Labor Shortages and Agricultural Trucking Rates

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March 27, 2024

Abstract

In the U.S., truck rates for perishable food, the per-mile rate charged for trucking services to move perishable food from farms to stores, rose substantially in the post-COVID-19 pandemic era. We argue that rising truck rates is a signal of a broader shortage of truckers, but the connection between labor shortages, rising truck rates, and a lack of trucking services has yet to be established empirically. In this paper, we develop an empirical examination based on an equilibrium job search, matching, and bargaining framework in which we estimate the role of labor shortages in accelerating driver-wage growth, and truck rates for agricultural products. We estimate the model by combining U.S. Bureau of Census Current Population Survey data on truck driver wages with USDA-Agricultural Marketing Service Service data on truck rates to establish the linkage between trucker supply and the demand for trucking services. We find that the COVID-19 pandemic was responsible for a rise in for-hire trucker wages of some 38%, a rise in average truck rates of nearly 50% and that the gap between trucker-job openings and successful matches explains a significant, but small, rise in truck rates.

keywords: Bargaining, COVID-19, labor market, supply chain management, trucking shortage.

JEL Codes: J24,J43,L92,Q11

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1 Introduction

Immediately following the COVID-19 pandemic, there was plenty of evidence of transportation shortages in the U.S. food supply chain (Cheeseman-Day & Hait 2019; Costello & Karickhoff 2019; Sowder 2022). Many attribute the shortage of transportation services – whether in rail, trucking, or shipping – to a confluence of issues, from heightened demand due to COVID-19 fiscal and monetary programs, to COVID-induced labor shortages, and bottlenecks in the physical movement of containers, trucks, and rail cars.[1] Resolving transportation issues in agriculture is core to both ensuring the integrity of the food supply chain, because most consumer-ready food moves by truck from processing and distribution centers to retail and food service outlets, and for limiting food's contribution to the overall level of consumer price inflation. In this paper, we investigate the extent to which cost and access problems in the transportation sector were due to insufficient labor and, if so, how much labor contributed to the unprecedented increase in truck transportation rates for fresh foods.

The trucking industry depends on labor. While the public image of the truck-transport sector is primarily of machinery, the reality is that the truckers represent the key constraining input to moving more products by truck. More generally, the food and agriculture industry depends on trucks, and their drivers, as fully 72% of cargo in the U.S. moves by truck (ATRI 2021; BLS 2020). Moreover, existing truck drivers are aging out of the industry, while younger drivers are becoming more difficult to attract from other low- and semi-skilled industries (Cheeseman-Day & Hait 2019). Industry analysts argue that turnover, or the share of drivers that need to be replaced each year, is very high: In the long-distance,

[1] The U.S. government enacted dozens of programs to prevent economic decline due to the COVID-19 pandemic. We do not intend to isolate the effect of any single program, but the measures that were likely most important for labor-market outcomes included unemployment insurance extension, initially through the Families First Coronavirus Response Act (FFCRA), direct loans and grants to maintain employment through the Payroll Protection Plan (PPP), and the massive injection of fiscal dollars through the Coronavirus Aid, Relief, and Economic Security Act (CARES, consisting of $2.3 trillion in direct federal dollars, an additional $600 per week of unemployment through July 31, 2020, and some ten other programs). Arguably, however, the most important driver for the "Great Reshuffle" (Krugman 2022) witnessed in 2021 was through monetary policy, as lower interest rates inflated stock and home valuations, and allowed workers to retire early, setting off a cascade of labor shortages, higher wages, and firms poaching workers from their rivals.

truckload (TL) segment of the industry turnover is approximately 94%, which means that nearly everyone who enters the industry in a given year is no longer driving just one year later (Burks & Monaco 2019). Once attractive to workers seeking the appeal of the open road, increasing competition in the trucking industry has placed greater demands on drivers, so fewer workers are choosing the trucking industry as a career (ATRI 2021). We examine the extent to which turnover, and changing industry demographics, may contribute to a broader shortage of drivers in the industry as a whole.[2]

Conditions in the trucking industry have long been a concern to researchers in agricultural economics, and public policy more generally, due largely to the importance of long-distance bulk transport to the stability of food supply chains. In the U.S., agricultural trucking was exempt from entry and rate restrictions under the 1935 Motor Carrier Act, with the intent of protecting farmers from the higher rates that the new-deal era legislation was intended to create (Black 1955; Farmer 1964). Deregulating the rest of the U.S. trucking industry through the Motor Carrier Regulatory Reform and Modernization Act of 1980, however, meant that agricultural products had to compete head-on with non-agricultural products in a nearly-free market for trucking services. As a result, truck transportation rates for farm products in the U.S. became relatively competitive (Beilock and Shonkwiler 1983; Beilock, Garrod, & Miklius 1986). Canadian trucking firms face similar competitive conditions, as rate-and-entry regulations in Canada were removed by the 1987 Motor Vehicle Transport Act. Further, subsequent free trade agreements with the U.S. through the Canada-U.S. Free Trade Agreement (CUSFTA) in 1988 and the North American Free Trade Agreement (NAFTA) in 1994 meant that Canadian trucking firms had to lower rates and improve service to compete with U.S. carriers (Barzyk 1996). As a consequence of NAFTA, Canadian trucking re-oriented from east-west to north-south, and became both more efficient and perilously

[2]Miller, et al. (2020) and Phares & Balthrop (2021) make the important distinction between firm-turnover, or the rate at which a firm needs to replace its drivers, and industry-turnover, or the rate at which drivers exit the industry. We are more concerned with the latter as our interests lie in examining the resilience of the food supply chain, although we recognize that firm-level costs associated with turnover are substantial, and important.

similar to the U.S. in its reliance on owner-operators for the bulk of over-the-highway goods movement. Gray (2020) argues that this "...decentralized nature..." of the Canadian trucking industry should mean that the industry is relatively resilient to a shock like the COVID-19 disruption of 2020, but Gill & MacDonald (2013) explain that the long-run dynamics of the Canadian and U.S. trucking industries are very similar, forecasting a roughly 10% shortage of truck drivers only seven years after their study. Therefore, our insights into the impact of COVID-19 on the U.S. agricultural trucking industry should hold valuable lessons for Canada as well.

There is a deep literature on job turnover, drawing from the economics, logistics, and transportation literatures.[3] The primary insight from this literature is that workers tend to enter new jobs, and exit old ones, according to the tenets of neoclassical sectoral-migration models (Roy 1951) in which workers consider the marginal benefit of increased wages in another sector against the cost of what they are currently earning (Burks & Monaco 2019; Phares & Balthrop 2021). While firm-level turnover is critically important to firms themselves, in terms of the financial costs of lost productivity, retraining costs, decline in safety, and onboarding costs (LeMay, et al. 1993; Stephenson & Fox 1996; Min & Lambert 2002; Garver, et al. 2008; Taylor, et al. 2010; Cantor, et al. 2011; Miller, et al. 2021), the shortage of truck drivers in aggregate is of greater concern to the economy as a whole, and the stability of trucking as a core element to the national supply chain for agricultural commodities.

We frame our analysis of trucker shortages in terms of a model of equilibrium job search and matching (Van den Berg & Ridder 1998; Pissarides 2010; Dey & Flinn 2005; Flinn 2006), in which workers search optimally for jobs, taking into account the cost of search, the probability of finding a job, and of losing their current job, and the extent of bargaining power they take to any new negotiations. Unlike the previous literature, firms in our model play an active role, searching for the best fit from among available workers and taking into account their expected productivity. In this context, any increase in search costs will reduce

[3]See Miller, et al. (2021) for a comprehensive review of the previous literature on job turnover in logistics and transportation.

the propensity of truckers to move to the industry, while an increase in productivity will move firms to offer better paying jobs and increase the expected benefits of switching. Most importantly, econometric models of labor-market equilibrium allow us to estimate the extent of shortage over time, and by industry.

Shortages are often manifest in rising prices. While there is ample anecdotal evidence of driver shortages, primarily from industry sources (Costello & Karickhoff 2019; ATRI 2021), most of the literature on driver turnover focuses on whether there really is a shortage of drivers at any point in time (Burks & Monaco 2019; Miller, et al. 2021; Phares & Balthrop 2021), and there are no empirical studies that test directly for driver shortages. We follow Miller, et al. (2020) and focus on the price-effect of driver shortages on truck rates, but do so within an equilibrium framework that admits a direct test of whether driver shortages can help explain the rise in truck rates following the COVID-19 pandemic, and policy response. We use an empirical model of labor search, firm productivity, and Nash bargaining (Eckstein & Wolpin 1995; Dey & Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, & Robin 2006; Shimer 2006; Flabbi & Moro 2012) to identify rates of job creation and job destruction, and worker bargaining power that vary over time. We then use these parameters to explain industry-level truck rates from the United States Department of Agriculture, Agricultural Marketing Service (USDA-AMS 2022). With this model, we determine whether the market for a key input – labor services – is in surplus or shortage (or neither) over space and time and quantify the extent to which labor market disequilibria are related to trucking service prices.

Our synthesis of the industrial organization, labor economics, and supply chain management literatures on the trucking transportation industry reflects Card's (2022) call to use insights from industrial organization to better understand the nature of imperfect competition in labor markets, and its implication for downstream industries. There is a growing interest in agricultural supply chain resilience in general, and imperfect competition defined generally forms a key motivation (Hadachek, Ma, & Sexton 2023; Stevens & Teal 2023) as does the role of upstream labor markets (Wahdat & Lusk 2023). In this paper, we follow this literature in considering a modern approach to studying labor markets (Flinn 2006) and its implications for supply-chain performance downstream.

For our structural analysis, we combine data from the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS, Flood, et al. 2022) data set for drivers in any trucking occupation, with truck-rate data from the USDA-AMS (USDA-AMS 2022) over a 2011 - 2021 time period. In this regard, we follow others in the transportation (Burks and Monaco 2019), logistics (Miller et al. 2021; Phares & Balthrop 2021) and the economics literature (Cahuc, Postel-Vinay, & Robin 2006; Flinn 2006) in recognizing the value of data on worker-level job-choices, demographics, and compensation in understanding the dynamics of market equilibria.[4] Unlike these authors who use the CPS Outgoing Rotation Group (ORG), we use the CPS Annual Social and Economic Supplement (ASEC) longitudinal data in order to exploit clear within-worker changes in job choice to identify the key parameters of interest. For summary purposes, we estimate a series of reduced-form regressions to examine whether changes in trucker wages across source-destination pairs are statistically associated with changes in USDA-reported truck rates. Our measure of aggregate, industry-average earnings in this exercise is from the U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), which reports both employment and average weekly earnings at the NAICS industry level for each state, over the entire 2011 - 2021 sample period.

Our empirical analysis consists of three stages. First, we begin with a reduced-form analysis of job transitions in order to examine wage patterns in the data, which suggests that the market for trucker labor appears to be moving quickly toward a new, higher-wage equilibrium. Second, we estimate an empirical model of labor-search and Nash-bargaining (Dey & Flinn 2005; Flinn 2006) that allows us to recover time-varying parameters of job creation, job destruction, and worker bargaining-power. Although structural models of search, matching, and bargaining are relatively abstract, we believe that a structural approach like this is

[4] One alternative is the CPS Outgoing Rotation Group (ORG) data, but our ASEC sample provided roughly 10 times the number of usable observations relative to the ORG sample.

necessary in order to recover the parameters that are able to characterize both a shortage of labor (job creation and destruction) and its consequences (bargaining power and wages). Our estimates from this model permit direct tests of whether the market for truckers appears to be in disequilibrium, defined as inequality between the rates of job destruction and formation, or whether the market is instead in equilibrium. Estimates of worker bargaining power allow us to examine how changes in the labor market likely affect worker welfare and firm profitability. Third, we estimate the impact of labor-market disequilibrium on the path of truck rates over time. If the market for truckers is indeed evolving as industry sources suggest, then we expect to find that labor-market dynamics explain a substantial portion of changes in truck rates over the sample period.

We reveal a number of important facts about the market for truckers. First, our summary analysis of the USDA-AMS truck rate data shows that rates for refrigerated trucking services increased substantially in the post-COVID period. Consistent with media reports of rising transportation costs throughout the economy, the per-mile cost of refrigerated trucking services across some 90 source-destination pairs increased by almost 50% between our baseline 2019 period, and the post-COVID period that we define as including the entire 2021 calendar year.[5]

Second, reduced-form models linking variables we would expect to be important to trucking costs (i.e., distance and trucker wages) show elasticities of refrigerated truck rates with respect to wages of about 0.17, so each 10% increase in wages is associated with a 1.7% increase in trucking rates.

Third, our structural model of labor-market equilibrium finds that workers earn about 38% of the employment surplus earned by trucking firms, but that amount rose by over 1.2% due to the COVID-19 pandemic.[6] Finally, using the structural model to calculate annual

[5]We understand that defining 2021 as "post-COVID" is not without controversy as the pandemic was still spreading. But, our USDA-AMS data show that truck rates remained elevated through 2022 so 2021 serves as a benchmark for the immediate post-COVID period.

[6]The increment in bargaining power due to COVID-19 induced labor shortages is smaller than that found by Richards and Rutledge (2023) in the food and agriculture industry (21%), perhaps due to the smaller base level of bargaining power exercised by workers in food and agriculture (27%) and generally-lower level

rates of labor-market disequilibrium, we find that a 10% increase in job openings relative to jobs lost is associated with a 0.3% increase in truck rates, and an 0.8% reduction in the availability of trucking services. We interpret this latter result as pointing to the fact that a greater demand for truckers means an increase in the perceived shortage of workers in the trucking industry. Combined with our summary findings on transitions into and out of trucking, our results suggest that tightness in the market for truckers is not only more consistent with the "Great Reshuffle" due to the COVID-19 pandemic (Krugman 2022) than it is the "Great Resignation" (Cohen 2021), but explains at least some of the rapid rise in truck rates seen throughout the U.S. economy, and in the food industry in particular.[7]

Our findings, and theoretical framework, contribute to the emerging literature on agricultural supply-chain resilience, the logistics literature on trucking shortages and the cost of trucking, the literature on labor search and bargaining, and the literature on regulation and pricing in the trucking industry more generally.

First, we contribute to the emerging literature on agricultural supply chain resilience, both in the supply-chain management (Behzadi, et al. 2018; Stone & Rahimifard 2018) and agricultural economics literatures (Hobbs 2020; Chenarides, Manfredo, & Richards 2021; Hadachek, Ma, & Sexton 2023; Stevens & Teal 2023; Wahdat & Lusk 2023). While Wahdat & Lusk (2023) point to the vulnerability of animal processing to upstream labor in a simulation framework, we examine a similar question using archival data and focus specifically on the agricultural trucking industry. Our research is similar to both Hadachek, Ma, & Sexton (2023) and Stevens & Teal (2023) in the sense that we examine the resilience of agricultural supply chains through an industrial organization lens, but we base our insights instead on a structural analysis of imperfect competition in the market for labor and not the organization of trucking firms themselves. We contribute to this literature by demonstrating the importance of labor in food distribution, and how resilience can be measured through its impact

of base wages.

[7] Anthony Klotz initially coined the term the "Great Resignation" in an interview with Bloomberg Businessweek.

on prices for key food-system inputs (labor).

Second, we contribute to the logistics literature in developing a theoretical and empirical explanation for trucker shortages, workplace transitions, and the rise in trucking rates. Others in the recent literature focus on job turnover in the trucking industry (Burks & Monaco 2019; Phares & Balthrop 2021; Miller, et al. 2021), but do so using reduced-form approaches that are not framed in terms of formal models of search, matching, and bargaining equilibrium that are now standard in the labor economics literature (Dey & Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, & Robin 2006). By allowing departures from equilibrium to directly affect truck rates, we extend the insights in Miller, et al. (2020) by formally connecting labor-market outcomes to pricing in the market for trucking services.

Third, we contribute to the literature on labor search and bargaining by extending the empirical model developed by Flinn (2006) to the individual level, and by allowing for a richer parameterization of the core bargaining power parameter. In this way, we develop an explanation for the COVID-19 induced Great Reshuffle in a formal model of labor-market equilibrium.

Fourth, we contribute to the literature on how government policy, and shocks to the macroeconomy, affect pricing and worker outcomes in the transportation industry. While others in this literature use policy-induced shocks from changes to the Motor Carrier Act (Rose 1987; Hirsch 1988, 1993) to identify changes in worker bargaining power indirectly, we demonstrate a structural approach that explicitly accounts for regulatory shocks to bargaining power. While we do not explicitly account for imperfect competition in the trucking industry to explain the sharp changes in truck rates as Beilock, et al. (1986), Guadalupe (2007), and MacDonald (2013) do in other settings, and previous policy changes, we show that at least some of the rapid rise in truck rates following the COVID-19 pandemic can be explained by driver-shortages in the market for long-distance trucking.

In the next section, we outline a model of labor-market equilibrium in which employees search optimally for jobs, bring match-specific capital to potential employers, and then bargain over their share of the resulting match-surplus with employers. In Section 3, we describe an econometric model that we use to estimate the key parameters of our equilibrium model, including the degree of bargaining power, and show how we allow both bargaining power and the extent of labor-market disequilibrium to vary over time. In this section, we also show how we connect the degree of disequilibrium in the market for truckers each year to changes in observed truck-rates, or the price of trucking services. In Section 4, we describe the two primary data sets we use to examine this problem, and explain how the key parameters of the model are identified. We present and interpret our findings in Section 5, including those pertaining to the parameters of the structural model and the empirical model of refrigerated truck rates. In the final section, we offer some general conclusions that follow from our findings, including a set of implications for management and supply-chain resilience.

2 Theoretical Model of Trucker Shortage

We frame our empirical insights into the market for truck drivers in an explicit theoretical model of labor-market equilibrium. In this model, workers search for employment matches with firms until the marginal benefit of search is equal to the marginal cost of doing so (Burdett & Mortensen 1998), while firms search for employees that maximize the amount of surplus they derive from the employment transaction. Firms and workers bargain over the terms of employment contracts, so the wage outcome is not take-it-or-leave-it in the sense of Burdett & Mortensen (1998), Van den Berg & Ridder (1998), and Eckstein & Van den Berg (2007), but rather mediated by conditions that affect the relative bargaining power workers and firms bring to the table.[8] Bargaining occurs according to an axiomatic Nash (1951) process, so bargaining power is exogenous, and it depends on the negotiating abilities of each side, which are influenced by endowed or acquired attributes like skill or education, or perhaps economic conditions that provide a structural advantage to one side or

[8]We note that this 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, & To 2002; Manning 2003; Ashenfelter, Farber, & Ransom 2010; Ransom & Oaxaca 2010; Hamilton et al. 2021) without necessarily having market power in the traditional sense that it is usually used in the context of output markets.

the other.[9] In the current application, we consider how fundamental changes in the market for truckers following the COVID-19 pandemic has affected wage outcomes, bargaining power, and ultimately the price of trucking services.

We begin by summarizing a simplified version of the search and bargaining model of Dey & Flinn (2005) and Flinn (2006) without minimum wages in order to highlight the role of each of the structural parameters. In this stylized model, the primary objective is to explain wages in terms of a Nash bargaining process in which each party's share of the match surplus is determined by the interaction between the exogenous levels of bargaining power (α), and the endogenous bargaining position of each party. The primary determinant of each party's bargaining position is their "disagreement profit" or the value of the next best alternative should negotiations break down. Intuitively, the higher is a party's disagreement profit, the stronger their bargaining position as they have less to lose if negotiations fail. In this setting, the employee's disagreement profit (V_n) is the next-best job offer, and we normalize the employer's disagreement profit to zero as it makes no surplus from the transaction if the employee is not hired.

More formally, 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.

When workers search optimally, therefore, equilibrium wages will reflect the rate at which

[9] We are not the first to apply a structural model of search-and-bargaining to examine labor market problems as Flinn (2006) considers the impact of minimum-wage laws on wage outcomes, how healthcare benefits either raise or lower negotiated wages (Dey & Flinn 2005), or the effect of gender differences on wages (Flabbi & Moro 2012).

new job opportunities appear, existing jobs are destroyed, the distribution of productivity, the prevailing wage paid to others in the industry, and the relative balance of bargaining power between workers and firms. Each of these parameters are identified in the structural econometric model developed in the next section. This model provides many insights into how we expect the market for truckers to function – insights that are not available from older theory in this area (Roy 1951), nor reduced-form models of labor market outcomes.

Flinn (2006) next solves the generalized Nash problem in (1) for the set of equilibrium wages, as a function of the primitives of the model. Equilibrium wages are determined from equation (1) by parameters that govern 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 govern equilibrium match-values, job creation and destruction, and labor productivity.

A nontrivial share of truck drivers are paid the minimum wage, so we follow the modeling approach of Flinn (2006) by allowing the minimum wage to affect the labor market equilibrium. 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 and is developed in more formal 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.

Our theoretical model of search, matching, bargaining, and wage determination generates a set of testable hypotheses regarding the performance of the market for truckers, and for trucking services. Importantly, these hypotheses are simply not testable with reduced-form econometric models of wage setting and determination as they follow from the structure of how we believe labor markets arrive at equilibria between firms searching for employees, and *vice versa.*

First, the difference between the rates of job creation (λ) and destruction (η) provide a measure of labor-market disequilibrium that we can use to explain changes in wages, and hence trucking rates over time. Namely, after estimating the parameters of the structural model, we can form a measure of disequilibrium, $\lambda - \eta$, that we interpret as the excess of firms looking for workers over the number of jobs that disappear each period, or of general market tightness. We expect higher values of this measure to be associated with higher wages, lower trucker-availability, and higher truck rates.

Second, we test the indirect effect of the COVID-19 pandemic, and the associated policy responses, on the degree of bargaining power possessed by truckers relative to the firms that hire them. That is, if the conditions that lead to the Great Reshuffling caused workers to move between firms at a higher rate, as suggested by our data, then we would expect to see higher values of α in periods immediately following the COVID-19 pandemic, relative to prior years. Greater bargaining power manifests in both higher wages, of course, and likely higher rates of transition between jobs as opportunities to use bargaining power typically only arise when workers are actively on the job market, moving either from one firm to another, or from unemployment back to employment. We describe how we test these hypotheses in the next section, beginning with a description of our data sources and a summary analysis, and then proceding with our empirical application of the theoretical framework after

3 Econometric Model of Bargaining

In this section, we summarize our data sources and identification strategy, and then follow with our application of Flinn (2006). We leave a detailed derivation of his econometric model to Appendix D, however, and refer interested readers, and those who may want a more detailed derivation of the econometric model, to the original article.

3.1 Data Sources and Identification

In this sub-section, we explain the sources of our data, how the key elements of our model are identified, and provide some summary and reduced-form evidence regarding the relationship between the market for truckers and truck rates, and characteristics of truck drivers more generally.

We combine three main data sources for our analysis: (1) USDA Specialty Crop Truck Rate Report (USDA-AMS 2022) for data on truck rates and truck service availability, (2) U.S. Bureau of Labor Statistics Quarterly Census of Employment and Wages (US-BLS 2022) data for aggregate trucker wages and employment by state, and (3) US Bureau of Census CPS data on individual trucker work experiences, including the length of any unemployment spell, their individual hourly wages, and demographic variables (Flood, et al. 2022). We describe each of these data sets in turn, including their temporal and geographical dimensions, and their role in our analysis.

First, we use monthly refrigerated truck-rate data from USDA-AMS data over the 2011 - 2021 time period for a large set of matched source-destination pairs, for several commodities, in order to measure the cost of trucking services and the USDA evaluation of trucking availability.[10] We interpret the per-mile prices for trucking services in the USDA truck rate data as a measure of the equilibrium price in the truck market. Availability in the USDA-AMS truck data consists of a Likert-scale index, compiled by AMS field staff that varies from 1 = high availability to 5 = low availability. We use all origin-destination pairs in the data for our statistical analysis below, but present summary data below for a select set of the most important source-destination pairs.

We begin by deriving some model-free evidence that examines trends in truck rates. We first summarize the USDA truck rate data for a period immediately before the COVID-19 pandemic (2019), and one after the worst of the pandemic was likely over, for a curated set of source-destination pairs (2021, table 1).[11] In general, the data in these tables show that

[10]The data are disaggregated over a large set of commodities and commodity pairs. For our empirical analysis, we select the 20 most important by frequency, including: Potatoes, onions, sweet potatoes, apples, potatoes and onions combined, apples and pears combined, melons, lettuce and mixed vegetables combined, carrots and grapes combined, cabbage, carrots, tomatoes, watermelons, mixed vegetables, citrus, citrus and avocados combined, pears, onions and potatoes (different combination), and asparagus. We control for item fixed effects in our summary regression below, but use weighted averages for summary purposes in table 1 and figure 1.

[11]Although our choice of 2021 as a comparison year is subjective, it was the first full year following the direct impact of the initial spread of COVID-19 and rates in 2021 are the most likely to be affected by the totality of the U.S. COVID stimulus policies that were enacted in 2020.

average truck rates, defined on a per-mile basis, increased in all of the source-destination pairs in the table, and increased an average of over 36.2% across all pairs (figure 1).[12] Among all destinations, Atlanta shows the largest increases (48.5%, averaged across all source-regions), which suggests that either demand pressures were particularly strong for goods in the Atlanta region or, more likely, it experienced greater cost pressures. If COVID-19 represented an accentuation of previous trends toward more short-haul trucking runs, due to the expansion of e-commerce, and a greater share of deadhead (empty truck) backhauls due to more point-to-point deliveries, then these higher truck rates are easily, but only partially, explained as inefficient use of more-expensive labor (ATRI 2021).[13] Indeed, because labor forms some 42% of the marginal cost (per mile) of operating a long-distance truck, it is likely that much of the geographic heterogeneity in cost is due to regional differences in wages (and the total cost of labor once benefits are included, ATRI 2021), and increases in labor-cost over time. Whether this is the case, however, requires more careful econometric analysis.

[Table 1 in here]

[Figure 1 in here]

Second, we measure aggregate wages at the state level over the 2011-2021 sample period using the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW). Our purpose in using the QCEW data is to determine whether there is any evidence of a summary relationship between earnings from the trucking sector and truck rates. If the summary evidence does not reveal a statistical link between truck driver earnings and truck rates, it would be difficult to justify a more in-depth examination into the causal impact of earnings on truck rates. In our structural analysis below, conducted at the level of the individual worker, we use individual wages using the CPS data. For purposes of this section, to determine whether further investigation is warranted, we merge the USDA truck rate

[12] Note that figure 1 presents an exhaustive set of source-destination pairs, including all markets in the USDA truck rate data, except for "Other" and "Indiana," which has only one source-destination connection. Table 1, however, is a curated sub-set of source-destination pairs in order to keep the table tractable and clear.

[13] Between 2018 and 2019, the share of deadhead deliveries rose from 16.6% of all trips, to over 21.0% (ATRI 2021). Trips with empty trucks represent pure cost, with no corresponding increase in revenue.

data with state-level trucking-wage data (NAICS industry code = 484) from the QCEW.[14] QCEW data is valuable in helping explain temporal and spatial variation in truck rates because it captures variation in labor costs in very specific industries, here the exact type of transportation labor covered by the truck rate data, and for state-level geographies that match the truck rate source descriptions. QCEW is relevant for this purpose as it is a census of wage and salary workers covered by U.S. state unemployment insurance laws. Consequently, it should encompass the majority of truckers in the U.S. Given that our analysis for this segment does not require data on aspects like job transition or demographic details of truckers—information not present in the QCEW—we favor using the QCEW over the CPS. We assume that truckers are paid a wage that reflects demand and supply conditions for trucking labor at the origin of the truck, and not its destination.

The results from our reduced-form regression models are displayed in table 2 below. Note that both the dependent and independent variables are expressed in logs, so the parameters on the continuous values (miles and wages) are interpreted as elasticities of truck rates with respect to each variable. Model 1 includes the distance variable as the sole regressor, Model 2 adds quarter, destination, source, and commodity fixed effects as well as a time trend, Model 3 adds the wage variable, and Model 4 includes a set of trucking availability index dummies where the reference group is comprised of categories 1 and 2 (a surplus or slight surplus of trucking services). Using the best-fitting model for interpretation purposes (Model 4, based on the R^2 value), truck rates trended upward over the 2011 - 2021 sample period by about 2.7% per year, which is in line with general price inflation over this time period. Perhaps as expected, truck rates are sharply lower in the first quarter than the fourth-quarter reference period, and rise sharply in the spring (Quarter 2) with a resumption of business in colder climates. Further, truck rates fall in distance traveled with an elasticity of about 0.43, meaning that a 10% increase in route-distance reduces the per-mile rate by

[14] We could use a more specific NAICS code for refrigerated products, or agricultural products in general (NAICS = 484230), but because trucker skills are fungible across types of trucking, general trucking-wage data is more relevant to the general trucker market.

some 4.3%. Clearly, trucking firms offer distance discounts as a considerable amount of the cost of operating a trucking route consists of fixed costs, including depreciation of the truck itself, administration, and other general expenses. Most importantly, we find that truck rates rise in the level of trucker wages with an elasticity of 0.17, and this elasticity is statistically significant at any reasonable level of confidence. Finally, the results in table 2 show that the USDA measure of availability, which is based on interviews with industry members, suggests that there is about a 1% difference in truck rates under conditions of observed shortage relative to either a "surplus" or "slight surplus" (availability categories 1 and 2). To summarize these findings, therefore, it is clear that there is indeed a strong relationship between trucker wages and truck rates, and that conditions of shortage lead to higher truck rates as well.

[Table 2 in here]

We provide more summary evidence on recent trends in the trucking industry by referring again to the QCEW data, but focusing specifically on the number of truckers in NAICS = 484. From the data in figure 2, we see that the number of truckers in the U.S. was increasing steadily through 2019 before falling sharply in 2020, and recovering in fits and starts through the end of our data in 2021. This figure shows that the looming shortage of truckers referred to in both the trade press and in our data does not appear to be driven by the number of employment-matches in the industry, but perhaps more to aggressive growth assumptions regarding future demand for truckers. Regardless, the growth in trucker demand since 2011 is clear, but perhaps constrained by the number of workers willing to become truckers. We provide further summary evidence on trends in job matches in Appendix B below.

[Figure 2 in here]

Our third data set provides data on individual-level job choices, compensation, and industry transitions that allows us to estimate the parameters of our econometric model of labor-market equilibrium. Specifically, we follow Burks & Monaco (2019) and Phares & Balthrop (2021) in using the Bureau of Census Current Population Survey (CPS) data, accessed through the University of Minnesota IPUMS data management system, again for the sample period 2011 - 2021 (Flood, et al. 2022). Unlike these other studies, however, we use longitudinal samples from the Annual Social and Economic Supplement (ASEC), which provide 12-month apart observations for each subject in the CPS sampling frame. The ASEC data uses the sample of March-only observations, and contains a unique CPS identifier that allows the ASEC data set to be merged with other CPS data sets. Within ASEC, we choose variables from the "Work," "Demographics," and "Core" data series in order to capture annual income, usual hours worked per week, number of weeks employed, and unemployed, as well as a host of demographic and socioeconomic variables. Importantly, the ASEC data contains information on the subject's occupation, and industry, both in the current period and 12 months previous.

Our sample from the CPS data is best described as repeated two-year observations (short panels) within a repeated cross-section framework. Following Burks & Monaco (2019), we restrict our sample to ASEC respondents who report a trucking occupation in either Year 1 or Year 2 of their reporting period, and who are legal to drive long-distance commercial trucks each year ($21 \leq \text{Age} \leq 65$). The total universe of all workers in the CPS ASEC sample from 2011 - 2021 is $N = 497,207$. Applying our age and industry restrictions, however, our estimation sample yields a total of $N = 8,133$ individuals.

Even within this sample, there are compelling reasons to analyze specific subsets of individuals who identify as truckers separately (Burks & Monaco 2019; Phares & Balthrop 2021). Specifically, the trucking industry in the U.S. is sharply segmented, consisting of a substantial number of "for hire" truckers (FHT), or those who work for trucking firms that contract out their services to firms who require transportation services, and "private carrier" truckers (PCT), who drive trucks for firms that own their own vehicles, and need their products delivered from one location to another. In our CPS sample, the share of truckers who are PCT is 75.3%, while the remainder (24.7%) are FHT.[15] Burks & Monaco (2019)

[15] An example of a FHT would be a trucker who drives for J. B. Hunt Transport Services, which is one of the largest trucking firms in the U.S., and an example of a PCT would be a trucker who drives for Walmart,

point out that there is a substantial difference between turnover rates in FHT and PCT, as the for-hire market is intensely competitive, so wages and benefits are not as attractive as in the PCT market.

We examine this question more carefully below, but begin by summarizing the CPS-ASEC data in table 3, averaged over the FHTs and PCTs each year, in order to provide a sense of more general trends in the trucker market. The data in this table show a remarkable degree of both demographic and economic stability in the industry, with very little change in the profile of what the typical truck driver in the U.S. looks like, and how much they work. On average, over the entire sample period, a trucker works approximately 35 hours per week, for 44.4 weeks of the year, earning $18.69 per hour, and is about 45.5 years of age, with 12.4 years of schooling, and is male with a probability of 92.4%. Other than the hourly wage, which drifts upward at a rate of $0.645 per hour per year, the work and demographic profile changes little from year to year.

[Table 3 in here]

These summaries, however, are averaged over the FHT and PCT sub-sectors. As a result, any distinctions in turnover rates between the two might be obscured when we examine them together. In table 4, we compare the hourly wages and usual hours worked between for-hire and private-carrier drivers in the CPS ASEC data, as a comparison to table 2 in Burks & Monaco (2019), who argue that it is essential to treat for-hire and private-carrier drivers separately, as their jobs are "systematically different." The data in our table 4 show that for-hire drivers do indeed work more hours, in every year of our sample, relative to private-carrier drivers, but the wage premium enjoyed by for-hire drivers thought to be a feature of the data is not true in any year of the sample, and does not appear to be a rule in our more-recent data.[16] In 2021, for example, even the large absolute gap in hourly wages ($10.50 /

moving goods from distribution centers to stores, or from import points to distribution centers.

[16] In Appendix C, we present a replication of the summary data in Burks & Monaco (2019) and similar data in Phares & Balthrop (2021) on job transitions between trucking and other industries in order to demonstrate the similarity of the CPS-ASEC data to their CPS-ORG data. Our insights from this analysis is indeed similar to theirs, although our turnover rates are substantially lower – roughly 74.4% of sample respondents who were truckers in the previous period remain truckers in the next period. This is much lower

hour premium for for-hire drivers) is not statistically significant due to the large spread in wages that emerged after the COVID-19 pandemic. This finding is both interesting, and indicative of the lengths for-hire companies went to in 2021 in order to attract drivers from other industries. Regardless, this comparison suggests that it may indeed be necessary to control for differences in for-hire and private-carrier truckers in terms of their hourly work commitments, and in their hourly compensation if we seek to explain the changes that occurred in the trucking industry between 2019 and 2021. In our empirical analysis below, we account for the differences between truckers in each sub-sector through a set of fixed effects.

[Table 4 in here]

In order to estimate the likelihood function in (17), we require sufficient variation in unemployment spells, wages, and minimum wages at the individual level in order to identify each of the parameters in the model. The summary data presented in tables 3 and 4 suggest that there is indeed substantial variation over individuals in the sample, but we also exploit the longitudinal nature of the ASEC March samples in order to leverage both variation across individuals at each point in time, and within individuals from the first to second reporting period. We also control for state, job, sector, FHT and PCT status, demographics, and citizenship effects in order to isolate the variation in job choice and bargaining power. Flinn (2006), however, notes that the bargaining power parameter (α) is easier to identify when the model is estimated with both supply and demand-side information. Demand-side information is defined as data that captures likely variation in the marginal value product of hired workers, which depends on the productivity of the worker, and the price of his or her output. Flinn (2006) uses a single observation of the ratio of labor compensation to output for a major fast-food chain in order to identify α, but our aim is to estimate the contribution of labor to the rise in trucking rates for agricultural products.[17] Therefore, we incorporate

than the 90%+ turnover rate claimed by industry sources (ATRI 2021). Expressed as a percentage of the number of truckers each period who either enter, exit, or remain in the industry, the average is closer to 45% (see Figure 3).

[17]Flinn (2006) uses a series of Monte Carlo experiments under different parametric assumptions for the

demand-side information in a manner similar in concept to Flinn (2006), but we include more variation over time and across industries.

Our approach is the following. First, we obtain data on the labor-share of revenue for workers for the trucking industry (NAICS = 484) for each year in our data. Our revenue data is defined as total gross receipts for all firms, which is taken from the U.S. Bureau of Labor Statistics (BLS) Multifactor Productivity data, along with the trucking sector labor compensation measures. Our assumption in using these data is that the labor share of revenue captures variation in the marginal revenue product of workers in the trucking industry 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 (17) 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).

3.2 Empirical Application

Our application involves a number of extensions to the base search, match, and bargaining model developed above. First, minimum wages are an important feature of the market for truckers, so we follow Flinn (2006) and account for the likelihood that a worker is actually paid at, or near, the minimum wage by including the probability that a worker is paid the minimum wage in estimating the equilibrium wage equation. Second, we allow the employment surplus earned by truckers, α, to vary between pre- and post-COVID-19 periods in order to test whether there is any structural evidence that truckers were able to use alleged shortages to increase their bargaining power *vis a vis* employers. Third, we explicitly account for demographic, job description and state-level factors that may otherwise explain variation

distribution of match values, G, to show 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 our CPS sample, this hypothetical sample is many times larger than our actual sample ($N = 8,133$), so we may need something more.

in observed wages in estimating our model parameters by estimating the model in "hedonic corrected" wages, or wages with each of these influences removed. In this section, we provide an intuitive explanation of the empirical model in Appendix D.

We assume labor markets are imperfect, in the sense that workers search for jobs while unemployed, possess match-specific capital, and experience search frictions and other forms of search cost that may lead to imperfect matches (Burdett and Mortensen 1998; Pissarides 2000, 2011). After workers find a matching employer, and *vice versa*, the parties bargain over wages according to a Nash (1951) bargaining process. Because of these market imperfections, employers and employees share the rents that arise due to the match, or the difference between the inherent productivity of the worker and the threshold wage that leads the worker to accept the position. Using the Flinn (2006) empirical model that is based on these assumptions, we identify each of the structural parameters described above with only observations on equilibrium wages for worker i (w_i), the length of any spell of unemployed search (t_i), and the minimum wage they face (m_i).

As we show in Appendix D, the structural econometric model that follows from equation (5) uses variation in wages and unemployment durations to estimate the parameters that underlie the log-normal distribution of employee-employer match-productivity (μ and σ), the rates of job creation (λ), and destruction (δ), the threshold match value that induces workers to accept a job offer (θ^*), and the parameter that allocates the share of match-rents between workers and employers, or the bargaining power parameter (α). The likelihood function that follows from (5) is derived more formally in Appendix D, so we only explain the intuition here.

The likelihood function addresses the three regimes in the data: Workers who are unemployed for a duration of length t_i, workers who are hired and paid a minimum wage (m_i), and workers who are hired and paid a wage above the minimum (w_i). These three regimes represent the probability of remaining unemployed for a certain length, the probability of being employed in a minimum wage job, and being paid in a relatively high wage job, respectively. The regimes are exhaustive of all subjects in our CPS data, so the wage and unemployment variation in our sample are sufficient to identify all of the parameters of the model. We refer readers to the Flinn (2006) article for more details, and for extensions that consider endogenous contact rates (rates at which employees take jobs that are offered).

Recall that our primary hypothesis maintains that trucker bargaining power increased in the post-COVID period, due to the apparent shortage of truckers. We test this hypothesis by allowing the bargaining power parameter (α) to vary between the pre- and post-COVID regimes in our data.[18] We also recognize that identifying regime-varying bargaining power requires that we control for unobserved individual heterogeneity, so allow the bargaining power to also vary randomly over our sample subjects, so that $\alpha = \alpha_0 + \alpha_1 \nu$, where $\nu \sim N(0, 1)$. We estimate the model that results using simulated maximum likelihood, and control the number of draws using Halton sequences as is common in this literature.

4 Results and Discussion

In this section, we present our findings, and provide some evidence of their robustness. We begin by presenting the estimates from different specifications of our structural model in equation (17), and interpret the estimates in terms of their implications for labor-market equilibrium and bargaining power. Next, we use the structural parameter estimates to generate a market disequilibrium variable, which is used as the main explanatory variable of interest in a regression model. We use this regression framework to quantify the extent to which labor-market disequilibrium influences truck rates and truck service availability as reported by USDA-AMS.

Our structural model estimates are in table 5 below. In this table, we show estimates from a base model (Model 1), a model that uses demand-side information to help identify the bargaining power parameter (Model 2), a model that extends Model 2 by allowing bargaining to vary between pre- and post-COVID-19 regimes (Model 3), and a final model that builds

[18] Our CPS-ASEC are only reported annually, and we recognize that a more granular analysis of specific COVID-19 programs would require monthly data.

on Model 3 by allowing bargaining power and the rates of job creation and destruction to vary across all of the observations in our data set (Model 4). We interpret the findings from each of these models in turn.

[Table 5 in here]

The parameter estimates from Model 1 suggest that jobs were created in the trucking industry over our sample period at a rate of approximately 22.7% per year, while jobs disappeared only at a rate of about 0.3% per year. This not only suggests a relatively rapid rate of job creation, but a slow rate of job loss. We return to the importance of this difference below, but we interpret the difference between these two estimates as a measure of disequilibrium in the market, as they would be exactly equal if the rate of job creation were exactly equal to the rate of job destruction. In our structural model, the amount of surplus in the employment transaction – or how much profit the trucking company makes from hiring a worker at the estimated match value – is equal to the difference between the point estimate of the expected value of θ (the implicit value of a match), and the critical match-value estimate (θ^*). Calculated from the estimates in Table 5, under the assumption of log-normality for G, the implicit value of a match in the trucking industry is $20.34 in the base model, while the critical match value, or the value necessary to induce labor supply, is only $4.60.[19] Therefore, our model estimates suggest an employment surplus of $15.74 per hour. Of this surplus, the bargaining power estimate of 38.3% implies that the employee retains some $6.03 per hour, while the employer retains the remainder. In general, our bargaining power estimate is high relative to others in this literature (Dey & Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, & Robin 2006), albeit in very different contexts.

In Model 2, we include demand-side information on the revenue-share of trucker compensation in the industry to help identify the bargaining power parameter. Comparing the fit of Model 2 with Model 1 using a likelihood ratio test ($LR = 2 * (LLF_1 - LLF_0) \sim \chi^2$),

[19] Note that, because wages are expressed on a $/hour basis, the units of measure for all parameters in the model are the same. From the perspective of the trucking firm, therefore, the value represents the implicit productivity of a worker, measured on a per hour basis.

we find that Model 2 provides a substantially better fit to the data ($LR = -16,656.5$), so we conclude that demand-side information does produce a better model, simply in terms of fitting the data. Despite the improvement in fit, the parameter estimates from Model 2 are very similar to those reported from Model 1, except for the rates of job creation and destruction. Namely, the estimate of λ from Model 2 implies a much higher rate of job creation (28.1%) and lower rate of job destruction (0.1%). In terms of employment surplus, however, adding demand-side information leads to a slightly lower equilibrium match value ($20.16) and nearly identical critical match value ($4.62), so the implied level of employment surplus is slightly lower, at $15.54 per hour. Further, the employee share is also lower (36.9%), which means that employees earn on average $5.73 of employment surplus per hour. The fact that these two models produce estimates of employee returns that differ by only 5.2% suggests that the model is robust to changes in specification.

The next two models – Model 3 and Model 4 – allow the bargaining power parameter to differ in the post-COVID-19 era, and all of the key parameters to vary randomly over CPS-ASEC sample members, respectively. Because the estimates from these two models are so similar, and Model 4 produces a significant improvement in fit ($LR = -4,938.3$), we will only interpret the estimates from Model 4. Somewhat surprisingly, the estimates from this model are very close to those of Model 1, with rates of job creation and destruction 22.9% and 0.5%, on average. Further, the marginal value of an employment match to firms is $17.34 per hour, and the critical match value from the employees' side is just over $4.5 per hour, so the amount of employment surplus is $12.81 per hour. Accounting for the mean level of bargaining power over the sample (again 38.3%), employees earn $4.91 of employment surplus per hour. In the post-COVID-19 era, we find that bargaining power rises by a small, yet statistically significant 0.5%, so workers earn $4.97 of employment surplus per hour, or a $0.06 per hour rise just due to the labor-market tightness associated with COVID-19 recovery, and the associated exodus.

In Model 4, we allow the parameters that estimate the rates of job creation and destruction to vary by observation, so we are able to recover a measure of labor market disequilibrium, or the difference between these two values, for every observation. We interpret this variable as a measure of "disequilibrium" as it is akin to the ratio of openings to hires in Figure 4 in Appendix B – when this value rises, the number of potential matches available to be made rises above the matches that dissolve. In this sense, it measures the net number of employers that are seeking employees. Empirically, allowing this measure to vary over the entire data set means that we have a measure of disequilibrium for all regions and time periods in the data. As a final step, we estimate simple regression models with the disequilibrium rate and distance as explanatory variables, explaining variation in the regional truck rate each year. We estimate a similar model in which we explain the USDA measure of trucking availability described above. Our models include region fixed effects to control for time-invariant regional factors and year fixed effects to control for time-varying factors common to all regions. We also estimate a separate random parameters model to account for other sources of unobserved heterogeneity.

Our hypothesis is that as our measure of disequilibrium rises, truck rates should rise as employers are bidding up wages to attract additional workers so their costs rise. On the other hand, a higher rate of disequilibrium means that there are fewer effective matches being made if labor supply falls, so the availability of trucking services should fall. Because the USDA availability index is defined such that higher values indicate lower availability, or a greater likelihood of shortage, we hypothesize a positive relationship between our disequilibrium measure and the USDA availability index.

We present estimates from these regressions in table 6 below. In the upper panel, we show the relationship between labor shortages (disequilibrium) and truck rates, controlling for distance, yearly fixed effects, and source-region effects (sources are the USDA-AMS truck rate sources identified in figure 1). The estimates in this table suggest that there is a positive relationship between disequilibrium and truck rates. Interpreted at the means of the data, the estimates from the preferred model (Model 2) suggest that a rise in the disequilibrium gap from 22.4% to 23.4% is associated with a \$0.03 / mile rise in truck rates, or from \$3.31 to \$3.34 per mile. While this effect is small, the range of the disequilibrium gap over the entire sample is roughly 17.0% to 28.0%, and it is statistically significant, so our estimate implies that an 11-point change in the gap means that rates can change by \$0.37 / mile, simply in response to labor-market tightness. Expressed differently, our estimates imply an elasticity of truck rates with respect to disequilibrium of 0.028 – inelastic, to be sure, but economically important when labor markets are changing quickly, and large disequilibria likely.

Similarly, in the lower panel of table 6 we show the estimates from a regression of the USDA availability index on our measure of disequilibrium. We interpret the coefficient on the disequilibrium variable as the marginal effect of a percentage-point change in the gap between job creation and destruction on the USDA availability index, so an estimate of 0.95 in the preferred model means that a percentage-point rise in the gap between creation and destruction leads to a 0.95 point rise in the index, which means a decrease in availability.[20] Recall that our definition of disequilibrium is the difference between job creation and destruction, so as more jobs are created than lost, there is clearly more demand for truckers than there is effective supply, which will appear as a shortage of truckers. At the means of the data, this means that a rise in the disequilibrium gap from 22.4% to 23.4% is associated with a rise in the availability index (a greater likelihood of shortage) from 3.33 to 3.42, or an elasticity of 0.08 - still inelastic, but substantially more elastic than the wage-sensitivity to disequilibrium.

[Table 6 in here]

Our findings are important both for management purposes in the trucking industry, and for policymakers interested in agricultural supply chain disruptions arising from the transportation sector. From a managerial perspective, our findings suggest that there is a persistent tightness in the market for truckers that appears to have been made worse by the

[20]We aggregate the integer availability index over all commodities from a particular source region, so the dependent variable is no longer an integer measure. We attempted to control for both regional and commodity fixed effects in these regressions, but the correlation between regions and commodities was too high to produce reliable regression estimates.

COVID-19 pandemic, and policy responses to it. While truckers may indeed be responding to economic incentives as in Burks & Monaco (2019) and Phares & Balthrop (2021), there appears to be deeper problems in the market for truckers as the gap between jobs being created and destroyed suggests a disequilibrium gap that is not getting smaller. We find a smaller rate of job turnover than reported by industry sources, but turnover is not necessarily a problem when the value of a match exceeds its cost. As market tightness leads to greater bargaining power exercised by workers, the cost of finding matches is rising, and there are fewer and fewer value-creating matches than there were before the pandemic.

From a policy perspective, it appears that the incentive to remain out of the labor force, or to change jobs in search of higher wages once in the labor force, is feeding into the inflation cycle. Labor shortages lead to higher wages, which lead to higher truck rates and higher operating costs for farm businesses that use trucks, or at least contract for trucking services. Although higher unemployment benefits during the COVID-19 pandemic, and looser monetary policy to spur economic activity, may have both had the desired effect of lessening the damage from the pandemic itself, it appears as though much of the long term damage will be felt through the labor market and the associated rise in costs throughout the product supply chain. Tackling food-price inflation, therefore, may be more difficult than initially thought if the primary cause comes from supply-chain tightness and not monetary sources.

In terms of agricultural supply-chain resilience, our findings highlight the idea that prices – both wages and prices for trucking services – are indirect measures of supply chain resilience. When supply chains experience shocks from either demand- or supply-side factors, prices embody the incentives felt by agents on both sides of the market to move toward a new, hopefully stable, equilibrium. Further, we show that labor-market shortages can contribute to a lack of resilience, and that labor-markets policies should take the implications for resilience into account.

5 Conclusions

In this paper, we examine how the labor market for truckers affects the price of trucking services. Worker turnover is an ongoing problem for trucking company owners, and many others in the literature have examined the empirical drivers of turnover, and whether the market for truckers appears to function normally. We take a different approach, and present the problem of turnover directly as an equilibrium phenomenon. That is, we frame our main analysis in terms of a structural model of job search, matching, and bargaining in which workers search optimally, bring match-specific capital to negotiations with potential employers, and then bargain for wages according to an axiomatic Nash bargaining process. We estimate our model using an individual-level data set drawn from the CPS-ASEC universe, which we merge with productivity data from the Bureau of Labor Statistics in order to help identify the key bargaining parameter. We then use the estimates from our structural model to help explain truck rates, and the availability of trucking services over time.

Our reduced-form analysis shows that trucker wages, perhaps as expected, are strongly related to the cost of trucking services. We also find evidence, mostly from other data sets, that job openings are increasing rapidly in the trucking industry, and the newly-open jobs are not necessarily being taken by available workers. Our structural findings are consistent with this summary evidence, as we find that the trucker market appears to be in persistent disequilibrium, with new jobs created at a far greater rate than existing employment relationships are dissolved. Perhaps as a result of the growth in trucking jobs, we find that truckers enjoy a level of bargaining power that is both higher than in most other industries (38%) and rose significantly through the COVID-19 pandemic. We also find that the extent of disequilibrium is a significant explainer of both higher truck rates, but greater availability of trucking services as trucking firms create more jobs than are lost over time.

Our findings are important both for managerial and policy purposes. Owners and managers in the trucking industry understand that there is a shortage of drivers, and know that turnover rates are very high, but they likely do not know the empirical value of an employment match, and how much a new worker is worth to their firm. Specifically, our estimates show that the surplus created through the employment relationship in the trucking industry is about \$12.81 per hour, while truckers, even after the rise in bargaining power associated with the COVID-19 pandemic, earn only about 1/3 of this total. On a deeper level, our analysis points to the central position of labor in the supply chain – until autonomous trucks become a viable option, truckers are necessary to ensure trucks can operate, and how much they are compensated determines the cost of trucking services. On the policy level, arguably, price inflation is one of the most important policy problems, both in the U.S. and in Canada, that emerged from the COVID-19 pandemic. Our findings show how labor market disruptions can contribute to price inflation through higher wages, and that higher wages are, in turn, a structural outcome from not having enough workers take the jobs that are available.

Although we frame our research in a U.S. setting, and use data describing the U.S. trucking experience, we believe our findings have important implications for the Canadian agricultural trucking industry. Gill & MacDonald (2013) document a similar shortage of drivers in Canada as others document in the U.S. (Burks & Monaco 2019), so we can expect that truck rates likely rose by similar amounts in Canada during the COVID-19 pandemic and are headed in the same direction until the shortage of drivers is addressed. However, to the extent that the trucking industry in Canada is nearly as competitive as the U.S. market we study here, rates are bound to be as resilient to shocks like COVID-19 as we show in this paper.

We make use of several related data sets, but our analysis could be improved with more detail on specific trucking contracts. Because our trucker data are at the individual-job level, and the truck-rate data are aggregated over routes and products, the relationship between equilibrium in the market for truckers and truck rates is only indirect. Second, while the number of respondents in the CPS-ASEC data set is very large, once filters are applied to narrowly describe workers in the trucking industry, the sample size becomes relatively small. A deeper data set on job choice in the trucking industry would be an improvement. Third, the CPS-ASEC data are only reported annually, but a more detailed analysis of specific COVID-19 programs would use data that followed worker experiences on a monthly, or more frequent, basis. Finally, we control for as much heterogeneity in the trucker job market as practical in our analysis, but there is much more variety in the types of jobs that are actually done that may explain some of our findings.

6 Appendix A: Minimum Wages

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:

$$w(\theta, V_n(m)) = \alpha\theta + (1-\alpha)\rho V_n(m), \tag{6}$$

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

$$\hat{\theta}(m, V_n(m)) = \frac{m - (1-\alpha)\rho V_n(m)}{\alpha}, \tag{7}$$

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 (6) 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:

$$\rho V_n(m) = b + \frac{\lambda}{\rho + \eta}\left\{\int_m^{\hat{\theta}}[m - \rho V_n(m)]dG(\theta) + \alpha\int_{\hat{\theta}}[\theta - \rho V_n(m)]dG(\theta)\right\}, \tag{8}$$

so the new equilibrium wage distribution that solves equation (8) 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 (6):

$$pr(w; V_n(m)) = \left\{ \begin{array}{ll} [g(\hat{\theta}(w, V_n(m))]/\alpha G(m), & w > m \\ [G(m) - G(\hat{\theta}(w, V_n(m)))]/G(m), & w = m \\ 0, & w < m \end{array} \right\}, \tag{9}$$

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.

7 Appendix B: JOLTS

In this appendix, we document trends in the number of job openings, and hires in the trucking industry. Consistent with the industry narrative of a persistent and worsening shortage of workers in the trucking industry, the data in Figure B1 below shows that the ratio of job hires to job openings in the trucking industry between 2011 and 2021 fell from 1.87 – or nearly 2 job openings for every new hire – to 0.6 or slightly more than half of all job openings are filled. The data in this figure supports the notion that labor shortages in the trucking industry may be due as much to a skills mismatch as they are to either shortages in the number of people willing to work, or work only part time as there are far more open positions than successful matches, even when unemployment was relatively high in 2020. The data in this figure also suggest that industry projections of growing shortages of truckers may indeed be true as the gap between openings and matches is due mostly to rising demand, rather than a decline in the supply of workers.

[Figure B1 in here]

8 Appendix C: Job Turnover

In this appendix, we provide summary data on job turnover among truckers in our sample data. For purposes of Table C1 below, we focus only on CPS-ASEC respondents who report working in the trucking industry in either the first or second period of the ASEC longitudinal survey. If they report work as a trucker in the first and second period, they are determined to have stayed in the industry, but if they report working as a trucker in the first period and something different in the second, they are defined as an "exiter." Similarly, if they were not a trucker in the first period, but report working as a trucker in the second period, they are defined as an "entrant." For each entrant and exiter, we report the industry they either entered from (or from unemployment) or exited to, including unemployment. In general, the data in Table C1 suggests that truckers tend to enter from and exit to office work, other jobs in transportation – likely dock workers and others closely related to the trucking or logistics activity, and unemployment. Of all those who were truckers in the first period, fully 74% stay as truckers in the next period. Normalized by the numbers who either enter, exit, or stay in the industry, the proportion of truckers who remain truckers is closer to 45% each year. Consistent with the data presented in the text, this summary data suggests that turnover in the trucking industry is not nearly as problematic as industry sources would suggest (ATRI 2021).

[Table C1 in here]

9 Appendix D: Likelihood Function Derivation

In this appendix, we summarize the likelihood derivation in Flinn (2006) as it applies to our sample of CPS-ASEC workers in the trucking industry. We depart from Flinn (2006) by allowing the bargaining parameter, α, to vary systematically with a COVID dummy that takes a value of 1 during or after the year 2020, and 0 before. In this section, we derive the likelihood function from Flinn (2006) based on the structural model of labor-market equilibrium above that accounts for features of the trucking market, and captures the likely effect of the COVID-19 pandemic on drivers' decisions to enter, or to exit, the industry.

We begin our equilibrium search-and-bargaining model with the approach taken by Flinn (2006), but modify his approach to suit our application to the CPS-ASEC data described above, and the unique nature of the trucking industry. 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 (dropping the i individual subscript for clarity):[21]

$$f_u(t|u) = \lambda G(m) \exp(-\lambda G(m)t), \tag{10}$$

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:

$$pr(u) = \frac{\eta}{\eta + \lambda G(m)}, \tag{11}$$

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

$$f(t, u) = \frac{\eta \lambda G(m) \exp(-\lambda G(m)t)}{\eta + \lambda G(m)}, \tag{12}$$

and we adopt the usual assumption that G is log-normal, so $G(\theta) = \Phi((\ln(\theta) - \mu)/\sigma)$, where Φ is the standard normal distribution function, μ is the mean, and σ is the standard deviation.

We account for workers who are paid at, or near, the minimum wage by including the probability of a worker falling into the set of minimum-wage workers, and variation in the share of rents earned by these workers. In general, allowing for minimum-wage workers is necessary to identify the parameters of our model as the share of rents earned by employees constrained by the minimum wage will differ from the rest of the sample. 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. More formally, the likelihood contribution from minimum-wage employees is given by:

$$pr(w = m, e) = \frac{\lambda \left[G(m) - G\left(\frac{m - (1-\alpha)\rho V_n(m)}{\alpha} \right) \right]}{\eta + \lambda G(m)}, \tag{13}$$

[21] 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.

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:

$$f(w|w > m, e) = \frac{\frac{1}{\alpha} g\left(\frac{w-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{G\left(\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}\right)}, \tag{14}$$

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:

$$pr(w > m|e) = \frac{G\left(\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{G(m)}, \tag{15}$$

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

$$f(w, w > m, e) = \frac{\frac{\lambda}{\alpha} g\left(\frac{w-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{\eta + \lambda G(m)}. \tag{16}$$

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:

$$\begin{aligned} LLF = {} & [\ln(\lambda) - \ln(\eta + \lambda G(m))] + \delta_U[\ln(\eta) + \ln G(m)] - \\ & \lambda G(m)\delta_U t_i + \delta_M \ln\left(G(m) - G\left(\frac{m-(1-\alpha)\theta^*}{\alpha}\right)\right) - \\ & \delta_H \ln(\alpha) + \delta_H \ln\left(g\left(\frac{w_i-(1-\alpha)\theta^*}{\alpha}\right)\right), \end{aligned} \tag{17}$$

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 above, we obtain estimates of the key parameters that characterize the labor-market equilibrium, including the bargaining power parameter that shows the share of total employment surplus earned by workers.

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Table 1. Change in Truck Rates for Selected Origin and Destination Pairs: 2019 versus 2021

	Destination											
Source	Atlanta		Baltimore		Boston		Chicago		New York		Philly	
	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021
Arizona	$2.67	$3.41	$2.65	$3.14	$2.57	$3.07	$2.49	$3.06	$2.66	$3.19	$2.65	$3.13
California	$2.41	$3.82	$2.41	$3.64	$2.38	$3.53	$2.25	$3.58	$2.44	$3.61	$2.41	$3.61
Florida	$2.54	$3.49	$2.28	$3.21	$2.43	$3.28	$1.75	$2.56	$2.52	$3.62	$2.30	$3.22
Great Lakes	$3.34	$3.99	$3.78	$4.49	$3.47	$4.16	$4.17	$4.51	$3.94	$4.73	$3.73	$4.25
Mexico-Arizona	$2.46	$3.38	$2.47	$3.46	$2.54	$3.45	$2.13	$2.95	$2.36	$3.50	$2.37	$3.51
Mexico-Texas	$2.32	$3.29	$2.31	$3.18	$2.28	$3.06	$2.15	$2.78	$2.41	$3.27	$2.28	$3.16
Midatlantic	$2.46	$4.17	$8.90	$11.33	$3.96	$5.87	$1.71	$3.03	$6.14	$6.98	$7.29	$9.05
New York	$2.54	$4.63	$4.96	$6.82	$9.98	$14.79	$3.27	$5.40	$10.70	$14.31	$6.87	$10.15
PNW	$2.38	$3.04	$2.36	$3.12	$2.31	$3.08	$2.43	$3.00	$2.44	$3.26	$2.37	$3.07
Southeast	$5.23	$6.47	$5.23	$5.91	$3.82	$4.47	$3.12	$4.10	$4.40	$5.23	$4.59	$5.09
Texas	$2.56	$4.19	$2.40	$3.77	$2.35	$3.62	$2.27	$3.46	$2.56	$3.74	$2.42	$3.75

Note: Data are from selected destination markets from the USDA-AMS Speciality Crop National Truck Rate report. Rates are average, per-mile rates over the 2019-2021 sub-sample period. NA refers to a Region-Destination pair that does not appear in the USDA-AMS data. Data are averages over all commodities shipped. Average rate of increase over all destination-origin pairs in the data is 36.20%.

Table 2. Reduced-Form Regression Models: Truck Rates

	Model 1		Model 2		Model 3		Model 4	
	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
Constant	0.9515***	0.0226	0.4441***	0.0695	0.5612***	0.0686	0.5622***	0.0684
Trend			0.0319***	0.0008	0.0270***	0.0015	0.0272***	0.0015
Quarter 1			-0.0547***	0.0036	-0.0343***	0.0063	-0.0277***	0.0062
Quarter 2			0.0246***	0.0095	0.0358***	0.0097	0.0355***	0.0085
Quarter 3			0.0049	0.0081	0.0085	0.0080	0.0158***	0.0077
Distance	-0.2968***	0.0292	-0.4241***	0.0247	-0.4246***	0.0248	-0.4260***	0.0247
Wages					0.1789***	0.0388	0.1725***	0.0394
A = 3							-0.0733***	0.0064
A = 4							-0.0409***	0.0042
A = 5							0.0089***	0.0041
Destination?	No		Yes		Yes		Yes	
Source?	No		Yes		Yes		Yes	
Item?	No		Yes		Yes		Yes	
R^2	0.3771		0.7919		0.7925		0.7962	
F	106,701.90		15,244.37		14,961.68		14,347.44	

Note: All data from USDA-NASS Refrigerated Truck Rates data, and US Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW). N=176,303. Trend is an annual time trend, Quarter(i) are quarterly indicator variables, Distance is the source-destination pair distance in miles, Wages are the log of annual-average weekly wages in NAICS = 484 in the Source region, Availability is the USDA-AMS indicatore of availability, with A = 3 representing adequate supply and A = 5 representing a shortage of trucking services. All data are in logs, so coefficients represent elasticities of truck rates with respect to each explanatory variable. Standard errors are clustered at the source-destination pair level. A single asterisk indicates significance at a 10% level, ** at 5%, and *** at 1%.

Table 3. Summary of CPS Trucker data: 2011 - 2021

Year	N	Hours #		Weeks #		Wage $ / Hr		Age Years		Gender % Male		Education Years		Citizenship % Non-Citizen	
		Mean	Sdv.	Mean	Sdv.	Mean	Sdv.	Mean	Sdv.	Mean	Sdv.	Mean	Sdv.	Mean	Sdv.
2011	831	31.790	21.612	42.199	17.205	14.942	21.532	44.725	11.105	0.934	0.248	12.302	1.630	0.071	0.257
2012	864	33.795	21.049	44.222	15.668	17.670	34.695	45.170	11.613	0.939	0.239	12.194	1.738	0.090	0.286
2013	833	32.681	20.760	43.686	16.462	16.526	22.615	45.140	11.282	0.941	0.235	12.338	1.751	0.085	0.280
2014	827	35.611	18.921	44.403	15.867	16.683	26.838	46.068	11.094	0.904	0.294	12.331	1.749	0.094	0.293
2015	642	34.934	18.452	45.034	15.731	16.196	14.474	45.238	11.665	0.944	0.231	12.240	1.856	0.095	0.293
2016	720	35.687	19.530	46.119	13.957	19.738	32.358	45.181	11.912	0.933	0.250	12.314	1.837	0.084	0.277
2017	709	35.954	18.308	46.380	13.738	20.556	34.234	45.889	11.991	0.925	0.263	12.509	1.712	0.073	0.261
2018	733	36.014	18.900	46.723	13.267	20.124	27.040	45.953	11.916	0.911	0.285	12.349	1.627	0.074	0.262
2019	703	35.939	18.772	46.293	13.914	20.451	26.547	45.252	12.485	0.910	0.287	12.501	1.813	0.083	0.276
2020	664	35.225	19.483	45.927	14.475	21.185	28.908	45.629	12.407	0.906	0.292	12.425	1.623	0.075	0.263
2021	604	34.613	18.806	44.405	15.360	21.502	20.463	45.788	12.327	0.918	0.275	12.433	1.806	0.084	0.278

Note: Year 2 of CPS ASEC data for each individual, sample averages. Data are averaged over all industries and occupations within general "trucking" occupational classification (averaged over for-hire and private-carrier truckers). Age limits between 21 years of age, and less than 65 years of age, so legal to own commercial trucking license in all states.

Table 4. Private-Carrier vs For-Hire Trucking

	Private-Carrier Trucking						For-Hire Trucking			
		Hours		Hourly Wage			Hours		Hourly Wage	
Year	N	Mean	Sdv.	Mean	Sdv.	N	Mean	Sdv.	Mean	Sdv.
2011	618	38.290	15.343	20.570	22.685	213	44.756	15.997	23.683	33.431
2012	638	39.898	14.971	24.804	53.103	226	46.898	15.213	23.597	32.335
2013	649	40.379	14.077	21.259	25.189	184	45.603	18.355	20.808	18.006
2014	626	39.599	14.351	21.440	46.314	201	44.856	15.657	17.868	12.128
2015	475	39.568	14.120	23.396	86.482	167	46.994	13.712	19.871	12.008
2016	551	40.906	13.483	23.528	33.022	169	47.219	13.378	21.293	13.421
2017	531	39.727	14.370	25.925	52.179	178	46.006	14.023	29.690	57.542
2018	550	41.893	13.307	22.905	31.066	183	45.344	16.726	20.319	14.031
2019	527	40.429	14.098	22.795	28.764	176	45.409	14.261	23.892	17.372
2020	504	39.492	13.501	28.937	71.352	160	46.788	15.369	25.366	17.584
2021	456	38.879	13.928	24.422	20.981	148	45.318	16.159	34.922	74.716

Note: Data are from U.S. Census Bureau, Current Population Survey (CPS) Annual Economic Supplement (ASEC) for drivers defined to be in the for-hire (IND = 6170) or the private -carrier (IND = all else) market segments. Sdv. = standard deviation.

Table 5. Structural Model Estimation Results

	Model 1		Model 2		Model 3		Model 4	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
λ	0.2271***	0.0077	0.2806***	0.0081	0.1963***	0.0065	0.2293***	0.0049
η	0.0028***	0.0006	0.0013***	0.0003	0.0015***	0.0003	0.0054***	0.0001
μ	2.8781***	0.0153	2.9255***	0.0070	2.7899***	0.0105	2.7813***	0.0047
σ	0.5189***	0.0100	0.3961***	0.0030	0.3897***	0.0059	0.3792***	0.0018
θ^*	4.5958***	0.0203	4.6152***	0.0178	4.3800***	0.0157	4.5302***	0.0190
α	0.3827***	0.0017	0.3690***	0.0015	0.3527***	0.0014	0.3829***	0.0017
COVID					0.0042***	0.0012	0.0049***	0.0001
State Effects?	Yes		Yes		Yes		Yes	
Job Effects?	Yes		Yes		Yes		Yes	
Demographics?	Yes		Yes		Yes		Yes	
FHT?	Yes		Yes		Yes		Yes	
COVID?	No		No		Yes		Yes	
Random Parameters?	No		No		No		Yes	
LLF	-2,435.7		7,392.5		2,169.2		-300.001	
AIC/N	0.312		-0.994		-0.276		0.029	

Note: All models estimated with Current Population Survey (ASEC, Bureau of Census) data. Model 1 is base model with no demand-side information for α. Model 2 is base model with labor-share-of-revenue data used to identify the bargaining power parameter. Model 3 is Model 2 with heterogeneity in bargaining. Model 4 is Model 3 with random variation in α. A single asterisk indicates significance at a 10% level, ** at 5%, and *** at 1%. N = 15,866. FHT = indicator for For Hire Trucking observations.

Table 6. Shortage, Truck Rates and Availability

	Fixed Parameters		Random Parameters	
Truck Rates	Estimate	Std. Err.	Estimate	Std. Err.
Distance	-0.0014***	0.0003	-0.0014***	0.0005
Shortage	0.5151*	0.2722	0.4174***	0.0668
Year Effects?	Yes		Yes	
Regional Effects?	Yes		Yes	
Random Parameters?	No		Yes	
LLF	811.137		890.711	
AIC/N	-0.124		-0.111	
Availability				
Distance	-0.0010	0.0006	-0.0010***	0.0004
Shortage	0.9511*	0.4835	0.9512***	0.0817
Year Effects?	Yes		Yes	
Regional Effects?	Yes		Yes	
Random Parameters?	No		No	
LLF	-2,262.512		-2,262.503	
AIC/N	0.292		0.292	

Note: Model estimated with CPS ASEC data, and USDA-AMS Refrigerated Truck Rate data over 2011 - 2021 time period. Distance is the distance in miles between routes in the USDA-AMS data, and Disequilibrium is the estimated difference between the rates of job creation and destruction from the CPS-ASEC data. All standard errors are clustered at the state level. A single asterisk (*) indicates significance at 10%, ** at 5%, and *** at 1%.

Table D1. Job Transitions by Sector, CPS-ASEC

	From Trucking		To Trucking	
Sector	N	%	N	%
Management	113	5.58%	116	5.54%
Foodservice	58	2.86%	54	2.58%
Building Grounds	66	3.26%	57	2.72%
Sales	152	7.51%	173	8.27%
Office	240	11.85%	263	12.57%
Construction	147	7.26%	170	8.12%
Installation	83	4.10%	95	4.54%
Production	144	7.11%	144	6.88%
Transportation	289	14.27%	300	14.33%
All Other	377	18.62%	345	16.48%
Not Employed	356	17.58%	376	17.96%

Note: Estimates averaged over 2010 - 2021 sample period, using CPS ASEC longitudinal data sample. Totals imply 74.14% of all drivers stay in the industry from the first sample period to the second.