Work from Home Patterns Across COVID-19 Waves: Implications for Future Transportation

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ABSTRACT

The unprecedented rise in work from home (WFH) during COVID-19 poses challenges for the transportation engineers and planners with the travel demand forecasting. If WFH persists post-pandemic, it could influence traffic patterns, reducing peak-hour congestion. However, the evolution of WFH decisions across pandemic phases and varying socio-economic contexts remains unclear. This study examines factors influencing WFH choices using data from the US Census Bureau's Household Pulse Survey. Findings reveal a decline in WFH participation from 60% during the first wave to 38% by the third wave of the COVID-19 pandemic. A Geographically Weighted Regression model highlights the influence of socio-economic, household, and COVID-19-related variables, with notable spatial variability. Results show that younger individuals, females, and households with children are consistently more likely to WFH, while non-white and higher-income individuals increasing likelihood for WFH as the pandemic progresses. These insights inform future transportation planning, emphasizing equity and decentralization strategies for post-pandemic commuting.

INTRODUCTION

The COVID-19 pandemic has emphasized the critical role of information and communication technologies (ICTs). ICT facilitates the opportunity for virtual engagement. Work from home (WFH) is one of many online engagements. WFH is changing the workforce and economy during COVID-19. Many workers (full-time and part-time) have the opportunities to work from home, which can bring significant changes in their personal travel behavior. It is estimated that in 2017, before the pandemic, 12% of people were engaged in work from home, which was expected to increase further in the future years (NHTS 2017). In fact, in 2020, during the pandemic, the percentage of people working from home went over 50%. More specifically, WFH among knowledge workers grew exponentially to 61% within a few months of the pandemic in 2020 (Slason 2020). As more workers are working from home, fewer vehicles are being driven by commuters. In April 2020, Google mobility data (2020) reported a 40% reduction in workplace travel activity. However, residential travel activity went up by 13%, indicating that employers and employees are shifting to remote work. Unacast (2020) also reported similar drops in commuter travel during the pandemic compared to pre-COVID-19.

Presumably, working from home is associated with several potential benefits, including reduced traffic congestion, lower emissions, cost savings on office space, and increased flexibility for employees (Drucker and Khattak 2000). WFH provides benefits for highway travel to be spread more evenly throughout the day and a reduction in peak hour traffic. More households may choose to share one car while also using transit or other modes of travel. The presence of kids in households may motivate people to make fewer trips and work from home. However, people who work from home may also take more non-essential trips. All these conflicting natures of WFH render it important to be investigated during COVID-19.

During the pandemic, WFH makes the transportation engineers and planners struggle with the travel demand forecasting implications. If people are likely to work from home even after the pandemic, what will this mean for forecasting and infrastructure planning? It is crucial that our travel models and their underlying economic assumptions need to be changed to keep pace with the ongoing progression of travel behavior. Besides, we may expect some degree of a permanent shift in travel behaviors. Therefore, this study aims to analyze the household, socio-economic, and locational factors that motivated people to work from home in different pandemic waves, which may suggest directions to reshape commute and the related travel pattern.

LITERATURE REVIEW

Work from home (also known as telework or remote work) can be defined as a kind of work arrangement where employees of an organization work from/at home instead of working in person in offices (Yap and Tng 1990). This is possible through improved ICTs, e.g., internet, computers, telephones, voice mail systems, etc. WFH can also be hybrid, where an employee works at home a few days a week and also, he/she works at the office on the remaining weekdays (NHTS 2017). The implications of WFH on travel demand and urban sustainability goals largely depend on policy measures (Gillespie 2000). While it is commonly assumed that WFH reduces overall travel demand, Gillespie (2000) argued that its impact on travel substitution is more complex than often presumed. Similarly, Mokhtarian (1998) highlighted that WFH, paradoxically, could lead to more dispersed and car-dependent work patterns despite reducing congestion. Visser & Lanzendorf (2004) suggested that WFH might even contribute to increased overall mobility, including both personal travel and freight transport. Empirical studies further illustrate these nuanced effects. For example, Loo and Wang (2017) found that individuals with higher education levels are more likely to work from home and take fewer commute trips, possibly due to their familiarity with ICT tools and greater negotiating power with employers. Silva et al. (2018) examined the relationship between WFH and travel patterns in one-worker households in Great Britain, concluding that WFH is often a strategy to avoid long and costly commutes. However, their findings also suggested that WFH could lead to increased weekly travel distances, making it an ineffective strategy for reducing total travel demand. On the contrary, the findings of Graaff (2004) suggest a substitution between ICT and commuting, referring that more working at home decreases travel time. However, if total travel is considered, the relationship becomes complex.

Research shows contradictory findings on the correlation of gender on WFH. For example, Belanger (1999) found that females are more interested in WFH compared to their male counterparts. On the contrary, Lim and Teo (2000) reveal that both men and women are not that different in their attitude toward WFH; however, they found that married individuals are more prone to WFH. Drucker and Khattak (2000) found in their study that males and drivers are more prone to telework than females and non-drivers. The study also reported that the presence of a kid in a household prompts people to work from home. Regarding transport accessibility, a study shows that the lack of free parking in workplaces encourages people to work from home (Drucker and Khattak 2000). Besides, organizational commitment is typically negatively associated with the favor of WFH (Bélanger 1999). Furthermore, the pandemic can affect the travel and satisfaction level of WFH. The findings of Tahlyan et al. (2022) indicated that old and younger people get lower satisfaction (e.g., benefits) and higher obstacles to WFH than middle-aged people. Beck and Hensher (2022) suggested that WFH will continue in the form of a hybrid work system with flexible working hours and places, after finding its positive unintended consequence for future transportation planning. However, it is unclear how these factors may change the WFH decisions in different regions considering the socio-economic and demographic context in the US during an exogenous shock or uncertainty like the COVID-19 pandemic. As WFH increased during COVID-19 than the pre-COVID-19 periods, it is imperative to know how WFH will have an impact on the future travel demand and what components of the travel model need to be adjusted. To fill these research gaps, this study primarily aims to explore the factors affecting WFH decisions across the US states during the pandemic waves using Geographically Weighted Regression Model and provides important policy implications.

CONCEPTUAL FRAMEWORK

Although most people prefer working from home during the pandemic, we can expect that older ones are more interested in working from home (WFH) than younger ones since older people may be more immune compromised against the coronavirus than the younger ones. Therefore, they may not want to travel to the office. Considering the COVID-19 severity, it can also be expected that females are more interested in working from home than males. Besides, people with higher education are usually more likely to work from home. Moreover, the eagerness of higher-income individuals to work from home can be anticipated to be higher than the low-income individuals. Households with more children may prefer to work from home. It can be assumed that vaccinated people are less enthusiastic about working from home compared to non-vaccinated people due to the contentedness of safety after getting the vaccine. The non-white population can be more prone to work from home than the white population during COVID-19. The overall study framework is presented in Figure 1 below.

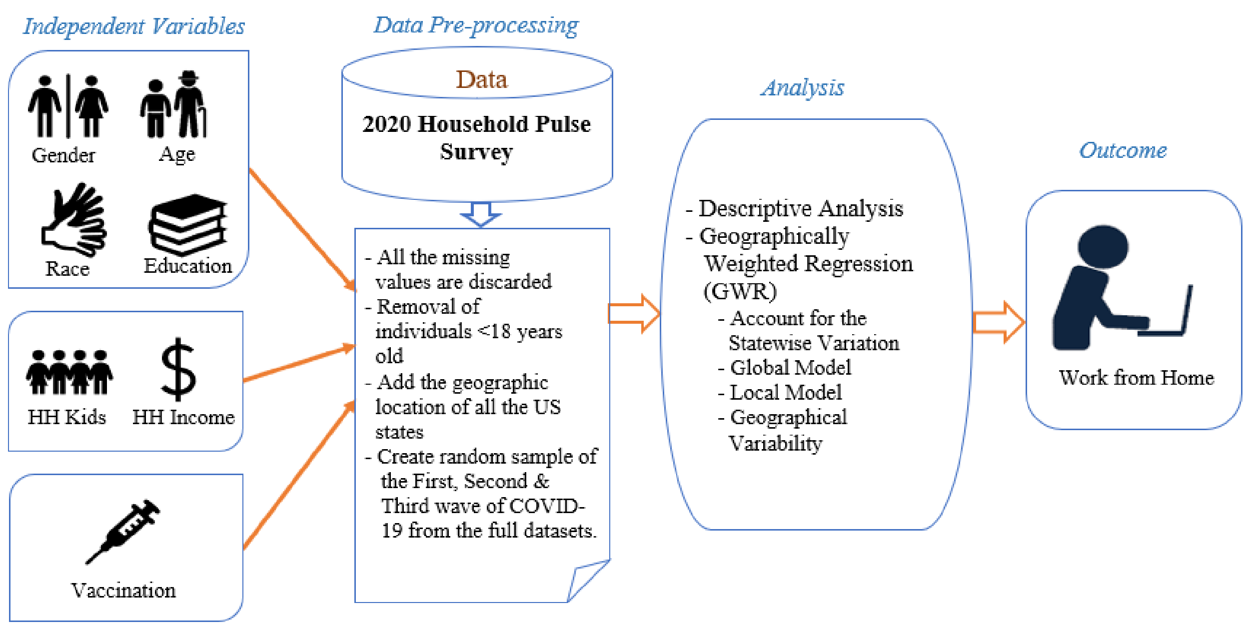

Figure 1. Study Framework

METHODOLOGY

Data

This study utilizes data from the US Census Bureau's Household Pulse Survey (HPS), an experimental survey designed to rapidly assess how the COVID-19 pandemic has influenced travel behavior (HPS 2021). The survey collects data from all U.S. states on a regular basis, with phase 1 conducted weekly, while phases 2 and 3 follow a biweekly collection schedule. This study uses person level data from week 23 (i.e., January 20 - February 1, 2021), week 37 (September 1 - September 13, 2021), and week 42 (January 26 – February 7, 2022) from the survey. These three weeks fall in the pandemic waves, i.e., wave 1, wave 2, and wave 3, respectively (Johns-Hopkins 2022) (Figure 2). The temporal data (panel) of the survey could not be used, as the respondents are not the same over different weeks of the survey. To ensure data quality, invalid responses were removed, and individuals under 18 years old were excluded. Additionally, responses with missing values (e.g., due to skip logic or "prefer not to answer") and outliers (fewer than 1% of observations) were discarded. Since running GWR on the full dataset requires substantial computational power, a random sample of 1500 person-level observations for each wave has been generated. Correlations between the independent variables are performed, where all the correlation values are found to be less than +/-0.5. Overall, the data underwent rigorous cleaning and validation through descriptive analysis to ensure accuracy and reliability.

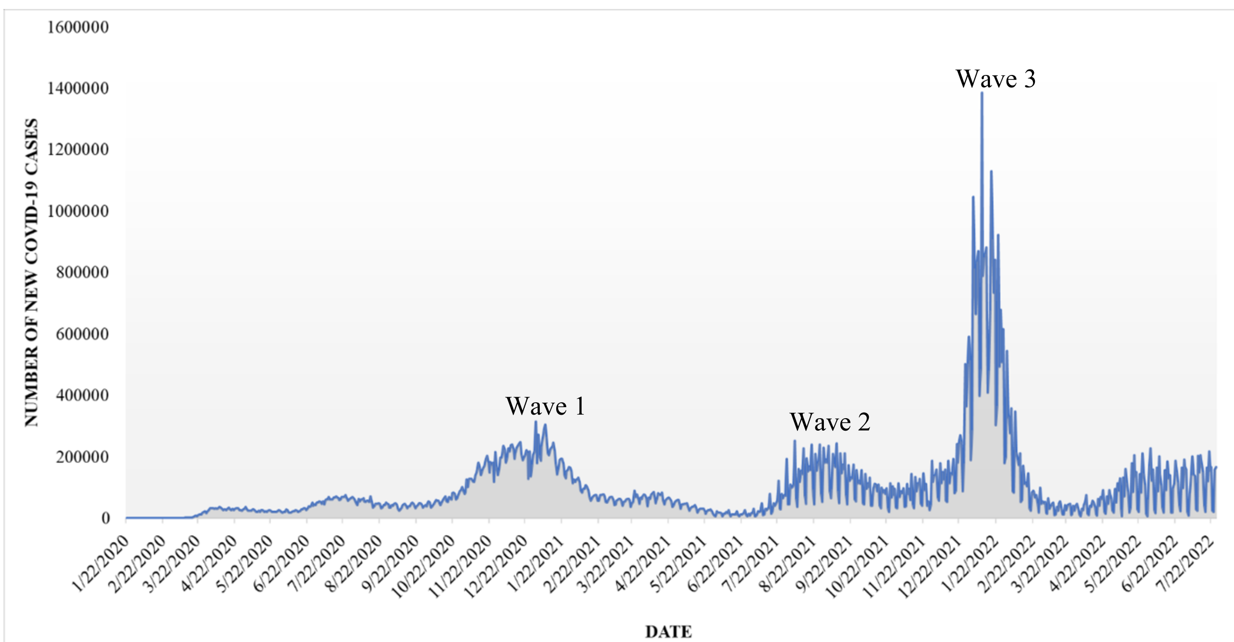

Figure 2. COVID-19 cases over time (generated by authors, *Data Source: Johns Hopkins University CSSE COVID-19 Data* (Johns-Hopkins 2022))

The descriptive analysis in Table 1 shows the frequency percentages of all the categorical variables of all the three pandemic waves' random samples. It shows that 60% of people aged 18 or older live in households where at least one person teleworked to substitute the work trips during the first wave of the pandemic. However, the percentages decreased in wave 2 and 3 to 40% and 38%, respectively. On the other hand, COVID-19 vaccination increased from 12% in wave 1 to 91% in wave 2. In wave 1, it is not surprising that fewer people are vaccinated considering the survey date. All the remaining variables show similar patterns across the pandemic waves. In the samples, about 40% are male, 30% have bachelor's degrees, and 70% are from households having an income of more than 50,000. The number of kids in a household is the only discrete variable used in the analysis, which is not reported in the data frequency table below. The variable specifies that the maximum number of kids in a household is five, and the minimum is 0.

Table 1. Descriptive Statistics of Categorical Variables

Variables	Description	Wave 1 (N=1,500)		Wave 2 (N=1,500)		Wave 3 (N=1,500)	
		Freq.	%	Freq.	%	Freq.	%
Work from home*	Whether at least 1 person in a household telework during COVID-19						
	0 = No	596	40%	896	60%	926	62%
	1 = Yes	904	60%	604	40%	574	38%
Gender	0 = Female	912	61%	876	58%	856	57%
	1 = Male	588	39%	624	42%	644	43%
Age	0 = ">34"	1277	85%	1303	87%	1273	85%
	1 = "18-34"	223	15%	197	13%	227	15%
Race	0 = Non-white	220	15%	235	16%	247	17%
	1 = White	1280	85%	1265	84%	1253	83%
Education	0 = Graduate/ Professional degree	404	27%	383	26%	385	25%
	1 = Bachelor's degree	605	40%	618	41%	611	41%
	2 = Some College degree	491	33%	499	33%	504	34%
Household Income	0 = HH income < 50,000	429	29%	454	30%	485	32%
	1 = HH income >= 50,000	1071	71%	1046	70%	1015	68%
Vaccination	0 = No	1323	88%	144	10%	150	9%
	1 = Yes	177	12%	1356	90%	1350	91%

** Dependent Variable; N= Sample Size*

Model

This study aims to examine the factors influencing work from home decisions during the COVID-19 pandemic while assessing the presence of spatial non-stationarity. To capture regional variations across US states, Geographically Weighted Regression (GWR) models are employed using a randomly generated sample dataset for each wave of the pandemic. The GWR approach accommodates spatial heterogeneity by allowing model parameters to vary across locations (Haque et al. 2022), making it well-suited for this analysis. Additionally, GWR is applicable in cases where the dependent variable is binary, further justifying its use in this study.

RESULTS

Table 2 represents the results of the global model with the coefficients, significance level, and marginal effect. The estimations for the pandemic waves, i.e., wave 1, 2, & 3, are shown in columns (i), (ii), and (iii), respectively. The model significance test shows the model fits the data well. The t-value greater than 1.67 or less than -1.67 designates that the variables are statistically significant at 90% confidence level and specifies a p-value of less than or equals to 0.10. It is found that vaccination and education1 dummy are not statistically significant. The findings suggest that males are 1.3% less likely to WFH than females during COVID-19 in wave 1, as we expected. There can be several reasons. Females may choose more WFH to continue with domestic responsibilities. Besides, the flexible nature, convenience, and the freedom to work in free time make it favorable for females to WFH. The results show that younger people are 17% more interested in working from home during COVID-19 than older ones, which can be counterintuitive. As we anticipated, the probability of WFH for people with some college degrees is 23.4% lower than the ones with graduate degrees. In wave 3, this percentage further lowered to 26.2%. It makes sense since the work from home decreased in wave three compared to wave 1. More non-essential workers with some college degrees are returning to in-person work with more people being vaccinated, and the initial subside of the pandemic after a wave. Besides, more kids in a household increase the probability of WFH by 2.6% during COVID-19. Also, as we predicted earlier, affluent people are more prone to WFH than lower-income people. This relationship increases from 13% in wave 1 to 26% in wave 3. On the other hand, the results suggest that the chance of WFH is 1.9% lower for the white population than for the non-white population during COVID-19. However, it is not statistically significant in the wave 3 model.

Table 2. Results of the GWR Global Model

Variable	**(i) Wave 1**		**(ii) Wave 2**		**(iii) Wave 3**	
	Coef.	**Marginal Effect**	**Coef.**	**Marginal Effect**	**Coef.**	**Marginal Effect**
Constant	-1.35***	-	-1.33***	-	-1.49***	-
Gender (Base: Female), Male	-0.14***	-0.013	-0.05	-0.010	-0.02	-0.004
Age (Base: >34), "18-34"	0.20***	0.170	0.86***	0.181	0.80***	0.163
Race (Base: Non-white), White	-0.13**	-0.019	-0.22	-0.045	-0.21	-0.043
Education1 (Base: graduate degree), Bachelor's degree	-0.06	-0.085	-0.27**	-0.058	-0.41***	-0.091
Education2 (Base: graduate degree), Some college degree	-0.11**	-0.234	-0.79***	-0.167	-1.28***	-0.262
No. of Kids in a household	0.14***	0.026	0.23***	0.047	0.18***	0.036
Vaccination (Base: Non-vaccinated), Vaccinated	0.02	0.022	0.14	0.028	0.61	0.115
Household Income (Base: <50,000), >=50,000	0.55***	0.133	1.50***	0.303	1.32***	0.260
Model Fit Statistics						
N	1500		1500		1500	
AIC	1837.88		1812.04		1751.99	
BIC	1822.12		1831.58		1769.36	

Note: *** and *** denote 5% and 1% significance level, respectively.*

The results of the local model across the three waves are presented in Table 3, which includes key distribution parameters such as the median, first and third quartiles, and the Monte Carlo significance test for the estimates. These metrics provide insight into the variation of parameters across space. The Monte Carlo test indicates that three variables (i.e., Race, Education2, and Household Income) exhibit significant spatial variability at the 90% confidence level. Overall, the local model demonstrates a better fit to the data compared to the global model, as reflected in the lower AIC and BIC values. The directional signs of the estimates remain consistent with those observed in the global model. The extent of variation can be assessed through the median and interquartile range for each variable. Notably, for most variables, the median coefficient values in the local model closely align with their global counterparts. For example, the "Age" variable has an interquartile range of 0.18 to 0.23, with a median of 0.21, which is identical to its global estimate.

Figures 3, 4, and 5 visualize the spatial distribution of local parameter estimates in the first wave across US states. Note that while the data is at the person level, geographic identifiers are available only at the state level, which is why the spatial analysis was conducted at this scale. The local parameter estimates are averaged at the state level to capture regional variations in the model's results. The figures display the average local parameter estimates for each state, with darker shades of blue representing higher values of the WFH coefficient and lighter shades indicating lower values. Notably, Alaska is excluded from the color legend due to the absence of data for this region. These visualizations highlight the geographic variability of parameter estimates across different regions of the US. For example, higher spatial variability of household income is witnessed in the north-eastern regions of the US compared to the west and north-western regions. One thing can be presumed that higher population density in the northeast states could play a role. During the pandemic, most people didn't expose themselves to the larger crowds due to social distancing and mask mandates. Also, most of these areas are transit oriented. As the public transport ridership plummeted due to the virus exposure and scar, the closure of some transit routes might have forced the employees to work from home. The variations in the other two variables support this assertion. It also captures the correlations of the pandemic that vary differently across the states depending on the economic conditions, organization, and leadership. The authorities and policymakers need to leverage this situation in the post-pandemic era by promoting work from home rather than commuting to the workplace. This might ease the congestion levels, especially in busy cities like New York City. According to Choo et al. (2005), the reduction in vehicle miles traveled from working from home may appear to be small; however, it has far more effective policy than other investments in public infrastructure. Although WFH has some disadvantages, e.g., the loss of networking opportunities, the difficulty of managers to monitor employees, and technology limitations, organizations should train managers with new skills to improve their ability to manage employees with the help of a technology advanced virtual environment.

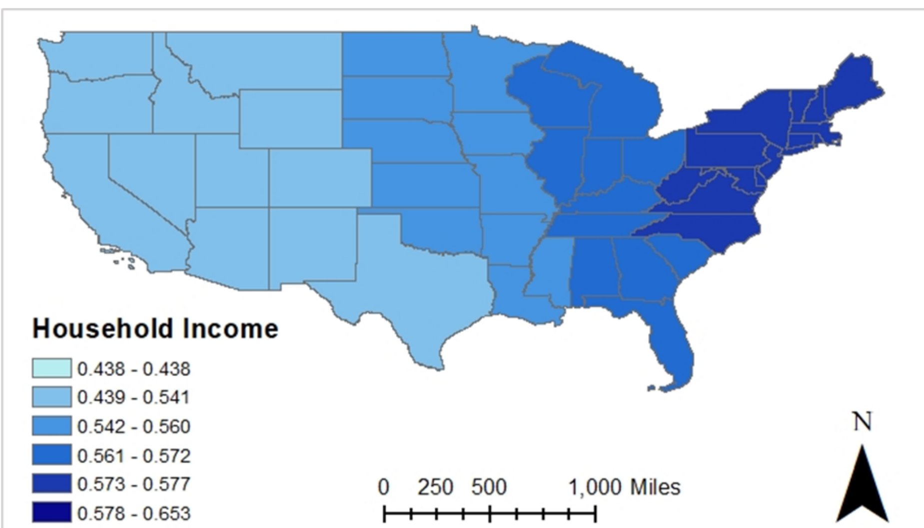

Figure 3. The spatial variation of household-income across US states (generated by authors)

DISCUSSION: DRIVING TOWARDS SUSTAINABLE TRANSPORTATION

The COVID-19 pandemic has brought drastic changes in the way we work and travel. It has highlighted the limitations of our current transportation system systems which were primarily

Table 3. GWR Local Model Results

Variable	(i) Wave 1				(ii) Wave 2				(iii) Wave 3			
	Median	**Q1**	**Q3**	**Monte Carlo Test (p-value)**	**Median**	**Q1**	**Q3**	**Monte Carlo Test (p-value)**	**Median**	**Q1**	**Q3**	**Monte Carlo Test (p-value)**
Constant	-1.35	0.32	0.37	0.54	-1.27	-1.20	-1.18	0.06	-1.50	-1.50	-1.50	0.13
Gender (Base: Female), Male	-0.14	-0.17	-0.10	0.36	-0.08	-0.06	0.01	0.20	-0.02	-0.03	-0.02	0.47
Age (Base: >34), "18-34"	0.21	0.18	0.23	0.62	0.86	0.87	0.87	0.81	0.80	0.80	0.81	0.28
Race (Base: Non-white), White	-0.13	-0.15	-0.11	0.08	-0.33	-0.29	-0.27	0.16	-0.23	-0.23	-0.21	0.08
Education1 (Base: graduate degree), Bachelor's degree	-0.07	-0.08	-0.07	0.64	-0.30	-0.27	-0.26	0.31	-0.41	-0.41	-0.40	0.31
Education2 (Base: graduate degree), Some college degree	-0.13	-0.15	-0.08	0.04	-0.77	-0.77	-0.77	0.76	-1.28	-1.28	-1.28	0.10
No. of Kids in a household	0.14	0.11	0.17	0.37	0.23	0.24	0.24	0.77	0.18	0.18	0.18	0.71
Vaccination (Base: Non-vaccinated), Vaccinated	0.02	0.03	0.03	0.39	0.13	0.11	0.14	0.15	0.63	0.62	0.64	0.22
Household Income (Base: <50,000), >=50,000	0.55	0.53	0.57	0.09	1.48	1.49	1.49	0.06	1.32	1.32	1.32	0.11
Model Fit Statistics												
N	1500				1500				1500			
AIC	1807.21				1809.16				1735.06			
GW Deviance	1798.01				1793.26				1752.07			
BIC	1812.10				1799.14				1755.31			

Note: *Q1 = First Quartile and Q3 = Third Quartile*

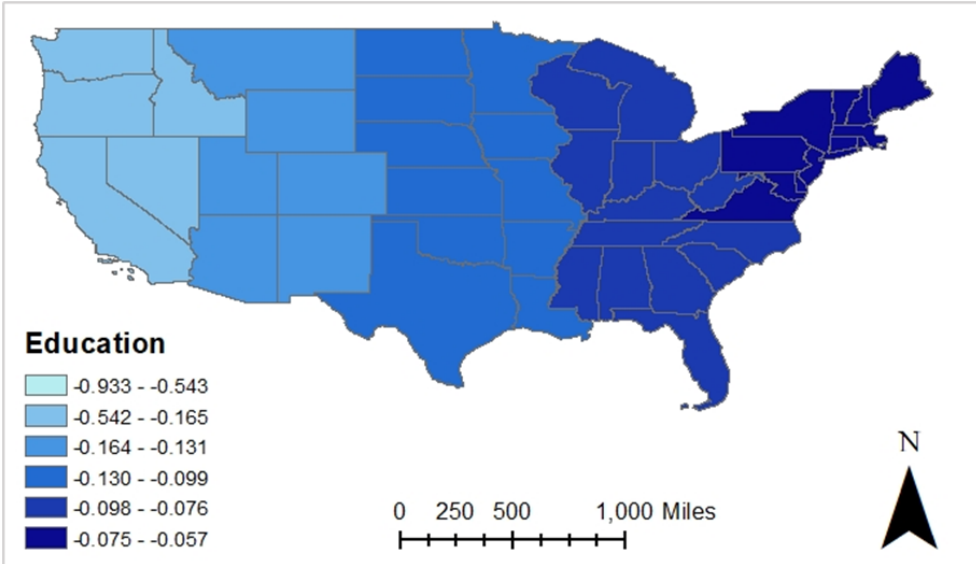

Figure 4. The spatial variation of education across US states (generated by authors)

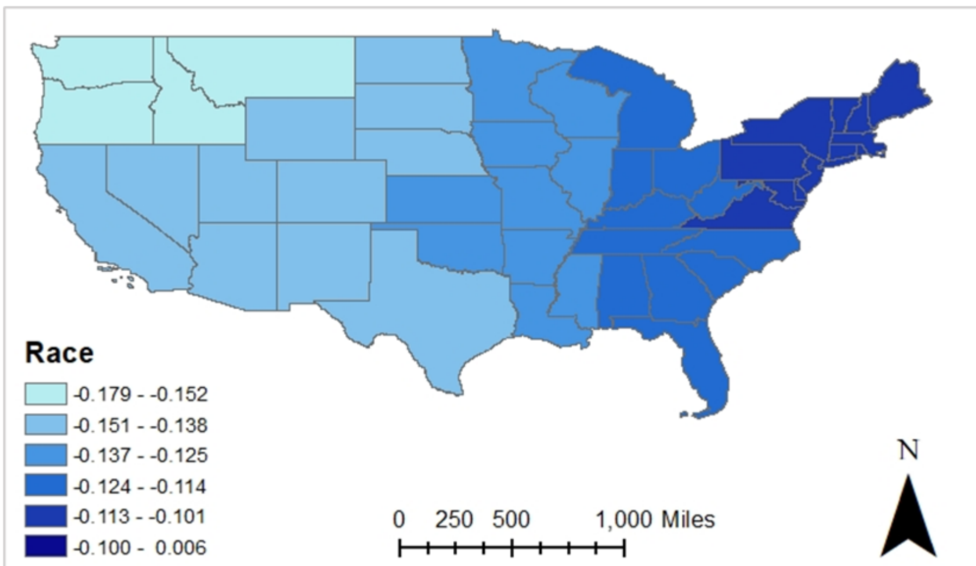

Figure 5. The spatial variation of race across US states (generated by authors)

designed to accommodate traditional commuting patterns. With more and more people working from home, there has been a noticeable decrease in commute trips.

This study highlights that household characteristics, such as the presence of children, significantly influence WFH decisions. Safety concerns and family responsibilities have made WFH an attractive alternative during COVID-19, which could offer flexibility to balance work and caregiving duties. Transportation planners could integrate these behavioral shifts into infrastructure strategies, supporting remote work and decentralized commuting through flexible policies, such as staggered scheduling and telework incentives.

Literature showed WFH generate more online shopping and more delivery services (Patwary and Khattak 2022). In our study, household income shows positive association for WFH, which is supported by Patwary and Khattak (2022). They also found that higher-income people have higher propensity of online shopping. Therefore, more people working from home has resulted in an increased demand for home delivery services as more individuals are staying at home to work. As the future of work becomes more hybrid, policymakers and transportation planners need to adapt and create more flexible transportation infrastructure to support these changes. To adapt, transportation systems could prioritize sustainable options like bicycle lanes, shared e-mobility solutions (i.e., e-bike and e-scooter), and pedestrian-friendly infrastructure. These measures align with the evolving hybrid work landscape and reduce reliance on single-occupancy vehicles.

Overall, the COVID-19 outbreak has propelled the need for embrace flexibility and sustainability in transportation planning. As people shift towards remote working and demand more flexible modes of transport, the traditional ways of transportation preparation that relied on fixed routes and schedules have become obsolete. In response governments and policymakers may rethink about the transportation system strategies to be more dynamic, adaptable, and resilient. This would entail embrace new technologies and innovative ideas in mobility like ride-sharing electric cars, and autonomous vehicles. The pandemic has shown us that the world can change rapidly, and we need transportation systems that can adapt just as quickly.

CONCLUSIONS

The COVID-19 pandemic has significantly affected the global economy, with the transportation sector experiencing major shifts. Travel patterns have undergone significant transformations, particularly in the realm of commuting. As a fundamental aspect of local mobility, commuting influences various aspects of transportation systems. However, the pandemic has accelerated the adoption of working from home, reducing the need for daily commutes and altering traditional travel behaviors. Transportation planners and engineers are struggling with the existing travel demand models and their implications. It is important to adopt new changes COVID-19 enforced to the models. WFH can make peak hours traffic spread out throughout the day. However, it is unclear how COVID-19 changes the WFH decisions over different waves of the pandemic in regions with different socio-economic and demographic contexts. All these conflicting natures of WFH make it imperative to investigate the associated travel, locational, and socio-economic factors further. Therefore, this study attempts to analyze the factors affecting the WFH decisions during an uncertainty like COVID-19 by using newer data (i.e., US Census Bureau's Household Pulse Survey data) and an application of contemporary methodology (i.e., geographically weighted regression model).

Empirical investigation from this study suggests that the WFH percentage decreased from 60% in the first wave to 38% in the third wave. GWR global model's results reveal some important findings. It is found that highly educated, young and females are encouraged to frequent WFH during COVID-19. These results are aligned with the literature. Belanger (1999) found that the interest in WFH in females is higher than in males. Wang and Loo (2017) indicated that people with higher education and younger people are more prone to WFH than some college degrees and older people. Our results also suggest that the presence of a kid in a household motivates people to WFH, which is consistent with the findings of Drucker and Khattak (2000). Besides, higher-income people are found to choose WFH more often than lower-income people. This effect increases with the progression of the pandemic. This is also consistent with the literature (Loo and Wang 2017). Moreover, the result of this study indicates that non-white people are more likely to work from home than the white population. The GWR local model's coefficients are almost similar to the global model. More importantly, it is found that three local parameters, i.e., higher education, race, and higher-income households, have spatial variations. Overall, the findings are based on the data from the US. They cannot not be generalized to the context of other countries.

The findings have implications for future transportation planning. Study findings point out to more sprawled-out development and greater digital connectivity in the long run. WFH may support long-term decentralization plans with evenly distributed networks of services and quality public transit to provide equal access to jobs and education for the underprivileged population, while travel demand forecasting usually depends greatly on the economic conditions, including employment growth and settlement patterns of the traffic zones. Thus, the study findings may help to anticipate new planning scenarios in future. The travel demand models' ability to adapt to different future scenarios may be invaluable to organizations in formulizing and preparing plans.

This work reflects how agencies and the private sector can deal with WFH and COVID-19 shocks and how much variation are there over space and time. However, this research needs further extensions in future. Future research may work on the travel characteristics of the people working from home. For example, people working from home may take other non-essential trips, which could increase other trip purposes, including personal business trips, social/ entertainment trips and shopping trips. While analyzing WFH, efforts need to be made to include some other important variables, e.g., technology accessibility, transportation accessibility, employment, etc.

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