COVID-19, Truck Rates and Trucking Shortages

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Abstract

Media and industry reports maintain that the U.S. long-distance trucking market is experiencing a shortage of drivers, and that the shortage is expected to persist well into the future. At the same time, reports of supply-chain disruption throughout U.S. industry focus on a lack of transportation infrastructure, which generally means trucking in the U.S. Truck rates, or the per-mile rate charged for trucking services, rose substantially in the post-COVID-19 pandemic era, suggesting that the market was responding to market signals. However, the connection between labor shortages, rising truck rates, and an apparent lack of trucking services has yet to be established empirically. In this paper, we develop an empirical approach based on an equilibrium search-matching-and-bargaining framework in which we estimate the role of labor shortages in accelerating driver wages, and truck rates. We estimate the model by combining U.S. Bureau of Census Current Population Survey data on truck drivers, with USDA-NASS 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%, and 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. Our empirical findings point to a fundamental mismatch in the skills required in the trucking industry, and the workers attracted to trucking as a profession. If market incentives are unable to attract more drivers to the industry, more public-option trucking schools are likely part of a long-term solution.

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

1 Introduction

There is plenty of anecdotal evidence of transportation-shortages throughout the economy, both pre-COVID and particularly in the post-COVID expansionary phase of the US economy (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 stimulus, to COVID-induced labor shortages, and bottlenecks in the physical movement of containers, trucks, and rail cars. 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 are due to insufficient labor and, if so, how much labor has contributed to the unprecedented increase in truck transportation rates.

The trucking industry depends on labor. While the public image of the truck-transport sector is primarily of machinery, the reality is that it is the truckers themselves who represent the key constraining input to moving more agricultural 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 and 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, 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 and 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 (Burks and Monaco 2019). In fact, there is some evidence that truckers are becoming older, working less, and more likely to be immigrants to the U.S. (Cheeseman-Day and Hait 2019). 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.[1]

[1] Miller, et al. (2020) and Phares and 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

Labor compensation, and hence the supply of labor, is inseparable from competitive conditions in the market for labor services, and in the downstream product market. Therefore, in order to explain conditions in the trucking-labor market, it is critical to understand how trucking firms compete against each other in the market for trucking services. Probably the best example of this interdependency lies in the deregulation of trucking in the early 1980s (Rose 1987; Hirsch 1988, 1993; Guadalupe 2007). Rose (1987) and Hirsch (1988, 1993) both find that the 1980 Motor Carrier Act, which removed "entry and rate restrictions" from the general (i.e., non-agricultural) trucking industry, lead to rapid entry of non-union carriers.[2] As a result, worker bargaining power and wages fell, and private motor carriers came to dominate the industry. More recently, Guadalupe (2007) examines the impact of competition in the product market on labor compensation, the returns to human capital, and the extent of wage inequality. Using a pair of quasi-natural experiments in the UK, she finds that the returns to skill actually rise in the level of product-market competition.[3] That is, the more competitive the downstream market, the more firms reward measures of skill. There are similar examples in the US, as Beilock, et al. (1986) and MacDonald (2013) examine transportation-service pricing data in the U.S. for evidence of price discrimination. Unlike Beilock, et al. (1986), MacDonald (2013) approaches the data with a rigorous theoretical model of how price discrimination should appear in the price data. Specifically, he examines price-discrimination in the railroad industry during three different periods: pre-Interstate Commerce Act (1870-1886), the period in which railroads suffered losses to inter-modal carriers, services were highly regulated, and service quality arguably declined (1945-1975), and the period following the broad deregulatory period that began during the Carter Administration, and picked up steam during the Reagan Era (1980-1996). He finds extensive evidence of price discrimination in each period, but for different reasons, and to different extents. However, he does not extend the implications of output-market price discrimination to labor markets as does Guadalupe (2007). We contribute to this literature by examining how changing economic conditions in a range of industries have impacted job turnover,

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.

[2] As Farmer (1964) explains, agricultural trucking was always 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.

[3] She uses the UK entry to the Single Market Program (SMP) in 1992, and the rapid appreciation of the pound in 1996 as events that plausibly shocked the level of competition in UK business, and controls for individual heterogeneity (and job composition) by using a UK data set that tracks individual workers over time. She controls for skills-based technical change, union wage compression, and other sources of wage inequality in order to identify a robust effect of increased competition.

and worker bargaining power, over time.

There is a deep literature on job turnover, drawing from the economics, logistics, and transportation literatures.[4] 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 and Monaco 2019; Phares and Balthrop 2021). In the specific context of trucking, Miller, et al. (2021) show that higher industry wages have a convex effect on switching rates, while Phares and Balthrop (2021) find wage elasticities, or the responsiveness of job-choice to changes in wages, in trucking are just as responsive to wage changes as workers in other industry-occupations, if not more so. Consequently, the market for truckers is not "broken" in the sense of Burks and Monaco (2019) as truckers appear to respond to wage incentives as expected.[5] 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 commodities and manufactured goods. Further, none of these empirical analyses frame their notion of industry equilibrium in terms of a modern model of job-search (Van den Berg and Ridder 1998; Pissarides 2010; Dey and 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 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 the propensity of truckers to move to the industry, while an increase in productivity will move firms to offer better jobs, increasing the expected benefits to 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

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

[5] Note that most of the literature concerns firm-level turnover, or the number of drivers who leave their current job with a particular firm, and not the more economically-relevant measure of industry turnover, or the number of drivers who simply leave trucking for some other career pursuit each year.

shortages, primarily from industry sources (Costello & Karickhoff 2019; ATRI 2021) and most of the literature on driver turnover is framed in terms of studying whether there really is a shortage of drivers at any point in time (Burks and Monaco 2019; Miller et al. 2021; Phares and Balthrop 2021) there are no empirical studies that test directly for driver shortages. We follow Miller, et al. (2020) in focusing 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 and Wolpin 1995; Dey and Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, and Robin 2006; Shimer 2006; Flabbi and Moro 2012) to identify rates of job creation, job destruction, and worker bargaining power that vary over time, and then use these parameters to explain industry-level truck rates from the USDA (USDA-NASS 2022). With this model, changes in the price of trucking services are directly related to whether the market for a key input – labor services – is in surplus, shortage, or neither over time and space.

Although we do not explicitly model the impact of minimum wages as a policy tool, because truck drivers are generally highly compensated, the fact that many of the industries that either supply drivers to the trucking industry or attract drivers from trucking are populated by semi-skilled workers, minimum wages are an important feature of the more general driver market. In our CPS data sample of workers, who either are or were in trucking, some 4.5% of individuals earned the minimum wage in their state of residence.[6] Therefore, we need to account explicitly for the potential effect of minimum wages on unemployment-to-work transitions, and vice versa.

For our structural analysis, we combine data from the IPUMS Current Population Survey (CPS, Flood, et al. 2022) data set for drivers in any trucking occupation, with truck-rate data from the USDA (USDA-NASS 2022). In this regard, we follow others in the transportation (Burks and Monaco 2019), logistics (Miller et al. 2021; Phares and Balthrop 2021) and the economics literature (Cahuc, Postel-Vinay, and 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. Unlike these authors, however, 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

[6] Note that 7 states (AL, LA, MS, SC, TN, GA, and WY) either do not have minimum wages, or have minimum wages that were below the federal minimum ($7.25 / hr) during our sample period. Workers in each of these states were assigned the federal minimum.

to examine whether changes in trucker wages are statistically associated with changes in USDA-reported truck rates. Our measure of aggregate, industry-average wages 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 wages on a three-digit NAICS level for each state, over the entire 2010 - 2021 sample period.

Our empirical analysis consists of three stages. First, we begin with a reduced-form analysis of job transitions in order to identify patterns in the data that appear to support our maintained hypothesis 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 and Flinn 2005; Flinn 2006) that allows us to recover time-varying parameters of job-creation, job-destruction, and worker bargaining-power. Our estimates from this model permit direct tests of whether the market for truckers appears to be in equilibrium, defined as equality between the rates of job destruction and formation, or whether the market is instead moving toward equilibrium. Estimates of worker bargaining power allow us to examine how changes in the labor market are likely to be affecting worker welfare, and firm profitability. Third, we then estimate the impact of labor-market disequilibrium, defined as the difference between job creation and destruction, 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-NASS 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 2010 - 2015 period, and the post-COVID period that we define as including both 2021 and 2022. Second, reduced-form models of variables thought to be important to trucking costs, such as distance and trucker wages, and we find an elasticity of rates with respect to wages of about 0.052, so each 10% increase in wages is associated with a 0.5% 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.[7] Finally, using the structural

[7] The increment in bargaining power due to COVID-19 induced labor shortages is smaller than that found by

model to calculate annual rates of labor-market disequilibrium, we find that a 10% increase in job openings relative to jobs lost is associated with a 4% increase in truck rates, and an 8% increase in the availability of trucking services. 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.[8]

Our findings, and theoretical framework, contribute to the logistics literature on trucking shortages and the cost of trucking, the literature on labor search and bargaining, the literature on regulation and pricing in the trucking industry, and on supply-chain resilience more generally. First, 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 and Monaco 2019; Phares and Balthrop 2021; Miller, et al. 2021), but do so using different empirical models 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 and Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, and Robin 2006). By allowing departures from equilibrium to directly affect truck rates, we extend the insights in Miller, et al. (2020) in formally connecting labor-market outcomes to pricing in the market for trucking services.

Second, 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.

Third, 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 for explicitly accounting 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

Richards and Rutledge (2021) 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 of base wages.

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

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.

Fourth, we contribute to the relatively-recent literature on supply-chain resilience in the food and agriculture industry (Hobbs 2020; Chenarides et al. 2021; Luckstead, Nayga and Snell 2021). While research conducted at the outset of the pandemic speculated on the likely importance of workers to maintaining the integrity of the food supply chain, we have the benefit of hindsight, and revealed-choice data, to examine exactly what one critically-important class of workers actually did during the pandemic. In that regard, we use choices made by workers during the COVID-19 period to help identify our model, and to help identify the relationship between worker choices and the cost of 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 the parameters of the structural model, and of 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 and 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 and Mortensen (1998), Van den

Berg and Ridder (1998), and Eckstein and Van den Berg (2007), but rather mediated by conditions that affect the relative bargaining power workers and firms bring to the table.[9] Bargaining occurs according to an axiomatic Nash (1951) process, so bargaining power is exogenous, and depends on the negotiating abilities of each side, endowed or acquired attributes like skill or education, or perhaps economic conditions that provide a structural advantage to one side or the other.[10] 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 (Miller et al. 2021).

In this section, we develop four hypotheses that follow from our theoretical model, which we test with the econometric model in the next section. All details of the theoretical model are in e-supplement A for the main model, and e-supplement B for the model with minimum wages.

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 can 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 summary data, then we would expect to see higher values of α in periods immediately following the COVID-19 pandemic, relative to prior years. Greater

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

[10] 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 and Flinn 2005), or the effect of gender differences on wages (Flabbi and Moro 2012)

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 job market, moving either from one firm to another, or from unemployment back to employment.

Third, the model in (13) suggests that the effect of minimum wages on labor-market outcomes is more subtle than textbook analyses would have us believe (Manning 2021). Specifically, orthodox theory implies that higher minimum wages lead to lower levels of employment, and unambiguously negative welfare effects for firms. There is a large volume of empirical research that challenges this conclusion when labor markets are imperfectly competitive (Card and Krueger 1994, 2000) or firms pay "efficiency wages" (Rebitzer & Taylor 1995), but our model of labor market equilibrium admits a wider range of outcomes when markets are not only imperfectly competitive, but workers actively search, bring match-specific capital to the negotiations, and bargain for wages.[11]

Fourth, we examine the effect of labor-market policies that potentially alter workers' disagreement profit, or threat point (V_n in equation (9)) and thereby affect the endogenous part of workers' bargaining position, and their equilibrium wage offers. For example, higher unemployment payments enacted in response to the COVID-19 pandemic were blamed, in part, for the decline in employment witnessed in late 2020 and 2021. Our model suggests a very specific mechanism through which this effect is likely to travel, as higher unemployment compensation should raise V_n, increasing workers' disagreement profit and hence their equilibrium wages. Because higher wages are costs to firms, we expect unemployment compensation to flow through to higher truck rates through this wage effect. We demonstrate these effects by conducting a set of counterfactual simulations with the empirical version of our theoretical model developed above.

3 Econometric Model of Bargaining

Despite the fact that trucking is not necessarily a low-skilled industry, we show above that minimum wage compensation is an important feature of our data. Because match values in many employment relationships are likely to run up against the minimum-wage constraint, we follow Flinn (2006) by including the probability of minimum-wage compensation explicitly in the model. On an intuitive level, workers' exercise of bargaining power in the model is constrained by the minimum wage as employers are forced to pay low-productivity workers an artificially-high share of employment

[11] We define imperfect competition consistent with Manning (2003), which includes not only firms with market power in the traditional sense, but allows for search frictions and imperfect information, or any other source of rents in the employment transaction.

surplus. We depart from Flinn (2006) by estimating the model at the level of the individual worker, so we derive a micro-level version of his aggregate-data model.

Our core hypothesis maintains that the COVID-19 pandemic or, more accurately, the federal policy response to the COVID-19 pandemic, endowed workers with greater bargaining power than they would have had otherwise. For example, during the pandemic workers at the margin between working and not working had access to larger unemployment benefits, while cash infusion more generally increased the demand for goods, and for shipping services. Meanwhile, asset inflation allowed workers – surprisingly, across the age spectrum – to leave the workforce and live off of cash generated by investments in equity markets, housing, or over-inflated asset-rental markets. Employers were forced to bid wages up across the economy in an attempt to attract workers back into the workforce and, within each industry, the competition by firms with industry-specific skills caused the labor shortage generated by the Great Resignation to become the secular competition for skills now known as the Great Reshuffle (Krugman 2022). In terms of our econometric model, we capture the effect of the COVID-19 policy response on bargaining power 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 a likelihood function 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. Our econometric model assumes workers search for jobs while unemployed, but experience search frictions of the sort described by Burdett and Mortensen (1998) and Pissarides (2000, 2011), possess match-specific capital, and bargain with respective employers over the terms of new wage agreements. Each of these features mean that search is costly and likely to result in rents earned by both sides of the employment contract. In the data, we observe hourly wages paid to individual i upon acceptance of a job in which the wage exceeds his or her reservation wage (b_i), and the length of each spell of unemployed search (t_i). We also use time-varying demand-side information from the trucking industry (workers' share of gross revenue) to identify the bargaining power parameter, α, or the relative share of rents earned by the worker, and the firm $(1 - \alpha)$.

Assuming an exogenous distribution of worker-firm productivity for a match value of θ, and an exogenous rate of job-destruction (η), the density of an unemployment spell of length t_i implied by the search function is:[12]

$$f_u(t|u) = \lambda G(m) \exp(-\lambda G(m)t), \tag{1}$$

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:

$$pr(u) = \frac{\eta}{\eta + \lambda G(m)}, \tag{2}$$

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

$$f(t,u) = \frac{\eta \lambda G(m) \exp(-\lambda G(m)t)}{\eta + \lambda G(m)}, \tag{3}$$

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

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:

$$pr(w = m, e) = \frac{\lambda \left[G(m) - G\left(\frac{m - (1-\alpha)\rho V_n(m)}{\alpha} \right) \right]}{\eta + \lambda G(m)}, \tag{4}$$

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:

$$f(w|w > m, e) = \frac{\frac{1}{\alpha} g\left(\frac{w - (1-\alpha)\rho V_n(m)}{\alpha} \right)}{G\left(\frac{m - (1-\alpha)\rho V_n(m)}{\alpha} \right)}, \tag{5}$$

[12] 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.

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:

$$pr(w > m|e) = \frac{G\left(\frac{m-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{G(m)}, \tag{6}$$

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

$$f(w, w > m, e) = \frac{\frac{\lambda}{\alpha} g\left(\frac{w-(1-\alpha)\rho V_n(m)}{\alpha}\right)}{\eta + \lambda G(m)}. \tag{7}$$

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

$$\begin{aligned} LLF = {} & [\ln(\lambda) - \ln(\eta + \lambda G(m))] + \delta_U[\ln(\eta) + \ln G(m)] - \\ & \lambda G(m)\delta_U t_i + \delta_M \ln\left(G(m) - G\left(\frac{m-(1-\alpha)\theta^*}{\alpha}\right)\right) - \\ & \delta_H \ln(\alpha) + \delta_H \ln\left(g\left(\frac{w_i-(1-\alpha)\theta^*}{\alpha}\right)\right), \end{aligned} \tag{8}$$

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

4 Data and Identification

In this 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 two data sources for our analysis. First, we use the USDA-NASS Truck Rate (USDA-NASS 2022) data in order to measure the cost of refrigerated trucking services, for a large set of matched source-destination pairs, for several commodities, on a monthly basis over our 2011 - 2021 sample period. 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. Although refrigerated trucking services constitutes only 6% of total cargo truck traffic (citation), the fact that perishable goods travel by refrigerated trucks means that the price is more likely to be driven by competition in the output market, and less likely to exhibit rigidities driven by long-term haulage contracts (Miller, et al. 2021). Further, there are very few comprehensive data sources that cover enough of the industry, at sufficient frequency, and at a relevant level of geographic specificity to be amenable to econometric estimation. For example, the study closest to ours, Miller, et al. (2021), uses quarterly, national truck-rate data from the Bureau of Labor Statistics (U.S. BLS), which we argue is not detailed enough to capture differences in the demand for trucking. Trucking demand varies by product, region, and week as regional import and export demand flows change with seasonal demand, and product availability.

We begin by presenting some model-free evidence that examines trends in truck rates, and the workers that drive trucks. We first summarize the USDA truck rate data for a period well before the COVID-19 pandemic (2010 - 2015), and one after the pandemic-related stimulus programs likely took effect (see tables C1 and C2 in e-supplement C). In general, the data show that truck rates, defined on a per-mile basis, increased in all but two of the source-destination pairs in the table, and increased an average of over 40% across all pairs. Among all source regions, the New York region shows the largest increases (119.5%), which suggests that either demand pressures were particularly strong for items from the New York region or, more likely, the cost-pressures were greater. 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. We provide additional summary evidence of structural changes in trucking wages, and employment in e-supplement D.

Our second data set provides data on individual-level job choices, compensation, and industry

[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.

transitions that allows us to accurately estimate the parameters of our econometric model of labor-market equilibrium. Specifically, we follow Burks and Monaco (2019) and Phares and 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).[14] 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. We also use data from the Employee Tenure and Occupational Mobility Supplement (ETOMS) in order to measure job tenure, and industry transitions in job choice. Our sample from the CPS ASEC data is best described as repeated two-year observations (short panels) within a repeated cross-section framework. Following Burks and Monaco (2019), we restrict our sample to ASEC respondents who report a trucking-related job 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 $N = 8,133$ observations.

In order to estimate the likelihood function in (8), we require sufficient variation in job-duration, employment and 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 e-supplement C, table C3 suggests 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 / PCT, demographics, and citizenship effects in order to isolate the variation in job choice and bargaining power. Flinn (2006), however, notes

[14] IPUMS orginally stood for Integrated Public Use Microdata Series, but now not all of their data sets are micro-data, and not all are public use, so IPUMS is now simply an acronym.

that bargaining power parameter (α) is difficult to identify without more demand-side information. He uses a single observation of the ratio of labor compensation to output for a major fast-food chain in order to identify α with success.[15] Our aim is to estimate the contribution of labor to the rise in trucking rates for agricultural products. More generally, Flinn (2006) uses a series of Monte Carlo experiments under different parametric assumptions for the 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 the Results section below, we show that our model is identified in our base sample, likely due to the strong identification properties of our CPS-ASEC sample. However, we incorporate demand-side information in a manner similar to Flinn (2006) in order to ensure the key bargaining power parameter is identified. That is, we use demand-side information to estimate a flexible bargaining-power function that is more likely to be identified than if we were to use the worker-only information in the CPS-ASEC data.

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, and is from the U.S. Bureau of Labor Statistics (BLS) Multifactor Productivity (USBLS) data. Labor compensation is from the BLS for the trucking industry as reported in the multifactor productivity data set. 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 (8) 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).

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

5 Results and Discussion

In this section, we present our findings, and provide some evidence of their robustness and perhaps alternative stories that may explain our observations. We begin by presenting the estimates from different specifications of our structural model in equation (8), and interpret the estimates in terms of their implications for labor-market equilibrium and bargaining power. Next, we use the parameters from the structural estimates to estimate simple regression models of truck rates and labor-market disequilibrium. In these models, we examine the implications of labor-market disequilibrium for both truck rates and truck-availability reported by USDA-NASS.

Our structural-model estimates are in Table 1 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 allows bargaining to vary between pre- and post-COVID-19 regimes (Model 3), and a final model that allows 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 1 in here]

The parameters of 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 at worker at the estimated match value – is equal to the difference between the point estimate of G (the implicit value of a match), and the critical match-value estimate (θ). Calculated from the estimates in Table 1, 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.[16] Therefore, our model estimates suggest an employment surplus of \$15.74 per hour. Of this surplus, the bargaining

[16] 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.

power estimate of 38.3% implies that the average 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 and Flinn 2005; Flinn 2006; Cahuc, Postel-Vinay, and 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 ($LR = 2 * (LLF_1 - LLF_0) \sim \chi^2$), 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 economic 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 in the latter case. 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. 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, 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 e-supplement C – 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. In our final empirical step, therefore, 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. We also control for regional and yearly fixed effects in order to control for otherwise unobservable factors, and a version of the model with random parameters to allow for any 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 less effective matches being made, so the availability of trucking services should fall.

We present estimates from these regressions in Table 2 below. In the upper panel, we show the relationship between labor shortages (disequilibrium) and truck rates. The estimates in this table suggest that there is a positive relationship between disequilibrium and truck rates. Interpreted at the means of the data, a rise in the disequilibrium gap from 22.4% to 23.4% is associated with a $0.04 / mile rise in truck rates, or from $3.31 to $3.35 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 $0.44 / mile, simply in response to labor-market tightness. Expressed differently, our estimates imply an elasticity of truck rates with respect to disequilibrium of 0.27 – inelastic, to be sure, but economically important when labor markets are changing quickly, and large disequilibria likely. Similarly, in the lower panel of Table 2 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 -0.08 in the preferred model means that a percentage-point rise in the gap between creation and destruction leads to an 8 point increase in availability.[17] While this result may seem counterintuitive, recall that our definition of disequilibrium is the difference between job creation and destruction. As more jobs are created than lost, there are likely to be more trucks on the road, and greater availability. 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 reduction in the availability index from 3.33 to 3.25, or an elasticity of 0.55 - still inelastic, but substantially more elastic than the wage-sensitivity to disequilibrium.

[Table 2 in here]

Our findings are important both for management purposes in the trucking industry, and for policymakers interested in 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 COVID-19 pandemic, and our policy responses to it. While truckers may indeed be responding to economic incentives as in Burks and Monaco (2019) and Phares and 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 businesses that use trucks. 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.

[17] We aggregate the integer availability index over all commodities from a particular source region, so the dependent variable is no longer an integer measure.

6 Conclusions

In this paper, we examine how the 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 labor 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 value of an 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 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.

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. 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.

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Table 1. 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 2. Disequilibrium, Truck Rates and Availability

	Fixed Parameters		Random Parameters	
Truck Rates	Estimate	Std. Err.	Estimate	Std. Err.
Distance	-0.0014***	0.0004	-0.0014***	0.0007
Diequilibrium	0.1295	0.1428	0.0423***	0.0196
Year Effects?	Yes		Yes	
Regional Effects?	Yes		Yes	
Random Parameters?	No		Yes	
LLF	787.577		787.572	
AIC/N	-0.098		-0.098	
Availability				
Distance	-0.0010****	0.0005	-0.0010***	0.0004
Disequilibrium	-0.2642	0.1741	-0.0823***	0.0237
Year Effects?	Yes		Yes	
Regional Effects?	Yes		Yes	
Random Parameters?	No		Yes	
LLF	-2,316.44		-2,316.41	
AIC/N	0.298		0.298	

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

7 E-Supplement A. Theoretical Model of Search, Matching, and Bargaining

In this e-supplement, we begin by considering a simple version of the search-and-bargaining model of Dey and Flinn (2005) and Flinn (2006) without minimum wages. In this stylized model, the primary objective is to explain wages in terms of a Nash (1951) 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, while 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:

$$w(\theta, V_n) = \arg\max_w [V_e(w) - V_n]^\alpha \left[\frac{\theta - w}{\rho + \eta}\right]^{1-\alpha}, \tag{9}$$

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 job destruction rate.

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

We next solve the generalized Nash problem in (9) for the set of equilibrium wages, as a function of the primitives of the model. Equilibrium wages are determined from equation (9) 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:

$$V_e(w) = \frac{w + \eta V_n}{\rho + \eta}, \tag{10}$$

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:

$$\rho V_n = b + \frac{\alpha\lambda}{\rho + \eta} \int_{\rho V_n} [\theta - \rho V_n] dG(\theta) \tag{11}$$

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 (9) and solving gives an expression for the equilibrium wage contract as:

$$w(\theta, V_n) = \alpha\theta + (1 - \alpha)\theta^*, \tag{12}$$

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.

We now introduce minimum wages, as there are a substantial number of jobs in the trucking industry that pay either at, or slightly above, the minimum wage. 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 E-supplement B: 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 E-supplement B, the resulting equilibrium wage distribution that captures the three possible relationships between the market-wage offer and the mandated minimum wage is given by:

$$pr(w;V_n(m)) = \left\{ \begin{array}{ll} [g(\hat{\theta}(w,V_n(m))]/\alpha G(m), & w > m \\ [G(m) - G(\hat{\theta}(w,V_n(m)))]/G(m), & w = m \\ 0, & w < m \end{array} \right\}, \tag{13}$$

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.

8 E-Supplement B: Minimum Wages

In this e-supplement, we describe the derivation of equation (13) in the text from Flinn (2006). As explained above, the existence of an effective minimum wage serves as a constraint on firms' exercise of their usual degree of bargaining power. There may be matches that provide some surplus, but not at the level of unconstrained wage offers and worker-bargaining power implied by the unconstrained model. In order to see this logic more formally, first recognize that firms cannot generate positive surplus with match values less than the minimum wage ($\theta < m$) because their surplus depends on the difference between match values and wage offers ($\theta - w$), so any values of θ below m would imply negative surplus. Therefore, there has to be a threshold match value ($\hat{\theta}$) that separates wage offers that are not constrained by the minimum wage, recognizing that firms and workers tend to share the amount of available surplus, and those that are constrained. Without the minimum wage constraint, and general search value of $V_n(m)$, the equilibrium wage solves:

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

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

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

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

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

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

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

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

9 E-Supplement C: Summary Analysis

In this e-supplement, we first provide summary evidence on the change in truck rates pre- and post-COVID from the USDA-NASS truck rate data set, and then further evidence from other public-access data sets on the market for truckers in the U.S. In tables C1 and C2 below, we provide the summary data that underlies our narrative discussion in the Data section of the main paper.

[tables C1 and C2 in here]

Before examining more detailed data on the market for truckers, we determine whether there is even evidence of a summary relationship between trucker wages, and truck rates. If there is no evidence of a cost-price linkage between wages and rates, then there is little need to proceed with a deeper examination. For this purpose, we merge the USDA Truck Rate data with regional trucking-wage data (NAICS industry code = 484) from the U.S. Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW). The QCEW is valuable in helping explain temporal and spatial variation in truck rates because it captures data on 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. Moreover, the QCEW is a census as it is developed from data submitted by employers used to administer state-level unemployment insurance programs. Although the QCEW includes several data fields representing employment, number of establishments, and other variables, we are only interested in the average weekly compensation for drivers in the trucking industry for each source region (WAGE). Our assumption here is 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. We use this data to help explain variation in truck rates over time, as reported by the USDA, in addition to the elements internal to the USDA data.

Our results from this reduced-form regression are in Table C3 below. Note that both the dependent and independent variables are expressed in logs, so the parameters on all continuous values (miles and wages) are interpreted as elasticities of truck rates with respect to each variable. Using the best-fitting model for interpretation purposes (Model 4, based on the R^2 value), wages 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 travelled with an elasticity of about 0.43, meaning that a 10% increase in route-distance reduces the per mile rate by 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 C3 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 C3 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 1, we see that the number of truckers in the U.S. was declining 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 industry and the 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 2010 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 e-supplement C below.

[Figure 1 in here]

With respect to the second, ASEC data set, there are reasons to possibly draw sub-samples from all those who identify as truckers (Burks and Monaco 2019; Phares and Balthrop 2021). That is, 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. Over our sample period, the share of truckers who are PCT is 75.3%, while the remainder (24.7%) are

FHT.[18] Burks and Monaco (2019) 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 C4, averaged over FHT and PCT for-hire and private-carrier drivers 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 C4 in here]

These data, however, are averaged over the FHT and PCT sub-sectors, so may mask differences among jobs that may increase the rate of job turnover within the industry. In Table C5, 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 and 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 C5 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.[19] In 2021, for example, even the large absolute gap in hourly wages ($10.50 / 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,

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

[19] In E-supplement E, we present a replication of the summary data in Burks and Monaco (2019) and similar data in Phares and 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 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).

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 in the main text we account for the differences between truckers in each sub-sector through a set of fixed effects.

[Table C5 in here]

10 E-Supplement D: JOLTS

In this e-supplement, 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 2 below shows that the ratio of job hires to job openings in the trucking industry between 2010 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 lack of workers.

[Figure 2 in here]

11 E-Supplement E: Job Turnover

In this e-supplement, we provide summary data on job turnover among truckers in our sample data. For purposes of Table E1 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 E1 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 E1 and Figure 3 in here]

Table C1. Origin and Destination Pairs w Rates: 2010 - 2015

	Destination									
Region	Atlanta	Baltimore	Boston	Chicago	Dallas	L.A.	Miami	New York	Philly	Seattle
Arizona	\$2.40	\$2.32	\$2.31	\$2.05	\$2.81	\$6.34	\$2.19	\$2.36	\$2.33	\$2.30
California	\$2.45	\$2.42	\$2.39	\$2.26	\$2.80	\$6.04	\$2.31	\$2.44	\$2.41	\$2.77
Florida	\$2.68	\$2.53	\$2.45	\$2.09	\$2.60	\$1.18	\$2.96	\$2.61	\$2.46	N.A.
Great Lakes	\$2.82	\$3.22	\$3.03	\$3.76	\$2.70	N.A.	\$2.66	\$3.41	\$3.13	N.A.
Indiana	\$3.62	\$3.10	\$2.54	\$3.87	N.A.	N.A.	N.A.	\$3.04	\$3.03	N.A.
Mexico-Arizona	\$2.33	\$2.28	\$2.38	\$2.08	\$2.47	\$2.00	\$2.26	\$2.41	\$2.39	\$2.31
Mexico-Texas	\$2.14	\$2.17	\$2.25	\$1.89	\$2.44	\$1.56	\$2.17	\$2.21	\$2.18	N.A.
Midatlantic	\$2.26	\$8.60	\$3.96	\$2.18	N.A.	N.A.	N.A.	\$6.25	\$6.84	N.A.
New York	\$2.25	\$4.30	\$7.92	\$1.50	\$1.93	N.A.	\$2.23	\$8.14	\$5.39	N.A.
Other	\$2.44	\$2.57	\$2.67	\$2.22	\$3.18	\$1.73	\$2.28	\$2.77	\$3.31	N.A.
PNW	\$2.16	\$2.22	\$2.19	\$2.02	\$2.19	\$1.84	\$2.11	\$2.28	\$2.20	\$6.99
Southeast	\$4.17	\$4.01	\$3.43	\$3.11	\$2.75	\$2.07	\$3.00	\$3.75	\$3.83	N.A.
Texas	\$2.53	\$2.44	\$2.47	\$2.22	\$3.27	\$1.71	\$2.35	\$2.49	\$2.45	N.A.

Note: Data are from USDA-NASS Refrigerated Truck Rates and Availability data set. Rates are average, per-mile rates over the 2010-15 sub-sample period. NA refers to a Region-Destination pair that does not appear in the USDA-NASS data.

Table C2. Origin and Destination Pairs w Rates: 2021 - 2022

	Destination									
Region	Atlanta	Baltimore	Boston	Chicago	Dallas	L.A.	Miami	New York	Philly	Seattle
Arizona	$3.41	$3.14	$3.07	$3.06	$4.03	N.A.	$3.24	$3.19	$3.13	N.A.
California	$3.85	$3.67	$3.54	$3.63	$4.42	$13.17	$3.57	$3.63	$3.62	$3.99
Florida	$3.47	$3.21	$3.28	$2.55	N.A.	N.A.	$2.71	$3.62	$3.22	N.A.
Great Lakes	$4.13	$4.59	$4.21	$4.63	$3.27	N.A.	$3.42	$4.80	$4.36	N.A.
Indiana	N.A.	N.A.	N.A.	$6.32	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Mexico-Arizona	$3.46	$3.53	$3.53	$3.07	$4.01	$2.78	$3.33	$3.57	$3.58	N.A.
Mexico-Texas	$3.39	$3.28	$3.13	$2.85	$3.50	$2.09	$3.00	$3.35	$3.25	$2.71
Midatlantic	$4.17	$11.33	$5.87	$3.03	N.A.	N.A.	N.A.	$6.98	$9.05	N.A.
New York	$4.73	$7.57	$16.06	$5.40	N.A.	N.A.	$3.91	$16.81	$11.17	N.A.
Other	$3.28	$2.94	$2.77	$3.01	$4.65	$2.17	$2.92	$3.45	$2.99	N.A.
PNW	$3.15	$3.21	$3.18	$3.11	$3.12	$2.69	$3.03	$3.37	$3.16	$8.34
Southeast	$6.46	$5.92	$4.52	$4.11	$3.47	$2.02	$4.15	$5.24	$5.11	N.A.
Texas	$4.19	$3.77	$3.62	$3.46	$5.11	$2.43	$3.09	$3.74	$3.75	$2.93

Note: Data are from USDA-NASS Refrigerated Truck Rates and Availability data set. Rates are average, per-mile rates over the 2021 - 2022 sub-sample period. NA refers to a Region-Destination pair that does not appear in the USDA-NASS data.

Table C3. 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	0.0008	0.4441	0.0101	0.5612	0.0113	0.5622	0.0112
Trend			0.0319	0.0008	0.0270	0.0002	0.0272	0.0002
Quarter 1			-0.0547	0.0012	-0.0343	0.0015	-0.0277	0.0015
Quarter 2			0.0246	0.0012	0.0358	0.0013	0.0355	0.0013
Quarter 3			0.0049	0.0012	0.0085	0.0012	0.0158	0.0012
Distance	-0.2968	0.0009	-0.4241	0.0009	-0.4246	0.0009	-0.4260	0.0009
Wages					0.1789	0.0078	0.1725	0.0077
A = 3							-0.0733	0.0019
A = 4							-0.0409	0.0012
A = 5							0.0089	0.0015
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 log-miles, Wages are annual weekly log-wages in NAICS = 484 in the Source region, Availability is the USDA-NASS indicator of availability, with A = 3 representing adequate supply and A = 5 representing a shortage of trucking services, based on interviews with service-demanders. All data are in logs, so coefficients represent elasticities of truck rates with respect to each explanatory variable. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%.

Table C4. 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 C5. 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 E1. 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.

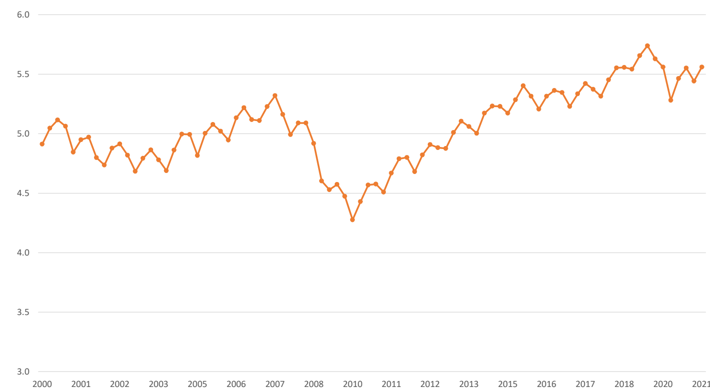

Figure 1: Employment in Trucking Industry, millions

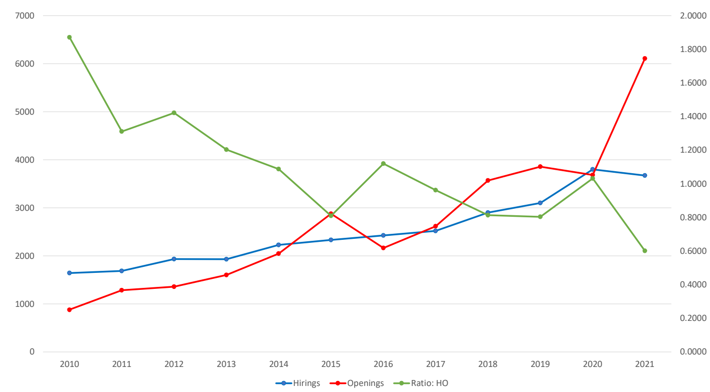

Figure 2: Job Openings and Hires, Transportation

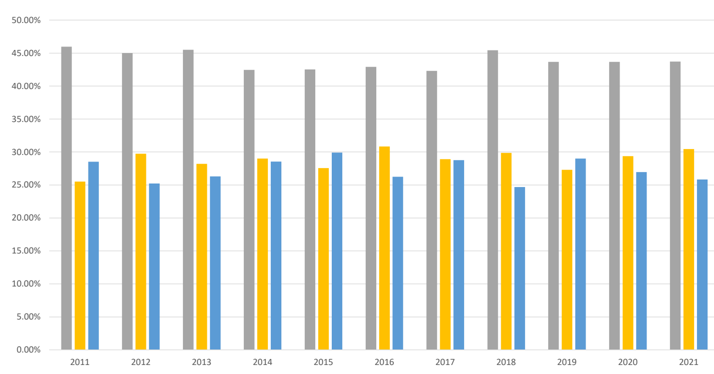

Figure 3: Trucking Jobs, Entry and Exit, 2011 - 2021