Assessing Alternative Occupations for Truck Drivers in an Emerging Era of Autonomous Vehicles

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Abstract

This study identifies alternative occupations for heavy truck drivers and to evaluate the relative attractiveness of these alternatives in terms of compensation, ease of entry and future job growth. We also evaluate the geographic correspondence between truck driving jobs and available alternatives within the same state given research evidence about geographic rigidities in job seekers. We develop two strategies for identifying alternative occupations. One approach suggests that there may not be sufficient job alternatives for displacement of 35% or more of the truck-driving workforce. The second alterative suggests insufficient job alternatives when displacement levels exceed 50%. Despite these varied pictures, our results present some important trends among job alternatives. Most alternatives were in Job Zones 1 and 2 which require little additional training and/or education for displaced drivers. Unfortunately, the identified alternatives paid lower wages than did truck-driving jobs, indicating a potential loss of income. The projected demand for alternative jobs also varied by occupation. Some alternatives are projected to have employment growth, while others are projected to have jobs losses. Lastly, there were geographic trends in states projected to experience greater losses of driving jobs, and that do not have sufficient alternative jobs for workers. Our findings indicate that this is particularly true for states located in Middle America. Proactive labor policies that are tailored to the regional labor market and available job alternatives will be needed to help truck drivers transition into new occupations. These policies should be particularly mindful of the specific characteristics of the truck-driving workforce.

Keywords: autonomous vehicles, trucking, job displacement, occupational mobility, automation, technological change

1. Introduction

Autonomous vehicles (AVs) are a more recent technological advancement that use Internet connections, AI sensors, and algorithms to monitor and control cars. While not yet widely adopted, these vehicles are anticipated to have transformative impacts on the driving workforce (Beede et al., 2017; Groshen et al., 2018), impacting occupations ranging from truck, ride-hailing, taxi, bus, and delivery service drivers (Yankelevich et al., 2018). Trucking is projected to be one of the earliest affected industries. Forecasts about the development of autonomous trucks (ATs) in the United States indicate that truck platooning with only a driver in the leading vehicle will appear between 2022 and 2025, AT fleets without drivers will start running on interstate highways between 2025 and 2027, and ATs without drivers from loading to delivery on all types of roads will appear as early as 2027 (Chottani et al., 2018). The persistent shortage of workers in truck driving occupations (Costello, 2017; LeMay and Taylor, 1989; Short, 2014) may hasten the adoption of ATs to overcome the challenge of finding workers.

It is also important to understand the workforce impacts of AVs on the trucking industry because of the importance of the freight transport industry in the United States. Trucking is among the top ten most common occupations in fifteen U.S. states (Shoag et al., 2021). In 2019, trucking revenue accounted for 80.4% of the nation's freight bill (Asher, 2019). In this same year, there were 1,856,130 people working as heavy and tractor-trailer truck drivers (U.S. Bureau of Labor Statistics, 2021a). It is therefore crucial to study how AVs will reshape the truck driving labor force because such impact will likely be significant, affecting a large proportion of the U.S. workforce that is employed in trucking and related industries.

Studies are beginning to evaluate the transformative impacts of ATs on the driving workforce and the implications for workers in these occupations (Yankelevich et al., 2018; Gittleman and Monaco, 2020). Unfortunately, we do not have information about potential alternative occupations for truck drivers, nor do we have a clear understanding of how easy it may be for truck drivers to transition into these alternatives. We also lack information about the geographic distribution of driving occupations and viable alternatives, which is important to examine because the occupational profile of places can shape the growth prospects of regional economies (Moretti, 2012).

Given these research and policy needs, the purpose of this study is threefold. One, to identify alternative occupations for heavy truck drivers given the possibility that they may be displaced partially or entirely by AVs. Two, to evaluate the relative attractiveness of these alternatives in terms of compensation, ease of entry and future job growth. Three, to evaluate the geographic correspondence between truck driving jobs and available alternatives within the same state, given research evidence about geographic rigidities in job seekers (Greenwood et al., 1986; Şahin et al., 2014) and the localized nature of labor markets (Acemoglu and Restrepo, 2018a; Acemoglu and Restrepo, 2018b). In doing so, we contribute to existing research on the workforce impacts of automation and the societal impacts of autonomous vehicles. From a policy perspective, this knowledge is critical for understanding the regional economic impacts of the next wave of automated technologies on transportation work and regional economies. Knowledge gained from this study is also critical for promoting a smooth transition to alternative career paths for workers who may be displaced or disadvantaged by AVs.

2. Technological Change and the Workforce

Periods of rapid industrialization have been characterized by the emergence of new jobs, activities, industries and tasks (Acemoglu and Restrepo, 2018b). The rise of artificial intelligence (AI) and other automated technologies has prompted renewed concerns about potential job elimination and skill obsolescence. It is expected that AI and automation will transform occupations by raising the productivity of some workers while also replacing the jobs of other workers (Frank et al., 2019). AI-related technologies are forecasted to render lower-skilled jobs obsolete (Brynjolfsson et al., 2002; Ford, 2015; Pierce et al., 2019). AI and automation are also projected to replace jobs that deal with routine and repetitive tasks (Ernst et al., 2019). Leduc and Liu (2019) showed that local labor bargaining strength is weakened when facing the potential of automation, thereby reducing real wages. This effect appears to arise through the mere threat of automation as well as through the implementation of automation.

2.1. Adoption and Workforce Impact of Autonomous Vehicles

In the transportation industry, manual labor occupations, like truck driving and machine operators, are at high risk for job losses due to automation (Arntz et al., 2016; Frey and Osborne, 2017). Shared autonomous vehicle services are also envisioned to provide a new mobility option that reduces the demand for professional drivers (Jiang et al., 2020; Wadud, 2017; Wang et al., 2020; Zhang et al., 2020). An international online survey found that AVs were perceived as a significant employment disruptor in the transportation industry (Nikitas et al., 2021). A report published by the Center for Global Policy Solutions (2017) projected that over four million jobs would be lost with a transition to AVs. This report projected the following driving occupations would be most heavily affected: delivery and heavy truck drivers, bus drivers, taxi drivers, and chauffeurs. A potential adverse outcome, which may be more pronounced in some local markets than others, is the prevalence of widespread automation over many related occupations.

Based on the job requirements and industry characteristics, Gittleman and Monaco (2020) estimated that 300,000 – 400,000 heavy truck drivers in the long-haul trucking segment are the group that will be first affected by Level 4 automation. Viscelli (2018) also argued that while there are millions of heavy-duty truck drivers in the U.S., a large proportion of those jobs are in industry segments that would not be automated in the near future. Rather, he estimated that only 294,000 driving jobs, mainly in highway driving and in large firms, are at high risk of being displaced. He also asserted that we are unlikely to see a significant labor impact of AVs in the next decade, supporting the findings of Yankelevich et al. (2018).

While some drivers may be able to transition into alternative, transport-related occupations like vehicle maintenance (Pettigrew et al., 2018), forced early retirement is also a possibility for aging workers displaced by automation. In the U.S., Shoag et al. (2021) conducted a survey to investigate how truck drivers plan on adapting to automated driving systems. They found that truck drivers had mixed views on the displacement risk they faced, with about half of the respondents very or somewhat worried about the adoption of AVs. Furthermore, despite the worries about automation, truckers showed little willingness to participate in professional retraining programs that will help them transition into other jobs. This was particularly the case with long-haul truck drivers, who have indicated a low willingness to participate in retraining (Shoag et al., 2021). The age of truck drivers may be a factor that explains this low willingness to retrain, as many drivers in the U.S. expect to retire by the time AVs are commercially available (Mohan and Vaishnav, 2022). Drivers' lack of interest in retraining is consistent with meta-analytic findings that older workers tend to be less interested in training (Ng and Feldman, 2012). Yet, the literature on older workers also suggests that this disinterest may be due to stereotypes about their ability to learn new information, which may be internalized and prompt older workers to have negative expectations about training being too difficult for them (Maurer et al., 2003; Posthuma and Campion, 2009). The Shoag et al. (2021) study also suggests that overestimates of retraining costs may deter drivers from participation in relevant programs. However, even if truckers were aware of the correct information, many of them still preferred to stay in trucking in a scenario where half of the job opportunities may disappear because of the adoption of AVs. This finding highlighted the importance of identifying suitable alternative jobs for displaced workers and promoting professional training.

2.2 The Geographic Distribution of Workforce Impacts of Automation

From a geographic perspective, it is important to understand the distribution of workforce impacts for several reasons. First, geographic skills mismatch can be a source of unemployment (Greenwood et al., 1986; Şahin et al., 2014). This mismatch may be exacerbated by an unwillingness of workers to seek employment in other locations (Marinescu and Rathelot, (2018). Recent information also suggests that moving for work is becoming less common in the United States (Challenger, Gray and Christmas, Inc, 2018; Gibson, 2018; White, 2017), particularly among workers over the age of 35 due to economic factors and embeddedness in social networks (White, 2017). Second, research about the geography of jobs indicates that the occupational profile of places can shape the growth prospects of regional economies (Moretti, 2012). These impacts are evident in the divergent economic trajectories of locales in the current global knowledge economy. For example, labor markets around Silicon Valley thrive while manufacturing-oriented regions in the deindustrialized Midwest struggle with higher rates of unemployment and economic stagnation. Lastly, studies highlight the localized nature of labor markets (Acemoglu and Restrepo, 2018a), which indicates the workforce impact of automated technologies is likely to vary by region. Further, the jobs projected to be impacted by these technologies (e.g., manual labor) often co-locate to take advantage of agglomeration economies (Glaeser and Maré, 2001; Moretti, 2010; Rosenthal and Strange, 2004). Thus, it is reasonable to expect that some regional labor markets will be impacted more than others because of simultaneous displacement across multiple occupations.

3. Data

In the analysis that follows, we focus on the availability of jobs within a particular state given the geographic rigidities in job seekers and the localized nature of labor markets discussed above. This geographic scale is also necessary because state-level data are the finest level of geography for which occupational data are available in the U.S. We focus our analysis on heavy and tractor-trailer truck driving based on the findings of prior work that suggest these driving jobs are at greater risk of automation relative to other truck driving jobs (Gittleman and Monaco, 2020).

3.1. Occupational Employment and Wages Statistics

The primary data source for this paper is the annual release of labor statistics by the Occupational Employment and Wages Statistics (OEWS), a program of the U.S. Bureau of Labor Statistics (BLS). We use the May 2020 OEWS dataset released on March 31, 2021 (U.S. Bureau of Labor Statistics, 2021b).[1] The OEWS program collects employment and wage data by occupation for each state, the District of Columbia, and territories of the United States. OEWS data are place of work oriented because the BLS collects data from establishments (U.S. Bureau of Labor Statistics, 2022). Each year of the OEWS data release consists of a panel of data for the current year combined with the previous two years' data. For example, the 2020 data release is the average statistic over the years 2020, 2019, and 2018. The number of occupations also varies by state in the OEWS data release.

We extracted OEWS data for the contiguous 48 states in the U.S. and linked occupation information across OEWS and O*NET by using the 6-digit OEWS occupation codes corresponding with the Standard Occupational Classification (SOC) 2018 classification system.[2] Based on this classification system, we define heavy truck driving jobs using occupational code 53-3032 (Heavy and Tractor-Trailer Truck Drivers).

3.2. Data About Occupational Requirements

To identify occupational alternatives for heavy truck drivers we use the O*NET data release version 25.0 from the Occupational Information Network (O*NET) (O*NET, 2020). O*NET is the foremost repository for descriptive occupational information in the U.S. and is supported by the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA). The O*NET database contains information about the human capital requirements for occupations, including the knowledge, skills, abilities, work activities, interests, work styles, and work values that are important for a total of 974 occupations.

4. Methods

The trucking industry is an essential component of the U.S. economy and labor force. Nearly eight million people work in trucking-related jobs and half of those were truck drivers in 2021 (American Trucking Associations, 2022). Truck-driving jobs are dominated by non-Hispanic white males (Zippia, 2021). The average (48) and median age (46) of U.S. truckers is older than what is found in many other sectors, since younger workers (e.g., post-Baby Boomer generations) are not seeking employment in this industry (CDL jobs, 2022; Ji-Hyland and Allen, 2022; Zippia, 2021). The average educational attainment of truck drivers is lower than the general working population. About half of truckers have a high school education or less, while just 37% of adult workers have this level of educational attainment (US Census Bureau, 2022; Zippia, 2021). About 80% of truck drivers work for more than 40 hours a week (ONET, 2021). According to the U.S. Bureau of Labor Statistics 2020 Occupational Employment and Wages data, the median annual wage for heavy truck drivers was $47,130, the highest among all driving jobs, including bus drivers ($45,900), other passenger vehicle drivers ($32,320), ambulance drivers ($27,930), and light truck drivers ($37,050) (U.S. Bureau of Labor Statistics, 2020).

We use two strategies for identifying occupational alternatives with the information provided by the O*NET database. The first strategy is comprehensive and considers occupational similarity across multiple dimensions including knowledge, abilities, skills, education, experience, training, work activities, values, and interests. Principal components analysis (PCA) is used to extract critical information about the 220 occupational descriptors based on information from the O*NET database. Next, a Ward agglomerative hierarchical

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[1] Before March 31, 2021, the name of the program was Occupational Employment Statistic (OES).
[2] Details of the SOC 2018 system can be found at: https://www.bls.gov/soc/2018/home.htm.

clustering technique is used to generate a four-level hierarchy of occupations, comprised of 8 macro-clusters, 17 meso-groups, 40 sub-groups, and 59 micro-groups (the full list of the micro-group that includes heavy truck drivers can be found in the Appendix **Error! Reference source not found.**). Occupations within the micro-groups are most similar to one another in terms of knowledge, abilities, skills, education, experience, training, work activities, values, and interests. Based on this similarity, we assume it will be easier for workers to move between jobs within micro-groups and extracted occupations from micro-group 50, which contains heavy and tractor-trailer truck driving. Column 2 of **Table 1** lists the occupations within this micro-cluster.

The PCA-based approach described above captures similarities between occupations across multiple dimensions. Yet, it may also be too restrictive and may exclude occupations that are similar to heavy truck driving and require minimal retraining. Therefore, we used a second, more top-down method of identifying likely transition occupations for truck drivers. This skill search approach includes occupations determined to be similar to truck driving in terms of skills, tasks, and job area (e.g., industry, job family with related transportation jobs). Compared to the PCA approach, the skill search is a faster and simpler method based on established judgments of similarity between occupations.

For the skill search approach, we identified occupations based on the strategy outlined by Van Fossen et al. (2022). This approach identified alternative occupations based on skill similarity to truck driving (e.g., monitoring, troubleshooting, etc.) using the "Skills Search" function provided in O*NET Online (National Center for O*NET Development, n.d.). Second, we extracted occupations that shared work activities or tasks with truck driving or were in the same industry, career cluster, or job family as truck driving, as indicated by the O*NET database. Further detail on these exact search methods may be found in Van Fossen et al. (2022). These searches resulted in a list of 38 occupations. Research indicates that these 38 jobs are indeed more similar to truck driving than other jobs, in terms of shared skills, knowledge topics, interests, and values, and also suggests that truck drivers themselves are interested in them as transition occupations (Van Fossen et al., 2022).

We grouped the resulting 38 jobs using both the skills search and shared work/industry search into one list. We then excluded jobs that required medium or more preparation based on their job zone information (explained in the next section). **Table 1** presents the final list of 25 alternative occupations identified by the PCA approach and the shared skills/industry approach (6 occupations were identified by both approaches, and five occupations did not exist in the new SOC system). Column 2 of **Table 1** presents the alternative occupations identified from the PCA-based approach. Column 5 of this table presents the alternative occupations based on similar skills and industry, as identified from O*NET. Both approaches identify jobs in 53-4000: Rail Transportation Workers and 53-7000: Material Moving Workers. That said, the PCA-based approach is more restrictive (15 occupations) than the skills-based approach (21 occupations). Outside of the commonly identified occupations in rail transportation, the PCA approach also suggests different occupations than does the O*NET approach. For example, the PCA approach identifies similar occupations in extraction work (e.g., Continuous Mining Machine Operators and Roof Bolters) while the skills-based O*NET approach identifies similar occupations in 49-3000: Vehicle and Mobile Equipment Mechanics, Installers, and Repairers, and 53-5000: Water Transportation.

There might be a concern that some alternative occupations like passenger vehicle drivers are likely to also be displaced when autonomous trucks displace truck drivers. However, we keep all identified alternative occupations on the lists generated by the two methods for two reasons.

One, the long-haul trucking sector is likely to be an early adopter of AVs (Heineke et al., 2021). Many trucking companies (e.g., UPS) and autonomous system providers (e.g., TuSimple) have already been piloting fully autonomous trucks on highways. A survey with 75 executives from automotive, transportation, and software companies indicated that the fully autonomous trucking services are expected to be commercially available in 2026 or later (Heineke et al., 2021). Second, the trucking industry has more motivations to adopt AVs compared to the passenger transportation industry. Industry professionals and scholars project that autonomous trucks will be commercially available sooner than autonomous passenger vehicles because businesses are not as resistant to technological changes compared to the public; traffic and driving on the highways is also more consistent and predictable compared to urban roads (Curoe, 2017; Vector, 2020). Further, trucking companies expect autonomous trucks to reduce costs by reducing labor and increasing fuel efficiency, productivity, and safety (Curoe, 2017; Shah and Piragine, 2018). Thus, based on the literature and evidence, truck drivers may still be able to shift to alternative jobs like passenger vehicle driving when autonomous trucks are commercially available.

Table 1. Alternative Occupations for Heavy and Tractor-Trailer Truck Drivers

Based on PCA clustering approach			Based on O*NET skill searching		
SOC code	Occupation title	Job zone	SOC code	Occupation title	Job zone
45-4022	Logging Equipment Operators	1	47-4061	Rail-Track Laying and Maintenance Equipment Operators	2
47-2221	Structural Iron and Steel Workers	2	49-3021	Automotive Body and Related Repairers	2
47-5011	Derrick Operators, Oil and Gas	1	49-3092	Recreational Vehicle Service Technicians	2
47-5041	Continuous Mining Machine Operators	2	51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers	2
47-5042	Mine Cutting, Channeling Machine Operators		53-3058	Passenger Vehicle Drivers	2
47-5043	Roof Bolters, Mining	2	53-4011	Locomotive Engineers	2
53-4011	Locomotive Engineers	2	53-4012	Locomotive Firers	
53-4012	Locomotive Firers		53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers	2
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers	2	53-4022	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	2
53-4022	Railroad Brake, Signal, and Switch Operators and Locomotive Firers	2	53-4031	Railroad Conductors and Yardmasters	2
53-4041	Subway and Streetcar Operators	2	53-4041	Subway and Streetcar Operators	2
53-5022	Motorboat Operators	2	53-5011	Sailors and Marine Oilers	2
53-7021	Crane and Tower Operators	3	53-5021	Mates- Ship, Boat, and Barge	2
53-7032	Excavating, Loading Machine, Dragline Operators		53-5022	Motorboat Operators	2
53-7041	Hoist and Winch Operators	2	53-6051	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	2
			53-7032	Excavating, Loading Machine, Dragline Operators	
			53-7041	Hoist and Winch Operators	2
			53-7071	Gas Compressor and Gas Pumping Station Operators	2
			53-7072	Pump Operators, Except Wellhead Pumpers	2
			53-7073	Wellhead Pumpers	2
			53-7121	Tank Car, Truck, and Ship Loaders	2

Note: Shaded occupations do not exist in the 2018 SOC classification system.

5. Results

Figure 1 presents the distribution of employment for heavy and tractor trailer driving occupations based on their location quotients (LQs). An LQ measures a region's industrial specialization relative to a larger geographic unit (U.S. Bureau of Economic Analysis, 2008). In this study, an LQ of heavy truck drivers in a state is calculated with the following equation:

$$LQ_i = \frac{T_i}{G_i} \div \frac{\sum T_n}{\sum G_n} \quad \text{Eq. 1}$$

where LQ_i is the LQ for State i ($i \in \mathrm{n}$). T is the number of heavy and tractor-trailer truck drivers. G is the total number of jobs.

Three states (Wyoming, Nebraska, and Nebraska) have concentrations of truck driving employment followed by four other states (North Dakota, Idaho, Mississippi, and Tennessee), as indicated by an LQ greater than 1. These are states likely to be impacted by job losses related to the adoption of AVs. States least likely to be impacted by AV adoption in the trucking industry based on their current distribution of employment (LQ value less than one) are located on the coasts and Western States such as Arizona and Colorado.

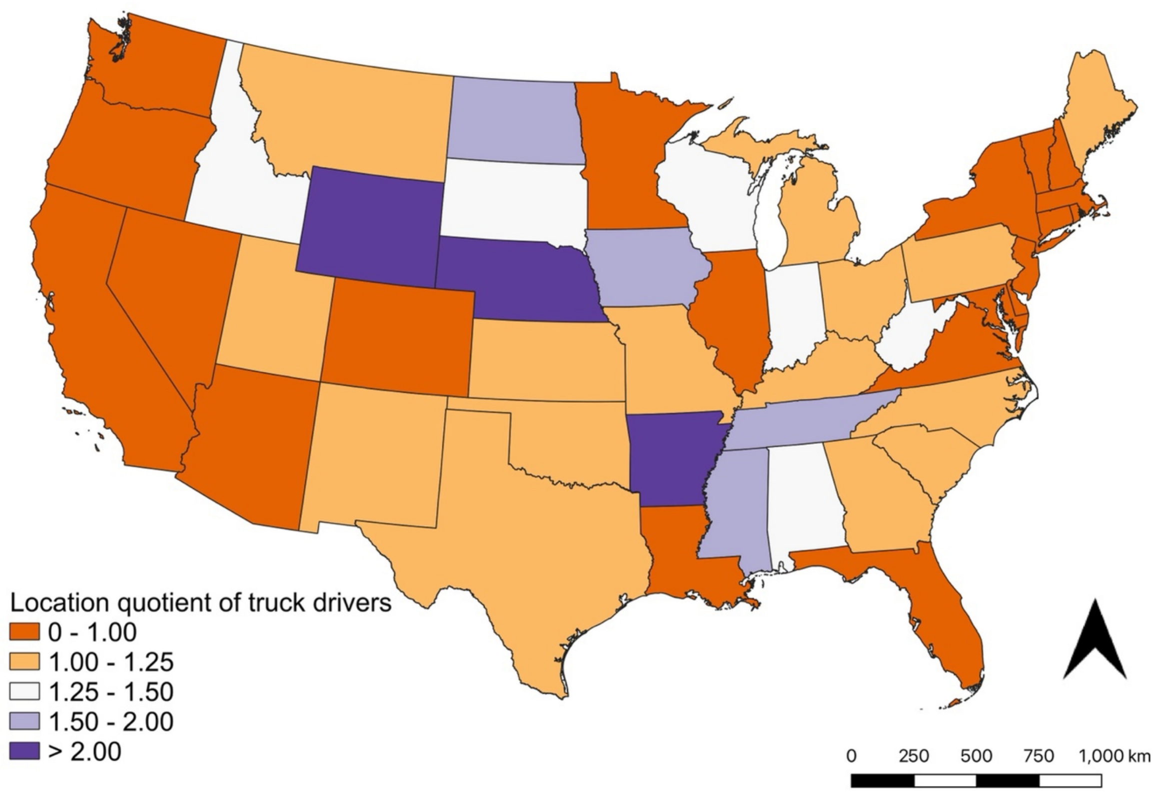

Figure 1. Location Quotient of Heavy and Tractor Trailer Driving Occupations by State

5.1 Available Employment in Alternative Occupations

Figure *2* and **Figure *3*** present the distribution of alternative jobs by state for truck-driving jobs via a ratio of alternative jobs to truck-driving jobs. A ratio greater than one means that there are more than enough jobs for truck drivers to transition into while a ratio less than one means there are fewer alternative jobs for truck drivers. **Figure 2** highlights that there are not enough alternative jobs, as identified in the PCA-based approach, for truck drivers to transition into, should they be displaced by AVs; all states have an alternative ratio less than one. **Figure 3**, which presents the alternative ratio based on occupations identified by the O*NET skills approach, presents a somewhat different picture. It indicates only two states, Louisiana and New York, have sufficient employment for truck drivers to transition into alternative occupations. For New York, there are a large number of passenger vehicle drivers; for Louisiana, there are a large number of sailors and marine oilers. These two occupations make the total alternative jobs exceed the number of heavy and tractor-trailer truck drivers in these two states. For a complete list of the alternative ratio values for both approaches, please refer to Appendix **Table TA1**.

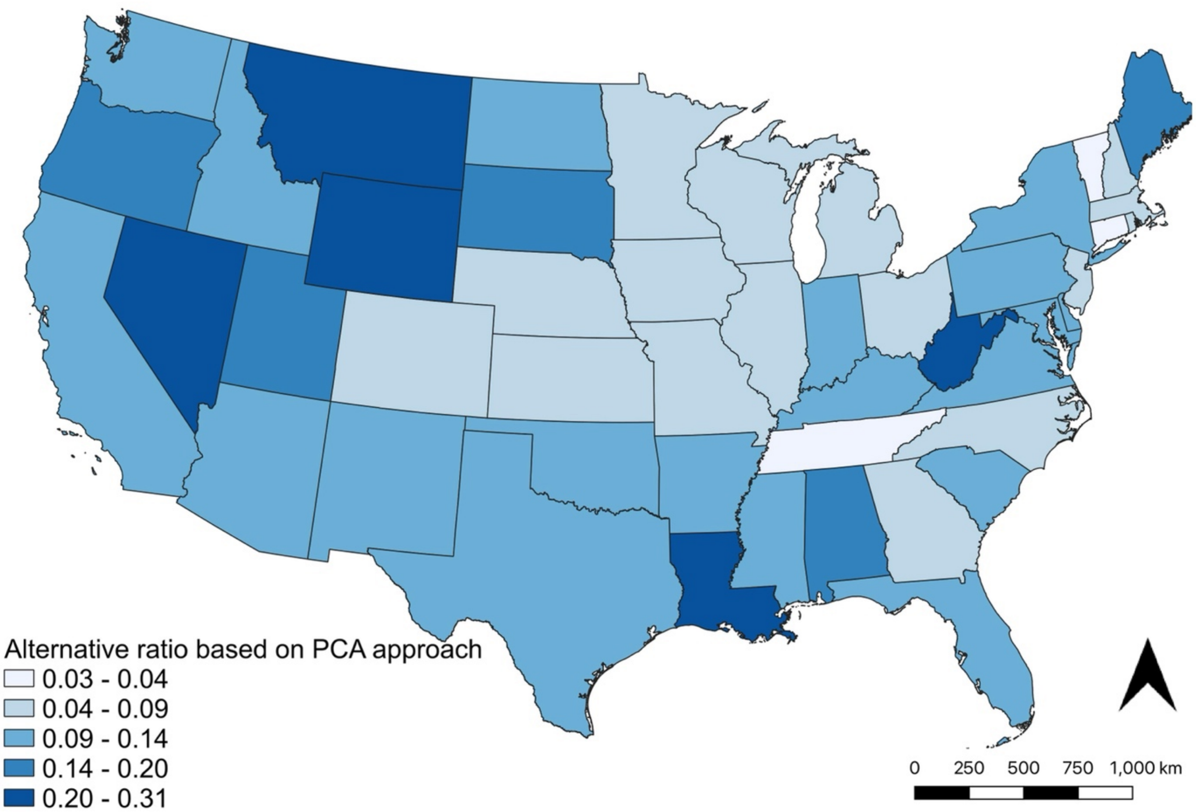

Figure 2. Alternative Ratio for Heavy and Tractor Trailer Driving Occupations by State Based on the PCA-based Approach

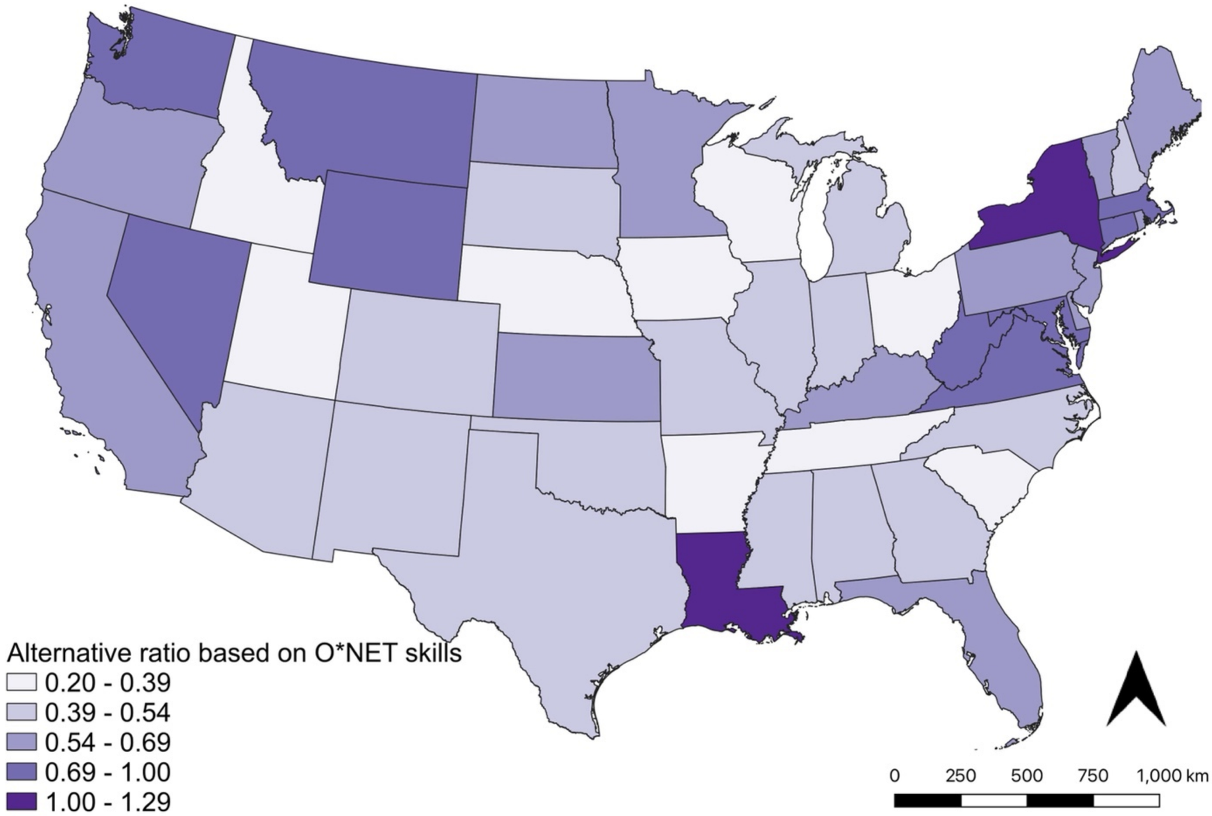

Figure 3. Alternative Ratio for Heavy and Tractor Trailer Driving Occupations by State Based on the O*NET Skills Approach

5.2 Level of Preparation

Table 1 presents information about the job zone of each occupation which is an indication of the necessary preparation for these occupational alternatives. This is important to consider because the more preparation required for truck drivers to transition into alternative jobs, the less likely the drivers could be motivated and/or capable of transitioning into that occupation. O*NET specifies five *Job Zones* for occupational preparation based on education, experience, and on-the-job training, that range from Zone 1, requiring little or no preparation, to Job Zone 5, that requires extensive preparation. The heavy/tractor trailer truck driver occupation is in Job Zone 2, which requires a high school diploma and some preparation, such as an apprenticeship period of a few months to one year working with experienced employees. All listed alternative occupations fall in Zone 1 or Zone 2 except "Crane and Tower Operators," which is in Zone 3. This indicates that most alternative occupations need fairly little preparation, and suggests that the transition into one of these jobs from working as a heavy/tractor trailer truck driver may be fairly easy.

5.3 Level of Compensation in Alternative Occupations

Wage is another critical consideration when changing occupations because an alternative job may not be as attractive if it pays less than the previous job. To examine the wages of alternatives, **Figures 4 – 11** present information about wage differentials associated with select alternative occupations by state. Here, a wage differential is defined as the difference (positive or negative) between truck driving occupations and alternative occupations. Blue indicates a positive wage differential (the alternative job pays more than truck drivers, and orange indicates a negative wage differential (the alternative job pays less). For a complete list of wage differentials by state, please refer to Appendices **Table TA2** and **Table TA3**.

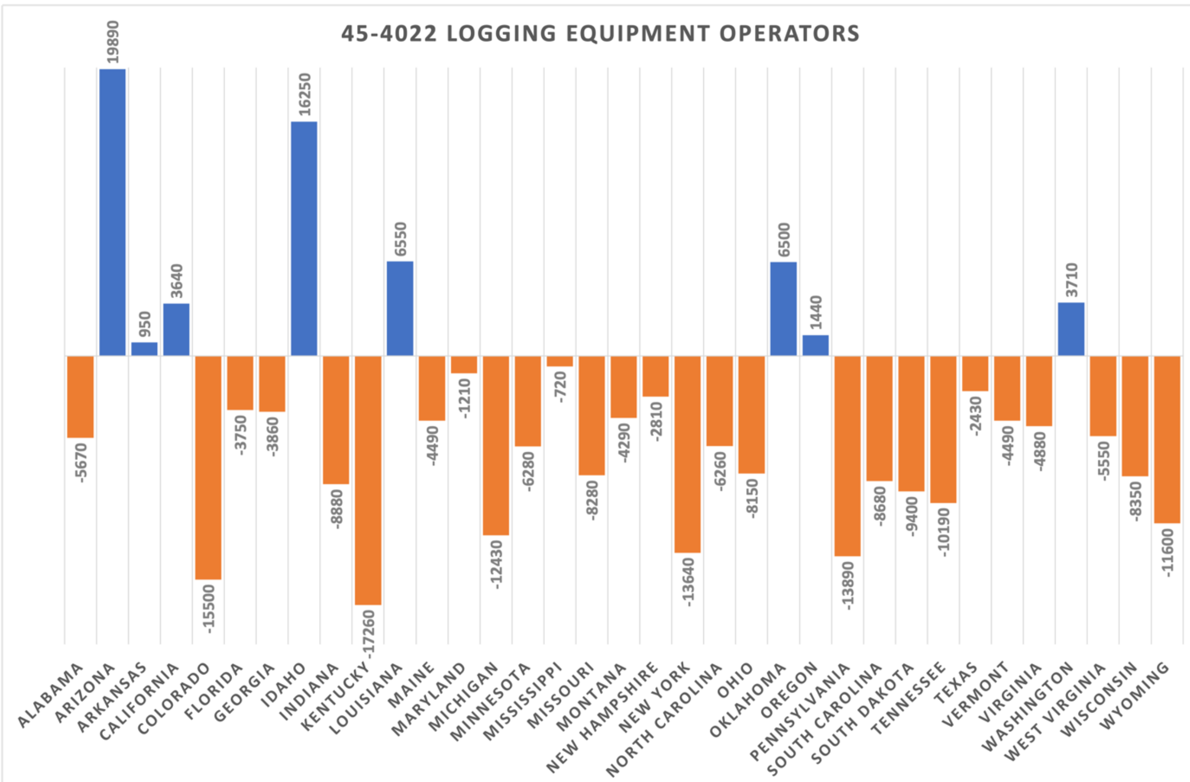

Figure 4. Wage Gap for 45-4022 Logging Equipment Operators

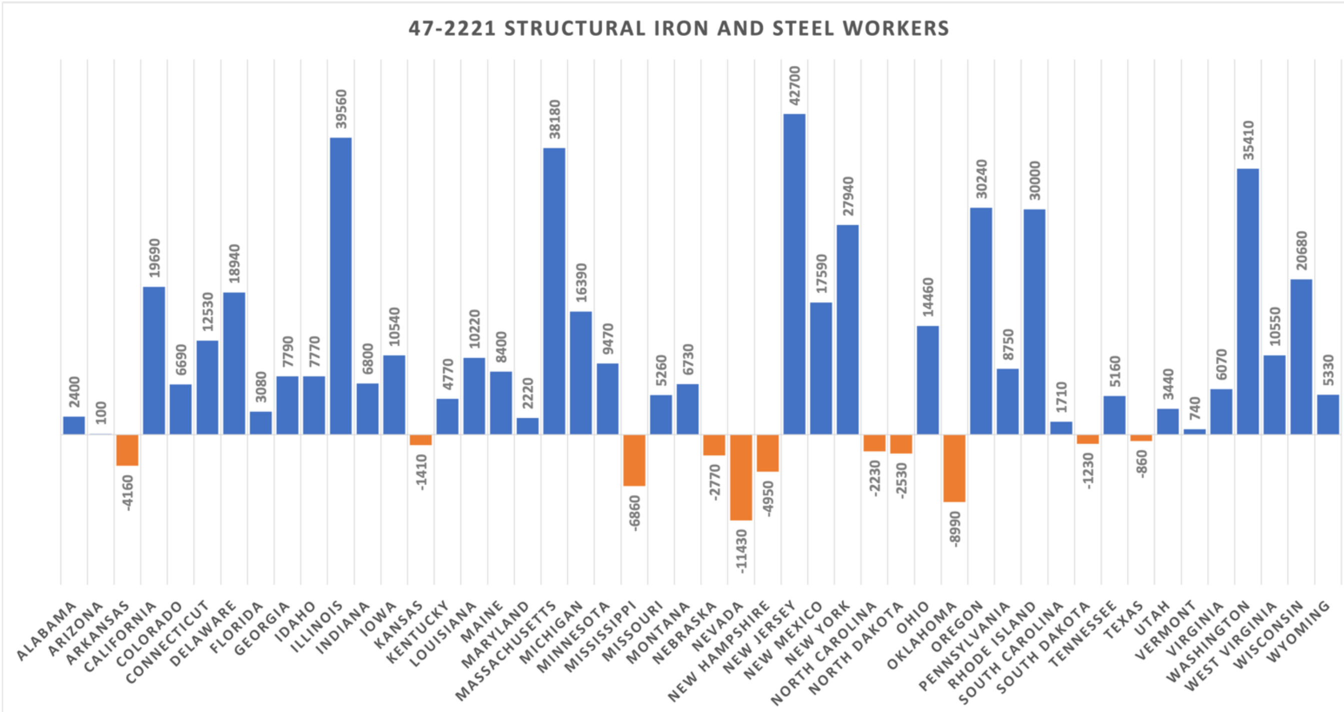

Figure 5. Wage Gap for 47-2221 Structural Iron and Steel Workers

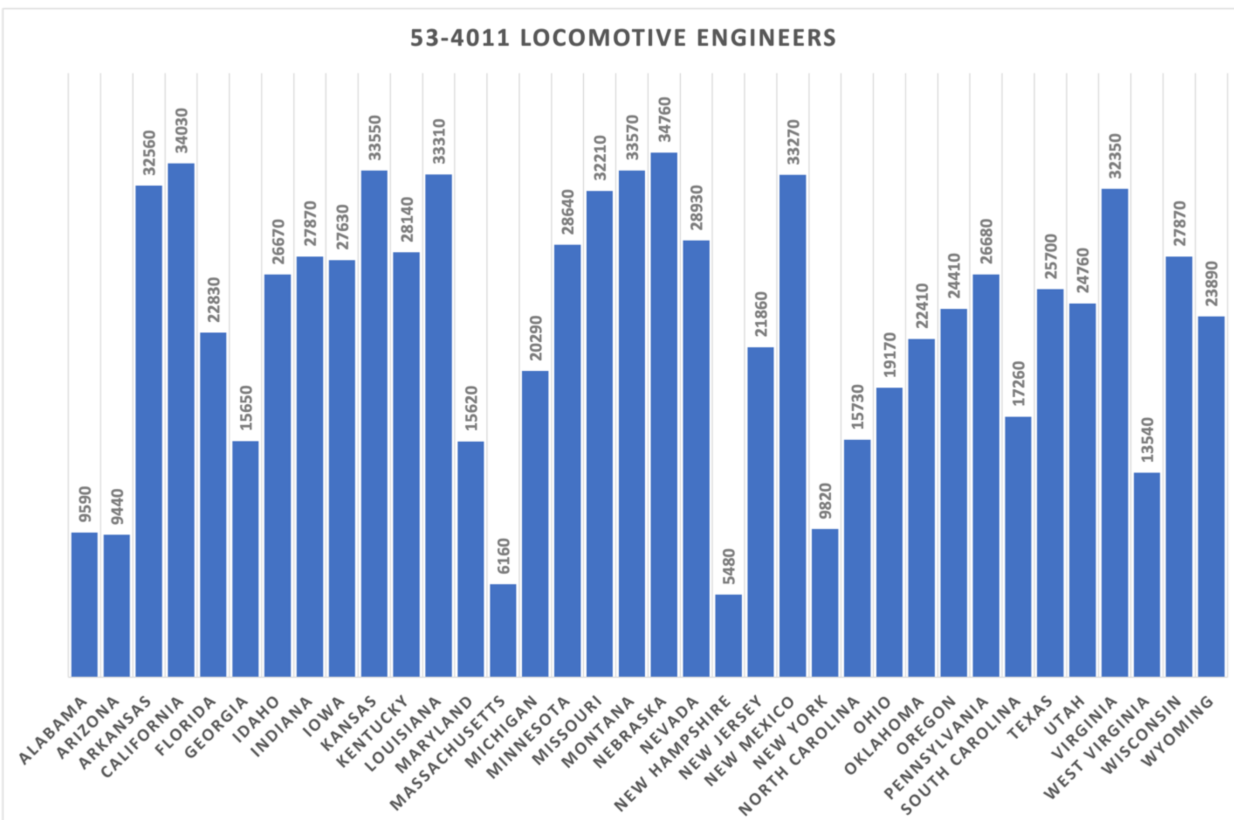

Figure 6. Wage Gap for 53-4011 Locomotive Engineers

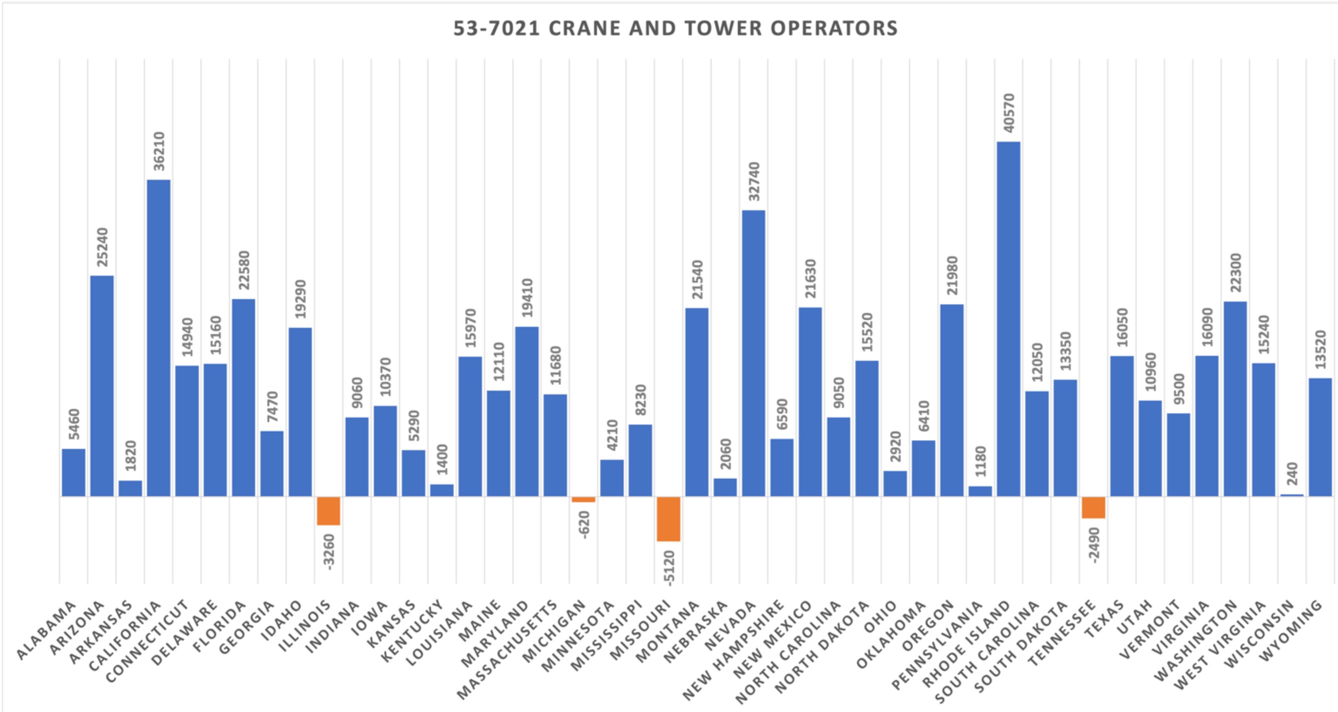

Figure 7. Wage Gap for 53-7021 Crane and Tower Operators

Figures 4 – **7** illustrate the wage gap by state for four alternative jobs identified by the PCA clustering approach. As indicated by **Figures 4** and **5**, jobs that pay less than truck-driving across several states include logging equipment operators (45-4022) and structural iron and steel workers (47-2221). In contrast, locomotive engineers (53-4011) and crane and tower operators (53-7021) pay more than truck drivers in most states (**Figures 6** and **7)**.

Figures 8 – **11** illustrate the wage differential by state of four alternative jobs identified by the O*NET skills-based approach. Some jobs pay less than truck-driving. Examples of these jobs include automotive body and related repairers (49-3021) (**Figure 8**) and passenger vehicle drivers (53-3058) (**Figure 9)**. Examples of occupations with a positive wage differential include mates-ship, boat and barge (53-5021), petroleum pump system operators, refinery operators, and gaugers (51-8093), and railroad brake, signal, and switch operators and locomotive firers (53-4022). On the other hand, pump operators, except wellhead pumpers (53-7072) (**Figure 10**) and tank car, truck, and ship loader (53-7121) (**Figure 11**) have varied wage differentials across states.

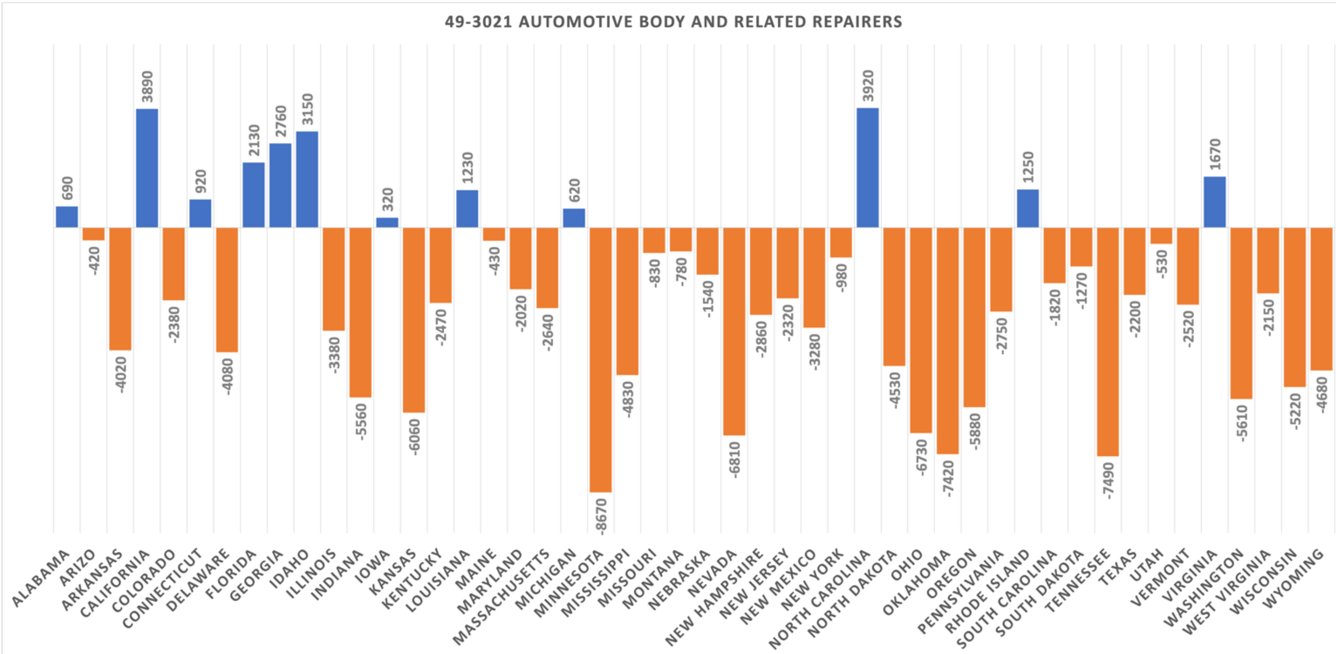

Figure 8. Wage Gap for 49-3021 Automotive Body and Related Repairers

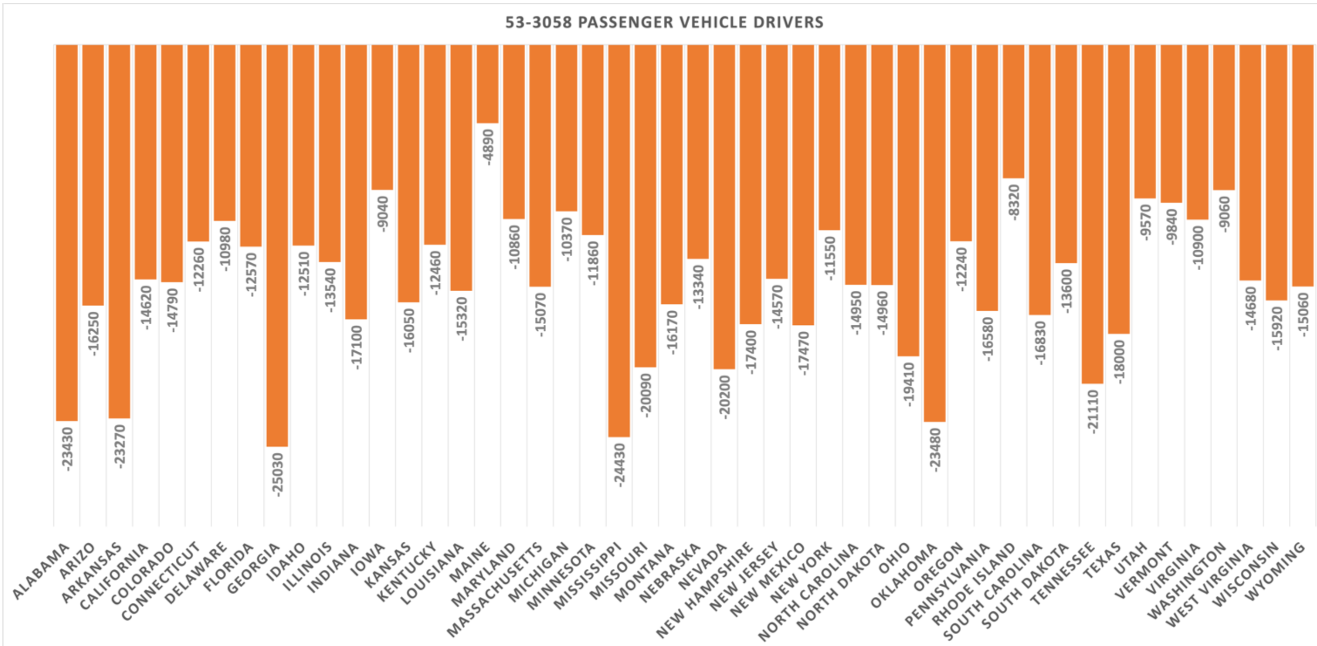

Figure 9. Wage Gap for 53-3058 Passenger Vehicle Drivers

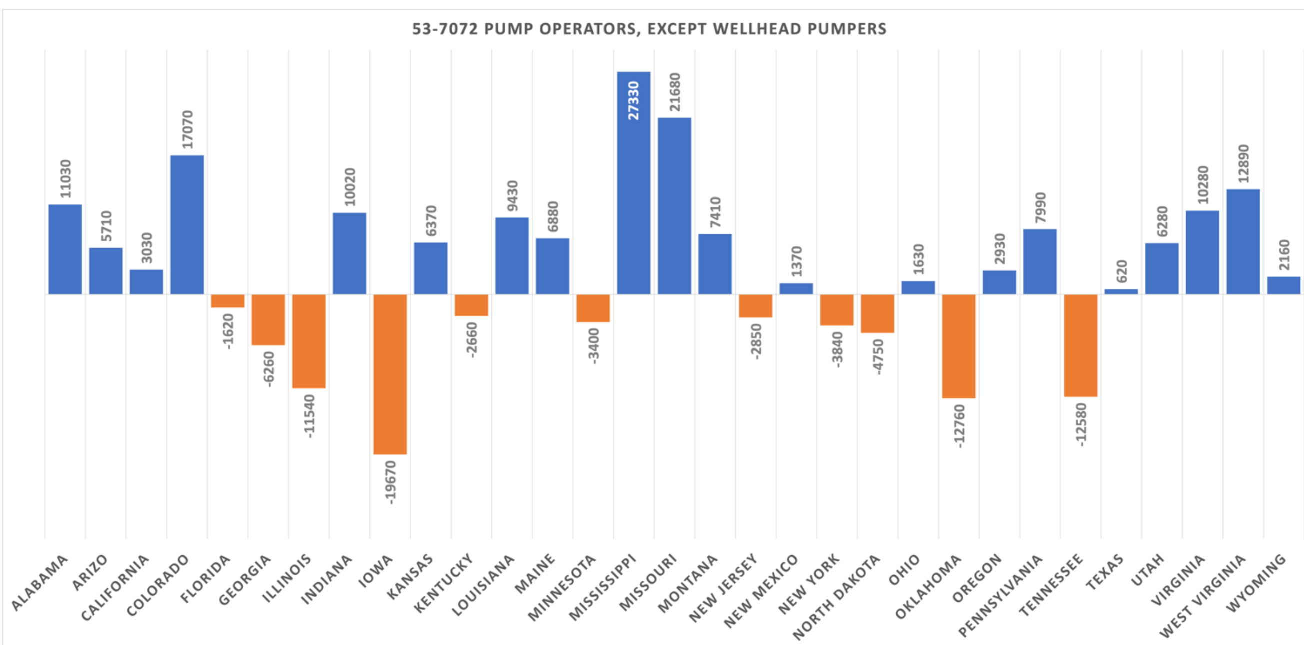

Figure 10. Wage Gap for 53-7072 Pump Operators, Except Wellhead Pumpers

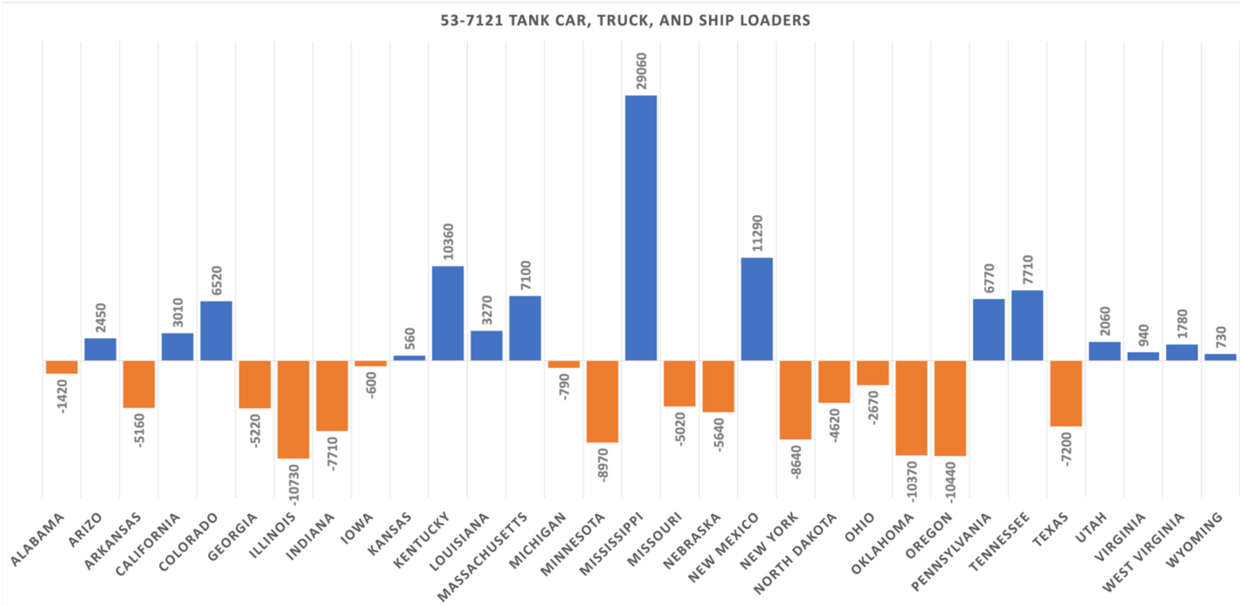

Figure 11. Wage Gap for 53-7121 Tank Car, Truck, and Ship Loader

5.4 Employment Growth of Alternative Occupations

Aside from the level of preparation and wages of job alternatives, it is important to consider the demand for job alternatives. If demand for alternatives is shrinking, the transition to alternatives may be a short-term solution to job losses from AVs. To evaluate demand prospects in the future,

Table ***2*** presents the projected percentage change in employment for alternative jobs. The statistics were derived from the BLS employment projections (EP) database (U.S. Bureau of Labor Statistics, n.d.). Since the 2020 OEWS data are average statistics for 2018, 2019, and 2020, we assume employment in the dataset as the baseline scenario for the year 2019 and calculate the 2029 employment for each alternative occupation in each state given the projected percentage change. For both sets of alternatives, the growth prospects are mixed. Some occupations will experience growth in the next ten years while others will decline.

Table 2. Projected Employment Trend 2019 – 2029

Alternative occupations	Projected employment trend 2019 – 2029
Alternative occupations based on the PCA clustering approach:	
Roof Bolters, Mining	-16%
Logging Equipment Operators	-13%
Railroad Brake, Signal, and Switch Operators and Locomotive Firers	-7%
Rail Yard Engineers, Dinkey Operators, and Hostlers	-6%
Hoist and Winch Operators	-5%
Locomotive Engineers	-4%
Motorboat Operators	0%
Continuous Mining Machine Operators	2%
Crane and Tower Operators	2%
Structural Iron and Steel Workers	5%
Subway and Streetcar Operators	5%
Derrick Operators, Oil and Gas	31%
Alternative occupations based on O*NET skill searching (overlapped jobs excluded):	
Tank Car, Truck, and Ship Loaders	-2%
Gas Compressor and Gas Pumping Station Operators	-2%
Railroad Conductors and Yardmasters	-2%
Passenger Vehicle Drivers	-1%
Mates- Ship, Boat, and Barge	0%
Sailors and Marine Oilers	1%
Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	2%
Rail-Track Laying and Maintenance Equipment Operators	3%
Automotive Body and Related Repairers	3%
Wellhead Pumpers	4%
Recreational Vehicle Service Technicians	5%
Petroleum Pump System Operators, Refinery Operators, and Gaugers	6%
Pump Operators, Except Wellhead Pumpers	10%

Note: Table is based on the employment projections data from the Bureau of Labor Statistics which contains information about the 10-year employment change for occupations. Shaded occupations are common in both alternative job groups.

5.5 Job Alternatives Based on Varying Levels of Displacement

To this point in time, our analysis of the availability of alternative employment assumed 100% displacement of truck drivers by AVs. This is an extreme outcome of AV adoption. Previous studies have examined some scenarios that AVs partially displace truck drivers' positions (Mohan and Vaishnav, 2022). Therefore, we conducted a sensitivity analysis of the results presented in Figure ***2*** and Figure ***3***. **Figure 12** displays the number of states that have enough alternative jobs should truck drivers be displaced by AVs under varying levels of displacement. The blue bars, which are based on the PCA alternatives, indicate that after 10% displacement, the number of states with enough employment in alternative jobs declines substantially. At 10% displacement, 27 states have sufficient employment in alternatives. At 15% displacement, this number declines to ten. At 20% displacement, just five states have sufficient employment in alternatives. Beyond 35% displacement, no state has sufficient employment in alternatives. The orange bars, which are based on the O*NET alternatives, display a very different picture than do blue bars. It highlights that 30 states have sufficient alternative jobs up until 50% displacement of workers. Thus, the extent that there are enough jobs for workers to move into depends very much on the identification of alternatives. Appendices **Figure TA1** and **Figure TA2** show the curve of the alternative ratio by state for both approaches when the percentage of displacement varies from 0 to 100%.

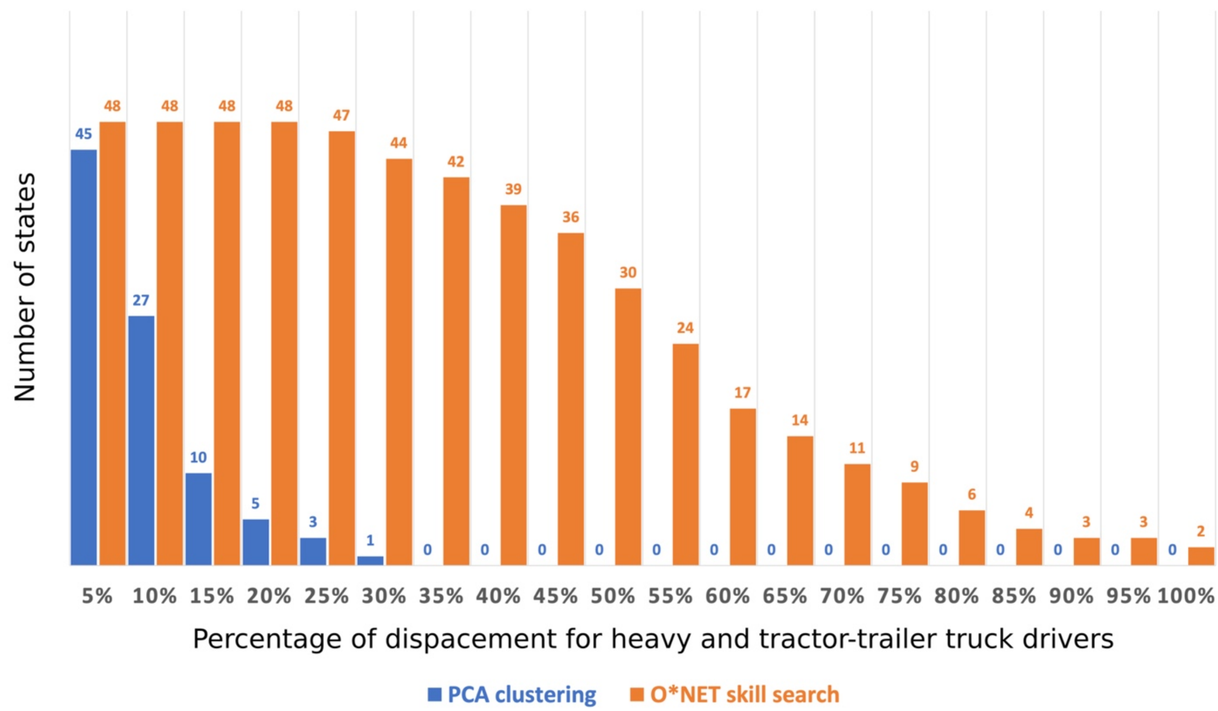

Figure 12. Number of States that Have an Alternative Ratio Greater than 1

6. Discussion

Artificial intelligence (AI) technologies, which include AVs, represent the latest wave of disruptive technologies for workers. Although it is not yet clear what types of jobs will be replaced or altered by AI, some researchers project that trucking will be one of the earliest affected industries (Chottani et al., 2018). These impacts may be hastened by persistent truck driver shortages which can cause disruptions in supply chains (Min and Lambert, 2002). Given these potential disruptions to the trucking workforce, the purpose of this paper was threefold. One, to identify alternative occupations for heavy truck drivers given the possibility that they may be displaced partially or entirely by AVs. Two, to evaluate the relative attractiveness of these alternatives in terms of compensation, ease of entry and future job growth. Three, to evaluate the geographic correspondence between truck driving jobs and available alternatives within the same state given research evidence about geographic rigidities in job seekers (Greenwood et al., 1986; Şahin et al., 2014).

Two strategies for identifying alternative occupations were used. These strategies yielded different pictures of the future employment prospects for drivers displaced by AVs. The PCA clustering method accounted for a wide range of factors to determine job similarity and viable job alternatives including: required knowledge, skills, and abilities (KSA), education, experience, and training (EET), work activities, values, and interests (AVI). The ONET skill search method, however, focused on the similarity of KSA. Therefore, the PCA clustering approach identified fewer alternative occupations for truck drivers, resulting in low alternative ratios for all states. In contrast, the O*NET skill search approach identified more alternative occupations and suggested that many states can offer adequate job opportunities to truck drivers even when half of the truck driving positions are eliminated. It should be noted that the results of the two methods would be closer if passenger vehicle drivers were excluded from the list generated with the O*NET skill search approach. The alternative ratios by state based on the O*NET skill search approach that excludes passenger vehicle drivers are reported in Appendix Table **TA2**.

Because the alternative job opportunities for truck drivers are generated by projections, we are not able to determine which approach is closer to reality. Nevertheless, both approaches show similar spatial patterns across states, although the PCA clustering approach generated more conservative results than the O*NET skill search approach. This is because the PCA clustering approach accounts for more factors than the O*NET skill search approach when identifying alternative occupations. Future studies can examine which set of alternative occupations is closer to reality when AVs start displacing truck drivers' jobs.

Our results, which presented varied pictures of displacement depending on the strategy used to identify jobs for truck drivers, present some important trends among job alternatives. Most alternatives were in job zones 1 and 2 which require little additional training and/or education for displaced drivers. Unfortunately, the identified alternatives paid lower wages than did truck-driving jobs, indicating a potential loss of income. The projected demand for alternative jobs also varied by occupation. Some identified alternatives are projected to have employment growth between 2019 and 2029 such as derrick operators, oil and gas (31%), subway and streetcar operators (5%), and pump operators (10%). Others are projected to have jobs losses (e.g., logging equipment operators and roof bolters, mining) which means the ability of truck drivers to move into these jobs may be limited. Lastly, there were geographic trends in the states projected to experience greater losses of driving jobs, and that do not have sufficient alternative jobs for workers to transition into as AVs become more pervasive in the trucking industry. Our findings indicate that this is particularly true for states located in Middle America (e.g., Minnesota, Iowa, Missouri).

In states with limited job alternatives, retraining and reskilling programs may need to be more extensive to prepare displaced workers to enter occupations that differ more from their previous work. Retraining programs and career planning agencies can also focus on advertising and preparing displaced drivers for occupations that will see a greater demand for labor in the future (e.g., pump operators). Specific federal workforce retraining initiatives may also be needed. This could be accomplished by partnerships between federal and state agencies (e.g., US Department of Labor, Federal Motor Carrier Safety Administration with trucking companies and organizations to provide retraining programs. Governments could also subsidize universities and community colleges to offer continuing education programs for truck drivers. These retraining initiatives may need to be tailored to viable alternative jobs that are available in each specific state, given that individuals are less likely to make geographic transitions for jobs in recent years. Finally, in addition to the importance of retraining programs, the transition driven by AVs may also be a trend for unemployment relief services to be prepared for. These potentially include additional financial assistance programs for older truck drivers displaced by AVs.

Two additional considerations are worth mentioning that are specific to transitioning truck drivers to alternative occupations. One, our analysis accounted for the gap in knowledge, skills, and abilities (KSA) and the ease of preparation for transitioning by including the O*NET job zone classification when identifying alternative jobs for truck drivers by eliminating jobs that require medium or more preparation. However, there may be some challenges for truck drivers and their transition to the alternative jobs identified by each of these strategies. Transitions to alternative jobs may be hampered by the current level of educational attainment of many truck drivers. Recent data indicate truck drivers have lower educational attainment levels than does the rest of the adult workforce in the United States (Sieber et al., 2014). The average age of truck drivers in the low 50s may also impact potential job transitions. In addition, older truck drivers may not be as willing or able to transition to new jobs that require high technological proficiency (OECD, 2016). Promoting truck drivers' KSA and education level can expand the pool of alternative jobs for them. Truck drivers may also need continuing professional education or retraining if moving to an alternative job that requires new skills, particularly technological skills.

A second consideration regarding the workforce impacts of automated vehicles on truck drivers is that truck drivers tend to be older compared to the general working population (Costello, 2017; Short, 2014). Thus, early retirement could be a more feasible option for truck drivers who are displaced compared to other workers. Nonetheless, some displaced drivers may desire to continue working, to meet their subsistence needs and/or sense of challenge or purpose. Workers' individual needs and interests also relate to whether or not they engage in bridge employment, including in the same or different field as their career job (Wang et al., 2008). Bridge employment is part-time or temporary employment occurring as a transition between the end of working in one's career job and full retirement and exit from the labor force (Wang et al., 2008). Bridge employment may be a fitting strategy for older displaced drivers who may be nearing retirement age yet desire or need to continue working.

Given the older age of the truck driving population, a more pressing challenge may be the omnipresence of stereotypes in companies about older workers being less adaptable and willing to adjust to change (Rossier et al., 2012; Tladinyane and Van der Merwe, 2015). Additional research is needed to investigate the extent to which age-related stereotypes will present as a barrier to displaced truck drivers, including whether there may similarly be regional differences regarding the extent to which age-related stereotypes may hinder displaced older drivers' occupational transitions and opportunities. There may also be the potential for automated features to assist older drivers, and help them to remain in the job comfortably for longer, which in the short-term could help to mitigate the driver shortage (Costello, 2017).

That said, it is important to note some limitations of the data and present analysis. First, the OEWS program only collects employment and wage data on workers in nonfarm establishments (U.S. Bureau of Labor Statistics, 2021b). Therefore, we do not have data on the self-employed since they are unlikely identified in establishments. Second, we assume that the employment and skill requirements of alternative occupations will remain consistent when heavy truck driving is first affected by AVs. This assumption is based upon the projection that the trucking industry will be one of the earliest adopters of AVs. However, it is possible that some alternative occupations will be disrupted by other technological changes simultaneously. In other words, the lack of alternative occupations could be more severe than is illustrated in this study. Further research is needed to continue to gauge the extent to which automated technologies will displace human workers, including variability in displacing workers within the same industries and job families of related occupations (e.g., within the transportation industry and between drivers of different types of vehicles). Finally, our estimation could not account for any future occupations (e.g., remote controllers of AVs) that are possibly created by technological advancements. These new occupations could also be opportunities for displaced truck drivers.

7. Conclusion

As the deployment of autonomous vehicles continues to evolve over time, monitoring potential job transition opportunities within states and across the U.S. will be vital to helping truck drivers maintain employment during times of technology disruption. Researchers must also continue to investigate workers' willingness, as well as abilities, to transition into different jobs as technology advances. If workers are not willing, nor capable, of making these transitions, they may be further disadvantaged as AVs become more pervasive in the trucking industry and society. The goal of the present analysis was to outline a methodology for identifying feasible alternative occupations for truck drivers should AVs displaced them and analyze the geographic distribution of truck driving jobs and identified alternatives. As our knowledge about the workforce impacts of AVs continues to evolve, the analysis presented in this study can be modified to incorporate new information about new jobs and job obsolescence related to AVs to update our understanding of the changing job prospects for workers in an era of ongoing technological change.

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Appendix

Table TA1. The Listing of Occupations in the Micro-group identified by the PCA Clustering Approach

Cluster 7, Group 15, Subgroup 32, Micro-group 50 (n=16)	
45-4022	Logging Equipment Operators
47-2221	Structural Iron and Steel Workers
47-5011	Derrick Operators, Oil and Gas
47-5041	Continuous Mining Machine Operators
47-5042	Mine Cutting, Channeling Machine Operators
47-5043	Roof Bolters, Mining
53-4011	Locomotive Engineers
53-4012	Locomotive Firers
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers
53-4022	Railroad Brake, Signal, and Switch Operators and Locomotive Firers
53-4041	Subway and Streetcar Operators
53-5022	Motorboat Operators
53-7021	Crane and Tower Operators
53-7032	Excavating, Loading Machine, Dragline Operators
53-7041	Hoist and Winch Operators

Source: occupations are clustered using Ward hierarchical method based on 72 principal components derived from 220 occupational descriptors from O*NET.

Table TA1. Alternative Ratios and Location Quotient for Truck Drivers

State	Alternative ratio 2019 based on PCA clustering	Alternative ratio 2029 based on PCA clustering	Alternative ratio based on O*NET skill search (including passenger vehicle drivers)	Alternative ratio based on O*NET skill search (excluding passenger vehicle drivers)	Location quotient for transport jobs	Location quotient for total jobs
Alabama	0.16	0.15	0.47	0.16	1.28 †	1.30 †
Arizona	0.11	0.11	0.49	0.13	0.86	0.84
Arkansas	0.11	0.10*	0.32	0.12	1.88 †	2.34 †
California	0.14	0.14	0.59	0.23	0.69	0.67
Colorado	0.08	0.08	0.52	0.23	0.89	0.78
Connecticut	0.04	0.04	0.99	0.17	0.76	0.64
Delaware	0.12	0.12	0.67	0.13	0.88	0.81
Florida	0.10	0.10	0.55	0.24	0.84	0.79
Georgia	0.09	0.09	0.49	0.15	0.95	1.11 †
Idaho	0.14	0.14	0.28	0.10	1.64 †	1.46 †
Illinois	0.08	0.08	0.53	0.21	0.82	0.96
Indiana	0.10	0.10	0.46	0.17	1.10 †	1.34 †
Iowa	0.07	0.07	0.27	0.11	1.81 †	1.97 †

Kansas	0.07	0.07	0.60	0.23	1.12 †	1.13 †
Kentucky	0.13	0.12*	0.57	0.19	0.88	1.19 †
Louisiana	0.27	0.26*	1.29 §	1.13 §	0.87	0.88
Maine	0.18	0.16*	0.57	0.15	1.35 †	1.24 †
Maryland	0.13	0.14	0.83	0.23	0.77	0.71
Massachusetts	0.08	0.08	0.90	0.21	0.82	0.59
Michigan	0.07	0.07	0.44	0.13	1.10 †	1.09 †
Minnesota	0.08	0.08	0.65	0.18	1.11 †	0.98
Mississippi	0.12	0.11*	0.49	0.18	1.26 †	1.56 †
Missouri	0.08	0.07*	0.53	0.19	1.27 †	1.21 †
Montana	0.24	0.23*	0.81	0.42	1.23 †	1.08 †
Nebraska	0.08	0.08	0.20	0.05	1.98 †	2.21 †
Nevada	0.31	0.31	0.78	0.17	0.70	0.74
New Hampshire	0.08	0.07*	0.54	0.13	0.98	0.85
New Jersey	0.07	0.07	0.58	0.20	0.77	0.99
New Mexico	0.13	0.14	0.50	0.18	1.47 †	1.14 †
New York	0.10	0.10	1.28 §	0.41	0.70	0.52
North Carolina	0.08	0.08	0.40	0.12	1.01 †	1.04 †
North Dakota	0.10	0.11	0.59	0.37	1.73 †	1.93 †
Ohio	0.08	0.08	0.36	0.16	1.01 †	1.09 †
Oklahoma	0.13	0.14	0.51	0.31	1.32 †	1.25 †
Oregon	0.20	0.18*	0.59	0.20	0.93	0.93
Pennsylvania	0.11	0.11	0.61	0.22	1.02 †	1.13 †
Rhode Island	0.08	0.09	0.69	0.26	0.88	0.62
South Carolina	0.11	0.10	0.39	0.11	1.02 †	1.06 †
South Dakota	0.19	0.19	0.45	0.19	1.38 †	1.28 †
Tennessee	0.04	0.04	0.27	0.12	1.24 †	1.62 †
Texas	0.11	0.12	0.45	0.25	1.24 †	1.24 †
Utah	0.19	0.19	0.32	0.16	1.32 †	1.15 †
Vermont	0.03	0.03	0.63	0.12	1.10 †	0.80
Virginia	0.11	0.11	0.75	0.23	0.96	0.87
Washington	0.14	0.13*	0.75	0.29	0.86	0.75
West Virginia	0.25	0.24*	0.74	0.28	1.30 †	1.26 †
Wisconsin	0.06	0.06	0.38	0.12	1.38 †	1.43 †
Wyoming	0.23	0.23	0.74	0.47	1.95 †	2.12 †

Note: * indicates the alternative ratio declines; § indicates the alternative ratio is greater than 1; † indicates the location quotient is greater than 1.

Table TA2. Wage Gap between Truck Drivers and Alternative Jobs Based on the PCA Clustering Approach

State	*WAGE GAP = ANNUAL MEDIAN WAGE* (alternative occupation) - *ANNUAL MEDIAN WAGE* (truck drivers)												
	Truckers' wage	SOC 45-4022	SOC 47-2221	SOC 47-5011	SOC 47-5041	SOC 47-5043	SOC 53-4011	SOC 53-4013	SOC 53-4022	SOC 53-4041	SOC 53-5022	SOC 53-7021	SOC 53-7041
Alabama	42000	-5670	2400*		8980*		9590*	5250*	-500			5460*	4630*
Arizona	47040	19890*	100*		2110*		9440*		1180*		3730*	25240*	
Arkansas	44280	950*	-4160	-1490	410*		32560*	-750	16200*			1820*	
California	49570	3640*	19690*	5990*	-800		34030*	5410*	11700*	9020*	1480*	36210*	25240*
Colorado	50670	-15500	6690*	-10130	15180*	20480*				-4860			
Connecticut	50230		12530*									14940*	
Delaware	47440		18940*									15160*	
Florida	40640	-3750	3080*		16410*		22830*		12820*	140*	1360*	22580*	-8740
Georgia	46940	-3860	7790*				15650*	-7040	3180*	-12290		7470*	23810*
Idaho	42310	16250*	7770*		9180*		26670*					19290*	
Illinois	49990		39560*		9820*	10180*		14550*	12320*	25930*		-3260	
Indiana	46680	-8880	6800*		2830*		27870*	11900*	16250*			9060*	-890
Iowa	44060		10540*		2510*		27630*		12610*			10370*	
Kansas	46380		-1410	-2740			33550*	-2350				5290*	
Kentucky	46730	-17260	4770*		5460*	8440*	28140*	4050*	-3610			1400*	-11000
Louisiana	42390	6550*	10220*	6230*			33310*	9000*	14130*			15970*	-4680
Maine	42180	-4490	8400*									12110*	
Maryland	48580	-1210	2220*				15620*			17720*		19410*	1140*
Massachusetts	50260		38180*				6160*		17030*		-6760	11680*	
Michigan	45440	-12430	16390*	-1630	-9040*		20290*		9010*			-620	-2710
Minnesota	49790	-6280	9470*		24970*		28640*	12630*	8240*			4210*	43170*
Mississippi	44140	-720	-6860					4320*	7210*			8230	
Missouri	47050	-8280	5260*				32210*	1550*	14570*			-5120	-10160
Montana	48900	-4290	6730*		24110*		33570*					21540	
Nebraska	45950		-2770				34760*					2060*	
Nevada	49760		-11430		17370*		28930*		10410*			32740*	
New Hampshire	48170	-2810	-4950				5480*					6590*	
New Jersey	51640		42700*				21860*		20420*		-11480		26540*
New Mexico	42940		17590*	3540*			33270*					21630*	29150*
New York	51500	-13640	27940*				9820*	1520*	-520		22440*		13580*
North Carolina	44760	-6260	-2230		14100*		15730*	-4770	13470*			9050*	
North Dakota	53880		-2530	920*				-410				15520*	
Ohio	46420	-8150	14460*	400*	7510*		19170*	4330*	1990*			2920*	-6190
Oklahoma	48410	6500*	-8990	7270*	-16030		22410*	10910*	17320*			6410*	
Oregon	48950	1440*	30240*				24410*		12330*			21980*	3020*
Pennsylvania	48190	-13890	8750*	-1190	1690*		26680*	8060*	11130*			1180*	-1880
Rhode Island	47820		30000*									40570*	
South Carolina	41980	-8680	1710*				17260*	4970*				12050*	

Note: * indicates the alternative occupation has a higher median annual wage than truck drivers; blank indicates that a wage estimate is not available

Table TA3. Wage Gap between Truck Drivers and Alternative Jobs Based on O*NET Skill Searching

	WAGE GAP = ANNUAL MEDIAN WAGE (alternative occupation) - *ANNUAL MEDIAN WAGE* (truck drivers)																		
State	SOC 47-4061	SOC 49-3021	SOC 49-3092	SOC 51-8093	SOC 53-3058	SOC 53-4011	SOC 53-4013	SOC 53-4022	SOC 53-4031	SOC 53-4041	SOC 53-5011	SOC 53-5021	SOC 53-5022	SOC 53-6051	SOC 53-7041	SOC 53-7071	SOC 53-7072	SOC 53-7073	SOC 53-7121
Alabama	3810*	690*	-6180	8670*	-23430	9590*	5250*	-500	17370*		220*	32610*		35490	4630	5190	11030		-1420
Arizona	5050*	-420	-15050	6890*	-16250	9440*		1180*	8320*				3730	16540			5710		2450
Arkansas	3880*	-4020	-350	25290*	-23270	32560*	-750	16200*	18660*		-6060			36290					-5160
California	10730*	3890	-9250	43010*	-14620	34030*	5410*	11700*	18730*	9020*	-4630	31530*	1480	26660	25240	-5980	3030	-1800	3010
Colorado	-4740	-2380	-1510	40090*	-14790				-1950	-4860				16000		13420	17070	25630	6520
Connecticut		920*		15510*	-12260						-11410	8290*		30030					
Delaware		-4080			-10980							16400*							
Florida	6170*	2130*	6850*	11310*	-12570	22830*		12820*	24630*	140*	-4480	25010*	1360	48250	-8740	27350	-1620		
Georgia	6150*	2760*	-4500	7110*	-25030	15650*	-7040	3180*	22310*	-12290	-10470	18480*		49210	23810		-6260		-5220
Idaho		3150*	390*		-12510	26670*								54990					
Illinois	7510*	-3380	-10180	10690*	-13540		14550*	12320*	14470*	25930*	-1220	32440*		40180			-11540	-11110	-10730
Indiana	13190*	-5560	-3090	6740*	-17100	27870*	11900*	16250*	15020*		-1510	57850*		4770	-890		10020		-7710
Iowa		320*	-1580	29940*	-9040	27630*		12610*			-4530	38510*		35460			-19670		-600
Kansas	-590	-6060	-5620	15430*	-16050	33550*	-2350		13690*					19290		18740	6370	8130	560
Kentucky	8130*	-2470		27790*	-12460	28140*	4050*	-3610	13760*		-8280	36700*		31330	-11000		-2660	10050	10360
Louisiana	9510*	1230*	-4710	35520*	-15320	33310*	9000*	14130*	23580*					45750	-4680		9430	18910	3270
Maine	3050*	-430	-1680		-4890						-4300	38340*		62780			6880		
Maryland	15290*	-2020	-13340	-300	-10860	15620*			12840*	17720*	9480	40700*		6230	1140				
Massachusetts		-2640	-1600	13660*	-15070	6160*		17030*	21340*		-6260	17490*	-6760	19180		16800			7100
Michigan	12120*	620*	-9170	27150*	-10370	20290*		9010*	17720*		-2810	11220*		42740	-2710				-790
Minnesota	6110*	-8670	-8340	14250*	-11860	28640*	12630*	8240*	14570*			25870*		34480	43170		-3400		-8970
Mississippi		-4830	-6770	39770*	-24430		4320*	7210*	17030*		-3560	40820*		21180			27330	16940	29060
Missouri	16180*	-830	-9490	9360*	-20090	32210*	1550*	14570*	20470*		-1360	32540*		38190	-10160		21680		-5020
Montana		-780	-9490	45110*	-16170	33570*								1840			7410	16250	
Nebraska	3010*	-1540	-9610		-13340	34760*			27080*					49260		28550			-5640
Nevada	3080*	-6810	160*		-20200	28930*		10410*	11890*					52080					
New Hampshire		-2860	-4070		-17400	5480*			-2060			8240*		51740					
New Jersey	2770*	-2320	-1460	39030*	-14570	21860*		20420*	24450*		2050*	36950*	-11480	14690	26540	23650	-2850		
New Mexico	5920*	-3280	-10970	46760*	-17470	33270*			26030*					10900	29150	26650	1370	30140	11290
New York	20010*	-980	-13000	1110*	-11550	9820*	1520*	-520	8940*		70*	25120*	22440	25570	13580	19790	-3840		-8640
North Carolina	10130*	3920*	-5250	19390*	-14950	15730*	-4770	13470*	14890*		-5750	12160*		38790					
North Dakota		-4530	-9270	9760*	-14960		-410							43880		18730	-4750	9560	-4620
Ohio	4680*	-6730	-8770	42540*	-19410	19170*	4330*	1990*	11510*		-6850	7300*		12280	-6190	30930	1630	-7520	-2670
Oklahoma	-10610	-7420	-3990	29180*	-23480	22410*	10910*	17320*	21480*					15660		19440	-12760	8080	-10370
Oregon	17490*	-5880	-5670		-12240	24410*		12330*	13450*		-2480	23040*		27020	3020		2930		-10440

State	*WAGE GAP = ANNUAL MEDIAN WAGE* (alternative occupation) - *ANNUAL MEDIAN WAGE* (truck drivers)																		
	SOC 47-4061	SOC 49-3021	SOC 49-3092	SOC 51-8093	SOC 53-3058	SOC 53-4011	SOC 53-4013	SOC 53-4022	SOC 53-4031	SOC 53-4041	SOC 53-5011	SOC 53-5021	SOC 53-5022	SOC 53-6051	SOC 53-7041	SOC 53-7071	SOC 53-7072	SOC 53-7073	SOC 53-7121
Pennsylvania	5780*	-2750	-9710	17730*	-16580	26680*	8060*	11130*	14580*			27930*		27140	-1880	24120	7990	-4970	6770
Rhode Island		1250*			-8320						-9780	26660*							
South Carolina	30310*	-1820	-3710		-16830	17260*	4970*		20210*		-2740	17660*		25890					
South Dakota		-1270	-10780		-13600									-1870					
Tennessee	-460	-7490	-9270	32610*	-21110						-5400	4790*		44860	-2250	-4000	-12580		7710
Texas	11200*	-2200	-560	35680*	-18000	25700*	5780*	10420*	16820*	5350*	-3640	18420*	16790	42700		-410	620	16940	-7200
Utah	1210*	-530	-8780	44010*	-9570	24760*			10120*	2420*				-2530			6280	15950	2060
Vermont	4570*	-2520			-9840							50110*							
Virginia	19830*	1670*	-7840	24000*	-10900	32350*		17410*			-1650	28950*	7890		-5730	25710	10280		940
Washington	-1180	-5610	-10430	18310*	-9060			1590*	9370*		1160*	30560*	17030	37870	5030	-13680			
West Virginia	3840*	-2150	-9800	27740*	-14680	13540*			16260*			41350*		25210	17760	28730	12890	-2130	1780
Wisconsin	9430*	-5220	-7390	17560*	-15920	27870*	11900*	9790*	14100*			190*		52570					
Wyoming	5890*	-4680	-16310	28630*	-15060	23890*		4730*	11300*					-9700		18030	2160	10790	730

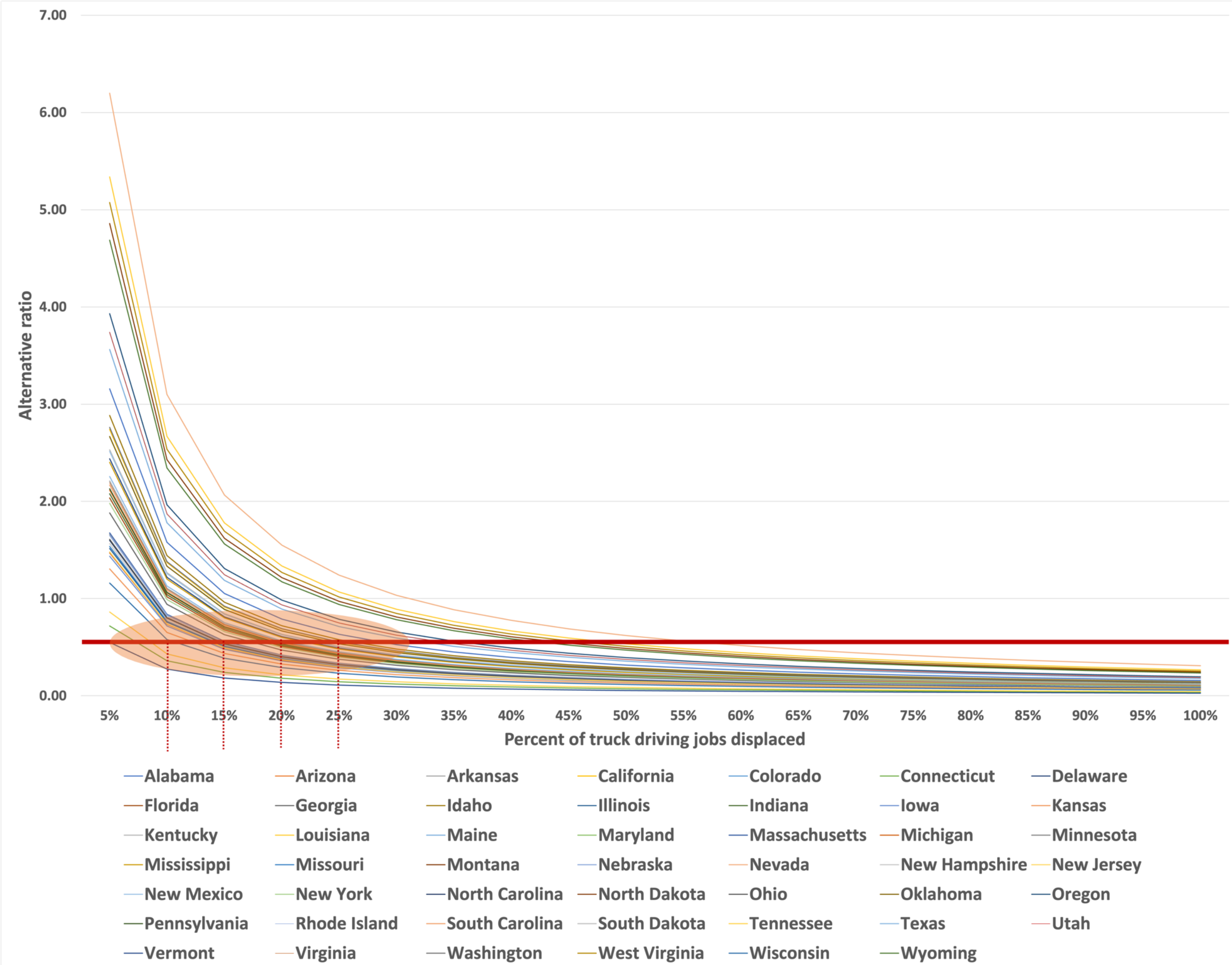

Figure TA1. Trend in Alternative Ratio for Different Job Displacement Scenarios (PCA Clustering)

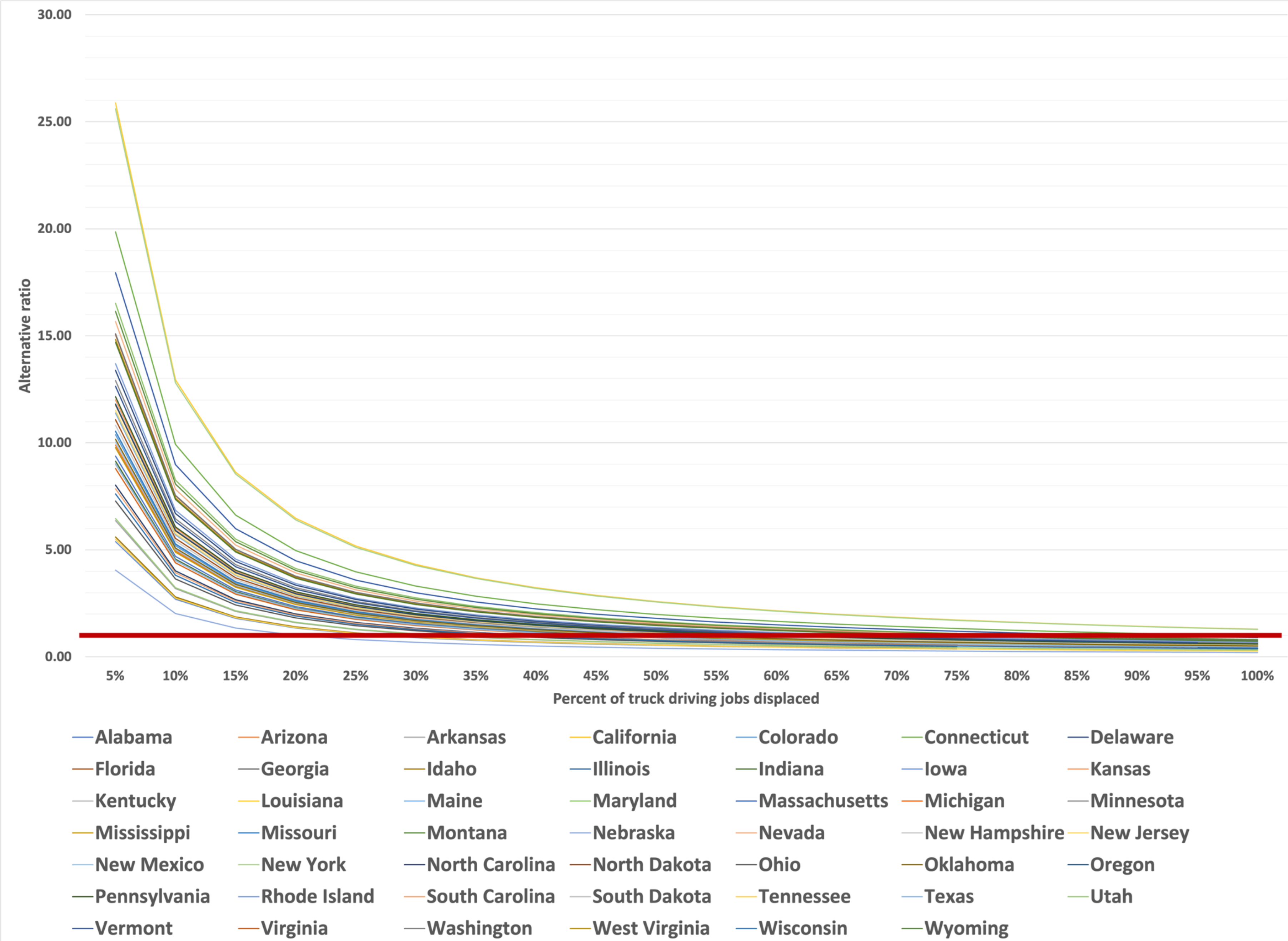

Figure TA2. Trend in Alternative Ratio for Different Job Displacement Scenarios (O*NET Skills)