Agricultural Labor and Bargaining Power

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Abstract

Historically, pandemics lead to labor shortages, and the COVID-19 pandemic of 2020-21 proved to be no different. While there are many explanations for supply-chain issues reported in a number of industries, the proximate cause for ongoing problems in producing, processing, and delivering food to consumers has been attributed to a lack of labor. If this is the case, then the apparent shortage is likely to be manifest in greater bargaining power by workers in the food and agriculture industry, defined generally, during the COVID pandemic. Still, unemployment remained historically high until well into 2020, lagging economic growth by several quarters, which suggests that workers remained in a disadvantaged bargaining position until well into the pandemic. In this paper, we test whether the COVID-19 pandemic is associated with greater bargaining power among food and agriculture workers using a structural model of labor search-and-bargaining. Using data from the American Community Survey (ACS, Bureau of Census) for wage outcomes in 2019 and 2020, we find that the COVID pandemic was responsible for a 21% increase in bargaining power for employed workers, an increase in labor-share-of-revenue that is likely responsible for higher food prices, and a general decline in firm profitability.

keywords: bargaining power, farm labor, search-and-matching.
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1 Introduction

Supply chains for a wide range of consumer products essentially fell apart after the start of the COVID-19 pandemic in 2020. While there is no single cause, the "great resignation" of workers likely contributed to a shortage of labor in all phases of distribution, from manufacturing, to transport, wholesaling, and final sale (Sheffi 2021).[1] Labor shortages may have also played a critical role in the rapid rise of consumer prices, as labor comprises a substantial part of total cost at each part of the food value chain. Exactly how labor shortages are reflected in wages, however, remains an open question. In the labor economics literature, it is well-understood that employers and employees share any surplus available from the employment transaction according to the relative balance of bargaining power (Mortensen and Pissarides 1999; Dey and Flinn 2005; Cahuc, Postel-Vinay, and Robin 2006). If the COVID-19 pandemic created a shortage of workers, then we should see a rise in bargaining power exercised by labor in the wake of the pandemic, as well as higher labor costs for firms.[2] In this paper, we examine whether workers in the food and agriculture industry experienced a rise in bargaining power as a result of the COVID-19 pandemic that began in early 2020.

Our hypothesis is that worker bargaining power rose during the COVID-19 pandemic due to the fact that government policy responses (e.g., unemployment insurance expansions and extensions) made the alternative to work – leisure – more attractive, increasing the value

[1] While there is as yet no conclusive evidence on the exact mechanisms behind the loss of workers that began in 2020, Van Dam (2021) argues that the "...pandemic economy created some of the strongest incentives to retire in modern history, with generous federal stimulus, incredible market gains, skyrocketing home values and health concerns drawing many Americans into early retirement..."

[2] Economic problems emanating from pandemics are not new. In fact, Edward III of England experienced the same sort of problems facing the medieval English economy following the Black Death pandemic in the 14th century as "The poll taxes tapped a deeper root of resentment that had been building in England's towns and villages since the middle of the century. The Black Death had returned again to England in 1379, in an epidemic that eventually lasted for four years. The effect of this, coming on top of the first wave, in 1348 and 1349, and the Children's Plague during 1361 and 1362, was to cause the entire structure of medieval society to creek and change. Labor, once abundant in an overpopulated realm, became scarce and expensive. To combat the threat to landowners, Edward III's government had passed restrictive labor legislation, setting limits to wages, and punishing anyone who took or received more than the legal day rate for anything from mowing fields and reaping crops to mending roofs and shoeing horses..." (Jones 2013, p. 835). Whereas King Edward had recourse in paternalistic policies that current governments could only dream of, the intent was clear: To control the unfettered exercise of labor bargaining power wrought by a shortage of all types of labor.

of workers' next-best option. If unemployment insurance becomes more lucrative, workers' disagreement profit rises, their bargaining position is stronger, and they extract more of the labor-employment surplus from employers. Further, worker bargaining power also rose due to the more general withdrawal of workers from the labor force, perhaps through retirement due to asset-price inflation, as there were fewer workers for the same number of open positions. In short, we expect to find that workers' bargaining power was substantially higher in 2020 than it was in 2019, likely due to COVID-19 induced labor shortages.

We test our hypothesis using a structural Nash bargaining model in which firms and workers bargain over the available surplus in employer-employee relationships, using the onset of the COVID-19 pandemic in 2020, and the associated policy responses, in a structural, event-study framework. In the general economics literature, econometric models of search, matching, and bargaining equilibria have emerged as powerful ways to explain the effect of the returns to education (Eckstein and Wolpin 1995), the "job lock-in" effect of tying healthcare coverage with employment (Dey and Finn 2005), the effect of minimum wages on market wages, employment, and productivity (Flinn 2006), and the impact of differences in job-skill level on the degree of bargaining power exercised by employees (Cahuc, Postel-Vinay, and Robin 2006). In each case, these empirical models extend the basic search-and-matching model of Burdett and Mortensen (1998) and Postel-Vinay and Robin (2002), as applied to the analysis of farm-labor shortages in Richards (2018), by including a bargaining element adapted from the theoretical framework in Wolinsky (1987). In an agricultural context, including a prominent role for bargaining promises to be particularly valuable given the clear potential for bargaining asymmetry due to the lower-skilled nature of many jobs in the food and agriculture industry, the predominance of undocumented workers (Mercier 2014; Charlton, Rutledge, and Taylor 2021), and the labor-market shock due to the COVID-19 pandemic (Aradhyula et al. 2021; Luckstead, Nayga, and Snell 2021). In this paper, we develop an empirical model of search, matching, and bargaining, and apply it to a large, repeated cross-sectional sample of workers in the food and agriculture industry from the

American Community Survey (ACS, Bureau of Census) data set.

We control for three prominent features of the agricultural labor market on the relative level of bargaining power among workers and employers: State-by-state variation in the use of collective bargaining associations, such as the National Union of Farmworkers, the share of undocumented workers in the pool of available employees, and unobserved heterogeneity at the individual level, to isolate the effect of the COVID-19 pandemic of 2020 on worker bargaining power. In a general framework of imperfectly-competitive labor markets, asking how bargaining power varies over time and how employment rent is shared between employers and employees when changes occur in the market environment are clear and important questions.

Generalized search, matching, and Nash bargaining models are now prominent in the general labor economics literature (Mortensen and Pissarides 1999). With this approach, employees not only search among available employers until the marginal cost of search exceeds the marginal benefit of doing so, and are matched with employers for whom their skills are best suited (Burdett and Mortensen 1998), but they then bargain for wages in an axiomatic Nash (1951) bargaining framework.[3] In a Nash bargaining setting, workers are endowed with a certain amount of exogenous bargaining power, which depends on either their own skill in negotiation or perhaps institutional features of their industry, and an endogenous bargaining position component that depends on each party's disagreement profit, or the value of their next-best alternative. Both of these elements are critical in any employment contract as each affects the allocation of surplus in the employee-employer relationship. The underlying modeling framework has emerged as a dominant paradigm in the general empirical labor economics literature (Eckstein and Wolpin 1995; Dey and Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, and Robin 2006; Shimer 2006; Gertler and Trigari 2009; Flabbi and Moro 2012). It is somewhat surprising, however, that this framework has not been applied to

[3]In the empirical industrial organization literature, the Nash-in-Nash, or vertical Nash, model has become something as a workhorse in studying vertical relationships between agents in food-product supply chains (Draganska, Klapper, and Villas-Boas 2010; Bonnet and Bouamra-Mechemache 2016; Collard-Wexler et al. 2019; Yonezawa, Gomez, and Richards 2020; Richards, Bonnet, and Bouamra-Mechemache 2018).

study labor-market outcomes in an agricultural setting.

We extend the search-and-matching framework of Burdett and Mortensen (1998) to consider more general issues of bargaining between agricultural employers and employees in a manner similar to Dey and Flinn (2005), Flinn (2006), Cuhac, Postel-Vinay and Robin (2006), and others in the recent labor-economics literature. In this approach, workers exert effort to search for jobs that fit their skills, are matched according to a stochastic job-arrival process, and then bargain for wages with the employer that emerges as a match. Estimating how bargaining power and position vary across different types of employees, employers, and institutional features of each relevant market is of particular interest in agriculture because of the prevalence of immigrants in the sector who tend to be more vulnerable to exploitation (Christiansen, Rutledge, and Taylor 2021) and because of the low-skilled nature of the work (Bagger, et al. 2014; Lise, Meghir, and Robin 2016). Importantly, the COVID-19 pandemic exposed the dependence of agricultural producers, processors, and others in the agri-food system, on manual labor, as it became clear that the resilience of the US food supply chain depends on a reliable supply of productive, yet lower-skilled workers (Chenarides, et al. 2021). In this paper, therefore, we examine the extent to which the COVID-19 pandemic changed bargaining power relationships in agri-food sector employment contracts and how bargaining power affected the supply of workers in the food system.

Our research is of broader, macroeconomic interest due to the central role of labor in determining food production costs. Between 2020 and 2021, the rate of food-price inflation went from 2.0% to 6.0%, raising general concerns of a resurgence of price inflation that has not been seen since the early 1990s (Trading Economics 2022). Some attribute the relative lack of general price inflation to the declining share of labor in national gross-domestic product (De Loecker, Eeckhout, and Unger 2020), so if the imbalance of job openings and matches leads to a rise in labor's share, then there is a direct path to higher costs, and higher prices more generally. If labor is able to extract a greater share of created-value, however, the consequent rise in labor income, and perhaps decline in inequality, may offset higher prices and produce a greater level of welfare among lower-skilled, lower-income workers. Although econometric models of search-matching-and-bargaining are structurally complex, the intuition that underlies their value, and the insights they produce are clear.

We apply our empirical model of labor search-and-bargaining to a sample of employment and wage outcomes from workers in the Public Use Microdata Sample (PUMS) of the ACS, focusing on NAICS codes for workers in food and agricultural industries. While there are a number of employee-level data sets that are potentially useful in examining wage-negotiation outcomes for workers in the food and agriculture industry, defined generally, the ACS is preferred because it is timely, very deep in terms of the total number of respondents in the data, and it includes exactly the variables needed to estimate empirical models of search-and-bargaining. Because our objective is to study the impact of COVID-19-related worker decisions on wages and employment, we draw a sample of workers in the relevant industries from both 2019 and 2020. With over $N = 200,000$ employee-level observations for workers in food and agriculture alone, we believe our data are sufficiently deep to allow for clear identification of the mechanisms we are interested in, and some others that are perhaps beyond our primary focus, but are likely to be of general interest.

We find support for our theoretical expectations through both our reduced-form (i.e., model-free) and structural estimates. In terms of our reduced-form evidence, we find a clear pattern of wage escalation between 2019 and 2020. While this finding is not likely to be a surprise, the fact that the general inflation pressures that took hold late in 2020 were not likely to be reflected in the entire 2020 wage sample suggests there was something else occurring through the early COVID period. We interpret the rapid wage growth in our data as evidence of increased labor shortages, greater surplus available to firms in the food and agriculture industry, and a higher labor-share earned by workers who either remained on the job and bargained for higher wages, or moved jobs and increased their hourly wage due to greater bargaining power. In our structural model, we find that bargaining power rose by some 21.0% between 2019 and 2020. While we cannot attribute this finding directly to any measure of labor shortage, we control for many other factors that may explain this finding, including state-level variation in unemployment, which leads us to conclude that there were likely COVID-19-induced effects on bargaining power in the food and agriculture industry.

Our counterfactual simulations examine the impact of bargaining power, minimum wage laws, and unemployment insurance benefits on equilibrium wages. Compared to the base case of 2019, we find that the increase in bargaining power associated with labor shortages in 2020 is responsible for a 3.2% increase in wages. More generally, we find that reducing minimum wages allows for higher average equilibrium wages as firms are less constrained in allocating match-surplus to workers who are willing to accept offers. Finally, we show that more generous unemployment benefits are associated with higher equilibrium wages as firms are forced to overcome workers' higher opportunity costs of leisure in order to attract the workforce they need.

We contribute to the literature on food and agricultural labor markets in several ways. First, to the best of our knowledge, we are the first to examine the effect of COVID-19-induced shocks (Chenarides et al. 2021; Sumner 2021; Luckstead, Nayga, and Snell 2021; Aradhyula et al. 2021) on workers' manifestation of bargaining power. While others provide narrative arguments for how labor shortages can lead to supply chain problems in food and agriculture, we offer a formal economic mechanism and empirical test. Second, we contribute a more general explanation for shortages and price increases for products of all types, not only agricultural goods. While there continues to be vigorous debate as to whether the origins of the rise in inflation in 2021 were real or monetary in nature (Smialek 2021), our analysis provides at least one partial explanation, that COVID-19-related job-market exits can explain some of the rise in wages, through a worker-bargaining-power mechanism. Third, we contribute to the historical literature on agricultural labor markets by connecting pandemic-related job shortages to broader economic problems in the real economy. In this regard, our consideration of the impact of minimum wage laws and unemployment benefits on equilibrium wages provides a rigorous foundation for labor-market policy analysis that has been absent from the agricultural-labor literature.

In the next section, we outline a theoretical model of labor seach-matching-and-bargaining in which we show how bargaining outcomes are determined in a model in which workers search for employment optimally, employers choose workers who are likely to add the most value to their firm, and the resulting surplus is shared according to axiomatic Nash bargaining rules (Nash 1951). We use this theoretical model to derive an empirical framework for testing our hypotheses regarding worker bargaining power in Section 3, where we explain more carefully how we implement our econometric model. In Section 4, we describe our data, explain our identification assumptions, and describe some reduced-form features of our data to show whether observational patterns are consistent with our theoretical expectations. We show and interpret our results in Section 5, focusing on how bargaining power varies over workers and time in our sample data and drawing broader implications for labor-market outcomes in the food and agriculture industry. A final section concludes and offers insights about policies that may help address the market imperfections implied by our empirical findings.

2 Theoretical Model

In our model, workers and firms search optimally, and matches occur that maximize the trade surplus between workers and firms. However, the existence of bargaining power implies that the outcome is not a "take it or leave it" proposition as in Burdett and Mortensen (1998), Van den Berg and Ridder (1998), and Eckstein and Van den Berg (2007), but is rather a negotiated outcome between workers and firms, perhaps mediated by institutions such as trade associations or worker-organizations (unions).[4] Many others include bargaining power in models of optimal search-and-matching outcomes to explain such things as how minimum-wage laws affect equilibrium wages and employment (Flinn 2006), how wage compensation differs for workers with healthcare benefits relative to those who do not (Dey and Flinn

[4] We note that our model of search frictions falls in the general class of labor-market model in which firms have oligopsony power in the labor market (Bhaskar, Manning, and To 2002; Manning 2003; Ashenfelter, Farber, and Ransom 2010; Ransom and Oaxaca 2010; Hamilton et al. 2021) without necessarily having market power in the traditional sense in the output market.

2005), or how wage differences vary by gender within the same occupations (Flabbi and Moro 2012).[5] In this paper, we follow the general theoretical model of Flinn (2006) in examining how bargaining for workers in minimum-wage industries is likely to be affected by a pandemic-induced shock to labor supply, and other important features of the food and agricultural labor market.

We begin our exposition of the model by considering a simple version in which minimum wages do not exist. In Flinn's (2006) bargaining framework, which we adapt to our case, equilibrium wages, w, solve the generalized Nash bargaining problem:

$$w(\theta, V_n) = \arg\max_w [V_e(w) - V_n]^\alpha \left[\frac{\theta - w}{\rho + \eta}\right]^{1-\alpha}, \tag{1}$$

where θ is the "match value" of the employee, or his or her productivity to the firm, $\theta^* = \rho V_n$ is the critical match value from the firm's perspective, such that $\theta > \theta^*$ results in employment, ρ is the time value of money, V_n is the employee's disagreement value (or threat point, value of the next-best alternative offer), V_e is the value to the employee of being employed at a wage w, $\alpha \in (0, 1)$ is the exogenous bargaining power of the employee, or the share of employment rents, and η is the probability of unemployment.

Equilibrium wages in the model reflect the opportunities available to workers, the distribution of worker-productivities in the industry, the cost of employment, and the relative bargaining power of workers and employers. The structural econometric model that will be used to estimate the parameters of this model follows the general specification in Richards (2018) but accounts for bargaining power by weighting each wage-and-productivity outcome by the bargaining power parameter, α. This framework allows the econometrician to identify each of the model primitives using repeated cross-sectional data such as that available in the Current Population Survey (CPS, Flinn 2006), the Survey of Income and Program Participation (SIPP, Dey and Flinn 2005), the French National Statistical Institute (INSEE, Cahuc, Postel-Vinay, and Robin 2006), and, for the case of agriculture, NAWS data (Richards 2018,

[5] The minimum-wage question is contentious, as the implication that minimum wage laws can, in fact, increase employment in oligopsony labor markets, remains controversial (Card and Kruger 1994, 2000; Neumark and Wascher 1995; Dube, Lester, and Reich 2016; Manning 2021).

2020). For our purposes, we use a repeated cross-section of worker-level observations from the ACS, while focusing on occupations specific to the production and distribution of food.

In these data, equilibrium wages are determined from equation (1) from primitives on both the worker and firm sides of the job-matching relationship. From a worker's perspective, the value of a job with wage w is:

$$V_e(w) = \frac{w + \eta V_n}{\rho + \eta}, \tag{2}$$

or the discounted value of an employment opportunity, taking into account the possibility of a reversion to unemployment in the future. The value of unemployed search (ρV_n) has to equal the potential value of taking a job in equilibrium, which depends on the worker's reservation wage, b, and the discounted value of finding an acceptable job, or:

$$\rho V_n = b + \frac{\alpha\lambda}{\rho + \eta} \int_{\rho V_n} [\theta - \rho V_n] dG(\theta) \tag{3}$$

where $G(\theta)$ is the distribution governing potential match values, or the productivity implications of each match of an employee to a firm, and λ is the exogenous rate of "job contacts," or the creation of jobs by employers contacting potential employees.

Substituting these two relationships into the Nash bargaining solution in (1) and solving gives an expression for the equilibrium wage contract as:

$$w(\theta, V_n) = \alpha\theta + (1 - \alpha)\theta^*, \tag{4}$$

where θ^* is the threshold match value that determines whether workers are willing to supply labor at the offered wage, or not. Equilibrium wages, therefore, depend critically on the degree of bargaining power exercised by workers, and by the parameters of the distribution that governs equilibrium match-values, job creation and destruction, and labor productivity.

Minimum wages affect the equilibrium wage distribution by acting as a constraint on the wages that can represent an acceptable match to the firm. Because the firm cannot offer wages for match-values less than the minimum wage, m, they essentially give up some of their surplus to workers with a match value below that point. The intuition of the constrained solution is straightforward, but is described in more detail in Appendix A: When the minimum wage is binding, or reflects a match value that generates positive profit for the firm, then the firm would rather hire the worker at the mandated minimum wage, and give up some of the surplus that would arise in the unconstrained equilibrium, than take a surplus of zero. From Appendix A, the resulting equilibrium wage distribution that captures the three possible relationships between the market-wage offer and the mandated minimum wage is given by:

$$pr(w; V_n(m)) = \left\{ \begin{array}{ll} [g(\hat{\theta}(w, V_n(m))]/\alpha G(m), & w > m \\ [G(m) - G(\hat{\theta}(w, V_n(m)))]/G(m), & w = m \\ 0, & w < m \end{array} \right\}, \tag{5}$$

where w is the equilibrium wage offer, and $\hat{\theta}$ is the threshold match value that separates unconstrained wage offers from those that are constrained by the minimum wage.

We use this theoretical model of bargaining power and wage determination to test a number of hypotheses that are of general interest to the performance of labor markets for workers in the food and agriculture industry, and of specific interest to the policy response to the COVID-19 pandemic. First, and most obviously, we test whether workers' exercise of bargaining power changed from 2019 to 2020 as a result of COVID-19 induced labor shortages. If labor markets were indeed in shortage as a result of either the well-reported surge in resignations, or workers' avoidance of jobs they feel would expose them to greater risk of COVID-19, then we expect to observe higher values of α during 2020 relative to the 2019 base period. Second, we use a set of counter-factual simulations of the wage distribution in (5) to examine the difference in equilibrium wages between 2019 and 2020. Third, we also use the model in (5) to investigate how variations in the minimum wage can influence equilibrium wages, given that the effect is not as obvious as it may seem, based on prior research on minimum-wage impacts (Card and Krueger 1994, 2000).[6] Fourth, unemployment-insurance

[6]Flinn (2006) argues that minimum wages are a "blunt" tool to affect worker welfare, but one of the only ways policymakers can influence market outcomes.

benefits during COVID-19, for example the $600 increase in payments that lasted until July 31, 2020, raise workers' threat point (V_n in equation (1)) so should raise the endogenous part of workers' bargaining position, and their equilibrium wage offers. Because they make unemployment more attractive to workers, however, we also expect to see higher levels of aggregate unemployment as a result of the program. We demonstrate these effects again by simulating the equilibrium wage and unemployment-rate models above.

3 Econometric Model of Bargaining

In our setting, minimum wages are a prominent feature of the labor market, as most jobs are unskilled, or semi-skilled, so the match values of many employment relationships are constrained by the minimum wage (Buccola and Reimer 2012). Therefore, we follow Flinn (2006) by explicitly considering the probability that a worker is paid the minimum wage in estimating the equilibrium wage equation. Conceptually, the exercise of bargaining power is constrained by the level of the minimum wage, as employees who earn the minimum wage essentially earn an artificially-high share of the employment surplus. Bargaining power likely depends on other factors associated with the inherent productivity of the worker.

In this paper, we parameterize the share of employee rents, α, with variables that capture institutional features of the market that are likely to influence the relative level of bargaining power between employees and employers. Ideally, we would allow bargaining power to be a function of state-level COVID-19 case rates, shelter-in-place orders, and other measures of disease spread, so we would estimate the precise effect of an expected worker shortage on employee welfare. However, there is no indication in the ACS data as to the exact month in which each subject filled out the survey, so we are left with a simple 2020 COVID-19 indicator to separate pre- from post-COVID-19 labor market outcomes. Therefore, in this section we derive a likelihood function designed to estimate the parameters of the theoretical model above, which we use to populate the counterfactual simulation model that we use to examine our main hypotheses.

3.1 Likelihood Function Derivation

We begin our equilibrium search-and-bargaining model with the approach taken by Flinn (2006) but extend his model to accommodate our application to the ACS data set, which is necessary to address problems relevant to a broad sample of workers in the food and agriculture industry. Our econometric model assumes workers search for jobs while unemployed, but experience search frictions of the sort described by Burdett and Mortensen (1998) and Pissarides (2000, 2011), possess match-specific capital, and bargain with respective employers over the terms of new wage agreements. Each of these features mean that search is costly and likely to result in rents earned by both sides of the employment contract. In the data, we observe hourly wages paid to individual i upon acceptance of a job in which the wage exceeds his or her reservation wage (b_i), and the length of each spell of unemployed search (t_i). Unlike Flinn (2006), who uses the CPS individual-level data to identify the parameters of labor supply, we use a large sample from the ACS data, and bring in demand-side information from firm profitability to identify the bargaining power parameter, α, or the relative share of rents earned by the worker, and the firm $(1 - \alpha)$.

Assuming an exogenous distribution of worker-firm productivity for a match value of θ, and an exogenous rate of job-destruction (η), the density of an unemployment spell of length t_i implied by the search function is:[7]

$$f_u(t|u) = \lambda G(m) \exp(-\lambda G(m)t), \tag{6}$$

where we recall that λ is the exogenous rate at which employers create jobs, and m is the administratively-determined minimum wage. With exogenous rates of job destruction, the probability of becoming unemployed becomes:

$$pr(u) = \frac{\eta}{\eta + \lambda G(m)}, \tag{7}$$

[7] The nature of the distribution $G(\theta)$ is generally assumed to be determined by the production technology of the firm, so it is determined outside of the labor-employment relationship.

so that the joint probability of observing unemployment for a spell of length t is:

$$f(t,u) = \frac{\eta\lambda G(m)\exp(-\lambda G(m)t)}{\eta + \lambda G(m)}, \tag{8}$$

and we adopt the usual assumption that G is log-normal, so $G(\theta) = \Phi((\ln(\theta) - c)/d)$ and Φ is the standard normal distribution function.

In our application, minimum wages are a critical feature of the labor market, as explained above, and the differences in labor-market outcomes for workers paid at, or above, the minimum wage are necessary to identify the parameters of our model. Therefore, we break the likelihood function into regimes that represent workers paid at the minimum wage, workers paid above the minimum wage, and those who are unemployed. With this in mind, the likelihood contribution from minimum-wage employees is given by:

$$pr(w = m, e) = \frac{\lambda\left[G(m) - G\left(\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}\right)\right]}{\eta + \lambda G(m)}, \tag{9}$$

which is the likelihood of being employed (e) and being paid a wage equal to the minimum (m), given the firm's willingness to employ a worker at the minimum wage. Further, the probability that the wage exceeds the minimum, and the threshold necessary to induce the employee to accept employment is given by:

$$f(w|w > m, e) = \frac{\frac{1}{\alpha}g\left(\frac{w-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{G\left(\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}\right)}, \tag{10}$$

as the wage has to exceed the match-minimum of $\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}$. Therefore, the probability that a sample member is paid greater than the minimum, conditional on being employed, is given by:

$$pr(w > m|e) = \frac{G\left(\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{G(m)}, \tag{11}$$

and the likelihood contribution of observing an employee accepting a job, and being paid a wage that is above the minimum is:

$$f(w, w > m, e) = \frac{\frac{\lambda}{\alpha}g\left(\frac{w-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{\eta + \lambda G(m)}. \tag{12}$$

Combining observations from individuals who are paid at the minimum wage with those who are paid above the minimum wage, the log-likelihood function becomes:

$$
\begin{aligned}
LLF = {} & [\ln(\lambda) - \ln(\eta + \lambda G(m))] + \delta_U[\ln(\eta) + \ln G(m)] - \\
& \lambda G(m)\delta_U t_i + \delta_M \ln\left(G(m) - G\left(\frac{m-(1-\alpha)\theta^*}{\alpha}\right)\right) - \\
& \delta_H \ln(\alpha) + \delta_H \ln\left(g\left(\frac{w_i-(1-\alpha)\theta^*}{\alpha}\right)\right),
\end{aligned} \tag{13}
$$

where δ_U = an indicator that the individual belonged to the set of unemployed workers (U), δ_M = an indicator that the individual belongs to the set of workers who are paid the minimum wage (M), δ_H = an indicator that the individual belongs to H, the set of workers paid above the minimum wage, and $\theta^* = \rho V_n(m)$ = the implicit minimum wage. With this likelihood function, and the data described in the next section, we obtain estimates of the key parameters of the labor-market equilibrium, including the bargaining power parameter that shows the share of total employment surplus earned by workers.

We test our core hypothesis – that bargaining power differs between the pre-COVID period in 2019 and the post-COVID period in 2020 – by estimating the model in (13) for 2019 and 2020 subsamples of the data. By allowing bargaining power to vary between pre-COVID and post-COVID regimes, we are able to estimate the impact of the COVID-19 pandemic on worker bargaining power, and how any change in bargaining power may have affected wages, costs, and retail food prices.[8] Further, in order to isolate the effect of fiscal and monetary stimulus, as opposed to the expected negative effect on bargaining power due to the COVID-induced unemployment, we include a measure of unemployment that varies by state and year in the bargaining power model.

Prior to describing our data sources, however, we provide more details on how we use counterfactual simulation to make our empirical insights more concrete, and relevant to the types of policies that were used in 2020, and to address labor-market issues more generally.

[8] Our initial approach sought to allow only bargaining power to vary between 2019 and 2020, but this approach is inconsistent with the underlying theory as all parameters of the model are determined together, in equilibrium, each period.

3.2 Counterfactual Simulations

As explained briefly above, we use counterfactual simulation to examine three implications of our theoretical model: The effect of market shocks associated with the COVID-19 pandemic (and policy response) on equilibrium wages, the general impact of minimum wages in the food and agriculture industry on equilibrium wages, and the effect of unemployment insurance supplements on equilibrium wages, and unemployment. Our first hypothesis, that the COVID-19 pandemic was associated with a higher level of bargaining power on the part of workers, is tested directly in our structural econometric model. In each of the other three cases, we use the structural parameters from the best-fitting model reported in the Results section below in order to simulate likely market outcomes in each scenario.

In the first case, we use the parameter estimates from our structural model to populate the equilibrium wage model in equation (5). We then simulate the implied equilibrium wage for every observation in the data set, taking into account the difference in bargaining power between our base year (2019) and labor-market outcomes during the COVID-19 pandemic of 2020, and the unobserved heterogeneity in our empirical model. We then average the implied wages for workers in each year, each industry, and over a range of different demographic and socioeconomic profiles for bargaining-power counterfactuals that are 25% and 50% above the estimated levels, and 25% and 50% below the base case. With this simulation, we draw conclusions regarding the net effect of COVID-19 and bargaining power, on equilibrium wages.

In the second simulation, we consider the effect of minimum wages on equilibrium wage outcomes. We simulate equilibrium wages using model in (5) as in the previous simulation, but because minimum wages are exogenous policy tools, we are able to vary minimum wage levels in each state in order to measure the implied impact on equilibrium wages in each industry, and state. Because market outcomes are more sensitive to changes in minimum wages than they are to bargaining power, the "Low" and "High" counterfactuals in this case refer to a range of simulated minimum wages from 20% below the observed values to 20%

above, in 10% increments.

Finally, we use the model in (5) to simulate the effect of changing unemployment benefits on equilibrium wage outcomes, and employment. In the equilibrium-wage model, the distribution of match values, G, depends on the value of search to potential employees, $V_n(m)$. Match values, in turn, depend on workers' next-best alternative to employment, which is typically unemployment. By raising the amount of unemployment insurance benefits, policymakers increase the value of the outside option to unemployed workers, and improve their bargaining position *vis a vis* employers. In this case, we simulate the implied effect on equilibrium wages through (5), and on the probability of remaining unemployed through (7). Although there are a number of other possible policy simulations we could undertake, we believe that this minimal set is sufficient to provide a general picture of what happened to agricultural labor markets during the COVID-19 pandemic, and in response to policy measures designed to counteract the worst effects. We model this effect by varying $V_n(m)$ over a range of -10% to $+10\%$ of the observed values (in 5% increments).

Although each of these scenarios is necessarily artificial, we believe they span a set of values that are both realistic and relevant to the actual policy responses that were enacted in response to the COVID-19 pandemic, or are descriptive of observed market responses.

4 Data

4.1 Data Sources and Summary

Our primary data source is the Public Use Microdata Sample (PUMS) from the American Community Survey (ACS) from the U.S. Bureau of Census, for the years 2019 and 2020.[9] While there are many alternative sources of individual-level employment data for U.S. workers (e.g., CPS, NLSY, NAWS), the ACS is the only data source that provides

[9] Note that the Bureau of Census cautions ACS data users that their response rate during the onset of the COVID-19 pandemic was adversely affected by shelter-in-place rules, and other restrictions put in place at the time, and describes the 2020 ACS data as "experimental." For our purposes, however, we do not rely on the ACS as a representative sample of workers in either year, and instead only compare results for a matched set of workers in our focal industry from one year to the next. Therefore, we are confident that our findings are not biased due the experimental nature of the 2020 data.

duration-of-employment data for agricultural workers before, during and after the start of the COVID-19 pandemic.[10] For our purposes, we focus on workers employed in either agricultural production, agricultural processing, or in food distribution and retailing. Our focus on the food industry allows us to control for other factors that may confound our insights into how bargaining power varies over time, and over regions, for workers in a specific supply-chain.[11] Further, it allows us to examine whether well-reported food supply-chain problems (Chenarides, et al. 2021) during the early days of the COVID-19 pandemic in 2020 may have been driven by fundamental changes in the relationship between employers and employees during the pandemic.

For our purposes, it is necessary to define unemployment spells for all respondents who report less than 52 weeks of work in the previous year. There are some inconsistencies reported in the data, namely respondents who report having worked 52 weeks in the past 12 months, but not the week previous, or having worked in the past week, with very few reported weeks of work. Therefore, we define an individual as belonging to the set of unemployed if they report a value of the ACS variable "WKWN," or weeks worked in the past 12 months, of less than 52. Respondents to the ACS do not report vacation weeks as "not worked," so the weeks worked variable should accurately reflect whether individuals had at least one spell of unemployment during the previous 52 weeks. We create an alternative definition of unemployment that uses each respondent's answer to a question regarding whether they worked during the previous week (the ACS "WRK" variable). If this variable suggests the respondent did not work in the previous week, we define the current spell of unemployment as the difference between the number of weeks worked in the previous 12 months and the

[10] We intended to expand the base period to include years prior to 2019, but the duration variable reported prior to 2019 in the ACS data (WKWN) is only categorical in nature, and does not provide enough individual-level variation to identify the econometric model. Simple, reduced-form wage regressions with the 2018 - 2020 data suggest that there was no difference in market outcomes between 2018 and 2019, but sharp differences between each year and 2020.

[11] The ACS data describes workers according to their "industry" of employment, defined in a highly granular way, or by their specific "occupation." We choose to classify workers within the agriculture in food industry according to the former as occupations can be more general than just the food industry. For example, a "cashier" can work in either a supermarket or a home-improvement store. Our industry classification avoids this sort of ambiguity.

total weeks in the year (52). Although this may misattribute some duration spells falsely to the current spell, the implied aggregate level of unemployment (about 10% of the total sample) is close to the number of workers either actively searching in the labor force, or not in the labor force (and hence not working) at all.

We also categorize workers as earning either at, or above, the minimum wage. However, hourly wages are not reported in the ACS and must be constructed using annual wage income, the number of weeks worked during the previous 12 months, and an estimate of the number of hours worked per week. Further, it is unlikely that estimated values of wage income, weeks worked, and hours per week are going to result in imputed wages that are exactly equal to the minimum. Therefore, in the absence of any data in the ACS that measures whether a respondent is literally paid the minimum wage, we infer any imputed wage that is within $1.00 per hour of the minimum wage in that state and year as being paid the minimum wage. We examine the sensitivity of our findings to definitions that vary from our baseline assumption up to $2.00 around the minimum wage, and our findings are qualitatively similar. Because some states have minimum wages of over $12.00 per hour (e.g., California and Massachusetts), while others use only the federal minimum of $7.25 per hour (e.g., Texas and Tennessee), the error induced by our classification assumption is much less than the variation in minimum wages earned by workers across states.

We summarize our ACS data in Table 1 below, and find several items worth noting. While the full ACS annual sample is intended to be representative of the U.S. population, our food-and-agriculture sub-sample is distinctly male, as roughly 67.0% of our observations describe labor outcomes for men. Further, the average number of weeks worked across 2019 and 2020 was about 45.0, while only 8.6% earned the minimum wage (which averages over $9.00 / hour,) and the average hourly wage was slightly over $30.00 / hour. These statistics speak to the heterogeneity of jobs in the broader food and agribusiness sector as there are many management and manufacturing jobs that are very different from the often-referred-to harvesting and processing jobs in agriculture itself.

Unemployment is also an important feature of our data, as over 10.5% of the sample report being unemployed at some point during 2019 - 2020, and the average unemployment spell was approximately 7.0 weeks. Over 81.0% of the jobs covered by our data are in the private, for-profit sector, and nearly 9.0% of the ACS workers were not U.S. citizens. With over $200,000$ observations in total, and substantial cross-sectional variability in the elements critical to a search-and-matching model (unemployment duration, wages, and workers earning the minimum wage), our structural model is also likely to be well-identified. In order to include the aggregate level of unemployment as a control for state- and year-variation in bargaining power, we include a measure of unemployment at the state and annual level from the Federal Reserve Economic Data (FRED) database (Federal Reserve Board).

[Table 1 in here]

Because our sample is comprised of workers from many different sub-sectors of the food-and-agriculture industry, some of the wage outcomes that drive our econometric model may be due to changes in the composition of jobs from year to year, and not necessarily general pressures within each industry. Therefore, we summarize the difference in wages for each industry in our data in Table 2 below. This table illustrates the dramatic rise in wages in some industries that has been reported elsewhere. Namely, the average rise in hourly wages across the entire agriculture-and-food industry was over 19.0% between 2019 and 2020, with workers in the Agricultural Chemical and Farm Product Wholesaling industries earning hourly wages in 2020 that were more than 50.0% higher than the previous year. Although there were small changes in the share of ACS workers in each industry between 2019 and 2020, none of the percentage-differences in shares rose above 1.0%, with the largest changes in Animal Production (+0.52%) and Supermarkets (+0.28%). Neither change was large enough to represent an outsize influence on wage changes between the two sample time periods.

[Table 2 in here]

We include data on demand-side elements of wage-setting and negotiation from both the USDA-NASS (National Agricultural Statistics Service), and US BLS (Bureau of Labor Statistics) in order to help identify the bargaining power parameter in our model above (α). These data are critical to our identification strategy, so we explain them in more detail in the next section.

4.2 Identification

Identification of the key parameters of our model follows others in this literature (Dey and Flinn 2005; Flinn 2006). As in Flinn (2006), identification in our model relies heavily on steady-state assumptions, so comparing outcomes between workers in 2019 and 2020 reflects fundamental changes in the labor market that occurred between these two periods. In our application, the primary parameter of interest in equation (13) is the bargaining power parameter, α, which measures how the surplus available from each employment transaction is shared between the employee (α) and the employer ($1 - \alpha$). As Flinn (2006) explains, bargaining power cannot be identified from supply-side data alone, as in his CPS data because bargaining outcomes are necessarily determined by disagreement values (bargaining position) on both sides of the transaction, and employment surpluses that demand some variation on the employer side of the transaction. In the absence of matched employee-employer data of the sort used by Cahuc, et al. (2006), we follow Flinn (2006) in combining observed data that are likely correlated with employer profit, with the survey data from, in our case, the ACS. For our purposes, however, we focus on employers in the agricultural industry, throughout the food value chain, so we cannot use the same sort of financial statement information used by Flinn (2006).

Flinn (2006) reports his findings from a series of Monte Carlo estimates under different parametric assumptions for the distribution of match values, G, and notes that the model is fundamentally unidentified under the assumption of normality, but is identified by the non-linearity of log-normality. More importantly for our purposes, his Monte Carlo experiments show that the estimates "...faithfully reproduced the population values with little variation across replications..." with sample sizes of the order of $250,000$ (p. 1033). Due to the size of the ACS sample, this hypothetical sample is only slightly larger than our actual sample ($N = 200,000$), so we are confident that our model is able to estimate the population parameters accurately as well.

We depart from Flinn (2006) in terms of the detail of his approach, but use demand-side information to help identify the bargaining power of workers in our data using a method that is similar in intent. That is, we use demand-side information to estimate a flexible bargaining-power function that is more likely to be identified than if we were to use the worker-only information in the ACS.[12]

Our approach is the following. First, we obtain data on the labor-share of revenue for workers in each of the industries represented in our data. At the NAICS-code level, for food and agriculture that comprises 24 different industries, for both 2019 and 2020. Our revenue data is defined as total gross receipts for all firms, and is from USDA-NASS for NAICS codes 111 - 115 (USDA-NASS), and from the U.S. Bureau of Labor Statistics (BLS) Multifactor Productivity (USBLS) data for all others. Labor compensation is from the BLS for all industries covered by the multifactor productivity data set, and USDA-NASS for NAICS codes 111 - 115. Our assumption in using these data is that the labor share of revenue captures variation in the marginal revenue product of workers across industries and time under the constant-returns to scale assumption in Flinn (2006).

Second, we then embed a least-squares estimator for the bargaining power parameter (α) into the likelihood function for equilibrium wages with search-and-bargaining (13) above, where α is a simple function of the labor share of revenue in each industry. We estimate both in one procedure, so the estimate of α reflects both demand- and supply-side information as in Flinn (2006).

Third, we then estimate more complex functions for α, using the same approach, where

[12] Note that Flinn (2006) actually uses the labor-share of revenue from one firm – McDonalds, Inc. – for the year 1996 because it is a large employer and is particularly dominant among the set of employees in his data (18 - 24 year olds). Because McDonalds is publicly traded, its labor-share of revenue is readily available from financial statement information.

bargaining power is assumed to depend on exogenous attributes of each observation. These attributes are thought to be relevant to each worker's likely exercise of bargaining power, including whether the data reflects pre- or post-COVID employment outcomes, citizenship status (primarily focusing on non-citizen status) and gender. In this way, we are able to identify the bargaining power parameter, and test the core hypotheses of our paper.

4.3 Reduced-Form Evidence

Prior to estimating the structural model of search-matching-and-bargaining described above, we first estimate a series of reduced-form models in order to examine the data for any patterns that may be apparent in both the wage and labor-share data. In Table 3, we report reduce-form regression results in which we examine wage patterns reported in both 2019 and 2020 of our sample of agriculture and food-industry workers in the ACS. Controlling for all other factors in the data that may be associated with hourly wage differentials, including regional, job, gender, and citizenship status, we find that wages in 2020 were some 9.3% higher than in 2019. Although there are clearly some other explanations that may be at work here, there is at least summary evidence of COVID-induced wage pressures in 2020. Higher wages, however, are only indirect evidence of greater bargaining power, because if the amount of surplus in the employment transaction rises more than wages, bargaining power may actually have declined.

[Table 3 in here]

As suggested above, the immediate post-COVID period saw unprecedented shocks to economic growth, and unemployment. Although economic growth came back quickly in the third quarter of 2020, likely due to strong fiscal and monetary policy intervention, unemployment remained relatively high throughout the rest of 2020. In fact, Figure 1 shows that the unemployment rate stayed above 6.0% until early 2021. By recent historical standards, therefore, the rate of unemployment was still high enough to suggest that there were many workers who would have preferred to be employed, but could not find a job. With the decline in retail and foodservice jobs associated with pandemic-related shutdowns, and the move to a "delivery economy," many of these unemployed workers could have been transitioning to different jobs throughout most of 2020. Transitioning employees, or workers in industries that are changing the way they operate in the post-COVID economy, are not likely to have much bargaining power. Consequently, the trend of unemployment suggests that the immediate effect of the COVID pandemic may have been to reduce labor bargaining power, not increase it.

[Figure 1 in here]

In fact, the labor-share-of-revenue in our data supports this observation. In 2019, the mean labor-share of revenue in our sample industries was roughly 16.4%, but declined to 16.0% in 2020. Controlling for all of the other elements in Table 3, the regression coefficient on a COVID-indicator variable in a model of labor-share-of-revenue shows that mean labor share was some 0.3% lower. Again, however, our labor-share data, and summary regression, reflects only a partial perspective on bargaining power, as it does not control for the other elements of the search-match-and-bargaining equilibrium model outlined above. Based on this summary evidence, therefore, there is no clear pattern in the data that suggests bargaining power is either higher or lower during COVID, *a priori*. We present the results from our structural model next in order to more carefully control for the potential barriers to identifying exactly what happened to worker bargaining power during 2020.

5 Results

We begin presenting our results with a base model of search-and-bargaining in which the bargaining power is identified by supply-side data only, and then with demand-side data from the labor-share of firm revenue in the industries represented in our data. We then allow bargaining power to vary by year, and by the level of unemployment in each state. This approach is intended to capture any variation in bargaining power that may rise from the well-documented labor shortages that emerged during the COVID pandemic, relative to the temporary increase in unemployment during the summer of 2020. We then describe our findings from applying our structural model to economic and policy simulations, including variation in the level of bargaining power, minimum wages, and the critical match value (θ^*) for each worker.

The results from the base model of search-and-bargaining are in Table 4 below. Beginning from Model 1, or the model that uses only supply-side data from the ACS to identify the primitives of the model, we find that all of the structural parameter estimates appear to be plausible and are very precisely estimated. In terms of the individual parameters, the estimates from Model 1 show that λ, or the rate of job-contact creation, is about 35.0%, which means that there is a roughly 35.0% chance that an employer will contact an unemployed worker each year with a potential job. Again using the estimates from Model 1 to provide intuition for the structural parameter estimates, the value of η (the rate of job destruction) implies that there is a roughly 1.8% chance that job held by an employed worker will disappear, by whatever means, every year. Further, the distribution of match values, G, implies that the mean match value, or productivity, in the ACS data is about \$46.69 per hour.[13] Compared to the critical match value ($\theta^* = \rho V_n$) of \$4.07 per hour, therefore, there appears to be a substantial amount of potential surplus in the average employment relationship. Most importantly, the estimate of α for Model 1 implies that workers earn roughly 27.6% of the employment surplus, and firms the remainder. In our data, therefore, the balance of bargaining power clearly lies with firms.

[Table 4 in here]

Relying on supply-side data only, however, invites the sort of identification issues raised by Flinn (2006). Therefore, we examine two other specifications that use demand-side data to estimate α along with the remaining parameters of the model. We estimate a base version of our demand-side model (Model 2), and one that allows for unobserved heterogeneity in the key model parameter (α, Model 3 in Table 4). From the results reported in Table 4,

[13] Recall that match values are assumed to be log-normally distributed, so the value of \$50.91 per hour is calculated from the estimate in the table.

it is clear that allowing for unobserved heterogeneity is important, as Model 3 provides a substantially better fit to the data than either Models 2 or 1 ($\chi^2 = 2.31 * 10^5$ versus Model 2). In this model, the rate of job creation (λ) is less than half that estimated in Model 1 (16.0% versus 35.0%) while the rate of job destruction is roughly one-quarter that reported in the base model (0.5% versus 1.8%). Further, the implied match value is substantially higher than the base model (Model 1) above, as the distribution of G suggests a match value of about \$191.94 per hour. Although the critical match value in our preferred model is also much higher than in the base model ($\theta^* = \$4.18$ per hour), there still appears to be a large amount of surplus to be allocated between workers and firms, on average, in the industry. That said, the balance of bargaining power still lies with employers after considering the inherent difference in productivity among workers ($1 - \alpha = 68.2\%$).[14] Even though we control for wage differences between 2019 and 2020 in the Table 4 models, these models do not yet recognize that there may have been inherent differences in bargaining power over this time period. We consider this possibility next.

Allowing bargaining power to vary between 2019 and 2020 provides unique insights into how the labor market changed over the sample period, perhaps due to the structural dislocations associated with the spread of COVID-19. Our findings from the structural model of COVID-19 impacts are found by comparing the estimates in Tables 5 and 6 below. As in the previous table, we estimate three different specifications, Model 1A in which bargaining power is identified only by the supply-side (ACS) data, Model 2A in which bargaining power is identified by both supply-side and demand-side factors, and Model 3A which allows for unobserved heterogeneity. In each of these models, we also include a variable that measures the impact of labor-market deterioration as measured through the aggregate level of unemployment. As in the previous set of results, the best-fitting model is the one that allows for demand-side identification, and unobserved heterogeneity, so we interpret the results from

[14] In this sense, our finding is similar to that found in the "state dependence" literature (e.g. Keane 1997) in that it is impossible to ascribe differences in labor-share among employees entirely to bargaining power, without accounting first for the fact that unobserved heterogeneity is likely to drive the bulk of differences in a worker's share of employment surplus in reality.

those models.

[Tables 5 and 6 in here]

Our findings in Tables 5 and 6 are interpreted similarly to those in Table 4. That is, focusing on the best-fitting model in the 2020 sub-sample (Table 6) the estimates imply a mean rate of job-contact creation (λ) of 16.3%, which is considerably smaller than in the base model. Controlling for variation in unemployment, and unobserved heterogeneity, draws a far less optimistic picture of the rate of job creation than otherwise. Further, the estimates of η, or the rate of job destruction, of 0.5% is smaller than in the best-fitting model in Table 4, so our findings suggest a more nuanced picture of the labor market than if the COVID-impact on bargaining is not taken into account. There is also substantially less surplus available for allocation between workers and firms as the mean match-value, or implicit productivity estimate, in Model 3A is \$23.53 / hour, while the critical match value (θ^*) is \$4.23 per hour.

Most importantly, comparing the bargaining power estimates in Table 6 with those in Table 5 provides a means of testing whether the level of bargaining power, on average, changed between 2019 and 2020. Our baseline estimate of bargaining power, or the intercept in the α function, in 2020 is roughly 32.0%, relative to 26.5% in 2019. This estimate suggests that workers in 2020 were in a much more favorable bargaining position relative to where they were in 2019. In fact, the difference in the two estimates suggests that bargaining power rose by some 20.8%, on average, between 2019 and 2020. Further, the estimated effect of unemployment on bargaining power is of the expected sign, and is statistically significant. That is, we expect that higher unemployment will be associated with a lower level of bargaining power across the industry. Based on these findings, it is clear that workers in the food and agriculture industry were indeed able to extract a greater share of the employment surplus in 2020 than they did prior to the COVID-19 pandemic.

It remains, however, to show the implications of our structural estimates for average wage outcomes, and for policy. We use counterfactual simulations of four scenarios – both market- and policy-driven – to demonstrate the importance of the interaction between policy instruments and bargaining power for equilibrium wages. The results of these simulations are in Table 7 below. The first simulation in Table 7 shows the impact of varying bargaining power from the base case (2019) values to the estimated impact of the COVID-19 pandemic, and related labor-market shortages, in 2020. This effect is shown by comparing the Base Case wages in 2019 with those implied by the new Base Case equilibrium in the middle row of the Model 1 columns. Comparing these outcomes shows that average wages, over all jobs, states, and demographics, were some 3.2% higher ($30.59 per hour in 2020 versus $29.64 per hour in 2019) due only to the difference in bargaining power over these two years. As discussed above, there were many other factors that may have changed between 2019 and 2020 but, controlling for as many as possible, we attribute the difference specifically to the higher bargaining power possessed by workers in 2020.

The Model 1 simulation makes this point more clearly by holding everything else constant in the 2020 sample, and allowing only the bargaining power parameter (α) to vary upward and downward by 50%, in increments of 25%. In this simulation, we find that equilibrium wages vary from $29.52 per hour (not statistically different from the 2019 wage outcome) with 50% lower bargaining power relative to the estimated 2020 value, to $31.29 per hour (5.6% higher than 2019 wages) with 50% higher bargaining power than our estimated value.[15] Based on these results, it is clear that variation in bargaining power has an important impact on wages, and hence firm costs.

[Table 7 in here]

Our second simulation examines the effect of minimum-wage variation on equilibrium wages. There are two possible outcomes for this simulation: Either higher minimum wages lead employers to bid up wages across the entire range of job classifications, or a "wage compression" effect, or lower minimum wages leave more of the match surplus to employers, and allow them to pay higher wages to more workers who accept their offers. In the lat-

[15] Note that the 25% and 50% bargaining-power-increase scenarios yield wages that are significantly different from the 2019 estimates at a 5% level, but not the 25% and 50% reductions.

ter case, the unconstrained equilibrium wage may even be higher than the minimum-wage constrained equilibrium wage. We find strong support for an inverse relationship between minimum and equilibrium wages, as a 20% lower minimum wage results in equilibrium wages that are 12.2% higher than the 2019 base case, and minimum wages that are 20% higher result in equilibrium wages that are very close to the 2019 level, even with the higher base wages in 2020. The strength of this effect suggests that using minimum wages as a policy tool is indeed effective, but likely in the opposite direction than most policymakers expect.

The third simulation examines a policy response that resembles the higher unemployment insurance compensation included in the Coronavirus Aid, Relief, and Economic Security Act (CARES, 2020). While we cannot model specifically the $600 per month in additional unemployment insurance, we consider instead parametric changes in workers' disagreement profit ($V_n(m)$), or the amount they expect to earn if they remain unemployed, rather than accept a possible employment match. In order to examine the qualitative effect of varying unemployment insurance around a reasonable range, we vary workers' threat point up and down by a maximum of 20% in either direction. In this case, we find that a 20% higher threat point results in wages that average $31.11 per hour (5.0% higher than the base 2019 case), or $29.70 per hour if the threat point is reduced by 20% (equilibrium wages are not statistically different from the 2019 level). Finding that equilibrium wages rise in the level of unemployment insurance is intuitive, as employers argued that higher insurance rates reduce the supply of available labor, and force them to compete more aggressively for available labor. In this sense, unemployment insurance essentially subsidizes worker leisure, raises reservation wages, and causes the market wage to increase for those who are willing to take jobs.

Our findings have important implications for both firm-management in our focal industries, for labor-market performance, and for food prices more generally. Managers in the firms captured by our data are the people who make the day-to-day decisions that are reflected in the ACS wage data reported by our sample subject. In that regard, they translate their perceptions of labor-shortage, and the bargaining power held by current and incoming employees, into higher hourly wages. During the pandemic-affected year of 2020, it appears as though they felt pressure to offer a greater share of employment surplus, or profit, to employees. Although unemployment was still relatively high for most of the year (Figure 1), it is well understood that many workers were transitioning out of the workforce, so finding skills matches was likely increasingly difficult as the year wore on. In terms of the labor market for workers in the food and agriculture industry, wage gains were understandably robust as concerns over the resilience of the food supply chain rose in prominence (Chenarides, Manfredo, and Richards 2021; Christiaensen, Rutledge, and Taylor 2021; Charlton, Rutledge, and Taylor 2021). Firms' attempts to mitigate labor-access issues are manifest in our data as higher wages, and higher bargaining power. Our findings also suggest that broader concerns over food price inflation are also well-founded, as greater bargaining power appears to have translated directly into higher wages. Given the importance of labor-costs in many food-production and distribution sectors, the link to higher prices is clear.

6 Conclusions

In this paper, we adopt a structural approach to examining the impact of COVID-19 related labor-shortages on the bargaining power possessed by workers in the food and agriculture industry. Using a structural search-matching-and-bargaining model developed by Flinn (2006), we compare the extent of bargaining power exercised by workers in 2019 with a similar sample of workers in 2020. We find that bargaining power was roughly 21.0% higher, with clear implications for wages in the food and agriculture industry, and for food prices more generally.

In recent years, managers, policymakers, and researchers alike have become increasingly concerned with labor shortages in agriculture (Richards 2018; Christiaensen, Rutledge, and Taylor 2021). In this paper, we leverage the labor-market dynamics associated with the "Great Resignation" of 2020 to examine this question more broadly, to move beyond production agriculture to consider jobs in the greater food and agriculture sector more generally. Our findings provide a framework, and important insights, into exactly how labor shortages are likely to be felt by firms in the industry, as they have to compensate for the perceived lack of well-matched skill sets by offering higher wages to those that are deemed suitable. If workers with necessary skills are in short supply, then their wage demands are reflected in higher bargaining power.

There are many policy implications that follow from our findings. Beyond the insights for management and firms outlined above, policymakers concerned with agricultural labor markets in particular need to recognize the fundamental nature of the changes in labor-market outcomes we describe here. For example, if the adverse-effect wage rate (AEWR), or the wage that must be paid to H-2A non-immigrant guestworkers, is to track actual wage conditions in agricultural labor markets, then basing the wage on lagged Farm Labor Survey (FLS) wages is likely to dramatically understate the actual cost of guestworker labor. Other policymakers who may be concerned with food prices should recognize the important role played by labor costs, and perhaps consider higher wages as part of an explanation for higher prices instead of consolidation, which did not change from 2019 to 2020.

In conducting this research, we sought the most detailed and relevant data available. However, because the ACS is not specifically designed for agricultural-worker research, future research in this area may consider applying similar structural models of labor-market outcomes to either the Current Population Survey (CPS) or National Agricultural Workers Survey (NAWS). Better yet, if researchers have access to matched employer-employee data as in Cahuc, Postel-Vinay and Robin (2006) or Bonhomme, Lamadon, and Manresa (2019), then they will likely be able to draw far more detailed insights on the firm-worker bargaining dynamic than we could here.

Further, our measure of the COVID-19 impact was necessarily very blunt, as we have no way to identify temporal variations in pandemic effects across the state-level geographies in our data. If our data contained information on specific months in which the survey was carried out, we could use state-to-state variations in COVID-19 cases, lockdowns, and shelter-in-place orders to help identify the true COVID-19 impact. With more granular data, we could answer many more, important questions regarding the drivers of bargaining power. For example, in the related meatpacking sector, the invocation of the Defense Production Act led to some counties and states limiting the unemployment benefits that packing plant workers were eligible for, which substantially reduced the value of these employees' next best alternative (Saitone, Schaefer and Scheitrum 2021). If the data were available, we could also allow bargaining power to vary with the proportion of undocumented workers in each county, which is available in the NAWS data. With the NAWS data, we could also examine the effect of undocumented hiring on the share of surplus earned by farm workers. Future research may also consider the impact of collective bargaining on the labor-share of surplus by examining the share of workers covered by collective bargaining agreements in each year, and region.

7 Appendix A: Derivation of Constrained Wage Distribution

In this appendix, we describe the derivation of equation (5) in the text from Flinn (2006). As explained above, the existence of an effective minimum wage serves as a constraint on firms' exercise of their usual degree of bargaining power. There may be matches that provide some surplus, but not at the level of unconstrained wage offers and worker-bargaining power implied by the unconstrained model. In order to see this logic more formally, first recognize that firms cannot generate positive surplus with match values less than the minimum wage ($\theta < m$) because their surplus depends on the difference between match values and wage offers ($\theta - w$), so any values of θ below m would imply negative surplus. Therefore, there has to be a threshold match value ($\hat{\theta}$) that separates wage offers that are not constrained by the minimum wage, recognizing that firms and workers tend to share the amount of available surplus, and those that are constrained. Without the minimum wage constraint, and general search value of $V_n(m)$, the equilibrium wage solves:

$$w(\theta, V_n(m)) = \alpha\theta + (1-\alpha)\rho V_n(m), \tag{14}$$

so that workers are paid m when there is a value of $\hat{\theta}$ such that:

$$\hat{\theta}(m, V_n(m)) = \frac{m - (1-\alpha)\rho V_n(m)}{\alpha}, \tag{15}$$

or the threshold value of θ that separates "rational" minimum-wage contracts from those that include a market-level wage. When $\theta \in [m, \hat{\theta})$, the wage offer implied by implied by (14) would be less than the minimum wage, but the firm is constrained to pay at least m, so chooses to pay that level, and give up some surplus for all $\theta \in [m, \hat{\theta})$. Flinn (2006) then shows that the steady-state value of search under a minimum-wage law is given by:

$$\rho V_n(m) = b + \frac{\lambda}{\rho+\eta}\left\{ \int_{m}^{\hat{\theta}} [m - \rho V_n(m)]dG(\theta) + \alpha \int_{\hat{\theta}} [\theta - \rho V_n(m)]dG(\theta) \right\}, \tag{16}$$

so the new equilibrium wage distribution that solves equation (16) implies a "wedge" between the minimum wage, and the minimum acceptable wage offer implied by $\rho V_n(m)$. Reflecting this wedge, the equilibrium wage distribution under minimum wages consists of three regimes, depending on the relative values of the minimum wage and the offer implied by (14):

$$pr(w; V_n(m)) = \left\{ \begin{array}{ll} [g(\hat{\theta}(w, V_n(m))]/\alpha G(m), & w > m \\ [G(m) - G(\hat{\theta}(w, V_n(m)))]/G(m), & w = m \\ 0, & w < m \end{array} \right\}, \tag{17}$$

where w is the equilibrium wage offer. Simulating this theoretical wage distribution under different bargaining power values, therefore, shows how bargaining power and labor-market policies interact to affect market wages.

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Table 1. Summary of ACS Data

Variable	Units	Mean	Std. Dev.	Min.	Max.	N
Age	Years	43.56	16.30	16.00	95.00	201179
Education	Years	17.02	3.70	1.00	24.00	201179
Gender	% Male	66.96%	47.04%	0.00%	100.00%	201179
Weeks Worked	#	44.91	14.63	1.00	52.00	201179
Minimum Wage	$ / Hour	9.16	2.01	7.25	13.50	201179
Hourly Wage	$ / Hour	30.07	125.38	0.00	10000.00	201179
High-Paid	%	79.67%	40.25%	0.00%	100.00%	201179
Minimum Wage	%	8.64%	28.10%	0.00%	100.00%	201179
Unemployed	%	10.54%	30.71%	0.00%	100.00%	201179
Duration Unemployed	Weeks	7.09	14.63	0.00	51.00	201179
Private, For-Profit	%	81.42%	38.90%	0.00%	100.00%	201179
Private, Not For-Profit	%	1.46%	11.98%	0.00%	100.00%	201179
Local Government	%	0.26%	5.14%	0.00%	100.00%	201179
State Government	%	0.32%	5.66%	0.00%	100.00%	201179
Federal Government	%	0.35%	5.91%	0.00%	100.00%	201179
Self Employed, Unincorporated	%	9.97%	29.96%	0.00%	100.00%	201179
Self Employed, Incorporated	%	5.44%	22.67%	0.00%	100.00%	201179
Small Business, or Family Farm	%	0.78%	8.81%	0.00%	100.00%	201179
Born in U.S.	%	83.12%	37.46%	0.00%	100.00%	201179
Born in U.S. Territory	%	0.44%	6.62%	0.00%	100.00%	201179
Born Abroad to U.S. Parents	%	0.84%	9.10%	0.00%	100.00%	201179
Naturalized	%	6.93%	25.40%	0.00%	100.00%	201179
Not U.S. Citizen	%	8.67%	28.14%	0.00%	100.00%	201179

Note: All data from American Community Survey, 2019-2020 samples, agriculture and food NAICS codes only.

Table 2. Summary of Wages by Industry and Year

Industry	Year	N	Wage	Year	N	Wage	Change	% Change
Crop Production	2019	14427	$40.55	2020	12167	$51.86	$11.31	27.89%
Animal Production	2019	7659	$30.62	2020	6838	$31.91	$1.29	4.22%
Support Activities	2019	1993	$32.24	2020	1602	$32.06	-$0.18	-0.55%
Animal Food, Grain, and Oilseed Milling	2019	1944	$36.08	2020	1671	$35.29	-$0.79	-2.18%
Sugar and Confectionary	2019	875	$40.52	2020	761	$37.94	-$2.58	-6.36%
Fruit and Vegetable Preserving	2019	1753	$28.39	2020	1332	$33.64	$5.24	18.47%
Dairy Products	2019	1796	$27.71	2020	1533	$30.32	$2.60	9.40%
Animal Processing	2019	4404	$21.03	2020	3739	$23.89	$2.86	13.61%
Retail Bakeries	2019	1808	$19.11	2020	1513	$24.95	$5.84	30.55%
Bakeries and Tortillas	2019	2003	$22.92	2020	1486	$26.90	$3.98	17.38%
Seafood and Other Misc.	2019	2432	$33.67	2020	2139	$33.59	-$0.08	-0.22%
Beverage Mfg.	2019	2970	$33.69	2020	2293	$36.85	$3.16	9.38%
Agricultural Chemical	2019	415	$34.39	2020	349	$52.02	$17.63	51.28%
Agricultural Implement	2019	1337	$30.05	2020	1230	$34.39	$4.34	14.45%
Grocery Wholesalers	2019	7928	$30.63	2020	6325	$35.12	$4.49	14.67%
Farm Product (Raw) Wholesalers	2019	973	$29.68	2020	969	$48.33	$18.65	62.84%
Alcoholic Beverage Wholesalers	2019	1398	$34.58	2020	1044	$38.54	$3.97	11.47%
Farm Supplies Wholesalers	2019	699	$35.74	2020	615	$37.28	$1.55	4.33%
Supermarkets and Other Grocery	2019	26281	$19.81	2020	22089	$25.63	$5.82	29.39%
Convenience Stores	2019	3464	$17.27	2020	2855	$24.28	$7.01	40.57%
Specialty Food Stores	2019	2368	$23.49	2020	1707	$31.47	$7.99	34.00%
Beer, Wine, And Liquor Stores	2019	1574	$25.48	2020	1330	$37.14	$11.67	45.80%
Truck Transportation	2019	19481	$33.09	2020	15780	$37.76	$4.67	14.10%

Note: All data from American Community Survey. Note Bureau of Labor Statistics caveat on 2020 data due to relatively low response rate during the pandemic year of 2020. Industry names are summarized from ACS convention due to space limitations. Change is defined as 2020 relative to 2019.

Table 3. Reduced Form Wage Evidence

	Model 1		Model 2		Model 3		Model 4	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
COVID	0.0895	0.0041	0.0927	0.0039	0.0928	0.0039	0.0929	0.0039
Age			0.0348	0.0007	0.0338	0.0007	0.0350	0.0007
Age^2			-0.0003	0.0001	-0.0003	0.0000	-0.0003	0.0001
Education			0.0339	0.0005	0.0342	0.0005	0.0321	0.0006
Gender			0.1626	0.0044	0.1614	0.0044	0.1603	0.0044
Private, Not For-Profit					-0.0275	0.0163	-0.0285	0.0163
Local Government					-0.0221	0.0379	-0.0260	0.0379
State Government					-0.1402	0.0345	-0.1433	0.0345
Federal Government					0.0005	0.0329	-0.0005	0.0329
Self Employed, Unincorporated					-0.1189	0.0074	-0.1233	0.0074
Self Employed, Incorporated					0.0973	0.0089	0.0954	0.0089
Small Business, or Family Farm					-0.6375	0.0223	-0.6429	0.0223
Born in U.S. Territory					-0.1057	0.0295	-0.1191	0.0295
Born Abroad to U.S. Parents					0.0187	0.0214	0.0077	0.0214
Naturalized					0.0237	0.0079	0.0050	0.0081
Not U.S. Citizen							-0.1001	0.0077
F	179.1000		350.8000		327.3000		325.7000	
R^2	0.0618		0.1198		0.1253		0.1261	

Note: All models estimated with agriculture-and-food industry ACS sample for 2019 - 2020.

Base category for worker classification is Private, For Profit, and for citizenship is Born in U.S.

N = 201,179.

Table 4. Structural Estimates of Wage Bargaining Model

	Model 1		Model 2		Model 3	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
λ	0.3564***	0.0028	0.0529***	0.0005	0.1672***	0.0016
η	0.0183***	0.0002	0.0061***	0.0000	0.0059***	0.0005
μ	3.5420***	0.0072	3.2176***	0.0019	3.8458***	0.0176
σ	0.7765***	0.0048	0.4146***	0.0008	1.6801***	0.0188
θ	4.0725***	0.0030	4.3389***	0.0040	4.1848***	0.0043
α	0.2759***	0.0004	0.2975***	0.0005	0.3181***	0.0006
State Effects?	Yes		Yes		Yes	
Job Effects?	Yes		Yes		Yes	
Demographics?	Yes		Yes		Yes	
COVID?	Yes		Yes		Yes	
Random Parameters?	No		No		Yes	
LLF	31,736.9		37,120.7		152,656.5	
AIC/N	-0.316		-0.368		-1.512	

Note: All models estimated with American Community Survey (Bureau of Census) data. Model 1 is base model with no demand-side information for alpha. Model 2 is base model with labor-share-of-revenue data used to identify alpha. Model 3 is Model 2 with heterogeneity in bargaining. A single asterisk (*) indicates significance at 1%, ** at 5%, and *** at 1%. N = 201,179.

Table 5. Structural Estimates of COVID Impact on Bargaining: 2019

	Model 1A		Model 2A		Model 3A	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
λ	0.3998***	0.0070	0.2488***	0.0045	0.3610***	0.0066
η	0.0042***	0.0004	0.0037***	0.0003	0.0039***	0.0000
μ	5.6621***	0.0605	4.4750***	0.0295	5.8505***	0.0595
σ	2.0434***	0.0362	1.4232***	0.0192	2.1887***	0.0366
θ	3.8652***	0.0030	3.9250***	0.0035	3.9331***	0.0035
α	0.2397***	0.0004	0.2700***	0.0006	0.2648***	0.0005
Unemp	0.0236***	0.0006	-0.0149***	0.0010	-0.0021***	0.0002
State Effects?	Yes		Yes		Yes	
Job Effects?	Yes		Yes		Yes	
Demographics?	Yes		Yes		Yes	
COVID?	Yes		Yes		Yes	
Random Parameters?	No		No		Yes	
N	109,939		109,939		109,939	
LLF	13058.2		-1761.0		5736.0	
AIC/N	-0.237		0.032		-0.104	

Note: All models estimated with American Community Survey (Bureau of Census) data. Model 1A is Model 1 from Table 4 with COVID impact on bargaining. Model 2A is Model 2 from Table 4 with COVID impact on bargaining, and Model 3A is Model 3 from Table 4 with COVID impact. A single asterisk (*) indicates significance at 10%, ** at 5%, and ** at 1%. N = 109,939.

Table 6. Structural Estimates of COVID Impact on Bargaining: 2020

	Model 1A:		Model 2A		Model 3A	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
λ	0.1484***	0.0021	0.2231***	0.0045	0.1631***	0.0027
η	0.0011***	0.0001	0.0010***	0.0009	0.0005***	0.0000
μ	3.6436***	0.0083	3.4838***	0.0088	3.0607***	0.0028
σ	0.7155***	0.0046	0.6684***	0.0047	0.4419***	0.0015
θ	4.3159***	0.0058	4.4242***	0.0066	4.2290***	0.0055
α	0.3212***	0.0009	0.2933***	0.0009	0.3198***	0.0010
Unemp	-0.0412***	0.0006	0.0072***	0.0008	-0.0194***	0.0009
State Effects?	Yes		Yes		Yes	
Job Effects?	Yes		Yes		Yes	
Demographics?	Yes		Yes		Yes	
COVID?	Yes		Yes		Yes	
Random Parameters?	No		No		Yes	
N	91,230		91,230		91,230	
LLF	-3,221.7		-13,535.6		-9,870.7	
AIC/N	0.071		0.297		0.217	

Note: All models estimated with American Community Survey (Bureau of Census) data. Model 1A is Model 1 from Table 4 with COVID impact on bargaining. Model 2A is Model 2 from Table 4 with COVID impact on bargaining, and Model 3A is Model 3 from Table 4 with COVID impact. A single asterisk (*) indicates significance at 10%, ** at 5%, and *** at 1%. N = 91,230.

Table 7. Counterfactual Simulation Results

	Base 2019 Wages		Model 1			Model 2			Model 3		
	Mean	Std. Dev.	Estimate	Std. Dev.	% Change	Estimate	Std. Dev.	% Change	Estimate	Std. Dev.	% Change
Base - High			\$29.52	\$123.51	-0.40%	\$33.26	\$144.32	12.21%	\$29.70	\$126.17	0.20%
Base - Low			\$30.09	\$126.07	1.52%	\$31.16	\$133.41	5.13%	\$29.94	\$127.31	1.01%
Base	\$29.64	\$126.01	\$30.59	\$128.69	3.21%	\$30.59	\$128.69	3.21%	\$30.59	\$128.69	3.21%
Base + Low			\$30.99	\$130.61	4.55%	\$29.73	\$126.33	0.30%	\$30.61	\$130.65	3.27%
Base + High			\$31.29	\$132.04	5.57%	\$29.44	\$124.89	-0.67%	\$31.11	\$133.14	4.96%

Note: Base case is 2019 wages, at 2019 bargaining power. Model 1 is the base (2020) wage-distribution simulation model in equation (5) with bargaining power set to 2020 estimated value, and ranging from 50% below to 50% above estimated value. Our estimate of 2020 bargaining power is 20.7% above base-case 2019 values. Model 2 allows minimum wages to vary over a smaller range - 20% below to 20% above the observed 2020 values (in 10% increments), with 2020 bargaining power values. Model 3 varies $V_n(m)$, the threshold value of θ in equilibrium, over a similar +/-20% range.

Figure 1. U.S. Unemployment Rate, 2019 - 2021
Source: U.S. Bureau of Labor Statistics