

Retail Concentration and Wages

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May 1, 2024

Abstract

Antitrust policy in the U.S. now explicitly includes labor-market outcomes as measures of interest when considering the potential anticompetitive effects of mergers or acquisitions. Concentration in the food retailing industry is of particular concern due to several recent high-profile mergers, and a troubling increase in concentration at the national and local levels. We study this problem using both causal reduced-form models and a structural model of search, match, and bargaining. Our reduced-form models show no relationship between concentration and wages, but our structural model finds that concentration is associated with substantial wage suppression.

Keywords: concentration, food price inflation, Hirschman-Herfindahl Index, imperfect competition, retail wages.

JEL Codes: D43, L13, M31

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1 Introduction

In 2021, the President’s Executive Order on Promoting Competition in the U.S. Economy expanded the focus of antitrust policy from prices and other consumer-centric welfare measures (i.e., variety of choices, the pace of innovation, and quality of service, for example) to include labor-market outcomes (POTUS 2021). In the retail food industry, public concern regarding concentration among food retailers now extends beyond the impact of reduced competition on the price of goods and includes wages, employment, and labor-market mobility (MacDonald, Dong, and Fuglie 2023). More generally, the declining value-share of labor and rising income inequality serves as motivation for an emerging literature that examines the role of imperfect competition in labor markets from a macroeconomic (De Loecker, Eeckhout, and Unger 2020; Autor et al. 2020; Berger, et al. 2023) and microeconomic perspective (Azar, et al. 2020; Arnold 2021; Azar, et al. 2022; Benmelech, Bergman, and Kim 2022; Yeh, Macaluso, and Hershbein 2022; Rinz 2022; Qiu and Sojourner 2023). Perhaps not surprisingly, researchers generally find a negative association between employer concentration and the wages paid to employees, and interpret their findings as evidence of monopsonistic wage suppression. However, none of the research on this question focuses on the food retail industry, despite the significant media attention paid to supermarket concentration (POTUS 2021; Creswell 2023). Moreover, most of this literature fails to adequately address important identification issues that plague these “neo-structure-conduct-performance (N-SCP)” models (Berry, Gaynor, and Scott-Morton 2019; Syverson 2019; Miller, et al. 2022). In this paper, we estimate the relationship between industry concentration and labor-market outcomes in the retail grocery industry while disentangling the true market-power effect of concentration, and recognizing the unique nature of labor markets.

The relationship between market concentration and wages is not as obvious as it may seem because concentration itself does not necessarily lead to adverse outcomes for employees *a priori* (see Berry, Gaynor, and Scott-Morton (2019) and Syverson (2019) for a general criticism of the N-SCP approach). In fact, concentration may arise for many reasons – an increase in fixed costs across the industry, import competition or exit of inefficient firms – that do not create the usual conditions for market power in an industry. Therefore, empirical research is necessary to examine whether firms exercise market power in input markets as we cannot presume that workers are being exploited simply because employers are large and have a large share of the output market. Similar to the “contestable market” arguments that held sway in antitrust law in the 1970s and 1980s (Brock 1983), this perspective is more nuanced in that it connects conduct with outcomes and not

structure. Structure is only an indirect measure of potential market power but is not the same as the exercise of market power.¹ We show how empirical insights drawn from reduced-form models of concentration and labor market outcomes differ qualitatively from models that estimate the effect of the exercise of market power on labor markets, and not merely the potential exercise of labor market power.

Estimating the impact of market structure on equilibrium outcomes should also reflect the fact that labor markets differ from product markets in fundamental ways. Whereas product markets are relatively easy to define based on how consumers substitute among products with similar end-uses, over relatively small geographic areas in the case of retail food products, labor is much more fungible than consumer products. Geographically, labor markets are often defined in terms of industry or occupation and commuting zone combinations (Azar, et al. 2020; Arnold 2021; Azar, et al. 2022; Benmelech, Bergman, and Kim 2022; Yeh, Macaluso, and Hershbein 2022; Rinz 2022; Qiu and Sojourner 2023). Focusing on industries, however, embodies a strong assumption that workers, and their skills, are not fungible across industries. On the other hand, our approach recognizes that labor markets consist of individuals in occupations and not individuals in industries.

We estimate the causal impact of changes in industry concentration on wages in the grocery industry by following the recent literature on this topic, and then by extending their analysis using a structural model of labor market power. Specifically, we instrument for endogenous concentration in two different ways. First, we begin by using firm-level observations of mergers and acquisitions (M&A) in the TDLinx database as an instrument for concentration in an econometric model of wages in the grocery industry from the Quarterly Census of Employment and Wages (QCEW). Second, we then instrument for concentration using a leave-one-out measure of the inverse number of employers in the local market. Both wages and our instruments are defined at the commuting-zone level. With this data, we find concentration-wage elasticities very similar to those reported in the literature, so we trust that our initial approach provides insights that meet the causal-identification standards that are well accepted in this literature.

We then expand our analysis beyond industry-specific data to include occupation-specific data from the

¹Autor, et al. (2020) point to the importance of this distinction. Whereas others claim that the secular decline in labor’s share of economic value has risen because of increased concentration in local labor markets (Manning 2011, De Loecker, Eeckhout and Unger 2020), Autor et al. (2020) instead show that markets have become more concentrated in the US due to the rise of “superstar” firms. Whether these firms grow through advances in technology, globalization or some other mechanism, they have evolved to dominate many industries in the US (not just technology), and earn margins that are far higher than their smaller competitors. Attracting the best employees, the fact that they are able to charge high prices in the output market means that labor compensation as a share of profit is relatively low despite paying competitive wages. This example demonstrates that concentration does not necessarily imply that firms exercise monopsony power, *per se*, even though some statistics (labor share of output value) may suggest that it does.

Current Population Survey (CPS) and American Community Survey (ACS). These data allow us to address four of the primary identification challenges when estimating the effect of concentration on labor market outcomes: (1) the definition of a “labor market,” (2) the endogeneity of concentration, (3) the potentially-confounding impact of product-market power on labor market outcomes, and (4) the difference between the potential and actual exercise of market power in concentrated industries.

First, most research in this area defines labor markets on an occupation-geography basis using some objective definition of an industry to control for the type of job (NAICS or SIC codes) and Commuting Zones (CZs) to define the geographic extent of the market (Azar, et al. 2020; Azar, et al. 2022; Rinz 2022).² However, this labor-market definition implicitly treats all jobs in a particular industry the same, whereas we show that jobs tend to be fungible across industries as skills tend to be job-specific and not industry specific. Arnold (2021), for example, uses Longitudinal Employer-Household Dynamics (LEHD) datasets from the US Census to define the share of industry-level job-to-job transitions and calculates an index of substitutability among jobs in the U.S. at the CZ level. We follow his approach and use data from the CPS and ACS surveys in order to measure concentration at the job-level instead of the industry-level. We find that industry-level wage suppression does not exist at the occupation level.

Second, we use M&A transactions, or the change in concentration in a particular market, in order to address the endogeneity of observed concentration levels (Berry, Gaynor, and Scott-Morton 2019; Syverson 2019; Miller, et al. 2022). Specifically, we use changes in ownership in the TDLinX data to identify mergers or acquisitions within the supermarket NAICS definition (4451) and changes in employment and wages over the sample period 2004 - 2022.³ In TDLinX, we observe both the enterprise and establishment, similar to the Longitudinal Business Database (LBD) used in Arnold (2021). Establishment identifiers describe individual locations of a business, and specify exact locations and the nature of the business. Enterprise identifiers, on the other hand, provide a unique code for the owner of the establishment so if the establishment identifier stays constant – say the retail banner remains “Grocer A” at a specific location in the Phoenix metro area – but the enterprise code changes, then we tag this as a M&A observation. Using TDLinX in this way provides a much more comprehensive and objective way of identifying M&A transactions that are relevant to our objectives than scraping Hart-Scott-Rodino filings (Arnold 2021) as official filings only reflect mergers

² “Commuting Zones” are defined by the U.S. Census Bureau as contiguous regions within defined labor market areas (LMAs) that in which workers appear to commute frequently, and in large numbers. They are defined using hierarchical cluster analysis, so are fact-based measures of revealed commuting behavior, and are not simply political boundaries as are counties or states.

³ We intend to estimate our model using a range of NAICS definitions from general retail at the 2-digit NAICS level (code = 44) to the 6-digit NAICS level (code = 445110) in order to examine the sensitivity of our findings to how we define industry and, implicitly, jobs.

that involve asset values greater than \$50.0 million. This approach also addresses the empirical weaknesses of using continuous concentration measures over time because M&A transactions directly affect changes in concentration that are likely to change the actual exercise of market power.

Third, we estimate the impact of changes in retail grocery concentration on labor market outcomes (wages, employment and total compensation) by instrumenting for endogenous concentration using M&A transactions to separate concentration from changes in concentration (Miller, et al. 2022).⁴ We also follow the recent literature (Azar, et al. 2022; Qiu and Sojourner 2023) by using a leave-one-out measure of the inverse number of employers in CZs other than the focal CZ as an alternative instrument. By controlling for a complete set of geography level control variables, including CZ-level economic trends, our identification strategy addresses concerns regarding the potential endogeneity of merger activity as in Drewianka and Johnson (2006), Hosken, Olson and Smith (2018), and Arnold (2021). Our estimates using either of these identification strategies are not qualitatively different, so we are confident in the robustness of our treatment-effect estimates.

Finally, we extend the reduced-form, casual inference approach in the literature (Azar, et al. 2020; Arnold 2021; Azar, et al. 2022; Benmelech, Bergman, and Kim 2022; Yeh, Macaluso, and Hershbein 2022; Rinz 2022; Qiu and Sojourner 2023) by using a structural search, match, and bargaining approach to estimate the relationship between concentration and the actual exercise of market power, rather than just its potential exercise. Berger, et al. (2023) emphasize that monopsony wage suppression is only one potential source of imperfection in local labor markets, while search and informational frictions explain much more of the variation in local wages for similar workers in similar jobs. In fact, they find that monopsony wage suppression explains only 1/3 of the observed gap between labor marginal-value products and market wages. We use data from the ACS for occupations in the retail grocery industry in a search, match, and bargaining framework to disentangle search and matching imperfections from the impact of labor-market concentration on worker bargaining power (Pissarides 2000; Dey and Flinn 2005; Flinn 2006). By allowing the share of employment surplus, or bargaining power in an equilibrium search, match, and bargaining framework, to vary with the degree of concentration in the retail-food labor market we provide the key link between market structure and conduct that is otherwise missing in the empirical literature on this topic.

Using this approach, we find that concentration explains some 42% of the deviation between observed

⁴Despite the fact that M&A transactions occur at different points in time, our treatment-effect estimates do not suffer from the staggered-treatment OLS bias described in Goodman-Bacon (2021) and Callway and Sant’Anna (2021) because our employee-employer data compares units that are always treated (employees in merged employer) with units that are never treated (employees with firms that are never merged).

wages in the grocery industry and the marginal value of equilibrium employer-employee matches. Although our treatment-effect models find no consistent relationship between retail concentration and wages, our structural model finds that monopsony wage suppression accounts for a significant reduction in wages below their competitive level. If wages were set at a competitive level, employees would earn the full amount of employment surplus available from a typical match, or \$59.43 in our preferred model. Instead, they earn an average wage of \$33.52, or some 56.4% of the competitive level. We attribute this markdown to monopsony behavior, but condition our findings with the caveat that deviations between competitive and observed wages in a search, match, and bargaining framework are also due to search frictions, transactions costs, or factors that may not reflect the actual exercise of market power over workers (Berger, et al. 2023). Our findings are nonetheless important as they provide the first estimates of the impact of concentration in the retail grocery industry on worker wages, and likely welfare outcomes due to rising concentration (MacDonald, Dong and Fuglie 2023).

Our findings contribute to the literature on imperfectly competitive labor markets (Flinn 2006; Naidu, Posner, and Weyl 2018; Manning 2021; Card 2022), specifically as it relates to the food retailing industry. Although there is a growing literature that examines the relationship between concentration and labor market outcomes in the general economy (Azar, et al. 2020, 2022; Yeh, Macaluso and Hirshbein 2022; Rinz 2022; Qiu and Sojourner 2023; Arnold 2021), there is no empirical research that focuses specifically on labor markets in the agriculture and food industry. Insights from other sectors may not be relevant to the food retailing industry due to the prevalence of minimum-wage jobs in food retailing, the ubiquity of food retailers in nearly every county of the US, and the importance of food retailing to consumer welfare.

We also contribute to the concentration-and-wages literature by providing a key link between concentration and the exercise of market power, rather than just concentration – or market structure – *per se*. Although measures of market structure, typically (Herfindahl-Hirschman Index (HHI)), play a prominent role in antitrust guidance from the Federal Trade Commission and the Antitrust Division of the Department of Justice, they remain proxy measures for the likely use of market power and do not provide direct evidence of either imperfectly competitive pricing or wage-setting, as the case may be. In this paper, we demonstrate the weakness in using concentration measures in reduced-form models of wage determination, and provide what we think is a more structurally-sound way of connecting market concentration to the actual wage setting process.

Third, we contribute to the policy conversation surrounding the importance of labor-market outcomes

for antitrust evaluation. From a broader welfare perspective, it is inarguable that worker outcomes are as important, and often more important, than traditional consumer-level welfare measures (Naidu and Posner 2022; Qiu and Sojourner 2023). Because labor-market outcomes are critically important to industrial policy, it is important that we develop a new set of methods that are generally regarded as correct, and credible, for measuring the impact of increasing concentration on workers. In this paper, we provide empirical evidence on the relationship between concentration and wages in the retail food industry and, more generally, develop an empirical framework for testing the structural relationship between concentration and wages that may be useful in other industries, and other settings.

The rest of the paper is structured as follows. In the next section, we provide some background on the importance of industrial policy in the retail food industry, and wage setting in labor markets more generally. In the third section, we describe our empirical models, first a reduced-form approach to estimate the causal effect of retail concentration on wages, and then a structural framework to estimate how concentration affects the exercise of market power in labor markets. In the fourth section, we describe the data used in both our treatment-effect and structural models and provide some model-free evidence of the relationship between concentration and wages. We follow in the fifth section by presenting the results from both our reduced-form and structural models, and offer some policy guidance that follows from our findings. We conclude in the sixth section and offer some suggestions for future research in this area.

2 Background

The importance of labor market outcomes for the conduct of antitrust policy is clear from both guidance from federal officials, and the actions of firms seeking to merge with others.

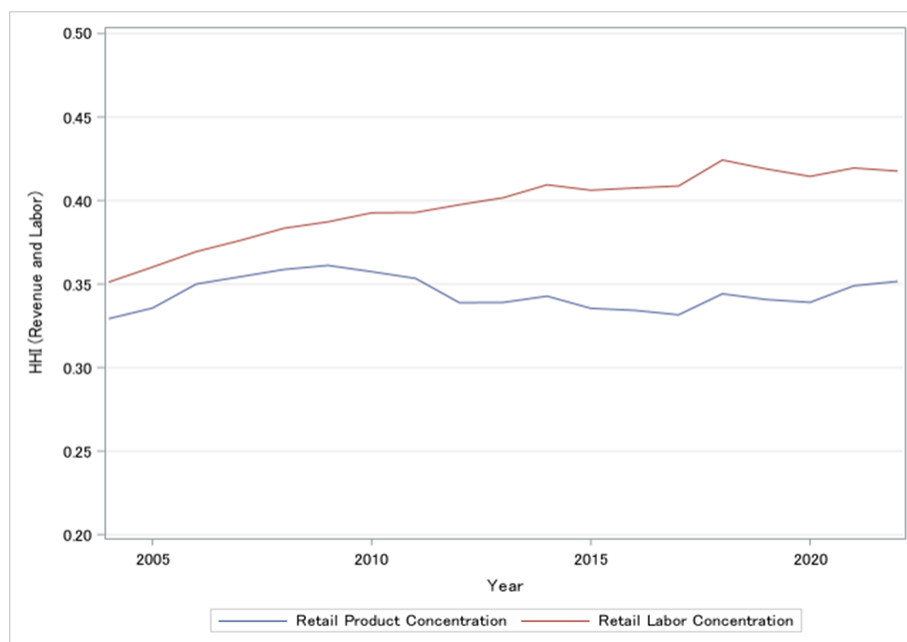
First, the Executive Order on Promoting Competition in the U.S. Economy in 2021 made the concern for labor explicit in revising the goals of antitrust policy (EO, POTUS 2021). In expressing the goals of federal antitrust policy, the EO states “...to combat the excessive concentration that...has increased the power of corporate employers, making it harder for workers to bargain for higher wages and better work conditions...” (POTUS 2021), which is the first time that concerns for the labor market appear as primary concerns in policy communications, presumably reflecting a change in Federal Trade Commission policy goals as well.

Second, in announcing a planned divestiture, pursuant to a potential resolution of federal antitrust concerns regarding their proposed merger with Albertson’s, officials at Kroger, Inc. explained that the buyer of the divested stores “...commits to honoring all collective bargaining agreements which include industry-

leading benefits, retaining frontline associates and further investing for growth...” (PRNewswire 2023) again anticipating concerns regarding the labor-market implications for their proposed merger. From the Federal Trade Commission side, their focus on labor market outcomes is clear as they argue that ”...Kroger’s proposed acquisition of Albertsons would immediately erase aggressive competition for workers, threatening the ability of employees to secure higher wages, better benefits, and improved working conditions...” in opposing the merger (FTC 2024).

More generally, labor markets are now more important than perhaps ever. With unemployment rates persistently below what was once believed to be the ”natural rate” of 4.0%, labor markets are historically tight, with implications throughout the economy, from shortages of agricultural workers (Richards 2018, others) to record-breaking strike activity from newly empowered worker groups. In short, labor concerns are now critically important to a range of federal policy decisions.

Figure 1: Product Market and Labor Market Concentration in U.S. Food Retailing, 2004-2022



Note: Data from NielsenIQ TDLinX, 2004-2022, sample of retail grocery-industry firms (NAICS=445), at the commuting-zone level. Commuting zones defined using data from ERS-USDA.

Modern antitrust considerations reflect the social and local-market impact of consolidation of legislators in the rapidly-transforming 1920s and 1930s. Indeed, anti-chain-store activists in the 1930s sought, and

ultimately received, legislation targeting the spread of the Great Atlantic and Pacific Tea Company (Purnell 2007), and similar arguments followed Walmart’s growth in the 1980s - 2000s (Basker 2005, 2007a,b; Drewianka and Johnson 2006; Dube, Lester, and Eidlin 2007; Sobel and Dean 2008; Neumark, Zhang, and Ciccarella 2008). Our analysis of the labor-market impacts of food retail mergers and acquisitions will follow the literature regarding Walmart’s impact on labor market outcomes during its expansion phase in the 1990s through the current century. Whether dynamics among and within retail chains lead, follow, or cause economic decline is an empirical question. In this study, we will examine whether retail mergers in the US affects employment, wages, and the total welfare of employees.

Concentration in the food retailing sector, at least measured as product-market concentration, has been rising for many years (MacDonald, Dong, and Fuglie 2023). Figure 1 shows the path of retail product-market concentration from 2004 to 2023, and a similar measure showing CZ-level labor-market concentration. This figure shows that both measures have been rising rapidly over the past 20 years, but labor-market concentration remains relatively low. Further, we show below that there is no clear relationship between either measure and the path of wages in the retail grocery industry so careful empirical analysis is necessary.

3 Empirical Model

3.1 Overview

In this paper, we divide our empirical approach into two sections: The first establishing credible causal effects of industry concentration on wages and employment, and the second a structural analysis of the how concentration is related to the actual exercise of market power, and similar labor market outcomes to our first approach. We outline each in this section.

3.2 Treatment Effect Analysis

In the first of our empirical models, we estimate instrumental variables models for the relationship between concentration and wages using data from TDLinx and the American Community Survey (ACS, Bureau of Census) to measure concentration and both QCEW and ACS to measure wages at the local labor-market (commuting zone) level. Our approach recognizes that concentration is endogenous (Arnold 2021; Miller et al. 2022), so our main reduced-form evidence comes from instrumental variable strategy which we discuss below. To get a baseline set of results, we also implement the following equation where we endogenize

concentration:

$$\log(y_{ct}) = \alpha \log(HHI_{ct}) + \phi_c + \phi_t + \phi_c \times t + \theta \mathbf{X}_{ct} + \varepsilon_{ct}, \quad (1)$$

where the outcome variable y_{ct} denotes the wage (average weekly) of grocery workers in commuting zone c in year t , HHI_{ct} is a measure of the CZ-level labor market concentration (HHI), ϕ_c are commuting zone fixed effects, ϕ_t are year fixed effects, $\phi_c \times t$ is a set of commuting zone time trends, \mathbf{X}_{ct} is a vector of potentially time-varying commuting-zone attributes (population, income, average age, education level), and ε_{ct} is the error term. In this specification, the parameter α measures the treatment effects of HHI on CZ-level wages of workers in retail grocery establishments.

Our main IV model leverages Hausman-like instrumental variables for endogenous employment-HHI levels. Specifically, Azar, et al. (2022), Rinz (2022) and Qiu and Sojourner (2023) each use the average concentration for the same occupation across all other CZs in the same year (a “leave-one-out” instrumental variable (LOOIV)). This is similar to the Hausman-instrumentation strategy (Hausman, Leonard, and Zona 1994) that is frequently used in the empirical industrial organization literature, and is based on the assumption that local labor-demand shocks are independent of national labor-demand shocks that may cause all local concentration levels to move together. In order to maintain comparability with the existing literature, we present estimates using this IV strategy as our primary results as opposed to results from number of CZ-level mergers as an IV for HHI.

As robustness checks, we estimate versions of equation (1) without commuting-zone level controls, fixed effects, and commuting-zone level trends. Further, we estimate specification (1) using number of mergers as an IV for HHI, similar to the strategy in Arnold (2021). In this case, we find point estimates of the HHI-wage relationship that are consistently negative, but again not significantly different from zero, as in our estimates with the LOOIV (see table A1 in the appendix). Our preferred instrument also aligns with the notion that mergers are themselves endogenous (Gowrisankaran (1999); Hosken, Olson, and Smith (2018)). We also estimate the specification with wages measured using the ACS data rather than with QCEW. As we show below, our findings from all of these model variations are qualitatively consistent, and show that there is little statistical evidence of a direct relationship between concentration in the retail labor market and wage outcomes. However, our findings do not rule out an indirect, structural relationship between concentration, bargaining power, and wages. In the next section, we describe a structural model that is able to disentangle the actual mechanism that underlies the relationship between concentration and wages.

3.3 Structural Model Analysis

In this section, we explain how we test the linkage between concentration and employee-level outcomes through a structural approach in which bargaining and search frictions are as likely to affect wages as monopsony-driven wage suppression.

We apply a model of labor market search, matching, and bargaining developed by Flinn (2006) to examine equilibrium employment, wage, and productivity outcomes among our sample of retail workers. Job duration, unemployment, and wages are each equilibrium outcomes in the sense that firms search optimally for workers, workers search optimally for jobs, and search occurs until the point at which the marginal benefit of additional search effort is just equal to the marginal cost of doing so (Stigler 1961). When both firms and workers optimize, the “employment surplus,” or the amount of value created by the worker for the firm, is at a maximum. Our framework departs from the usual “take it or leave it” assumption in the labor economics literature (Burdett and Mortensen 1998; Van den Berg and Ridder 1998; Eckstein and Van den Berg 2007) by allowing workers and firms to bargain over wage outcomes. Negotiation between firms and workers, or their representative, means that the amount of employment surplus is shared between workers and firms according to their relative bargaining power, which is exogenous to each party and is usually determined by individual attributes, is interpreted as negotiating “skill” (Nash 1950; Muthoo 1999), and is estimated in the data. In our model, one of the primary attributes that determines the balance of bargaining power between firms and workers is the relative number of employers and employees in each labor market, or the concentration measures developed in the previous section. In this way, the exercise of market power (bargaining power) is mediated by the potential for market power as measured by the degree of concentration in each market.⁵

An equilibrium model of search, match, and bargaining is appropriate for the problem at hand because equilibrium models are necessary to account for many well-understood sources of labor-market imperfection: Search frictions, transactions costs, and partial information regarding job openings and opportunities (Berger, et al. 2022; Berger, et al. 2023). Once we control for all other possible labor-market imperfections that can lead to rents in labor-market transactions, the only other logical factor left is simply employer monopsony power. With our structural model, we allow the structure of the market for retail workers to explain the allocation of rents left over after accounting for all of these other factors. In this way, our structural model

⁵Our model belongs in the general class of “imperfectly competitive” labor market models in which both workers and firms can profit from the employment relationship. In these models, imperfection refers to the existence of search frictions, and not the usual market power relationships of monopsony hiring or monopoly labor unions (Bhaskar, Manning, and To 2002; Manning 2003; Ashenfelter, Farber, and Ransom 2010; Ransom and Oaxaca 2010; Hamilton et al. 2021).

provides a clean test of the potential for labor market power to lead to adverse outcomes for workers.

We are not the first to use a formal model of optimal search, match and bargaining to explain labor market outcomes, as Flinn (2006) examines how minimum wage laws affect equilibrium wages and employment, Dey and Flinn (2005) consider how wages differ between those who have healthcare and those who do not, and Flabbi and Moro (2012) consider gender differences in compensation. We are the first, however, to explore how wages, and more precisely employment-surplus allocation, depends on market structure or the potential exercise of market power.⁶ In this section, we provide a brief explanation of the core of our theoretical model, and use this model to derive several testable hypotheses regarding the relationship between concentration and wages, and the allocation of employment surplus, productivity, job duration, and unemployment duration.

Following the standard approach in this literature (Pissarides 2000; Flinn 2006), our model assumes that match productivity (ϕ) is distributed across the sample of workers according to a distribution function, $f(\phi)$, which is assumed to be log-normal and is determined by the production technology used by the firm. We follow Flinn (2006) in what follows, and assume that both firms and workers observe the productive value of the match, ϕ , and that match productivity is exogenously determined by attributes of the employee, and the quality of the match with a particular employer. The exogenous rate of job termination for employed workers is δ , the exogenous rate of job contacts, or the rate at which jobs are created, for unemployed workers is τ , and the discount rate is $\beta > 0$. Workers negotiate with an exogenously determined amount of bargaining power, $\lambda \in (0, 1)$, which reflects the share of the match surplus they retain from the employment relationship.

Labor is considered the only factor of production, so firms earn zero profit, and derive no value from participating in the labor market if they do not employ workers. The profit from employing a worker is the difference between their productivity value and the wage, or $\phi - w$, where w is the wage paid to employees. Employers and employees negotiate according to a Nash (1950) bargaining framework in which the strength of each player's bargaining position depends on the value of their next best alternative, or their "disagreement profit" in Nash bargaining terminology. From the worker's perspective, the disagreement profit is the value of staying unemployed, during which time they are assumed to continue searching for a job, so their next best alternative is the value of ongoing job search efforts, denoted by W_u . At a certain point, there is a threshold wage, the critical match value, ϕ^* , that determines whether an unemployed worker will accept a

⁶In our context, "employment surplus" essentially refers to the difference between the marginal value product of an employee, and his or her threshold compensation level – the amount they require to accept a job from a particular employer.

job offer. The critical match value is given by $\phi^* = \beta W_u$, and determines whether labor will be supplied, as all values of ϕ that meet or exceed ϕ^* will result in employment while those that are lower will not. Once a worker accepts a job offer, the value of employment depends on the wage, $W_e(w)$.

With these assumptions, the value to a worker of taking a job is the present value of their wage, plus the expected present value of reverting to unemployment, or:

$$W_e = \frac{w + \delta W_u}{\beta + \delta}, \quad (2)$$

where the “effective” discount rate includes a risk premium for the possibility of becoming unemployed. At the same time, the value of unemployed search is equal to the reservation wage (or the utility of consuming leisure, R) plus the expected present value of the surplus earned from taking a job at any wage greater than the critical match value:

$$\beta W_u = R + \frac{\lambda \tau}{\beta + \delta} \int_{\beta W_u} [\phi - \beta W_u] df(\phi), \quad (3)$$

where the expected value is over the entire distribution of possible match values above the reservation value.

From the firm’s perspective, the value of employing a worker with productivity level ϕ is simply the present value of the amount of employment surplus, discounted at the same rate as the employee, or:

$$W_f = \frac{\phi - w}{\beta + \delta}, \quad (4)$$

where the wage is the observed, hourly wage for a typical worker.

Once a match occurs, employers and employees bargain for wages at all values of $\phi \geq \phi^*$, that solve the generalized Nash bargaining problem:

$$w(\phi, W_u) = \arg \max_w [W_e(w) - W_u]^\lambda \left[\frac{\phi - w}{\beta + \delta} \right]^{1-\lambda}, \quad (5)$$

where λ measures the share of employment surplus earned by the employee, and $(1 - \lambda)$ the share earned by the employer, recalling that the disagreement profit for the firm is zero. In the absence of any consideration for minimum wages, the wage that solves (5) is given by:

$$w(\phi, W_u) = \lambda \phi + (1 - \lambda) \beta W_u, \quad (6)$$

where recall that $\beta W_u = \phi^*$ is the threshold match value for the employee. However, minimum wages are an important feature of the low- and semi-skilled retail labor market (7.4% of our sample), so we follow Flinn

(2006) in modifying the problem to explicitly allow for the imposition of minimum wages on market-driven wage bargaining.

Minimum wages constrain the wages employers can pay. However, because employers earn some surplus on each employee, depending on the realized values of ϕ and λ , they have the ability to give up some surplus to hire workers with ϕ greater than the minimum wage (w_m) even though the minimum wage may be greater than the equilibrium wage suggested by (6). To see this more formally, assume the value of unemployed search is now a function of the minimum wage, and solve for the threshold value of $\hat{\phi}$ that holds when $w = w_m$, or

$$\hat{\phi}(w_m, W_u(w_m)) = \frac{w_m - (1 - \lambda)W_u(w_m)}{\lambda},$$

so the minimum wage defines regions of the equilibrium match value that separate workers who are paid clearly above the minimum wage, those who are paid the minimum wage, and those who are not hired at all. Because minimum wages impose a discontinuity on the distribution of wages, the value of unemployed search becomes:

$$\beta W_u(w_m) = R + \frac{\tau}{\beta + \delta} \left\{ \int_{w_m}^{\hat{\phi}} [w_m - \beta W_u(w_m)] df(\phi) + \lambda \int_{\hat{\phi}}^{\infty} [\phi(h) - \beta W_u(w_m)] df(\phi) \right\}, \quad (7)$$

which changes the solution for the equilibrium market wage. Substituting (7) back into the Nash bargaining problem in (5) and solving for the equilibrium wage distribution leads to:

$$g(w; W_u(w_m)) = \begin{cases} [f'(\hat{\phi}(w, W_u(w_m)))/\lambda f(w_m), & w > w_m \\ [f(w_m) - f(\hat{\phi}(w, W_u(w_m)))]/f(w_m), & w = w_m \\ 0, & w < w_m \end{cases}, \quad (8)$$

for workers that are paid above the minimum wage, at the minimum wage, or who are not hired, respectively. We use the equilibrium wage distribution in (8) to derive several hypotheses regarding the likely impact of labor-market concentration on equilibrium wages, employment, and the duration of unemployment.

We estimate the model with data on observed wages (w_i) and the amount of time spent unemployed during the past year (t_i) for a repeated cross-section of some $N = 426,000$ worker-year observations for employees in the U.S. who work in occupations relevant to the retailing industry. We describe our data in more detail below but find that it is sufficient to identify all of the parameters of the wage distribution above, including the Nash bargaining parameter, λ , that determines the share of employment surplus earned by employees, and by firms. In this section, we derive the log-likelihood function developed by Flinn (2006) that is used to estimate the parameters of search, matching, and bargaining models such as ours. We then

explain how we test the hypotheses derived above regarding the impact of healthcare coverage on wages, productivity, and job duration.

Because minimum-wage employment is common in retailing, we follow Flinn (2006) and break the likelihood function into three parts: (1) the probability that a worker is unemployed for a duration of t weeks, (2) the probability that a worker is employed and paid a wage that is equal to the minimum wage, and (3) the probability that a worker is employed and paid more than the minimum wage.

For the first component of the likelihood function, we have to assume a distribution for unemployment durations, in general. In this regard, like Flinn (2006), we follow common practice and assume the distribution of the population duration function is negative exponential, so we write the individual-density of job duration as the mean, or:

$$pr(t|u) = \tau f(w_m) \exp(-\tau f(w_m)t), \quad (9)$$

where the parameters and minimum wage variable are as defined above. We use the parametric rate of job destruction to infer that the probability of a worker becoming unemployed during the year is:

$$pr(u) = \frac{\delta}{\delta + \tau f(w_m)}. \quad (10)$$

Multiplying the conditional probability of observing a spell of length t , given that the worker is unemployed, by the marginal probability of becoming unemployed gives the joint probability of observing an employee becoming unemployed for a period of length t , or:

$$pr(t, u) = \frac{\delta \tau f(w_m) \exp(-\tau f(w_m)t)}{\delta + \tau f(w_m)}, \quad (11)$$

and we assume f is log-normal, with parameters μ for the mean and σ for the standard deviation.

Second, we derive the likelihood-component that captures the probability that a worker is employed and paid the minimum wage. Recall that the primary implication of a minimum wage regime is to constrain the range of equilibrium productivity values to those that lie above the minimum wage. With this in mind, the likelihood contribution from minimum-wage employees is given by:

$$pr(w = w_m, e) = \frac{\tau \left[f(w_m) - f\left(\frac{w_m - (1-\lambda)\beta W_u(w_m)}{\lambda}\right) \right]}{\delta + \tau f(w_m)}, \quad (12)$$

which represents the probability a worker is employed (e) but is paid the minimum wage, so the firm is willing to give up some surplus in order to hire a worker that still produces value greater than the level of the minimum wage.

A third segment of workers are employed and paid above the minimum wage. For these workers, the minimum wage is still relevant, however, as it remains an element of the value of unemployed search which, in turn, determines the threshold match value for employment. The probability of observing a wage w for an employed worker, therefore, is the product of the conditional probability of observing a worker being paid above the minimum wage, conditional on being employed, and the probability of observing a particular wage above the minimum. The second element of this expression, therefore, is given by:

$$pr(w|w > w_m, e) = \frac{\frac{1}{\lambda} f' \left(\frac{w - (1-\lambda)\beta W_u(w_m)}{\lambda} \right)}{f \left(\frac{w_m - (1-\lambda)\beta W_u(w_m)}{\lambda} \right)}, \quad (13)$$

as the wage has to exceed the match-minimum of $\frac{w_m - (1-\lambda)\beta W_u(w_m)}{\lambda}$. Meanwhile, the conditional probability that a worker's wage is above the minimum, conditional on employment, is:

$$pr(w > w_m|e) = \frac{f \left(\frac{w_m - (1-\lambda)\beta W_u(w_m)}{\lambda} \right)}{f(w_m)}. \quad (14)$$

Multiplying these two expressions together provides the joint probability, and likelihood contribution, of observing a wage w that is above the minimum w_m for an employed worker:

$$f(w, w > w_m, e) = \frac{\frac{\tau}{\lambda} f' \left(\frac{w - (1-\lambda)\beta W_u(w_m)}{\lambda} \right)}{\delta + \tau f(w_m)}. \quad (15)$$

Combining all three elements, taking logs, and summing over all individuals in the data set provides a likelihood function that recovers all of the parameters of interest:

$$\begin{aligned} LLF = & [\ln(\tau) - \ln(\delta + \tau f(w_m))] + d_U [\ln(\delta) + \ln f(w_m)] - \\ & \tau f(w_m) d_U t_i + d_M \ln \left(f(w_m) - f \left(\frac{w_m - (1-\lambda)\phi^*}{\lambda} \right) \right) - \\ & d_H \ln(\lambda) + d_H \ln \left(f' \left(\frac{w_i - (1-\lambda)\phi^*}{\lambda} \right) \right), \end{aligned} \quad (16)$$

where d_U is a binary indicator of whether the worker is unemployed ($d_u = 1$) or employed ($d_u = 0$), d_M is a binary indicator that the worker is paid above the minimum wage, and d_H is a binary indicator that the worker is paid above the minimum wage. With this likelihood function, we estimate the implicit minimum wage as $\phi^* = \beta W_u(w_m)$, and capture the possibility that the surplus-allocation function depends on market structure by allowing the Nash bargaining parameter, λ , to be a linear function of local labor-market concentration. That is, we estimate a version (16) that includes: $\lambda = \lambda_0 + \lambda_1 HHI$, where HHI is the Hirschman-Herfindahl Index (HHI) of local (commuting zone) labor market concentration. If concentration alone provides employers sufficient market power to suppress equilibrium wages below the competitive level,

holding all other sources of market imperfection constant, then $\lambda_1 < 0$. In the next section, we provide more detail on the data we use to estimate this model, how we define local labor market concentration, and provide some model-free evidence on the relationship between concentration and labor-market outcomes.

4 Data and Identification

Our primary data sources for this paper is the TDLinX retailer-attributed data set from NielsenIQ, the Quarterly Census of Employment and Wages (QCEW, Bureau of Labor Statistics, U.S. Department of Labor), the Current Population Survey (CPS, Bureau of Census), and the American Community Survey (ACS, Bureau of Census), the latter two data sets we access through iPUMS (Ruggles, et al. 2023). We explain exactly how we use each data set in this section but, to summarize, we use TDLinX to measure the number of workers employed by each firm in each market, which we define as a commuting zone, the QCEW to measure weekly wages for workers in the food retailing industry (NAICS = 445), and the other data sets to measure the number of workers in retailing-related occupations in each market. We also use the ACS data exclusively to estimate the equilibrium model of search, match, and bargaining.

Our store-level retail-employment data are from NielsenIQ’s TDLinX Store Characteristics Dataset, which provides detailed estimates of annual store-level store volume (measured in terms of dollar sales), the number of employees, and a variety of other store-attribute variables that permit a granular and detailed description of each establishment. Most importantly, we know the exact location of each store, its format classification, its ownership group, and whether it changes ownership from one year to the next.⁷ We use this information to infer whether or not each location was part of a merger or acquisition during the sample year. We use the geographic information in TDLinX to associate each store with a county (FIPS code), and then use a cross-walk file from ERS-USDA to associate each county with a commuting zone.⁸ We choose a relatively long sample period – 2005 to 2022 – in order to capture as much of the rise in retail concentration as possible, and wage changes in each retail occupation. Our geographic sample frame is the entire U.S., so our data represents workers from some 45,000 grocery stores, covering over 12.9 million workers in the most

⁷It is important to note that TDLinX tracks the building itself, so we ensure that we track true openings and closures and not merely changes in ownership at the same location.

⁸In this literature, it is well-understood that the geographic extent of a labor market is appropriately described as commuting zone. The ERS-USDA data documentation describes the need for commuting zones as "...County boundaries are not always adequate confines for a local economy and often reflect political boundaries rather than an area’s local economy. CZs and LMAs [Labor Market Areas] are geographic units of analysis intended to more closely reflect the local economy where people live and work. Beginning in 1980 and continuing through 2000, hierarchical cluster analysis was used along with the Census Bureau’s journey to work data to group counties into these areas..." (ERS-USDA 2023). We are also careful to track changes in county boundaries that occur over the sample period.

recent years in the data. For our initial models, we calculate local labor-market concentration by calculating the share of retail grocery workers employed by each ownership group, and then calculate the Hirschman-Herfindahl Index (HHI) of local labor market concentration by squaring and summing the shares over all employers in the same commuting zone. With this measure of concentration, therefore, the denominator in our share calculations is the total employment by all food retailers in the local market.

We measure wages in the grocery industry using the QCEW data set. QCEW is an administrative data set collected by the U.S. Department of Labor. It is particularly useful for this purpose as QCEW is a census as all employers that participate in state-level unemployment insurance programs are required to submit data on compensation and employment to their respective state agencies, who then report their data on employment and wages (and, implicitly, the number of establishments based on the number of firms that report) to the BLS. In this way, the QCEW provides a consistent measure of average weekly wages over the entire sample period, and at the same level of geographic disaggregation as our TDLinX data.⁹ In order to focus our empirical model on the food retailing sector, we extract data for NAICS = 445 (Supermarkets and other Grocers) for every year and geography in our sample frame. Our final data set consists of a total of $N = 45,180$ commuting-zone-year-quarter observations. We summarize the combined TDLinX and QCEW in table 1 below.

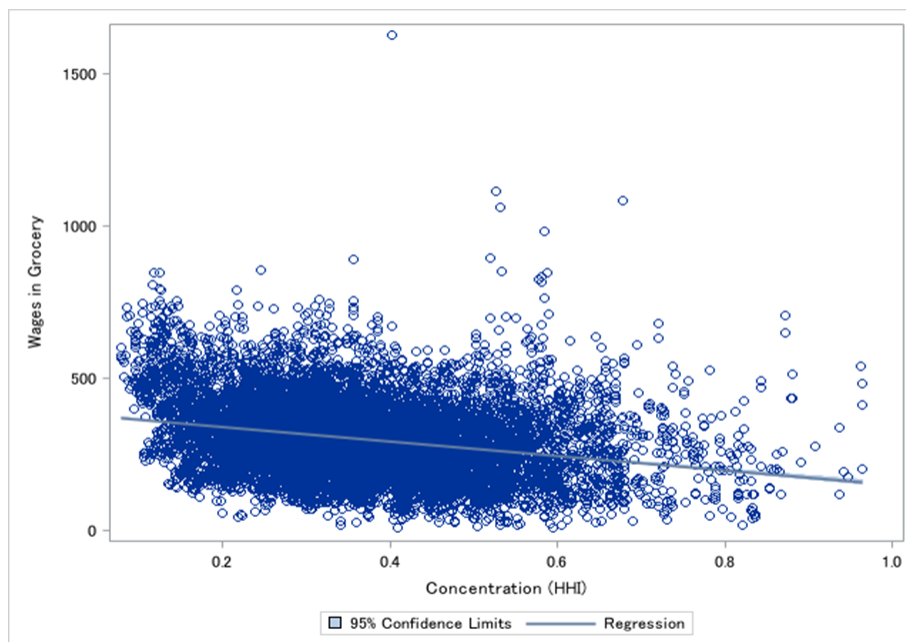
[table 1 in here]

Insights regarding the relationship between concentration and wages are relatively clear from the combined TDLinX and QCEW data. In Figure 2 below, we show a summary relationship from a simple scatterplot of wages for food-retailing workers on the vertical axis and retail-labor concentration (measured using the HHI) on the horizontal axis (each dot represents a quarter/commuting zone observation). Without controlling for any other variables that may affect the relationship between concentration and wages, this figure shows, roughly, what others in the empirical literature document more formally: A concentration-wage elasticity of roughly -0.05 , which is relatively small but statistically significant. Approximately at the mean of the concentration data ($\text{HHI} = 0.4$) this means that an increase in concentration to 0.5 (25%) would be associated with a decline in wages of 1.25% (Figure 2). Although small, for low-wage workers a reduction in income of this magnitude would be important.

Workers in the TDLinX data, however, represent only a small slice of the total number of people who

⁹The BLS reports QCEW on a FIPS (county) basis, so we match to the TDLinX data through the same county-to-commuting zone crosswalk file that we refer to above.

Figure 2: Retail Labor Concentration and Wages



Note: Data from NielsenIQ TDLinx and Bureau of Census (QCEW), 2004-2022, sample of retail grocery-industry firms and workers (NAICS=445), at the commuting-zone level. Commuting zones defined using data from ERS-USA.

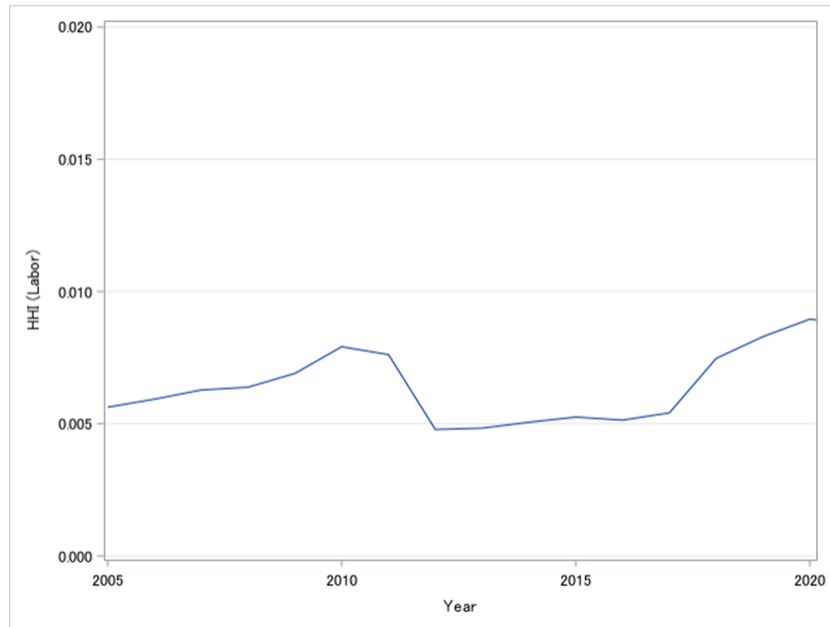
could likely fill the jobs represented in the data. If the objective is to measure job market concentration and not product market concentration, then it is necessary to find a broader measure of the number of workers in retailing jobs rather than just those currently employed in the retailing industry. For example, cashiers in the food retailing industry could just as easily be cashiers in the tire-store industry, sporting-goods industry, or any other set of firms who employ cashiers. Therefore, we broadened our search for workers in the retailing industry to the CPS (Bureau of Census) in order to determine what fraction of retail occupations were actually employed in the food retailing industry. For the same sample period, we adopted a conservative approach (as there are likely to be workers with the same skills in many other industries) and isolated our search to a sample of workers from NAICS two-digit codes 44 and 45 and examined the range of occupations across of the sub-industries involved. As shown in table 2 below, the most common retailing occupations are Retail Supervisors and Managers and Retail Salespersons, followed by Cashiers. More importantly, we find that of the 31,852 CPS workers in any retailing occupation, only 1,463 (4.6%) were employed in food retailing. Because food retailing represents only a small part of the market for retailing jobs, it is necessary to define job-market concentration using the entire market for retailing jobs, and not just those employed directly in food retailing. Although it is possible to use the CPS sample weights to generalize this insight to the entire U.S. economy, there are many commuting zones that are not represented in the relatively small sample of CPS workers. Therefore, we further broadened our search for retailing jobs to the much larger ACS data set.

[table 2 in here]

The ACS is generally regarded as the definitive survey of the U.S. population for demographic, geographic, housing, and work attributes (Antman, Duncan, and Trejo 2023; Richards and Rutledge 2023). In order to get a better picture of the totality of employment in U.S. retailing, and its relationship to concentration in the food retailing industry, we drew a sample of ACS workers equivalent to the CPS sample described above, including workers in the same industries and occupations as in our CPS data. Over the entire 2005 – 2022 time period, our ACS sample of retail workers produced $N = 4.258$ million observations. Because ACS is still a sample, however, we then used the ACS sample weights to construct a data set of the total number of workers in each retailing occupation, on a commuting-zone basis, and merged it with the TDLinx data in order to calculate a revised set of labor-market HHI measures that represent the true share of retail workers employed by food-retailing workers in each commuting zone. Figure 3 below shows the path of retail-worker concentration from the merged ACS-TDLinx data, which shows a very different picture from the TDLinx-

only data in Figure 2. Measured across all retailing-relevant occupations, the average ACS-HHI value is 0.006, or an order of magnitude lower than measured using food retailing workers alone. Yet, Figure 4 shows that the negative relationship appears to persist, despite greater skew in the distribution of the measure of concentration at the commuting zone level. Clearly, we require a more careful econometric analysis to determine whether this summary relationship is statistically significant.

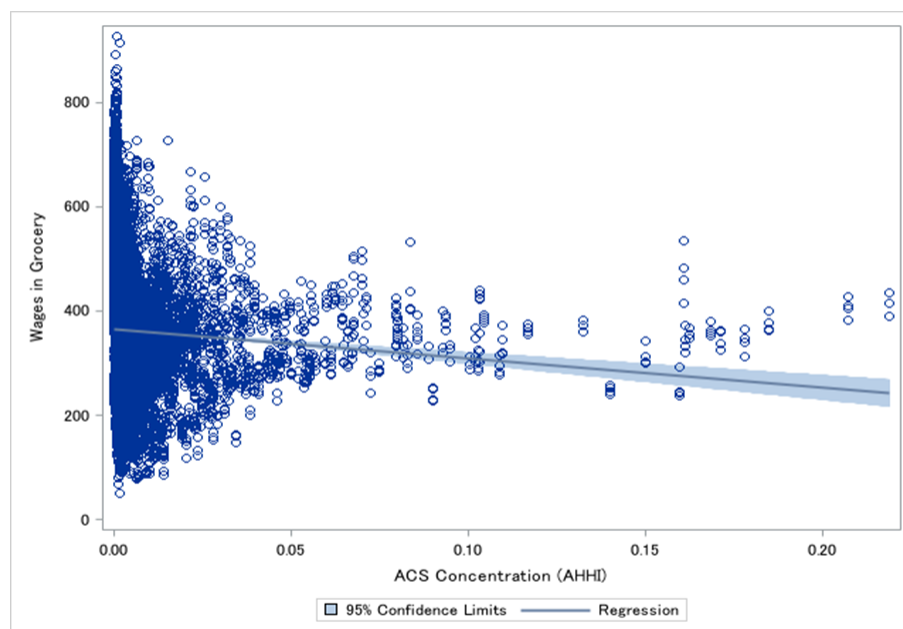
Figure 3: Retail Labor Market Concentration: 2005 - 2022, by Commuting Zone, ACS Data



Note: Data from NielsenIQ TDLinx and Bureau of Census (ACS), 2004-2022, sample of retail grocery-industry firms and workers (NAICS=445), at the commuting-zone level. Commuting zones defined using data from ERS-USDA.

We also use the ACS data for the search, match, and bargaining analysis that connects concentration to wages through the actual exercise of market power, and not just its potential. Search, match, and bargaining models of the sort developed by Pissarides (2000) and Flinn (2006) require individual-level data on hourly wages, unemployment duration (in the past 52 weeks), minimum wages in the employee's jurisdiction, and demographic and socioeconomic variables in order to control for any systematic variation in wages that is not otherwise explained by the search process, and the equilibrium that is assumed to result. Structural models, however, are more computationally difficult than the treatment-effect models described above, so we sample 10% of the ACS sample described above, which is more than enough to identify the structural bargaining

Figure 4: Retail Labor Market Concentration and Wages: 2005 - 2022, by Commuting Zone



Note: Data from NielsenIQ TDLinx and Bureau of Census (ACS), 2004-2022, sample of retail grocery-industry firms and workers (NAICS=445), at the commuting-zone level. Commuting zones defined using data from ERS-USDA.

parameter according to the Monte Carlo experiment described by Flinn (2006). For the wage-estimation equation that we embed in the structural bargaining model, we include state, occupation, and industry fixed effects, and age, age squared, education, gender, marital and citizenship status among the other covariates. Each of these variables is statistically significant in the wage equation. We merge the ACS data with state-level minimum wages from the St. Louis Federal Reserve Board (FRED 2023), and the TDLinx data above in order to allow the bargaining parameter to vary with commuting-zone level labor-market concentration values described above. In this way, we test our core hypothesis that concentration affects retail-worker wages, and their share of the equilibrium employment surplus.

5 Results, Robustness and Discussion

In this section, we present our empirical results and robustness checks. We begin by presenting a series of reduced-form models of the relationship between labor-market concentration, first using the TDLinx data exclusively, then the CPS data to define the relevant labor market, and finally a labor-market definition based on ACS data. We follow by presenting the findings from our structural model of labor market equilibrium in which concentration is allowed to impact the allocation of employment surplus between employers and employees in each market.

5.1 Reduced-Form Estimates

Table 3 shows our econometric estimates for the relationship between labor-market concentration and wages using only the TDLinx data, and a number of alternative models intended to examine the robustness of our maintained model. In this table, the concentration index (HHI) is defined as the sum of squared shares of each retailer relative to the total number of workers employed by all retailers in the same market. We use this “naive” measure of concentration to demonstrate the difference between econometric estimates using a traditional, industry-based definition of concentration. In table 3, we make no attempt to control for the likely endogeneity of labor-market concentration (Berry, Gaynor, and Scott-Morton 2019; Syverson 2019; Miller et al. 2022) in order to establish a baseline set of results.

Beginning from the simplest model (Model 1) that includes only the HHI as a regressor, the results show a strong negative correlation (elasticity of -0.337) between concentration and wages. In a very general sense, these results are consistent with the recent literature on this topic (Rinz 2022; Azar, et al. 2022; Qiu and Sojourner 2023) in that we find that as concentration rises, observed wages fall, presumably due to the

monopsony suppression of wages. However, if we add a set of minimal controls to the OLS model (Model 2, population, income, age, and unemployment rate) in order to capture the likelihood that wages depend on the relative strength of local economic activity, most of the negative effect goes away and the point estimate of -0.026 is not significantly different from zero.¹⁰ That is, most of the observed negative relationship between concentration and wages is explained by local economic activity, and not wage suppression. If we control for unobservable factors at the CZ (Model 3) and annual (Model 4) levels, the point estimate becomes more negative, but is still not statistically different from zero. Finally, in the most comprehensive model, we account for CZ-level trends, which account for changes in the local economic conditions over time as an explanation for observed wages (Model 5). In this model, the point estimate is nearly zero, and remains not significantly different from zero. In summary, the OLS evidence shows no support for a negative concentration-wage relationship. But, the estimated negative relationship in Qiu and Sojourner (2023) was also very close to zero before instrumenting for the endogeneity of local-labor-market concentration.

[table 3 in here]

In table 4, therefore, we control for HHI endogeneity by instrumenting for local concentration in a manner similar to Azar, et al. (2022) and Qiu and Sojourner (2023). Specifically, we calculate the leave-one-out inverse number of employers in all other commuting zones (LOOIV), and use two-stage-least-squares (2SLS) to estimate the effect of instrumented-concentration on the log of average weekly wages. Following Qiu and Sojourner (2023) we believe that this instrument is likely to be valid because changes in the number of employers on a national level is likely to be driven by broader economic forces that are independent of local wages, and yet highly correlated with changes in local labor-market concentration. For example, if an economic downturn has a cleansing effect (Barlevy 2002) that increases the productivity of workers who remain on a reduced-number of jobs, there is likely to be a lower number of employers, both locally and nationally. The number of employers in other commuting zones, therefore, is likely to be highly correlated with concentration in each local market and yet the change in the number of employers nationally does not have any logical connection to local monopsony wage suppression. In fact, in our first-stage IV regression, the F-statistic in a regression of only local HHI on the LOOIV produces an F-statistic of 378.4, which is far above the Andrews, Stock and Sun (2019) threshold of 10.0.

Our IV estimates in table 4 show an entirely different picture of the relationship between concentration

¹⁰As a robustness check, we included product-market concentration (revenue) as an additional regressor as in Qiu and Sojourner (2023), but our results do not change qualitatively. Because of the obvious endogeneity of product-market concentration (Miller et al. 2022), we do not include output-market concentration among our formal robustness checks.

and wages in local labor markets. In the base model (Model 1) in which we estimate the effect of concentration on wages only, with no other controls, we find a significant and positive effect of local HHI on wages. However, when we account for the same set of CZ-level controls as in the table 3 models, we find that the positive point estimate remains, but the estimate becomes not statistically different from zero in our preferred specification.¹¹ Namely, after controlling for the endogeneity of concentration, we still continue to find that occupation-based employment concentration in the retail food industry has no effect on wages. However, estimating with the TDLinx data only account only for an industry-based definition of concentration and not occupation-based.

[table 4 in here]

In tables 5 and 6, therefore, we use an ACS-based measure of concentration, as described above. As with the TDLinx analysis in tables 3 and 4, we begin by estimating the same set of models as in table 3, but defining concentration as the HHI calculated from the share of workers in the retailing industry employed by each store as a ratio of the total number of workers in retailing occupations. Our HHI measure in this case is likely to be a more accurate measure of the concentration of grocery retailers in the market for retail workers, rather than just the number of supermarket workers as in tables 3 and 4. In table 5, we see that the reduced-form estimates of the concentration-wage effect is generally negative for all five specifications, supporting the findings of others in this literature (Rinz 2022; Azar, et al. 2022; Qiu and Sojourner 2023). In fact, our point estimates for the first model (Model 1, no controls or fixed effects) is very similar to theirs. However, once we account for CZ-level controls, and fixed spatial and temporal effects (Model 4), the negative effect becomes very small (elasticity = 0.018). Finally, once we control for CZ-level trends the estimate is not significantly different from zero. Again, there appears to be no relationship between concentration and wages in reduced-form models.

[table 5 in here]

Our conclusion in table 5 remains after accounting for the endogeneity of labor-market concentration, using both the leave-one-out instrumental variable (LOOIV) described above, and the number of mergers and acquisitions in each local market as in Arnold (2021). In fact, in the preferred estimate in table 6 (Model 5), the point estimate is again positive and not precisely estimated.¹² Therefore, based on this occupation-

¹¹We examine the robustness of this finding by instrumenting for endogenous concentration using the number of mergers and acquisitions in each local market, each year. This instrument is valid in that mergers among retail chains reflect broader economic trends than present in local markets (Arnold 2021) and is also highly correlated with local HHI ($F = 2,341.4$). Our point estimates remain positive, but not statistically different from zero in the preferred model (Model 5). See table A1 in the Appendix.

¹²Estimates using the alternative, mergers and acquisitions, instrument are also not statistically different from zero.

based definition of concentration, we still find no relationship between concentration and wages in local labor markets. As we argue above, however, concentration measures only the potential exercise of market power and not the actual use of it. In the next section, we describe our search, match, and bargaining model estimates that allow worker bargaining power to vary with the level of concentration.

5.2 Structural Bargaining Power Estimates

In table 7 below we first present and interpret our baseline structural estimates in order to establish the validity of our search, match, and bargaining power estimates, and then allow bargaining power to vary with the level of local labor market concentration. Although our estimates in this model are still subject to the criticism that concentration is a weak measure of market power, these models provide the critical linkage between market structure and the exercise of market power that is absent in simple models of concentration and wage setting. In this regard, our models in this section follow the more recent macroeconomics literature in Berger, et al. (2022) and Berger, et al. (2023) in examining monopsony wage suppression using the exercise of market power as our metric.

In Model 1 of table 7, we estimate a base SMB model in which we do not include any measure of concentration in order to establish a baseline set of parameters that appear to characterize equilibrium bargaining among retail workers. In the case of Model 1, the structural parameters imply that matches are destroyed, or current workers are fired or laid off (δ), at a rate of 6.96% per year, and that firms and workers create matches for those who are currently unemployed at a rate of only 0.03% per year. This finding suggests that there is very little recruitment out of the unemployed, so most new hires must be currently-employed individuals moving between firms, which is a common occurrence when wages are rising (Richards and Rutledge 2023b). Further, the parameters of the match-productivity function (μ and σ) imply an equilibrium match value of \$67.69 per hour which, when compared to the threshold match value workers require to enter the workforce ($\phi^* = \$5.91$ / hour) implies a surplus per worker of \$61.78 per hour.¹³ Workers and firms bargain over this surplus, and workers earn a $\lambda = 52.29\%$ share, according to our baseline bargaining power estimates. Relative to other estimates of bargaining power exercised by workers in the food system more generally (Richards and Rutledge 2023), this estimate is quite high and suggests that workers in the retail food industry enjoy a relatively high degree of bargaining power, yet still give up nearly half of their earned surplus to employers.

¹³Recall that match-productivity is distributed log-normal, so we calculate the value of a match as $f = \exp(\mu + 0.5\sigma^2)$.

[table 7 in here]

In Model 2 of table 7, we extend our base model results (Model 1) to account for the fact that bargaining power may vary across markets with different levels of labor-market concentration among the top employers. We estimate the same model as in Model 1, but add an interaction effect between the ACS definition of HHI and the bargaining power parameter. In this way, we account for the possibility that bargaining power, and hence wages, depend directly on concentration in a structural way. In Model 2, the estimates in table 7 show that all of the parameters change slightly with the addition of concentration as an argument of bargaining power. Specifically, the estimate of job destruction (δ) rises to 15.95% per year, while the estimate of job creation remains virtually unchanged. The estimated threshold match value rises to $\phi^* = \$6.33$ per hour, suggesting that workers require slightly more to move into a job, while the equilibrium productivity of a match is marginally lower at \$59.43 per hour. Combining these estimates, we find that equilibrium surplus is now \$53.10 per hour, with workers earning over $\lambda = 56.31\%$ of the equilibrium surplus. Most importantly for our purposes, we find that worker bargaining power falls significantly in the level of market concentration. Given that we calibrate the HHI index so that a value of $\text{HHI} = 0$ represents a perfectly competitive industry and $\text{HHI} = 1$ implies monopoly, an increase of HHI of 0.1 in our calibration (or moving from an HHI of 2,500 to 3,500 using the Federal Trade Commission calibration of HHI) is associated with a reduction in bargaining power from $\lambda = 56.31\%$ to $\lambda' = 53.95\%$, or a reduction in the amount of surplus paid to workers of roughly \$1.25 per hour. At the mean level of wages in the data (\$27.87 per hour, see table 1), concentration in the retail food industry is responsible for a 4.49% reduction in average wages. While this is a relatively small decrease, it is economically significant for most workers.

Our findings are of practical and policy importance, and are remarkably similar to the findings in the rest of the concentration-and-wages literature (Azar, et al. 2020; Rinz 2022; Azar, et al. 2022; Qiu and Sojourner 2023) despite the fact that we use an entirely different approach. Our results imply that mergers that result in a 1,000-point increase in the Federal Trade Commission HHI measure can be expected to lead to substantial reductions in retail-grocery workers' wages. In the context of the proposed merger between Kroger and Albertsons in the fall of 2022, for example, many of the markets in which the two firms overlap were expected to experience a rise in HHI of this magnitude. Whereas traditional merger analysis would have only taken the price effect of a merger into account, our findings show that wages should also be taken into account.

6 Conclusions

Antitrust policy has a new focus on labor market outcomes, specifically monopsony wage suppression. Empirical research that addresses the relationship between monopsony power and labor market outcomes tends to use reduced-form approaches that examine measures of labor-market structure on wages, employment, and sometimes job mobility. In this paper, we argue that this focus on market structure ignores both the fundamental endogeneity of market concentration (Miller et al. 2022) and the behavioral gap between market structure and the actual exercise of market power. To that end, we study the relationship between market structure, market power, and wages in the retail food industry using both reduced form and structural models of monopsony wage suppression.

We combine firm-level data from NielsenIQ’s TDLinX data product with worker-level data from the ACS (U.S. Bureau of Census 2023). Because TDLinX contains data on outlet- and firm-level employment, we are able to construct commuting-zone (CZ) level measures of labor-market concentration, but we argue that measuring concentration at the industry level ignores the inherent fungibility of jobs across retail industries. That is, workers who take jobs in supermarkets can use their skills in many other industries, so labor markets are better described by occupations than industries. We apply this insight by defining labor market concentration across all retail occupations in each CZ in the U.S., and use worker-level outcomes from the ACS and retail-industry wages from the Quarterly Census of Employment and Wages (BLS, U.S. Department of Labor, 2023) to estimate the effect of labor-market concentration on wages in both reduced-form and structural modeling frameworks.

Our structural model connects labor market concentration, or our measure of the structure of local labor markets, to the exercise of market power in the same markets. Creating this link is critically important because market structure only captures the potential exercise of market power, and not its actual exercise. We use a structural model of search, matching, and bargaining to connect market structure to equilibrium bargaining power exercised by firms and employees in order to estimate the ultimate effect of labor-market concentration on wages.

Estimates from reduced-form models show that there is no statistical relationship between concentration and wages in local markets for retailing labor, after controlling for a wide range of covariates and methods of addressing the clear endogeneity of market concentration. Although our estimates from models in the ACS data show a negative correlation between job-market concentration and wages similar to others in the

literature, the relationship is not robust to controlling for the endogeneity of concentration. We interpret this finding as suggesting that many of the same factors that drive increasing concentration in the retail food industry – increasing competitiveness and the need to control costs – are also responsible for the relative decline in retailing wages over time. However, once we control for endogenous job formation and bargaining between retailers and their employees, and allowing concentration to moderate the level of bargaining power exercised by workers, we find that retailers do indeed have greater bargaining power in markets that are more concentrated. Consequently, we find that wages in these markets are lower than in markets that are less concentrated, all else constant.

Our findings are important as they provide a key link in the new approach to empirical antitrust analysis that has been missing to this point. Reduced form models of concentration and wages simply miss the point – structure does not imply outcomes but market conduct, or the exercise of market power, certainly does. Our findings provide an important step in the analysis of the effect of mergers and acquisitions on worker welfare, and the likely effect on wages in markets that are already highly concentrated. Empirical antitrust analysis of any proposed merger, therefore, needs to go the extra mile and connect any change in market concentration on the exercise of market power and not its potential.

The analysis in our paper contains inevitable weaknesses, many of which can be addressed through better data. First, matched employer-employee data remains the gold standard for labor-market analysis such as this. While there are some initial efforts in that regard in the U.S. using data from the Longitudinal Employer-Household Dynamics (LEHD, U.S. Census Bureau) and Longitudinal Business Database (LBD) (Arnold 2021), access to this data remains restricted, is available only on a confidential basis, and merging the two remains uncertain at best. Matching employees to employers as in Cahuc, Postel-Vinay, and Robin (2006) or more recently in Berger et al. (2023) using European data represents the ideal in this literature. Second, there are many ways to define occupations across different industries, so our reliance on ACS categorizations is indeed only imperfect and a weakness in our approach. Third, TDLinx is a census of retail operations, but does not include all of the employees in the retail food industry. To the extent that TDLinx misses some of the workers employed by major food retailers in the U.S., our concentration measures will contain some error.

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Table 1. Summary of Estimation Data

Variable	Source	Units	Mean	Std. Dev.	Min.	Max	N
Wage	QCEW	\$ / Week	361.76	117.84	50.29	926.75	14,372
Employment	QCEW	# Workers	2,157	3,572	132	32,996	14,372
Retail Labor HHI	TDLinx	Index	0.2250	0.0740	0.0709	0.5475	14,372
Retail Output HHI	TDLinx	Index	0.2663	0.0882	0.0783	0.5465	14,372
ACS HHI	ACS	Index	0.0066	0.0151	0.0001	0.2189	14,372
Income	Census	\$ / Year	52,874	12,377	23,188	117,948	14,372
Unemployment	Census	%	6.32	2.71	2.05	27.20	14,372
Population	Census	,000	1,283	1,926	104	18,700	14,372
Age	Census	Years	39.26	2.37	31.40	48.66	14,372
Employers	Census	#	15.79	8.97	4.00	66.00	14,372
LOOIV	Census	#	1.16	0.08	1.06	1.33	14,372
Number of Mergers	Census	#	20.76	34.27	0.00	517.00	14,372

Note: All data on a commuting-zone basis from 2004 - 2022 from either the Quarterly Census of Employment and Wages (QCEW, Bureau of Labor Statistics), American Community Survey (ACS, Census Bureau), Census of Bureau, or TDLinx (NielsenIQ). All Hirschman-Herfindahl Indices (HHI) are divided by 10,000 from the usual definition for estimation purposes.

Table 2. Top 10 Occupations in US Retailing, CPS Data, 2010-2023

Occupation	OCC 1 Code	Frequency	%	OCC 2 Code	Frequency	%
Retail Supervisors & Managers	4700	3231	15.61	4700	3271	15.8
Retail Salespersons	4760	2917	14.09	4760	3165	15.29
Cashiers	4720	1940	9.37	4720	1893	9.14
Not Specified	0	1768	8.54	0	1538	7.43
Customer Service Reps	5240	583	2.82	5240	689	3.33
Inventory Clerks	5620	423	2.04	5620	339	1.64
Freight and Stock Managers	9620	422	2.04	9620	445	2.15
Pharmacists	3050	401	1.94	3050	421	2.03
Truck Drivers	9130	399	1.93	9130	416	2.01
Stockers and Order Fillers	9645	364	1.76	9645	507	2.45

Note: Data in OCC 1 reflect occupations for CPS - ASEC 12-month apart samples in the first year, and OCC 2 reflect occupations for the same individuals 12 months later. Top 10 total for OCC 1 is 60.12% of employees in US retailing, and for OCC 2 is 61.26% of sample employees. Ranked by Year 1 frequency. $N = 20,704$ workers.

Table 3. Regression Estimates for NAICS = 445, HHI and Wages, CZ Level

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
log(HHI)	-0.3373***	0.0330		-0.0136	0.0344		-0.0536***	0.0224		-0.0459***	0.0221		-0.0249	0.0261	
Controls	No			Yes			Yes			Yes			Yes		
CZ Effects	No			No			Yes			Yes			Yes		
Year Effects	No			No			No			Yes			Yes		
CZ Trends	No			No			No			No			Yes		
R^2	0.1016			0.2799			0.8163			0.8224			0.8616		
RSS	9,052.79			7,242.51			1,847.35			1,785.93			1,391.70		

Note: All estimates with TDLinx and QCEW data for NAICS = 445 (Grocery Retailers) on a commuting-zone basis for the years 2005-2022. HHI is defined as the Hirschman-Herfindahl Index of employer concentration in each commuting zone, which forms an "industry" definition of the relevant labor market. Model 1 consists of HHI only, Model 2 is Model 1 plus controls (population, income, age, and unemployment rate), Model 3 is Model 2 plus CZ fixed effects, Model 4 is Model 3 with year fixed effects, Model 5 is Model 4 with CZ-level trends. All standard errors are clustered at the CZ level. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%. Dependent variable is QCEW average weekly wages at a CZ level.

Table 4. IV Model Estimates for NAICS = 445, HHI and Wages, CZ Level

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
log(HHI)	1.3734***	0.1015		0.2025***	0.0795		0.0164	0.1644		0.0192	0.0489		0.0228	0.0413	
Controls	No			Yes			Yes			Yes			Yes		
CZ Effects	No			No			Yes			Yes			Yes		
Year Effects	No			No			No			Yes			Yes		
CZ Trends	No			No			No			No			Yes		
R^2	0.0721			0.2481			0.8159			0.8220			0.8615		
RSS	35,373.18			5,977.52			1,851.84			1,789.68			1,392.69		

Note: All estimates with TDLinx and QCEW data for NAICS = 445 (Grocery Retailers) on a commuting-zone basis for the years 2005-2022. HHI is defined as the Hirschman-Herfindahl Index of employer concentration in each commuting zone, which forms an "industry" definition of the relevant labor market. Model 1 consists of HHI only, Model 2 is Model 1 plus controls (population, income, age, and unemployment rate), Model 3 is Model 2 plus CZ fixed effects, Model 4 is Model 3 with year fixed effects, Model 5 is Model 4 with CZ-level trends. IV models use a leave-one-out (commuting zone and year constant) measure of inverse employer numbers (Azar et al. 2022; Qiu and Sojourner 2023). All standard errors are clustered at the CZ level. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%. Dependent variable is log mean weekly wage from QCEW at a CZ level.

Table 5. OLS Regression Estimates for NAICS = 445, HHI and Wages, ACS Occupations

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
log(HHI)	-0.0681***	0.0135		-0.0279***	0.0121		-0.0175***	0.0063		-0.0184***	0.0063		-0.0037	0.0050	
Controls	No		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		
CZ Effects	No		No	No		Yes	Yes		Yes	Yes		Yes	Yes		
Year Effects	No		No	No		No	No		Yes	Yes		Yes	Yes		
CZ Trends	No		No	No		No	No		No	No		Yes	Yes		
R^2	0.0677		0.2981	0.8958		0.9027	0.9219								
RSS	1,563.47		1,176.09	174.56		163.02	130.84								

Note: All estimates with ACS, TDLinx and QCEW data for NAICS = 445 (Grocery Retailers) on a commuting-zone basis for the years 2005-2022. HHI is defined as the Hirschman-Herfindahl Index of employer concentration in each commuting zone, on an ACS-occupation basis, which forms an occupation definition of the relevant labor market. Model 1 consists of HHI only, Model 2 is Model 1 plus controls (population, income, age, and unemployment rate), Model 3 is Model 2 plus CZ fixed effects, Model 4 is Model 3 with year fixed effects, Model 5 is Model 4 with CZ-level trends. All standard errors are clustered at the CZ level. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%. Dependent variable is QCEW average weekly wages at a CZ-level.

Table 6. IV Estimates for NAICS = 445, HHI and Wages, ACS Occupations

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
log(HHI)	0.2800***	0.0413		0.0767***	0.0413		0.1619***	0.2029		0.1337***	0.0929		0.0033	0.0853	
Controls	No			Yes			Yes			Yes			Yes		
CZ Effects	No			No			Yes			Yes			Yes		
Year Effects	No			No			No			Yes			Yes		
CZ Trends	No			No			No			No			Yes		
R^2	0.0761			0.1693			0.8395			0.8652			0.9219		
RSS	4,528.32			1,391.89			269.01			225.84			130.90		

Note: All estimates with ACS, TDLinx and QCEW data for NAICS = 445 (Grocery Retailers) on a commuting-zone basis for the years 2005-2022. HHI is defined as the Hirschman-Herfindahl Index of employer concentration in each commuting zone, on an ACS-occupation basis, which forms an occupation definition of the relevant labor market. Model 1 consists of HHI only, Model 2 is Model 1 plus controls (population, income, age, and unemployment rate), Model 3 is Model 2 plus CZ fixed effects, Model 4 is Model 3 with year fixed effects, Model 5 is Model 4 with CZ-level trends. Instrument is defined as the leave-one-out inverse employer county by CZ and Year. All standard errors are clustered at the CZ level. A single asterisk (*) indicates significance at a 5% level, ** at 5%, and *** at 1%. Dependent variable is QCEW average weekly wages at a CZ level.

Table 7. Structural Model of Concentration and Wages

Parameter	Model 1			Model 2			Model 3			Model 4		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
δ	0.1831***	0.0001		0.1464***	0.0001		0.1407***	0.0001		0.1133***	0.0001	
τ	0.0332***	0.0001		0.0280***	0.0001		0.0252***	0.0001		0.0263***	0.0001	
μ	2.9648***	0.0001		3.0067***	0.0001		3.0100***	0.0001		2.9507***	0.0001	
σ	1.0800***	0.0001		1.1740***	0.0001		1.1197***	0.0001		1.3257***	0.0001	
ϕ	4.1237***	0.0014		4.2713***	0.0013		4.1624***	0.0022		5.2290***	0.0005	
λ	0.4891***	0.0002		0.4932***	0.0002		0.5096***	0.0012		0.4703***	0.0002	
$\lambda(HHI)$				-0.1164***	0.0065		0.0071	0.0045		-0.0629***	0.0203	
LLF/N	18.1586			22.4359			11.0281			12.8731		
N	425,404			425,404			425,404			425,404		

Note: Estimated with 2004 - 2022 American Community Survey (ACS, U.S. Census) data for workers in retailing occupations. Model 1 is the base search, match, and bargaining model with corrected (with demographic attributes) real wage data. Model 2 allows concentration to mediate the bargaining power parameter. Model 3 uses the TDLinx definition of concentration on an industry, instead of occupation, basis. Model 4 accounts for HHI endogeneity using a control-function approach and the leave-one-out IV from tables 4 and 6. A single asterisk indicates significance at at 10% level, ** at 5%, and *** at 1%.

7 Appendix: Robustness Checks

In this appendix, we present the estimates from estimating the models in Table 4 in the main text using a commuting zone-level count of mergers and acquisitions as an instrument for the retail HHI variable in the empirical model (Arnold 2021). Table A1 shows that none of the HHI estimates are statistically different from zero, but the point estimates are negative.

Table A1. IV Model Estimates for NAICS = 445, HHI and Wages, CZ Level

Variable	Model 1			Model 2			Model 3			Model 4			Model 5		
	Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.		Estimate	Std. Err.	
log(HHI)	-0.6764***	0.0685		-0.0346	0.0316		0.0450***	0.0132		-0.0169	0.0158		-0.0022	0.0149	
Controls	No			Yes			Yes			Yes			Yes		
CZ Effects	No			No			Yes			Yes			Yes		
Year Effects	No			No			No			Yes			Yes		
CZ Trends	No			No			No			No			Yes		
R^2	0.0459			0.2799			0.8162			0.8222			0.8616		
RSS	9,613.12			7,242.49			1,848.67			1,787.65			1,391.97		

Note: All estimates with TDLinx and QCEW data for NAICS = 445 (Grocery Retailers) on a commuting-zone basis for the years 2005-2022. HHI is defined as the Hirschman-Herfindahl Index of employer concentration in each commuting zone, which forms an "industry" definition of the relevant labor market. Model 1 consists of HHI only, Model 2 is Model 1 plus controls (population, income, age, and unemployment rate), Model 3 is Model 2 plus CZ fixed effects, Model 4 is Model 3 with year fixed effects, Model 5 is Model 4 with CZ-level trends. IV models use the log of the number of mergers and acquisitions in the retailing industry in each CZ-year observation (Arnold 2021). All standard errors are clustered at the CZ level. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%. Dependent variable is QCEW average weekly wages at a CZ level.