The Impacts of the COVID-19 Pandemic on Transportation Employment: A Comparative Analysis

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Abstract

The COVID-19 pandemic caused a variety of social, economic, and environmental changes. This paper examines the employment-related impacts of the pandemic on workers in the transportation industry compared to other industries, and within different transportation sectors. We estimated random effects logistic regression models to test the following three hypotheses using the monthly Current Population Survey micro-data. One, the transportation industry experienced a greater incidence of unemployment than other industries. Two, there is heterogeneity in employment impacts within the transportation sector. Three, specific sectors within the transportation industry experienced more employment impacts than other essential industries, as designated by the Centers for Disease Control and Prevention (CDC) Phase 1a vaccination guidelines. Model results highlight that workers in the transportation sector were 20.6% more likely to be unemployed because of the pandemic than workers in non-transportation industries. Model results also indicate large intra-sector heterogeneities in employment impacts within the transportation sector. Taxi and limousine drivers were 28 times more likely to be unemployed compared to essential workers. Scenic and sightseeing transportation workers were 23.8 times more likely to be unemployed compared to essential workers. On the other end of the spectrum, however, postal workers and pipeline workers were 84% and 67% less likely to be unemployed compared to essential workers, respectively. From a policy perspective, these results suggest that attention to several aspects of transportation work are needed in the coming years to prepare for future interruptions to the transportation industry.

Keywords: COVID-19; Transportation workers; Essential workers; Transportation systems; Unemployment; Pandemic

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1. Introduction

The COVID-19 (also known as SARS-CoV-2 or coronavirus) pandemic upended the global economy. In the United States (U.S.) alone between March 21st and April 25th of 2020, the total number of initial unemployment claims filed reached 30.3 million people, and the unemployment rate for May was projected to reach 16% compared to 4.4% in March (Şahin et al., 2020). These pandemic related job losses exceed those lost from the Great Recession (Coibion et al., 2020; Nguyen et al., 2020). The impacts of the pandemic were also noticeable from changes in consumer spending. In the early portion of the pandemic (February 26-March 10), consumer spending increased by over 40% in efforts to stockpile goods and in anticipation of an inability to visit retailers (Baker et al., 2020). Consumers also spent between 25% and 30% less on restaurant, entertainment and travel related expenses during this period retailers (Baker et al., 2020). Perhaps most visible were the reductions in mobility across multiple sectors of the transportation industry, as a variety of global restrictions (e.g., border restrictions, travel bans, quarantines and curfews, stay-at-home orders, closure of various amenities and services) reduced demand in the transportation sector (Abu-Rayash and Dincer, 2020).

This reduction in mobility had impacts on the transportation industry. Globally, direct aviation jobs potentially fell by 43% and total aviation supported jobs fell by 52.5% from pre-COVID levels(Air Transport Action Group, 2020). In the U.S., the number of total commercial flights fell from a total of 218,346 on March 8 to 58,113 on April 19, 2020; a reduction of 73% (U.S. Bureau of Transportation Statistics, 2020a). Truck tonnage in the U.S. fell by 9.18% between March and April 2020 (U.S. Bureau of Transportation Statistics, 2020b). On March 13, 2020 the U.S. government declared a state of emergency in response to the pandemic (The White House, 2020). Highway congestion in major cities dropped substantially in 2020 compared to the previous year: 36% in Los Angeles, 30% in New York and 25% in Miami (Kelly and Sharafedin, 2021).

Given the magnitude of economic and social impacts associated with the COVID-19 pandemic, the research community is beginning to disentangle these impacts to determine who, when, and where people and industries are most intensively impacted. To this end, studies are looking at job losses (Montenovo et al., 2020) as well as the ability of people to work from home during the pandemic (Kearney and Pardue, 2020). De Haas et al. (2020) reported that 39% of the annual household survey data respondents in the Netherlands worked almost all of their hours from home in 2020, compared to only 6% in 2019. They are also beginning to look at impacts on various industries hit hardest by the pandemic. For example, studies highlight that workers in non-essential industries (e.g., leisure and hospitality) were significantly more likely to be unemployed during the pandemic (Fairlie et al., 2020; Montenovo et al., 2020). In contrast, workers in essential industries, were less likely to be unemployed but were also at higher risk of exposure to the virus due to the nature of their jobs (Kearney and Pardue, 2020; The Lancet, 2020).

This study will conduct an industry level analysis of unemployment trends as a result of the COVID-19 pandemic, with a focus on the transportation industry. To do this, the study leverages monthly survey data from the Current Population Survey which contains information about people prevented from working during the pandemic, as well as associated demographic and socio-economic information between May 2020 and December 2020. These data are incorporated within a random effects panel logit model to determine the impacts of the pandemic on workers in the transportation industry compared to other essential and non-essential industries. Results of the analysis of these survey data indicate that workers in the transportation industry were about 20% more likely to be unemployed due to COVID-19 compared to workers in other (non-transportation) industries. They also show that several sociodemographic groups, including older workers, non-Whites or Hispanics, immigrants, less educated people, and unmarried people were more likely to be prevented from working during the pandemic. In addition, the results illustrate a decreasing likelihood of being unemployed due to COVID-19 over time. They also uncover heterogeneous impacts within the transportation industry. Workers in customer-oriented transportation sectors (e.g., taxi, scenic, water, bus, and air) were more likely to be unemployed compared to workers in other transportation sectors and essential non-transportation industries.

2. Relevant Literature

The present study will examine the employment impacts on the transportation industry of the COVID-19 pandemic. To do so, we draw on two bodies of related work which inform our model specification and results in later sections of the paper. One, work on the employment impacts of the pandemic. Two, work on COVID-19 impacts on the transportation industry related to changes in mobility patterns, transit ridership, and social equity issues pertaining to both industry workers and riders.

2.1. Employment Impacts of COVID-19

A review of work on the economics of COVID-19 notes that by June of 2020 there were 160 working papers from the National Bureau of Economic Research (NBER) on this topic (Brodeur et al., 2020). A large segment of this work analyzes how many and what types of workers were affected by the pandemic. One study of employment impacts in the first few months of the pandemic (April and May) found that a large proportion of losses were in jobs that could not be conducted remotely and that required a lot of interpersonal contact (Montenovo et al., 2020). The same study found that even after accounting for job sorting, or how market forces partition people into jobs, demographic characteristics including gender, race, and age were statistically significant explanatory factors of unemployment due to the pandemic. Specifically, model results highlight that single parents (who are overwhelmingly females), Blacks, Hispanics, and younger workers have been disproportionately impacted by pandemic-related employment losses (Montenovo et al., 2020).

Related research finds that racial/ethnic minorities, particularly African Americans and Latinx workers, had the largest spikes in unemployment in the early months of the pandemic (Fairlie et al., 2020). Of these two groups, Latinx workers experienced the largest spikes in unemployment because of their concentration in particular industries. These higher levels of unemployment among Latinx workers are likely explained by an overrepresentation in industries most heavily impacted by the pandemic (e.g., Leisure and Hospitality, Wholesale and Retail Trade, Construction, and Services) and an underrepresentation in industries less intensively impacted by the pandemic (e.g., Management, Business, and Financial Occupations, Professional and Related Occupations).

Pandemic-related employment studies have also examined unemployment trends related to stay at home orders and the ability to telework. Dingel and Neiman (2020) estimated that in the

United States, 37% of jobs can be performed entirely from home. They also estimated the share of jobs that can be done at home by industry; their results showed that the share of transportation-related jobs such as transportation and material moving occupations was only 0.03, which indicated a low telework ability for these jobs. Results of the Dingel and Neiman (2020) study also found that "remote jobs" pay more and make up a substantial percentage of wages earned in the United States (46%). This same study also found regional variations in the percentage of jobs with remote work capabilities. Metropolitan areas including San Jose-Sunnyvale-Santa Clara, CA (Silicon Valley) and Washington-Arlington-Alexandria, DC have at least 50% of jobs that can be done entirely remotely while other metropolitan areas such as Baton Rouge, LA, Las Vegas-Henderson-Paradise, NV, and Scranton-Wilkes-Barre-Hazleton, PA only have 30% of remote jobs.

Research on stay-at-home orders and employment trends finds that these orders raised the unemployment rate but that the unemployed were concentrated in particular segments of the population. Beland et al. (2020) found that the people most likely to be unemployed from stay-at-home orders were racial/ethnic minorities, younger workers, people that were not married, and the less educated. A study of essential workers, defined as those with an inability to telework, found that they are disproportionately non-White, make lower earnings, are male, and have lower levels of educational attainment (Kearney and Pardue, 2020). The Kearney and Pardue (2020) study also finds that Blacks are more likely to be essential workers. A related study of the impacts of the pandemic on immigrant workers finds that, within this group, men and undocumented workers were hit hardest by the pandemic due to their inability to telework (Borjas and Cassidy, 2020). Mongey et al. (2021) analyzed the impact of social distancing policies on workers that were not able to work from home and require close physical proximity to others. They produced similar findings to Beland et al. (2020) and Kearney and Pardue (2020); these workers make lower incomes and are less educated. A new insight from Mongey et al. (2021) is that those unable to work from home and that work in close physical proximity to others have lower financial liquidity and are more likely to rent their homes.

Gezici and Ozay (2020) took a slightly different approach from the previous studies. They incorporated data from the April 2020 Current Population Survey into probit regression models to estimate the probability of unemployment during this period of the pandemic. They found racial/ethnic and gender differences in the probability of being unemployed, even after controlling for the ability to telework. Specifically, Black and Hispanic women were more likely to be unemployed even if they were able to telework, which suggests discrimination may be behind higher instances of unemployment in these groups.

2.2. COVID-19 Impacts on the Transportation Industry

Transportation-related research work on COVID-19 impacts is focused in three areas: trends in mobility, usage of different transportation modes, and equity impacts of changes in transportation. Several studies have analyzed mobility patterns during the pandemic. In a study in Colombia, Arellana et al. (2020) analyzed the short-term impacts of the pandemic on air, freight and urban transport. They found that government policies, which included a ban on air passenger travel, reduced mobility, transit ridership, and congestion. Within the U.S., Riggs and Appleyard (2020) analyzed shifts in travel behavior due to telework during the pandemic by using survey data collected in the initial months of the pandemic (March and April of 2020). Interestingly, many of the increased foot and bike trips for recreational purposes were induced by telework (i.e., additional trips generated while working from home).

Abouk and Heydari (2021) analyzed Google data on daily location trends for two time periods, a pre-pandemic period (January 3-February 6) and a post-pandemic period (February 15-April 25). They found that mobility in the following locations declined during the pandemic: transit stations, pharmacies, retail, grocery stores, and recreation. In an Australian survey-based study in March of 2020, Hensher et al. (2021) estimated the number of days people work from home based on the characteristics of their jobs and employers, and investigated its subsequent impacts on their commuting trips. Their study found that low-income group workers were less likely to be able to work from home, while females and younger workers were more likely to be able to work from home. Lou et al. (2020) used county-level data from the COVID-19 Impact Analysis Platform at the University of Maryland to compare the mobility of low-income and high-income groups after the implementation of stay-at-home orders. Their trip dataset included information about the total number of trips and trips for work and non-work purposes. Based on these data, the study found heterogeneous impacts across income groups of stay-at-home orders on the number of trips taken. Specifically, stay-at-home orders did not reduce trips for either work or non-work purposes for the lowest income group in the study (<$30,000). However, these orders did significantly decrease work and non-work trips (with the exception of park visits) for middle- and higher-income groups in the study. From a policy perspective, Bian et al. (2021) investigated the time lag effects of pandemic-related policies on transportation systems in the U.S cities of New York and Seattle. They reported that vehicular traffic and transit ridership in both cities dropped significantly after the implementation of social distancing restrictions. They also found a faster recovery in vehicular traffic prior to reopening, but did not observe a recovery in transit system usage, which highlights important differences in impacts by transportation mode of COVID-19 restrictions.

Another facet of transportation research related to the pandemic examined trends in the use of transportation modes. Air transportation was one of the most affected sectors during the COVID-19 pandemic, exhibited by a substantial reduction of air passengers and a large number of flight cancellations worldwide (Suau-Sanchez et al., 2020; Sun et al., 2021). Using Flightradar24 data that covered 150 airlines between 2,751 airports globally, Sun et al. (2020) examined the changes in global passenger flights from December 16th, 2019, to May 15th, 2020. They found that starting from mid-March of 2020, the number of served origin-destination airport pairs dropped by about 75%, and the number of active aircraft decreased by two-thirds. In a related paper, Sun et al. (2021) investigated the influence of COVID-19 on air transportation systems, air passenger experience, and the long-term effects on aviation by reviewing 110 research papers. This review uncovered several important trends that are likely to occur in the aviation industry post-COVD including: the emergence of hub-operation reducing super long-haul flights, the application of a worldwide immunity license, and the development of competing and substitute transportation modes (e.g., high-speed rail and connected and automated vehicles).

Long-distance railway transportation was another sector hit hard COVID-19, especially in Asia and Europe (Rothengatter et al., 2021). The two biggest rail companies in Europe, Deutsche Bahn (Germany) and SNCF (France), both reported significant passenger and financial losses for their rail lines in the first half of 2020 (Rothengatter et al., 2021). Similarly, major intercity railway companies in Japan experienced a more than 30% decrease in either ridership or revenue (Ding and Zhang, 2021). In July 2020, the International Union of Railways (UIC, 2020) estimated an econometric model based on data obtained from various sources, including railway revenue data and economic forecast scenarios. According to their prediction, the missed revenues for the global passenger railway industry would reach $22 billion under a slow recovery scenario and $6.2 billion under a quick recovery scenario for the year 2021 (UIC, 2020).

Road transportation displayed divergent patterns for different transportation modes. Islam (2020) found that vehicle usage declined in the U.S. during the pandemic in terms of total hours of use and total number of vehicle miles traveled. A case study indicated that the demand for taxis in Shenzhen, China shrank by more than 85% during the lockdown period and experienced a delayed recovery in demand, compared to overall vehicle travel in the city (Zheng et al., 2021). In the U.S., Riggs and Appleyard (2020) found a reduction in vehicle miles driven but an increase in foot and bike trips for recreational purposes. Buehler and Pucher (2021) found that 11 European countries experienced an 8% increase in biking on average, and weekends had a much larger increase than weekdays. Recreational cycling in the U.S. and Canada also increased significantly during the pandemic (Buehler and Pucher, 2021; Fischer and Winters, 2021). Another study in the U.S. used data from New York City Bike Share and the Metro Transit Authority to compare bike sharing system and subway system use between February and March of 2020 (Teixeira and Lopes, 2020). It reported that although subway ridership dropped by 90% and bike sharing use dropped by 71%, the comparatively muted decline in bike sharing use suggests that this system perhaps provided a critical lifeline to low-income groups in need of public transit. This result provides support for prior work finding that bike sharing systems are critical to low-income groups as a means of transit (Reilly et al., 2020).

Water transportation also exhibited notable impacts influenced by the COVID-19 pandemic. Based on panel data for 14 major ports in China between January to October 2020, Xu et al. (2021) found that the severity of the pandemic, measured by the cumulative number of confirmed cases, had a significant negative effect on both import and export cargo throughputs due to the large-scale shutdown of factories. An Australian study based on information from numerous sources including but not limited to Google, Apple, Moovit, and interviews with transportation stakeholders predicted that water-based freight transportation declined by 9.5% as a result of the pandemic (Munawar et al., 2021). At the global level, Cullinane and Haralambides (2021) revealed that many major ports with a strong gateway function experienced a container throughput plunge in the first half of 2020, but also experienced a large rebound in activity in the second half of 2020. The fast transition in demand resulted in shortages in equipment, truck drivers and dock labor, and congestion and long turnaround times in these ports.

Trends in urban public transit are of concern because of the increased risk of transmission due to the large number of touch surfaces on which the virus can survive for several days, and also the close proximity of people in a confined, closed environment (Musselwhite et al., 2020; Vitrano, 2021). A longer-term concern about transit systems is the financial impact of reduced ridership on systems that are already challenged fiscally (Hörcher et al., 2020). Overwhelmingly, this group of studies find that public transit ridership decreased during the pandemic (Aloi et al., 2020; de Haas et al., 2020; Jenelius and Cebecauer, 2020) with understandable variations across study regions and type of system in question. In South Korea, for example, Park (2020) examined the impact of the pandemic on subway ridership between the third week of January and the first week of March and found a reduction of 40.6% in the average daily number of passengers. A study of rail transit in China used survey data to understand the likelihood that commuters would use this form of transit during the pandemic (Tan and Ma, 2020). They found several factors that impacted the probability of taking rail transit during the pandemic, including occupation, pre-pandemic mode of transport, and possibility of infection in a private car and on rail transit. In particular, self-employed or free-lance people were more likely to take public transit as were people that commuted via rail transit prior to the pandemic. In the U.S., Islam (2020) utilized data from the National Transit Database between 2012 and 2020 to examine the impacts of the COVID-19 pandemic on public transit ridership. The study found declines in travel via public transit. Stay-at-home policies did not explain these declines in public transit usage.

2.3. *Social Equity Impacts of COVID-19 Related Changes in Transportation*

Social equity issues are a well-noted issue in public transit research (Glaeser et al., 2008; Martin et al., 2016) and several studies have examined the extent that the pandemic exacerbated already inequitable access to public transit (Chen et al., 2021; Tirachini and Cats, 2020). In a study of King County, Washington, Brough et al. (2021) used a combination of mobile phone data, sensor data collected from county buses, transit fare card data, and surveys to assess mode substitution and travel intensity during the initial months of the pandemic (February, March, and April of 2020). They found that in the early stages of the shutdown, higher socio-economic status individuals used public transit less than their counterparts. As the pandemic wore on, however, this difference disappeared. The same study also found differences in travel intensity across individuals of varied levels of educational attainment and socio-economic status. Specifically, they found that individual with less education and lower incomes had higher travel intensities than individuals with more education and higher incomes. Brough et al. (2021) suggest that this difference in mobility responses is explained by an inability of lower income and less educated individuals to work from home and a greater need to travel to work in essential jobs. A study of COVID-related impacts on service adjustments (i.e., change in the number of unique trips) in North America, using Census block group level data from the General Transit Feed Specification (GTFS), found that reduced trip frequency has disproportionately affected low income and vulnerable populations in 30 U.S. and 10 Canadian cities (DeWeese et al., 2020). In their analysis of changes in public transit ridership in Nashville, Tennessee during the pandemic between January 1, 2019 and July 1, 2020, Wilbur et al. (2020) found a higher incidence of reduced ridership in higher income areas relative to lower income areas; ridership was 19% lower in higher income areas as compared to lower income areas. Emerging research suggests this increased reliance on public transport may disproportionately expose low-income and racial/ethnic minorities, who are more likely to be essential workers, to COVID-19 (Sy et al., 2020).

While there is a large and growing body of work on the employment impacts and transportation trends/impacts associated with COVID-19, there is little work at the intersection of these two research strands. It is important to fill this research gap because anecdotal evidence suggests that transportation workers have been hit hard by the pandemic in terms of COVID-19 cases and deaths (The Lancet, 2020). Research notes about the early months of the pandemic projected negative impacts on commercial truck drivers' health, safety, and stress exacerbated the older age of drivers, and unhealthy aspects of this line of work (e.g., poor diet and sleep, lack of physical activity, smoking) (Lemke et al., 2020a, 2020b). Aside from these potential impacts on truck driving occupations, we know little about the employment impacts within the transportation industry and the profiles of transportation workers most and least affected by the pandemic. We also do not know how employment trends among transportation workers compares to workers in other industries. This is important to ascertain given the heterogeneity of essential and non-essential occupations in the transportation industry. Given this heterogeneity, we propose three hypotheses. First, the transportation industry experienced a greater incidence of unemployment than other industries. Second, there is heterogeneity in employment impacts within the transportation sector. Third, specific sectors within the transportation industry experienced more employment impacts than essential non-transportation industries.

3. Methodology

3.1. Data Extraction and Preprocessing

To test the aforementioned hypotheses, this study uses the Current Population Survey (CPS) data between May 2020 and December 2020 (Flood et al., 2020). The CPS is a monthly survey of over 60,000 households administered by the United States Census Bureau (U.S. Bureau of Labor Statistics, 2020). The CPS is designed to represent the civilian noninstitutional population of each state (and the District of Columbia) in the U.S. based on a scientifically selected multistage probability-based sample of households (U.S. Bureau of Labor Statistics, 2018). The CPS data has a panel structure with multiple responses from the same households and individuals over consecutive months (a maximum of eight times). These data are well suited for comparing unemployment impacts related to COVID because it contains a survey question that asks respondents whether they were unable to work because of the pandemic (IPUMS, 2021).The survey also collects demographic and socio-economic information that prior studies have noted to explain employment impacts related to the pandemic (e.g., age, marital status, race/ethnicity, gender) (Beland et al., 2020; Borjas and Cassidy, 2020; Cowan, 2020; Fairlie et al., 2020; Montenovo et al., 2020). Table 1 presents the code and description of the variables from the CPS data used in this study, as well as their recoding for analyses.

Industry information in the CPS is based on the Survey of Income and Program Participation (SIPP) public use industry code list and the 2017 North American Industry Classification System (NAICS) codes (U.S. Census Bureau, 2020). Using these codes, it was possible to identify and classify respondents into two mutually exclusive categories, those working in the transportation industry and those not working in the transportation industry. It was also possible to further segment respondents into the following mutually exclusive categories: transportation industries, essential non-transportation industries (or 'other essential industries'), and non-essential non-transportation industries (or 'other non-essential industries'). Essential and non-essential industries were identified based on the recommended essential industry classification for phased allocation of COVID-19 vaccines in the U.S. (Centers for Disease Control and Prevention, 2021). There were three phases of vaccine allocation: 1a, 1b, and 1c. In this study, industries that were included in Phase 1a are considered to be essential industries, and the rest as non-essential industries. See Appendix A for a comprehensive list of transportation, essential non-transportation, and non-essential non-transportation industries.

Table 1 Variable Description and Recoding

Variable Code	Description	Recoded Variables
CPSIDP	Unique identifier for individual respondents	None (used to define the panel structure)
COVIDUNAW	Identifies if respondent was unable to work during the previous four weeks because their employer closed or lost business due to COVID-19	COVIDUNAW: 1 if unable to work due to the COVID-19 pandemic; 0 otherwise
AGE	Age	<u>YOUTH</u>: 1 if age is between 16 and 24 years; 0 otherwise MIDDLE-AGED: 1 if age is between 25 and 54 years; 0 otherwise OLDER: 1 if age is 55 years or above; 0 otherwise
SEX	Sex	FEMALE: 1 if female; 0 if male
RACE & HISPAN	Race & Hispanic origin	<u>WHITE</u>: 1 if White and not Hispanic; 0 otherwise BLACK: 1 if Black and not Hispanic; 0 otherwise ASIAN: 1 if Asian and not Hispanic; 0 otherwise AMERICAN INDIAN: 1 if American Indian and not Hispanic; 0 otherwise HISPANIC: 1 if Hispanic; 0 otherwise OTHER: 1 if none of the above; 0 otherwise
CITIZEN	Citizenship status	CITIZEN: 1 if U.S. citizen (born or naturalized); 0 otherwise
EDUC	Educational attainment, as measured by the highest year of school or degree completed	<u>NO HIGH SCHOOL</u>: 1 if no high school diploma; 0 otherwise HIGH SCHOOL: 1 if high school diploma; 0 otherwise COLLEGE: 1 if some college or associate degree; 0 otherwise BACHELOR: 1 if bachelor's degree; 0 otherwise GRADUATE: 1 if greater than bachelor's degree; 0 otherwise
VETSTAT	Veteran status	VETERAN: 1 if veteran; 0 otherwise
MARST	Marital status	MARRIED: 1 if currently married; 0 otherwise
IND	Type of industry in which the respondent performed his or her primary occupation	TRANSPORTATION: 1 if industry sector is transportation and warehousing; 0 otherwise
MONTH	Calendar month of the data (in the year 2020)	<u>MAY</u>: 1 if month is May; 0 otherwise JUNE: 1 if month is June; 0 otherwise JULY: 1 if month is July; 0 otherwise AUGUST: 1 if month is August; 0 otherwise SEPTEMBER: 1 if month is September; 0 otherwise OCTOBER: 1 if month is October; 0 otherwise NOVEMBER: 1 if month is November; 0 otherwise

		DECEMBER: 1 if month is December; 0 otherwise
ESSENTIAL INDUSTRIES AND TRANSPORTATION SECTORS[1]	Essential industry classification for non-transportation industries based on phased allocation plan of COVID-19 vaccines and industries in the transportation sector	<u>ESSENTIAL</u>: 1 if essential non-transportation industry (i.e., vaccine phase allocation 1a); 0 otherwise NON-ESSENTIAL: 1 if non-essential non-transportation industry; 0 otherwise AIR: 1 if sector is air transportation; 0 otherwise BUS: 1 if sector bus service and urban transit; 0 otherwise COURIER: 1 if sector is couriers and messengers; 0 otherwise PIPELINE: 1 if sector is pipeline transportation; 0 otherwise POSTAL: 1 if sector is postal service; 0 otherwise RAIL: 1 if sector is rail transportation; 0 otherwise SCENIC: 1 if sector is scenic and sightseeing transportation; 0 otherwise INCIDENTAL: 1 if sector is services incidental to transportation; 0 otherwise TAXI: 1 if sector is taxi and limousine service; 0 otherwise TRUCK: 1 if sector is truck transportation; 0 otherwise WAREHOUSING: 1 if sector is warehousing and storage; 0 otherwise WATER: 1 if sector is water transportation; 0 otherwise

[1] Variable is defined using multiple datasets
<u>Underlined recoded variables</u> are used as reference variables in their respective categories

Data preprocessing revealed apparent inconsistencies (e.g., change in age by more than a year in consecutive months) for a small proportion of CPS respondents with multiple observations (0.5% of responses). These data were not included in our 401,794 samples from 169,713 respondents for analysis (see Appendix B for more details on data validation).

3.2. Statistical Modeling

Random effects panel logit models were estimated to investigate the disproportionate impacts of the COVID-19 pandemic on survey respondents' inability to work because of closed or lost business at their employer. A random effects specification was selected over a fixed effects specification because we are interested in modeling unemployment variability between individuals over time rather than the variation in employment status within individuals over time. Above and beyond its relevance to our primary research question, a random effects specification allows for the inclusion of time-invariant characteristics while a fixed-effects specification does not (Bell and Jones, 2015).

In these logit models, our dependent variable, COVIDUNAW, has a binary outcome: the respondent was able to work, or the respondent was unable to work (see Table 1 for details). The modeling structure of the estimated random effects logit models is illustrated as follows. Let y_{ij} denote the binary outcome of the dependent variable COVIDUNAW for observation j of respondent i, where $j \in \{1, \dots, n_i\}$ and n_i is the number of observations for the respondent i. Then, the probability that the respondent i was unable to work due to the COVID-19 pandemic during observation j (i.e., $y_{ij} = 1$) for a given vector of explanatory variables X_{ij} and the respondent-specific random effect parameter u_i is given by Equation 1.

$$\Pr(y_{ij} = 1 \middle| X_{ij}, u_i) = \frac{1}{1 + e^{-\left(\beta_0 + X_{ij}^T \beta + u_i\right)}} \tag{1}$$

In Equation 1, β_0 denotes the model intercept and β denotes the vector of coefficients for the explanatory variables. The random effects parameter u_i is assumed to be normally distributed with mean 0 and variance σ_u^2; $u_i \sim N(0, \sigma_u^2)$. This is a common assumption in the literature for such models made for computational convenience (Agresti et al., 2004). Since y_{ij} is binary, the probability of $y_{ij} = 0$ can be calculated by Equation 2.

$$\Pr(y_{ij} = 0 \middle| X_{ij}, u_i) = \frac{1}{1 + e^{\left(\beta_0 + X_{ij}^T \beta + u_i\right)}} \tag{2}$$

Then, the panel-level likelihood l_i of all observations for respondent i is given by Equation 3.

$$l_i = \Pr\left(y_{i1}, \dots, y_{in_i} \middle| X_{i1}, \dots, X_{in_i}\right) = \int_{-\infty}^{\infty} \frac{e^{-\frac{u_i}{2\sigma_u^2}}}{\sqrt{2\pi}\sigma_u} \left\{ \prod_{j=1}^{n_i} \Pr\left(y_{ij},\ \beta_0 + X_{ij}^T \beta + u_i\right) \right\} du_i \tag{3}$$

Since l_i has the form $\int_{-\infty}^{\infty} e^{-x^2} h(x) dx$, it can be approximated with M-point Gauss-Hermite quadrature (Naylor and Smith, 1982). The log likelihood L, which is the sum of the logs of the l_i for all respondents, can be approximated by adaptive Gauss-Hermite quadrature (stata.com, n.d.). We used the 'xtlogit' command with 'mvaghermite' integration method in STATA 15.0 (stata.com, n.d.) to estimate the random effects logit model. The number of integration points in 'mvaghermite' were set to 12.

Model fitness for the fixed effects was assessed using Wald chi-square test, with p-value less than 0.05 indicating a good model fit. The suitability of panel structure (i.e., random effects model) was tested using intra-class correlation coefficient (ρ), which examines the proportion of panel-level or random effects variance component (σ_u^2) and unit-level variance component, as illustrated in Equation 4. A higher value of ρ favors the random effects model. Note that the unit-level variance component is not identifiable for the random effects logit model, and it is assumed to follow standard logistic distribution, which is equals to $\pi^2/3$, instead of 1 to avoid overestimation of ρ (Rodríguez and Elo, 2003).

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \pi^2/3} \tag{4}$$

All models incorporated sociodemographic covariates (including age, sex, race/ethnicity, citizenship status, education level, veteran status, and marital status). They also include time fixed effects (i.e., monthly dummy variables) to capture unemployment trends related to the public response to the pandemic as well as the implementation of various safety measures (e.g., stay-at-home orders) which were implemented at different times across the United States (Moreland et al., 2020).

Two separate specifications of our model are used to test the three hypotheses proposed in this study. The main source of variation in these models is the dummy variable that compares the transportation industry to other industries. In the first model, we use a dummy variable that compares the transportation industry to all other industries. This variable is used to test our hypothesis that workers in the transportation industry experienced a greater incidence of unemployment than other industries. In the second model, we use a different dummy variable that segments industries into thirteen categories as outlined in Table 1 above: transportation sub-industries, essential industries, and non-essential industries. This classification enables us to test our hypothesis that there is heterogeneity in employment impacts within the transportation industry. It also enables us to compare each transportation sub-industry to essential and non-essential industries and test our third hypothesis: specific sectors within the transportation industry experienced more employment impacts than other essential industries.

4. Results and Discussion

4.1. Descriptive Statistics

The final data contained 401,794 samples from 169,713 respondents. Figure 1 displays the inability to work due to COVID-19 by month for the full CPS sample, the transportation and warehousing industries, the essential non-transportation industries, and the non-essential non-transportation industries between May and December of 2020, compared to the number of newly confirmed cases by month in the U.S. during the same period. The number of new COVID-19 cases were obtained from Trading Economics, which reorganizes data from the World Health Organization (Trading Economics, 2021). It demonstrates that the unemployment rate for workers in the transportation and warehousing industries was higher than the other two categories and the full sample throughout the study period. The unemployment rates for all categories showed a downward trend and reached the bottom around October, whereas the number of new cases kept increasing. Figure 2 illustrates the percentage of people unable to work due to the pandemic for multiple sociodemographic characteristics. Appendix C provides more detailed descriptive statistics of our study sample for the explanatory variables (sociodemographic characteristics) used in estimating the model. It also shows the number of respondents that were either unable to work due to the COVID-19 pandemic (‘Yes’) or were not affected (‘No’) for each subcategory, along with their corresponding percentage split. It indicates that although the pandemic did not affect the ability to work for most people, workers belonging to certain minority groups (e.g., females, non-White or Hispanic, non-citizens, and people with lower level of education) were disproportionately more affected compared to their counterparts.

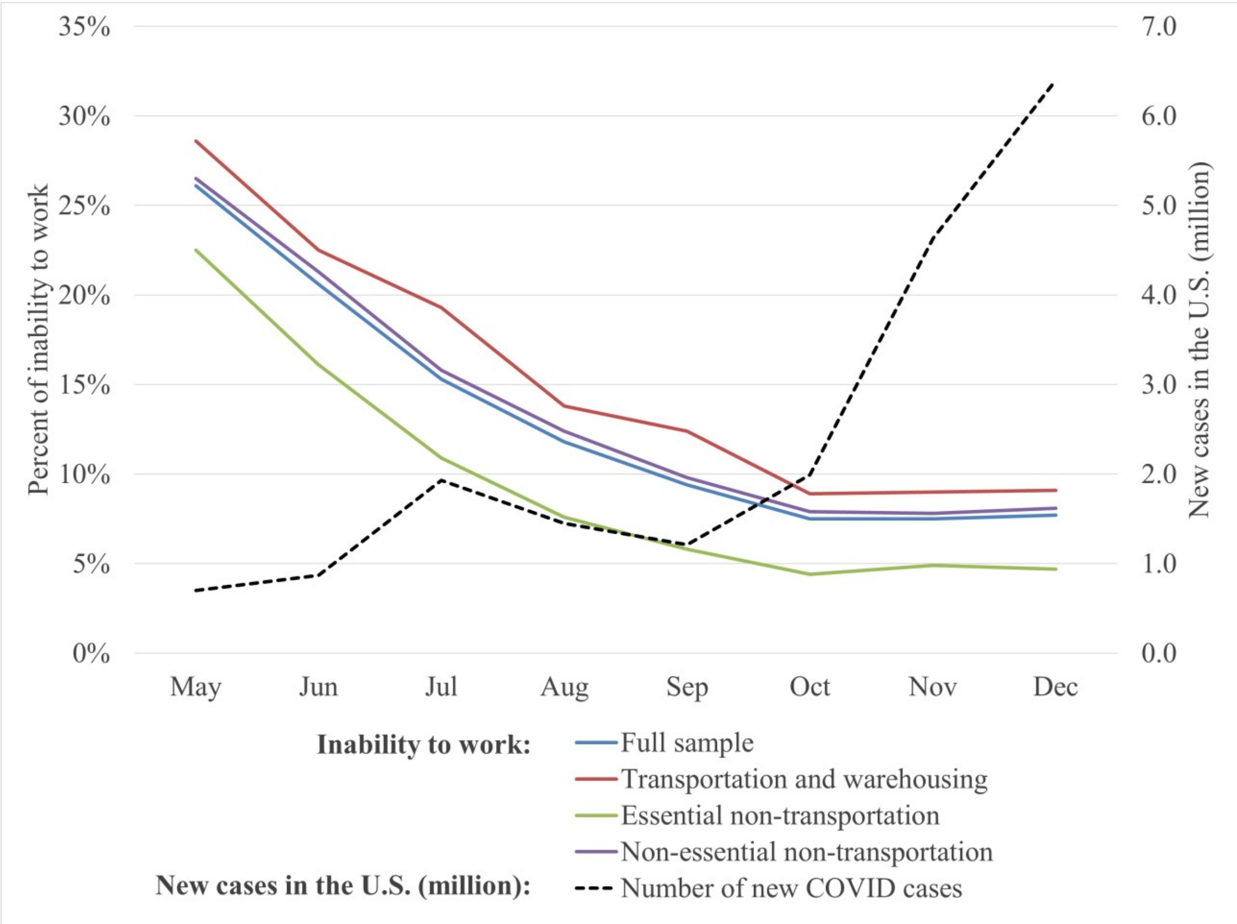

Figure 1 Monthly Inability to Work Due to COVID-19 and Number of New COVID-19 Cases in the U.S.

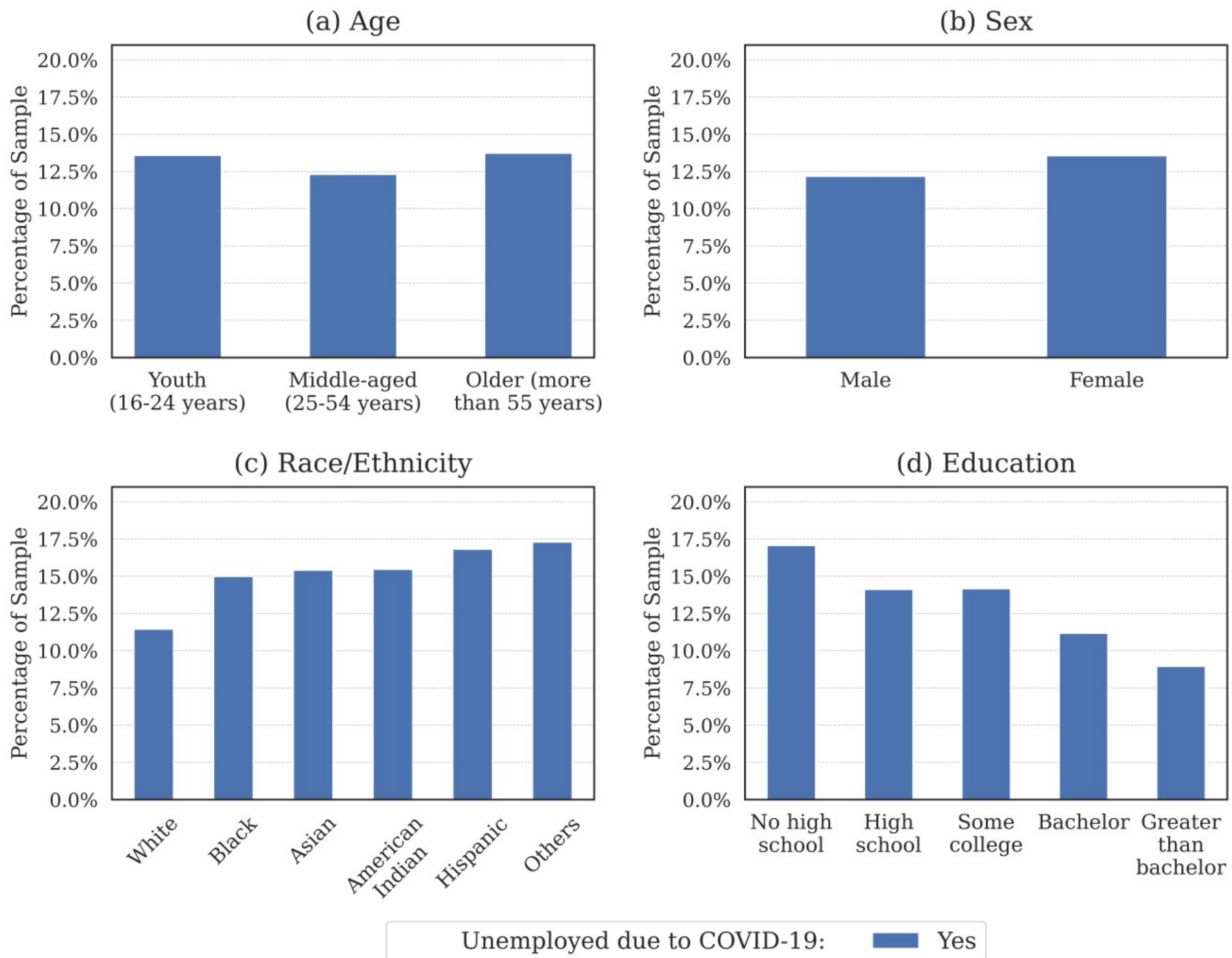

Figure 2 Unemployment Distribution by Sociodemographic Characteristics

Figure 3 shows the distribution of workers that were unable to work due to the pandemic in the transportation industry and other essential and non-essential industries. It also shows this distribution for different sectors within the transportation industry (see Appendix D for more details). If one computes the average across all sub-industries within the transportation sector, about 14.9% of respondents indicated they were unable to work because of the pandemic. This is certainly higher than 9.3% of workers in essential industries (e.g., Health Care and Social Assistance) and 13.3% of workers in non-essential industries (e.g., Accommodation and Food Services). Within the transportation sector, there is a great deal of heterogeneity in COVID-19 impacts. For example, only 2.9% of postal service workers were unable to work while 43.8% of taxi and limousine service workers were unable to work. Other transportation industries where workers were heavily impacted include scenic and sightseeing transportation (42.5%), water transportation (29.4%), and bus service and urban transit (29.0%).

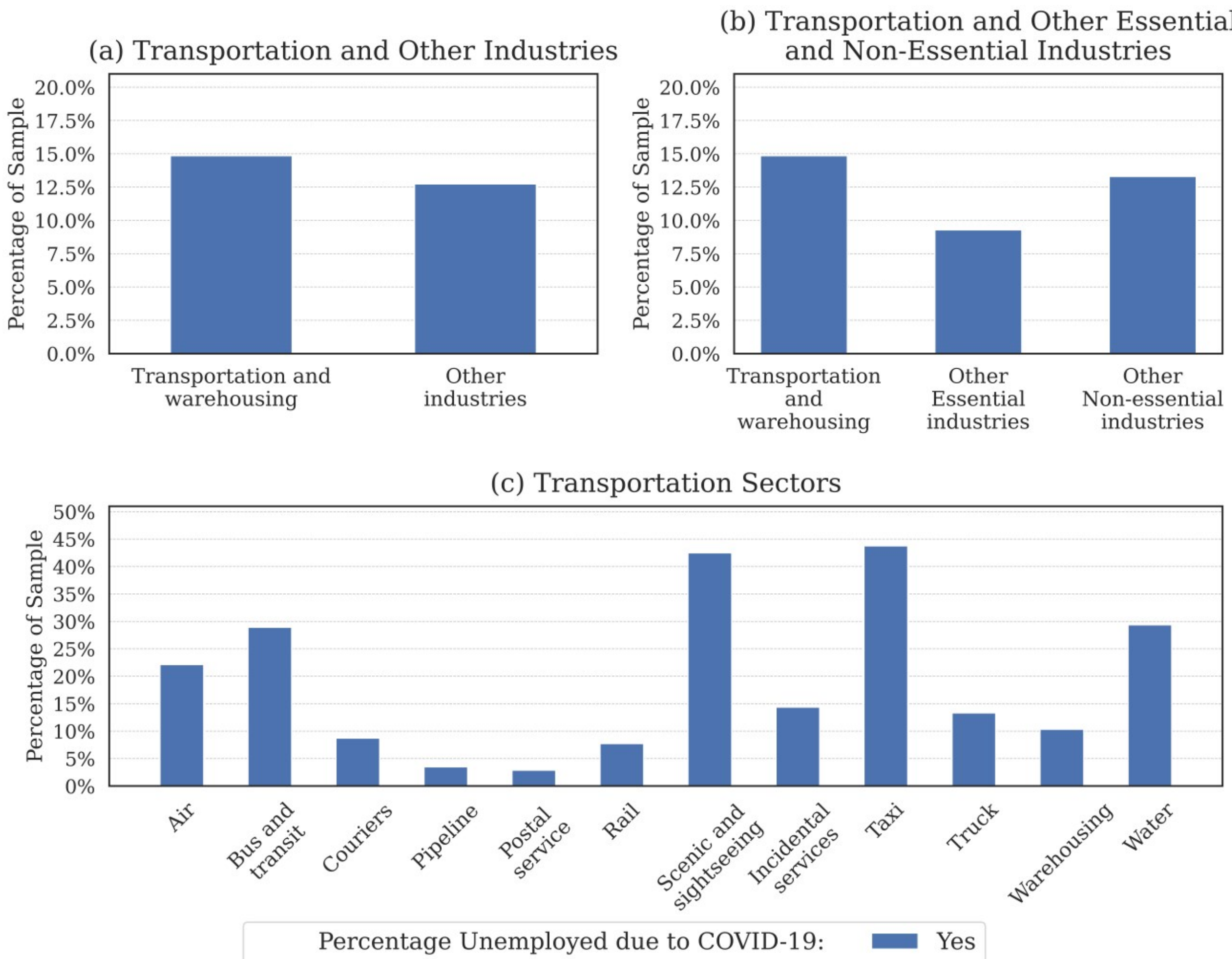

Figure 3 Unemployment Distribution by Industry Sectors

4.2. Model Results

To consider the likelihood that a survey respondent was unable to work because of the pandemic, accounting for all the factors presented in Table 1, multivariate logistic panel regression models were estimated. Table 2 presents the results of these models based on a segmentation of industries into transportation related and non-transportation related. The odds ratios presented in the table indicate how a unit change in each explanatory variable is associated with the changes in the odds of being able to work during the pandemic, compared to the odds of not being able to work. If setting p as the odds of being able to work, then the odds ratio can be expressed as $p/(1-p)$. For an explanatory variable X with a regression coefficient β, its odds ratio is calculated through the exponential function of the regression coefficient (e^{β}). An odds ratio equal to 1 indicates that the variable does not affect the odds of being able to work; an odds ratio that is greater than 1 indicates that the variable is positively associated with the odds, and an odds ratio that is smaller than 1 indicates a negative association with the odds. In the discussion that follows we will use the phrase "unemployed" as shorthand to refer to the "inability of people to work due to the COVID-19 pandemic."

These results indicate that workers in the transportation sector were 20.6% more likely to be unemployed because of the pandemic than workers in non-transportation industries. Relative to younger workers, middle aged and older workers were more likely to be unemployed during the pandemic. That said, older workers (ages 55 and older) were 57.3% more likely to be unemployed compared to young workers. This likelihood is greater than middle-aged workers (ages 25-54) who were 16.8% more likely to be unemployed compared to young workers. This result is different from prior work suggesting younger workers were more likely to be impacted by the pandemic (Beland et al., 2020; Cowan, 2020) but is in line with some research (Montenovo et al., 2020) and news sources suggesting older workers were more likely to be unemployed during the pandemic (Johnson, 2021; Sell, 2020; Terrell, 2020). Females were 29.2% more likely to be unemployed during the pandemic, which is consistent with prior research (Alon et al., 2020; Cowan, 2020; Montenovo et al., 2020) and news reports related to the pandemic (Bateman and Ross, 2020; Ellingrud and Segel, 2021).

Compared to White workers, racial and ethnic minorities were more likely to be unemployed, which is consistent with prior research (Beland et al., 2020; Cowan, 2020; Fairlie et al., 2020). Among racial and ethnic minorities, our model results indicate that survey respondents identifying as part of our other race group (e.g., multiracial people) were over two times more likely to be unemployed compared to Whites. Hispanic respondents were also more likely to be unemployed. However, U.S. citizens and married people were less likely to be unemployed. These results are consistent with prior work noting that foreign-born people are more likely to be unemployed (Cowan, 2020) as are unmarried people (Beland et al., 2020). Work on immigrants in particular notes that this community has been particularly hard hit by the pandemic due to their inability to telework (Borjas and Cassidy, 2020). Educational attainment is also linked to the inability to work and prior work notes that people with lower levels of educational attainment experienced the greatest employment impacts (Beland et al., 2020; Cowan, 2020). These studies reported a monotonic decrease in unemployment likelihood with higher education levels. Our results are consistent with this emerging body of work. People with higher levels of educational attainment are less likely to be unemployed during the pandemic. For example, people with a bachelor's degree are 48% less likely to be unemployed, compared to people without a high school diploma. People with a graduate degree are 66% less likely to be unemployed, compared to people without a high school diploma. These results may be linked to the ability of people with more education to work remotely and remain employed during the pandemic.

A final noteworthy aspect of model results are the fixed effects for time, which indicate a reduced likelihood of inability to work due to COVID-19. In May of 2020, the CPS data indicate that 26.5% of workers were unable to work due to the pandemic, and by December of 2020, this rate decreased to 8.1%. This decline in the inability to work is reflected in the odds ratios. The odds ratio for June for example, indicates people were 43% less likely to be unable to work compared to May. By December, they were 93% less likely to be unable to work.

Table 2 Model Comparing Transportation and Other Industries

Variable	Odds Ratio	Std. Err.	z	Significance Level
MIDDLE-AGED	1.168	0.041	4.410	***
OLDER	1.573	0.061	11.630	***
FEMALE	1.292	0.028	11.820	***

BLACK	1.600	0.058	13.070	***
ASIAN	1.940	0.090	14.220	***
AMERICAN INDIAN	1.684	0.182	4.830	***
HISPANIC	1.861	0.061	18.940	***
OTHER RACE	2.241	0.168	10.780	***
CITIZEN	0.579	0.025	-12.410	***
HIGH-SCHOOL	0.832	0.034	-4.440	***
COLLEGE	0.833	0.035	-4.340	***
BACHELOR	0.521	0.023	-14.760	***
GRADUATE	0.337	0.017	-22.100	***
VETERAN	0.823	0.041	-3.930	***
MARRIED	0.679	0.016	-16.960	***
TRANSPORTATION	1.206	0.055	4.080	***
JUNE	0.568	0.013	-23.890	***
JULY	0.290	0.008	-46.910	***
AUGUST	0.172	0.005	-61.160	***
SEPTEMBER	0.108	0.003	-72.410	***
OCTOBER	0.071	0.002	-80.410	***
NOVEMBER	0.069	0.002	-79.370	***
DECEMBER	0.070	0.002	-76.940	***
CONSTANT	0.250	0.016	-22.000	***
Log likelihood	-129054.360			
Wald chi-square test statistic	11029.870			
df for Wald test	23			
p-value for Wald test	0.000			
σ_u	2.696	0.020		
ρ	0.688	0.003		
Note: * 95% confidence level; ** 99% confidence level, *** 99.9% confidence level				

Given the heterogeneity of employment impacts on the transportation industry, an additional model was estimated to obtain odds ratios for sub-sectors within the transportation industry, and compare these sub-industries to essential and non-essential industries, as designed by the Centers for Disease Control and Prevention (CDC) Phase 1a vaccination guidelines. Table 3 presents these model results. By and large the odds ratios for the socio-demographic variables are consistent with those in Table 2, as are the monthly time dummy variables. The odds ratios for the transportation sectors do indicate heterogeneities in impacts within the industry, and the value of analyzing this industry from a more fine-grained perspective. During the 2020 months of the pandemic, taxi and limousine drivers were 28 times more likely to be unemployed compared to essential workers. Scenic and sightseeing transportation workers were 23.8 times more likely to be unemployed compared to essential workers. Notably, both these industries rely heavily on traveling customers for revenue, which was adversely affected by social distancing guidelines. Workers in other customer-oriented sectors (i.e., water, bus, and air) were more likely to be unemployed compared to workers in other essential and non-essential industries. The results also show that truck drivers and workers in services incidental to transportation were also more likely to be unemployed compared to essential workers. On the other end of the spectrum however, postal service workers were 84% less likely to be unemployed compared to essential workers. The likelihood of unemployment for workers in other transportation sectors did not show statistically significant differences (at 95% confidence level) compared to essential workers. Non-essential workers were about two times more likely to be unemployed compared to essential workers.

Table 3 Model Comparing Sub-Sectors Within Transportation and Other Essential and Non-Essential Industries

Variable	**Odds Ratio**	**Std. Err.**	**z**	**Significance Level**
MIDDLE-AGED	1.180	0.041	4.730	***
OLDER	1.565	0.061	11.540	***
FEMALE	1.418	0.031	15.860	***
BLACK	1.643	0.059	13.830	***
ASIAN	1.925	0.089	14.110	***
AMERICAN INDIAN	1.676	0.180	4.820	***
HISPANIC	2.214	0.165	10.670	***
OTHER RACE	1.860	0.061	19.020	***
CITIZEN	0.605	0.026	-11.500	***
HIGH-SCHOOL	0.850	0.035	-3.960	***
COLLEGE	0.872	0.037	-3.260	**
BACHELOR	0.533	0.023	-14.320	***
GRADUATE	0.361	0.018	-20.780	***
VETERAN	0.828	0.041	-3.830	***
MARRIED	0.684	0.016	-16.720	***
AIR	6.431	0.948	12.630	***
BUS	9.295	1.573	13.180	***
COURIER	0.885	0.112	-0.960	
PIPELINE	0.329	0.233	-1.570	
POSTAL	0.161	0.037	-7.900	***
RAIL	0.974	0.285	-0.090	
SCENIC	23.814	10.187	7.410	***
INCIDENTAL	2.449	0.326	6.730	***
TAXI	28.130	4.393	21.370	***
TRUCK	1.828	0.169	6.540	***

WAREHOUSING	1.037	0.152	0.250	
WATER	12.692	4.563	7.070	***
NON-ESSENTIAL	1.991	0.066	20.780	***
JUNE	0.569	0.013	-23.870	***
JULY	0.290	0.008	-46.890	***
AUGUST	0.173	0.005	-61.070	***
SEPTEMBER	0.108	0.003	-72.340	***
OCTOBER	0.071	0.002	-80.380	***
NOVEMBER	0.069	0.002	-79.260	***
DECEMBER	0.071	0.002	-76.800	***
CONSTANT	0.123	0.009	-29.150	***
Log likelihood	-128463.360			
Wald chi-square test statistic	11610.690			
df for Wald test	35			
p-value for Wald test	0.000			
σ_u	2.663	0.020		
ρ	0.683	0.003		
Note: * 95% confidence level; ** 99% confidence level, *** 99.9% confidence level				

5. Discussion and Conclusions

The economic impacts associated with the pandemic produced unemployment rates that exceeded the Great Recession of 2008 in the first three months of the pandemic (Kochhar, 2020). Given these unprecedented impacts, research has investigated who was more likely to be unemployed during the pandemic and found particular populations including racial/minorities, women, immigrants, and the less educated were disproportionately impacted (Beland et al., 2020; Cowan, 2020; Fairlie et al., 2020; Montenovo et al., 2020). Studies suggest these impacts are related to work in jobs with an inability to telework (Montenovo et al., 2020). The pandemic also had notable impacts on transportation activity (Arellana et al., 2020; Lou et al., 2020; Riggs and Appleyard, 2020). Due to these impacts, a parallel line of inquiry has transportation impacts in three areas: trends in mobility, public transit usage, and equity impacts of changes in transportation. These studies found declines in the availability and usage of many transportation modes, including air, long-distance rail, road, water, and public transit (Cullinane and Haralambides, 2021; Islam, 2020; Rothengatter et al., 2021; Sun et al., 2020). They also found changes in public transit availability negatively impacted low income and vulnerable populations (DeWeese et al., 2020; Wilbur et al., 2020). In addition, previous studies also revealed that transportation-related jobs had a low telework ability, which indicated greater economic and health risks for these jobs (Dingel and Neiman, 2020). To this point in time however, research has not connected these strands of inquiry to investigate and compare the impact of COVID on employment in the transportation industry.

To fill this gap in our knowledge, this study estimated random effects logit models using panel survey data from the CPS. Two models were estimated to test three hypotheses. One, the transportation industry experienced a greater incidence of unemployment than other industries. Two, there is heterogeneity in employment impacts within the transportation sector. Three, specific sectors within the transportation industry experienced more employment impacts than other essential industries. Model results indicate that the transportation industry experienced a greater incidence of unemployment than other industries. They also provided evidence of heterogeneity in the likelihood of being unemployed within the transportation industry. Transportation workers in tourism-related sub-sectors (e.g., taxi, scenic, air) were more likely to be unemployed as travel around the world plummeted during the pandemic. Transportation workers in public transit (e.g., bus) and cargo shipping related industries (e.g., water) were also more likely to be unemployed due to shutdowns of nearly all activity in the beginning months of the pandemic. These results suggest that workers in affected occupations lost income and experienced financial hardship because of the pandemic. Other industries were far less likely to be unemployed (e.g., postal) than essential workers because work in these transportation sub-sectors continued throughout the pandemic. These results suggest greater exposure to COVID-19 for workers that remained employed in transportation during the pandemic.

From a policy perspective, these results suggest that attention to several aspects of transportation work are needed in the coming years to prepare for future interruptions to the transportation industry. One, cross-training in work activities that could be conducted remotely or moved to remote work may alleviate some of the employment impacts. Two, provision of health care for workers that must work and cannot work remotely, above and beyond the provision of personal protective equipment (PPE), is critical. Three, although the U.S. government provided payroll assistance to some transportation sectors (i.e., air, rail, and transit) to cope up with lost business due to COVID-19 (Shepardson and Rucinski, 2020), such financial assistance programs also need to target workers in sub-sectors (e.g., taxi and scenic) that experienced significantly more adverse impacts of the pandemic in terms of employment. Lastly, for future crises, short-term emergency measures such as the Coronavirus, Aid, Relief and Economic Security (CARES) which provided funding to transit systems to keep them running (Courtney, 2020; Islam, 2020). Longer term financial solutions are also needed however to make up fare shortfalls from the pandemic to keep already financially strained transit systems running (TransitCenter, 2020), particularly for populations that rely on public transit as their only means of transportation (Blumenberg and Ong, 2001; Glaeser et al., 2008; Mensah, 1995).

Despite the insights and contributions, this study has a few limitations. One, although the CPS data provides a representative sample, some industry sectors (e.g., pipeline transportation) have a small sample size. This may have led to a large variance for those subsamples that affected the model estimation. Two, while our analysis illustrates the employment impact of the pandemic on transportation workers, the underlying causes of the impact remain unknown due to the limited information provided by the data. To inform effective policymaking, more in-depth explorations are needed in the future, including qualitative and survey research targeting this specific worker group. Three, the CPS data does not specify some emerging transportation-related jobs, such as ridehailing drivers, e-scooter allocators, and app-based delivery drivers. These workers may have distinct employment patterns compared to those in traditional transportation sectors, which need further investigations in the future. Finally, this analysis is specific to unemployment trends in the United States. While transportation workers around the world, particularly in the airline industry, were undoubtedly affected by the pandemic, these results may not translate to other countries for a variety of reasons including but not limited to: widely varying policy responses related to the pandemic, the elevated presence of transportation workers involved in the informal economy in the developing world, variations in demand across transportation modes, and variations in rates of personal car ownership. Given these sources of variation, future work should examine the impact of the COVID-19 pandemic on transportation workers around the globe to understand how these varying contexts may have translated to higher or lower unemployment rates for this segment of workers as compared to the United States.

The COVID-19 pandemic is the latest disruption to global transportation systems, and it will not be the last. This piece demonstrated the impact of the most recent pandemic on transportation employees and highlighted their unemployment vulnerability relative to other workers, including essential workers. As the world becomes increasingly integrated, the likelihood of disruptions to transportation systems from pandemics, terrorism and climate change is highly likely. Proactive planning for future disruptions to transportation systems is needed to protect the health and economic livelihoods of the people that keep this critical infrastructure running.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT Authorship Contribution Statement

Elizabeth A. Mack: Conceptualization, Methodology, Formal analysis, Writing – Original draft, Funding acquisition, Writing – Review & Editing. Shubham Agrawal: Methodology, Formal analysis, Data curation, Visualization, Writing – Original draft, Writing – Review & Editing. Sicheng Wang: Writing – Review & Editing, Visualization.

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Appendix A: Industry Segments

Industry Segment	NAICS Level 2 and Level 3 Industries[1]
Transportation and warehousing industries	Transportation and warehousing industries (Air transportation; Bus service and urban transit; Couriers and messengers; Pipeline transportation; Postal Service; Rail transportation; Scenic and sightseeing transportation; Services incidental to transportation; Taxi and limousine service; Truck transportation; Warehousing and storage; Water transportation)
Essential non-transportation industries	Health Care and Social Assistance (except, Community food and housing, and emergency services; Child day care services; Vocational rehabilitation services); Retail trade (Pharmacies and drug stores); Other Services, Except Public Administration (Funeral homes, and cemeteries and crematories)
Non-essential non-transportation industries	Accommodation and Food Services; Administrative and support and waste management services; Agriculture, Forestry, Fishing, and Hunting; Arts, Entertainment, and Recreation; Construction; Educational Services; Finance and Insurance; Health Care and Social Assistance (Community food and housing, and emergency services; Child day care services; Vocational rehabilitation services); Information; Manufacturing; Military; Mining, Quarrying, and Oil and Gas Extraction; Other Services, Except Public Administration (except, Funeral homes, and cemeteries and crematories); Professional, Scientific, and Technical Services; Public Administration; Real Estate and Rental and Leasing; Retail Trade (except, Pharmacies and drug stores); Utilities; Wholesale Trade

[1] Specific NAICS level 3 industries are listed in parentheses

Appendix B: CPS Data Validation

Variable Code	Validation Check	Respondents Removed	Samples Removed
AGE	Increases by at most 1 once	1798	5262
SEX	Does not change	301	861
RACE	Does not change	425	1289
CITIZEN	Does not change	195	569
VETSTAT	Does not change	184	547
Total[1]	**-**	**2483**	**7387**

[1] Total count does not add up to the individual counts due to overlapping data

Appendix C: Descriptive Statistics of the Study Sample

	Sample		Unable to work due to COVID-19			
	Frequency	**Percentage**	**Yes**	**Yes%**	**No**	**No%**
Age						
Youth (16-24 years)	45227	11.26	6148	13.59	39079	86.41
Middle-aged (25-54 years)	247211	61.53	30440	12.31	216771	87.69
Older (55 years and over)	109356	27.22	15029	13.74	94327	86.26
TOTAL	401794		51617		350177	
Sex						
Male	209682	52.19	25548	12.18	184134	87.82

Female	192112	47.81	26069	13.57	166043	86.43
TOTAL	401794		51617		350177	
Race/Ethnicity						
White	278987	69.44	31954	11.45	247033	88.55
Black	36639	9.12	5496	15.00	31143	85.00
Asian	22506	5.60	3469	15.41	19037	84.59
American Indian	3412	0.85	528	15.47	2884	84.53
Hispanic	53299	13.27	8967	16.82	44332	83.18
Other	6951	1.73	1203	17.31	5748	82.69
TOTAL	401794		51617		350177	
U.S. Citizenship Status						
Citizen	376023	93.59	46908	12.47	329115	87.53
Not a citizen	25771	6.41	4709	18.27	21062	81.73
TOTAL	401794		51617		350177	
Highest Education Attained						
No high school diploma	27958	6.96	4775	17.08	23183	82.92
High school diploma	104619	26.04	14779	14.13	89840	85.87
Some college or associate degree	110307	27.45	15635	14.17	94672	85.83
Bachelor's degree	98934	24.62	11058	11.18	87876	88.82
Greater than bachelor's degree	59976	14.93	5370	8.95	54606	91.05
TOTAL	401794		51617		350177	
Veteran Status						
Veteran	21971	5.47	2413	10.98	19558	89.02
Not a veteran	379823	94.53	49204	12.95	330619	87.05
TOTAL	401794		51617		350177	
Marital Status						
Currently married	222753	55.44	25994	11.67	196759	88.33
Currently not married	179041	44.56	25623	14.31	153418	85.69
TOTAL	401794		51617		350177	

Appendix D: Data Distribution by Industry

	Sample		**Unable to work due to COVID-19**			
	Frequency	**Percentage**	**Yes**	**Yes%**	**No**	**No%**
Industry						
Transportation and warehousing	18849	4.69	2802	14.87	16047	85.13
Other	382945	95.31	48815	12.75	334130	87.25
TOTAL	401794		51617		350177	

Non-Transportation Industry						
Essential industries	53653	13.35	4988	9.30	48665	90.70
Non-essential industries	329292	81.96	43827	13.31	285465	86.69
TOTAL	382945		48815		334130	
Transportation and Warehousing Industries						
Air transportation	1557	8.26	345	22.16	1212	77.84
Bus service and urban transit	1029	5.46	298	28.96	731	71.04
Couriers and messengers	2985	15.84	261	8.74	2724	91.26
Pipeline transportation	171	0.91	6	3.51	165	96.49
Postal Service	1759	9.33	51	2.90	1708	97.10
Rail transportation	632	3.35	49	7.75	583	92.25
Scenic and sightseeing transportation	127	0.67	54	42.52	73	57.48
Services incidental to transportation	2124	11.27	306	14.41	1818	85.59
Taxi and limousine service	1064	5.64	466	43.80	598	56.20
Truck transportation	5250	27.85	701	13.35	4549	86.65
Warehousing and storage	1930	10.24	200	10.36	1730	89.64
Water transportation	221	1.17	65	29.41	156	70.59
TOTAL	18849		2802		16047	