Farmworker Bargaining in US Agricultural Labor Markets

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Abstract

"Superstar firms" can be large and successful without necessarily exploiting market power over labor markets (Autor et al. (2020)). In this paper, we examine this idea in an agricultural labor market setting by studying the empirical relationship between employment surplus, which is essentially the excess of a worker's value marginal product over their wage, and wages. We use a model of search, match, and bargaining that explains how the surplus from worker's productivity is split between workers and employers. Our estimates show that workers' mean productivity is $8.67 per hour, and they receive 24.2% of employment surplus, but both exhibit substantial heterogeneity over workers. Heterogeneity in productivity and bargaining power suggests that workers who are able to generate "a bigger pie" may also earn a larger share of it. Consistent with this notion, our analysis shows a robust positive elasticity of surplus with observed wages, implying that agricultural firms gain more (surplus) by paying their workers higher wages and not necessarily through exploitation or "winner-take-all" strategy.

Keywords: labor, monopsony, agriculture, productivity, search-match-bargaining

JEL: C78, D43, J43, L13, Q12

1 Introduction

An expanding body of research examines labor market outcomes as equilibria in labor markets that are imperfectly competitive (Card et al. (2021); Card (2022); Berger, Herkenhoff, and Mongey (2022); Azar, Berry, and Marinescu (2022); Yeh, Macaluso, and Hershbein (2022); Richards and Rutledge (2023)). Imperfect competition in labor markets is commonly viewed as "worker exploitation" but, in reality, derives from heterogeneous preferences of workers regarding workplace amenities, similar in spirit to idiosyncratic consumer tastes leading to product market power in industrial organization literature (Bhaskar, Manning, and To (2002); Azar, Berry, and Marinescu (2022)), rising ownership consolidation (Arnold (2021)), or frictions on the job search and matching (Manning (2003); Berger et al. (2023); Jarosch, Nimczik, and Sorkin (2024)). While the US agricultural sector is critical to feeding the nation, it is plagued by acute and prolonged labor shortages (Richards (2018); AgAmerica (2022); U.S. Department of Agriculture (2023)), which suggests that workers may also exercise a substantial degree of bargaining power in choosing to work in agriculture. Although studies on other sectors of the US economy find substantial evidence of imperfect competition in labor markets, the magnitude of this imperfect competition and its implications in farm labor markets remain unclear. Besides, given the rise of "superstar firms" (Autor et al. (2020)), it is also crucial to reconsider the classical notion of "labor market power" as worker exploitation and instead focus on market imperfections from bargaining equilibria, surplus distribution, and wage-profitability link. In this paper, we examine this question and estimate the relationship between farmworker productivity-generation and wages using a sample of US farmworker data and a model of search, match, and bargaining.

Our study builds on a notion from Autor et al. (2020) that highly productive and innovative or *superstar* firms can have high markups and profits that do not necessarily derive from pushing wages down.[1] That is, high profitability and better worker compensation are not

[1] Autor et al. (2020) use this idea to reconcile observations of a generally-declining labor share of value with increasing product-market concentration and relatively high compensation by successful firms.

mutually exclusive, as efficient firms need not be the ones that suppress wages. Specifically, as Autor et al. (2020) note, superstar firms can dominate industries for reasons that reflect idiosyncratic competencies, globalization, and technological advancements but not necessarily input market power. In the broader food system, for example, summary evidence shows that more profitable firms actually pay higher wages (Figure 1), which is intuitive, but completely at odds with the traditional notion of large firms exercising exploitative market power over workers. We explore the possibility that farm employers in our setting can attain similar superstar status, perhaps through good management, product innovations, and decisions to grow the right crops on fertile land. We test this hypothesis by examining the relationship between equilibrium wages and earned surplus, taking into account heterogeneity in both workers' productivity and bargaining power.

Studying workers' labor market position in US agriculture is important for at least three reasons. First, the agricultural sector has a chronic shortage of workers—both domestic and immigrant—due to a multitude of issues that include aging laborers, declining interest in farming, rigid immigration policies, and increasing demands for wages (Fan et al. (2015); Richards (2018); Richards (2020)).[2][3] Second, from 1989 to 2022, almost 48 percent of the farm workers are undocumented, nearly 72 percent of the total workers are hired directly by growers, and close to 88 percent of the workers are paid on hourly basis (Tables 1 and 2). These conditions highlight job-differentiation within farm labor markets, and heterogeneity in employment terms and worker attributes forms a workforce which likely faces variations in job quality and compensation. Third, although there is an evolving literature that examines imperfect competition in labor markets in various sectors of the US economy (Arnold (2021); Yeh, Macaluso, and Hershbein (2022); Berger, Herkenhoff, and Mongey (2022); Azar, Berry, and Marinescu (2022)), there is not enough parallel empirical research in agricultural settings,

[2] In our study period 1989-2022, crop workers had an average age of 35 years, and 40 percent of workers in 2022 were over 47 years, both indicating an aging workforce (authors' calculation based on the NAWS data from https://www.dol.gov/agencies/eta/national-agricultural-workers-survey/data).

[3] In 2017, California lost nearly 40 percent of its farm workers between 2002 and 2014 according to https://www.economist.com/united-states/2017/07/27/if-america-is-overrun-by-low-skilled-migrants and https://www.nass.usda.gov/AgCensus/.

and it is not clear what imperfect competition means for wage outcomes for different types of agricultural workers.

Further, labor markets are at the center of an emerging policy narrative that focuses on imperfect competition, interpreted as monopsony exploitation (POTUS (2021)). However, unlike in the Executive Order on Promoting Competition (POTUS (2021)), we highlight the fact that bargaining equilibria do not need traditional monopsony explanations to yield a division of surplus between employees and employers. That is, we highlight the fact that earned employment surplus does not mean exploitation of labor, but rather arises from competitive markets that are subject to frictions such as imperfect information, heterogeneous preferences for job-related amenities, and search costs. As such, our argument aligns with Autor et al. (2020), who contend that large and productive firms are capable of earning high profits while paying *high* wages to their workers. Our departure from exploitation-narrative of market power also builds on Sexton (2013) who argues that firms hiring inputs (in our case, labor) in imperfectly competitive markets have no incentive to immiserate their suppliers (workers).

We measure imperfect competition in agricultural labor markets by estimating and characterizing workers' *bargaining power*, which measures the distribution of employment surplus or the gap between workers' marginal value product and the wage at which workers are indifferent between working and not working (Diamond (1982); Mortensen (1982); Mortensen and Pissarides (1994); Flinn (2006)). To this end, we build and estimate a structural model of search, match, and bargaining in the Diamond-Mortensen-Pissarides (DMP) tradition which lets us to directly estimate workers' bargaining power parameter $\lambda \in (0, 1)$, which is interpreted literally as the share of employment surplus that goes to workers, with the remaining share $1 - \lambda$ retained by employers. A higher value of λ indicates greater bargaining power, and wages get closer to productivity value, which is a competitive wage. In perfectly competitive labor markets, $\lambda = 0$ because workers and employers are both wage-takers as there is no room for individual bargaining. That is, market equilibrium from forces of labor demand and supply determines wages, and there is no surplus to negotiate. However, under imperfect competition, search frictions—including imperfect information regarding job opportunities and worker productivity—as well as preferences over job attributes lead to wage outcomes that are typically lower than those that would emerge in perfect competition.

We extend the classical model of search, match, and bargaining in Pissarides (2000) and Flinn (2006) by accounting for several institutional features of US agricultural employment. In the model, workers and employers both search for optimal wages and arrive at a match once there is no marginal benefit of searching for either side. The resulting matches generate an employment surplus, which workers and employers negotiate through a Nash bargaining framework. In equilibrium, the balance between the employer's and worker's bargaining power, together with the worker's productivity and job preferences, determines worker's wages. In our model, however, we allow both productivity and bargaining power to depend on attributes of individual workers, and of the jobs they do. In this way, our search, match, and bargaining model captures worker heterogeneity, and outcomes that vary across their individual employer-matches.[4]

We model the "superstar effect" in our framework by allowing worker productivity and bargaining power and, ultimately, wages to vary by observed worker attributes like age, gender, years of experience, foreign status, methods of payment, and hiring process. Several studies document bargaining and productivity heterogeneity along some of these variables. Due to occupational segregation and work interference, for example, women are likely to have less bargaining power (Blau and Kahn (2017). Age and experience can correlate negatively with productivity due to physical and cognitive declines from age or resistance to adapt in new working environments from more experience (Goebel and Zwick (2009)). Workers who are foreign-born are unlikely to provide higher value to their employer despite bringing diverse perspectives and skills, if they do not assimilate well in the new working conditions (Lazear (1999)). In contrast, workers who are hired directly by growers can have higher

[4]Note that our data does not describe individual firms, but search, match, and bargaining models capture equilibrium outcomes so firm choices are implicit in the deals accepted by workers.

productivity as they have better incentive structures and closer supervision relative to the ones hired by farm labor contractors. To test the superstar-firm hypothesis, we examine wage-surplus relationship based on this heterogeneity of productivity and bargaining power.

We use data from the National Agricultural Workers Survey (NAWS) which is collected by the US Department of Labor and is a nationally representative survey of demographic, health, business, immigration, and workforce attributes on randomly selected US crop workers. To ensure that the sample is representative of the US population of crop workers, NAWS employs a multi-stage sampling technique to interview possibly different sets of workers every year (National Agricultural Workers Survey (2023)). For this study, we use the restricted-version which contains cross-sectional information on about 25,000 workers in California from fiscal years 1989 to 2022.[5] Although the original dataset includes information for 48 states, we focus our analysis on California to ensure comparability across workers and avoid complexities of cross-state minimum wage variations.[6]

We find that workers earn roughly one-fourth of the employment surplus available for allocation between workers and their employers. In our preferred specification, after controlling for year, crop-type, and task-type fixed effects and worker attributes, we find that workers on average have a bargaining power parameter $\lambda = 0.242$. This means that they take 24.2% of the employment surplus, and employers take the remaining share, reflecting a notable gap in the surplus distribution and substantial power asymmetries in the agricultural labor market. Bargaining power is exogenous to the employment agreement, and depends on attributes of the employer and employee (Nash (1951)). That is, we explain how competitive wage outcomes vary over individuals according to their ability to extract their share from their employer. In the heterogeneity analysis, we find that bargaining power λ is heterogeneous across worker attributes.

[5] The public-version of NAWS data is available for the period 1989-2020 here: https://www.dol.gov/agencies/eta/national-agricultural-workers-survey/data.

[6] This means the workers in our final sample work in relatively-similar industries for employers that sell into similar output markets. Further, how state-level minimum wage policy applies to agricultural workers is generally unique to each state, and focusing on California avoids incorporating cross-state minimum wages (https://nationalaglawcenter.org/state-compilations/agpay/minimumwage/).

In our analysis, we recognize that size of the surplus also matters besides the distribution of the surplus.[7] While it may appear that sharing only 24.2% of the surplus implies worker exploitation, we argue otherwise by drawing on Autor et al. (2020), who highlight that large firms can be highly profitable without exploiting market power in either consumer or input markets. We examine this argument by estimating the relationship between worker surplus and equilibrium wages. We find a surplus-wage elasticity of $\epsilon = 0.162$ ($t-$ratio $= 29.54$), implying that farmers who pay higher wages also earn more surplus.[8] Further, we find that some workers such as males, piece-rate earners, and more experienced have lower bargaining power but higher productivity than their counterparts, and hence can still benefit if productivity effects offset bargaining disadvantages. That is, we emphasize that our findings do not suggest exploitation of certain worker classes, based purely on bargaining power effects, and focus instead on how surplus relate to wages and show a potential for workers to be better-off despite having lower bargaining power.

Contributions. Our study makes three main contributions to the literature on labor market power, agricultural labor shortages, and industrial policy more generally. First, the paper extends the current labor monopsony literature which examines labor market power from the lens of differentiated-jobs approach (Card et al. (2021); Berger, Herkenhoff, and Mongey (2022); Azar, Berry, and Marinescu (2022)), job-search frictions (Faberman, Mueller, and Şahin (2022); Richards and Rutledge (2023); Bhuller et al. (2023); Jarosch, Nimczik, and Sorkin (2024)), and production-function approach (Yeh, Macaluso, and Hershbein (2022); Rubens (2023)). While these studies are industry-specific and do document prevalence of employer power, there are no similar studies on US crop workers. Further, their insights are not directly relevant to understand bargaining equilibria in the US agriculture due to its

[7]This also aligns well with the concept of Nash bargaining equilibrium where the idea is to increase the "size of the pie", not just "share of the pie", so even the side with less bargaining power ends up with more surplus than would have been the case otherwise.

[8]We also note that this result on surplus-wage elasticity likely applies to broader food system as we show in a summary evidence that a sample of more profitable retail and wholesale firms actually pay higher wages (Figure 1), which is intuitive, but completely at odds with the traditional notion of large firms exercising exploitative market power over workers.

unique features such as continual labor shortage and large shares of undocumented workforce and hourly workers. Our paper fits in this monopsony literature as we re-frame the argument away from connotations of exploitation and market power that follow from the monopsony perspective, and more in terms of how real-world market outcomes reflect heterogeneity and informed business negotiations.

Second, our paper contributes to the growing literature on agricultural labor and labor shortages by highlighting the heterogeneity between workers' productivity, wages and the worker-share of employment surplus. When labor is in short supply, it is simply implausible that farmers are able to exploit workers, or even find that doing so is in their best interests. We examine the extent to which different attributes impact both workers' productivity and their share of employment surplus. In doing so, we identify the worker groups that generate more value relative to their total compensation. We argue that shifting the focus from labor market power, that is bargaining power effects on distribution of surplus, to the alignment between value creation and total compensation offers greater understanding of labor market inefficiencies. Most important, we find that superstar-firms argument in Autor et al. (2020) also applies to agricultural employers in that they earn more surplus by compensating their workers better and not inevitably through exploitation or zero-sum game between employers and workers.

Third, our paper contributes to the discussion on how industrial policy applies to labor markets (Naidu and Posner (2022); POTUS (2021); Federal Trade Commission (2023)). In 2021, President Biden released "Executive Order on Promoting Competition in the American Economy" expressing concerns for unfair treatment of family farmers and their workers, importance for raising workers' power to bargain for better wages and working conditions, and to "enforce antitrust laws to combat the harmful effects of monopsony in agricultural markets" (POTUS (2021)). In this study, we test the underlying assumption of labor market power in The Executive Order in the setting of crop workers in California. Further, we offer a more nuanced view of labor market outcomes in agriculture by considering differences in wages as outcomes of negotiated equilibria, and not exploitative relationships. Our analysis examines wages through the lens of imperfectly competitive markets, and we show that unequal sharing of surplus is an outcome of bargaining equilibria, and is not necessarily related to classical notions of market power.

The rest of the paper proceeds as follows. Section 2 presents the structural model and identification and estimation strategies. Section 3 describes the data and some stylized facts about the US agriculture. Section 4 illustrates the results from the structural model. Finally, section 5 concludes.

2 Model Intuition

Our conceptual model assumes workers and employers optimally search for jobs and workers, respectively, until a match is created, which happens when marginal cost of search equals marginal benefit for either side. After the match, they negotiate for wages based on their bargaining power, which is exogenous to both and depend on their negotiating skills.[9]

Our structural approach has several advantages. First, it integrates labor market search, match, and bargaining to provide a comprehensive understanding of equilibrium wages, employment, and productivity. Second, the model is a realistic depiction of how workers and employers optimize their search efforts for employment surplus and how both negotiate or bargain for wages based on their individual and market attributes, in contrast to rigid wage-setting models in the literature.[10] Third, it provides econometrically clean way to estimate and characterize the extent of imperfect competition in US agricultural labor markets by examining the distribution of employment surplus between employers and workers. It does this by addressing other sources of labor market imperfections like search frictions, information asymmetry, and idiosyncratic preferences for job attributes. Fourth, it generates hypotheses

[9]Bargaining power parameter is a statistic which summarizes "labor market position" of a firm or a worker (Flinn (2006)). For example, low-skilled workers for whom there are many substitutes may have lower bargaining power than high-skilled workers with smaller number of substitutes.

[10]This does not imply that employers and workers literally negotiate each term of their employment contract one-on-one; rather, it means every labor market produces outcomes that resemble the optimal search behavior of the two parties (Burdett and Mortensen (1998); Flinn (2006)).

that are testable on our data. In particular, we are able to analyze the relationship between worker attributes and various labor market outcomes such as wages, employment surplus, and productivity.

If workers and employers search optimally, then our model implies that employers will earn some surplus, defined as the difference between the marginal value product of the worker and his or her "threshold wage" that would otherwise keep them at home, and workers with higher productivity will earn higher wages, depending on their ability to extract surplus from their employer. This framework generates a structural econometric model of labor market outcomes that we describe in more detail in Appendix A.

3 Data

In this section, we describe our data sources, focusing on the National Agricultural Workers Survey (NAWS) conducted by the US Department of Labor, and stylized facts about crop workers in California. NAWS is highly appropriate for this study as it contains a comprehensive and representative dataset on US crop workers across multiple dimensions that include demographics, employment characteristics, and income. The NAWS data follows a multi-stage sampling procedure, ensuring that it reflects the broader population of crop workers and making it valuable to study labor market dynamics in the agricultural sector.

Although the data covers crop workers across the United States, we focus on workers in California. There are two main reasons for this. First, different states implement minimum wages in agriculture differently, and analyzing effects of cross-state minimum wage is very challenging. The second reason is that focusing on California involves analysis of workers in similar industries and employers that sell in similar markets.

We also illustrate key stylized facts about agricultural labor market in California, examining trends in workers' age and average wage, types of crops and tasks, and how factors like gender, immigration status, hiring process, and payment methods are related to workers' real hourly wages. By showing these stylized facts, we aim to emphasize important patterns and differences within farmworkers in California. Our fundamental goal, however, is to understand how these labor market factors influence the allocation of employment surplus between workers and employers.

3.1 Data Sources and Summary Statistics

We use two datasets in our analysis: the National Agricultural Workers Survey (NAWS) and minimum wage series for the period 1989-2022. The NAWS data is from the US Department of Labor and contains nationally and regionally representative data on demographic, health, business, immigration, and workforce attributes on randomly selected US crop workers. To ensure that the sample is representative of the US population of crop workers, NAWS employs a multi-stage sampling technique to interview possibly different workers 3 seasons or cycles (spring, summer, and autumn) each year from about 90 county clusters which are selected based on the intensity of farm activity and county's share in a season's total payroll (Kandilov and Kandilov (2010); Fan et al. (2015); Li and Reimer (2021); National Agricultural Workers Survey (2023)). The sampling procedure is described in detail in National Agricultural Workers Survey (2023) and involves randomization in each of the following levels: cycle, region, single counties or county clusters called farm labor areas (FLA), county, ZIP code, employer, and crop workers. For this study, we use the retricted-version containing cross-sectional information on about 25,000 crop workers in California.[11]

NAWS provides details about farm workers along multiple dimensions—demographics, job attributes, housing, income—but our study employs only the first two categories. For demographic variables, we observe worker's place of birth, race, age, ethnicity, marital status, gender, work authorization, marital status, and years of education. Second, NAWS describes features of agricultural jobs such as crop and job types, hiring process (that is whether a employee works under Farm Labor Contractor (FLC) or grower), wages, and working hours. We summarize a list of the NAWS variables we use in our estimation in Table 1.

[11]Full list of NAWS 12 regions and states in each region is available at: https://www.dol.gov/sites/dolgov/files/ETA/naws/pdfs/Map_of_Naws_17_Sampling_Regions.pdf.

NAWS specifically surveys workers in crop-related jobs in establishments that fall under two NAICS codes (Gold et al. (2019)). First, it targets workers in NAICS 111 or Crop Production which includes enterprises such as farms, orchards, groves, greenhouses, and nurseries primarily involved in cultivating crops, plants, vines, or trees, along with their seeds. In our sample, farmworkers are involved in industries such as corn, wheat, barley, oats, and rice (Figure 4). Second, NAWS interviews workers in NAICS code 1151 or Support Activities for Crop Production which includes establishments offering assistance for crop growth such as labor supply, aerial spraying, cotton ginning, cultivation services, farm management services, crop planting, and vineyard cultivation services. Our sample of NAWS workers in California perform duties in various aspects of crop production and related tasks such as arrangement, cleaning, harvesting, machinery operation, pest control, and crop packing (Figure 4). In our analysis, we include fixed effects across task and crop types to account for the fact that wages are likely to reflect differences in job responsibilities and crop industries.

Our model accounts for the importance of minimum wages in agricultural employment, and how minimum wage laws constrain negotiated wage outcomes. In our study period 1989-2022, we find that California's minimum wage policy impacts wage distribution for substantial portion of the agricultural workforce on at least two grounds. First, 24.1 percent of the crop workers in California earn within 1 percent of the state minimum wage adjusted in real terms. Second, over the 33-year study horizon, California adjusted minimum wage policy on 16 instances (with the first in 1989) when considered in nominal terms, and it changed every year in real terms. Because minimum wage is binding in our data, it imposes a lower limit on the set of wages employers are required to pay. That is, distribution of wages after a binding minimum wage is in place is different from wage distribution without a binding minimum wage. Thus, our study introduces minimum wage data, which we collect from Vaghul and Zipperer (2022). It contains information on yearly changes of minimum wages in California for 1989-2022. The second panel on Figure 3 plots the evolution of state minimum wages, rising from \$9 per hour to \$13 per hour (both in real terms) in our study period.

In our analysis, we characterize crop workers based on two variables: hourly wage rate for employed and duration of unemployment in the past year for unemployed. This helps to bring our theoretical model to data as we use this information to build a likelihood function for workers who are unemployed, who earn the minimum wage, and those earning above the minimum wage. We measure workers' wages and state minimum wages to real terms by deflating them with an appropriate price index. We measure the (un)employment duration using the "weeks worked" variable, which reports the number of weeks each worker was working in the previous 52 weeks. We also use the fact that the NAWS data is a repeated cross-sectional survey, and that it provides retrospective account of workers' employment record over the past year.

We summarize our NAWS data in Table 1 and highlight a few important facts about farmworkers in California. First, the second panel in Figure 2 shows average age of crop workers is rising over time and has reached 44 years in 2022, up from 34 in 1989. Over 50 percent of the workers are over 43 years of age in 2022. An aging workforce indicates more farm experience, and likely higher productivity, but it can also signal "lock-in effect" where workers find it difficult and costly to switch jobs, potentially leading to reduced bargaining power (Cahuc, Postel-Vinay, and Robin (2006)). We seek to test this hypothesis of lock-in effect in our analysis. Second, Figure 3 shows a dense concentration of real hourly wages at $9.6 and a small portion of the workforce earn over $20 per hour. The second panel in the same figure illustrates that both real hourly wages and state minimum wages trend upwards, at least after 2013. Upward-trending real wages suggest that workers are earning more of the employment surplus from firms, but it may also be the case that firm profitability (and hence marginal value products) are rising. Our empirical model disentangles these two explanations for rising wages.

In Table 2, we present demographic and employment data on crop workers, and highlight heterogeneity in their composition. We notice a workforce that is mainly male (80.5%) and foreign-born (94.6%), with a relatively similar distribution between documented (52.3%) and undocumented (47.7%) workers. Most workers are hired directly by growers (71.8%), while a substantial faction work for Farm Labor Contractors (FLCs) (28.2%). The majority receive hourly wages (88.3%), with a minor share are paid on a piece-rate basis (11.7%). Each of these features of our data are likely important to both the productivity of workers and how earned surplus is allocated between firms and workers, which we address in more detail below.

We show the distribution of jobs and crop categories that US crop workers are involved in the period 1989-2022 in Figure 4. From the first panel, we see that the most common tasks are semi-skilled, and in pre-harvesting, harvesting, and post-harvesting, while supervision is the least common task. The second panel indicates that majority of workers work in fruits, nuts and vegetable farms, while field crops and horticulture are also important crop industries. This concentration in particular types of crops and tasks can impact labor market dynamics as these activities are seasonal and labor-intensive in nature. We account for differences in wages across jobs and crops in our empirical model below as there is clearly substantial heterogeneity in this dimension in our data.

Our study explores how different groups of workers obtain different levels of compensation based on relative strength of their productivity level and bargaining power. As a first step in that direction, we examine the heterogeneity of how real hourly wages across key worker and employer attributes. The five panels in Figure 5 demonstrate evolution in real hourly wages across various worker groups—gender, employer type, foreign status, documented status, and payment method. While wages have generally increased during 1989-2022, the degree of increase differs among different groups. Male workers and those hired by FLCs have higher wages compared to their counterparts. Native, documented, and hourly-earning workers experience consistently higher wage growth than their counterparts. However, wages are only indirect measures of the value of workers to their employers in a setting with search frictions and other market imperfections. It is possible for some of these groups to have higher productivity but lower bargaining power, and relative effects of two forces can influence the ultimate wage determination.

In summary, the data suggests significant changes in the composition and wage distribution of California farmworkers, highlighting heterogeneity in demographics and employment characteristics. These trends imply an intricate interplay amongst labor market environment, worker productivity, bargaining power, and labor market outcomes. The patterns that we observe in our data necessitate a deeper investigation into how employment conditions define labor market outcomes, particularly the division of surplus across various worker groups. To perform a rigorous analysis of factors determining the surplus distribution and to have a nuanced understanding of agricultural labor markets, we develop an empirical model that assesses the how worker and firm attributes interact with wage outcomes.

3.2 Empirical Analysis

In this section, we describe how we bring our theoretical model of search, match, and bargaining (Appendix A) to the data. We discuss the mathematical derivation of our empirical model in Appendix B and only describe our strategy here. Given that the NAWS data is repeated cross-sectional and not matched employer-employee data, which is ideal for estimation, our study follows other in the literature (Flinn (2006); Richards and Rutledge (2023)) to estimate the model parameters. The approach involves building a likelihood function that uses individual-level observations of real hourly wages and unemployment duration to evaluate model parameters such as the job arrival rate, job separation rate, bargaining power, and productivity distribution.

The likelihood function forms a core part of our empirical strategy, and we build it by classifying workers into three distinct groups: those who are unemployed (and hence "earning" less than state minimum wage), those who earn exactly the minimum wage, and those who earn wages above the minimum wage. We calculate the likelihood of group membership using the probability of specific unemployment durations within the population.

That is, each of the three segments of the labor market has a "likelihood contribution", and we combine the contributions of all three groups into a single likelihood function for estimation purposes.

For unemployed workers, the likelihood contribution assumes that the duration of unemployment follows a negative exponential distribution, which simplifies the empirical analysis by associating gap between job offers with Poisson process and making it mathematically tractable. The unemployment distribution is based on a hazard rate, which indicates the chance that a proposed job pays below the minimum wage. The likelihood of finding a given unemployment spell then results from this hazard rate, accounting for the rate at which unemployed workers get job offers.

The likelihood contribution from workers earning the minimum wage accounts for the probability that a worker who receives a job offer is constrained by the minimum wage. Specifically, we integrate the minimum wage constraint into the Nash bargaining framework which is used to model surplus distribution. Intuitively, this reflects the probability that their negotiated wage, which would otherwise be lower based solely on their productivity and bargaining power, is now raised above to the mandated minimum wage.

For workers earning higher than the minimum wage, the likelihood contribution captures the probability that a worker's wage is defined by the Nash bargaining framework, and not by utilizing the minimum wage floor. In this case, the wage reflects the worker's productivity, her bargaining power on how to split the employment surplus, and the overall market conditions.

We then combine these three likelihood contributions from workers who are unemployed, earn wages equal to the minimum wage, and those who have wages above the minimum wage into a single likelihood function. We use a maximum likelihood estimation strategy to find the set of model parameters—the job arrival rate (ψ), job separation rate (δ), workers' bargaining power (γ), mean of productivity distribution (μ_ϑ), standard deviation of productivity distribution (σ_ϑ), and reservation utility (ϑ^*)—that best fit the observed data.

In our analysis, we account for unobserved heterogeneity by including fixed effects for years and types of crops and tasks that workers are involved in during the NAWS interview. Additionally, we control for variables such as worker demographics (age, gender, citizenship status), job characteristics (hiring process, methods of payment, and experience). Further, we interact our key model parameters (productivity and bargaining power) across employer and worker attributes to understand how the estimates vary across different worker groups. This approach allows us to rigorously examine how different workers contribute to productivity (thus increasing the total size of the pie) and how they share the surplus (allocating the total pie). We discuss our results in Section 4.

Finally, we test whether high profitability and high wages are mutually exclusive for agricultural labor markets, which is not the case in Autor et al. (2020) due to "superstar-firms" argument. That is, we examine if the summary evidence—a positive correlation of wages and profits in a sample of US food retailers and wholesalers—in Figure 1 also holds for agricultural firms. To this end, we generate simulated values for productivity, bargaining power, and surplus across all observations in our data, and then explore the relationship between wages and employer's share of surplus through a summary regression. That is, we use parameters estimated from our preferred structural model specification—one where we interact both productivity and bargaining power with different attributes—and calculate implied values for each element across all observations. Since both productivity and bargaining power vary along heterogeneous attributes, we compute a range of (employer) surplus values as: $(\exp(\mu_\vartheta + \sigma_\vartheta^2/2) - \vartheta^*)(1-\gamma)$. Finally, we examine the surplus-wage relationship by conducting a logarithmic regression of these calculated surplus values against observed wages. We summarize our findings in Figure 8.

4 Results

In this section, we present our results from estimating the model in Appendix B. We describe our results in detail below but the summary is that while we find workers' bargaining power to be roughly 24%, we also document a robust positive elasticity of employer share of surplus and observed wages. This suggests that a view of bargaining power as a sufficient parameter to gauge worker exploitation can be misleading. Instead, we find employers in agriculture, and perhaps food system more generally, earn more surplus when they pay higher wages after we adjust for heterogeneity in bargaining power and productivity across different worker attributes.

Before we explain the results for superstar-firm hypothesis, we present the results about bargaining power and workers' productivity as they form a basis for estimation of the surplus-wage elasticity. Table 3 provides the estimates of structural parameters in the log-likelihood function (18) in the setting of crop workers in California from 1989-2022. Model 1 offers a baseline assessment that unemployed workers regularly face new job openings and have a modest bargaining power, getting about 23.5% of the employment surplus—the gap between worker's productivity and reservation wage. In Model 2, we interact the bargaining parameter with several worker and employer attributes, and find that factors such as citizenship, gender, and farm work experience enhance bargaining power.

Model 1 in Table 3 controls for year, crop, and task fixed effects, and for worker attributes: age, age-squared, gender, education, years of farm work, foreign-born, and citizenship status. It shows the job arrival rate (ψ) is 0.118, which means there is 11.8% probability that an unemployed worker will get a job offer in a year. The job separation rate (δ) is 0.180, reflecting that an employed worker has 18.0% chance of losing her job in a given year. Worker productivity has a lognormal distribution with parameters $\mu_\vartheta = 2.027$ and $\sigma_\vartheta = 0.192$. Using the expression of match-value, $\exp(\mu_\vartheta + \sigma_\vartheta^2/2)$, this translates to a mean productivity of \$7.734 per hour. Meanwhile, worker's reservation utility (ϑ^*) is \$3.232 per hour. As mean productivity is higher than reservation utility, our estimates imply an employment surplus of \$4.502 per hour. Workers and employers share this surplus based on workers' bargaining power parameter, $\lambda = 0.235$. This suggests that workers take an average of 23.5% of the surplus, and employers (FLC or growers) capture the remaining share.

Model 2 builds on Model 1 by interacting the bargaining power parameter with worker and firm attributes: citizenship status (= 1 if a worker is undocumented), gender (= 1 for males), Farm Labor Contractor (FLC = 1 if hired by a contractor), age, foreign born (= 1 for foreign born workers), and piece (= 1 if paid on a piece-rate basis). The purpose here is to understand how bargaining power varies by different labor-related characteristics. After the interaction, structural parameters take slightly different values. Workers' bargaining power is 24.4%, and it differs considerably across different worker groups. We find that workers who are undocumented, males, older, earn piece-rate, and with more farm experience have a lower bargaining power than their counterparts, which we hypothesize as resulting from vulnerability, limited mobility, and lack of legal protections for such worker groups. On the other hand, our analysis shows that workers who are hired by farm labor contractors and are foreign-born tend to have a higher bargaining power, a result likely driven by collective leverage, contractor negotiations, and stronger labor networks. We visually depict this heterogeneity of bargaining power in Figure 6.

One objective in this study is to understand not just bargaining power but also find how workers' productivity varies by worker and employer characteristics. To this end, we interact mean productivity with worker and employer attributes as above. Table 4 reports the findings. Model 1 has the same results as Model 1 in Table 3 because we do not change the baseline specificiation. Model 2 shows findings after the interaction. We notice that an increase in job creation rate ($\psi = 13.8\%$), separation rate ($\delta = 19.3\%$), mean productivity ($\mu_\vartheta = 2.132$), standard deviation of productivity ($\sigma_\vartheta = 0.273$), and reservation utility ($\vartheta^* = 3.234$), and a slight decrease in bargaining power ($\gamma = 0.234$), relative to the values in Model 1. As Model 2 has slightly higher LLF value and lower AIC value, we argue it indicates a better fit of our data than Model 1. Further, we interpret Model 2 results as correcting for omission of differential impacts of worker attributes. Applying the expression of match-value, $\exp(\mu_\vartheta + \sigma_\vartheta^2/2)$, gives workers' mean productivity as \$8.756 per hour. A heterogeneity analysis shows that μ_ϑ is lower amongst workers who are undocumented, older, and are foreign born, which is likely due to limited formal training, language barriers, or physical limitations. Similarly, we find it is higher amongst workers who are males, earn piece-rate, and with more farm experience, perhaps due to stronger physical abilities, alignment of incentives with output, and accumulated experience. We show the precise estimates of productivity for these groups in Figure 7.

Our next goal ties with Nash bargaining framework where the objective is to model how different agents contribute to "size of the pie" and not just "share the pie". That is, we want to understand how different worker groups share the employment surplus *relative to* their contribution to productivity. This informs whether workers' share of surplus is solely due to bargaining power effects or whether it aligns with their productivity levels.

To understand how surplus size relates to its distribution, we interact both mean productivity and bargaining parameters with different worker and employer attributes in the same baseline model discussed in Tables 3 and 4. Table 5 reports the findings. Compared to the baseline results in Model 1 in Table 3, we document higher values for job creation rate is (13.9%), job separation rate (19.3%), mean productivity (2.12), standard deviation of productivity (0.281), and workers' bargaining power (24.2%), and a lower value for reservation utility (3.226). Applying the same expression for match-value as above, we find that mean productivity is \$8.67 per hour. In the heterogeneity analysis, we find undocumented workers have lower productivity and lower bargaining power. Such workers likely have lower bargaining power because they are more likely to be in "take it or leave it" (or job-posting in the terminology of bargaining models) or are subject to jobs that are pre-arranged by their contractors. At the same time, worker productivity may be lower due to the likelihood that undocument workers have less training, are more likely to be migrant workers, or are otherwise more temporary and less committed to a particular workplace.

In Table 5, we also find that males, piece-rate earners, and workers with more years of farm work experience tend to have higher productivity but lower bargaining power. One possible rationale for piece-rate earners and experienced workers to have higher productivity is their familiarity with tasks and direct alignment of incentives with output. We also find that workers hired by contractors have same productivity as those hired by growers but the FLC workers have higher bargaining power, likely due to collective leverage, a result similar to Card, Lemieux, and Riddell (2004) who find workers with union membership have higher bargaining power. Finally, we find workers who are older and foreign born have lower productivity, possibly due to physical limitations and language barriers, but have higher bargaining power as they likely bring in diverse experiences and specialized skills. We summarize this heterogeneity in productivity and bargaining power in Table 6.

We exploit the heterogeneity in bargaining power and productivity to examine how observed wages relate to employers' share of surplus. We illustrate our findings in Figure 8. The graphs shows that higher wages are correlated with higher employer surplus, with surplus-wage elasticity $\epsilon = 0.1619$ and t-ratio 29.54. This aligns with both our summary evidence from food retailing (Figure 1) and Autor et al. (2020) who argue that wages are profitability are not always mutually exclusive for superstar firms. In our case, it means that agricultural employers can gain more surplus by compensating their workers with higher wages, and not always via traditional explanations of exploitation and "winner-take-all" approach.

In summary, we document the importance of looking at productivity effects, in addition to bargaining effects as done in classical studies of imperfect competition. Our analysis highlights how an employer-employee match both increases the size of the pie and examines how the pie is distributed amongst employers and workers. Specifically, we argue workers who have a lower bargaining power can still benefit by having higher productivity. While we do not have enough information in the NAWS data to make a definitive statement, it is possible that productivity effects offset the bargaining effects amongst workers who are male, piece-rate earners, and with more farm experience. If this is a case, such workers are still better-off despite having a lower bargaining power. Further, we document a robust positive elasticity of employer surplus with wages, suggesting that agricultural firms can gain more by paying higher wages to their workers. This explains how bargaining equilibria eliminates the notion of "zero sum game" in traditional models of imperfect competition.

Our central results on bargaining equilibria and surplus-wage elasticity are that productive and profitable firms cannot always be characterized as those who suppress wages or "exploit workers", and workers with low bargaining power can still be better-off by generating higher productivity to their employer. These findings do not align with usual policy interventions such as POTUS (2021) that maintain imperfect competition in labor markets leads to worker exploitation. Similarly, we challenge the narratives in popular media and public debates that productive and high-performing food-system employers necessarily win by making their workers lose. We argue that this zero-sum game do not hold at least in the setting of US crop employers and workers. Future policy designs for food sector should consider the possibility that a worker with a low negotiation power can skill be better-off by contributing higher value to her employer, and that employers can provide better compensation as they become more profitable.

5 Conclusions and Implications

In this paper, we examine the underlying tenets of the superstar-firm theory in an agricultural setting. We interpret the superstar effects as implying that firms can simultaneously earn higher profits and pay better wages to their workers. We document that agricultural firms gain more surplus by paying higher wages, a result similar to Autor et al. (2020). Our findings are in sharp contrast to more usual models of labor market power that imply worker exploitation and present imperfect competition as a zero-sum game, where workers lose when employers gain.

We test our hypothesis using a structural model of search, match, and bargaining from the Diamond-Mortensen-Pissarides tradition to assess the heterogeneity in bargaining power and productivity of crop workers using NAWS data for crop workers in California. First, the results from model estimation show that workers, on average, have a bargaining power parameter of 0.242, which implies they receive less than one-fourth of the employment surplus and their employers (growers or contractors) take the remaining share. Our heterogeneity analysis suggests that bargaining power differs across worker groups: Foreign-born workers and those hired by contractors have slightly higher bargaining power, while females, older workers, piece-rate earners, and more experienced farm workers have lower bargaining power relative to their corresponding counterparts.

Our study also suggests that the usual approach of labor market power, based solely on bargaining power effects, as a direct implication of exploitation may be oversimplified. Instead, we propose to focus on whether there is an alignment between workers' productivity and their share of the employment surplus. For instance, some workers can have high productivity but low bargaining power and can still manage to bargain for better offers due to the relative strength of productivity-effects over bargaining-effects. We examine how variables such as age, gender, experience, mode of payment, and immigration status affect both productivity and bargaining power. In doing so, we are able to understand which worker groups are likely undercompensated relative to their productivity. We argue that this approach improves theoretical understanding of labor market dynamics but can also reveal practical insights for policy-making. It emphasizes the importance of focused policies to make sure workers receive fair compensation relative to their productivity. Further, our results add to recent antitrust efforts to mitigate monopsony power in labor markets, but argue that productive and profitable firms need not always be the ones that exploit workers or under-pay the workers.

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Table 1: Summary of NAWS Variables Used in Estimation

Variables	N	Mean	St. Dev.	Min	Max
Hours Per Week	24,827	44.5	11.7	1	120
Age	24,827	36.5	12.7	14	88
Years of Education	24,827	7.5	3.5	1	21
Years of Farm Work Experience	24,827	14.1	11.5	0	78
Weeks Worked in Last 52 Weeks	24,827	7.5	9.8	0.0	52.0
Real Hourly Wage	24,827	11.2	3.2	2.7	44.8
Real Minimum Wage	24,827	9.3	1.4	7.0	13.4

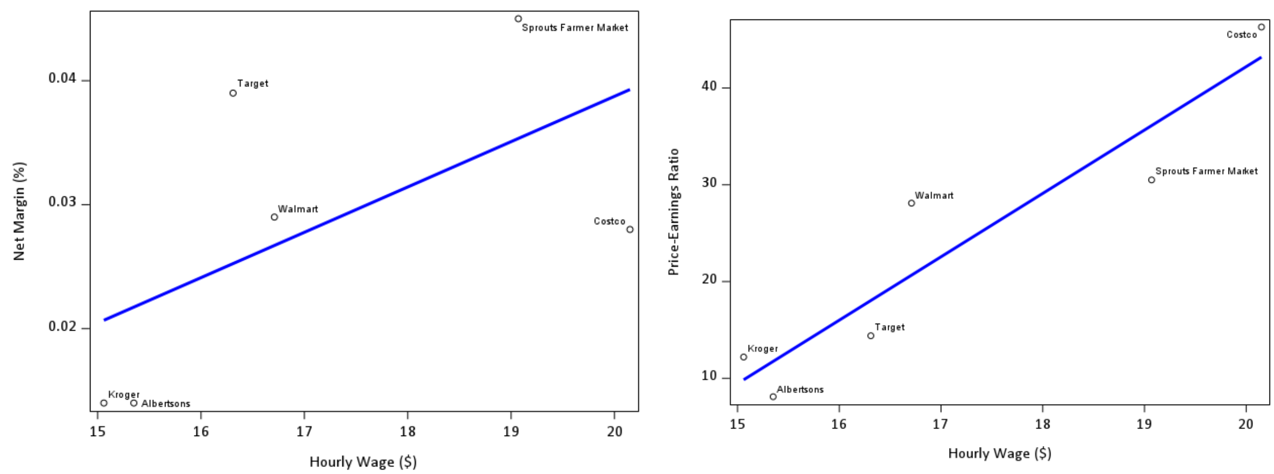
Notes: The table indicates a summary of statistics of crop workers in the NAWS sample period 1989-2022 for demographics and workforce variables. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Table 2: Frequency Distribution for NAWS Binary Variables

Binary Variable	Category & Share of Total Workforce	
Gender	Male	Female
	80.5%	19.5%
Employer Type	Grower	Contractor
	71.8%	28.2%
Foreign Status	Native	Foreign
	5.4%	94.6%
Wage Payment Method	Hourly	Piece Rate
	88.3%	11.7%
Status	Documented	Undocumented
	52.3%	47.7%

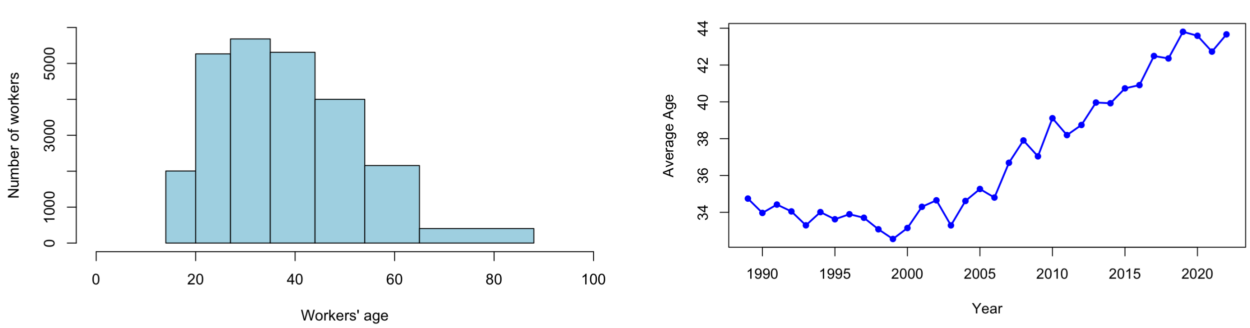
Notes: Share of workers for each class of binary variables in the NAWS data for the period 1989-2022. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Figure 1: Relationship of Hourly Wages to Price-Earnings Ratio and Net-Margins



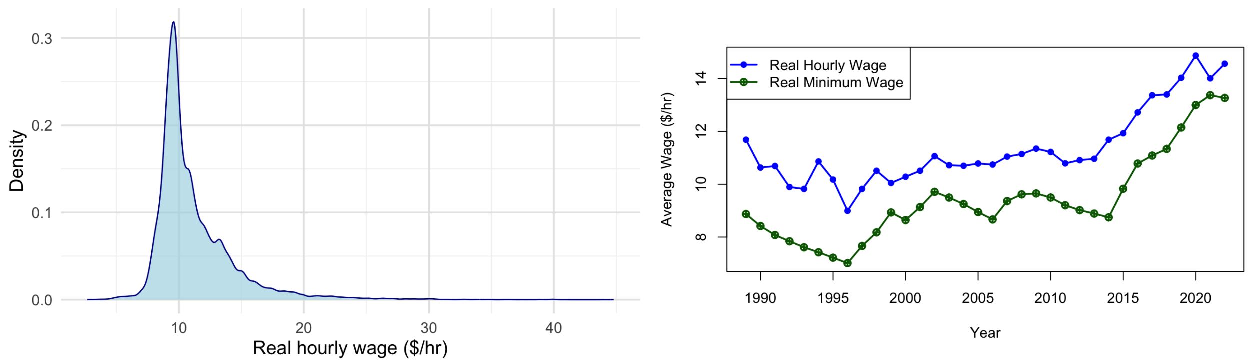
Notes: The two panels show a positive correlation of hourly wages with employer's net-margins and price-earning ratio for a sample of US retail and wholesale firms. The data source for price-earning ratio is Compustat (https://www.lseg.com/en/data-analytics/financial-data/company-data/fundamentals-data/standardized-fundamentals/sp-compustat-database). Hourly wage data is from https://www.indeed.com/companies/best-Retail--Wholesale-companies and is accessed on August 10, 2024.

Figure 2: Age Distribution and Trends in the Average Age of US Crop Workers



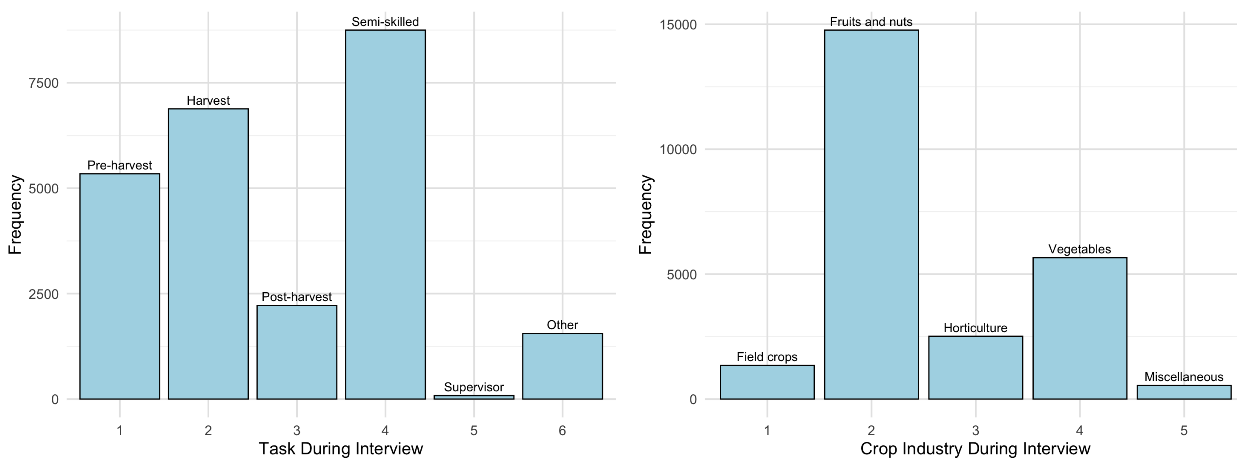
Notes: The first panel shows distribution of workers' age in NAWS data for the period 1989-2022. The median age is 35, and nearly 40 percent of workers are above the age of 40. The second panel shows evolution of average age of crop workers across years. Their average age in 2022 is 44 years, up from 34 years in 1989. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Figure 3: Wage Distribution and Trends in the Average Wage



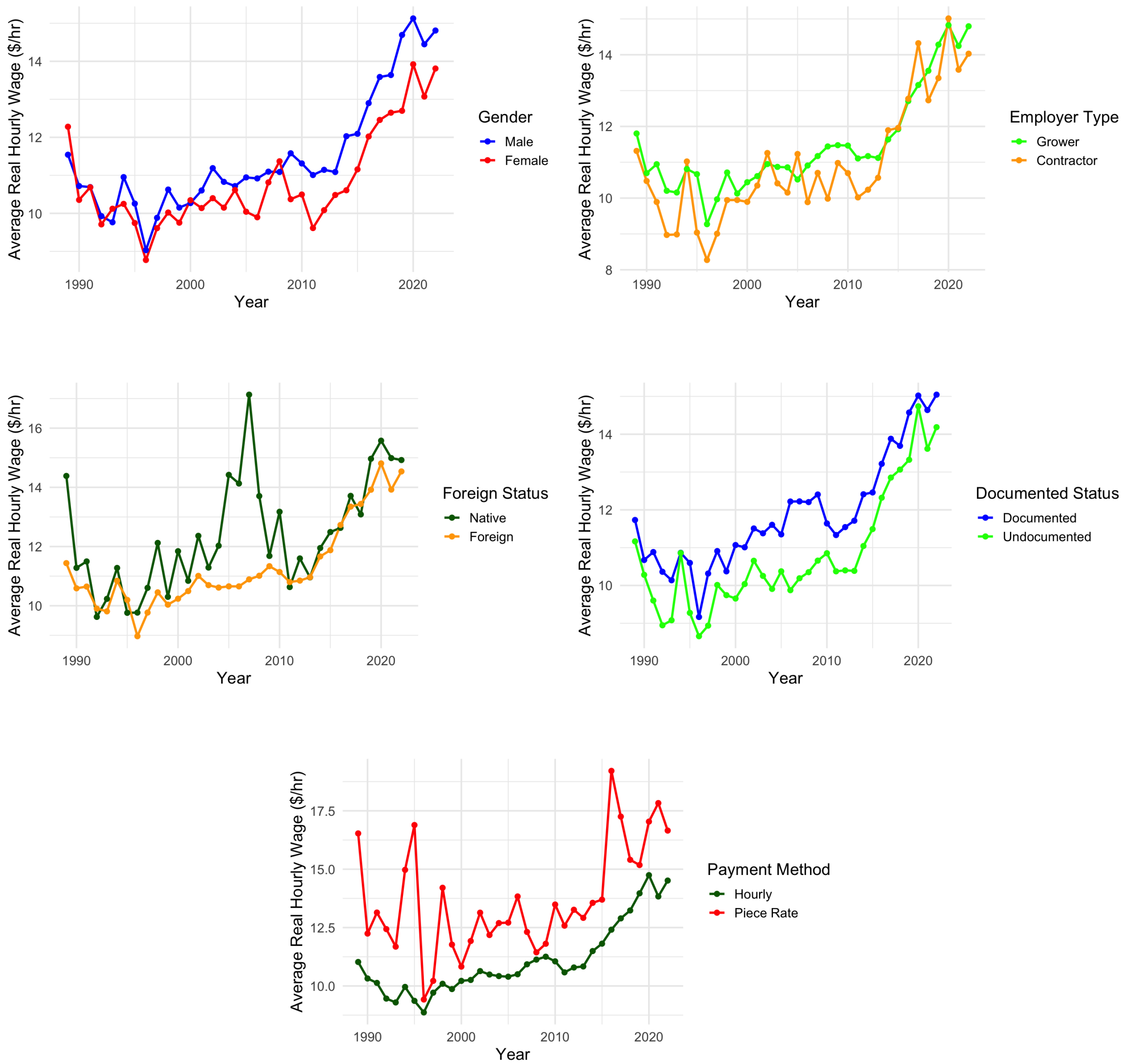
Notes: The first panel shows kernel density plot of workers' real hourly wage in NAWS data for the period 1989-2022. The plot peaks at hourly wage of $9.59, indicating wages are densely concentrated around this rate. The second panel shows evolution of average hourly wage of crop workers and state minimum wage across years. The two wage-types move nearly parallel and start to rise after 2013. The data source for real hourly wages is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey). Real minimum wage data is from https://github.com/benzipperer/historicalminwage/releases.

Figure 4: Types of Task and Crop During Interview of US Crop Workers



Notes: The first panel shows frequencies of types of tasks that workers in our sample are involved in the period 1989-2022. The second panel shows types of crop industries they work in during the interview. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Figure 5: Real Hourly Wages Across Years and by Worker Groups



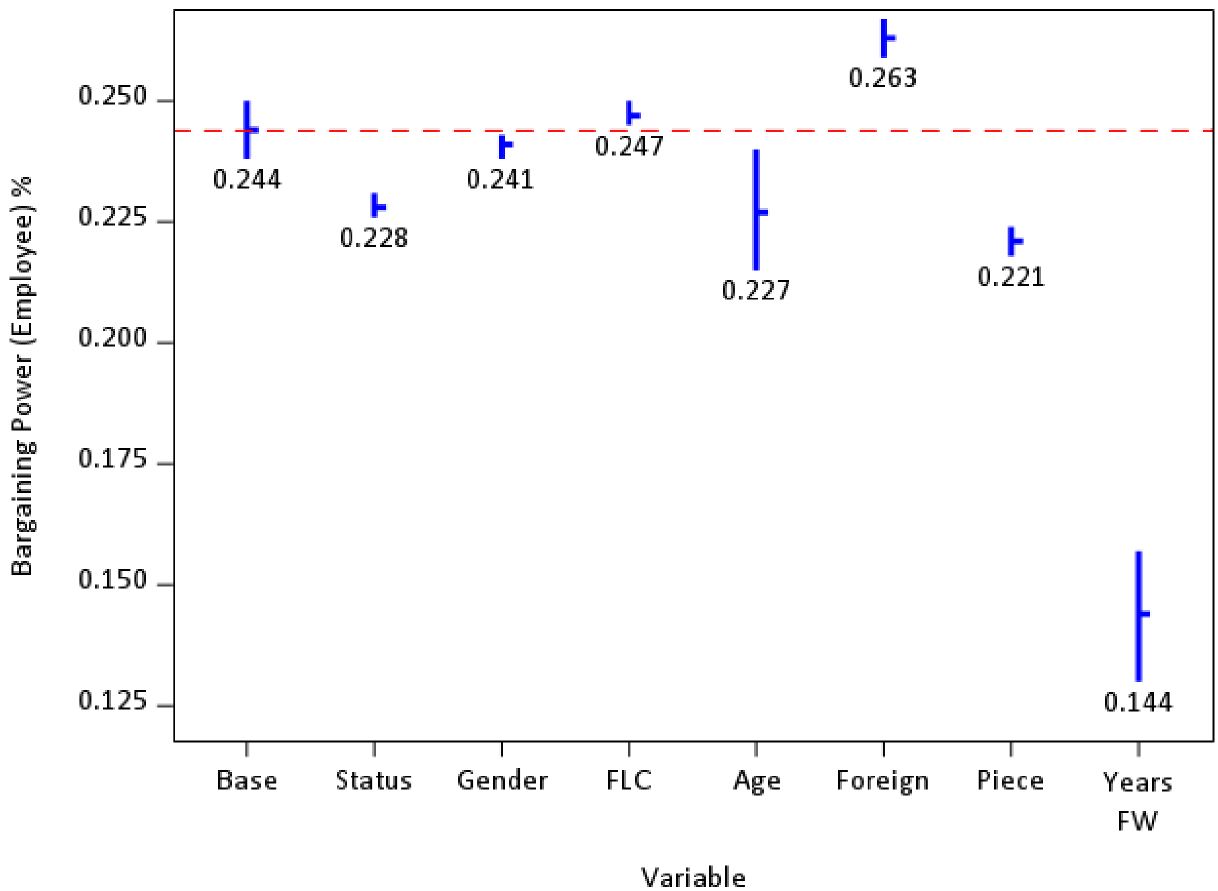
Notes: The five panels show the evolution of average hourly wages across years on the basis of five different variables for the period 1989-2022. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Table 3: Estimates of Worker Bargaining Power in California, 1989-2022

Parameter/Variable	Notation	Model 1 Est.	Model 1 Std. Err.	Model 2 Est.	Model 2 Std. Err.
Job Arrival Rate	ψ	0.118	0.002	0.116	0.002
Job Separation Rate	δ	0.180	0.004	0.180	0.004
Mean Productivity	μ_ϑ	2.027	0.006	2.021	0.006
Std. Dev. Productivity	σ_ϑ	0.192	0.010	0.187	0.010
Reservation Utility	ϑ^*	3.232	0.006	3.225	0.005
Workers' Bargaining Power	γ	0.235	0.001	0.244	0.003
Heterogeneity of γ:					
Citizenship Status				-0.016	0.001
Gender				-0.003	0.001
FLC				0.003	0.001
Age				-0.016	0.007
Foreign Born				0.019	0.002
Piece Rate				-0.023	0.001
Years Farm Work				-0.100	0.007
Controls:					
Year Fixed Effects?		Yes		Yes	
Crop Fixed Effects?		Yes		Yes	
Task Fixed Effects?		Yes		Yes	
Worker Attributes?		Yes		Yes	
LLF		-74703.51		-74159.7	
AIC/N		6.02		5.98	
Number of Observations		24827		24827	

Note: All estimates obtained with structural search, match, and bargaining model similar to Flinn (2006). Model 1 represents the base model with no heterogeneity in bargaining. In Model 2, we include various worker and employer attributes—worker's citizenship status, gender, Farm Labor Contractor (FLC), age, foreign, piece-rate, and years of farm work experience—in a single model in order to estimate the partial effect of each. Status = 1 if a worker is undocumented. Gender = 1 for males. FLC = 1 if worker is hired by a farm labor contractor, and is 0 if hired directly by a grower. Foreign = 1 for foreign-born workers. Piece = 1 if a worker is paid on a piece-rate basis, and 0 if paid hourly. We include year, crop, and task fixed effects, and control for following worker attributes: age, age-squared, gender, education, years of farm work, foreign-born, and citizenship status. The data source is NAWS, US Department of Labor for the period 1989-2022 (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Figure 6: Heterogeneity in Worker Bargaining Power in California, 1989-2022



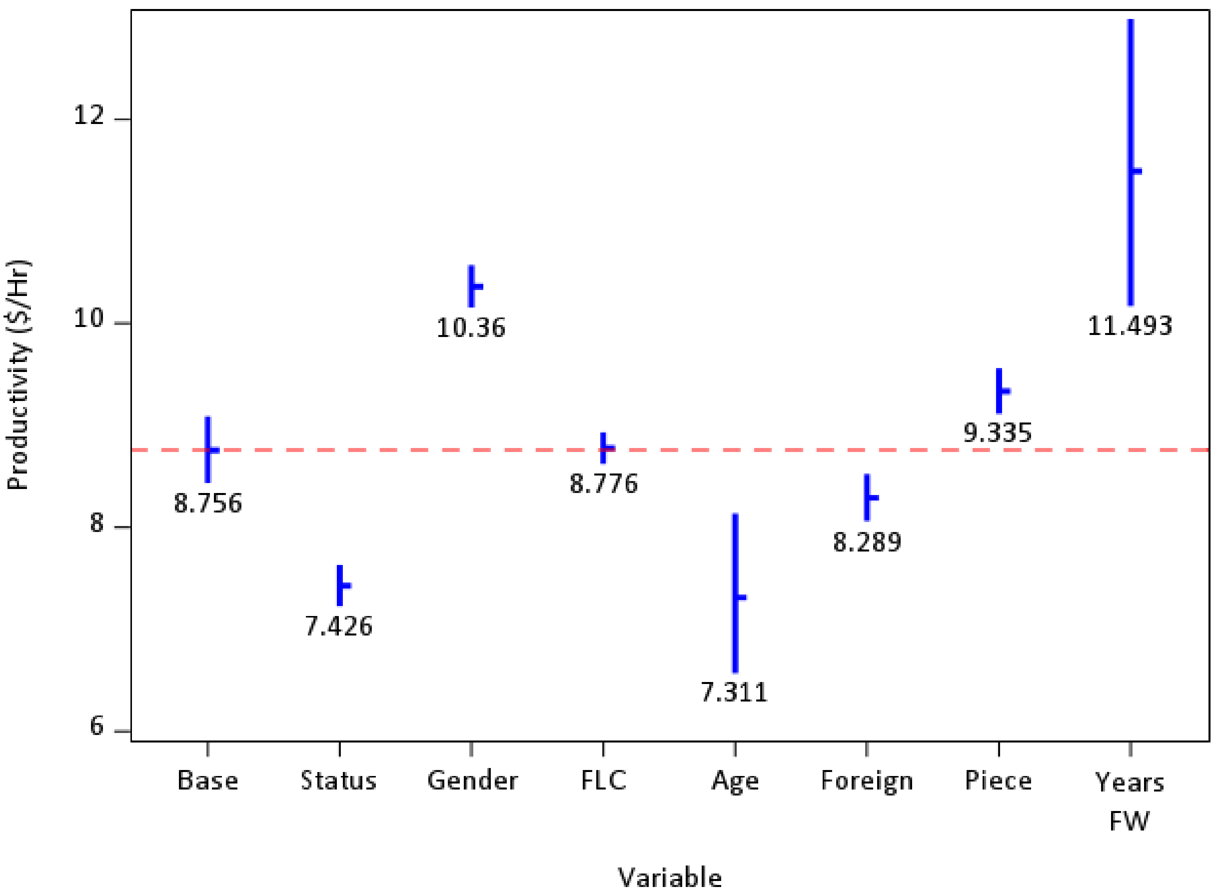
Notes: The figure shows how workers' bargaining power differs across worker and employer attributes: worker's citizenship status, gender, Farm Labor Contractor (FLC), age, foreign, piece-rate, and years of farm work experience. Status = 1 if a worker is undocumented. Gender = 1 for males. FLC = 1 if worker is hired by a farm labor contractor, and is 0 if hired directly by a grower. Foreign = 1 for foreign-born workers. Piece = 1 if a worker is paid on a piece-rate basis, and 0 if paid hourly. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Table 4: Estimates of Worker Productivity in California, 1989-2022

		Model 1		Model 2	
Parameter/Variable	Notation	Est.	Std. Err.	Est.	Std. Err.
Job Arrival Rate	ψ	0.118	0.002	0.138	0.002
Job Separation Rate	δ	0.180	0.004	0.193	0.004
Mean Productivity	μ_ϑ	2.027	0.006	2.132	0.019
Std. Dev. Productivity	σ_ϑ	0.192	0.010	0.273	0.012
Reservation Utility	ϑ^*	3.232	0.006	3.234	0.006
Workers' Bargaining Power	γ	0.235	0.001	0.234	0.001
Heterogeneity of μ_ϑ:					
Citizenship Status				-0.165	0.014
Gender				0.168	0.010
FLC				0.002	0.009
Age				-0.180	0.055
Foreign Born				-0.055	0.014
Piece Rate				0.064	0.012
Years Farm Work				0.272	0.062
Controls:					
Year Fixed Effects?		Yes		Yes	
Crop Fixed Effects?		Yes		Yes	
Task Fixed Effects?		Yes		Yes	
Worker Attributes?		Yes		Yes	
LLF		-74703.51		-74014.55	
AIC/N		6.02		5.97	
Number of Observations		24827		24827	

Note: All estimates obtained with structural search, match, and bargaining model similar to Flinn (2006). Model 1 represents the base model with no heterogeneity in productivity. In Model 2, we include various worker and employer attributes—worker's citizenship status, gender, Farm Labor Contractor (FLC), age, foreign, piece-rate, and years of farm work experience—in a single model in order to estimate the partial effect of each. Status = 1 if a worker is undocumented. Gender = 1 for males. FLC = 1 if worker is hired by a farm labor contractor, and is 0 if hired directly by a grower. Foreign = 1 for foreign-born workers. Piece = 1 if a worker is paid on a piece-rate basis, and 0 if paid hourly. We include year, crop, and task fixed effects, and control for following worker attributes: age, age-squared, gender, education, years of farm work, foreign-born, and citizenship status. The data source is NAWS, US Department of Labor for the period 1989-2022 (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Figure 7: Heterogeneity in Worker Productivity in California, 1989-2022



Notes: The figure shows how workers' productivity differs across worker and employer attributes: worker's citizenship status, gender, Farm Labor Contractor (FLC), age, foreign, piece-rate, and years of farm work experience. Status = 1 if a worker is undocumented. Gender = 1 for males. FLC = 1 if worker is hired by a farm labor contractor, and is 0 if hired directly by a grower. Foreign = 1 for foreign-born workers. Piece = 1 if a worker is paid on a piece-rate basis, and 0 if paid hourly. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Table 5: Estimates of Worker Productivity and Bargaining in California, 1989-2022

Variable/Parameter	Notation	Model 1 Est.	Model 1 Std. Err.	Model 1 Est.	Model 1 Std. Err.
Job Arrival Rate	ψ	0.139	0.002	0.139	0.002
Job Separation Rate	δ	0.193	0.004	0.193	0.004
Mean Productivity	μ_ϑ	2.120	0.020	2.120	0.020
Std. Dev. Productivity	σ_ϑ	0.281	0.013	0.281	0.013
Reservation Utility	ϑ^*	3.226	0.005	3.226	0.005
Workers' Bargaining Power	γ	0.242	0.003	0.242	0.003
Heterogeneity:		*Heterogeneity of μ_ϑ*		*Heterogeneity of γ*	
Citizenship Status		-0.155	0.014	-0.013	0.001
Gender		0.178	0.011	-0.007	0.001
FLC		0.000	0.009	0.002	0.001
Age		-0.169	0.057	-0.015	0.007
Foreign Born		-0.066	0.015	0.020	0.002
Piece Rate		0.081	0.013	-0.022	0.001
Years Farm Work		0.366	0.064	-0.099	0.007
Controls:					
Year Fixed Effects?		Yes		Yes	
Crop Fixed Effects?		Yes		Yes	
Task Fixed Effects?		Yes		Yes	
Worker Attributes?		Yes		Yes	
LLF		-73451.17		-73451.17	
AIC/N		5.92		5.92	
Number of Observations		24827		24827	

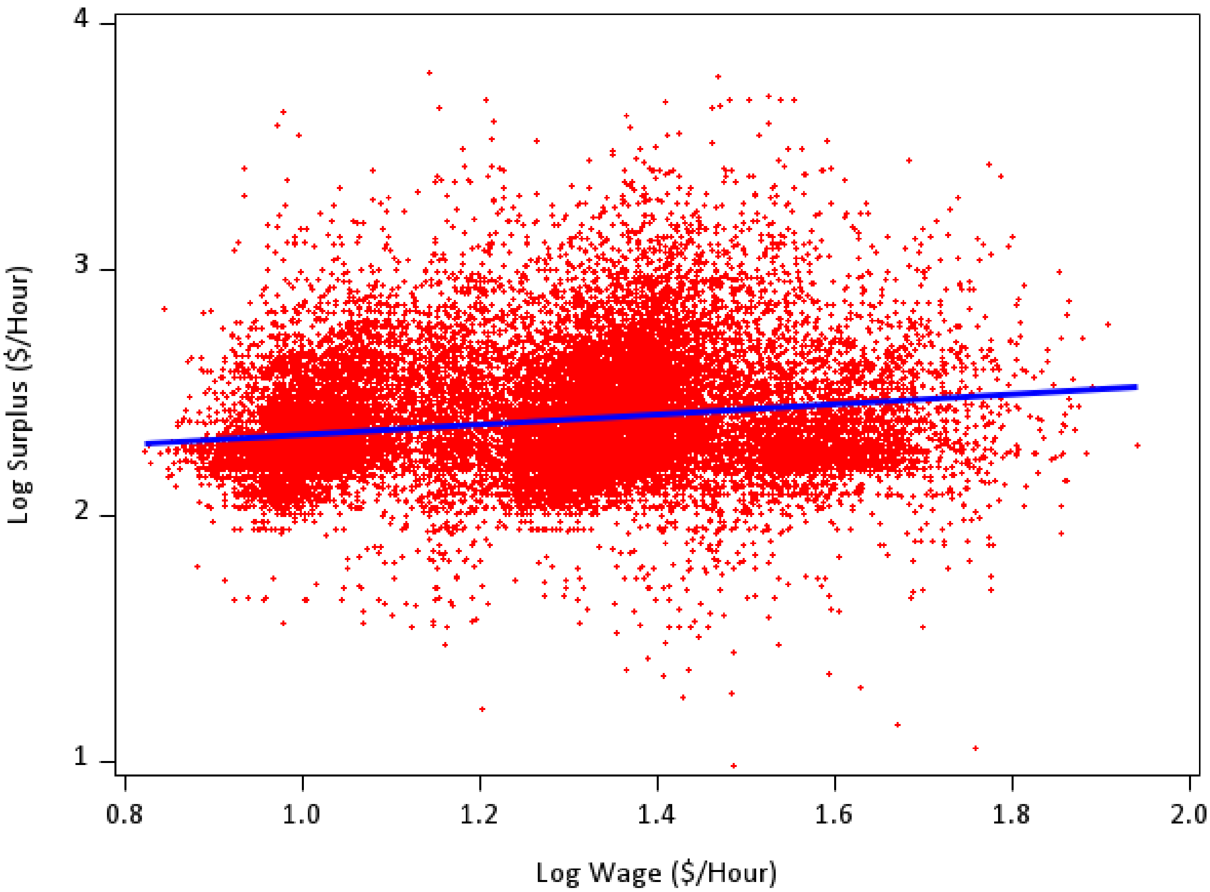
Notes: All estimates obtained with structural search, match, and bargaining model similar to Flinn (2006). The top part of the table represents baseline values for our structural parameters: $\psi, \delta, \mu_\vartheta, \sigma_\vartheta, \theta^*$ and γ. In the middle part, we include various worker and employer attributes in order to estimate the partial effect of each on both productivity and bargaining power. So, the middle part represents heterogeneity in productivity and bargaining power along different worker groups. We include various worker and employer attributes—worker's citizenship status, gender, Farm Labor Contractor (FLC), age, foreign, piece-rate, and years of farm work experience—in a single model in order to estimate the partial effect of each. Status = 1 if a worker is undocumented. Gender = 1 for males. FLC = 1 if worker is hired by a farm labor contractor, and is 0 if hired directly by a grower. Foreign = 1 for foreign-born workers. Piece = 1 if a worker is paid on a piece-rate basis, and 0 if paid hourly.We include year, crop, and task fixed effects, and control for following worker attributes: age, age-squared, gender, education, years of farm work, foreign-born, and citizenship status. The data source is NAWS, US Department of Labor for the period 1989-2022 (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Table 6: Changes in Mean Productivity and Bargaining Power by Worker Attributes

	Direction of Change	
Worker Attributes	Mean Productivity (μ_ϑ)	Bargaining Power (γ)
Undocumented	$\downarrow$	$\downarrow$
Male	$\uparrow$	$\downarrow$
Under FLC	No Change	$\uparrow$
Older	$\downarrow$	$\uparrow$
Foreign Born	$\downarrow$	$\uparrow$
Piece Rate	$\uparrow$	$\downarrow$
More Farm Experience	$\uparrow$	$\downarrow$

Notes: The table shows how workers' mean productivity and bargaining power vary across different worker attributes. Arrows indicate the increase ($\uparrow$) or decrease ($\downarrow$) in the respective attribute, while "No Change" signifies no significant change, relative to the corresponding counterparts of worker attributes.

Figure 8: Relationship Between Wages and Employment Surplus for CA farms



Notes: The figure shows how log of employment surplus relate to log wages for California crop workers. Surplus-wage elasticity is 0.16192 and t-ratio is 29.54. The data source is NAWS, US Department of Labor (https://www.dol.gov/agencies/eta/national-agricultural-workers-survey).

Appendix

A Model Details

In this section, we provide formal details of our structural model. We base the discussion on Pissarides (2000) and Flinn (2006) throughout and extend both to incorporate institutional features of labor market in the US crop sector.

A.1 Environment

Labor Market Status. The labor market consists of workers—either unemployed and looking for jobs or currently employed under a grower or a Farm Labor Contractor (FLC)—and employers (either growers or FLCs). The job arrival rate is ψ and denotes the probability that a worker gets a job offer in a given year t. The job separation rate is δ which is the probability that an existing job ends (that is, the employed worker becomes unemployed) in t. Both parameters ψ and δ are exogeneous. The employers and workers are forward-looking and discount the future at discount rate r.

Search, Match, and Bargaining. In the NAWS data, we do not observe workers looking for an alternate job while being currently employed. So our model excludes *on-the-job-search* aspect of the labor market.[12] A match between a worker and an employer generates the productivity-value or match-value ϑ. Both sides observe ϑ which is exogeneously determined as a function of worker attributes, employer's production technology, and quality of employer-employee match. We assume ϑ to follow a lognormal distribution: $\ln(\vartheta) \sim \mathcal{N}(\mu_\vartheta, \sigma^2_\vartheta)$.[13] Its cumulative distribution function is denoted as $\Phi(\vartheta)$ and probability density function as $\phi(\vartheta)$. The distribution of ϑ between employer and worker is based on worker's bargaining power parameter $\gamma \in (0, 1)$, equivalently employer's bargaining pa-

[12]See Dey and Flinn (2005), Cahuc, Postel-Vinay, and Robin (2006), Flinn (2006), and more recently, Gottfries and Jarosch (2023) for models incorporating on-the-job-search component of the labor market.

[13]The assumption of lognormal distribution of the match-value θ holds true empirically in wage and income data (Flinn (2006)).

rameter $1-\gamma$, which is exogeneous to both and measures "negotiation skills" determined by worker and market attributes. Intuitively, γ measures the fraction of the employment surplus that the worker receives.

Wage Setting Mechanism. The determination of a wage w follows a Nash bargaining framework, where worker's bargaining power informs how the productivity-value from an employer-employee match informs the distribution of employment surplus between the worker and the employer. In particular, the worker's wage is a weighted average of the worker's share of the employment surplus, which is determined by their bargaining power γ, and the outside option, such as the reservation wage b, called *worker's disagreement profit.* If the bargaining process results in a wage less than the binding minimum wage $w_{\min}$, then the wage w is raised to the level of $w_{\min}$. Hence, $w_{\min}$ acts as the greatest lower bound in the wage distribution.

A.2 Value Functions

The model comprises of three value functions denoting the utility of being unemployed, employed, and the firm's value of employing a worker.

Unemployed Worker's Value Function (U). An unemployed worker derives a utility b (that is, unemployment benefit) and has a probability ψ of finding a job in each period t. Thus, her utility or the value function from being unemployed is:

$$U = b + \underbrace{\psi\beta \int_{w_{\min}}^{\infty} \max(E(w) - U, 0) d\Phi(w)}_{\text{Expected present value of surplus}} \tag{1}$$

where $\beta = \frac{1}{1+r}$ is the discount factor with discount rate r, and $E(w)$ is the value function for an employed worker earning wage w. Here, the integral sums over the distribution of those wages that make employment more attractive than staying unemployed. The right-hand-side in equation (1) indicates expected present value of employment-surplus from a job with $w \geq w_{\min}$.

Employed Worker's Value Function ($E(w)$). An employed worker earns a wage w and encounters a job separation probability δ. The worker's value function from being employed is:

$$E(w) = w + \beta\left[\delta U + (1-\delta)E(w)\right] \tag{2}$$

where with probability δ, the worker becomes unemployed and receives the utility U. With probability $1-\delta$, the worker continues to be employed, earning the wage w and getting the value $E(w)$.

We solve the implicit equation (2) for $E(w)$ and get:

$$E(w) = \frac{w + \beta\delta U}{1-\beta(1-\delta)} \tag{3}$$

Firm's Value Function ($J(w)$). We assume that labor is the only means of production for the US crop employers. This means that employer's profit when there is no employer-employee match after a search process—its disagreement outcome—is zero as it does not hire a worker and hence makes no revenue. If the firm gets a match with productivity ϑ and hires the worker by paying wage w, then its profit is $\vartheta - w$ adjusted by the same discount factor as that of the worker:

$$J(w) = \vartheta - w + \beta(1-\delta)J(w) \tag{4}$$

where with probability $1-\delta$, the worker remains employed, and the firm continues to earn the surplus $\vartheta - w$.

We solve the equation (4) for $J(w)$ and get:

$$J(w) = \frac{\vartheta - w}{1-\beta(1-\delta)} \tag{5}$$

A.3 Wage Determination

After an employer-employee match, the two split the employment surplus and bargain for wages following a Nash bargaining framework:

$$w^* = \arg\max_{w}\left[E(w) - U\right]^{\gamma} \cdot \left[J(w)\right]^{1-\gamma} \tag{6}$$

Here, the two sides negotiate for wages based on individual bargaining power parameters. Intuitively, the idea is to increase the not just *share* of the "pie" (the surplus) but also to increase the *size* of the pie.

We substitute employed-worker's and employer's value functions (3) and (5) into the Nash bargaining equation (6) and get:

$$w^* = \arg\max_w \left[\frac{w + \beta\delta U}{1-\beta(1-\delta)} - U\right]^\gamma \cdot \left[\frac{\vartheta - w}{1-\beta(1-\delta)}\right]^{1-\gamma} \tag{7}$$

Taking the first-order condition with respect to w, we get the equilibrium wage that solves the Nash bargaining problem (7):

$$w^* = \gamma\vartheta + (1-\gamma)rU, \tag{8}$$

where rU is the present value of being unemployed.

Minimum Wage Constraint. We assume that minimum wage (w_{min}) is in place, and is exogeneous and binding to all the employers in our datasets. This means that employers are required to pay at least w_{min} and cannot compensate workers through other means to avoid this requirement. Further, it implies that employers earn positive profits only when $w_{\text{min}} > U$, that is when the minimum wage exceeds workers' disagreement profit, since workers do not accept job offers in the alternate scenario. Intuitively, an existence of the minimum wage imposes a lower bound on the set of the feasible wages, thus conditioning employers to sacrifice some of their employment surplus from hiring a worker.

If the minimum wage w_{min} exceeds the equilibrium wage w^*, then the wage distribution will have a mass point at w_{min}. Formally, the constrained Nash bargaining problem under minimum wage restriction is exactly the same as (7) but with an additional constraint $w \geq w_{\text{min}}$ in the optimization. The disagreement value to the worker is now a function of w_{min} instead of w.

A.4 Steady-State Conditions

For simplicity, we model the steady-state distribution of unemployment and wages. That is, we make two assumptions about employment and wages.

Assumption 1. We assume that the rate at which unemployed workers find jobs equals the rate at which employed workers lose their jobs:

$$u\psi \int_{w_{\min}}^{\infty} \phi(x)dx = \delta(1-u), \tag{9}$$

where u is the unemployment rate, ψ represents the job arrival rate, δ the job separation rate, and ϕ the probability density function of wages. In simpler terms, the left-hand-side represents the product of unemployment rate (share of the workforce that is unemployed), job creation rate (probability that an unemployed worker receives a job offer), and probability that the wage offered is atleast the minimum wage ($w_{\min}$). The integral accounts for the fact that workers do not accept all job offers as some offers might be below $w_{\min}$. The right-hand-side represents the rate at the employed workers lose their job and become unemployed.

Assumption 2. Next, we assume that the rate at which unemployed workers find jobs with wage w equals the rate at which employed workers leave jobs with that wage:

$$u\psi\phi(w) = \delta e(w), \tag{10}$$

where $e(w)$ is the density of employed workers earning wage w.

In summary, these stationary conditions imply that inflows into unemployment by job destruction balance the outflows into employment by job creation, making unemployment rate constant. They also ensure that the labor market has a stable distribution of wages. Further, as they define the probabilities of observing different labor market conditions such as being unemployed or earning a certain wage, we use them in constructing the likelihood function below.

B Model Estimation and Identification

In this section, we discussion estimation and identification of the search, match, and bargaining model developed in Appendix A.

Estimation Intuition. Our study employs repeated cross-sectional data on the US crop workers to estimate the parameters of the labor market model in Appendix A. While matched employer-employee data remain ideal for identifying the structural parameters as highlighted in Postel Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006), we follow others in the literature (Flinn (2006); Richards and Rutledge (2023)) and carry-out estimation using the strategies laid-out therein.

The estimation involves constructing a likelihood function for each individual who is characterized by two components: the duration of unemployment for individuals seeking employment and hourly wage rate for employed. The likelihood function uses this information to categorize individuals into one of the three groups: the unemployed, those earning the minimum wage, and those earning above the minimum wage. Precisely, we calculate the likelihood for the individual to belong to each group, leveraging the probability of being unemployed for a specific duration given the overall unemployment duration distribution within the population.

B.1 Likelihood Function Construction

Our estimation strategy proceeds by constructing likelihood functions for three categories of individuals. To this end, let (t_j, w_j) denote a pair of attributes of each individual in the data: length of unemployment spell in weeks (t_j), which is positive if the person is unemployed, and zero otherwise, and hourly wage (w_j) if the person is employed.

We build the likelihood function by categorizing workers into three groups: unemployed workers, workers earning the minimum wage, and those earning above the minimum wage.

Likelihood for Unemployed Workers. We assume that unemployment spell follows negative exponential distribution with rate parameter (or hazard rate) $\psi\Phi(w_{\min})$. Here,

$\Phi(w_{\min})$ represents the probability that an offered job has wage less than the minimum wage, and the rate parameter denotes how quickly unemployed workers get jobs paying less than $w_{\min}$. Then the conditional probability of observing an unemployment spell of t weeks given the individual is unemployed is:

$$P(t|\text{ unemp}) = \psi\Phi(w_{\min})e^{-\psi\Phi(w_{\min})t} \tag{11}$$

for minimum wage $w_{\min}$ and parameters defined before. The total probability of observing an individual who is unemployed at a given time is:

$$P(\text{unemp}) = \frac{\delta}{\delta + \psi\Phi(w_{\min})}. \tag{12}$$

Equation (12) denotes the steady-state unemployment rate by balancing the inflow and outflow of unemployment. Given equations (11) and (12), the joint probability of observing an individual who is unemployed for t weeks is:

$$P(t, \text{unemp}) = \frac{\delta\psi\Phi(w_{\min})e^{-\lambda g(w_m)t}}{\delta + \psi\Phi(w_{\min})}. \tag{13}$$

Likelihood for Workers Earning Minimum Wage. The second likelihood function is for an individual who is paid the minimum wage $w_{\min}$. Given that $w_{\min}$ is binding, the probability that the individual is employed and earns wage $w_{\min}$ is:

$$P(w = w_{\min}, \text{emp}) = \frac{\psi\left[\Phi(w_{\min}) - \Phi\left(\frac{w_{\min}-(1-\gamma)rU(w_{\min})}{\gamma}\right)\right]}{\delta + \psi\Phi(w_{\min})}. \tag{14}$$

The second expression $\Phi\left(\frac{w_{\min}-(1-\gamma)rU(w_{\min})}{\gamma}\right)$ in the numerator adjusts for the fact that all workers do not naturally earn $w_{\min}$; some would earn less if the minimum wage was not in place. This expression denotes the wages workers would naturally get based on their bargaining power before the minimum wage forces their wages up. The expression for the proportion of workers who would have been paid less than $w_{\min}$ but are now raised to $w_{\min}$ because of the minimum wage law is the difference $\Phi(w_{\min}) - \Phi\left(\frac{w_{\min}-(1-\gamma)rU(w_{\min})}{\gamma}\right)$. Multiplying this difference with the job arrival rate ψ, we get the numerator in equation

(14), that is the rate at which job offers which would have been below the minimum wage are rather raised to the minimum wage.

Likelihood for Workers Earning Above Minimum Wage. For the last component of the likelihood function, we need the share of individuals who earn more than the minimum wage. If an employee's wage exceeds $w_{\min}$, it means that the match-value ϑ is more than $\frac{w_{\min}-(1-\gamma)rU(w_{\min})}{\gamma}$, which is an effective wage offer without a minimum wage in place, taking into account the worker's bargaining power and the value of being unemployed. So, the conditional probability of observing a wage w given employment and that wage exceeds $w_{\min}$ is:

$$p(w|w > w_{\min}, \text{emp}) = \frac{\frac{1}{\gamma}\phi\left(\frac{w-(1-\gamma)rU(w_{\min})}{\gamma}\right)}{\Phi\left(\frac{w_{\min}-(1-\gamma)rU(w_{\min})}{\gamma}\right)}. \tag{15}$$

The conditional probability that the wage exceeds $w_{\min}$ given employment is:

$$p(w > w_{\min}|\text{ emp}) = \frac{\Phi\left(\frac{w_{\min}-(1-\gamma)rU(w_{\min})}{\gamma}\right)}{\Phi(w_{\min})}. \tag{16}$$

Multiplying (15) and (16), the joint probability that the individual is employed with wage greater than the minimum wage is:

$$p(w, w > w_{\min},\ \text{emp}) = \frac{\frac{\psi}{\gamma}\Phi\left(\frac{w-(1-\gamma)rU(w_{\min})}{\gamma}\right)}{\delta + \psi\Phi(w_{\min})}. \tag{17}$$

Aggregate Likelihood Function for NAWS Workers. Let T indicate the count of total individuals in the NAWS data, T_U that of unemployed, T_M that earning the minimum wage, T_A that earning greater than the minimum wage, A the set of workers who earn greater than the minimum wage, B the set of unemployed workers, and $\vartheta^* = rU(w_{\min})$ is the workers' reservation utility. Given this, we combine the likelihood functions for three groups in (13), (14), and (17) and get the log likelihood function for the entire NAWS workers:

$$
\begin{aligned}
LLF = {} & \underbrace{T[\ln(\psi) - \ln(\delta + \psi\Phi(w_{\min}))]}_{\text{Total Contribution}} \quad + \quad \underbrace{T_U[\ln(\delta) + \ln\Phi(w_{\min})]}_{\text{Unemp. Workers' Contribution}} \\
& - \quad \underbrace{\psi\Phi(w_{\min})\sum_{j\in B} t_j}_{\text{Penalty for Unemp. Duration}} \quad + \quad \underbrace{T_M \ln\left(\Phi(w_{\min}) - \Phi\left(\frac{w_{\min} - (1-\gamma)\vartheta^*}{\gamma}\right)\right)}_{\text{Minimum Wage Earners' Contribution}} \\
& \underbrace{- T_A \ln(\gamma) + \sum_{j\in A} \ln\left(\phi\left(\frac{w_j - (1-\gamma)\vartheta^*}{\gamma}\right)\right)}_{\text{Above Minimum Wage Earners' Contribution}}.
\end{aligned} \tag{18}
$$

The goal of estimating this LLF is to find the values of the structural parameters—$\psi, \delta, \gamma, \mu_\vartheta, \sigma_\vartheta$, and ϑ^*—that maximize the LLF, making the observed data as likely as possible under the model.