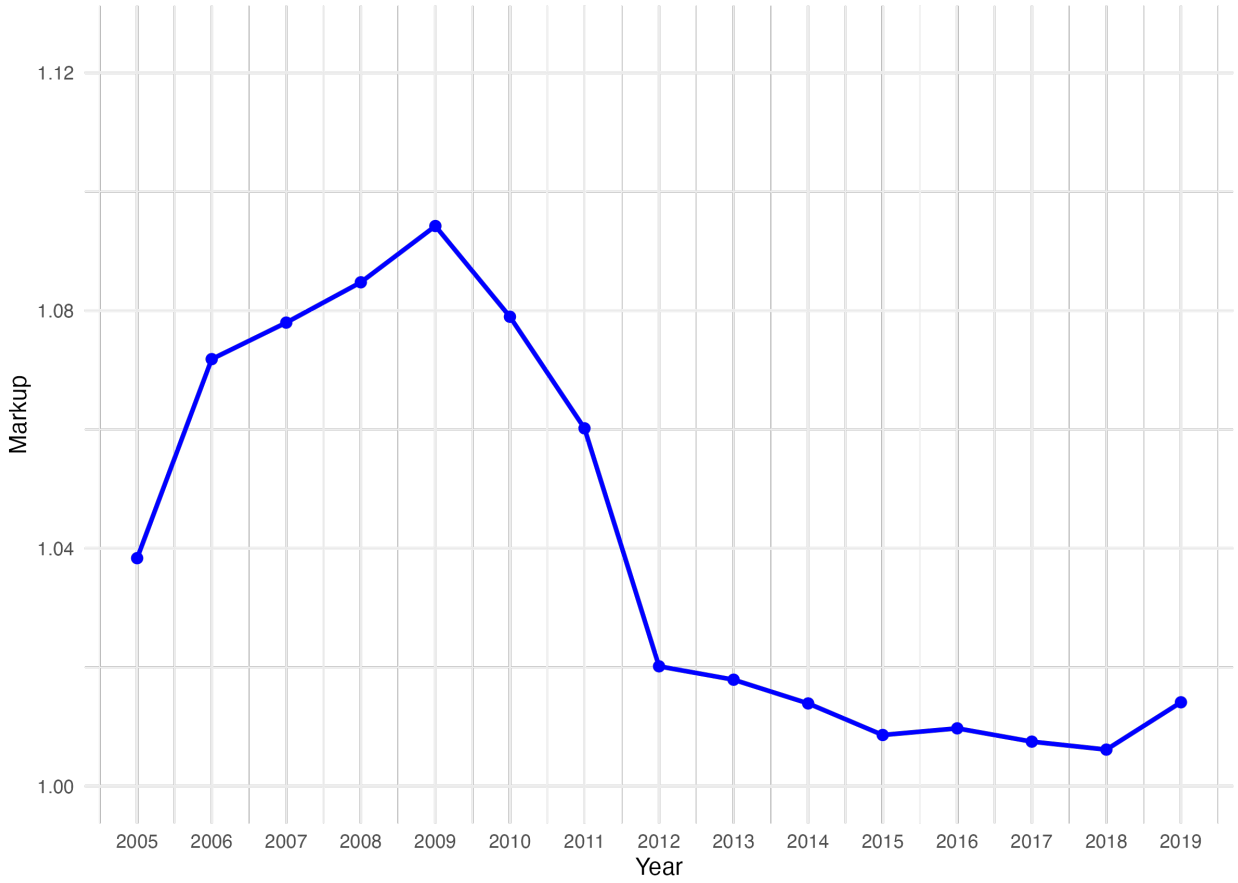
Notes: The figure shows how store's age relates to markdowns in a simple linear regression.

Table 11: IV Regression of Markdown on HHI Using LOOIV

	Log Store Markdown		
	(1)	(2)	(3)
Log HHI (LOOIV-Instrumented)	0.6283***	0.6004***	1.098***
	(0.1590)	(0.1551)	(0.3014)
FIPS FEs	No	Yes	Yes
Controls	No	No	Yes
F-test (1st Stage)	417.4***	833.9***	155.4***
Observations	74,929	74,929	74,929

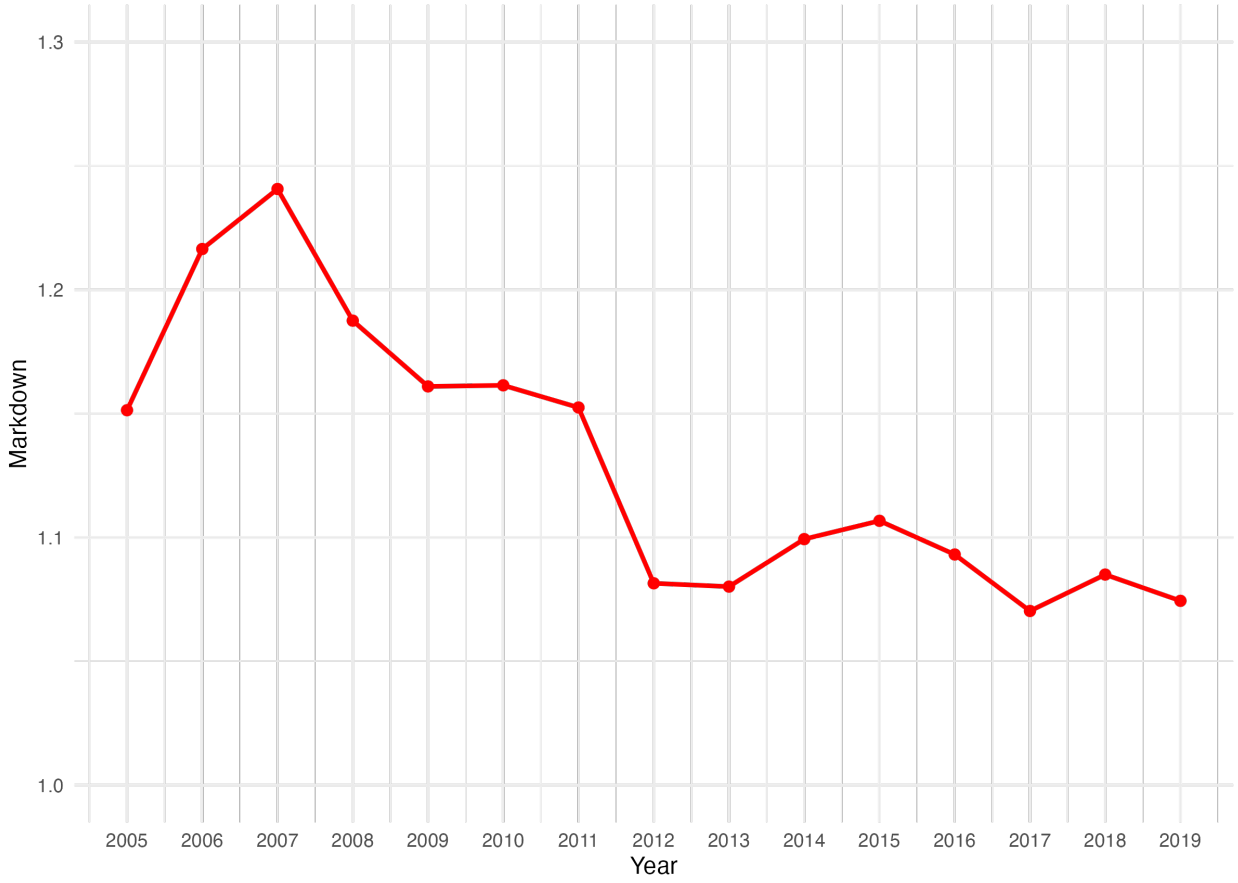
Note: The estimates are based on OLS specification with two-way fixed effects and no controls in the first step of GMM-IV procedure. The Clustered standard errors at the FIPS level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I define HHI at FIPS level as the inverse of total number of establishments (or employers) in food retailing sector. I define LOOIV, that is leave-one-out-IV, as the inverse number of total employers in all other FIPS except the focal one. This helps address endogeneity by isolating external variations in concentration that are not influenced by local labor market conditions.

Figure 9: Evolution of Aggregate Markups in US Food Retailing



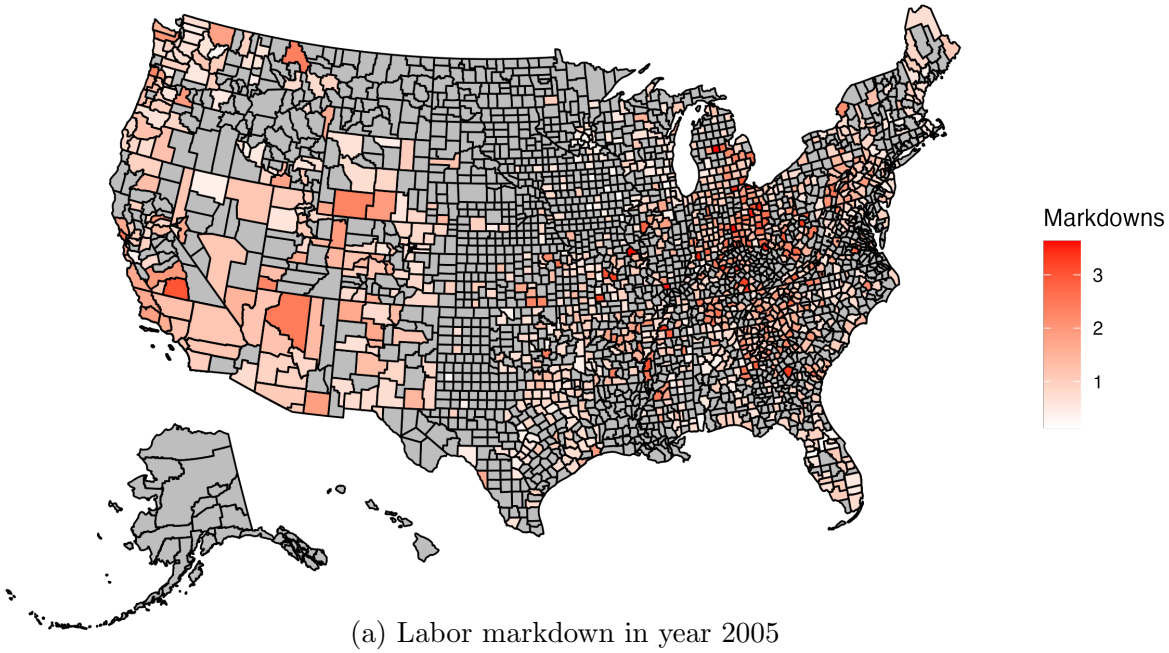
Notes: The figure shows evolution of aggregate markups in US food retailing sector. I follow the aggregation procedure described in Yeh, Macaluso, and Hershbein (2022). The estimates are based on OLS specification with two-way fixed effects and no controls in the first step of GMM-IV procedure. *Source:* Model estimates.

Figure 10: Evolution of Aggregate Markdowns in US Food Retailing

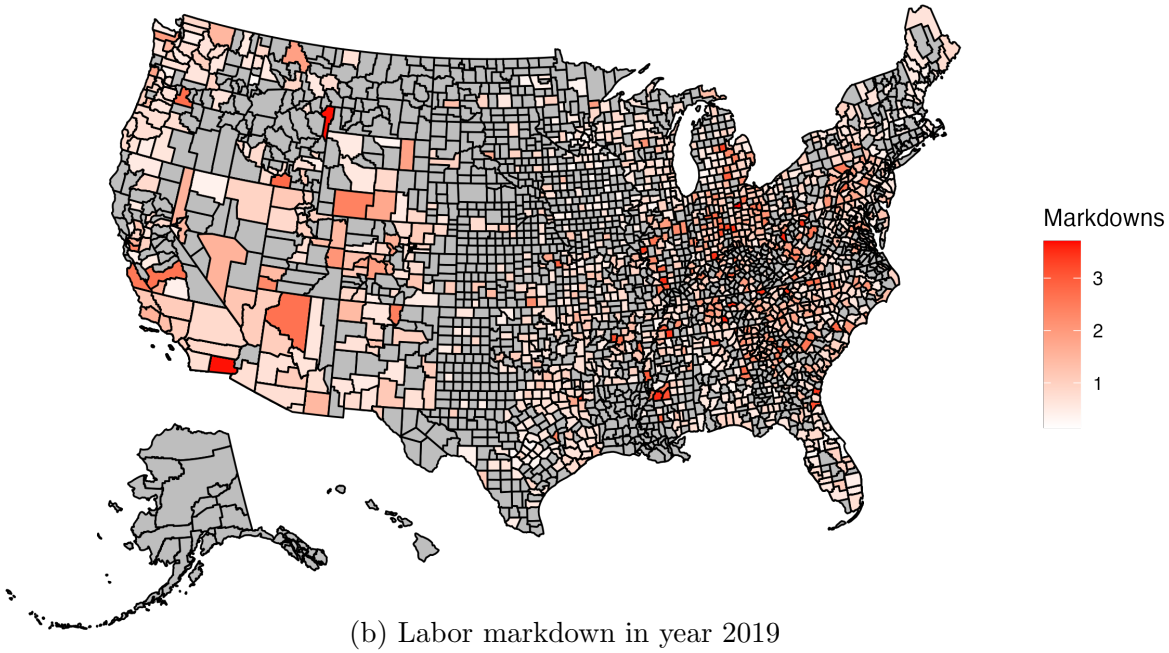


Notes: The figure shows evolution of aggregate markdowns in US food retailing sector. I follow the aggregation procedure described in Yeh, Macaluso, and Hershbein (2022). The estimates are based on OLS specification with two-way fixed effects and no controls in the first step of GMM-IV procedure. Source: Model estimates.

Figure 11: County Level Labor Markdowns



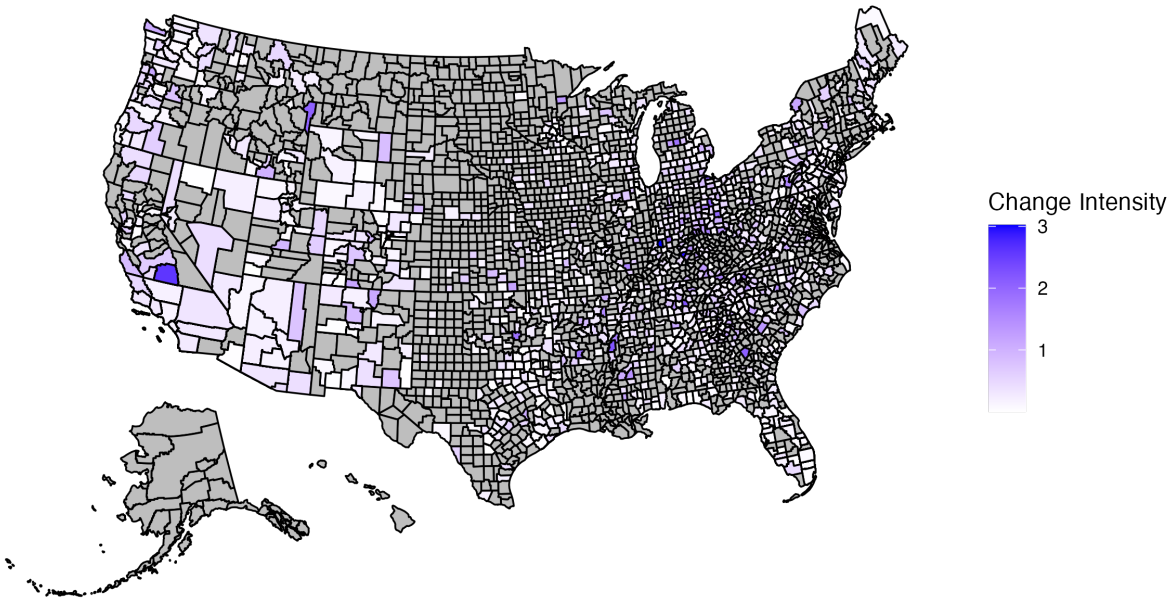
(a) Labor markdown in year 2005



(b) Labor markdown in year 2019

Notes: The two figures show labor markdowns at the county level in years 2005 (Panel (a)) and 2019 (Panel (b)). The dark red (light red or white) counties indicate high markdowns (low markdowns). The counties in grey color are not present in my sample. *Source:* Model estimates.

Figure 12: Intensity of Changes in County Level Labor Markdowns



Notes: The figure shows intensity of changes in labor markdowns between 2005 and 2019. Intensity of changes in concentration level ranges from 0 to 3, with 3 being the largest change, and 0 being the least change in markdown. The counties in grey color are not present in my sample. *Source:* Model estimates.

Table 12: IV Regression of Markdown on HHI Using Shift-Share IV

	Log Store Markdown		
	(1)	(2)	(3)
Log HHI (SSIV-Instrumented)	-0.3081**	1.002***	1.024***
	(0.1048)	(0.1253)	(0.1488)
FIPS FEs	No	Yes	Yes
Controls	No	No	Yes
F-test (1st Stage)	597.7***	46.8***	35.3***
Observations	74,929	74,929	74,929

Note: The estimates are based on OLS specification with two-way fixed effects and no controls in the first step of GMM-IV procedure. Clustered standard errors at the FIPS level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I define HHI at FIPS level as the inverse of total number of establishments (or employers) in food retailing sector. I define Shift Share IV (SSIV) in terms of mergers as follows. First, I identify the *shift* component captured by the national-level trend in mergers within the food retail industry. Next, I calculate the *share* component, which reflects each FIPS's pre-existing exposure to this national shock. I determine this by using local share of establishments or employers in the food retail industry (from QCEW data) relative to the national total. I then construct the SSIV by multiplying the national-level merger trend (shift) by each FIPS's pre-existing share of establishments (share). This creates an instrument that varies across FIPS based on their initial exposure to national mergers, isolating exogenous variation in local labor market concentration and addressing endogeneity concerns when estimating its impact on markdowns.

Table 13: Summary Statistics of Markdowns by Channel Category

Channel	Mean	Median	Min	Max	IQR	St. Dev.
Grocery	2.255	1.898	0.076	6.806	2.198	1.457
Mass Merchandiser	0.951	0.848	0.193	6.096	0.479	0.449
Entire Sample (Obs. = 74,929)	2.218	1.850	0.076	6.806	1.802	1.420

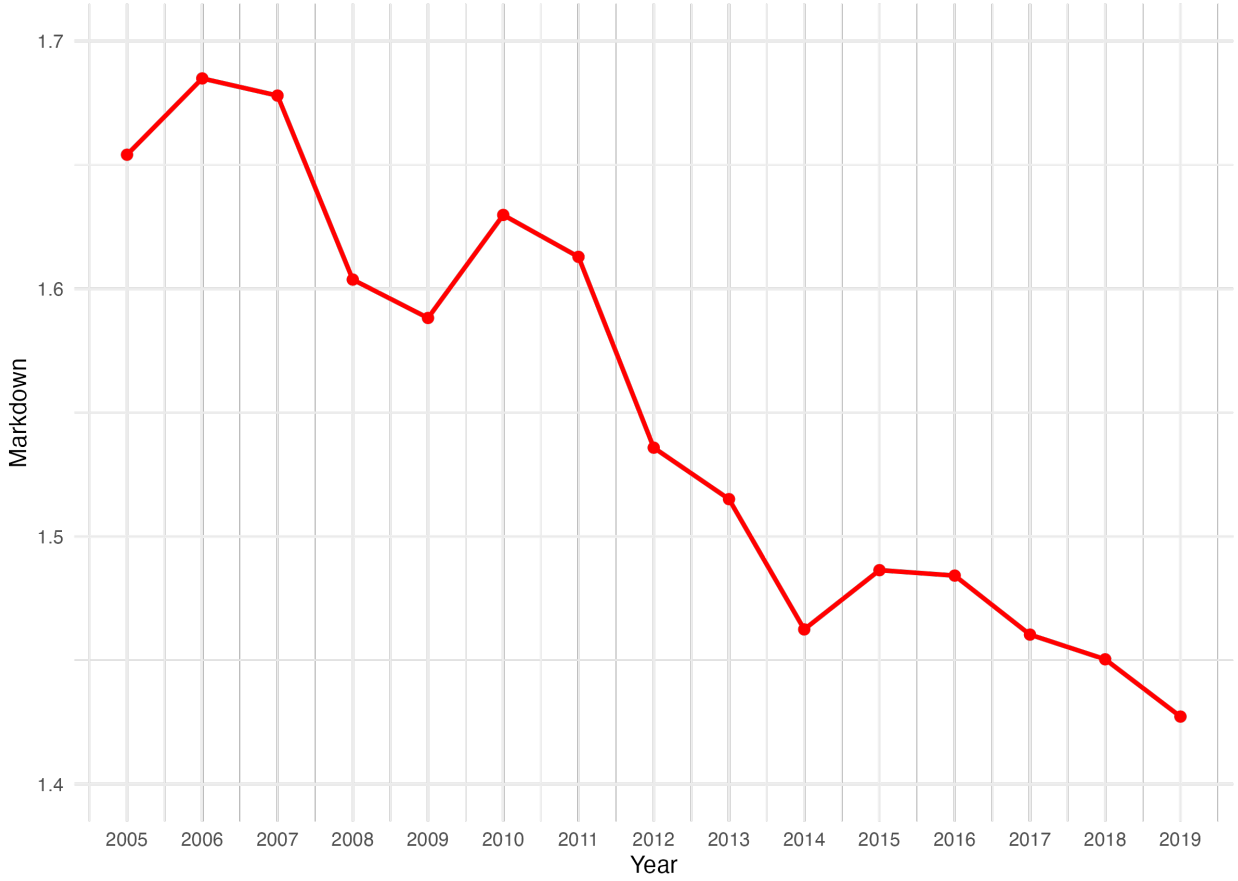
Note: The table shows summary statistics of store-level markdowns by channel category for 2004-2019. The estimates are based on OLS specification with no fixed effects and no controls in the first step of GMM-IV procedure.

Table 14: Summary Statistics of Markdowns by NAICS

NAICS	Mean	Median	Min	Max	IQR	St. Dev.
445110	2.907	2.85	0.076	6.806	1.793	1.386
455219	1.285	1.059	0.099	6.806	0.554	0.929
Entire Sample (Obs. = 74,929)	1.372	1.116	0.037	19.019	0.701	0.599

Note: The table shows summary statistics of store-level markdowns by 6-digit NAICS codes for 2004-2019. NAICS 445110 refers to "Supermarkets and Other Grocery Stores, Excluding Convenience Stores", and 455219 refers to "All Other General Merchandise Stores", according to NAICS Association (https://www.naics.com). The estimates are based on OLS specification with no fixed effects and no controls in the first step of GMM-IV procedure.

Figure 13: Evolution of Aggregate Markdowns in US Food Retailing



Notes: The figure shows evolution of aggregate markdowns in US food retailing sector. I follow the aggregation procedure described in Yeh, Macaluso, and Hershbein (2022). The estimates are based on OLS specification with no fixed effects and no controls in the first step of GMM-IV procedure. *Source:* Model estimates.

Table 15: IV Regression of Markdown on HHI Using LOOIV

	Log Store Markdown		
	(1)	(2)	(3)
Log HHI (LOOIV-Instrumented)	0.3780***	0.2699***	0.5895***
	(0.1012)	(0.0813)	(0.1743)
FIPS FEs	No	Yes	Yes
Controls	No	No	Yes
F-test (1st Stage)	411.9***	840.7***	157.8***
Observations	74,929	74,929	74,929

Note: The estimates are based on OLS specification with no fixed effects and no controls in the first step of GMM-IV procedure. The Clustered standard errors at the FIPS level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I define HHI at FIPS level as the inverse of total number of establishments (or employers) in food retailing sector. I define LOOIV, that is leave-one-out-IV, as the inverse number of total employers in all other FIPS except the focal one. This helps address endogeneity by isolating external variations in concentration that are not influenced by local labor market conditions.

Table 16: IV Regression of Markdown on HHI Using SSIV

	Log Store Markdown		
	(1)	(2)	(3)
Log HHI (SSIV-Instrumented)	-0.2513***	0.6338***	0.5081***
	(0.0874)	(0.0975)	(0.0802)
FIPS FEs	No	Yes	Yes
Controls	No	No	Yes
F-test (1st Stage)	845.1***	42.7***	58.0***
Observations	74,929	74,929	74,929

Note: The estimates are based on OLS specification with no fixed effects and no controls in the first step of GMM-IV procedure. Clustered standard errors at the FIPS level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I define HHI at FIPS level as the inverse of total number of establishments (or employers) in food retailing sector. I define Shift Share IV (SSIV) in terms of mergers as follows. First, I identify the *shift* component captured by the national-level trend in mergers within the food retail industry. Next, I calculate the *share* component, which reflects each FIPS's pre-existing exposure to this national shock. I determine this by using local share of establishments or employers in the food retail industry (from QCEW data) relative to the national total. I then construct the SSIV by multiplying the national-level merger trend (shift) by each FIPS's pre-existing share of establishments (share). This creates an instrument that varies across FIPS based on their initial exposure to national mergers, isolating exogenous variation in local labor market concentration and addressing endogeneity concerns when estimating its impact on markdowns.