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ABSTRACT

State-Level Trucking Employment and the COVID-19 Pandemic in the U.S: Understanding Heterogenous Declines and Rebounds*

Some of the U.S. states saw sharper declines in truck transportation payrolls at the onset of the COVID-19 shutdown, and others displayed differing trajectories in the rebound of truck transportation payrolls during the economic recovery. Analyzing why provides theoretical and practical insights regarding labor dynamics in the trucking sector. In this vein we extend factor market rivalry theory regarding labor dynamics in the trucking sector: we suggest that trucking firms have compound relations with demand generating sectors in that they may compete for the same workers. Sectors differ in how output changes affect both their demand for trucking freight and the extent of their labor poaching; this creates differing net effects on trucking employment. We create a state-level archival data set of truck transportation establishment payrolls from the Quarterly Census of Employment and Wages, which we combine with other archival sources. We test our hypotheses via discontinuous growth curve models estimated using the mixed effects modeling framework. Effects vary by time period and industry, but manufacturing and natural resource extraction stand out in perhaps surprising ways, and changes in demand for local freight movements are especially important. Our results align with our theory and have important implications for managers and policy makers.

JEL Classification: J21, L92, R41

Keywords: truck transportation, motor carrier, COVID-19, pandemic shutdown, pandemic recovery, trucking employment

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INTRODUCTION

Labor issues concerning truck driver recruitment (Costello and Karickhoff 2019; Phares and Balthrop 2022) and turnover (Miller et al. 2021a) have been central to the for-hire trucking industry since deregulation in the late 1970s and early 1980s (Belzer 2000). Such challenges have been magnified since the onset of the COVID-19 pandemic. Between March and April 2020, truck transportation establishments reduced seasonally adjusted payrolls by 78,800 (5.2%), in the sharpest contraction observed in data stretching back to 1990 (BLS 2023a). However, the rapid recovery of demand due to consumer spending on retail goods (Jaillet 2020) and the upheaval created in freight networks (Cassidy 2020), coupled with a slower recover of trucking capacity, resulted in the sharpest increase in truckload spot rates (BTS 2022) and contract rates (BLS 2022; Miller et al. 2021b) from June 2020 to December 2021 in 30 years. During this period of rising rates, news outlets extensively covered concerns about a "driver shortage" (Ngo and Swanson 2021; Smith 2021), though academic research suggests the labor market dynamics observed in trucking do not constitute a shortage as defined by Arrow and Capron (1959) (Burks and Monaco 2019; Miller et al. 2021a; Phares and Balthrop 2022).

This dynamic environment provides a fertile setting to extend existing theory regarding how truck transportation employment evolves as economic conditions change. While prior studies have examined how large carriers (e.g., Class 1 or Class 2 firms) changed size (Kling 1988; 1990; Rakowski 1988; 1994) and strategies (Corsi and Grimm 1989; Corsi et al. 1991; 1992; Corsi and Scheraga 1989; Feitler et al. 1997; 1998; Grimm et al. 1993; Pettus 2001) following deregulation, as well as the safety consequences of larger carriers changing their size (Miller et al. 2018), far less is understood regarding how industry-level trucking employment evolves as macroeconomic conditions change. Shifting focus away from studying large firms towards an industry-level analysis is useful in that (i) firms with less than 100 employees accounted for 40% of truck transportation employment in 2017 – 2019 (Cenusus Bureau 2019) and (ii) policy makers looking at changing laws regarding the age of truck drivers (FMCSA 2020) are concerned about industry-level employment.

This research takes a new look at industry-level evolution of truck transportation employment since the onset of the COVID-19 pandemic by leveraging monthly state-level payroll data. We engage in theory elaboration (Fisher and Aguinis 2017) by extending theory regarding factor market rivalry (FMR) (Ellram et al. 2013; Markman et al. 2009; Ralston et al. 2022) as it pertains to competing for the same labor pool (Ralston et al. 2017) by incorporating the concept of compound relationships (Ross and Robertson 2007). We suggest sectors such as trucking whose demand is derived from others' activity (e.g., manufacturing) (Allen 1977) have compound relations with their demand-generating sectors regarding obtaining labor because, on the one hand, increased activity in demand-generating sectors supports expanding trucking payrolls (the freight origination mechanism), but on the other hand, more competition for the same labor pool may reduce trucking payrolls (the labor poaching mechanism). We note the strength of the freight origination versus labor poaching mechanisms differs across sectors, with state-level recovery of trucking employment is being especially sensitive to employment in industries that generate demand for local transportation, such as natural resource extraction.

We assemble a panel dataset of monthly state-level observations of the payrolls for all truck transportation establishments with at least one employee using data from Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW) from January 2017 – December 2021. We combine these data with other archival sources including U.S. Census Bureau data for states that have large container ports as well as state-level unemployment benefits. We test our hypotheses by estimating discontinuous growth curve models (Bliese and Lang 2016) with employment in sectors which may generate demand and/or compete for labor included in the set of predictors.

This research makes multiple theoretical contributions. Per Makadok et al. (2018), we extend theory regarding labor dynamics in trucking by introducing a new unit of analysis: industry-level trucking employment at the state level. We contribute to theory regarding factor market rivalry as it pertains to labor (Ralston et al. 2017) by (i) incorporating the concept of compound relations (Ross and Robertson 2007) to suggest complex demand-generating versus labor poaching effects can exist between a focal sector and other sectors whose activity generates demand for the focal sector, and by (ii) explaining why demand-generating versus labor poaching mechanisms a focal sector engenders will have potentially heterogeneous effects on other sectors. Our theory stresses that the recovery of state-level trucking payrolls is especially sensitive to industries whose freight demand requires local transportation (e.g., trucking services for shale oil drillers) relative to freight demand that often involves longer hauls (e.g., manufacturing). This runs counter to the common narrative that trucking firms "compete" with companies such as shale oil drillers for the same workers, implying a zero-sum game. Our theory and empirics suggest the opposite.

Turning to practical implications, our results indicate that motor carrier managers have less to fear about some of their important customers competing over the same labor pool, as we find no evidence that increased growth in employment in sectors such as manufacturing, natural resource extraction, wholesaling, construction, warehousing, or courier & messengers negatively impacts the rate at which state-level trucking employment rebounded from lows set in April 2020. Quite the opposite, we find that state-level trucking employment rebounded more slowly in states that saw less growth in warehousing employment and especially in natural resource extraction employment. For policy makers, our results indicate the need to look beyond the “driver shortage” rhetoric to understand that the ability of trucking firms to increase payrolls is contingent upon there being strong freight originating activity, particularly within states where trucking operations are domiciled. This is consistent with findings that firms adjust employment levels symmetrically to positive or negative exogenous demand shocks only when these shocks are long-lasting (Carlsson et al. 2021). While not a core focus, policy makers should be aware that we find evidence that states that offered more generous maximum unemployment benefits did not see a slower recovery of state-level trucking payrolls, though they did see steeper declines in trucking payrolls at the pandemic’s onset. This provides some evidence contradicting concerns employers expressed about unemployment benefits reducing the incentive for workers to return (Cambon 2021).

The remainder of this paper is structured in five sections. The next section summarizes the literature. This is followed by the theory and hypothesis development. The methodology section explains the research design and describes the measures. The results section presents the econometric specification and provides results. The discussion section details theoretical contributions, describes implications to managers and policymakers, notes limitations, and suggests directions for future empirical inquiry.

LITERATURE REVIEW

Our literature review is organized into two sections. The first section concerns labor issues in truck transportation. The second concerns theory regarding factor market rivalry.

Labor Issues in Trucking

Labor issues in trucking have been a longstanding subject of logistics and supply chain (L&SCM) research, with particular attention focused on driver turnover (see Phares and Balthrop 2022 for a review). The driver turnover literature can be organized by level of analysis. At the driver level, antecedents to turnover include driver demographics such as age (Beilock and Capelle 1990; Suzuki et al. 2009); education (Beilock and Capelle 1990); experience and job tenure (Beilock and Capelle 1990; Burks et al. 2006; Phares and Balthrop 2022; Suzuki et al. 2009); number of dependents (Suzuki et al. 2009); and union status (Beilock and Capelle 1990). Physical and psychological factors have also been linked to turnover. Health-related issues leading to personal and job stress stress can lead to driver consider leaving their carrier and the driving industry (Williams et al. 2017). Burks, et al. (2009) found that stronger basic cognitive skills were predictive of lower turnover (voluntary and involuntary) among new-to-the-industry drivers during the period of their training contract. Psychological job strain and fatigue have been shown to increase voluntary turnover (de Croon et al. 2004). Schulz et al. (2014) found that truck driver psychological capital impacted turnover intention through job satisfaction and organizational commitment. Similarly, emotional exhaustion has been found to decrease internal commitment and organizational identification (Kemp et al. 2013). Other psychological factors that impact turnover include job satisfaction (Large et al. 2014; Kettinger et al. 2012; Prockl et al. 2017; Schulz et al. 2014), and driver attitude (Richard et al. 1995; Swartz et al. 2017).

Several driver-level studies also examine factors such as job characteristics and work environment that affect driver turnover. Job characteristics impacting driver turnover include pay and compensation (Burks and Monaco 2019; Conroy et al. 2022; Garver et al. 2008; Johnson et al. 2009; 2011; Morrow et al. 2005; Phares and Balthrop 2022; Prockl et al. 2017; Schulz et al. 2014; Stephenson and Fox 1996; Suzuki et al. 2009; Williams et al. 2011); hours worked and time away from home (Burks and Monaco 2019; Johnson et al. 2009; 2011; Morrow et al. 2005; Suzuki et al. 2009; Williams et al. 2011); productive work (Sersland and Nataraajan 2015; Suzuki et al. 2009); and work type, i.e., local and regional intermodal versus intermediate- and long-distance dedicated

(Burks et al. 2006). Work environment characteristics that impact driver turnover include lack of respect (Johnson et al. 2009; 2011; Williams et al. 2017); government regulations (Johnson et al. 2009; Williams et al. 2017); carrier safety climate (Swartz et al. 2017); and relationships with and behaviors of dispatchers and supervisors (Cantor et al. 2011; Johnson et al. 2009; Large et al. 2014; Morrow et al. 2005; Richard et al. 1995).

Researchers have also investigated driver turnover across multiple dispatchers within several carriers, producing findings that mirror driver-level studies. Factors impacting driver turnover include driver pay (Keller 2002; Keller and Ozment 1999a); home time (Keller 2002; Keller and Ozment 1999a); and dispatcher sensitivity and responsiveness to drivers (Keller 2002; Keller and Ozment 1999a; 1999b).

Carrier-level studies have examined factors that impact driver turnover, including driver demographics like job tenure, driving experience, and unionization (Min and Emam 2003); human resources management practices (Shaw et al. 1998); carrier size (Lemay et al. 1993; Min and Emam 2003); carrier type (Min and Emam 2003); non-driving activities (Min and Lambert 2002); career development opportunities (Min and Lambert 2002); and monetary incentives (Lemay et al. 1993; Min and Lambert 2002). To a lesser extent, researchers have examined the consequences of driver turnover, likely due to the implicit assumption that turnover is detrimental to carriers (Suzuki 2007). Indeed, turnover rate has been positively associated with lower operational performance (Saldanha et al. 2014) and higher rates of accidents (Corsi and Fanara 1988) as well as safety violations including unsafe driving, hours-of-service noncompliance, and vehicle maintenance issues, though there is evidence that the marginal impact of turnover declines as turnover rates increase (Miller et al. 2017; Shaw et al. 2005).

A paucity of research has looked at industry-level driver turnover. Miller et al. (2021a) report driver turnover is strongly procyclical with labor market conditions (e.g., carriers adding to payrolls and wage gains). Similarly, despite the attention given to turnover, there are only two studies we are aware of that have empirically examined factors that affect individuals' decisions to become truck drivers[1] versus entering other occupations. Burks and Monaco (2019) tried to isolate individuals who entered or exited the profession of driving heavy trucks to study factors that affected these decisions. They found strong evidence that economic incentives (wages, hours) shape entry and exit behaviors. Furthermore, truck drivers' occupational attachment was higher than in other blue-collar occupations. Phares and Balthrop (2022), examining all types of truck drivers and focus only on occupational entry, finding that wages have a stronger effect on entry into truck driving than entry to other occupations with similar human capital (e.g., warehousing).

In contrast, we are not aware of a single empirical investigation that has examined the longitudinal evolution of industry-level employment in the trucking sector. This lacuna is surprising given that understanding industry-level employment dynamics is essential to evaluating whether there is truly a structural shortage of truck drivers (Costello and Karickhoff 2019). To date, industry-level trucking employment has been utilized to predict driver turnover (Miller et al. 2021a) yet given that the ability of trucking firms to employ drivers is predicated upon freight demand (Chao 2016; Miller et al., 2023), employment itself is likely endogenous. The lack of industry-level inquiries into trucking employment likely stems from L&SCM researchers traditionally eschewing industry-level studies (*c.f.,* Swanson et al. 2016) until recently (*c.f.,* Darby et al. 2022; Miller et al. 2020; 2021b; 2022). Given the practical importance of understanding

[1] A limitation is that in Current Population Survey (CPS) data used in these studies, individual occupations can only be identified at a level that lumps together Driver/Sales Workers, Heavy and Tractor-Trailer Truck Drivers, and Light Truck Drivers. Also, the data in these two studies can identify changes of occupation, but *not* changes of employer while retaining the same occupation.

industry-level employment dynamics in the trucking sector, such research is uniquely positioned to both extend theory and be practically relevant (Craighead et al. 2019).

Our work extends theory regarding labor issues in the trucking sector along multiple fronts. First, we follow Makadok et al.'s (2018) strategy of making theoretical contributions by introducing a new unit of analysis in that we focus on industry-wide trucking employment at the state level. Doing so allows us to expand our understanding of trucking labor issues by expanding the array of questions that can be addressed (Ylikoski and Kuorikoski 2010). Second, we provide the first empirical examination of the heterogenous dynamics experienced by state-level trucking employment following the initial economic shutdown and subsequent recovery during the COVID-19 pandemic. As noted by Miller et al. (2022), COVID-19 upended the trucking sector with unprecedented suddenness; for example, dry van spot prices in the truckload sector went from levels so low that truckers were protesting in May 2020 (Roush 2020) to breaking the prior record high level of 2018, by September 2020 (BTS 2022). Examining how trucking employment displayed heterogeneous trajectories at the state-level helps shed light on forces that enabled or impeded trucking establishments adding to their payrolls. This provides a more nuanced look at claims of a driver shortage that tend to be positioned as industry-wide (Ngo and Swanson 2021).

Factor Market Rivalry (FMR) Theory

Factor market rivalry (FMR) theory concerns the rivalry over resources such as labor, patents, transportation capacity, and suppliers' research and development energy (Ellram et al. 2013; Markman et al. 2009). Ralston et al. (2022a; 2022b) highlight two conditions for FMR to occur: (i) there must be competition between firms over resources and (ii) the resource in question must be scarce[2]. As noted by Opengart et al. (2018), FMR is strong regarding labor given that labor is

[2] The temporal aspect of scarcity is important to note because a resource such as transportation capacity may be plentiful through most of the year but, due to the occurrence of peak season(s), be scarce at particular times—a

a highly versatile resource (Markman et al. 2009). This is especially the case in settings such as trucking, where individuals' skills are more occupational-specific than firm-specific, which encourages drivers to churn from one carrier to another seeking jobs than better fit their needs (Costello and Karickhoff 2019; Miller et al. 2021a).

To date, most of the research regarding FMR has been conceptual—which is to be expected with a nascent theory (Ralston et al. 2022). Researchers have focused on topics such as identifying how the versatility and mobility of resources affects FMR (Markman et al. 2009); sketching the types of actions firms can take in response to FMR (Schwieterman and Miller 2016); describing how firms can take actions through FMR to degrade their rivals' resource bases (Bell et al. 2015); highlighting concerns regarding managers having myopic FMR perceptions (Ralston et al. 2017) especially as it pertains to labor (Opengart et al. 2018); and explaining why FMR is ideally suited as a theory via which L&SCM researchers can develop unique insights (Ellram et al. 2013; Ralston et al. 2022a; 2022b). Empirical inquiries into FMR have primarily been conducted in the management field and concern firms poaching workers in settings such as mutual funds (Rao and Drazin 2002) and software (Gardner 2005), although FMR may help explain why the impact of higher industry-level driver turnover rates on industry-level trucking freight rates is more pronounced when employment is rising (Miller et al. 2020).

This research extends FMR in two ways. First, we introduce the concept of compound relations (Ross and Robertson 2007) to suggest that FMR regarding labor is more complex when demand for the focal sector is derived from another sector with whom the focal sector is competing for the same labor. The reason is this: without further elaboration, it is theoretically ambiguous

quintessential example is air freight capacity from Asia in the autumn just before the holiday shopping season (Ellram et al. 2013). Also, an input such as labor may be scarce in the short run, e.g., if there are few workers who are unemployed to draw from, but better supplied in the longer run, when wages rise and there is time for employed workers to switch occupations and for there to be new entrants to the labor market.

whether increased activity in the demand-generating sector will increase employment in the focal sector (by creating more need for workers due to higher demand) or decrease employment (by claiming a greater share of the labor pool). Based on empirical findings looking at demand propagation in supply chains (Carvalho et al. 2021; Decker et al. 2022; Fujii 2016), we expect that the demand-generating mechanism can override the labor poaching mechanism, suggesting an important boundary condition (Goldsby et al. 2013) for FMR. Second, we suggest the nature of this demand-generating mechanism as it pertains to trucking will differ based on the extent demand requires short versus long hauls. This suggests that state-level trucking payroll dynamics are likely to be especially sensitive to industries that generate a large volume of short-distance shipments.

THEORY & HYPOTHESES

Our theory can be categorized as middle-range (Pawson 2000; Stank et al. 2017) in that we draw on tenets from FMR theory and utilize top-down theoretical elaboration (Craighead et al. 2016) to incorporate contextual factors that explain why our postulated mechanisms operate to bring about the theorized effects (Astbury and Leeuw 2010). This aligns with Cronin et al.'s (2021) arguments that researchers should develop unit theories, i.e., those that make predictions in a specific context from more general programmatic theories.

We begin by focusing on the impact of state-level manufacturing employment on state-level trucking payrolls. Current conceptualizations of FMR focus only on how manufacturers compete with trucking firms for the same labor pool (Opengart et al. 2018). However, trucking firms have compound relations (Ross and Robertson 2007) with manufacturing firms in that manufacturing activity generates over 59% of ton-miles for for-hire trucking firms, according to the 2017 Commodity Flow Survey (CFS). Thus, while manufacturing firms compete with trucking firms over the same labor pool (Burks and Monaco 2019, Phares and Balthrop 2022), this labor poaching mechanism must be considered in conjunction with a demand generating mechanism. Increased employment in manufacturing plants within a state is likely to be correlated with increased output, given consistent findings from economists about constant returns to scale between labor and physical unit output in this sector (Syverson 2011). The question is: which mechanism is more powerful?

We submit that the demand generating mechanism will override the labor poaching mechanism for manufacturing plants. The reasons are twofold. First, manufacturing activity generates truck transportation not only for finished goods but also for the intermediate inputs (Lieb 1994). For example, higher output of motor vehicles not only generates demand for transporting those finished vehicles to local dealers, but it also generates demand for the shipment of components from Tier 1 suppliers to assembly plants (Carvalho et al. 2021). Furthermore, Fujii (2016) reports that firms whose customers are manufacturers see their sales strongly affected by the change in their manufacturing customers' sales. Taken together, this explains why local shocks to manufacturing employment cascade extensively through local economies (Adelino et al. 2017). Thus, the demand generating mechanism should be strongly present for manufacturing. Second, manufacturers make little use of private fleets based on the 2017 CFS—only 6.1% of ton-miles are hauled by private fleets. Consequently, the empirical effects of manufacturing's labor poaching mechanism should be limited. In fact, Burks and Monaco (2019) find only 9.6% of for-hire drivers come from manufacturing employment, 9% and leave for-hire driving to enter manufacturing employment, while Phares and Balthrop (2022) show 8.64% of drivers come from manufacturing employment, and 8.6% leave for manufacturing employment.[3] Importantly, manufacturing activity

[3]It is worth noting that Burks and Monaco (2019) find that the flow of private carriage drivers to and from manufacturing employment is higher than that of for-hire drivers: 16.4% coming from, and 15.5% leaving to, manufacturing employment, or about 70% greater.

fell steeply with the onset of the COVID-19 pandemic and, relative to retail activity, was far slower to recover (FRB 2022). There are few reasons to expect these mechanisms would have behaved differently during the initial onset of the pandemic versus the over the longer-term horizon. We therefore posit:

> ***H1a**: Comparing April 2020 to April 2019, states that saw a steeper decline in manufacturing payrolls at the onset of the COVID-19 pandemic saw a steeper decline in truck transportation payrolls.*

> ***H1b**: Comparing December 2021 to December 2019, states whose manufacturing employment more completely returned to pre-COVID levels saw a more rapid recovery of truck transportation payrolls.*

We now turn our attention towards trucking employment dynamics in response to employment changes in the natural resource extraction sector[4], which at the state-level is closely tied to activity in the energy sector (Agerton et al. 2017). As noted by Rickman and Wang (2020) and Allcott and Keniston (2018), sharp increases in energy prices result in energy booms that significantly increase demand for activities that support energy exploration, such as demand for warehouses that support fracking activity (Wang 2019). For example, Decker et al. (2022) document that geographic areas with extensive shale oil drilling saw a substantial increase in business formation of transportation and warehousing firms vis-à-vis a set of control counties that did not see an increase in shale oil drilling. This suggests that the freight generating demand of natural resource extraction was quite strong, and the fact that employment in transportation and warehouses increased in shale oil regions further suggests that this demand generating mechanism

[4] Natural resource extraction includes agriculture activities as well as mining activity. Unfortunately, separate state-level data on mining activity is suppressed for many states by the Quarterly Census of Employment and Wages for identity disclosure reasons. However, we find the same results when we utilize a state-level indicator for states where hydraulic fracturing activity occurs using data from Baker Hughes.

will override the labor poaching mechanism. Consistent with this, Jacobsen & Parker (2016) report that energy busts result in negative local labor market impacts.

We highlight these issues because the onset of the COVID-19 pandemic and the subsequent fall in oil prices resulted in a sharp contraction in the energy sector, suggesting a negative impact on state-level trucking employment both at the onset of the pandemic but especially as it pertains to recovery of state-level truck transport employment. We thus posit:

> ***H2a***: *Comparing April 2020 to April 2019, states that saw a steeper decline in natural resource extraction payrolls at the onset of the COVID-19 pandemic saw a steeper decline in truck transportation payrolls.*
>
> ***H2b***: *Comparing December 2021 to December 2019, states whose natural resource extraction employment more completely returned to pre-COVID levels saw a more rapid recovery of truck transportation payrolls.*

We next turn to comparing the magnitude of the effects of state-level manufacturing and natural resource extraction employment on the rate of recovery of truck transportation employment. We expect state-level natural resource employment dynamics will be more strongly related to the recovery of state-level trucking employment than state-level manufacturing employment dynamics. Two reasons undergird this prediction. First, the average transportation distance for truckload shipments from manufacturers is far longer than shipments from mining operations based on the 2017 CFS. For shipments $\geq$ 10,000 pounds, the average distance for a for-hire trucking shipment from a manufacturing plant was 350 miles, whereas the average distance from a mining establishment was just 61 miles. As discussed by Ouellet (1994), local natural resource shipments of this sort are often hauled by local carriers that tailor their operations to a small number of shippers. This is in part because many natural resource extraction products (e.g., coal or mineral ores) are lower in value per pound than consumer goods, which limits the range over which truck transportation is economically feasible. In comparison, the longer distance associated with a given shipment of manufactured products increases the likelihood that shipments are hauled by drivers not domiciled in establishments located in the same state. Second, whereas many manufacturing shipments can be hauled in general purpose dry van trailers, shipments associated with natural resource extraction generally require specialized equipment (e.g., pneumatic dump trailers) that can't be easily reallocated to other freight. Thus, whereas many dry van carriers that served manufacturers could transition towards hauling elevated levels of consumer freight following the onset of the COVID-19 pandemic (Caplice 2021), carriers servicing natural resource extraction shippers tend to lack this flexibility. This should likewise increase the sensitivity of state-level trucking employment to state-level natural resource extraction employment dynamics. We therefore posit:

> ***H3***: *Comparing December 2019 to December 2021, changes in state-level natural resource extraction employment will be a stronger predictor of changes in state-level trucking employment than changes in state-level manufacturing employment.*

We next turn our attention towards warehousing activity, where we focus theorizing only on the recovery of state-level trucking employment. We limit ourselves here because predictions at the pandemic's onset are difficult to discern *ex ante*; the problem is that warehousing activity supports both e-commerce sales, which exploded with the onset of the COVID-19 pandemic 2020 (U.S. Census Bureau 2021), and manufacturing and natural resource extraction (Deblanc et al. 2014), which fell sharply. Focusing on recovery of state-level trucking employment, we expect states that saw a larger increase in warehousing activity as of late 2021 relative to late 2019 will have seen a more rapid rebound in trucking payrolls than states that saw a smaller increase in warehousing activity over this period. We expect the freight generating mechanism to outweigh the labor poaching mechanism because warehousing activity has become increasingly synergistic with freight generation, due to the role of warehouses in supporting e-commerce activity. One reason for this is that e-commerce warehousing supports transloading operations, which less-than-truckload carriers have been pursuing (Cassidy 2022a; 2022b). As most of the increased activity in warehousing since the onset of the pandemic does not require the skills of trained truck drivers (Bhattarai 2021), there is little reason to expect the labor poaching mechanism has increased[5] since the onset of the pandemic. In fact, per Ouellet (1994) and Viscelli (2016), we would expect the nature of working as a picker at an e-commerce warehouse would likely not fit the job characteristics that truckers are looking for. We therefore suggest:

> ***H4****: Comparing December 2021 to December 2019, states that saw a larger increase in warehousing employment saw a more rapid recovery of truck transportation employment.*

We lastly turn to the topic of how we expect the recovery of trucking employment to be contingent on whether a state is home to a large container port. Because real imports of consumer goods were trending down in 2019 and early 2020 prior to the pandemic being formally declared (BEA 2023a), we do not have a theory-based prediction regarding how the presence of a port shaped the initial drop in trucking payrolls. However, we do expect states that are home to large container ports will have seen a more rapid recovery of trucking employment due to two complementary factors associated with the freight origination mechanism. First, the torrid pace of consumer spending following pandemic lockdowns that continued unabated (and accelerated) in 2021 created very strong demand for drayage drivers (Cassidy and Ashe 2022) due to the surge in containerized imports. For example, the National Retail Federation (2022) estimated that the twenty-foot equivalent units of containerized retail imports increased 17% in 2021 from 2020. Second, as noted by (Cassidy 2022a; 2022b), increased imports generate additional demand for transloading operations. This can support truck transportation employment because less-than-

[5] In fact, per Ouellet (1994) and Viscelli (2016), we would expect the nature of working as a picker at an e-commerce warehouse would likely not fit the job characteristics that truckers are looking for. Levy (2023) also notes that many individuals are attracted to over-the-road trucking precisely because they do not wish to work under direct managerial supervision.

truckload carriers have found diversifying into transloading is attractive. Doing this allows them to leverage their knowledge regarding how to disaggregate and reaggregate freight, akin to their diversification into last mile delivery (Peinkofer et al. 2020). There is little reason to expect container port operations to compete for the same labor pool, suggesting the labor poaching mechanism is unlikely to be strong. Thus, we posit:

> ***H5***: *States that are home to a large container port saw a more rapid recovery of truck transportation employment.*

RESEARCH DESIGN

Data Sources and Collection

To test our predictions, we assemble a unique state-level panel dataset on truck transportation establishment[6] payrolls, drawing primarily on the BLS's Quarterly Census of Employment and Wages (QCEW). QCEW relies on administrative records from establishments paying state-level unemployment insurance taxes and covers the near-universe of private employer operations—11.3 million establishments as of Q1 2022—in the United States (BLS 2023b). We collect data through 2021 because 2022 data are still preliminary and are only available through June 2022 as of the time of writing[7]. Given that state-level data can be substantially revised, we believe it is appropriate to utilize data that has been finalized by the BLS.

We believe QCEW data are superior for answering our research question as compared to data from the U.S. Department of Transportation's Motor Carrier Census (MCC) for several reasons. First, carriers need to complete the MCC biennially, meaning that monthly snapshots of

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[6] Per BLS (2023b; https://www.bls.gov/opub/hom/cew/concepts.htm), "An establishment is commonly understood as a single economic unit, such as a farm, a mine, a factory, or a store, that produces goods or services. Establishments are typically at one physical location and engaged in one, or predominantly one, type of economic activity for which a single industrial classification may be applied."

[7] Detailed QCEW data for state-level payrolls by industry are released ~6 months after the reference quarter in question (e.g., Q3 2022 data will be released in March 2023). 2022 data will not be finalized until September 2023 per the BLS (2023c; https://www.bls.gov/opub/hom/cew/design.htm).

all MCC files may not be representative of how industry capacity is changing (e.g., carriers could have had February 2020 MCC data that wasn't updated even by December 2021). Second, MCC data assigns all employees of a carrier to the state where a carrier is headquartered. However, data from the U.S. Census Bureau's Business Dynamics Statistics database (U.S. Census Bureau 2023a) indicates carriers with ≥ 500 employees operate an average of 18 establishments in 2017 – 2019, with carriers with ≥ 10,000 employees operating about 60 establishments per firm. Given large carriers locate drivers, in part, based on where their freight originates (Simão et al. 2010), establishment-level data is preferable to study our research question, given the heterogenous impact that COVID-19 had on freight markets (Caplice 2021).

A few additional features with QCEW data are worth noting. These data include all employees working at a given establishment classified in truck transportation (NAICS 484). This means that the data aren't just capturing truck drivers, but also dock workers, dispatchers, mechanics, and managers. However, data on occupational statistics by industry indicate that ~62% of individuals employed by truck transportation establishments work as motor vehicle operators (BLS 2023a). Thus, movements in payroll numbers will be heavily a function of movements in the number of truck drivers. Second, QCEW's coverage of independent owner-operators (IOOs) and leased owner-operators (LOOs) is unclear. The reason for this is that IOOs and LOOs need to have their own EINs for taxation purposes, and many adopt a legal form of organization where there are no employees (e.g., limited liability companies). Complexity exists because there are tax advantages for IOOs and LOOs to organize as S-Corps that allow for an owner to declare himself/herself an employee for tax purposes. The U.S. Census Bureau (2023b) indicates 58.1% of truck transportation establishments with less than 5 employees are organized as S-Corps, suggesting a not insignificant percent of IOOs and LOOs are captured in our data.

Variables

Our dependent variable is state-level, monthly payrolls for all private truck transportation establishments located in each state, sourced from QCEW. As states vary tremendously in their trucking employment—in 2019 Texas had over 150,000 employees in trucking, whereas Delaware had 2,400—we take the natural logarithm to focus on percent changes in employment. Our data covers 60 months from January 2017 – December 2021. While our interest is in dynamics from April 2020 onwards, we need data from 2017 – 2019 to reliably estimate seasonal adjustment factors for each month given the pronounced seasonality of trucking payrolls. We denote this variable as *LnEmploy*. We collect data for the contiguous 48 states, omitting Alaska and Hawaii due to their unique geography and industry composition. As can be seen in Figure 1a, state-level trucking employment exhibited heterogenous declines as of April 2020 relative to March 2020, with the state of Michigan—the heart of the automobile and light truck assembly sector that went into near-complete shutdown in April 2020 (FRB 2023a)—seeing the steepest declines. However, as shown in Figure 1b, which compares truck transportation employment as of December 2021 relative to December 2019, states like Michigan had seen a near complete recovery of trucking payrolls, whereas states like North Dakota and Wyoming had seen sustained declines of 18% and 15%, respectively. Moreover, states such as Florida, California, and Arizona saw substantial increases in trucking payrolls of 12%, 8%, and 8% respectively, over the same period. This points towards highly heterogeneous rebounds of trucking employment from the April 2020 lows.

Figure 1a: Map of state-level change in truck transportation payrolls as of April 2020 relative to March 2020.

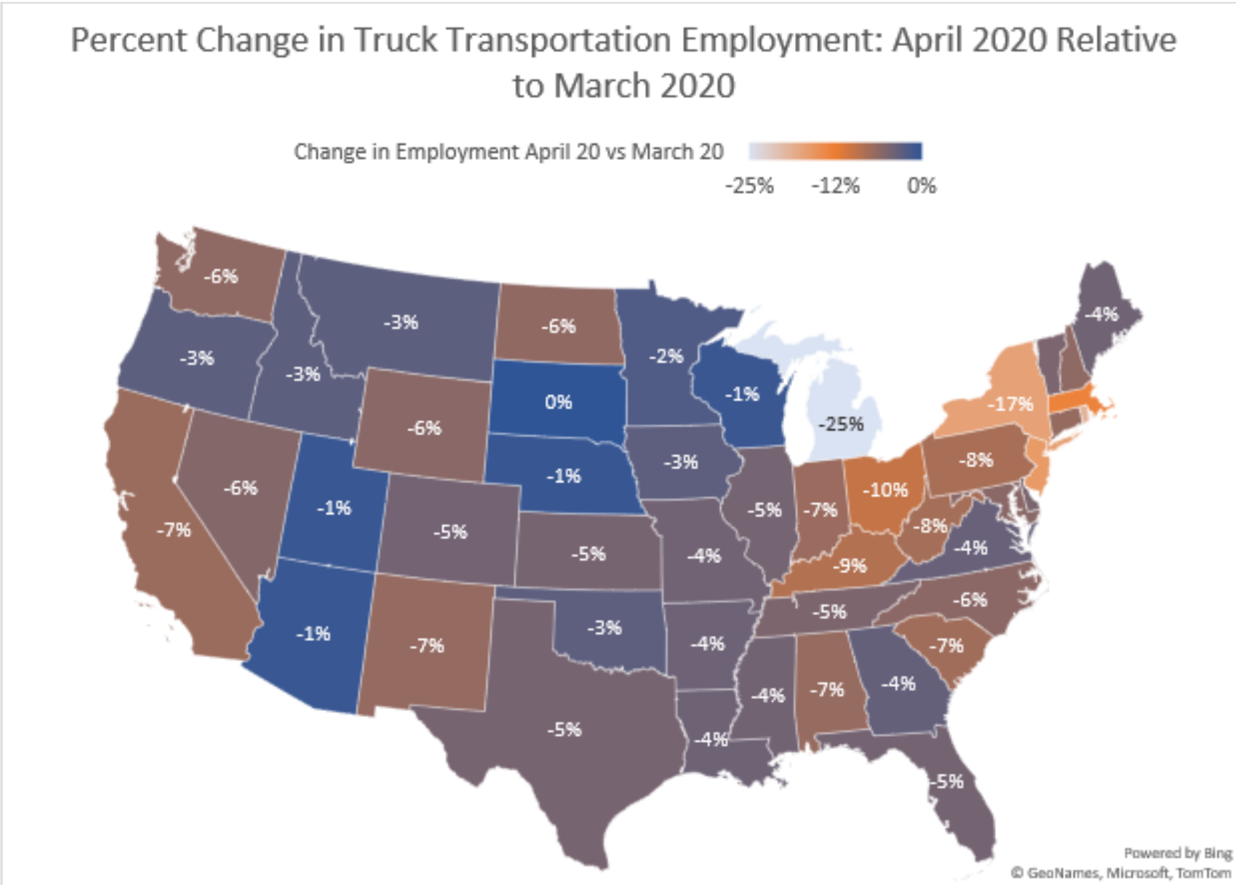
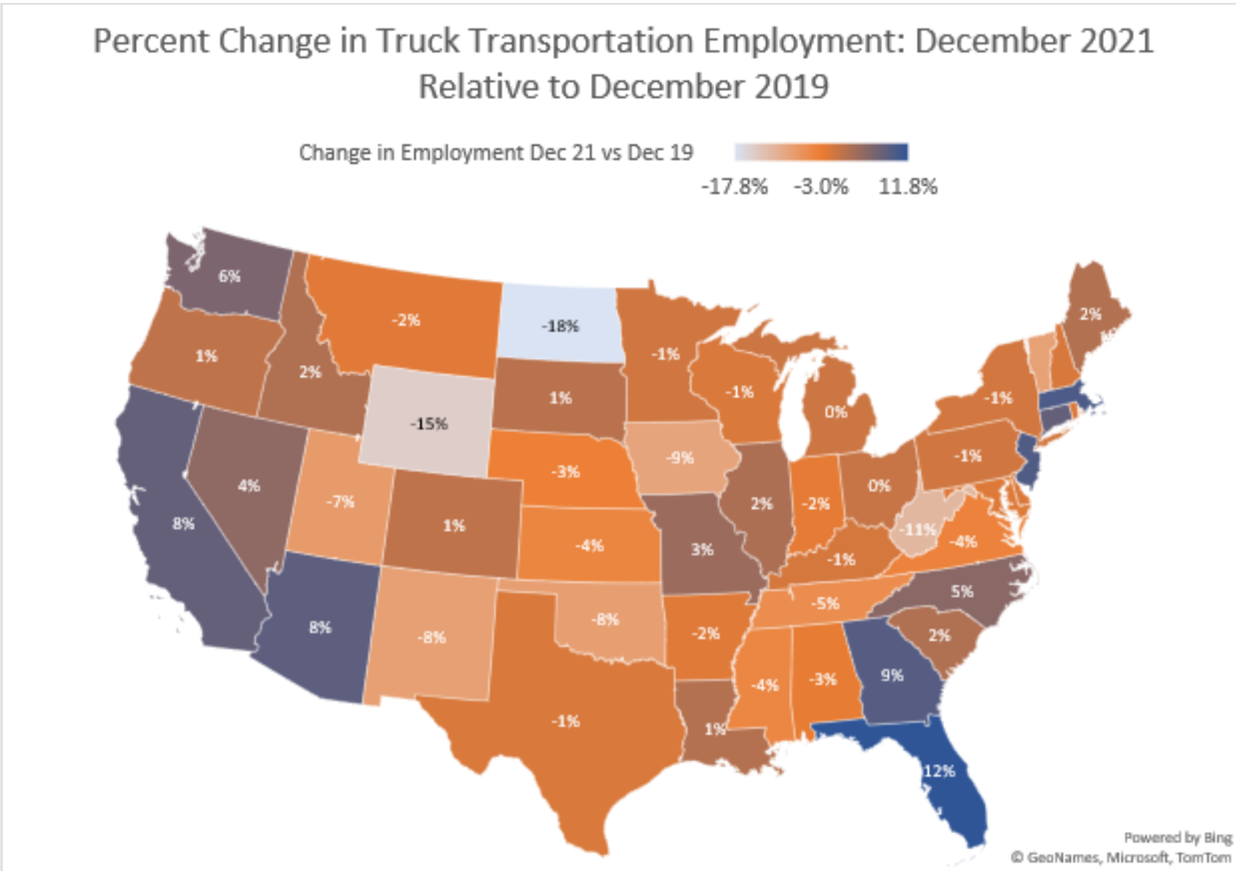


Figure 1b: Map of state-level change in truck transportation payrolls as of December 2021 relative to December 2019.



As we test our hypotheses using discontinuous growth curve models (Bliese et al. 2016), it is essential we appropriately operationalize our design matrix of variables to capture the passage of time. Figure 2a plots total truck transportation payrolls for the lower 48 states from QCEW. This plot demonstrates substantial seasonality, in addition to an upward trend that was sharply broken with the onset of the COVID-19 economic shutdown. To properly model change over time, we utilize a 4-piece specification characterized by a (i) linear trend from January 2017 – December 2019; (ii) a dummy variable from January 2020 – March 2020; (iii) a dummy variable for April 2020; and (iv) a linear trend from May 2020 – December 2021. We also include a vector of 11 month dummy variables to capture seasonality. This design matrix for a given state can be seen in Table 1. We include the dummy variable for January 2020 – March 2020 to account for the drug and alcohol clearing house taking effect, coupled with our desire to capture any effects of the pandemic's onset that may have manifested by the March 12 date for the March payrolls. Figure 2b demonstrates this specification, when fit to the natural log of trucking employment for the lower 48 states, accurately replicates the data (R^2 = 0.947). We label the four components *Trend19, DJanMar20, DApr20,* and *Trend21*, respectively. Our theorizing focuses on how our moderators affect *DApr20* and *Trend21*.

To proxy state-level changes in activity in various industries, we rely on state-level changes in employment in the respective industries. While we ideally would have access to state-level data on industry activity at a monthly level, such data do not exist at the state level. Series such as the Federal Reserve Board's industrial production indexes are only available nationally. However, we can obtain state-level monthly employment data for major industry sectors from QCEW. Given pervasive findings of constant returns to scale within various industries (Syverson 2011), state-level changes in employment by industry are a useful proxy, as they should be strongly correlated with state-level changes in industry output.

Figure 2a: State-level trucking employment for the lower 48 states.

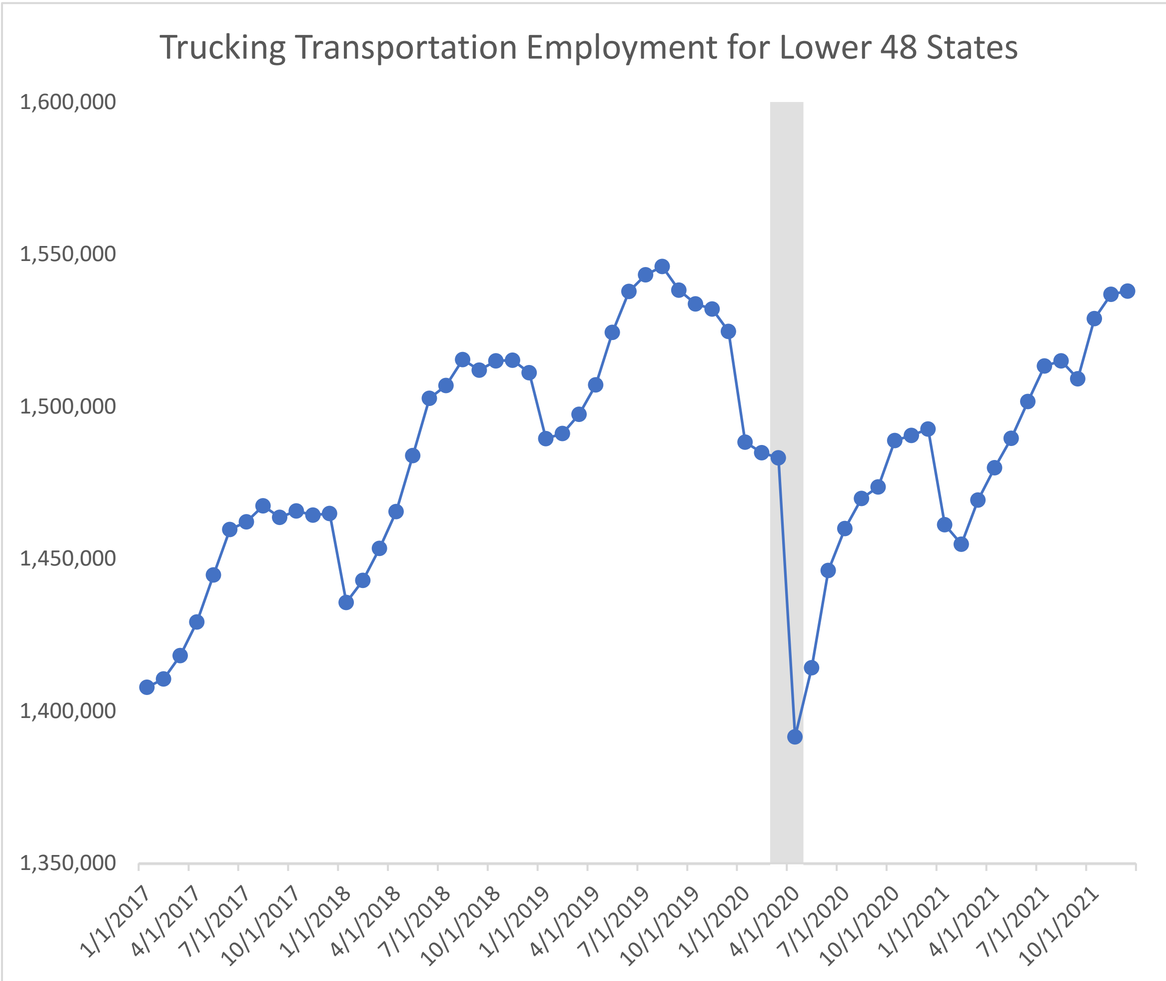


Figure 2b: Estimated discontinuous growth curve specification fit to the natural logarithm of total payrolls for the lower 48 states.

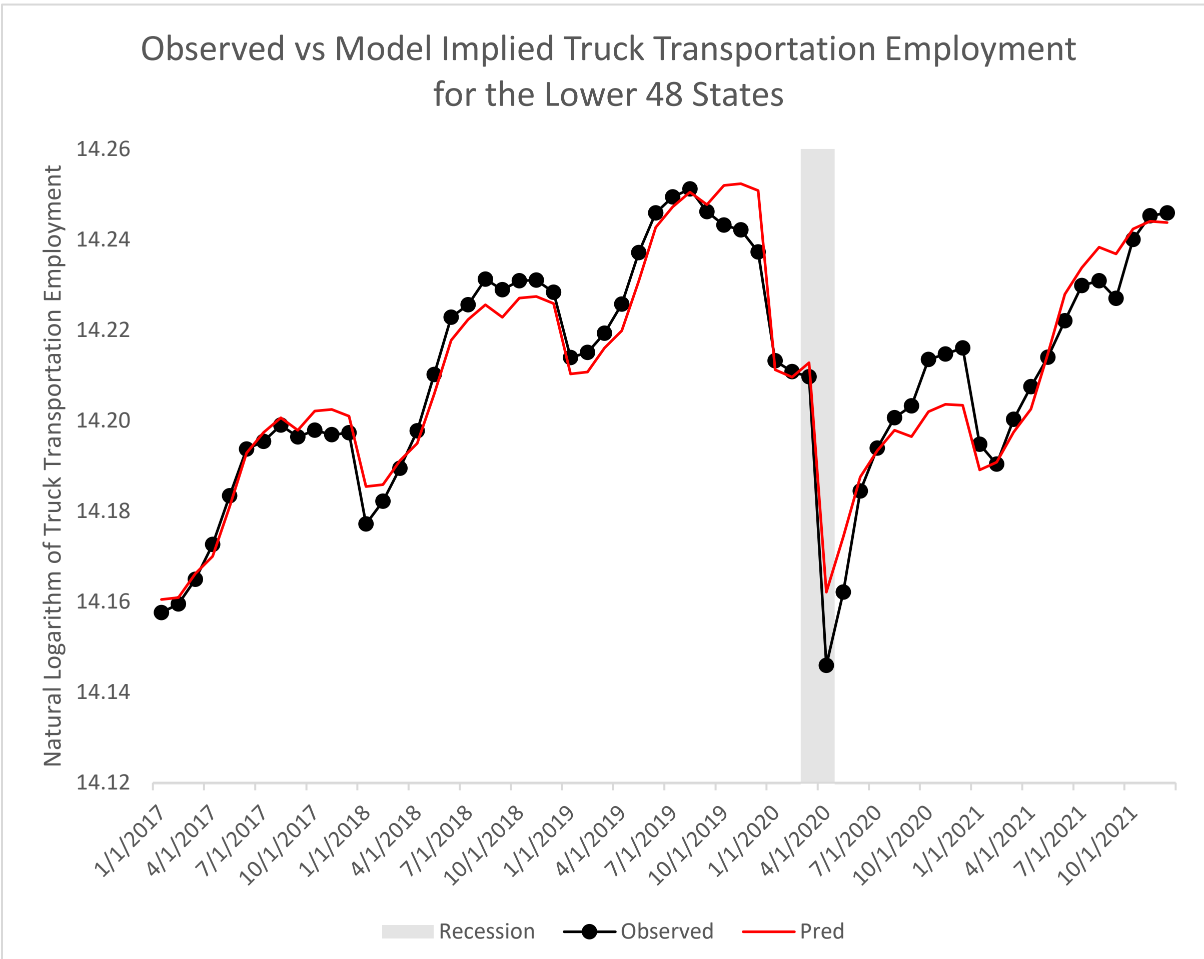


Table 1: Design matrix for discontinuous growth curve model.

1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	*Jan* 17
1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	*Feb* 17
1	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	*Mar* 17
1	3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	*Apr* 17
1	4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	*May* 17
1	5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	*June* 17
1	6	0	0	0	0	0	0	0	0	0	1	0	0	0	0	*July* 17
1	7	0	0	0	0	0	0	0	0	0	0	1	0	0	0	*Aug* 17
1	8	0	0	0	0	0	0	0	0	0	0	0	1	0	0	*Sept* 17
1	9	0	0	0	0	0	0	0	0	0	0	0	0	1	0	*Oct* 17
1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	1	*Nov* 17
1	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*Dec* 17
1	12	0	0	0	1	0	0	0	0	0	0	0	0	0	0	*Jan* 18
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
1	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*Dec* 19
1	35	1	0	0	1	0	0	0	0	0	0	0	0	0	0	*Jan* 20
1	35	1	0	0	0	1	0	0	0	0	0	0	0	0	0	*Feb* 20
1	35	1	0	0	0	0	1	0	0	0	0	0	0	0	0	*Mar* 20
1	35	1	1	0	0	0	0	1	0	0	0	0	0	0	0	*Apr* 20
1	35	1	1	1	0	0	0	0	1	0	0	0	0	0	0	*May* 20
1	35	1	1	2	0	0	0	0	0	1	0	0	0	0	0	*June* 20
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
1	35	1	1	20	0	0	0	0	0	0	0	0	0	0	0	*Dec* 21

Notes: Column 1 = Intercept; Column 2 = Trend from January 2017 – December 2019; Column 3 = Dummy for January 2020 – March 2020; Column 4 = Dummy April 2020; Column 5 = Trend from May 2020 – December 2021; Columns 6 – 16 = Monthly Dummies for January, February, etc.

Our first set of moderators concerns changes in manufacturing employment. We utilize two measures: (i) percent change in manufacturing employment as of April 2020 relative to April 2019 ($\Delta MfgApr20$) and (ii) percent change in manufacturing employment as of December 2021 relative to December 2019 ($\Delta MfgDec21$). We utilize year-over-year changes to account for different seasonal factors at the state level, which is permissible given the high persistence of employment (Sterk et al. 2021). Furthermore, this strategy avoids issues of excessive collinearity, which we encounter if we utilize change in employment as of April 2020 relative to March 2020 and then December 2021 relative to May 2020.

Our second set of moderators are (i) percent change in natural resource extraction employment as of April 2020 relative to April 2019 ($\Delta NatApr20$) and (ii) percent change in natural resource extraction employment as of December 2021 relative to December 2019 ($\Delta NatDec21$). Likewise, our third set of moderators are (i) percent change in warehousing employment as of April 2020 relative to April 2019 ($\Delta WareApr20$) and (ii) percent change in warehousing employment as of December 2021 relative to December 2019 ($\Delta WareDec21$). Lastly, our fourth moderator, *ConPort*, equals one if a state is home to a major container port and zero otherwise. States with major container ports were identified from Miller and Kulpa (2022).

While variance in our moderators is exogenous of trucking employment given that state-level manufacturing endowments develop over decades (Holmes 1998) and natural resource extraction is based on geological features (Decker et al. 2022), we control for several state-level factors that may impact results. The first set of controls are (i) percent change in wholesaling employment as of April 2020 relative to April 2019 ($\Delta WsaleApr20$) and (ii) percent change in wholesaling employment as of December 2021 relative to December 2019 ($\Delta WsaleDec21$). We control for wholesaling activity given that the 2017 CFS indicates wholesalers generate ~30% of for-hire trucking ton-miles and, furthermore, rely more extensively on private fleets (which may compete with for-hire carriers for truck drivers). Thus, wholesaling is expected to have both freight generation and labor poaching dynamics with truck transportation.

The second set are (i) percent change in construction employment as of April 2020 relative to April 2019 ($\Delta ConApr20$) and (ii) percent change in construction employment as of December 2021 relative to December 2019 ($\Delta ConDec21$). We control for changes in construction employment given construction activity also generates freight demand coupled with evidence that construction competes with trucking for the same labor pool (Burks & Monaco 2019, Phares and Balthrop 2022).

The third set are (i) percent change in courier & messenger employment as of April 2020 relative to April 2019 ($\Delta CourApr20$) and (ii) percent change in courier & messenger employment as of December 2021 relative to December 2019 ($\Delta CourDec21$). We control for changes in courier & messenger employment given the strong overlap between skillsets to drive large trucks versus delivery vehicles, as well as the fact that large firms in this sector (e.g., UPS) employ tractor-trailer drivers (2023)].

Our fourth control is dummy variable that equals one if a state had a Republican governor in office at the time of the COVID-19 pandemic (*Repub*). We control for this factor given Republican governors were generally more relaxed with COVID-19 restrictions, which could have affected employment levels. Lastly, we control for state-level maximum unemployment benefits (*Maxben*) to remove the possibility that firms would be more willing to let workers go if states offered more generous benefits and, furthermore, to address concerns that higher unemployment benefits may discourage workers from returning.

In addition to these controls that enter as interaction terms involving the discontinuous growth curve coefficients, we also include vectors of state fixed effects to remove any stable state-level variation that affects trucking employment. This results in our analysis having a within-state orientation (Ketokivi et al. 2021). The full correlation matrix, means, and standard deviations of the observed measures across all 48 states can be found in Table 2. It should be noted that the strong positive correlation amongst the discontinuous growth curve coefficients is expected (Cudeck and Harring 2007).

Table 2: Correlation matrix, means, and standard deviations of observed measures.

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*
1. LnEmploy	1.00																			
2. Trend19	0.00	1.00																		
3. DJanMar20	-0.01	0.73	1.00																	
4. DApr20	-0.01	0.66	0.90	1.00																
5. Trend21	0.00	0.52	0.72	0.80	1.00															
6. ΔMfgApr20	-0.10	0.00	0.00	0.00	0.00	1.00														
7. ΔMfgDec21	-0.06	0.00	0.00	0.00	0.00	0.25	1.00													
8. ΔNatApr20	0.02	0.00	0.00	0.00	0.00	0.10	0.31	1.00												
9. ΔNatDec21	-0.01	0.00	0.00	0.00	0.00	-0.26	0.17	0.55	1.00											
10. ΔWareApr20	0.31	0.00	0.00	0.00	0.00	0.05	0.10	-0.05	0.13	1.00										
11. ΔWareDec21	0.19	0.00	0.00	0.00	0.00	0.05	0.02	-0.07	-0.38	0.31	1.00									
12. ConPort	0.38	0.00	0.00	0.00	0.00	-0.01	-0.22	0.01	0.01	0.03	0.02	1.00								
13. ΔConApr20	0.01	0.00	0.00	0.00	0.00	0.57	0.50	0.30	-0.20	0.15	0.29	-0.11	1.00							
14. ΔConDec21	-0.08	0.00	0.00	0.00	0.00	0.06	0.42	0.53	0.53	0.00	-0.30	-0.21	0.32	1.00						
15. ΔWsaleApr20	0.03	0.00	0.00	0.00	0.00	0.57	0.35	0.30	-0.33	-0.18	0.10	-0.19	0.82	0.32	1.00					
16. ΔWsaleDec21	0.03	0.00	0.00	0.00	0.00	0.17	0.33	0.46	0.16	0.01	0.10	-0.08	0.50	0.69	0.55	1.00				
17. ΔCourApr20	0.01	0.00	0.00	0.00	0.00	0.11	0.03	-0.20	-0.05	0.39	0.22	0.09	0.16	0.08	-0.03	0.22	1.00			
18. ΔCourDec21	-0.04	0.00	0.00	0.00	0.00	0.18	0.24	0.04	-0.06	0.12	0.10	0.02	0.16	0.09	0.12	0.16	0.24	1.00		
19. Repub	-0.04	0.00	0.00	0.00	0.00	0.20	0.33	0.13	-0.10	-0.32	-0.16	-0.15	0.28	0.21	0.43	0.18	-0.04	0.02	1.00	
20. Maxben	-0.14	0.00	0.00	0.00	0.00	0.08	-0.28	-0.10	0.18	0.14	-0.09	0.12	-0.25	-0.10	-0.26	-0.26	0.12	-0.16	-0.29	1.00
Mean	9.89	24.50	0.40	0.35	3.50	-11.67	-1.24	-7.15	-3.62	6.48	25.88	0.17	-11.35	1.77	-6.66	-0.63	9.34	25.65	0.54	4.76
Standard Deviation	1.03	11.76	0.49	0.48	5.97	7.033	3.148	7.698	10.34	14.5	23.79	0.37	13.89	4.5	4.106	4.267	8.49	11.17	0.5	1.45

Statistical Model Formulation & Results

The statistical model we use to test our hypotheses is represented in Equation 1. Letting *s* index each state, letting *y* index each year, and letting *m* index the month of the year, we have:

$$LnEmploy_{sym} = \alpha_0 + \alpha_1 Trend19_{ym} + \alpha_2 DJanMar20_{ym} + \alpha_3 DApr20_{ym} + \alpha_4 Trend21_{ym} + (\beta_1 DApr20_{ym} \times \Delta MfgApr20_s) + (\beta_2 DApr20_{ym} \times \Delta NatApr20_s) + (\beta_3 DApr20_{ym} \times \Delta WareApr20_s) + (\beta_4 DApr20_{ym} \times ConPort_s) + (\beta_5 DApr20_{ym} \times \Delta WsaleApr20_s) + (\beta_6 DApr20_{ym} \times \Delta ConApr20_s) + (\beta_7 DApr20_{ym} \times \Delta CourApr20_s) + (\beta_8 DApr20_{ym} \times Repub_s) + (\beta_9 DApr20_{ym} \times Maxben_s) + (\delta_1 Trend21_{ym} \times \Delta MfgDec21_s) + (\delta_2 Trend21_{ym} \times \Delta NatDec21_s) + (\delta_3 Trend21_{ym} \times \Delta WareDec21_s) + (\delta_4 Trend21_{ym} \times ConPort_s) + (\delta_5 Trend21_{ym} \times \Delta WsaleDec21_s) + (\beta_6 Trend21_{ym} \times \Delta ConDec21_s) + (\beta_7 Trend21_{ym} \times \Delta CourDec21_s) + (\beta_8 Trend21_{ym} \times Repub_s) + (\beta_9 Trend21_{ym} \times Maxben_s) + \gamma_s + \theta_m + \varepsilon_{sym} \tag{1}$$

Note that after specifying the two trends and two time-related dummy variables mentioned above, our specification first interacts the dummy for April 2020, $DApr20_{ym}$, with all nine of our moderators and controls (β_i coefficients), and then interacts the Covid recovery trend, $Trend21_{ym}$, with the same nine moderators/predictors (δ_i coefficients); this is consistent with our theoretical focus on these relationships. **H1a** predicts β_1 will be positive, indicating that states that lost more manufacturing jobs with the onset of the COVID-19 pandemic saw a sharper decline in truck transportation employment. **H1b** predicts δ_1 will be positive, indicating that states whose manufacturing employment had declined more (less) as of December 2021 relative to 2021 would have a slower (faster) rebound of truck transportation employment between May 2020 and December 2021. **H2a** and **H2b** make analogous predictions, except in the context of natural resource extraction employment (captured by β_2 and δ_2). **H3** predicts that $\delta_2 > \delta_1$. **H4** regarding warehousing predicts δ_3 is positive, indicating that states whose warehousing employment had grown more (less) as of December 2021 relative to 2019 would have a faster (slower) rebound of truck transportation employment between May 2020 and December 2021. Lastly, **H5** regarding container port presence predicts δ_4 is positive, indicating that states with a large container port would have a faster rebound of truck transportation employment between May 2020 and December 2021. γ_s and θ_m represent vectors of state and month of year fixed effects, respectively. All continuous predictors were mean centered prior to creating interaction effects.

The model in Equation 1 was estimated using the PROC MIXED routine in SAS Version 9.4 using full information maximum likelihood. State-levels errors were allowed to follow an ARMA(1,1) process as in Miller and Saldanha (2016) given that state-level residuals were more persistent than allowed by an AR(1) process. The ARMA(1,1) is defined by two parameters, γ and ρ, where γ represents a stable correlation across time between occasions and ρ represents an autoregressive component that declines exponentially. Formally, with *n* representing the number of records within a subject, we have:

$$ARMA(1,1) = \begin{pmatrix} \sigma^2 & & & & \\ \gamma\sigma^2 & \sigma^2 & & & \\ \rho\gamma\sigma^2 & \gamma\sigma^2 & \sigma^2 & & \\ \rho^2\gamma\sigma^2 & \rho\gamma\sigma^2 & \gamma\sigma^2 & \sigma^2 & \\ \dots & \dots & \dots & \dots & \dots \end{pmatrix} \tag{2}$$

Influence statistic diagnostics indicated the state of Utah contributed multiple influential observations, which resulted in the decision to exclude Utah from the remained of the analysis. With Utah removed, residuals closely approximated a normal curve as assumed in the linear mixed model framework. The primary results are reported in Table 3.

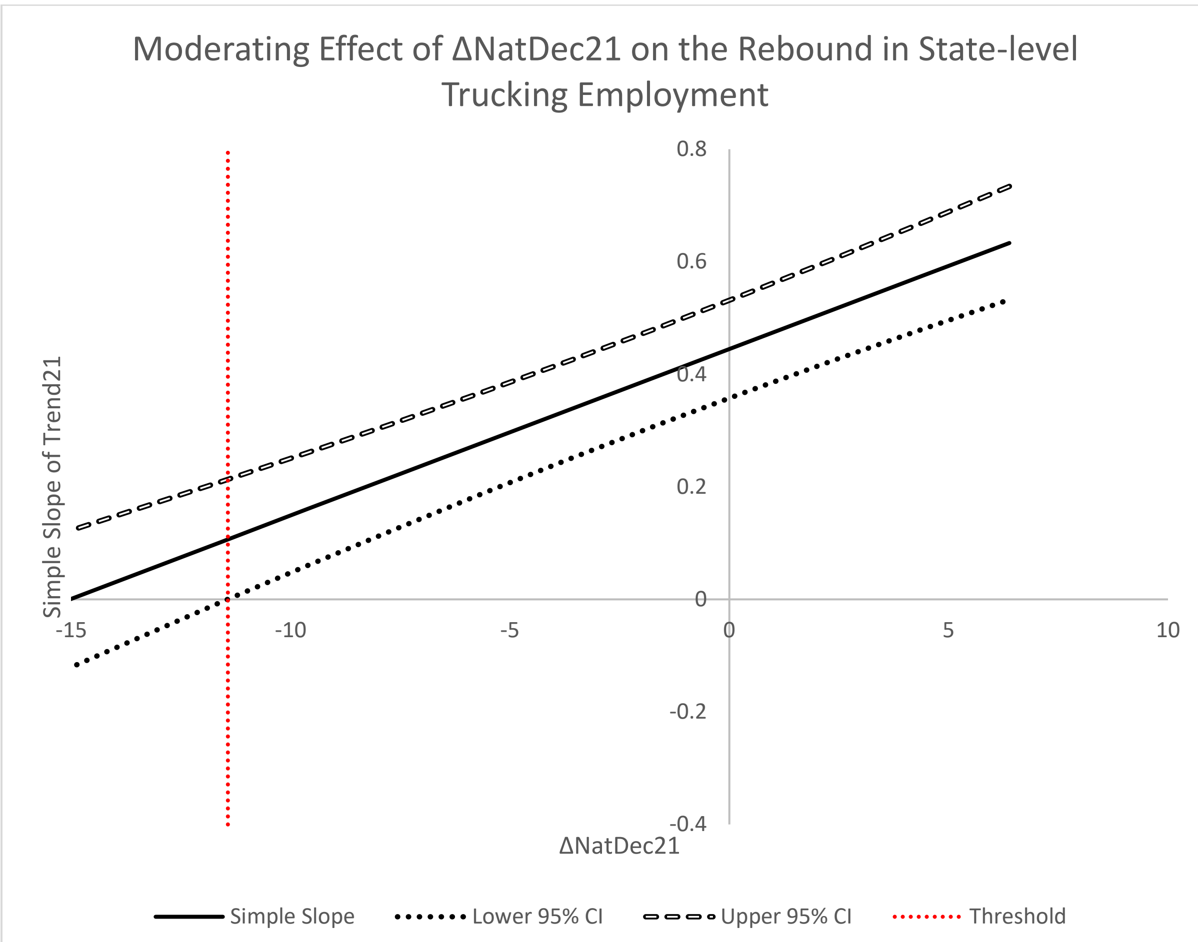
Table 3: Discontinuous growth curve model results

		Model 1: Baseline		Model 2: State by Month FEs	
	Parm	Estimate	Z-Value for Estimate	Estimate	Z-Value for Estimate
Intercept	α_0	823.04***	454.57	822.76***	366.95
Trend19	α_1	0.15***	8.33	0.14***	8.45
DJanMar20	α_2	-0.61***	-3.39	-0.62***	-4.25
DApr20	α_3	-5.98***	-21.64	-5.93***	-24.45
Trend21	α_4	0.34***	7.61	0.36***	8.79
DApr20 × ΔMfgApr20	β_1	0.32***	11.21	0.30***	11.28
DApr20 × ΔNatApr20	β_2	0.01	0.34	0.01	0.59
DApr20 × ΔWareApr20	β_3	-0.02*	-1.78	-0.03**	-2.32
DApr20 × ConPort	β_4	-1.02**	-2.37	-0.89**	-2.27
DApr20 × ΔWsaleApr20	β_5	0.62***	7.58	0.71***	9.37
DApr20 × ΔConApr20	β_6	-0.01	-0.40	-0.01	-0.44
DApr20 × ΔCourApr20	β_7	0.03	1.24	0.01	0.65
DApr20 × Repub	β_8	-0.93**	-2.56	-1.10***	-3.32
DApr20 × Maxben	β_9	-0.45***	-3.77	-0.49***	-4.45
Trend21 × ΔMfgDec21	δ_1	-0.01	-1.06	-0.01	-1.09
Trend21 × ΔNatDec21	δ_2	0.03***	9.05	0.03***	9.00
Trend21 × ΔWareDec21	δ_3	0.004***	2.86	0.004***	2.90
Trend21 × ConPort	δ_4	0.30***	4.24	0.29***	4.26
Trend21 × ΔWsaleDec21	δ_5	0.01	1.04	0.01	1.07
Trend21 × ΔConDec21	δ_6	-0.01	-1.24	-0.02	-1.56
Trend21 × ΔCourDec21	δ_7	0.00	0.17	0.00	0.59
Trend21 × Repub	δ_8	-0.11*	-1.91	-0.12**	-2.10
Trend21 × Maxben	δ_9	-0.03	-1.27	-0.02	-1.19
State Fixed Effects	γ_s	Included		———	
Month Fixed Effects	θ_m	Included		———	
State × Month Fixed Effects		———		Included	
-2 Log Likelihood		8455.6		7346.7	
AICC		8626.7		8836.4	
Rho		0.92***		0.96***	
Gamma		0.94***		0.96***	

We begin with results from Model 1. The parameter α_1 indicates that state-level truck transportation payrolls increased by 0.15% each month January 2017 – December 2019. The term α_2 indicates state-level truck transportation payrolls declined 0.61% on average in January 2020 through March 2020; whether this is due to the onset of COVID-19 or drug and alcohol clearing house starting is unclear. Parameters α_3 andα_4 can be interpreted as the conditional effect of the growth curve components when moderators have values of zero (i.e., at their means). α_3 indicates state-level truck transportation payrolls decreased a staggering 5.98% in April 2022 during the most stringent COVID-19 lockdowns. Lastly, α_4 indicates that state-level truck transportation payrolls increased by 0.34% each month from May 2020 – December 2021, slightly more than double the rate of growth during the 2017 – 2019 period.

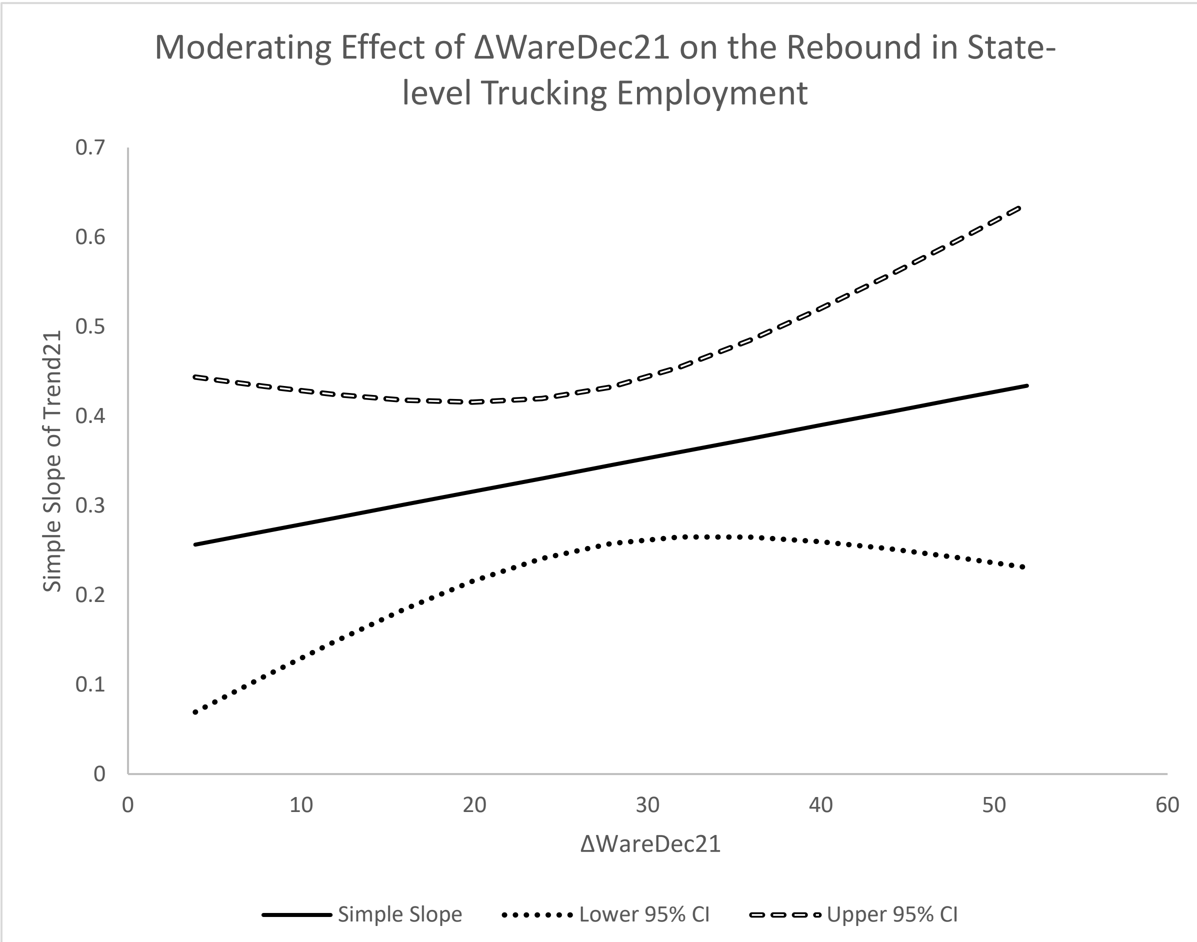
With this in mind, we are now in a position to interpret our moderation effects. Consistent with **H1a**, we see that each additional percentage point decline in state-level manufacturing payrolls at the onset of the COVID pandemic resulted in an additional truck transportation payroll decline of 0.32% (β_1 = 0.32, z = 11.21). However, inconsistent with **H1b**, we find no relationship between the change in state-level manufacturing payrolls as of December 2021 relative to 2019 and the recovery rate of state-level trucking payrolls (δ_1 = -0.01, z = -1.06). Turning next to the findings regarding natural resource extraction, we find the opposite pattern of effects. While state-level change in natural resource extraction employment with the onset of the pandemic did not moderate the drop in state-level trucking payrolls (β_2 = 0.01, z = 0.34), a one percent decrease in state-level natural resource extraction employment as of December 2021 relative to 2019 decreased the rebound of state-level trucking employment by 0.03% (δ_2 = 0.03, z = 9.05). The large z-value relative to the other moderators of employment recovery indicates a substantial effect (Bring, 1994). In Figure 3 we produce a Johnson-Neyman plot across the 10th to 90th percentile range of ΔNatDec21, which reveals that for states that saw natural resource extraction employment decrease by more than 11.5% between December 2019 and December 2021, there was no significant recovery of state-level trucking payrolls.

Figure 3: Johnson-Neyman plot for the region of significance of the moderating effect of ΔNatDec21 on the rate that state-level trucking employment rebounded from May 2020 – December 2021.



To test **H3**, we compare δ_2 and δ_1. While both ΔMfgDec21 and ΔNatDec21 are expressed as percent changes, Table 2 indicates the standard deviation of ΔNatDec22 is substantially larger than ΔMfgDec21, where the standard deviations are 10.34 and 3.15, respectively. This will automatically result in a more conservative test if we keep these variables on the same scale (which we do for simplicity). Using the rules of correlated random variables, $\delta_2 - \delta_1 = 0.04$, with a z-value of 3.58 ($p < 0.01$), providing strong support for **H₃**.

Figure 4: Johnson-Neyman plot for the region of significance of the moderating effect of ΔWareDec21 on the rate that state-level trucking employment rebounded from May 2020 – December 2021.



Turning now to **H₄**, consistent with expectations, we can see that each one percentage point increase in the rate that states added to warehousing payrolls between December 2019 and December 2021 resulted in a 0.004% increase in the rate that trucking payrolls recovered. In Figure 4 we likewise generate a Johnson-Neyman plot for the region of significance of this moderator across the 10th to 90th percentile range of ΔWareDec21, which reveals a less pronounced moderating effect as compared to ΔNatDec21. A state at the 90th percentile of warehousing growth was predicted to have a rate of trucking payroll recovery of 0.44% per month, as opposed to just 0.26% for a state at the 10th percentile. Thus, **H4** is corroborated.

We lastly turn to **H5**, where we find evidence that states that are home to a large container port saw far more rapid recovery of state-level trucking payrolls than states that are not home to a port (δ_4 = 0.30, z = 4.24). This indicates that all other moderators at a value of 0, states that were home to a major container port saw their state-level truck transportation employment rebound by 0.64% per month, nearly double the 0.34% per month observed in other states. As such, **H5** receives strong corroboration.

Lastly, while not a focus of our study, we wish to point to a few of our reported control variable effects. For example, while we observe that each $100 increase in maximum state-level unemployment benefits was associated with a 0.45% additional decline in payrolls with the onset of the pandemic, we find no evidence that states with more generous unemployment benefits saw a slower rebound in truck transportation employment. We also observe no relationship between state-level employment dynamics for construction or courier & messenger employment and state-level trucking employment. Especially concerning the courier & messenger sector, this suggests concerns of driver poaching may not be as severe as feared.

Robustness Testing and Reconciling Unsupported Predictions

For a robustness test, we re-estimated our model using state by month fixed effects (results reported as Model 2 in Table 3). We reach identical conclusions using this more expansive treatment of seasonality, suggesting our results aren't being driven by state-level heterogeneity in the seasonal patterns of trucking employment.

This brings us to the issue of our two uncorroborated predictions. There are several reasons—unfortunately unobservable in monthly, state-level data—that may explain why state-level change in manufacturing employment between December 2019 and December 2021 did not impact state-level recovery of truck transportation employment. First, national data from the Federal Reserve Board (2023b) on manufacturing activity indicates that U.S. manufacturing did not recovery to pre-COVID levels until October 2021. This slower recovery may have reduced the responsiveness of trucking employment to changing manufacturing output. Second, given the difficulty manufacturers had in finding labor, many firms invested in robotics and capital equipment to substitute for labor (Biron 2022), which may be affecting the relationship between manufacturing payrolls and output.

Regarding the fact natural resource extraction job losses didn't moderate the rate at which state-level trucking payrolls were shed, one explanation is that the drawdown of the drilling of oil and gas wells as measured by the Federal Reserve Board (2023c) took time, with activity not reaching a post-COVID nadir until July 2020. However, the fact oil and gas drilling had not recovered to 2019 levels by the end of 2021 is consistent with the finding we reported for ΔNatDec21. In sharp contrast, manufacturing activity fell very sharply in April 2020 per the Federal Reserve Board (2023b), which helps explain the different results.

DISCUSSION

Theoretical Contributions

This research makes theoretical contributions in four ways. First, this research extends theory regarding factor market rivalry by introducing a new unit of analysis. FMR is typically studied at the firm level, whereby firms from different or overlapping product markets compete in a factor market to secure resources (Markman et al. 2009). In this research, we examine FMR between industries at the state level, which highlights important differences from examination of FMR between firms. As detailed by Makadok et al. (2018), introducing a new unit of analysis can change understanding of phenomena. Our shift to the industry level highlights that discussions of firms in different industries competing for the same labor pool need to take into consideration the extent one industry may be a key customer of the other. This suggests a boundary condition for existing conceptualizations of FMR that have primarily emphasized labor poaching dynamics when discussing human resource issues (Opengart et al. 2018).

A second way our research extends theory is to introduce the concept of compound relations from Ross and Robertson (2007) into FMR theory, to allow researchers to develop more refined explanations regarding how firms in different industries interact. One of the strengths of FMR theory was that it acknowledged that competition wasn't limited to firms that competed in the same downstream geographic product markets (Markman et al. 2009). FMR theory suggested firms in distinct industry verticals that are minimally connected via supply chain relationships, such as clothing and electronics wholesalers, may compete for the same resources such as air freight capacity from China (Ellram et al. 2013). Extensions of FMR subsequently focused on identifying strategies firms could utilize to respond to FMR (Schwieterman and Miller 2016) or reduce the likelihood managers would suffer from myopia regarding FMR (Ralston et al. 2017). Introducing the concept of compound relationships provides a natural extension that highlights firms and industries may have multiple relationships that simultaneously coexist (Ross and Robertson 2007) which need to be considered when discussing FMR dynamics. Our research focused specifically on why labor poaching concerns may be outweighed by demand generation mechanisms when a focal industry (trucking) appears to compete for the same labor pool as its customers (e.g., manufacturers). This extension is important given increasing evidence that demand side factors play the overriding role in affecting firms' expansion or contraction of payrolls (Carlsson et al. 2021).

Our research also makes contributions to the broader programmatic (Cronin et al. 2021) efforts to understand labor market dynamics in truck transportation. Our research provides the first ever state-level analysis regarding how trucking employment responded heterogeneously to a massive economic shock—the onset of the COVID-19 pandemic. An important theoretical implication from our findings is that demand-side factors appear to play an overriding role in truck transportation employment dynamics (Ignaszak and Sedláček 2022). For example, states that lost more manufacturing employment at the start of COVID-19 saw far sharper declines in state-level truck transportation payrolls. This is exemplified by the state of Michigan seeing a 25% decrease in truck transportation employment between March 2020 and April 2020, which was driven by a 42% decline in manufacturing payrolls, which is in turn sensible given Michigan's dependence on automobile and light vehicle assembly. Similarly, states that were home to large container ports, which saw a surge of demand (BEA 2023b) due to the sharp increase in consumer spending on durable goods during the pandemic recovery (BEA 2023c), also saw growth rates of state-level trucking employment from May 2020 – December 2021 that were nearly double what other states experienced. To date, discussions of trucking employment dynamics have tended to focus on concerns of shortages, despite existing academic research suggesting that such shortage concerns have little basis (Burks and Monaco 2019; Miller et al. 2021a). In contrast, our theory suggests more attention be given towards examining how demand side factors may create conditions that affect trucking firms' expansion or contraction of payrolls, which aligns with studies by Carlsson et al. (2021) and Pozzi and Schivardi (2016) that suggest changes in demand are the primary driver of firms changing payrolls, as opposed to changes in supply side factors.

A fourth theoretical implication for the literature regarding trucking employment dynamics is that, at the state level, growth in trucking employment appears particularly sensitive to industries that generate freight that primarily requires shorter-distance transportation, which inherently favors carriers with establishments located within those states. For example, natural resource extraction efforts involve short distance shipments that average ~61 miles, based on the 2017 CFS. This helps explain why states whose natural resource extraction employment was gutted following the onset of COVID-19 (e.g., North Dakota, Wyoming, West Virginia, New Mexico, and Oklahoma) saw truck transportation employment fail to recover to pre-COVID levels by December 2021. Likewise, shipments originating at warehouses travel a shorter distance than manufacturing shipments per the 2017 CFS, which helps explain why states that saw more rapid growth in warehousing saw more rapid growth in trucking payrolls from May 2020 – December 2021. Finally, port drayage activity features short-distance local hauls, which favors carriers with local establishments. An implication from this finding is that researchers interested in studying job creation and new entry dynamics in trucking may be well-served to focus on demand shocks in industries requiring short-distance shipments, such as shale oil (Decker et al. 2022).

Managerial & Policy Implications

Our findings have important implications for for-hire carriers and shippers. For for-hire carrier managers, our findings reinforce the importance of understanding how net-demand-generating industries affect derived demand for freight transportation, and how these in turn affect the labor market for truck drivers. Our findings suggest that the demand for truck drivers at the state level is especially sensitive to changes in activity in industries that primarily generate shorter-distance shipments. This has important implications for driver recruitment and retention. For example, a dry van carrier with an establishment located in the Haynesville shale region in Louisiana and Texas should be aware that spikes in crude oil and natural gas prices that encourage additional drilling activity will likely result in the creation of new oil field service trucking companies that compete for truck drivers in that region (Decker et al. 2022). Likewise, the continued growth of warehousing activity in secondary and tertiary markets may spur additional competition for truck drivers in these areas (Young 2022).

A second implication for carrier managers is that there appears to be limited evidence that growth of employment in industries such as construction, wholesaling, and courier & messengers result in slower growth of truck transportation employment. This suggests that commonly expressed concerns about these industries poaching from the same labor pool may be overstated, at least at an industry level. For example, the state of Florida saw a strong growth of construction employment of 2.6% between December 2019 and December 2021 yet saw truck transportation payrolls increase by 11.8% over this same period (the fastest in the nation). In contrast, states such as North Dakota, Wyoming, New Mexico, Louisiana, and Oklahoma saw some of the steepest declines in construction employment over this period (-12.2%, -7.9%, -5.7%, -5.4%, and -4.6%, respectively) as well as the steepest declines in truck transportation payrolls. This suggests construction isn't so much a competitor of trucking labor, but instead construction activity (especially nonresidential construction) is derived in part from activity in other industries, such as manufacturing (Adelino et al. 2017) and natural resource extraction (Decker et al. 2022), that generate demand for freight movements.

Turning now to shippers, our findings suggest that demand shocks in industries that generate local trucking demand may cause challenges, especially in the shorter term, with obtaining capacity at facilities in those regions impacted by the demand shock. Consider, for example, a manufacturer with a plant outside of Phoenix that ships products around the country, where many of the loads are picked up by drivers who are domiciled at a long-distance dry van carrier's establishment in Phoenix. As Phoenix continues to see warehouse expansion (Young

2022), our findings suggest this will result in increased demand for truck drivers in Arizona, which may make it harder for the long-distance dry van carrier to retain its drivers, who may be attracted to shorter distance hauls to support to local warehouses. The same idea applies to shippers whose have facilities located in regions of major shale oil plays. Given that shale drilling activity can change relatively quickly based on changes in oil prices (FRB 2023c), this suggests a manufacturer with a plant in Pennsylvania in the same region as Appalachia shale oil activity may see additional challenges with obtaining capacity from dry van trucking companies whose drivers come from local establishments. If drilling activity increases, these dry van drivers may be lured away by specialized carriers serving the shale sector (Decker et al. 2022).

Turning to policy makers, our results call into question the idea that there is a systematic shortage of truck drivers for supply side reasons and, instead, point towards demand side factors as the prime mover of trucking employment dynamics (Ignaszak & Sedláček 2021). For example, states whose industry composition was favorably affected by the COVID-19 outbreak, such as California due to its three large container ports and expansive warehousing activity, ended 2021 with truck transportation payrolls well above their end of 2019 levels. The same applies for the states of Washington, New Jersey, and Georgia. If there was a systematic shortage of individuals willing to work in truck transportation, it seems difficult to understand how these pronounced increases could have been achieved, especially during a period of a “blue collar job boom” (Cambon 2021) where labor poaching should have been especially strong. In contrast, states reliant on natural resource extraction, especially coal mining and shale oil drilling, ended 2021 with their truck transportation employment down 7% or more from end of 2019 levels. Consequently, policy makers should recognize that changes in trucking companies’ payrolls tend to be primarily driven by changes in demand side factors as opposed to supply side factors, a pattern also found to hold in manufacturing (Carlsson et al. 2021; Pozzi and Schivardi 2016).

Thus, to paraphrase James Carville (Political Dictionary 2022) during the 1992 election cycle for U.S. President, "It's the demand, stupid," when it comes to understanding state-level trucking employment dynamics. Further, thinking about the truck driver labor market, we might even say "It's the local demand, stupid." Together with the assertion by the ATA's Bob Costello "that the [driver] shortage is generally contained to one segment of our industry: the over-the-road or long-haul for-hire truckload segment" (Costello 2019), our findings call into question arguments that the industry should expand interstate driving operations to 18-year-old individuals due to claims of a driver shortage (FMCSA (2020), Valdes-Depena 2022).

Limitations

As with all research, this our analysis has specific limitations that must be taken into consideration. First, we cannot directly measure state-level activity in sectors such as manufacturing and natural resource extraction, as monthly data such as the Federal Reserve Board's industrial production indexes are only published at the national level. Consequently, we are forced to rely on the common finding of constant returns to scale regarding labor inputs (Syverson 2011) to proxy state-level activity with changes in state-level employment by industry. Especially as it concerns manufacturing activity, given that many firms increased capital investment in response to labor challenges brought on by COVID-19 (Prang 2021), this may have introduced undesired noise. Second, we can only observe employment changes for truck transportation as a whole; it is therefore not possible to determine the extent to which observed employment changes are distributed across the subsegments of for-hire trucking (such as local versus long distance, truckload versus less-than-truckload, or general versus specialized freight). Third, while we can observe employment changes, we cannot ascertain whether the rebound in trucking payrolls after the April 2020 low were due primarily to existing firms hiring back workers or hiring workers new to the occupation. A related fourth limitation is that we cannot directly observe driver employment, as distinct from employment in other occupational categories, so inferences about driver employment use total employment as a proxy. This limitation is significantly mitigated by the fact that truck drivers make up ~59% of all employment in Truck Transportation (BLS 2022).

A fifth limitation is that we cannot observe state-level changes in self-employed workers in truck transportation, as these data are not tracked by QCEW. While the U.S. Census Bureau does publish statistics on non-employer establishments in truck transportation (which would capture all owner-operators not picked up in QCEW), these data are only available annually through 2019 (U.S. Census Bureau 2022). A sixth limitation, shared with all quantitative studies using archival data, is that we cannot directly observe or operationalize the mechanisms (Astbury and Leeuw 2010) that we theorize gave rise to our hypothesized outcomes (Miller and Kulpa 2022). This being said, we have sought to follow best practice (Stinchcombe 1987) by providing a variety of empirical effects that offer distinct tests of our demand generation mechanism, which increases confidence in its existence and effects (Keas 2018). At minimum, our findings suggest more work to untangle how downstream demand affects trucking employment is a worthwhile direction for further research (Nyrup 2015).

Directions for Future Research

Our manuscript suggests multiple directions for future research. One avenue is to explore how shocks in downstream freight generating markets affect trucking employment using more granular geographic data. For example, researchers could leverage the Country Business Patterns (CBP) database maintained by the U.S. Census Bureau to study how the boom-and-bust cycles in shale oil drilling impact trucking demand in the counties in question vis-à-vis a control set of counties not tied to shale oil activity (Decker et al. 2022). Similarly, it would be worthwhile to examine how the COVID-19 pandemic's shock to e-commerce demand and, subsequently, warehousing activity, affected trucking employment at the local level. This would help to corroborate our state-level results regarding warehousing employment. Researchers could also explore how the opening of large manufacturing plants affects local trucking employment relative to counties that did not win bids for such plants (Greenstone et al. 2010).

Another direction for further research is to explore job creation and job destruction dynamics (Haltiwanger et al. 2013) in the truck transportation sector. For example, the sharp rebound in state-level trucking payrolls observed from May 2020 through December 2021 obscures a high rate of job creation and job destruction that occurred across carriers (C.H. Robinson 2022). Likewise, it would be useful to study whether net employment growth since the pandemic has been driven more by new entrant carriers versus established carriers, questions that can be answered with the U.S. Census Bureau's Business Dynamics Statistics (BDS) database.

Finally, if L&SCM researchers can gain access to the U.S. Census Bureau's confidential microdata for the BDS program, a wide range of topics could be investigated including understanding whether trucking employment growth in local markets is more a function of new firm creation, existing firms opening new greenfield establishments in those local markets, or existing firms with establishments in local markets expanding operations (Decker et al. 2022). Researchers could also examine patterns of firm-level job creation and destruction in trucking to better understand how carriers grow or shrink. For example, existing research suggests firms' growth rates tend to follow a Laplace distribution which, compared with a normal distribution, as more weight at the mean and in the tails (Coad 2021). This would imply that the average trucking firm sees limited change in payrolls, but there are more carriers than expected by a normal distribution that see large gains or losses in jobs. Understanding firm-level payroll dynamics would help inform public policy (Richey & Davis-Sramek 2022) regarding trucking capacity.

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