In it for the longhaul: Occupational choice for blue-collar workers

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Abstract

In 2021 the American Trucking Association claimed the driver shortage reached about 80,000 drivers and predicted a shortage of 160,000 drivers by 2030. The perceived driver shortage is a major concern of both policymakers and firms. The 2021 Infrastructure bill authorized a trial program to allow 18–20-year-olds to drive commercial vehicles. In this paper, I use a Discrete Choice Mixed Logit model to estimate the impact of wage increases, education cost reductions, and the impact of opening truck driving to 18–20-year-olds on the share of truck driving employment in the blue-collar labor market. I use a control function approach to deal with endogeneity in wages and training costs. I use four data sets, the Survey of Consumer Finance March Supplement (ASEC), for individual and market share data. State-specific occupational wage data was sourced from the Occupational Employment Wage Survey (OEWS), Work setting variables were sourced from O*Net, and educational costs from the Integrated Postsecondary Education Data System (IPEDS). Results show that higher wages, reduced training costs, and including 18-20-year-olds increase the number of truck drivers. The largest potential increases come from adding 18–20-year-olds into the market, increasing trucking employment by about 70,000 new drivers nationally.

JEL Codes: L91, J24, J44

Keywords: Truck Driving, Driver Shortage, Mixed Logit

Introduction

Truck driving is a large profession in the United States. About 3.5 million people are employed as truck drivers in any given year. The 2017 Commodity Flow Survey estimated about 65% of all tonnage or 70% of all freight value in the United States was transported by truck only.[1] This figure excludes freight moved using multiple modes, for example, truck to rail. The prices both producers and consumers pay for shipping depend on the input costs of transportation services. Among them are fuel and wage costs. From the perspective of firms buying transportation services, they would like the lowest input costs to ship their freight. And of course, the drivers are interested in getting the highest price for their services.

A shortage of drivers is a perennial concern of firms in the trucking industry. In 2021 the American Trucking Association claimed the driver shortage reached about 80,000 drivers and predicted a shortage of 160,000 drivers by 2030.[2] The perceived driver shortage is a major concern of both policymakers and firms. However, it is not clear whether there is a true shortage or if there will be a shortage in the future as truck drivers age. The press and policymakers have fixated on the concept of a shortage, a Google search yields several articles from generally reliable sources such as the New York Times, NPR, CNBC, and Time Magazine discussing the causes and cures of a truck driver shortage. This concern about a shortage led the Biden administration to push for several programs in the 2021 Bipartisan Infrastructure Bill to increase the number of truck drivers. One of the policies is a trial apprenticeship program to allow 18–to 20-year-olds to drive commercial vehicles. Other important policies include expediting the CDL process across states, recruiting veterans, and other policies addressing the working conditions of truck drivers.

In this paper, I use a mixed logit model to estimate the impact of wage increases, education cost reductions, an aging labor market, and opening truck driving to 18–20-year-olds on the share of truck driving employment in the blue-collar labor market. I use a control function approach to deal with endogeneity in wages. I use four data sets, the Survey of Consumer Finance March Supplement (ASEC), for individual and market share data. State-specific occupational wage data was sourced from the Occupational Employment Wage Survey (OEWS), Work setting variables were sourced from O*Net, and educational costs from the Integrated Postsecondary Education Data System

1. Commodity Flow Survey 2017: https://www.census.gov/programs-surveys/cfs.html
2. American Trucking Association: Report

(IPEDS). Results show that higher wages, reduced training costs, and including 18-20-year-olds increase the number of truck drivers. The largest potential increases come from adding 18–20-year-olds into the market, increasing trucking employment by about 70,000 new drivers nationally.

Literature

Data

The data spans the period from 2010 to 2019. It is a combination of four public data sets the Current Population Survey ASEC March Supplement (CPS), Occupational Employment Wage Statistics (OEWS), Integrated Post Secondary Data System (IPEDS), and O*Net Occupational Characteristics. The CPS records economic and job data for a sample of American households. It allows me to observe the previous and current occupations of a worker. O*Net records hundreds of job characteristics for most occupations. OEWS is the source of all employment and wage data used in the analysis. Finally, IPEDS is the source of truck driver training programs by state and year.

The data contains a total of 69 occupations; 47 of the 69 occupations are blue-collar or white-collar with minimal education requirements. I excluded 22 occupations that are either educated white-collar, agriculture occupations, and occupations that have extremely small sample sizes. This restriction removes about one-third of the CPS sample. An exhaustive list of excluded occupations can be found in the appendix. However, some examples listed here are Advance Computer and Math Workers, Advanced Financial Workers, Advanced Medical Workers, Engineers and Architects, and Education Workers. These occupations tend to require advanced degrees such as an M.D. or Masters. I exclude these occupations for two reasons. The first is that my model is insufficient to explain the educational decision-making process of a worker pursuing an advanced degree. For example, a bachelor's degree can take 3-5 years, and more advanced degrees require more time. Most occupations in my sample take less than one year to train for. Secondly, the overlaps between my main occupation of interest and these higher education occupations are relatively small. About 80% of all educated white-collar workers in my sample are either not working or members of the educated white-collar category. The other 20% of educated white-collar occupations are distributed

among the other 50 occupations, including agriculture. The other 68 occupations also contribute a small share of workers to the total share of educated white-collar workers.

The occupations consist of two classification schemes: major and minor occupations. The minor occupation codes are broadly based on the Standard Occupational Classification System (SOC). However, each dataset I use uses a slightly different coding system. Both OEWS and O*Net use the Standard Occupational Classification System (SOC) code. O*NET uses the more modern 2019 codes and OEWS uses the 2018 (SOC) codes. Furthermore, the CPS uses a separate system based on the 2010 (SOC) Codes. I created my own occupational coding scheme to harmonize all these occupational systems. And reduce the dimensionality from 997 unique occupations to just 69. This process resulted in the 47 included and the 22 not included occupations mentioned earlier. The major occupation codes consist of 9 broad occupational classes based on the 69 occupations. I use 7 of these codes: white-collar worker, tradesman, manual laborer, service worker, production worker, transportation worker, and sales worker.

The CPS ASEC March supplement is a survey that asks detailed questions about the workforce. Each person is sampled twice, one year apart, and if a person switches occupations between samples, the survey will reflect that change. Within a given sample year, half of the sample is incoming, and the other half is outgoing. I use the incoming occupation as a measure of the previous occupation and the outgoing occupation of the same worker a year later as the measure of the current occupation. This takes the repeated panel structure and converts it to a repeated cross-section, where I observe a new set of individuals each year, but I have information on their current and previous occupation in that year. The CPS survey with the updated occupation codes is the main source of data for the analysis. Aside from measuring occupational switching, the CPS data contains multiple demographic characteristics of each worker in particular age and sex. I use age and sex as my main demographics in the analysis since two of the major concerns in the trucking industry are the ageing workforce and the heavy male distribution.

Most individuals in the sample do not move occupations (72.5% average retention) Table 1 shows the top and bottom ten occupations by retention in the sample. There is considerable heterogeneity across occupations in the retention rates, ranging from an average high of 80 % and a low of 18 %. Interestingly, truck drivers have one of the highest retention rates of all occupations in the sample. This suggests a policy that increases the number of truck drivers likely has to operate

through recruiting new workers rather than retaining the current workers. Hazmat workers have the lowest retention rate in the sample; given the danger of the occupation, this is not necessarily surprising.

Retention Rate (H-L)	Occupation	Retention Rate (L-H)	Occupation
0.80	Emergency Service/Criminal Justice	0.18	Hazmat Worker
0.74	Personal Appearance Workers	0.28	Information Clerks
0.68	Housekeeping/Janitorial Worker	0.35	Repair Worker
0.67	Bus and Taxi Drivers	0.35	Forestry Worker
0.67	Truck Drivers	0.36	Unemployed
0.65	Electrician	0.38	Gaming Service Worker
0.65	Courier	0.39	Laundry Workers
0.64	Rail Workers	0.40	Industrial Repair Worker
0.64	Food Preparation Worker	0.41	Advanced Electronics/Precision Installer
0.62	Funeral Workers	0.41	Material Movers

Table 1: TABLE 1

O*Net data consists of 877 occupations and corresponding characteristics in six general categories called the Content Model. The six categories are worker characteristics, worker requirements, experience requirements, occupation requirements, occupation-specific information, and occupation characteristics. I use a subset of occupational requirements, denoted as work context. The work context category is defined as the physical and social factors that influence the nature of work. These features describe the working conditions and pressures of an occupation. The characteristics are unchanging over time, and firms have very little ability to change their occupation characteristics. The easiest way to conceptualize these characteristics is to think of them as product characteristics in product choice models. For example, feature of products such as mpg, color, flavor, etc. The eight variables I use to distinguish work conditions are the consequence of error, contact with others, degree of automation, exposed to hazardous conditions, in an enclosed vehicle or equipment, outdoors exposed to weather, time spent using your hands, and time pressure. These variables are time constant and measure the characteristics of a particular occupation. Since I observe the current and previous occupations, I calculate the Euclidean distance in characteristics between the two occupations. The more similar an occupation the closer they are in distance, and the more dissimilar occupations are the larger the measure of distance.

OEWS is the source of market wages and employment. I use the median and the 25th percentile full-time wage income as the measure of the expected compensation. All market wages are converted to 2019 dollars using the Consumer Price Index (CPI). I do not distinguish between part-time and

full-time workers since I am modeling the choice of occupation, not the number of hours a worker chooses to work. To capture the differences in wages for incumbent and new workers, I use different measures of occupation wages. For incumbent workers, I use the median full-time annual income as the measure of market wages when they consider their incumbent occupation. However, if a worker considers an occupation that they do not currently occupy, they would observe the 25th percentile of annual income as their expected annual income.

IPEDS is the source of education training data for CDL programs in the United States. While all publicly funded institutions are required to submit their data to IPEDS, many training programs are missing from the data. For example, in 2019 10 states are missing from the dataset.[3]. In any given year for the states with at least one truck driving training program, I compute the mean of the training cost by averaging the observed costs of the training program for each school observed within the state and year. I use the average training cost within each state as the observed training cost in that state.

The final dataset consists of 48 states over nine years, excluding Alaska and Hawaii. There are three categories of variables. The individual-level data from the CPS varies across individuals and includes age, sex, and previous occupations. The State - Time variables that vary across states and time include expected wage and training cost. Finally, the occupation characteristics only vary across occupations.

The summary statistics are below in Table 2.

	Female		Age		Retention Rate		Distance		Earnings		Training
	Sample	Trucker	Sample	Trucker	Sample	Trucker	Sample	Trucker	25th Pctl	Median	CDL
Mean	0.40	0.04	46.5	49.1	0.61	0.68	2.09	2.87	$36,912.90	$46,611.33	$4,537.27
Std Dev	0.49	0.20	13.4	12.4	0.49	0.47	0.97	1.10	$15,022.12	$20,135.72	$2,959.29
25th Pctl	0	0	36	40	0	0	1.27	2.04	$25,496.75	$31,294.78	$2,461.42
50th Pctl	0	0	47	50	1	1	1.98	2.54	$33,569.24	$42,430.56	$3,588.63
75th Pctl	1	0	57	58	1	1	2.73	3.84	$45,815.06	$58,535.18	$5,364.65
Obs	95,496	3,966	95,496	3,966	95,496	3,966	37,663	1,264	35,744	35,744	380

Table 2: Summary Stats

Table 2 contains the various demographics of the entire sample and truck drivers, as well as the earnings distribution over occupations. There are 103,399 total individuals in the sample, of which 4,061 are truck drivers. About 3.9% of the sample consists of truck drivers, and the other 96.1% of

3. The missing states are: Colorado, Connecticut, Louisiana, Maine, Massachusetts, Nevada, New Jersey, Rhode Island, Vermont, and Wyoming

workers are employed in other occupations. No workers in the sample are unemployed. The age, percent female, and retention rate variables are calculated for the entire sample and truck drivers. The distance columns were calculated only for movers. Since all non-movers all move 0 distance, and about 78% of the sample stay in their previous occupation, computing the summary statistics with the non-movers is less informative. The statistics about how far movers move are more informative because they give some measure of where workers go when they leave their incumbent occupation. The annual earnings statistics are calculated from the state and year variation in real annual earnings across all occupations. Each incumbent worker will see the median annual earnings as their predicted wage for staying in their current occupation, and they will observe the 25th percentile for all other occupations.

The driver sample is both 2.6 years older on average and significantly more male than the average worker. This is a well-documented feature of the truck driving industry; many are concerned about an aging male-dominated workforce. The average age of truck drivers is 49.1, slightly higher than the sample average of 46.5. However, this difference is much less pronounced than the ratio between men and women in the sample. The share of women in truck driving is very small; only about 4% of the trucker sample is female compared to about 40% in the whole sample. The sample, on average, skewed more male, and truck driving is even more skewed. Truck driving has a higher retention rate than the sample average. If we consider this information in the context of a presumed worker shortage, the relatively high retention rate within the occupation is surprising but does not necessarily contraindicate a shortage.

Annual earnings are the real annual earnings converted into 2021 dollars, although the sample ends in March 2020. Each occupation is observed in the OEWS by state and year. To correct for the role of experience and tenure in an occupation, I make the assumption that new entrants are truly new. So, for example, using the numbers from the mean occupation, an incumbent worker would observe annual predicted earnings of about $47,000 if they were to stay in this fictional mean occupation. A potential entrant would observe $37,000 because they are new to the occupation. The occupations in the sample are not exceptionally high-paying occupations; About 75% of occupations have a median earning below $59,000.

The CDL training program costs are observed at the state level across multiple years, although due to data and computational limitations, I only use 2019 to estimate the model at the national

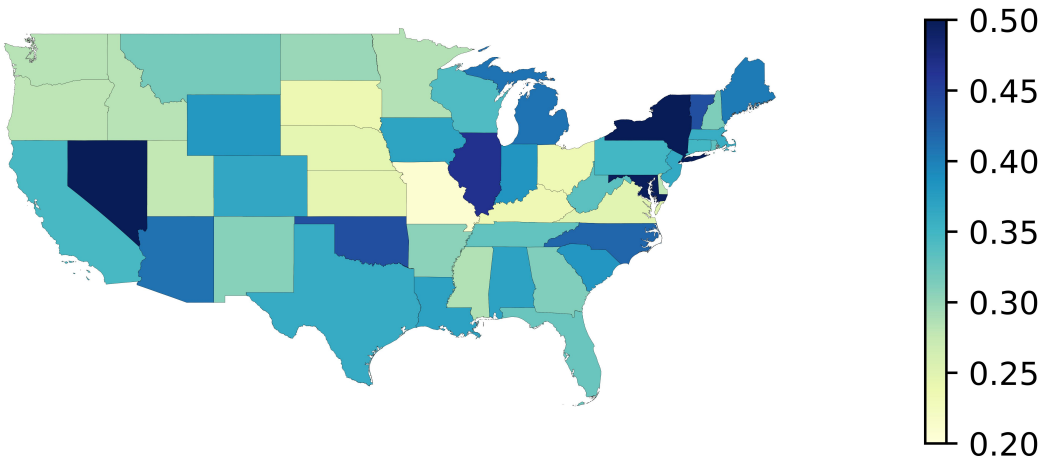


Figure 1: Share of New Truck Drivers by State

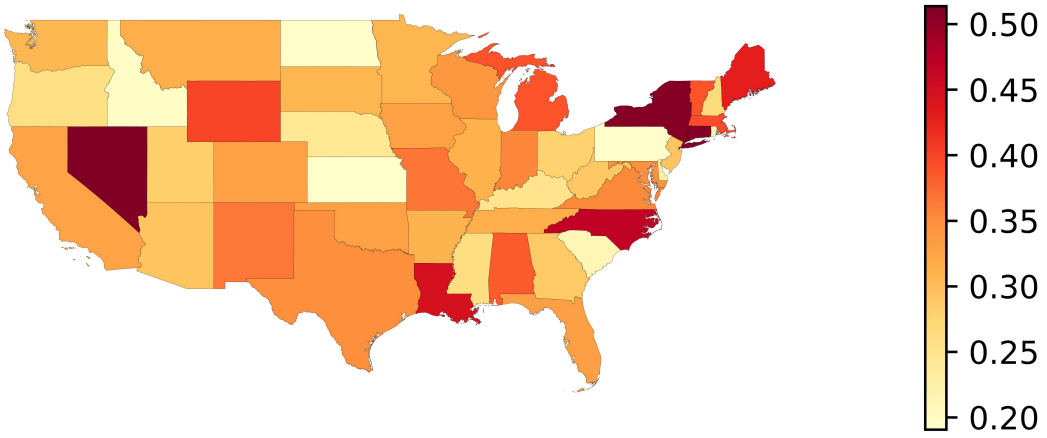
*The share of new drivers by a value of 1 would indicate all drivers in the sample in a given state are new. This figure uses all sample years to compute the flow.

level, using cross-sectional variation. This is for two pragmatic reasons. The first reason is due to my use of Google Colab to speed up the estimation process. The model takes time to converge, and using Google Colab helps speed up the process, but they have data limits on allowed RAM, which the full data set exceeds. The second is the MLE process struggles with the unbalanced cross-section since I observe some states in some periods but not others. The median program costs about $3,600 to complete, with a somewhat large standard deviation across states.

Figure 1 shows the geographic distribution of new truck drivers. The figure is a choropleth showing the share of new drivers within that state. The dark states are states where the largest share of the current truck drivers are recent entrants, and the lighter states are states with fewer entrants. A value of 1 in West Virginia for example, would indicate all drivers in the sample from West Virginia are new entrants. New York, Nevada, Illinois, and Maryland have the largest share of new entrants to incumbent drivers. Meaning these states have the highest rate of entry relative to other states.

Figure 2 shows the geographic distribution of former truck drivers. It is the exit rate by state in the truck driving occupation. Nevada, Maine, North Carolina, Louisiana, Vermont, Boston, Michigan and Wyoming all have the lowest retention rates. For example, a value of .3 means 30% of past truck drivers are not no longer truck drivers. Pairing Figure 1 and Figure 2 we can see that Nevada, New York, and to some degree North Carolina have a large degree of churning in

Figure 2: Share of Former Truck Drivers by State



labor market for truck drivers. Within these states, we have a high share of new entrants and a high share of people leaving the occupations. In contrast Illinois an Maryland appear to be a net gainers, having a large share of new drivers, but a low share of exiters relative to the size of their increases. Overall, there appears to be no clear geographic pattern, other than a high degree of churning in some states like Nevada and New York.

Model

Workers

I model the number of workers in an occupation as the outcome of many individual decisions about which occupation to occupy using a mixed logit model. The mixed logit approach allows more flexibility than conditional or multinomial logit alternatives or modeling the market shares of each occupation directly. Since individual-level data is available, I use individual decisions and aggregate them up to market outcomes. In this case, the mixed logit is particularly attractive because of the heterogeneity in preferences across workers, and the concern about an aging workforce and the potential to recruit younger workers. The mixed logit approach allows me to capture the heterogeneity in preferences of workers in blue-collar occupations, and capturing their preferences in a more sophisticated way allows for complex substitution patterns across occupations. Specifically, my modeling approach allows me to compute several counterfactuals, five of which I report in this paper.

A worker's choice probability of a given occupation depends on the characteristics of the past and current occupations, wages, education cost, worker demographics, and an idiosyncratic Gumbel taste shock. Workers take their past occupation as given and choose among 68 possible occupations. A worker observes the wage rate they would earn w_{js} if they select occupation j. If they are incumbent in occupation j, they observe the median wage rate of occupation j; otherwise, they observe the $25th$ percentile. The distance between occupations is calculated as the Euclidean distance between occupations in the characteristics space. Large values of $||x_j.x_k||$ indicate very different occupations and smaller values indicate more similar occupations. And naturally, when the $j = k$ the measure of distance is zero. The training costs are only observed for people considering truck driving as an occupation but are not already an incumbent driver. The training cost is measured as the average cost of a CDL training program in the driver's observed state. I consider two separate utility specifications, one nationally, which includes truck driving training program costs as a component of an individual's choice probability. The other utility specification is estimated state by state, allowing for more heterogeneity and variation in preferences by state. There is a trade-off between these two specifications. The state-by-state specification does not allow for the inclusion of the cost of truck driving training programs do to issues with the training cost variable. However, it allows for more flexibility. The national-level utility function is specified as follows:

$$u_{ijk} = (w_{js} - \text{FC}_s)\alpha_i + ||x_j.x_k||\beta_i + \xi_m + \varepsilon_{ijk} \tag{1}$$

Since the training cost and annual salary are pecuniary I deduct the cost of a truck driving training program from the expected annual salary of a new entrant. The new variable is the annual total compensation for choosing truck driving as a profession. All occupations other than truck driving don't have an observed training cost so the total compensation is just the annual wage rate. The training cost is an unobservable for all occupations other than truck driving, I will discuss the control function approach in a later section.

The second model, which I use for three of the four counterfactuals, allows richer heterogeneity across states, indicated by subscript s. The utility of job j for a worker i given their previous

occupation j and state s:

$$u_{ijks} = w_{js}\alpha_{is} + ||x_j.x_k||\beta_{is} + \xi_{ms} + \varepsilon_{ijks} \tag{2}$$

Where

$$\begin{pmatrix} \alpha_{is} \\ \beta_{is} \end{pmatrix} = \begin{pmatrix} \alpha_s \\ \beta_s \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ \beta_{Fs} & \beta_{As} \end{pmatrix} \begin{pmatrix} \mathbf{1}(Female = True) \\ Age \end{pmatrix} + N(0, \Sigma_s)$$

Both the national and state-by-state models use this random coefficient structure. The only difference between the state-by-state and national model, is the state specific standard deviation, and coefficients.

The wage response of worker i depends on the mean wage response in state s and individual specific draw a normal distribution with mean zero, and a standard deviation σ_s specific to state s. I capture all worker-level heterogeneity of wage responses within a state with the estimated standard deviation of the normal distribution. Workers' preferences on distance are more complicated; the preferences depend on a normal draw and the age and sex of a worker. β_{is} can be thought of as the disutility of adapting to a new occupation. For example, if a worker chooses to stay in occupation k, they would experience no disutility from moving. However, if a worker chooses to switch occupations, they would experience disutility in accordance with their value of β_{is}. Presumably, workers vary in their tastes for differences in occupations; it is plausible some people even experience positive utility from differences in occupations. Allowing the model to capture the heterogeneity of people's taste for differences is important. In particular, if women and aging populations are loath to move occupations, this will have important consequences as the workforce ages, and how effective recruiting women into truck driving will be.

The unobservable occupation characteristics are estimated at the major occupation code level. These are the characteristics not controlled for by the wages and differences in occupations. The ξ_{ms} for major code m is the mean utility for choosing an occupation within the major code m. ε_{ijks} is the unobservable factors that influence an individual's occupational choice. I assume ε_{ijks} follows the Gumbel distribution and is independently distributed across choices. I will discuss the unobservables contained in ε_{ijks} later.

The probability a worker i chooses an occupation j is:

$$L_{ij} = \frac{\exp\left(w_{js}\alpha_{is} + ||x_j.x_k||\beta_{is} + \xi_m\right)}{\sum_k^K \exp\left(w_{js}\alpha_{is} + ||x_j.x_k||\beta_{is} + \xi_m\right)} \tag{3}$$

Depending on the draws and characteristics of the worker, the probability a worker chooses a particular occupation changes. Across all individuals in the labor market, the observed share of workers in an occupation is σ_j:

$$\sigma_j = \int L_{ij} dF(\alpha_{is}, \beta_{is}|Age, Sex, \Sigma) \tag{4}$$

The aggregate share of workers in occupation j is the weighted sum of the choice probabilities using the probability density function of the parameters as weights. Using these models I consider four counterfactuals to increase the number of truck drivers: a wage increase for all truck drivers, a sign bonus for new truck drivers, allowing workers aged 18-20 to drive trucks, and a reduction in training costs. I compute a fifth counterfactual to investigate the impact of an aging workforce, and whether there will be a decline in the number of truck drivers as the workforce ages.

The wage and training cost elasticities are specified as follows:

$$e_{\sigma_j,\ell} = -\frac{w_\ell}{\sigma_j} \cdot \int \alpha_i L_{ij} L_{i\ell}\ dF(\alpha_{is}, \beta_{is}|Age, Sex, \Sigma) \tag{5}$$

$$e_{\sigma_j,j} = \frac{w_j}{\sigma_j} \cdot \int \alpha_i L_{ij} \cdot (1 - L_{ij}) d\ F(\alpha_{is}, \beta_{is}|Age, Sex, \Sigma) \tag{6}$$

$$e_{\sigma_j,\mathrm{FC}_\ell} = \frac{\mathrm{FC}_\ell}{\sigma_j} \cdot \int \alpha_i L_j(\beta) L_\ell(\beta)\ F(\alpha_{is}, \beta_{is}|Age, Sex, \Sigma) \tag{7}$$

$$e_{\sigma_j,\mathrm{FC}_j} = -\frac{\mathrm{FC}_j}{\sigma_j} \cdot \int \alpha_i L_j(\beta) \cdot (1 - L_j(\beta))\ F(\alpha_{is}, \beta_{is}|Age, Sex, \Sigma) \tag{8}$$

Control Function

I am assuming that firms have oligopoly power when hiring workers in blue-collar occupations. This varies across occupations and states, some firms can exert more market power than others. For example, 96% of trucking firms operate fewer than 10 trucks, so there are large numbers of buyers for any individual trucker's labor.[4] The market power any individual firm can exert on hiring a

4. American Trucking Association Industry Data: https://www.trucking.org/economics-and-industry-data

commercial driver is lower relative to an occupation with a more centralized market. Since there is a spectrum of markets, encompassing a variety of intensities in competition between employers. And firms exert their market power as downward pressure on wages. The levels of markdowns will vary across states and occupations. To estimate the impact of wages on occupational choice I need to control for the state specific markdowns as a source of endogeneity.

Firms are aware of their occupation's popularity among workers and leverage that knowledge as a downward pressure on wages. Firms know certain features of occupations Secondly, firms have information about unobserved job characteristics unavailable to researchers including training costs. Firms use this information to lower wages relative to less popular occupations. Explicitly, I model observed market wages as $w_{js} = \text{mp}_j + \gamma_{js}$, the average marginal productivity as a constant and a markdown γ_{js} based on the market power and unobserved occupation characteristics.

Since I estimate the model using maximum likelihood, I use a control function approach with two sets of instruments to control for endogeneity. The first instrument is a Hausman instrument. I calculate the mean within each occupation of each bordering state's median annual wage as the instrument. The features that are required for this instrument work are relatively straightforward. The marginal productivities of workers need to be correlated across states, and the state-specific markdowns on unobservables are uncorrelated across states. Consider the case of unobservable training costs, training cost is unobserved to the researcher for all non-truck driving occupations. However, firms observe these costs and account for the training costs when marking down the wage rate. If the relationship between training programs and markdowns are uncorrelated between states then the Hausman instrument should recover a consistent estimate of the coefficient on total compensation. Since truck drivers, plumbers, and other licensed trades in the sample are licensed at the state level it is more likely that the markets for training programs within states are uncorrelated with outside states. Formally I am assuming all sources of market power between states s, s' satisfy:

$$E(\gamma_{js}\gamma_{js'}|x_j) = 0$$

The second set of instruments are the observed occupation characteristics. These characteristics are assumed to be stable in the sample period, that is firms take the characteristics as given and they are constant across all states. These characteristics are relevant both to the decision of the firm in

determining the wage rate and the decision of the worker in choosing that occupation. Controlling for these characteristics is important because all firms observe these characteristics. This causes correlation in the markdowns across states since every firm is using the same information. I use both the Hausman instrument and observed characteristics as the instruments for the endogenous component of wages. Explicitly I model the source of endogeneity as:

$$u_{ijks} = w_{js}\alpha_{is} + ||x_j.x_k||\beta_{is} + \xi_m + \varepsilon^1_{ijks} + \varepsilon^2_{ijks} \tag{9}$$

Where ε^1_{ijks} is the additively separable component of the error term correlated with wages. Let z_{js} be the Hausman instrument and x_j be the observed product characteristics. By using $w_{js} = \text{mp}_j + \lambda_1 z_{js} + \lambda_2 x_j + \gamma^1_{js}$ to model wages, the new error term γ^1_{js} is unccorrelated with the endogenous component of wages. The utility model corrected for the endogenous component of wages then becomes:

$$u_{ijks} = w_{js}\alpha_{is} + ||x_j.x_k||\beta_{is} + \xi_m + \lambda\gamma^1_{js} + \varepsilon^2_{ijks} \tag{10}$$

Both the national and state-by-state models are estimated using the Hausman instrument.

Estimation

The two models are estimated using simulation-assisted maximum-likelihood, in Python using the package Xlogit. The national regression is estimated using 38 of the 48 states in a cross-section. The second model is estimated state by state. I chose to estimate the two models separately due to the following tradeoff. I can use a GPU-assisted estimation using Google Colab, but that requires reducing the sample size to fit the data within the memory constraints Google enforces. GPU-assisted estimation is attractive because it speeds up the estimation process and allows more draws to compute the random coefficients, leading to more accuracy in computing the random coefficients. However, with this approach, I lose the efficiency gained from joint estimation. While in principle I could estimate the model jointly without GPU assistance, the downside of this approach is my software is not capable of handling a large number of observations and choices. So I am forced to either estimate the model as a cross-section or state-by-state.

The first model is estimated as a cross-section almost entirely because of data constraints.

The IPEDs data has considerable inconsistencies year over year in its reporting of CDL training programs. Because of this, I can't get a consistent sample within states across time. So I use 2019 the most recent year and estimate the model in cross-section.

Using the state-by-state approach I can leverage my 9 years of data, and allow each state to differ in their coefficients. I do not have the same limitations with data consistency using OEWS and the CPS only.

Results

National Response

The regression results from Equation (10) at the national level are below. This model is estimated for 38 out of the 48 states in the sample since I don't observe the training cost data for 10 states in 2019. The data consists of a single cross-section of 38 states in 2019. There are 8,347 workers in the model, and they choose among 42 occupation, based on their initial occupation and observed wage rates.

	Coef	Std Error	z-Statistic
Total Compensation	0.0100	0.0000	302.06
Distance	-1.5404	0.0019	-812.82
Distance × Female	-0.3798	0.0011	-334.04
Distance × Age	-0.0128	0.0000	-332.50
Control Function	-0.0004	0.0000	-13.45
ξ_2	-1.0925	0.0015	-734.28
ξ_3	-0.1449	0.0017	-86.70
ξ_4	0.1877	0.0013	142.87
ξ_5	0.3627	0.0017	212.79
ξ_6	0.1609	0.0013	126.43
ξ_7	1.1010	0.0012	926.75
SD Total Compensation	2.92×10^{-5}	0.0001	-0.43
SD Distance	1.6129	0.0008	2072.32
Obs	8,347		
likelihood	-37,095,913		
First Stage F-stat	15,750		

*National cross-section using 2019 with 38/48 states in the sample

The results show that workers are more likely to choose higher-paying occupations ceteris-

paribus. More interestingly, the preferences for distance are considerably heterogeneous. On average workers prefer occupations that are more similar to their previous occupations. This preference is larger as workers age and for women. However, not all workers are averse to occupational differences. For example, taking a male with the average age in the sample (46.5), the mean response is a disutility of about 2.1 for a unit increase in distance between their current and past occupation. However, about 10% of the population of men age 46.5, will get positive utility for occupational differences. This increases as the age of the worker decreases, for male 21-year-olds about 15% receive positive utility for occupational differences.

The ξ_m are the major occupation unobservables. These are the utilities of choosing an occupation within the major occupation code. The utilities of each major code are normalized to the utility of choosing a non-credentialed white-collar occupation. The other six major codes are trades, manual labor, service, production, and transportation workers.

This set of estimates is used to calculate the reduction of training cost counterfactuals. The other four counterfactuals are calculated using the state-by-state estimates. The mean wage elasticities are reported for truck drivers and the 9 other occupations that have the largest cross-wage elasticities. It is a selection of occupations that experience the largest decrease in market share when the wages of truck drivers rise. That doesn't mean these occupations are the largest source of new truck drivers, because the initial share could be very small, it indicates the sensitivity of workers in these occupations to changes in truck driving wages.

		1	2	3	4	5	6	7	8	9	10
Adminstrator/Manager	1	0.0275	-0.0004	-0.0038	-0.0012	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002	-0.0001
Advanced Construction Workers	2	-0.0005	0.0140	-0.0006	-0.0006	-0.0002	-0.0005	-0.0003	-0.0003	-0.0006	-0.0004
Advanced Sales Worker	3	-0.0054	-0.0007	0.0274	-0.0016	-0.0002	-0.0002	-0.0003	-0.0002	-0.0004	-0.0002
Advanced Transportation Worker	4	-0.0014	-0.0005	-0.0013	0.0170	-0.0001	-0.0002	-0.0002	-0.0001	-0.0003	-0.0002
Bus and Taxi Drivers	5	-0.0002	-0.0003	-0.0004	-0.0002	0.0036	-0.0001	-0.0002	-0.0001	-0.0003	-0.0004
Construction Worker	6	-0.0003	-0.0008	-0.0003	-0.0004	-0.0001	0.0117	-0.0003	-0.0004	-0.0006	-0.0003
Courier	7	-0.0003	-0.0005	-0.0004	-0.0003	-0.0002	-0.0003	0.0061	-0.0002	-0.0004	-0.0014
Forestry Worker	8	-0.0002	-0.0005	-0.0003	-0.0002	-0.0001	-0.0005	-0.0002	0.0050	-0.0003	-0.0004
Rail Workers	9	-0.0003	-0.0006	-0.0004	-0.0003	-0.0002	-0.0004	-0.0003	-0.0002	0.0101	-0.0004
Truck Drivers	10	-0.0003	-0.0007	-0.0004	-0.0003	-0.0004	-0.0003	-0.0016	-0.0004	-0.0006	0.0062

Of the 10 occupations bus and taxi drivers have the smallest and management has the highest own wage elasticity, truck drivers' own elasticity is about .0062. Somewhat unsurprisingly couriers have the highest cross-wage elasticity with respect to a wage increase for truck drivers. Couriers deliver goods but do not drive vehicles large enough to qualify as truck drivers. The other occupations are a mix of construction, sales, and transportation-related fields.

The counterfactuals are computed using the 2019 data since this is the final year of data and is most germane to the current market. Each counterfactual modifies some component of 2019, for example, increases wages, and simulates the employment outcome as an increase in the number of workers and a percent change in the number of workers. It reflects how many more truck drivers would we have had in 2019 if wages were higher etc. Furthermore, it is not a simulation of the demand side, what employers are willing to pay is not captured by this model. For example, expanding the labor market of truck drivers by allowing 18-20-year-olds to enter the market is a classic supply shifter, all else equal this will weakly lower wages. However, since I do not measure the employers' demand elasticities I cannot compensate for the supply shift. Therefore, I assume the demand side elasticities are perfectly elastic, and as a consequence wages are constant. Therefore, the counterfactual allowing 18-20-year-olds to enter the truck driving market is likely to be an upper bound on the employment increase of that policy.

I simulated three of the 5 counterfactuals in two ways. For the three pecuniary counterfactuals, I compute two cases, a 1%, and a $1,000 change. The first counterfactual is a wage bonus to both incumbent and potential truck drivers. This is the largest employment increase of all pecuniary benefits at about 6,600 or 21,300 new drivers depending on the type of increase. From a firm's perspective, an increase in wages by $1,000 across the board is expensive. With about 3.5 million truck drivers in the United States, the increase in the wage bill of such a policy would be substantial. Another potential tool is to increase the wages of a new entrant. The sign bonus row is an increase in wages for a new entrant, but not incumbents. This is an attractive policy for firms because it does not increase the wage bill for all workers, just new entrants. Simultaneously, it has an effect size about 30% smaller than the previous counterfactual at a much lower cost. This trade-off may be attractive to firms since it gets most of the benefit with a much lower wage bill. The final pecuniary counterfactual is a decrease in training cost as either a 1% or $1,000 transfer. This policy has a relatively small impact compared to the wage and sign bonus. Since training costs are substantially smaller than wages, a 1% decrease in training cost works out to be a $24 scholarship at the mean cost so it is somewhat unsurprising the effect size is so small. However, for a $1,000 increase the impact is still about half of the impact of a $1,000 signing bonus. The 2 remaining counterfactuals are non-pecuniary, and adjust the age profile of the 2019 labor market. The first policy is to allow 18-20 year olds to enter the truck driving market. The policy results in an increase of about 100,000

	1% Increase		$1000 Increase	
	Employment	% Change	Employment	% Change
Wage Response	6,614	0.17%	21,292	0.54%
Sign Bonus	4,479	0.11%	15,469	0.39%
CDL School Cost	480	0.01%	7,151	0.20%
18-20 Year Olds	96,933	2.44%	96,933	2.44%
Aged 5 Years	18,965	0.48%	18,773	0.47%

drivers nationally. Two things are driving this result, first, younger people are more likely to switch to different occupations than older groups. Since all 18-20-year-olds by legislation are not engaged in trucking as an occupation the higher likelihood of them leaving their incumbent occupation leads them to be a good source of new drivers. To illustrate this, suppose 18-20-year-olds were extremely averse to new occupations relative to other groups, then it would be much harder to coax them from their incumbent occupation. Secondly, there are a large number of 18-20-year-olds in the blue-collar labor market, with about 3.99 million predicted using the CPS 2019. Since that pool of workers is so large, recruiting a modest share, about 3.2% on average results in big increases in truck drivers. In fact, almost all of the increase is coming from the expanding labor pool, since the increase in market share of truck driving only increases by about 0.000013. The final counterfactual simulates what happens when the age distribution increases by five years and workers are required to retire at 70. Aging the workforce decreases the moves between occupations since occupational differences cause more disutility as a worker ages. Aging the workforce results in about 13,400 more truck drivers. This is largely a consequence of higher retention in the truck driving profession, people who were more likely to move occupations when they were younger are less likely as they age.

State Responses

The next set of results focuses on four counterfactuals, using the state-specific responses. The progression of results follows the same structure as the national response table that is: wage increase, sign bonus, 18-20-year-olds, and shifting the age distribution. These results encapsulate which states are the biggest contributors to the increase in truck driving employment. All pecuniary counterfactuals are reported for a $1,000 change.

Both a thousand-dollar increase in truck driver wages and a sign bonus result in the following geographic pattern. This figure's legend records the percent increase in truck drivers by state for

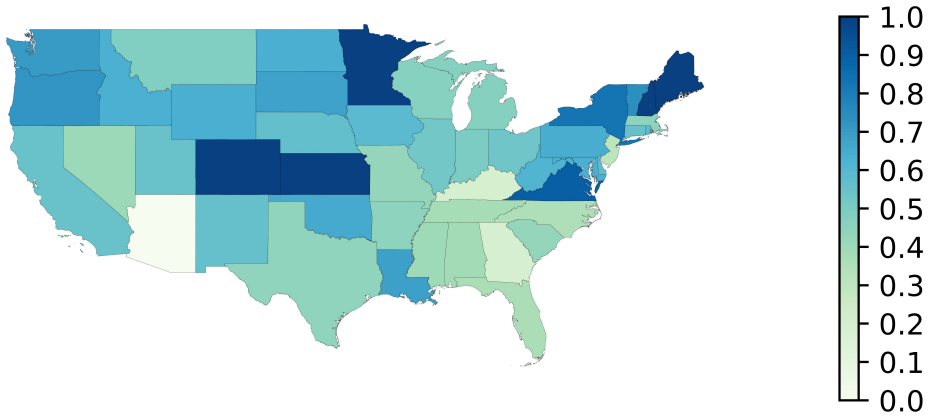


Figure 3: $1,000 Increase in Annual Earnings

*Percent change in the number of truck drivers for a $1,000 annual wage increase. Calculated from recomputing the market share of truck drivers after increasing the wage by $1,000.

a thousand-dollar increase in wages. The geographic pattern is equivalent to the signing bonus counterfactual. The only difference between the two counterfactuals is the size of the impact. The darker blue colors are associated with a larger response and the lighter the color the smaller the employment increase. Minnesota, Maine, Kansas, Colorado, and New Hampshire have the largest percentage increase in drivers within their state. Arizona is unique, with a response very close to 0. The Deep South as a group, with the exception of Louisiana, has reasonably small responses to wage increases. The Upper Midwest and Great Plains regions have higher responses relative to the southern regions. The geographic pattern is generated by the differences in the wage coefficient across states. States differ in the average impact of wage changes and the standard deviation of workers' wage responses. States with the largest average wage response have the largest elasticities in figure 3.

Allowing 18-20 year olds to become truck drivers has an interesting geographic pattern. Figure !! Shows the share of 18-20-year-olds that choose truck driving as an occupation. This counterfactual demonstrates the utility of a mixed logit approach since the state responses depend on the distribution of prior occupations, younger workers' preferences for different occupations, and the gender and age distributions within people's previous occupations. States where the 18-20-year-old demographic are more likely to be incumbents in occupations that are most similar to truck driving will simultaneously be the states that get the biggest gains from allowing 18-20-year-olds to enter the market. Essentially, this figure demonstrates the willingness of 18-20-year-olds to choose truck

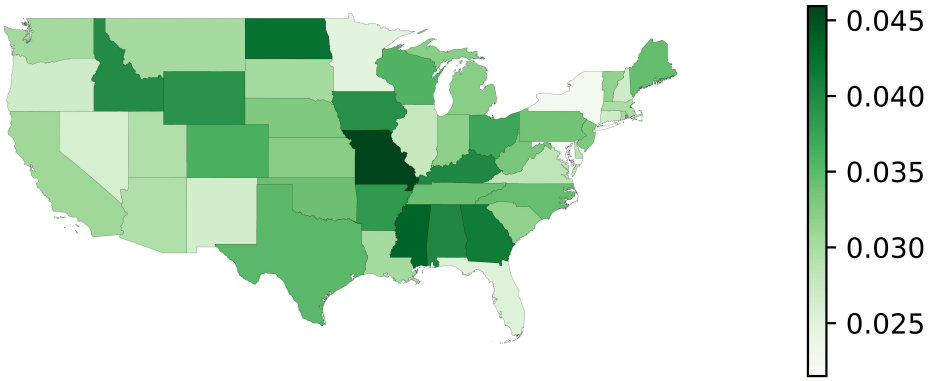


Figure 4: Share of 18-20-Year-olds that choose Truck Driving

*Share of 18-20-year-old workers that choose to enter the market for truck drivers. Calculated from computing the market share of 18-20-year-olds that choose truck driving as an occupation by state.

driving as a profession by state. The states where the largest share of 18-20-year-olds choose truck driving are Missouri, Arkansas, Georgia, North Dakota, Kentucky, Idaho, and Wyoming. Unlike the wage counterfactuals, the Southern states get large increases in truck drivers.

However, states also differ in the share of 18-20-year-olds in their workforce; states with the largest share of younger workers will get the largest increases in truck driving by letting them enter the market. Figure !! ignored the scale of the market by state; for example, a state like Texas has a modest share of 18-20-year-olds predicted to choose truck driving, but has one of the largest increases in the number of new truck drivers as demonstrated in figure !!!. Texas and California dominate the geographic pattern because these states have a large number of 18-20-year-olds. Ohio, Florida, and Pennsylvania also see moderately large increases. The low-population states in the Great Plains region see small increases relative to the share of 18-20-year-olds willing to choose truck driving in those states.

The final counterfactual is calculated by increasing the age distribution by five years and retiring workers 70 years and older. Figure !! Reports the percent change in truck driving employment by state. This counterfactual is interesting because some states experience a net decline in truck drivers, although the plurality of states will see increases. Nevada, New York, Maryland, South Carolina, and Massachusetts see declining numbers of truck drivers as the age distribution rises. This distribution of prior occupations in each state is important for determining whether a state sees an increase or decrease in the share of truck drivers. Individuals are less likely to switch to

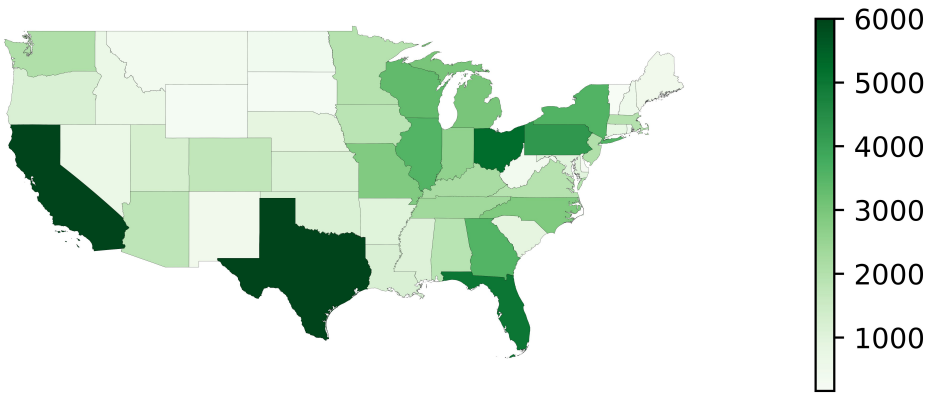


Figure 5: Increase in truck drivers allowing 18-20-year-olds enter the market

*Number of 18-20-year-old workers that choose to enter the market for truck drivers. Calculated from computing the market share of 18-20-year-olds that choose truck driving as an occupation by state and multiplying that by the total number of 18-20-year-olds in that state. The largest value are truncated at 6,000, since Texas and California exceed other state's effect sizes

more distant occupations as they age. As the workforce ages, if a greater share of the occupations in these states are more distant from truck driving, the likelihood of people switching to truck driving falls. To put it another way, the choice probabilities of occupations that are most similar to the incumbent occupation rise as the age distribution rises. Then, if there are a sufficiently large number of people in those occupations that are most similar to truck driving, the share of drivers will increase.

The declines also come from retirement. Since I force workers over the age of 70 to retire, all the drivers that exceed 70 will be dropped from the market. If either the gains from retaining more workers are less than then retirements or the distribution of prior occupations is sufficiently different from truck driving, we will observe a net decline in movers from other occupations. The red states are all states that see increases in the number of truck drivers as they age. New Mexico, Utah, Wyoming, and Indiana are the states that see the biggest increases in the share of drivers.

The final set of results tabulates the top ten states as measured by the employment increases for each of the counterfactuals. These employment increases do not lend themselves well to choropleths since a few states dominate the employment increases due to either their elasticity or large population. TABLE ?? contains the 4 state counterfactuals, with the two pecuniary counterfactuals computed for a $1,000 increase.

California, Texas, and New York are all very large states in terms of employment, typically

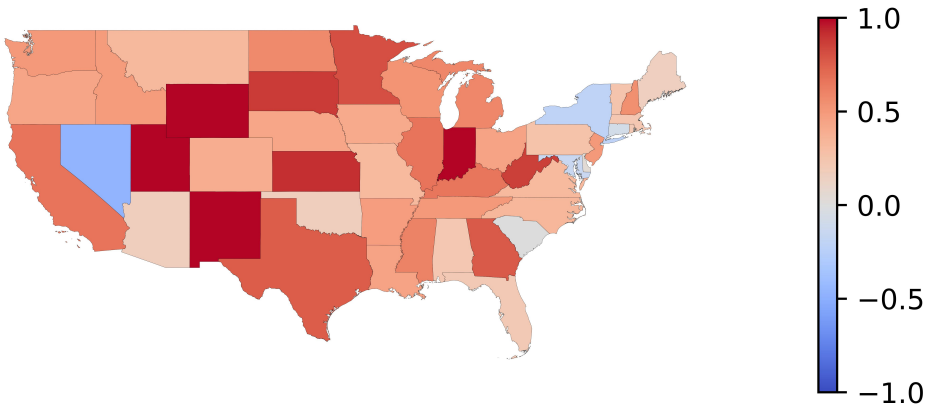


Figure 6: Real caption

a=

State	Wage	Sign Bonus	Share	State	18-20	Share	State	Aged 5 Years	Share
California	2,492	1,768	0.11	Texas	9,214	0.10	California	2,955	0.16
Texas	1,647	1,365	0.09	California	9,074	0.09	Texas	2,860	0.15
New York	1,567	1,191	0.08	Ohio	5,259	0.05	Georgia	1,333	0.07
Colorado	1,048	754	0.05	Florida	5,002	0.05	Indiana	1,175	0.06
Pennsylvania	1,000	677	0.04	Pennsylvania	4,253	0.04	Illinois	971	0.05
Ohio	947	655	0.04	New York	3,561	0.04	Ohio	790	0.04
Minnesota	874	619	0.04	Georgia	3,544	0.04	Michigan	585	0.03
Illinois	797	578	0.04	Illinois	3,541	0.04	New Jersey	557	0.03
Virginia	779	572	0.04	Wisconsin	3,341	0.03	Wisconsin	524	0.03
Florida	738	555	0.04	Michigan	2,993	0.03	Minnesota	499	0.03
National	21,292	15,469			96,933			18,773	

they contribute a large number of new truck drivers in each of the counterfactual scenarios. In the case of the wage increase and sign bonus counterfactual, the top 10 states contribute over 50% of the national increase in truck drivers. Allowing 18-20-year-olds to enter the truck driving market leads to the largest increase in truck drivers. Again Texas, California and New York are big contributors, however, some smaller states also contribute to the increase in drivers. Wisconsin, Michigan, Pennsylvania, Georgia, and Ohio as a group contributed about 20% of the increase in truck drivers. Finally, the increases from shifting the age distribution follow approximately the same pattern with the loss of New York as a big contributor. California and Texas are the top two states. New Jersey and Indiana are also large contributors which follows from FIGURE !!!.

Conclusion

I used four data sets to estimate a mixed logit model of occupational choice to compute 5 counterfactuals. Given the large concern of a truck driving shortage, my 5 counterfactual experiments address some of these concerns. The wage and sign bonus counterfactual demonstrates that workers are responsive to wage increases. A $1,000 increase in all wages nets about 21,100 more drivers nationally and a $1,000 sign bonus nets about 15,500. While these increases are small in the context of the approximately 3.5 million drivers in the United States, it is clear that workers respond to higher wages. An inelastic labor supply does not imply a shortage of workers. Firms may wish that smaller wage increases would coax enough workers into their occupations to cover the perceived shortfall. However, the small responses do not imply a shortage. A sign bonus is an attractive tool for firms to use, a larger bonus will induce more workers to switch occupations a reasonable cost, however, retaining them becomes a challenge. Presumably, such a policy would lead to a higher wage bill as firms pay more to retain their workers.

The aging of truck drivers has often been cited as a potential cause of the shortage. In my counterfactual, I age the distribution of workers by five years and retire all workers older than 65. Surprisingly, this counterfactual showed increases in the number of truck drivers in most states. Only Nevada, New York, Maryland, and Massachusetts experience declines in the number of drivers as their workers age. Of course, if all drivers get older and no young drivers enter the market, of course, the number of truck drivers will fall.

In the final and largest counterfactual, I allow 18-20-year-olds to enter work as truck drivers. Currently DOT regulation forbids 18-20-year-olds to drive commercial trucks across state lines. The Bipartisan Infrastructure Bill financed a trial program to authorize young workers to apprentice and work as truck drivers. My counterfactuals predict a nationwide increase of about 97,000 new drivers if 18-20-year-olds are allowed to enter the market. This result ignores the concerns about safety associated with allowing younger drivers to work as professional drivers. Other research into the unintended consequences of allowing young drivers to enter the market are needed.

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