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ABSTRACT

Bring Out the Bulls: Employment Dynamics of Trucking Firms During Highly Expansive Market Conditions*

Studying employment dynamics (i.e., rates at which firms add or shed workers) of small- and medium-sized enterprises (SMEs) like trucking firms is critical to inform labor market theory and public policy. We examine U.S. trucking firm employment dynamics during the highly expansive period of March 2020 – March 2021, when the COVID-19 pandemic delivered an exogenous shock that upended established freight networks and sharply expanded demand. We extend the supply chain management (SCM) literature on motor carrier growth and Penrose's theory of the growth of the firm (TGF), focusing on the mechanisms most likely to be involved. We test our hypotheses using Business Dynamics data from the Census Bureau for the population of trucking firms with at least one employee. Fitting mixed effects models, we find that both the increase in job gains and decrease in job losses during March 2020 – March 2021 were greater for younger as compared to older firms, and the effect on job losses was greater in absolute magnitude. Our work modifies TGF with regard to SMEs that make up the bulk of firms in industries traditionally viewed as central to SCM, and it adds to evidence against a long-term or systematic shortage of truck drivers.

JEL Classification: J21, L92, R41, J63

Keywords: labor demand, driver shortage, motor carrier, trucking, public policy

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INTRODUCTION

Small- and medium-sized enterprises (SMEs) constitute most firms engaging in manufacturing, wholesaling, retailing, consolidation, storage, and transportation activities that are core to the supply chain management (SCM) discipline (Darby, Fugate et al. 2022; Marzolf, Miller et al. 2024). For example, in 2021 the Census Bureau (2023g) reported that firms with 1 to 19 employees accounted for 73% of all firms engaged in manufacturing (NAICS 31-33), 90% of those in retail trade (NAICS 44-45), 87% of those in transportation and warehousing (NAICS 48-49), and 84%of those in wholesale trade (NAICS 42). Given ongoing concerns about labor shortfalls in many of these industries (Schollmeier and Scott 2024), better understanding employment dynamics—i.e., the rates at which firms add and shed workers—provides a means to extend theories regarding firm growth (Penrose 2009) as and to inform public policy (Richey and Davis-Sramek 2022).

Perhaps no industry with a preponderance of SMEs has seen more debate (and disagreement) about whether there is a systematic labor shortage than truck transportation (NAICS 484). The Census Bureau (2023j) reports 92% of firms in truck transportation have 1 to 19 employees, and thus is a quintessential example of a sector where employment dynamics of SMEs are of special interest. The American Trucking Associations (ATA) has promulgated a narrative of an ongoing driver shortage (Costello and Suarez 2015; Costello and Karickhoff 2019b), whereas others in industry, most notably Craig Fuller at *FreightWaves*, has called the ATA's driver shortage arguments a myth (Fuller 2019; Fuller 2023). Todd Spencer, President of the Owner Operator Independent Drivers Association (OOIDA) has agreed with Fuller (Schremmer 2021; Schremmer 2023), and a recent formal study for Congress also concluded there is no shortage (National Academies of Sciences Engineering and Medicine 2024).

Academic research examining the movement of workers into and out of the trucking profession (Burks and Monaco 2019; Phares and Balthrop 2022) has found evidence that the overall labor market for truckers behaves normally, and prior research seeking to identify labor shortages did not find the truck driving occupations to be among those occupations with characteristics consistent with a systematic shortage (Veneri 1999). Similarly, Miller, Bolumole et al. (2021) report that the ATA's truck driver turnover rate for large truckload carriers is strongly procyclical to labor market conditions in the truck transportation industry, i.e., when capacity is expanding, turnover rises, and vice versa. This finding aligns with standard labor market dynamics (Lazear and McCue 2018). However, what is not understood is how truck trucking employment dynamics behave during periods of expanding freight demand, periods in which labor shortage concerns are most relevant (Arrow and Capron 1959). For example, does a period of strongly expanding freight demand have a greater impact on job gains or on job losses of incumbent firms, and are job gain and job loss dynamics for incumbent firms more pronounced for younger versus older firms?

This research takes a first step towards examining employment dynamics in the trucking industry during a unique period of strongly expanding freight demand by leveraging the exogenous nature of the COVID-19 disruption (Fairlie, Fossen et al. 2023) that caused an unexpected positive shock to freight demand as well as the price of trucking services in the second half of 2020 (Caplice 2021). As described by Miller (2021), the COVID-19 pandemic upended established freight networks as some industries, such as canned food manufacturers (Dohmen, Merrick et al. 2023) and e-commerce shipments (UPS 2020), saw dramatic increases in demand starting in March 2020 due to consumers' changing spending patterns whereas other industries that were dependent on sectors such as entertainment and travel saw dramatic declines in demand (Fairlie, Fossen et al. 2023). This disruption of established freight patterns caused a massive influx in spot market truckload shipments (Caplice 2021) because carriers cannot easily handle overflow demand (Scott, Parker et al. 2017) due to pronounced economies of scope across hauls for truckload shipments (Muir, Miller et al. 2019; Miller and Muir 2020). This influx of spot market demand drove up spot market prices, which in turn drove up contract prices (Miller, Scott et al. 2021). We can thus leverage COVID-19's exogenous nature to facilitate causal identification, a challenge with studying macroeconomic effects (Nakamura and Steinsson 2018).

To test our theory, we assemble an archival panel dataset consisting of the job gain and job loss rates in the population of incumbent firms engaged in truck transportation that had employees using the Census Bureau's Business Dynamics Statistics (BDS) Program (Haltiwanger, Jarmin et al. 2013). Drawing on arguments from Coad (2018) and Pugsley and Șahin (2019), who highlight the critical role that firm age plays in shaping employment dynamics, we examine how job gain and job loss rates at incumbent trucking firms differed during the first year of the COVID-19 pandemic from those observed over the prior two decades. As we explain below, the BDS has numerous advantages for studying employment dynamics in the trucking sector compared to alternative sources such as historical Form M documents (Muir, Miller et al. 2019) or the Motor Carrier Census (Guntuka, Corsi et al. 2019) that enhance the confidence we can have concerning validity claims for the measures from this dataset (Miller, Davis-Sramek et al. 2021). We test our theorized predictions by fitting a series of mixed effects models to account for the nested structure of our data, finding results consistent with our theory.

This work makes numerous theoretical contributions. We extend theory regarding the related topics of the growth of motor carrier output and employment (Feitler, Corsi et al. 1998;

Pettus 2001), the evolution of strategic positioning (Corsi, Grimm et al. 1991; Grimm, Corsi et al. 1993), diversification (Hanna and Maltz 1998; Peinkofer, Schwieterman et al. 2020), and job gains and losses (Miller, Phares et al. 2024) by devising theory concerning how carrier age moderates the impact of expansive market conditions on employment dynamics. This issue has not been addressed to date in the SCM literature despite its critical importance in practice (Moscarini and Postel-Vinay 2012; Pugsley and Şahin 2019). In particular, we introduce the concept from Penrose's "Theory of the Growth of the Firm" (2009) (hereafter TGF) that firms' growth rates are inherently constrained to explain why we expect expansive market conditions to have a stronger effect on job loss rates than on job gain rates. However, our approach doesn't merely apply Penrose's (2009) TGF. Rather, we rely on techniques for theory elaboration (Fisher and Aguinis 2017) to modify Penrose's (Penrose) TGF so that it can be better applied to SMEs, especially young SMEs (Fort, Haltiwanger et al. 2013), which makes a theoretical contribution by expanding TGF's dynamic consilience (Thagard 1978).

This work also has implications for managers and policymakers. Our theory explains why incumbent carriers' abilities to expand operations, even in the most expansive of industry settings, is inherently limited not just due to the lead time it takes to procure equipment and hire drivers (Miller, Schwieterman et al. 2018), but also due to the limits in incumbent firms' existing managerial resources for on-boarding new employees and modifying existing administrative structures to handle higher output (Penrose 2009). This theory helps explain why the trucking sector can exhibit temporary shortfalls of capacity relative to demand, such as the one experienced in late 2017 and much of 2018, when trucking demand as measured by ton-miles grew by over 3% annually (Journal of Commerce 2024), without experiencing a true systematic shortage of drivers per the criteria outlined by Veneri (1999). Moreover, our finding that older carriers' job creation is less responsive to expansive conditions suggests that discussions of a potential truck driver shortage must consider the age distribution of trucking firms; employment more heavily concentrated in older carriers will be inherently likely to result in slower capacity adjustments to conditions of increased demand than if employment is more concentrated in younger carriers. To the best of our knowledge, no researchers to date have pointed towards the impact that incumbent carrier age could play in understanding how carriers add capacity during expansive market conditions, though this has been discussed in economics (Pugsley and Șahin 2019).

The remainder of this paper is structured in five sections. The first section summarizes the relevant literature streams. The second section sketches the logic for the hypothesized effects. The third section explains the data sources and variable construction. The fourth section describes how we formulate our econometric models and reports results. The fifth section delineates theoretical contributions, summarizes managerial and policy implications, notes limitations, and suggests directions for future investigation.

LITERATURE REVIEW

Motor Carrier Growth and Employment Dynamics

The literature on motor carrier growth and employment dynamics can be organized in five streams. The first stream examines the evolution of less-than-truckload carriers by comparing industry concentration and the size of the largest carriers prior to and after interstate deregulation by the Motor Carrier Act (MCA) of 1980. Rakowski (1988; 1994) and Kling (1988; 1990) reported that industry concentration and the size of the largest firms increased. The second stream explores how motor carriers' strategies evolved after the MCA. Corsi & Grimm (1987) examined how the use of owner-operators changed from 1977 (pre-MCA) to 1985 using data from annual reports filed with the ICC. They found that owner-operator use increased across both Class 1 and Class 2 carriers[1], with this increase being driven by greater owner-operator use in the household goods, truckload general freight, and LTL general freight segments. In a series of related studies, Corsi and colleagues (Corsi, Grimm et al. 1991; Corsi, Grimm et al. 1992a; Corsi, Grimm et al. 1992b; Grimm, Corsi et al. 1993; Feitler, Corsi et al. 1997) studied how general freight LTL carriers changed their strategies following the MCA.

A third stream examines carriers' diversification activities. Pettus (2001) reported that LTL carriers that diversified activities following a resource-based sequencing pattern outperformed other LTL carriers using public financials from 1980 through 1993. Hanna and Maltz (1998), using survey data from 61 Class 1 LTL carriers, reported that LTL carriers were more likely to vertically integrate into warehousing when they were large or when asset specificity was high. Burks, Guy et al. (2004) report that, following the MCA, for-hire trucking firms in the general freight sector increasingly specialized in either truckload or less-than-truckload services (i.e., the MCA reduced service diversification). Peinkofer, Schwieterman et al. (2020) reported that trucking firms that previously offered LTL or expedited services were more likely to subsequently offer final mile delivery of large, bulky products, with the marginal effect of LTL and expedited services on diversification into final mile delivery being less than additive.

A fourth stream examines carriers' change in size directly, with Balthrop (2021) and Giordano (2010; 2014) examining whether the distribution of carrier size was consistent with Gibrat's law that growth is independent of firm size; these authors reach different conclusions, with Giordano (2010; 2014) concluding Gibrat's law does not hold for large TL and LTL carriers,

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[1] This classification originated with the Interstate Commerce Commission's economic regulation of interstate motor freight from 1935 to 1980. Class I carriers have $5 million or more annual revenue, while the revenue of Class II carriers is greater than or equal to $3 million, and less than $5 million (Rothenberg 1994).

respectively, whereas Balthrop (2021) concludes Gibrat's law does hold across all motor carriers (including private fleets and parcel carriers). Miller, Schwieterman et al. (2018) report that carriers with more rapid growth rates exhibit more driving safety violations but fewer maintenance violations using the population of large, for-hire trucking firms.

The fifth stream, and the one with which this research shares the greatest overlap, examines employment dynamics across the population of truck transportation establishments using archival administrative records from the Bureau of Labor Statistics or the Census Bureau. Phares, Miller et al. (2023) examine state-level heterogeneity in the recovery of state-level trucking payrolls after the steep layoffs in April 2020 due to COVID-19 lockdowns (BLS 2024aa). They find that states which saw greater increases in warehousing employment or were home to large container ports saw more rapid recovery of trucking payrolls, whereas states that saw greater declines in natural resource extraction employment saw slower recovery of trucking payrolls. Miller, Phares et al. (2024), using data from 1995 through 2019, report that younger motor carriers have more rapid rates of job gains as well as job losses vis-à-vis older carriers. They further report that these firms' job gains and job losses are more sensitive to job gains and job losses in the manufacturing sector, even when holding constant the existence of a recession.

Our work builds on these studies in several ways. First, we introduce (Makadok, Burton et al. 2018) a novel argument, drawn from TGF, that the rate at which incumbent trucking firms can expand payrolls in response to expansive market conditions is more constrained than the rate at which they shed payrolls. This also aligns with arguments from Delmar, Wallin et al. (2022) that we shouldn't make the common assumption of symmetry for the processes that bring about growth versus contraction. This point has important implications for public policy as it pertains to the driver shortage, as the diverging theories concerning the existence of a shortage have yet to recognize that incumbent carriers are inherently constrained concerning how rapidly they can expand their payrolls. Second, we explain why older carriers are less likely to expand payrolls in expansive market conditions relative to younger carriers due to various factors associated with the liability of senescence, such as constraints imposed by existing customer relationships, as well as owners/managers having lower incentives to respond to market conditions (Barron, West et al. 1994). This suggests the important role of the age distribution the firms within the industry in explaining how trucking employment reacts to expansive market conditions, something yet to be recognized in the driver shortage debate.

Penrose's Theory of the Growth of the Firm (TGF)

As noted by Kor, Mahoney et al. (2016), Penrose's TGF focuses on the forces that drive firm growth, the direction of growth, and the factors that limit firms' growth rate. Concerning forces that drive growth, Penrose gives primacy to underutilized managerial resources within the firm, as opposed to external factors, as she assumes the general existence of "numerous opportunities for profitable production" (Penrose 2009, p. 41). Concerning the direction of growth, TGF predicts firms diversify in areas that overlap with their knowledge base (Penrose 2009), because opportunities that align with current knowledge are more likely to be identified and are easier to exploit given firms' current capabilities (Chandler 1992; Peinkofer, Schwieterman et al. 2020). Concerning factors that limit the rate of growth, Penrose (2009) identifies (i) managerial ability [internal] and (ii) product or factor markets [external]. However, Penrose (2009, p. 40) rules out external factors as the inherent constraint on firm growth rates by stating, "But a firm is not confined to particular products or locations by the supply of resources or the demand for products in the market, and provided that there are profitable opportunities open for the use of further or different resources obtainable in the market, the fundamental limit to the productive opportunity of the firm cannot be found in external supply and demand conditions; *we must look within the firm itself*," [emphasis added].

This research extends TGF in three ways. First, whereas TGF argues that forces within firms are the primary driver of growth, our theory argues that expansive product market conditions are a critical external enabler (Davidsson 2015) of young firms' growth because they are demand constrained relative to older firms (Foster, Haltiwanger et al. 2016), and face greater difficulty in obtaining financing than older peers (Gertler and Gilchrist 1994). Second, whereas Penrose TGF assumes relative homogeneity in firms' desires to expand, our theory recognizes that young firms are especially likely to desire growth, particularly during expansive demand conditions, because larger size increases survival chances (Starbuck 1965; Davidsson 1989). Allowing for age-related differences in the desire to grow results in the prediction that young firms will grow faster during strongly expansive conditions, a prediction not made by TGF. Third, TGF does not consider that older firms may have lower ability to grow due to structural inertia (Barron, West et al. 1994; Le Mens, Hannan et al. 2015). Our theory emphasizes that existing customer relationships may impose constraints that make it hard for older firms to expand in response to opportunities outside their current customers (Liu, Pólos et al. 2021), compounded by older firms having more rigid routines that make change harder (Hannan and Freeman 1984), or older firms becoming complacent after years of operating (Barron, West et al. 1994). Thus, our theory makes several changes to TGF that incorporate the central role of firm age in shaping growth dynamics (Pugsley and Șahin 2019), which enhances TGF's dynamic consilience (Thagard 1978)—one of the main ways for making a theoretical contribution (Keas 2018)—by expanding the phenomena that TGF can explain.

THEORY & HYPOTHESES

As a methodological note, the theory we devise is inherently of the middle range variety (Stank, Pellathy et al. 2017) in that we apply top-down theoretical contextualization (Craighead, Ketchen Jr et al. 2016) by drawing on elements (e.g., assumptions, constructs, mechanisms) from more general theories (e.g., TGF) and then contextualizing these elements to the trucking industry. We make a special effort to sketch the mechanisms (Astbury and Leeuw 2010) that we postulate bring about the hypothesized effects in accordance with Miller, et al.'s (2023) guidance that researchers clearly articulate these processes to achieve theoretical identification.

We begin by explaining what we mean by a strongly expansive industry environment. Specifically, we consider the period captured by the period of March 2020 – March 2021, as a period of exceptionally increasing demand for truck transportation. This aligns with Caplice's 2021) discussion regarding how spot market rates for truckload services exploded upward starting in July 2020 and continued unabated through this period (see Figure 1). Viewing spot rates as indicative trucking conditions aligns with Acocella, Caplice et al. (2020), who categorize market conditions as tight versus loose based on movements in spot market prices. Furthermore, Miller, Scott et al. (2021), document how changes in the BLS's producer price index for general freight trucking, long-distance, truckload (NAICS 484121), which primarily captures contract rates (Caplice 2007), is strongly predicted by changes in dry van spot rates, demonstrating that spot market prices are a leading indicator of changes in contract prices. Likewise, Miller, Darby et al. (2022) document that changes in spot market prices are a stronger predictor of new Class 8 truck orders than changes in contract prices. Consequently, there is strong reason to view the March 2020 – March 2021 period as one with strongly expanding market demand.

The rate of job gains in a firm age cohort in a year is defined by the Census Bureau as the number of employees added by the subset of trucking firms within the age cohort that had greater payrolls in March of the target year (year *t*, such as 2021) than they did in the prior March (year *t-1*, 2020 in this example), divided by the average total employment across all firms for the entire age cohort over the two years. As the March 2020-March 2021 period was strongly expansive, we would expect a high rate of job gains for the year ending in March 2021 relative to prior years (i.e., a positive average effect). However, we also expect this positive effect to be greater for young carriers. Several mechanisms undergird this prediction, though it is important to note that some researchers (Moscarini and Postel-Vinay 2012) have advanced an alternative argument[2] that proposes younger firms will exhibit payroll expansion that is less procyclical than larger firms.

The first mechanism that leads young SMEs like trucking firms to have higher rates of job gains during highly expansive periods is that such periods result in higher profits, which lets young SMEs fund payroll expansion through retained earnings (Miller, Darby et al. 2022). As young SMEs face greater difficulties in obtaining financing (Gertler and Gilchrist 1994; Doshi, Kumar et al. 2018), strongly increasing demand should be an especially important external enabler (Davidsson 2015) supporting expansion through firms' elevated profits[3]. The second mechanism is that young firms have greater incentive to grow than older firms, a boundary condition absent from Penrose's TGF. A strong argument can be made that this boundary condition exists. Starbuck (1965), based on conversations with managers, noted that the desire for stability is one of the strongest drivers for growth. Young firms desire stability because their limited time in business means they have fewer established relationships with customers,

[2] The crux of Moscarini & Postel-Vinay (2012)'s theorizing is that smaller firms face hiring constraints during procyclical periods because their pay is less than that of larger firms. As young firms tend to be smaller than older firms (Baron et al. 1994; Coad 2018), this generalizes to young firms. As a preview of our findings, our results show the opposite effect, which indicates that this mechanism, while possibly operating to some degree, is more than counterbalanced by other mechanisms such as those that we postulate (Astbury & Leeuw 2010).
[3] This aligns well with the findings from Miller, Darby, & Scott (2022) that capital investment by trucking companies is strongly procyclical, where procyclicality is measured by spot market prices.

suppliers, and financial institutions (Stinchcombe 1965). Relatedly, Davidsson (1989) reports that the entrepreneurs of the smallest firms, which tend to be young (Haltiwanger, Jarmin et al. 2013), have a strong growth orientation, driven in part by their desire to be more independent from any particular limited set of suppliers, customers, and lenders. The third mechanism, termed the "liability of aging" (Hannan 1998), postulates that older firms are more likely to have challenges in adjusting to changing demand conditions due to inertia that develops with age (Le Mens, Hannan et al. 2015). One reason for this structural inertia is existing customer relationships create constraints that can make expansion challenging (Liu, Pólos et al. 2021). Although this can apply in any part of for-hire trucking, it is especially likely in the long-distance truckload segment because of economies of scope that exist in established freight networks for truckload carriers (Caplice 2007; Muir, Miller et al. 2019; Miller and Muir 2020), which make expansion highly disruptive to existing operations (Powell and Mayoras 1996). We thus posit:

H_1: The effect of the strong demand expansion from March 2020 to March 2021 on the rate of job gains will be larger for younger firms. Thus, there will be a positive two-way interaction between an indicator variable for the 2020 – 2021 period relative to prior years and trucking firm youth for job gain rates.

We now turn to the impact of the highly expansive conditions on job loss rates—defined by the Census Bureau as the number of employees lost by the subset of trucking firms within a given firm age cohort that had smaller payrolls in year t than *t-1* divided by the average payroll total across all firms for the entire age cohort for *t-1* and *t*. As documented above, highly expansive conditions bring about higher freight rates which increase the revenue productivity of trucking firms industry wide (Strickland 2019). Because higher revenue productivity is a strong predictor of reduced firm exits (Foster, Haltiwanger et al. 2008), we expect carriers to have a lower job loss rate for the March 2020 – March 2021 period relative to prior years (e.g., a negative average effect[4]). Furthermore, we expect this negative average effect to be larger in magnitude for younger carriers. While this prediction runs counter to extant economy-wide findings from California—one of the largest states for trucking employment (Phares, Miller et al. 2023)—which reported an elevated rate of firm closures (and hence job losses), especially for the smallest of firms (Fairlie, Fossen et al. 2023), we expect to observe the opposite result due to the operation of two mechanisms.

The first mechanism concerns the long-distance truckload segment, in which the COVID-19 pandemic's upending of established freight networks forced a record number of shipments onto the spot market. For example, (Caplice 2021) notes that while about 10% of dry van truckload shipments moved under spot market pricing prior to COVID-19, this number soared to 25% by the second half of 2020. High volumes of spot market shipments should help young carriers' survival chances because younger firms tend to lack established relationships with customers (Stinchcombe 1965), which in the trucking setting represent shippers with contract freight (Li, Bolumole et al. 2022). For example, Ashe (2022) notes that many shippers will refuse to tender contract freight directly to carriers until they are a few years old[5]. As young firms tend to have lower levels of demand than older firms (Foster, Haltiwanger et al. 2016), and low levels of demand are linked to higher rates of exit (and hence job loss) (Foster, Haltiwanger et al. 2008), more spot market freight should help young carriers' survival chances, as these firms do not need contractual relations with shippers to access spot loads (e.g., they can do so by bidding

[4] It is worth emphasizing that job gain rates and job loss rates are not inherently linked (e.g., they stem from distinct data generating processes) (Davis and Haltiwanger 1992). For example, prior studies in manufacturing suggest asymmetric effects of recessions on job gain rates and job loss rates. Moreover, Decker et al. (2014) document a secular decline in both job gain rates and job loss rates for the first decade of the 2000s relative to the 1980s and 1990s. Thus, treating predictions about job gain rates and job loss rates as distinct is warranted.

[5] One author's engagement with industry corroborates this point, as one Fortune 100 firm that spends well over a billion dollars on for-hire truckload services noted that it requires carriers to have been operating for three years—with operations being inferred by the presence of multiple inspections as explained by Miller and Saldanha (2018)—before the carrier is allowed into that shipper's network.

on spot freight posted on load boards like DAT.com or Truckstop.com). In contrast, older carriers' existing contractual relationships limit the extent they can allocate trucks to spot loads, as doing so can imbalance their freight networks and result in poor service to contractual shippers.

The second mechanism concerns how revenue productivity (defined as revenue dollars per worker) affects firms' likelihood of exit, which is the primary margin through which carrier age affects job loss rates (Miller, Phares et al. 2024). As noted previously, higher rates that characterized the March 2020 – March 2021 period increase trucking firms' revenue productivity (Strickland 2019), and hence should decrease firms' likelihood of exiting (and thus contributing to aggregate job loss rates). However, Foster, Haltiwanger et al. (2016) find that revenue productivity is more strongly linked to establishment exit for young firms relative to older firms. A likely reason this should hold in trucking is that young carriers often have limited understanding of their cost structures (Caplice 2021). However, higher revenue productivity due to industry conditions should diminish the extent that carriers fail due to excessively high-cost structures, which mirrors findings from studies of concrete plants that firms with less competitive cost structures can survive in markets where competition is weaker (Syverson 2007). We therefore posit:

H_2: The strong demand expansion from March 2020 to March 2021 will reduce the rate of job losses more for younger firms. Thus, there will be a negative two-way interaction between an indicator variable for the 2020 – 2021 period relative to prior years and trucking firm youth for job loss rates.

For our next prediction, we explain why we expect the absolute value of the two-way interaction postulated in H_2 to exceed that postulated in H_1. As noted by Miller, Darby et al. (2022) and Miller and Kulpa (2022), comparisons regarding the magnitude of effects for two-way interactions are conceptually the equivalent of a three- way interaction, and thus represent very strong tests of theory given the number of conditions that must hold for these effects to materialize (Leavitt, Mitchell et al. 2010). The crux of our explanation is that job gain rates, even for young carriers during expansionary cycles, encounter constraints, whereas similar constraints do not exist for job loss rates. Numerous reasons exist to expect an upper bound for job gain rates. First, as Penrose (2009, p. 45) notes, "In small firms where managerial services are supplied by from one to half-dozen men who are fully occupied in running the firm, expansion sometimes depends on 'overtime' spurts of activity which can only occur periodically." Second, expanding operations by adding workers often necessitates changing administrative structures and operating routines (Chandler 1962). As noted by Maister (1980), the complexity of administrative structures needed to manage a very small trucking firm (e.g., 3 employees) differ substantially from those of managing a mid-sized carrier (e.g., 25 employees), which causes many carriers to stay small (Caplice 1996). Third, Marchington, Carroll et al. (2003) report many small trucking companies are resistant to growing for fear that they will lose their current market niche. Relatedly, Davidsson (1989) reports many owners of small firms are hesitant to grow their firms too large for fear of losing control over operations. Given that the owners of small trucking firms are often heavily involved in day-to-day operations (Ouellet 1994), there is good reason to expect this mechanism to be present. In contrast, during an expansive period, job loss rates don't encounter such constraints, especially given young firms in trucking tend to have job loss rates that exceed job gain rates (Miller, Phares et al. 2024). We therefore posit:

H_3: The effect of the strong demand expansion of March 2020 to March 2021 on younger firms will be larger on the job loss rate than on the job gain rate. Thus, the two-way interaction postulated in H_2 is larger in absolute value than the two-way interaction postulated in H_1.

METHODOLOGY

Research Design and Data

To answer our questions, we rely on the Census Bureau's population-level data for job gains and job losses from the Business Dynamics Statistics (BDS) database (Census Bureau 2024h). As noted by Sedláček and Sterk (2017), "The BDS database is based on administrative records of US firms covering 98 percent of private employment." While truck transportation (NAICS 484) has many non-employer firms (e.g., firms that don't have a single individual on payroll), separate data from the Census Bureau (2024a) suggests that ~82% of revenue in truck transportation is earned by employer firms, which fall within BDS's scope. BDS data have been extensively utilized in economics research (Moscarini and Postel-Vinay 2012; Sedláček and Sterk 2017; Pugsley and Şahin 2019; Ayres and Raveendranathan 2023).

Three aspects of BDS make it ideal for answering our questions. First, BDS is structured such that firms cannot be treated as exiting (and thus losing jobs) if they are sold, acquired, or merge (Haltiwanger, Jarmin et al. 2013). To quote from the BDS documentation, "All establishments owned by the firm must exit to be considered a firm death. This definition of firm death is narrow and strictly applied, so that a firm with 100 establishments would not qualify as a firm death if 99 exited while 1 continued under different ownership. Note firm legal entities that cease to exist because of merger and acquisition activity are not classified as firm deaths in the BDS data," (Census Bureau 2024j). This circumvents a known challenge with using the Motor Carrier Census files (Guntuka, Corsi et al. 2019). Second, BDS has a common approach for calculating firm age as the age of the oldest establishment that a firm operates (Haltiwanger, Jarmin et al. 2013). This eliminates the concern that a new firm purchases an establishment that has been operating for many years with stable customer base—something true young firms often lack (Foster, Haltiwanger et al. 2016)—but would be categorized as young. BDS's definition of age is well-aligned with Bakker & Josefy's (2018) definition of firm age as, "the length of time that an organization has existed since its founding." Third, BDS's reliance on administrative records, which heavily rely on IRS tax filings (Census Bureau 2024h), provides confidence that the data generating process is robust (Miller, Davis-Sramek et al. 2021) given severe penalties for falsified tax records.

Unit of Analysis and Measures

Before explaining our measures, we want to clarify the unit of analysis within BDS. We utilize BDS data organized at the 4-digit North American Industrial Classification System (NAICS) × firm age × year triplet. For truck transportation (NAICS 484), there are two 4-digit NAICS codes: general freight trucking (NAICS 4841) and specialized freight trucking[6] (NAICS 4842). These data thus represent cohorts of trucking firms, which is a commonly found unit of analysis in trucking industry studies (Baker and Hubbard 2004; Scott, Balthrop et al. 2021; Balthrop, Scott et al. 2023). It is important to emphasize that the number of firms in each 4-digit NAICS × firm age × year triplet is large: the average across the final sample we utilize is that each triplet captures data from 3,664 firms that employ 40,944 workers.

With this cohort structure in mind, our study examines data covering activity from March 12, 2002, through March 12, 2021. BDS data is annual and captures changes in employment as of March 12th of each year. Thus, the first record is for the year 2003 that captures employment dynamics from March 12, 2002, through March 12, 2003. Similarly, the last year is 2021 and captures employment dynamics from March 12, 2020, to March 12, 2021. Annual data are captured for each of the ten age cohorts (explained shortly) for the 19 years (inclusive) of data. We begin the analysis in 2003 for two reasons. First, given known changes in economy-wide

[6] Firms in general freight trucking (NAICS 4841) primarily haul goods that go into dry van trailers, whereas specialized freight trucking firms (NAICS 4842) haul goods that are not transported in dry van trailers (e.g., finished motor vehicles, bulk chemicals, logs, machinery, refrigerated cargo, etc.).

employment dynamics prior to the 2001 recession relative to afterwards (Decker, Haltiwanger et al. 2014), limiting the analysis to more recent years seems pertinent. Second, from a practical perspective, BDS's age data is left-censored such that we cannot know the age of firms who were in operation before March 12, 1977; firms that existed prior to this period fall into a "left censored" category. Starting the analysis in 2003 lets us maximize the number of age cohorts that can be utilized given BDS has an age cohort for firms that are $\geq$ 26 years old but started life after March 12, 1977.

Our first dependent variable is *Job Gain Rate* (*JGR*). Per the Census Bureau (Census Bureau 2024h), let *i* index each establishment and *t* index each year. Employment at an establishment a year can be notated as $E_{i,t}$. We can then denote employment change rate of an establishment as $\Delta E_{i,t} = \left(E_{i,t} - E_{i,t-1}\right)$. BDS defines the number of jobs gained for a given age cohort (denoted by *a*) in year *t* as $JG_{a,t} = \sum_{i \in a; \Delta E_{i,t} \geq 0}(E_{i,t} - E_{i,t-1})$. We can then define the rate of job gains ($JGR_{a,t}$) as $JGR_{a,t} = JG_{a,t}/\left(0.5 * (\sum_{i \in a} E_{i,t} + \sum_{i \in a} E_{i,t-1})\right)$. The term $\left(0.5 * (\sum_{i \in a} E_{i,t} + \sum_{i \in a} E_{i,t-1})\right)$ represents the Davis, Haltiwanger et al. (1996) denominator. Stated verbally, *JGR* for a given age cohort *a* for a given year *t* is the sum of the jobs gained for the subset of establishments that saw greater employment in year *t* relative to *t-1* divided by the average employment across all establishments in the age cohort in years *t* and *t-1*. *JGR* is calculated by the Census Bureau's BDS team (e.g., these data are directly downloadable).

Our second dependent variable is *Job Loss Rate* (*JLR*) (Census Bureau 2024h). BDS defines the number of jobs lost for a given age cohort (denoted by *a*) in year *t* as $JL_{a,t} = \sum_{i \in a; \Delta E_{i,t} < 0}(E_{i,t} - E_{i,t-1})$. We can then define the rate of job losses ($JLR_{a,t}$) as $JLR_{a,t} = JL_{a,t}/\left(0.5 * (\sum_{i \in a} E_{i,t} + \sum_{i \in a} E_{i,t-1})\right)$. In other words, the rate carriers in an age cohort lost jobs for a given year is the sum of the jobs lost by the subset of establishments that saw less employment in year *t* relative to *t-1* divided by the average employment across all establishments in the age cohort in years *t* and *t-1*. This measure is also reported directly in BDS.

Our focal predictor is a vector of categorical predictors structured using difference coding (UCLA Advanced Research Computing 2024) for each calendar year (e.g., 2004, 2005, … ,2021). For example, with this specification, the indicator for 2004 (*Y2004*) compares the dependent variable for the period March 2003 to March 2004 relative to March 2002 to March 2003; the indicator for 2005 (*Y2005*) compares the dependent variable for the period March 2004 to March 2005 versus the average of March 2002 to March 2003 and March 2003 to March 2004, etc. Therefore, with difference coding, the predictor *Y2021* indicates how the dependent variable compares for the period March 12, 2020, to March 12, 2021, relative to the average of the prior periods. This scheme is ideal to test our theoretical predictions and has been utilized in prior research (Miller and Kulpa 2022). In total, there are 18 difference coded categorical predictors in this vector.

Our focal moderator is carrier age. The most detailed age breakdown with public use BDS data identifies 12 bins: (i) new entrants; (ii) one-year-old firms; (iii) two-year-old firms; (iv) three-year-old firms; (v) four-year-old firms; (vi) five-year-old firms; (vii) six- to ten-year-old firms; (viii) 11- to 15-year-old firms; (ix) 16- to 20-year-old firms; (x) 21- to 25-year-old firms; (xi) 26-year-old or greater firms; and (xii) left-censored firms founded before March 12, 1977. We exclude new entrants from our analysis as new entrants can only gain jobs in the BDS database (and hence have a *Job Gain Rate* of 200%) (Haltiwanger, Jarmin et al. 2013). We likewise exclude left-censored firms since we can't know hold old these carriers are (e.g., Yellow Corp was founded back in 1914 (Page and Biswas 2023). For the age cohorts corresponding to a single year, age is straightforward. For the cohorts covering multiple years, we use the mid-point of the age window (e.g., for the 16–20-year-old age cohort, we use 18). The $\geq$ 26-year-old age cohort is unique because the cohort expands as time passes (e.g., for 2003, only firms founded between March 12, 1977, and March 12, 1978, are included, whereas by 2005, this cohort includes firms founded between March 12, 1977, and March 12, 1980). We thus assume the average age in this cohort increases by 0.5 years for each year (e.g., 26 for 2003, 26.5 for 2004, 27 for 2005, etc.) to account for the oldest firms aging and the addition of younger firms. We take the natural logarithm of carrier age given theoretical arguments from Bakker and Josefy (2018) that the passage of a year is much more meaningful for young firms than older firms. This further aligns with empirical findings that employment dynamics tend to be more pronounced for the youngest of firms (Coad 2018), including in trucking (Miller, Phares et al. 2024). We multiply the natural log of age by -1 so that the measure represents carrier youth, which we label *LnYouth*.

Since both firm age and the passage of time are strictly exogenous (Coad 2018), we select control variables to improve interpretability of estimated parameters and gain estimation efficiency, as opposed to trying to hold constant outside factors that create concerns of omitted variable bias (Miller and Kulpa 2022). Given our set of 18 difference coded predictors for the passage of time, we cannot include a linear time trend[7], as this trend would be perfectly colinear and, thus, be excluded from estimation. We include a dummy variable labeled *General Freight* (*GF*) that equals 1 for general freight trucking (NAICS 4841), leaving specialized freight trucking (NAICS 4842) as the reference category. This eliminates any stable differences in JGRs and JLRs across these sectors. Additionally, as a robustness test to rule out Paycheck Protection

[7] It should be stressed this set of 18 indicator variables for the passage of time fully absorbs any time-varying trends such as the decline in unionization, the increased prevalence of intermodal rail-truck freight, declining average length of haul, and increased adoption of technologies to improve safety (Miller et al., 2024).

Program effects on JLRs once COVID-19 hit, we utilize this variable as part of a three-way interaction. Our second control is the average size of firms in each age cohort, which is calculated as the natural logarithm of age cohort employment for a given year in our notation). We label this variable *LnSize*. We include this control for two reasons. First, as noted by Barron, West et al. (1994), holding firm size constant helps differentiate between the liability of newness versus liability of smallness. Second, Sedláček and Sterk (2017) document that average firm sizes differ systematically across age cohorts in BDS based on conditions at the time of firms' founding, with average firm size of entering firms being larger during expansive conditions. Thus, *LnSize* helps account for founding conditions, which can affect firm survival (Geroski, Mata et al. 2010).

The full correlation matrix, means, and standard deviations of our measures can be found in Table 1. As a note, during data screening, we identified two highly unusual cases (one for an abnormally large JGR for the 21-25 general freight age cohort in 2020 and one for an abnormally large JLR for the 16-20 general freight age cohort in 2021). We consequently dropped these two records; the latter was especially important to remove as its existence would make it easier to find evidence consistent with H_2 and H_3.

<<Insert Table 1 about here>>

RESULTS

Model Free Evidence

Following Davis-Sramek, Scott et al. (2023), in Figures 2a and 2b we plot JGRs and JLRs for general freight trucking firms (note, we have labeled the outliers, which as noted are excluded from the econometric models). These plots are consistent with our predictions, especially for

JLRs, where we see rates for the last year of data (March 12, 2020 – March 12, 2021) plunged for one- and two-year-old carriers.

<<Insert Figures 2a and 2b about here>>

Econometric Analysis

To formally test our predictions, we formulated the following model. For notational purposes, we denote industry subsector as captured by the NAICS system by *s*, firm age cohort by *a*, and year by *t.* Our baseline models can be written as:

$$JGR_{s,a,t} = \alpha_0 + \alpha_1 GenFreight_s + \alpha_2 LnSize_{s,a,t} + \alpha_3 LnYouth_a + \sum_{k=2004}^{2021} \beta_k D_t^k + \sum_{k=2004}^{2021} (\gamma_k D_t^k * LnYouth_a) + e_{s,a,t} \quad (1)$$

$$JLR_{s,a,t} = \delta_0 + \delta_1 GenFreight_s + \delta_2 LnSize_{s,a,t} + \delta_3 LnYouth_a + \sum_{k=2004}^{2021} \tau_k D_t^k + \sum_{k=2004}^{2021} (\varphi_k D_t^k * LnYouth_a) + u_{s,a,t} \quad (2)$$

In these equations, D_t^k represents each of the 18 difference coded predictors that compare each year *t* to the average of all prior years. Our hypotheses concern the two-way interactions between these vectors and *LnYouth*. Specifically, H_1 concerning job gain rates postulates that the interaction between D_t^{2021} and *LnYouth* (captured by parameter γ_{2021}) will be positive. Conversely, H_2 concerning job loss rates postulates that the interaction between D_t^{2021} and *LnYouth* (captured by parameter φ_{2021}) will be negative. H_3 postulates that the absolute value of φ_{2021} will be greater than that of γ_{2021}. It should be noted that the two continuous predictors (*LnSize* and *LnYouth*) were mean centered prior to the analysis.

We report the results from estimating our models in Table 2. These models were estimated using full information maximum likelihood using the general linear modeling procedure (PROC MIXED) in SAS Version 9.4. Since it is reasonable to expect residuals to be correlated for the same age cohort across years, we assumed residuals within an age cohort follows an autoregressive pattern of the first order (AR1), which is a common residual structure found in panel data (Cudeck and Klebe 2002), including motor carrier panel data (Miller and Saldanha 2016). We weight the residuals by the square root of the Davis, Haltiwanger et al. (1996) denominator to place greater weight on records with more employment per common practice in labor economics (Haltiwanger, Jarmin et al. 2013). Due to the number of parameters estimated in our models (40 regression weights including the intercepts for Equations 1 and 2), in Table 1 we selectively report results to conserve space (full results are available from the authors upon request).

<<Insert Table 2 about here>>

We begin by focusing on Model 1 where *Job Gain Rate* is the dependent variable. Consistent with expectations, parameter γ_{2021} capturing the two-way interaction between the difference coded predictor for 2021 (D^{2021}) and *LnYouth* was significant and positive (γ_{2021} = 1.42 (z = 3.49, p < 0.01)). To better understand this interaction, in Figure 3a we make a Johnson-Neyman plot using tools devised by Miller, Stromeyer et al. (2013) that show the conditional effect of D^{2021} as a function of carrier age (note, these results are expressed using the raw matrix for carrier age, not *LnYouth*). In Figure 3a, we see that the simple slope of D^{2021} is significant and positive for carriers that are 5 years or younger, with the effect being greatest for the youngest of carriers (i.e., those that are 1 or two years old). This finding closely aligns with our expectations, and thus H_1 is corroborated.

<<Insert Figure 3a about here>>

Turning now to Model 2 where *Job Loss Rate* is the dependent variable. Consistent with expectations, parameter φ_{2021} capturing the two-way interaction between the difference coded predictor for 2021 (D^{2021}) and *LnYouth* was significant and negative (φ_{2021} = -3.21 (z = -7.10, p

< 0.01)). To better understand this interaction, in Figure 3b we make another Johnson-Neyman plot. In Figure 3b, we see that the simple slope of D^{2021} is significant and negative for carriers that are nine years old or younger, with the effect being greatest for the youngest of carriers (i.e., those that are one or two years old). Furthermore, we find some evidence that carriers older than 17 years old saw significantly higher job destruction rates in the March 2020 – March 2021 period relative to the average of prior periods. While this may seem surprising, this finding is consistent with the fact that older firms tend to be more embedded in existing exchange networks (Liu, Pólos et al. 2021), and these existing exchange networks were heavily disrupted by the COVID-19 pandemic's onset (Caplice 2021). Since older firms tend to have difficulties in adapting operations to rapidly changing market conditions due to multiple mechanisms (Le Mens, Hannan et al. 2015), older carriers who served shippers that saw volumes severely negatively affected by the pandemic's onset likely had a harder time pivoting their assets, and hence were forced to downsize or exit. Thus, H_2 is corroborated.

To test H_3, we need to test whether the absolute value of φ_{2021} exceeds that of γ_{2021}. Following Mize, Doan et al. (2019), we can do this by testing whether the sum of these two parameters is less than zero (since φ_{2021} is negative whereas γ_{2021} is positive, our theory suggests $\varphi_{2021} + \gamma_{2021} < 0$). To do this test, most appropriately, we need to factor in how the residuals for *JGR* (captured by $e_{s,a,t}$) are correlated with the residuals for *JLR* (captured by $u_{s,a,t}$). To do this, we estimate Equations 1 and 2, output the $e_{s,a,t}$ and $u_{s,a,t}$, and correlate these variables (they are weakly correlated with r = 0.11). Per the mathematics of seemingly unrelated regression models (Zellner 1962; Greene 2017), we know that the regression weights φ_{2021} and γ_{2021} are correlated by this quantity. We can therefore test this prediction using the rules for random variables as noted by (Mize, Doan et al. 2019) by testing the following quantity: $z =$

$\frac{(\varphi_{2021}+\gamma_{2021})}{\sqrt{SE^2_{\varphi_{2021}}+SE^2_{\gamma_{2021}}+2*0.11*SE_{\varphi_{2021}}*SE_{\gamma_{2021}}}}$, where $SE_{\varphi_{2021}}$ is the standard error for φ_{2021} and $SE_{\gamma_{2021}}$ is the standard error for γ_{2021}. $\varphi_{2021} + \gamma_{2021}$ = -1.79, with the z-value for this difference being z = -2.79 (p < 0.01). As both *JGR* and *JLR* are rates, the comparison of these terms is inherently meaningful. Therefore, H_3 is corroborated.

Before moving to our robustness testing, we wish to point out a few features of our results. First, the very high weighted R^2 statistics suggest omitted variable bias is of minimal concern, because there is little unexplained variation remaining in our data. Thus, beyond the fact that firm age and passage of time are by definition exogenous and, consequently, cannot suffer from the common form of omitted variable bias that has become a key concern in SCM research (Miller and Kulpa 2022), our high R^2 values greatly reduce endogeneity concerns (Busenbark, Yoon et al. 2022). Second, the overwhelming impact of carrier age in explaining variance in both job gain and job loss rates cannot be overstated. Per Bring (1994), for a given regression model, the predictors with the largest absolute values of t-statistics indicate the predictors that are the most powerful partialed predictors of the dependent variable. As can be seen in Table 2, the coefficients for the first-order terms[8] for *LnYouth* are much larger than any of the other predictors. This highlights the overwhelmingly important role of carrier age in shaping employment dynamics, something we return to in the next section.

Robustness Testing

An important concern about our findings for D^{2021}, especially as it pertains to *Job Loss Rates*, is that the Paycheck Protection Program (PPP) was created in 2020 to preserve jobs (Fower et al. 2020). To rule out that this alternative mechanism is driving our results, we leverage the fact that

[8] Given *LnYouth* is mean centered, the fact that it is involved in two-way interactions doesn't affect these claims.

freight demand differed dramatically in the general freight sector (NAICS 4841) relative to the specialized freight sector after the onset of COVID-19. As noted by Caplice (2021), the onset of the COVID-19 pandemic caused an unprecedented boom in the demand for dry van freight as consumers increased spending on various goods like furniture, electronics, and toys. In contrast, specialized freight carriers did not experience such a boom and, in fact, many saw bust conditions due to sharp declines in heavy equipment construction (FRED 2024a) and hydraulic fracking (FRED 2024b). Consistent with this, the broader measure of freight rates given by the Producer Price Index for specialized freight trucking (NAICS4842) had an increase of only 5.4% from March 2020 to March 2021 (BLS 2024u), as compared to the increase of 20.4% for general freight long-distance truckload (BLS 2024b), and 16.4% for general freight overall (BLS 2024t) over the same period. In addition, some parts of specialized trucking showed PPI declines in this period (e.g. specialized freight local trucking, NAICS484220, which had a 2.2% PPI decrease between March 2020 and March 2021 (BLS 2024w).)

However, data from the Small Business Administration for all PPP loans above $150,000, released by *The Washington Post* through a FOIA (Fowers, Van Dam et al. 2021) and summarized in Table 3 for the two 4-digit NAICS trucking sectors, shows there was no difference in the proportion of jobs saved in general freight trucking versus specialized freight trucking where the proportion of saved jobs is calculated using each sector's total payroll from BDS for March 2020. Given these different demand dynamics, our theory makes two empirical predictions. First, we would expect a two-way interaction between D^{2021} and *GenFreight* to be negative such that the *Job Loss Rate* for general freight carriers was more negative than for specialized freight carriers for the March 2020 – March 2021 period relative to prior years. (That is, the reduction in job losses would be greater for general freight carriers.) Second, we would expect a negative three-way interaction between D^{2021}, *LnYouth*, and *GenFreight*. The reason for this is that a three-way interaction can be thought of as moderated moderation (i.e., a third variable alters the sign of a two-way interaction) (Hayes 2018). Thus, we would expect the two-way interaction between D^{2021} and *LnYouth* to be more negative for general freight carriers relative to specialized freight carriers. To test this prediction, we expand the model in Equation 2 as follows:

$$JLR_{s,a,t} = \delta_0 + \delta_1 GenFreight_s + \delta_2 LnSize_{s,a,t} + \delta_3 LnYouth_a + \sum_{k=2004}^{2021} \tau_k D_t^k + \sum_{k=2004}^{2021} (\varphi_k D_t^k * LnYouth_a) + \theta_1 (LnYouth_a * GenFreight_s) + \sum_{k=2004}^{2021} (\lambda_k D_t^k * GenFreight_s) + \sum_{k=2004}^{2021} (\omega_k D_t^k * LnYouth_a * GenFreight_s) + u_{s,a,t} \quad (3)$$

<<Insert Table 3 about here>>

Per our arguments, our theory predicts λ_{2021} and ω_k will be negative[9]. As reported in Model 3 in Table 2, this is indeed the case, with both interaction terms being significant at $p < 0.01$. To understand these effects, in Figure 4 we plot the simple slope of D^{2021} as a function of carrier age for general freight and specialized carriers. As can be seen in Figure 4, the simple slope of D^{2021} is more negative for the youngest of carriers, with this effect diminishing as carrier age increases. These results are highly consistent with the theory we advance and, given no difference in the proportion of jobs that were saved due to PPP loans, eliminates the possibility that our *Job Loss Rate* results for March 2020 – March 2021 are driven by the PPP program.

<<Insert Figure 4 about here>>

DISCUSSION

Theoretical Contributions

[9] While λ_{2021} is a constituent term, it is theoretically meaningful given we mean-centered *LnYouth* such that this term represents how the effect of D^{2021} differs for general freight carriers relative to specialized freight carriers at the average value of *LnYouth*.

The first theoretical contribution our manuscript makes is to extend the SCM literature that has examined carrier growth, especially in the period following deregulation (Kling 1988; Rakowski 1988; Kling 1990; Corsi, Grimm et al. 1991; Corsi, Grimm et al. 1992a; Corsi, Grimm et al. 1992b; Grimm, Corsi et al. 1993; Rakowski 1994; Feitler, Corsi et al. 1998), by documenting that younger carriers have higher rates of payroll expansion than older carriers during strongly expansive market conditions. The SCM literature has not considered how trucking firms' age affects their growth rates, which needs remedied given firm age has been found to be *the* most important factor that affects the pace of payroll expansion in the U.S. economy as a whole (Haltiwanger, Jarmin et al. 2013; Pugsley and Șahin 2019). Our finding that younger carriers expand payrolls even more rapidly than their older peers during expansive market conditions has important implications for understanding whether there is a systematic shortage of truck drivers. In particular, since younger firms face more hurdles than older peers when recruiting workers during expansive periods (Moscarini and Postel-Vinay 2012), the fact we find that younger trucking firms have higher rates of job creation during the most expansive period in recent trucking history—and very likely of all time (Caplice 2021) —speaks against the argument of a true systematic shortage, which further reinforces findings from academic studies and the recent National Academies study that challenge the driver shortage narrative (Burks and Monaco 2019; Miller, Bolumole et al. 2021; Phares and Balthrop 2022; Burks, Kildegaard et al. 2023; Phares, Miller et al. 2023; Miller, Phares et al. 2024; National Academies of Sciences Engineering and Medicine 2024).

Relatedly, we contribute to the SCM literature by devising theory describing *why*, by detailing multiple complementary theoretical mechanisms (Astbury and Leeuw 2010), older trucking firms are likely to face constraints in expanding payrolls relative to younger peers, even when market conditions are favorable. We build from the argument of Liu, Pólos et al. (2021) that time serving a given geographic target market (Chen 1996) can make it harder for firms to adapt to changes in market conditions because segment-specific resources developed over time via learning by doing (Foster, Haltiwanger et al. 2016) aren't easily fungible. Specifically, we contextualize (Johns 2006; Craighead, Ketchen Jr et al. 2016) this argument to the trucking setting by explaining that while the general argument applies to all segments of trucking, there is a special role for pronounced economies of scope in the long-distance truckload sector (Muir, Miller et al. 2019; Miller and Muir 2020) that can make it hard for carriers to pivot their capacity quickly in response to changes in demand (Caplice 2021). Recognizing that existing customer constraints may limit how quickly carriers, especially older operations, can expand payrolls even during expansive market conditions helps explain why capacity (i.e., supply) tends to lag demand during periods where carriers see sharp upticks in demand for their services (Burks, Kildegaard et al. 2023; National Academies of Sciences Engineering and Medicine 2024). This helps further dampen arguments that the trucking industry has a systematic shortage of truckers (Fuller 2019; Burks, Kildegaard et al. 2023; Fuller 2023; Schremmer 2023)).

A second way this research extends theory in SCM is explaining why the pace at which trucking firms can add to their payrolls in response to expansive market conditions is more constrained than the pace at which they shed payrolls. Making this distinction is important because, as Delmar, Wallin et al. (2022) argue, there is a tendency to assume symmetry in mechanisms that bring about expansion versus contraction (e.g., if high levels of Mechanism 1 can drive expansion, then low levels of Mechanism 1 may cause contraction). In contrast, we explain why payroll expansion, even for young firms with flexible administrative structures and a strong incentive to grow (Coad 2018), inherently faces constraints due to limited managerial time/resources (Penrose 2009); sharp increases in administrative complexity associated with carriers passing given size thresholds (Maister 1980; Powell, Sheffi et al. 1988); owners/managers fearing that too large a size will cause a loss of current market niche (Marchington, Carroll et al. 2003); and owners fearing that growing too large will cause a loss of operational control (Davidsson 1989). Recognizing these constraints is important because they further help explain why trucking capacity, across all segments of the industry, but especially in long-distance truckload, may take time to adjust upward in response to increased demand for trucking services without there necessarily being a systematic shortage of truck drivers.

Apart from contributing to the logistics literature, this research modifies TGF along three important dimensions. First, whereas TGF argues that the existence of underutilized resources within firms is the primary impetus for growth (Penrose 2009), our theory highlights that for industries dominated by SMEs, expansive conditions are likely to be a critical external enabler (Davidsson 2015)} of firm growth. In other words, we modify Penrose's theory—which was devised in the context of incorporated large manufacturing firms in the 1950s and 1960s—to place greater emphasis on external factors in driving SME growth. We explain that expansive conditions are especially likely to be important in enabling young firms' growth because young firms are demand constrained relative to older firms (Foster, Haltiwanger et al. 2016), and face greater difficulty in obtaining financing than older firms (Gertler and Gilchrist 1994). Second, whereas Penrose TGF assumes relative homogeneity to the extent firms are looking to expand, our theory postulates heterogeneity in the desire to grow because young firms have been found to especially desire expansion (Davidsson 1989). Third, TGF does not consider that older firms may be less able to expand operations even during expansive conditions due to structural inertia that can stem from numerous sources such as long-tenured managers resistance to change (Le

Mens, Hannan et al. 2015), routines that ossify and thus are hard to change (Hannan and Freeman 1984), or existing customer relationships (Liu, Pólos et al. 2021). Therefore, our theory can be considered a modified version of the broader programmatic theory (Cronin, Stouten et al. 2021) of firm growth that suggests different boundary conditions (Makadok, Burton et al. 2018) and predictions (Shugan 2007) than Penrose's TGF. Given our theory can account for a variety of empirical findings Penrose's TGF cannot explain, our version has greater dynamic consilience (Thagard 1978), a key dimension for contributions (Keas 2018).

Managerial Implications

This research has implications for carriers, shippers/brokers, and policy makers. Starting with carriers, our results indicate that for carriers seeking to expand by adding employees, they should be especially cognizant of factor market rivalry (Opengart, M. Ralston et al. 2018; Ralston, Schwieterman et al. 2023) from young trucking firms, as these firms tend to grow more rapidly than their older peers. This is especially the case during expansive market conditions. We emphasize the importance of firm age because conventional industry wisdom emphasizes carrier size to a much greater degree when talking about expansion of trucking capacity during expansive markets (Fuller 2023); our results suggest the emphasis on small size *per se* is misplaced given the larger effect of age (conditional on size) on job gain rates vis-à-vis size (conditional on age).

Turning next to shippers and brokers, our findings provide guidance concerning how these entities can go about adding additional transportation capacity. For shippers fortunate enough to experience especially strong demand conditions—a frequent occurrence based on administrative records (Kehrig and Vincent 2021)—that necessitate procuring more transportation capacity, young carriers appear to have greater potential to add capacity. This is especially true during highly expansive market conditions favoring trucking firms, which is the exact time that concerns about capacity shortages are most serious (Burks, Kildegaard et al. 2023). Thus, having some young carriers in a shipper's network provides a means to hedge on capacity, as opposed to needing to incorporate new carriers into the network. However, this benefit needs to be balanced against the fact that young firms, and especially the youngest of carriers (e.g., those that are 1 year old) tend to have more safety issues (Corsi 1989; Cantor, Corsi et al. 2017); Corsi and Fanara 1989). Given young carriers' safety trajectories (Miller, Saldanha et al. 2018), shippers and brokers may want to wait for carriers to reach about 1.5 to 2 years of operation before allowing them into their network. Moreover, shippers and brokers should be aware that carriers experiencing especially rapid expansion may be more likely to see an uptick in unsafe driving violations (Miller, Schwieterman et al. 2018), which are strongly correlated with accident rates (National Academies of Sciences Engineering and Medicine 2024).

Policy Implications

Turning now to policy makers, our results have numerous implications. First, the fact we found clear evidence that carriers, especially in the general freight sector, responded strongly to the very strong bull market conditions during the March 2020 – March 2021 period by expanding payrolls at an unusually fast pace speaks against the argument of a systematic shortage of truck drivers. This is especially true when we consider that this period saw record job creation by new entrant general freight trucking firms, with new entrants that started operations between March 2020 and March 2021 reporting ~55,000 on their payrolls as of March 2021. This figure is double the payrolls that new entrant general freight carriers added prior to the cohort of new entrants created between March 2018 and March 2019. In contrast, we do not see this surge in new entrants in the specialized freight subsector, which aligns with the much weaker demand conditions we described this sector experiencing in our robustness testing section. Thus, policy makers should recognize our results strongly corroborate arguments that the labor market for truck drivers behaves normally (Burks and Monaco 2019; Phares and Balthrop 2022; Burks, Kildegaard et al. 2023; National Academies of Sciences Engineering and Medicine 2024)).

A second implication from this research for policy makers is that there are several reasons why trucking capacity may be slow to adjust to increases in demand for truck transportation without there being a systematic shortage of workers that meets the criteria set forward by Veneri (1999). In particular, our theory highlights how existing customer relationships can constrain the ability of carriers to expand due to the pronounced economies of scope that exist in truckload operations (Muir et al. 2019). For example, Powell & Mayoras (1996) describe rapid expansion of carriers with established contractual relationships that can imbalance freight networks, which in turn can result in higher costs and poor service. Extant theory (Liu et al. 2021) suggests such customer-driven structural inertia should be greater for older carriers, a finding we corroborate with our findings that older carriers had far slower rates of job gains than young carriers during the March 2020 to March 2021 timeframe. Furthermore, policy makers should recognize such age-related structural inertia may be present due to multiple complementary mechanisms as outlined by Le Mens et al. (2015). To date, we have not seen the importance of considering age related structural inertia in the context of the debate about a systematic shortage of truck drivers.

A third implication from this research for policy makers is that the underlying age distribution of capacity in the trucking industry is likely to affect how quickly the sector can expand payrolls in response to expansive industry conditions. More specifically, our results suggest that a trucking industry in which more capacity resides at younger carriers will be more responsive to expansive market conditions. This is akin to arguments from Pugsley & Șahin

(2019) that a shift of employment towards older firms can make an economy less dynamic during a rebound from a recession because the rate of job creation is slower. For example, data from BDS shown in Figure 5 shows a dramatic increase in the percentage of employment residing at carriers ≤ 5 years of age (which includes new entrants) by March 2021. This fact may help explain why carriers ultimately added so much capacity as expansive conditions continued through early 2022 that the general freight sector entered a deep freight recession starting in the 3rd quarter of 2022, when demand began to fall in response to excessive accumulation of inventories coupled with the Federal Open Market Committee's interest rate hikes causing a swift decline in housing activity (Miller 2023). This reinforces the importance of considering carrier age in discussions of the truck driver shortage.

<<Insert Figure 5 about here>>

Limitations

As with all research, this manuscript has limitations. First, as with all archival studies using administrative records, we cannot measure the mechanisms that we theorized brought about our results (Astbury and Leeuw 2010). Rather, we infer whether these mechanisms could be operating by observing effects consistent with these mechanisms' predictions (Miller and Kulpa 2022). This said, we have sought to achieve theoretical identification (Miller, Balthrop et al. 2023) by providing strong arguments as to why we should expect our postulated mechanisms to operate, consistent with Ketokivi and Mantere (2021). Furthermore, the nuanced nature of our predictions helps eliminate alternative theories (Lipton 2004), as it is difficult to conceive of an alternative explanation that could give rise to our findings (Leavitt, Mitchell et al. 2010).

A second limitation is that because the BDS data only provide a breakout at the 4-digit NAICS level, while we can analyze differences between general freight and specialized freight, we cannot observe any finer-grained employment dynamics that may occur in subsegments of these two higher-level groupings. Some of our arguments and explanations of mechanisms behind the observed employment dynamics apply broadly across all segments of trucking that experience expansive conditions, but others are focused on the specific (large and central) segment of long-distance truckload. The limitations in the data mean we are not able to identify the specific characteristics of the dynamics in particular subsegments.

A third limitation of this research is that we cannot observe firm-level behavior, but instead, examine cohort-level aggregates, as firm-level microdata of this sort requires confidential access via a Census Bureau Regional Data Center. A fourth limitation is that our findings apply to one industry (truck transportation) in one country (the United States). Thus, generalizing our findings to industries with different cost structures (e.g., heavy manufacturing where fixed costs are high relative to variable costs) or different labor environments (e.g., France) may not be warranted.

Directions for Future Research

This manuscript suggests multiple directions for future research. One direction, which would require access to the Census Bureau's microdata, would be to study the distribution of trucking firms' growth during expansive market conditions. For example, given evidence that most young firms have very limited (if any) growth (Hurst and Pugsley 2011), were the very rapid job gain rates for the youngest of general freight carriers observed between March 2020 to March 2021 driven by a few superstar firms that grew dramatically or a general shift in the job gain distribution of young firms (Decker, Haltiwanger et al. 2016; Autor, Dorn et al. 2020)? A second direction would be to extend the present analysis to other sectors in logistics, such as warehousing (NAICS 493) or couriers and messengers (NAICS 492), both of which also entered dramatically expansive conditions with the onset of the COVID-19 pandemic.

Table 1: Correlation matrix, means, and standard deviations.

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*
1. Job Gain Rate	1.00																						
2. Job Loss Rate	0.70	1.00																					
3. LnYouth	0.87	0.86	1.00																				
4. LnSize	-0.71	-0.75	-0.85	1.00																			
5. General Freight	-0.09	-0.06	0.01	0.14	1.00																		
6. D2004	0.00	-0.02	0.00	0.00	0.00	1.00																	
7. D2005	-0.04	-0.03	0.00	0.00	0.00	0.00	1.00																
8. D2006	0.01	-0.05	0.00	0.01	0.00	0.00	0.00	1.00															
9. D2007	-0.04	0.06	0.00	0.00	0.00	0.00	0.00	0.00	1.00														
10. D2008	-0.11	0.05	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	1.00													
11. D2009	-0.15	0.18	0.00	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	1.00												
12. D2010	-0.06	0.02	0.00	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00											
13. D2011	0.10	-0.07	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00										
14. D2012	0.09	-0.10	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00									
15. D2013	0.00	-0.10	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00								
16. D2014	-0.02	-0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00							
17. D2015	0.00	-0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00						
18. D2016	-0.06	-0.01	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00					
19. D2017	-0.05	-0.07	0.00	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00				
20. D2018	0.02	-0.11	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00			
21. D2019	0.02	-0.11	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00		
22. D2020	-0.04	-0.02	0.01	-0.03	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	
23. D2021	0.03	-0.04	0.01	-0.03	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Average	16.29	19.75	-1.88	2.23	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standard Dev.	5.54	6.90	1.07	0.69	0.50	0.16	0.19	0.20	0.21	0.21	0.21	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22

Table 2: Results from mixed effects models.

Parameter		Model 1 DV: JGR		Model 2: DV: JLR		Model 3: DV: JLR
Intercept	α_0	16.96*** (82.93)	δ_0	20.26*** (64.44)	δ_0	20.22*** (111.64)
GenFreight	α_1	-1.34*** (-4.68)	δ_1	-1.09*** (-3.62)	δ_1	-1.04*** (-4.09)
LnSize	α_2	1.28*** (3.83)	δ_2	-0.33 (-0.95)	δ_2	0.73** (1.99)
LnYouth	α_3	5.17*** (21.15)	δ_3	5.31*** (20.59)	δ_3	5.21*** (23.68)
D_t^k	β_k	Included	τ_k	Included	τ_k	Included
D^{2021}	β_{2021}	0.82* (1.73)	τ_{2021}	-1.99*** (-3.76)	τ_{2021}	-0.39 (-0.55)
$D_t^k * LnYouth_a$	γ_k	Included	φ_k	Included	φ_k	Included
$D^{2021} \times$ LnYouth	γ_{2021}	1.42*** (3.49)	φ_{2021}	-3.21*** (-7.10)	φ_{2021}	-1.90*** (-3.02)
LnYouth × GenFreight					θ_1	1.37*** (5.03)
$D_t^k * GenFreight_s$					λ_k	Included
$D^{2021} \times$ GenFreight					λ_{2021}	-2.76*** (-2.93)
$D_t^k * LnYouth_a * GenFreight_s$					ω_k	Included
$D^{2021} \times$ LnYouth × GenFreight					ω_{2021}	-2.25*** (-2.76)
AR(1) Residual Structure	ρ	0.23*** (4.42)	ρ	0.17*** (3.22)	ρ	0.12** (2.18)
Sample Size		378		378		378
-2 Log Likelihood		1,613.1		1,703.5		1,614.2
Weighted R^2		0.854		0.889		0.913

Notes: * = p < 0.10; ** = p < 0.05; *** = p < 0.01 (two-tailed)
Z-values are reported in parentheses below regression coefficients.
Parameters estimated using the MIXED routine using full information maximum likelihood SAS Version 9.4.

Table 3: Summary of jobs retained by PPP loans that were ≥ $150,000.

Sector	Jobs Retained	March 2020 BDS Employment	Percent of Jobs Retained
General Freight (4841)	329,703	1,121,913	29.4%
Specialized Freight (4842)	149,454	503,148	29.7%

Figure 1: Aggregate linehaul rate for spot market truckload freight.

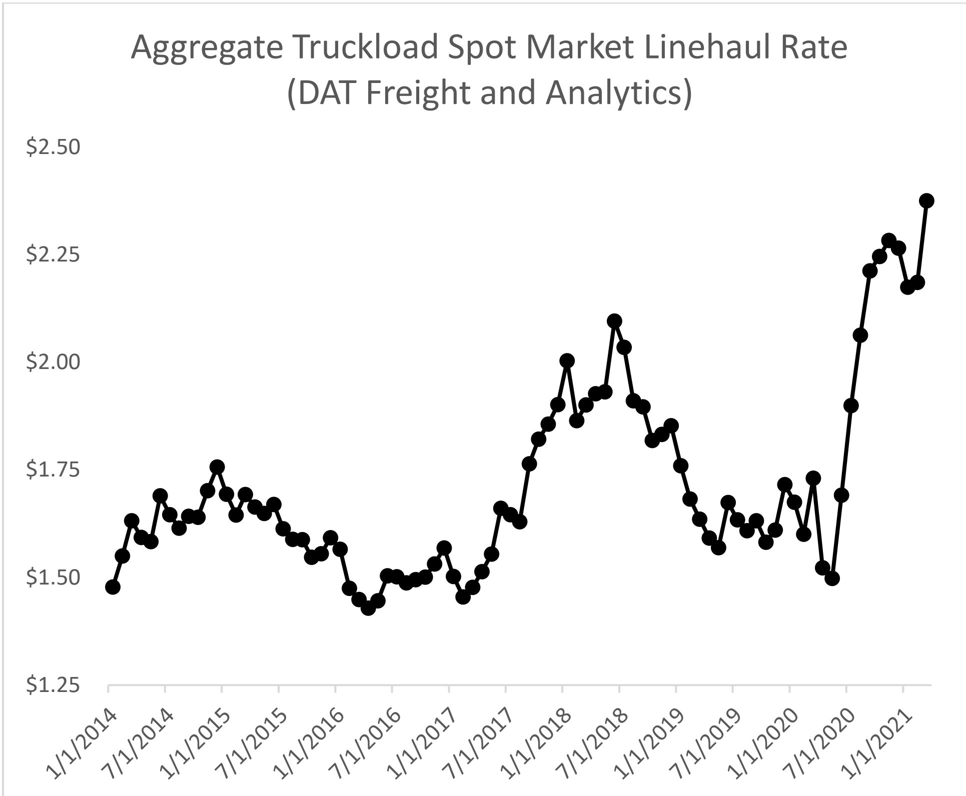


Figure 2a: Job gain rate for general freight trucking

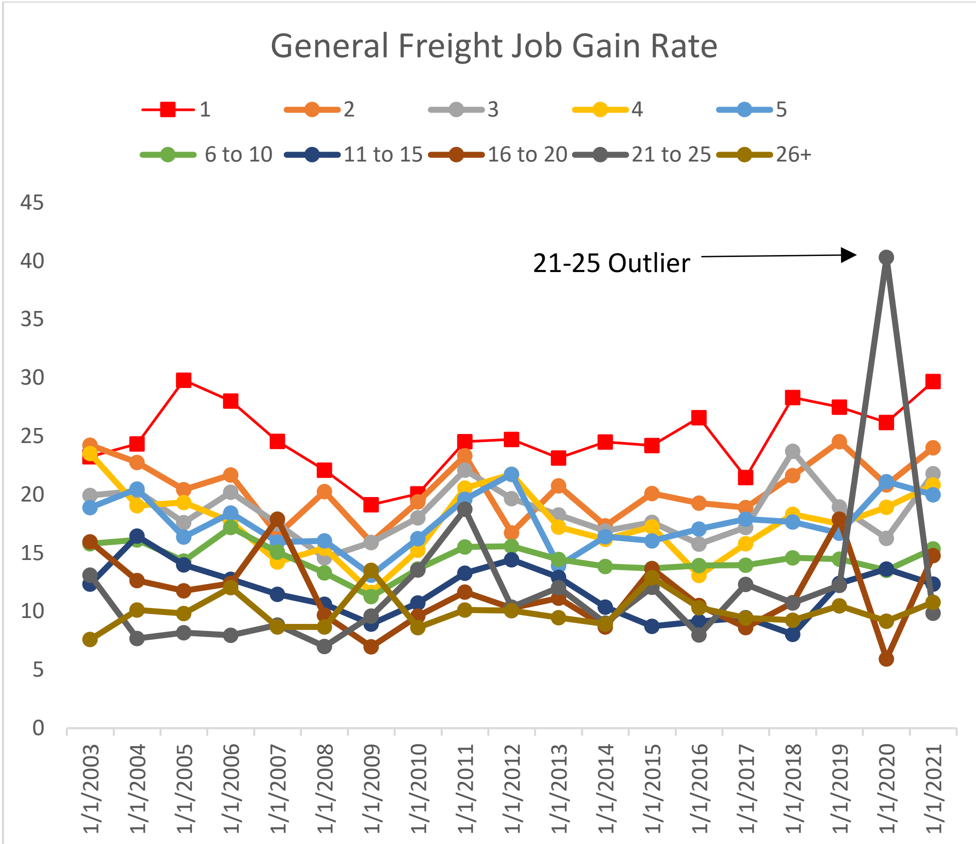


Figure 2b: Job loss rate for general freight trucking.

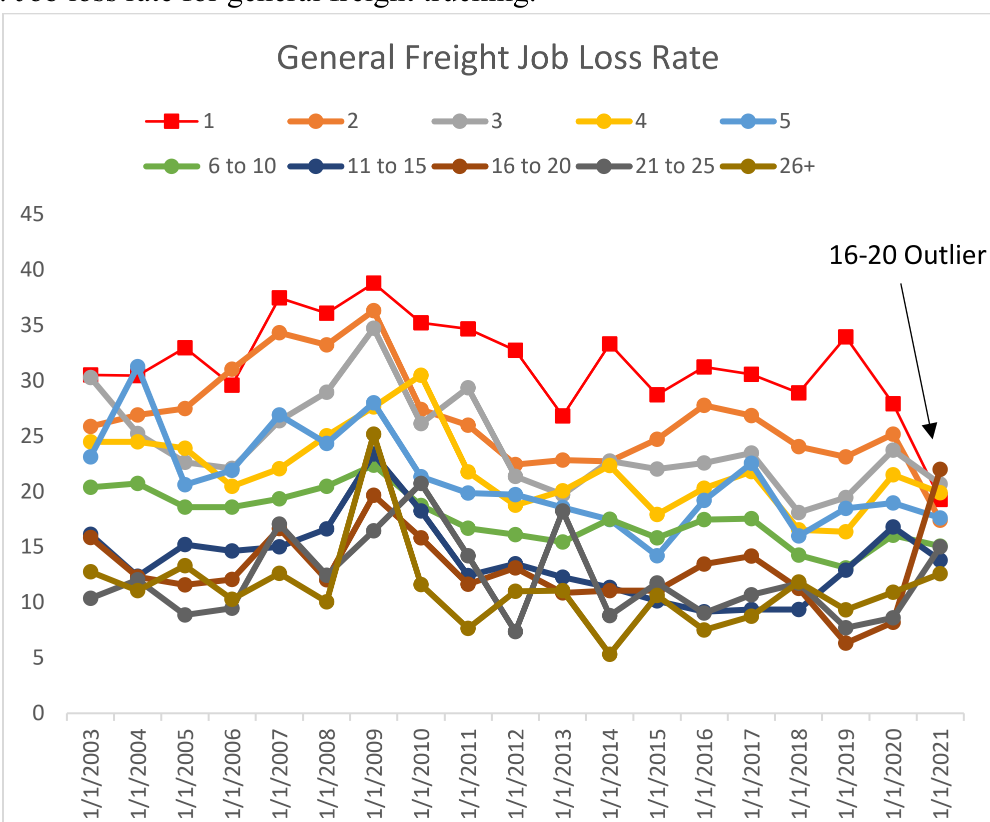


Figure 3a: Johnson-Neyman plot for the conditional effect of D^{2021} for *Job Gain Rate*.

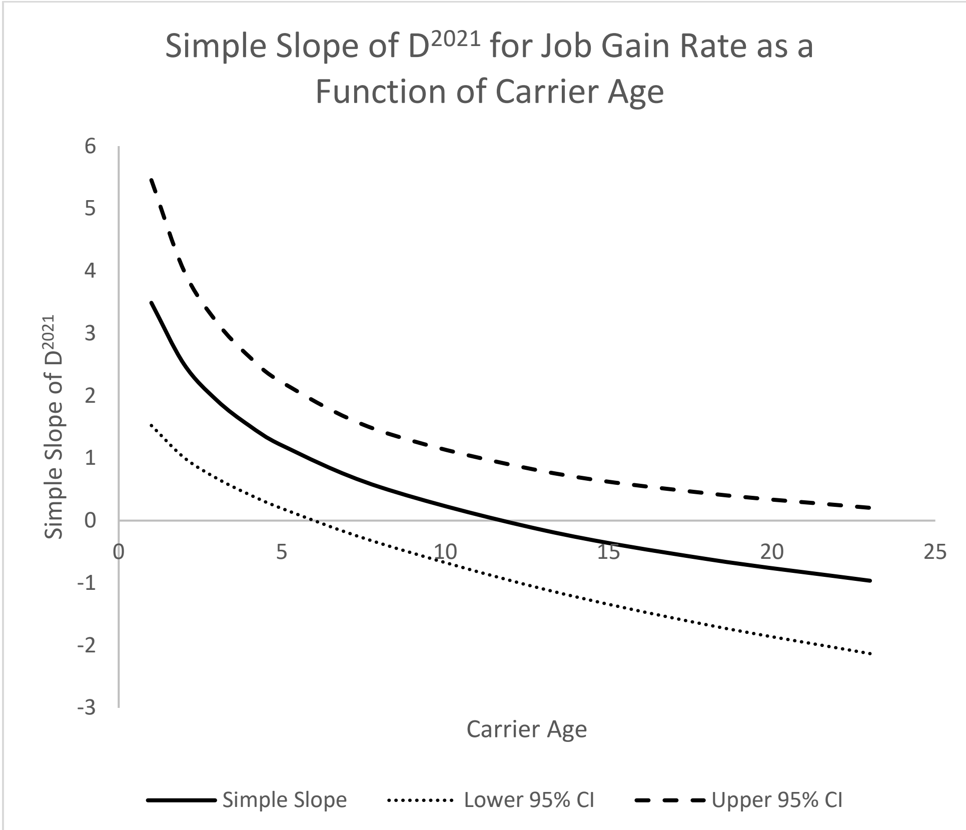


Figure 3b: Johnson-Neyman plot for the conditional effect of D^{2021} for *Job Loss Rate*.

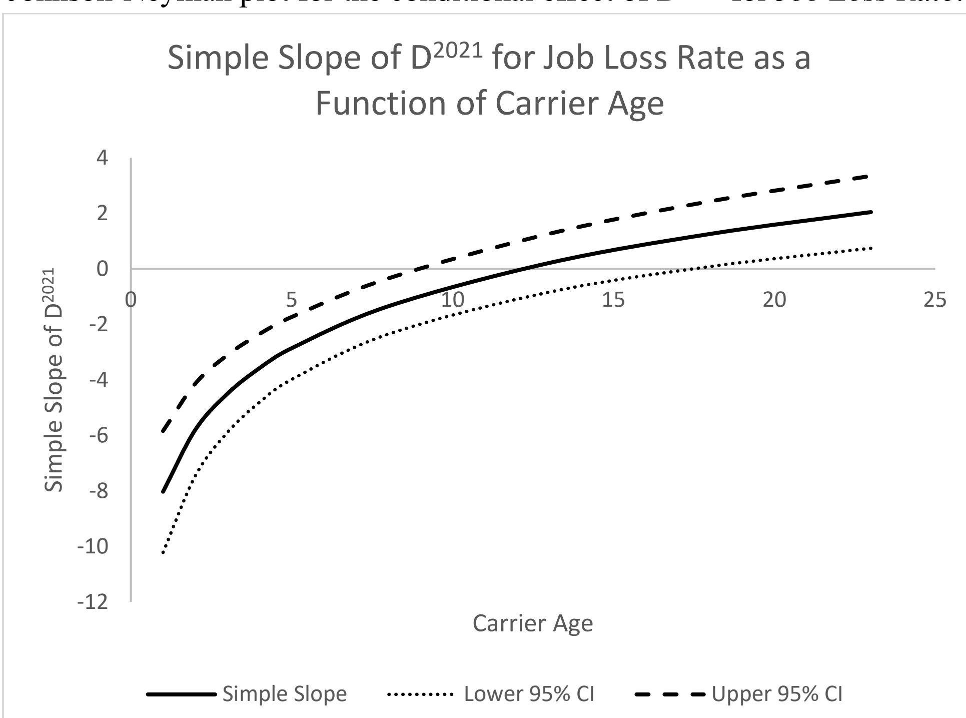


Figure 4: Simple slope plot of D^{2021} for *Job Loss Rate* for general freight versus specialized carriers.

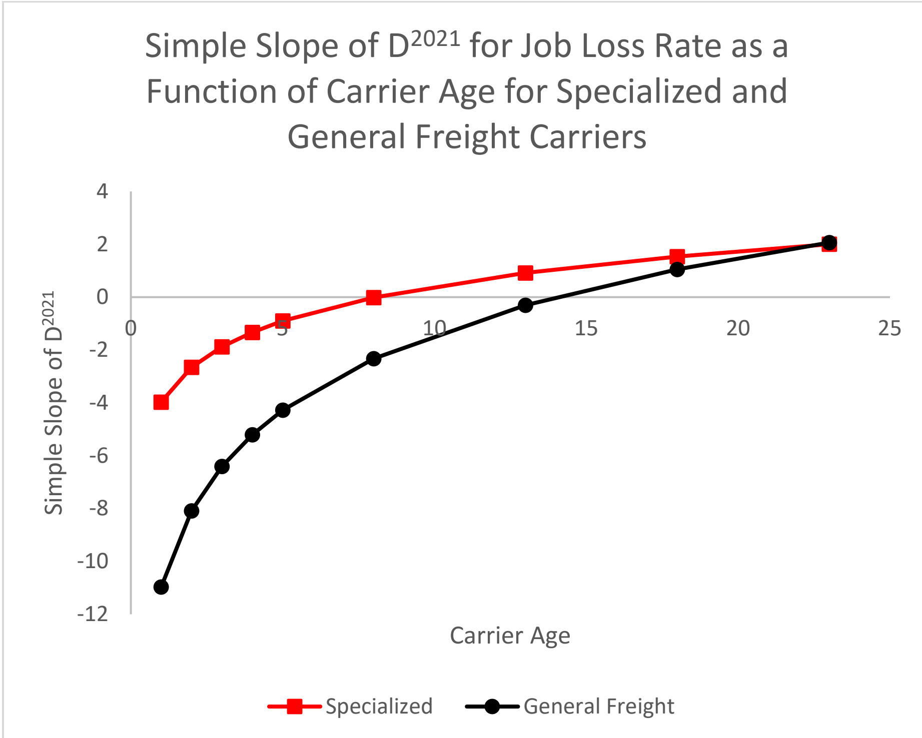
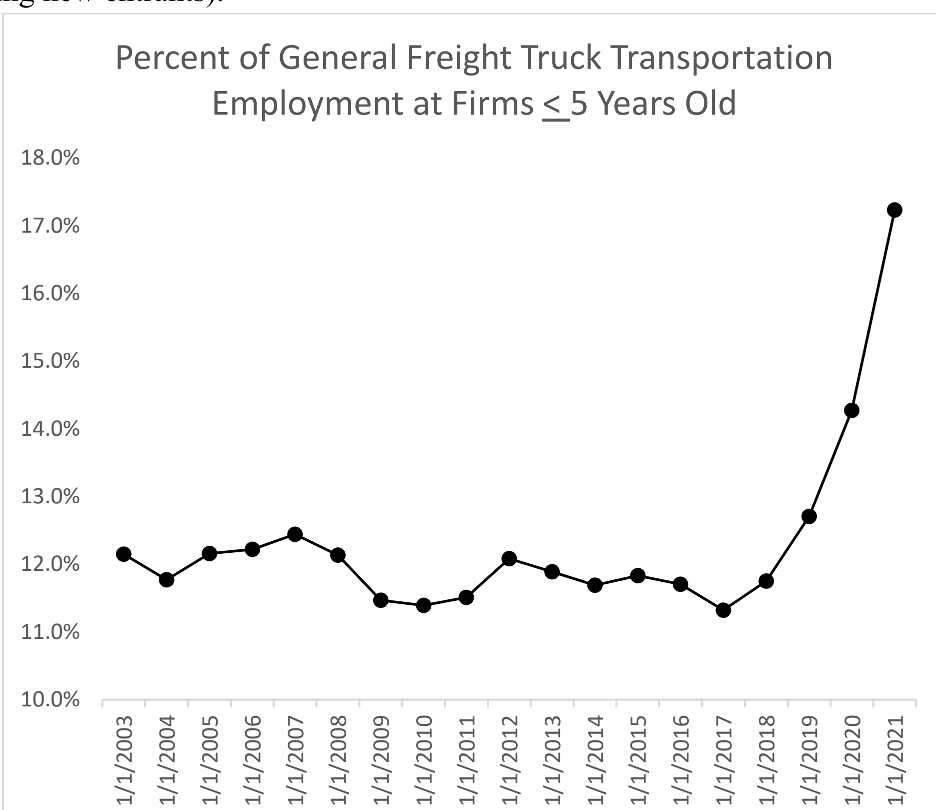


Figure 5: Percent of general freight truck transportation employment at firms that are ≤ 5 years of age (including new entrants).



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