Impact of the COVID-19 Pandemic on Commute Times of the US Working Age Population

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Abstract

The COVID-19 pandemic significantly disrupted various aspects of daily life, including transportation to work. This study investigates the impact of the pandemic on transit times for the working-age population in the United States. By analyzing data from the American Census Bureau pre- and post-pandemic, I examine changes in average transit times controlling for the influence of several socio-economic factors. Using multiple regression models, I find that transit times decreased by an average of 4.8 minutes post-pandemic, with a statistically significant t-value of 127.92. The analysis also explores the effects of variables such as home value, income, sex, age, poverty status, marital status, metropolitan status, industry of employment, and race on transit time. The findings highlight significant shifts in commuting patterns and provide insights into how the pandemic has reshaped urban mobility and work-life balance, shedding light on the broader impacts of the pandemic on workforce conditions, commuting patterns, and urban mobility.

Introduction

The COVID-19 pandemic refers to the worldwide outbreak of SARS-CoV-2 in 2020. The virus spread mainly through respiratory droplets, making it highly contagious. While symptoms vary from mild respiratory issues to severe illness, including pneumonia, they can be fatal, especially for older adults and individuals with preexisting health conditions (Sheikh, 2020). The pandemic profoundly disrupted daily life, healthcare systems, and economies worldwide, causing unprecedented challenges and changes across multiple sectors, including work, education, and transportation.

With this research, I am seeking to investigate how transit times to work were influenced as a result of the COVID-19 pandemic. The data compares rates before and after the pandemic to provide valuable information to quantify and better explain this relationship. Understanding how COVID-19 affected transit time to work sheds light on the broader impacts of the pandemic on daily life and urban mobility, while also highlighting changes in commuting patterns and transportation usage. It also offers insights into how workplaces have adapted and the potential long-term impacts on office culture and work-life balance. COVID-19 was an unprecedented pandemic that changed the lives of millions of Americans. The effects of the pandemic caused a multitude of workers to alter their working patterns, pushing a substantial amount of the workforce to adapt to remote working situations. This change resulted in increased reliance on digital communication and virtual cooperation platforms. Due to this widespread shift, I expect a decrease in transit times. As remote work becomes a more prominent fixture in the occupational landscape, I expect these changes to persist, leading to a decreased amount of transit time after the pandemic.

Data

This data is sourced from the American Census Bureau for the years 2019 and 2022. These years were specifically selected due to their relevance to the pandemic's timeline: 2019 represents the pre-pandemic period, and 2022 represents a period of adjustment with widespread vaccine use (Sencer, 2023). I was operating under the assumption that economic effects were caused by the pandemic due to its widespread impacts on all spheres of life– including economic, social, and political life.

The dependent variable was the average number of minutes it took an individual to get from their home to work in the week before the survey was conducted (***trantime***).

To control for other factors that might affect transit time, I also included variables of sex, marriage status, poverty status, industry of employment, race, house value, and metropolitan status. I cleaned and manipulated these variables to more singularly account for their effects on transit time. After cleaning the dataset, I retained over 1.5 million observations in total, and over 769,000 observations each for 2019 and 2022.

Post was a binary indicator variable I generated for the year of data collection (2019 or 2022), coded as 0 for pre-pandemic and 1 for post-pandemic observations.

I created a binary indicator variable, ***sex**,* to control for the effects of sex (male = 0, female = 1) in the analysis.

I generated a binary indicator for marriage status, ***marst***, to indicate if someone was married (1) or not (0).

Poverty was made into a binary indicator to represent if a household was above the poverty line (1) or at or below the threshold (0).

I also employed categorical variable ***metro*** which revealed the extent to which respondents lived in a metropolitan area. I excluded observations with indeterminable metropolitan status.

Log home value was a quantitative variable. I first limited ***valueh*** to retain only homes valued under $1,000,000 to exclude outliers that could skew the analysis. I then transformed the home values using the natural logarithm to handle right skewness in property values.

Log wage income was a quantitative variable, logged to account for right-skew. I first excluded invalid or placeholder ***incwage*** values (9999) and kept only positive, nonzero wage incomes within a reasonable range to ensure valid data. I then transformed the variable using the natural logarithm. This normalization addressed the right-skewness in income distribution, as higher incomes might correlate with shorter travel times due to better access to transportation options, or very high incomes could be associated with longer commutes from suburban areas.

Age and squared age were quantitative variables. I first limited ***age*** to observations within the working age population (16 to 65 years). I then squared to account for age's non-linear effect on travel time, as younger and older individuals might have different travel patterns compared to middle-aged individuals.

Race was a categorical variable whose nine original values I reclassified into five larger groups: White, Black, Native, Asian, and Other/Multiple races.

Table 1: Descriptive Statistics of Variables

Variable	Mean	Std Dev.	Minimum	Maximum
Transit Time (mins)	25.24037	23.82553	0	200
Log Home Value	12.47175	0.9184142	6.907755	13.81551
Log Wage Income	10.66494	1.092209	1.386294	13.58105
Sex	0.4824839	0.4996933	0	1
Age	43.61447	13.14813	16	65
Age Squared	2075.095	1118.026	256	4225
Poverty Status	0.9800926	0.139682	0	1
Marital Status	0.6092225	0.4879248	0	1
Metro Status				
Not in metro	0.1231846	0.3286491	0	1
In metro: main city	0.0971601	0.2961758	0	1
In metro: not main city	0.3869916	0.4870619	0	1
In metro: mixed	0.3926636	0.4883432	0	1
Race				
White	0.7501418	0.4329309	0	1
Black	0.0685375	0.252666	0	1
Native	0.0080864	0.0895601	0	1
Asian	0.0683003	0.2522606	0	1
Other/Multiple	0.104934	0.3064685	0	1
Post (Covid-19)	0.5002732	0.5000001	0	1
Industry (Indicators Included)				
Observations	**1,539,129**			

Methodology

I used multiple regression models to analyze the relationship between transit time and the independent variables. The regression models are specified as follows:

$$\text{Transit Time}_{2019} = \beta0_{2019} + \beta1\text{*Log Home Value}_{2019} + \beta2\text{*Log Income}_{2019} + \beta3\text{*Sex}_{2019} + \beta4\text{*Age}_{2019} + \beta5\text{*Age Squared}_{2019} + \beta6\text{*Poverty Status}_{2019} + \beta7\text{*Marriage Status}_{2019} + \beta8\text{*Metropolitan Status}_{2019} + \beta9\text{*Industry}_{2019} + \beta10\text{*Race}_{2019} + \varepsilon_{2019}$$

$$\text{Transit Time}_{2022} = \beta0_{2022} + \beta1\text{*Log Home Value}_{2022} + \beta2\text{*Log Income}_{2022} + \beta3\text{*Sex}_{2022} + \beta4\text{*Age}_{2022} + \beta5\text{*Age Squared}_{2022} + \beta6\text{*Poverty Status}_{2022} + \beta7\text{*Marriage Status}_{2022} + \beta8\text{*Metropolitan Status}_{2022} + \beta9\text{*Industry}_{2022} + \beta10\text{*Race}_{2022} + \varepsilon_{2022}$$

$$\text{Transit Time} = \beta0 + \beta1\text{*Log Home Value} + \beta2\text{*Log Income} + \beta3\text{*Sex} + \beta4\text{*Age} + \beta5\text{*Age Squared} + \beta6\text{*Poverty Status} + \beta7\text{*Marriage Status} + \beta8\text{*Metropolitan Status} + \beta9\text{*Industry} + \beta10\text{*Race} + \beta11\text{*Post} + \varepsilon_i$$

Results

As this research surrounds the effects of the pandemic, quantifying the relationship between transit time and periods before and after the pandemic allows for a comparison between the primary variables. The ***post*** variable served as an indicator of the year, offering a method for comparison between the regression models. The coefficient for this variable, -4.834, demonstrates a significant negative correlation between transit times before the pandemic and times afterwards. This means that, on average, transit times decreased by 4.8 minutes for the American working age population after the Covid-19 pandemic compared to times before the pandemic holding sex, age, poverty status, marital status, metropolitan status, income, home value, industry of work, and race constant.

For a two sided t-test, at $\alpha = 0.1$ and df = ∞, statistically significant t values are greater than 2.576. The absolute value of t_{post} = 127.92, which is significantly greater than 2.576. Thus, I would reject the null hypothesis, that there is no difference between transit times before and after the pandemic. This conclusion assumes no contemporaneous shocks and that there are no underlying trends in transit times. For all the post regression, I found an R-squared value of 0.047, for the 2019 regression I found an R-squared value of 0.046, and for the 2022 regression I also found an R-squared value of 0.047. This means the data generally fit the regression model at about 4.7%. This could mean that the model is not predictive, but it could also mean that there are confounding factors in the data or unaccounted variables that are lowering the R-squared.

Table 2: Multivariate Regression Results

VARIABLES	Post Transit Time	2022 Transit Time	2019 Transit Time
Log Home Value	0.101***	0.534***	-0.331***
	-0.0223	-0.0336	-0.0295
Log Income	1.359***	2.035***	0.646***
	-0.0226	-0.0326	-0.031
Sex	-2.492***	-1.916***	-3.042***
	-0.0425	-0.0617	-0.0581
Age	0.165***	0.175***	0.168***
	-0.0111	-0.0162	-0.0151
Age Squared	-0.00203***	-0.00231***	-0.00191***
	-0.000127	-0.000185	-0.000173
At or Below Poverty Line	-1.414***	-1.719***	-0.861***
	-0.139	-0.205	-0.189
Marital Status	-0.793***	-0.925***	-0.709***
	-0.0438	-0.0635	-0.0598
Metro: Main City	0.456***	1.622***	-0.779***
	-0.0848	-0.123	-0.116
Metro: Not Main City	2.547***	3.647***	1.406***
	-0.0646	-0.0937	-0.0883
Metro: Mixed	-1.317***	-0.814***	-1.833***
	-0.0638	-0.0926	-0.0871
Black	3.955***	4.359***	3.605***
	-0.0766	-0.11	-0.105
Native	1.106***	-0.119	1.659***
	-0.211	-0.335	-0.266
Asian	3.628***	4.476***	2.805***
	-0.0771	-0.113	-0.104
Other/Multiple Races	2.598***	2.532***	2.407***
	-0.0637	-0.123	-0.0733
Post	-4.834***		
	-0.0385		
Constant	7.240***	-6.980***	16.70***
	-0.456	-0.672	-0.616
^Industry variable fixed effects also controlled for			
Observations	1,539,129	769,144	769,985
R-squared	0.047	0.047	0.046

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

This study intended to observe how the COVID-19 pandemic has affected transit times to work for the working-age population of the United States by comparing data from 2019 and 2022. I observed a statistically significant decrease in transit times post-pandemic. The results indicate that the pandemic has led to notable changes in commuting patterns, likely due to increased remote work and other adaptations in workplace practices.

These findings underscore the broader impacts of the pandemic on daily life and urban mobility, revealing significant shifts in how people interface with their work. These insights are crucial for policymakers and urban planners in understanding and addressing the long-term implications of the pandemic on, for example, transportation infrastructure and urban development.

Future research could explore the specific causes of reduced transit times, such as remote work trends and changes in public transportation usage. Additionally, examining the impact of the pandemic on other aspects of transportation, such as traffic congestion and environmental effects, would provide a more comprehensive understanding of the pandemic's influence on urban life.

References

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