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Impact of working from home on activity-travel behavior during the COVID-19 Pandemic: An aggregate structural analysis

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ABSTRACT

The ongoing COVID-19 pandemic has created significant public health concerns that led the public and private sectors to impose stay-at-home and work-from-home policies. Although working from home has been a conventional albeit infrequent behavior, the prevalence of this option was significantly and rapidly accelerated during the pandemic. This study explored the impacts of working from home on activity-travel behavior during the pandemic. Both work and non-work activity participation declined during the pandemic but to what extent was this due to working from home? How did working from home affect other measures of travel such as person-miles traveled? We approached these questions by developing a Structural Regression model and using cross-sectional data for the early phase of the pandemic when the infection curve was flattened and activity-travel behavior became relatively stable following the drastic changes observed during the pandemic's initial shock. Combining U.S. county-level data from the Maryland Transportation Institute and Google Mobility Reports, we concluded that the proportion of people working from home directly depended on pandemic severity and associated public health policies as well as on a range of socio-economic characteristics. Working from home contributed to a reduction in workplace visits. It also reduced non-work activities but only via a reduction in non-work activities linked to work. Finally, a higher working from home proportion in a county corresponded to a reduction in average person-miles traveled. A higher degree of state government responses to containment and closure policies contributed to an increase in working from home, and decreases in workplace and non-workplace visits and person-miles traveled in a county. The results of this study provide important insights into changes in activity-travel behavior associated with working from home as a response strategy to major disruptions such as those imposed by a pandemic.

1. Introduction

The COVID-19 pandemic created significant public health concerns that led the public and private sectors to impose stay-at-home and working-from-home policies. *Working from home* (WFH), commonly known as *teleworking*, can be defined as a work arrangement where workers spend some portion of their employment hours working in their home. In general, teleworking includes people who

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work in telecommuting centers instead of or in addition to their home. Working from home also includes people who do not usually commute to an office, whether they use information technology as part of their work or not. A related term is *telecommuting*, which can be defined as a sub-set of teleworking but implies explicitly replacing a physical commute with telecommunications. An employee working remotely, at home or in a telework center, is foregoing or reducing work commutes and is performing work tasks remotely. From this perspective, someone who does not have an office to which to commute is not a telecommuter. In this study, we used the term working from home throughout the paper to be consistent with our data. A recent survey estimated that between February and May 2020, over one-third of the American labor force replaced in-person work with working from home, which increased the share of remote working to nearly 50 percent of the nation's workforce (Brynjolfsson et al., 2020). The massive changes in work arrangements and subsequent activity-travel participation may have long-term impacts on activity and travel, including how people organize their work, where the work is performed, and how activities and travel are scheduled. In this respect, it is important to understand the impacts of working from home practice on activity-travel participation during the pandemic.

The rise of the working from home phenomenon during the pandemic and its associated impacts have been studied in recent research. Based on a primary survey in Australia, Beck and Hensher (2020a) found that working from home was a positive experience with a sizable portion of individuals who expressed a preference to continue to work in this mode even after the pandemic is over. Research by Barrero et al. (2020) estimated the total time savings in the U.S. due to not commuting to workplaces as about 10 billion hours during the first six months. They also found that one-third of the savings was put back into the primary job and the rest was spent for leisure and household production activities. Conway et al. (2020) analyzed the likelihood of workers continuing their work from home in the post-pandemic future and concluded, based on their survey data, that the trend of working from home was likely to continue when the pandemic is over. They also documented various reasons that contributed to the change in productivity in work among those who started working from home. The top reason for increased productivity was reported to be "no commute time", whereas the top reason for decreased productivity was a higher level of distraction at home. Other research suggests an increase in telecommuting over the next two years is possible because of less concern from employers, lower travel cost, more time saving, and higher sustainability impacts (Amekudzi-Kennedy et al., 2020). These studies imply that increased work-from-home practice is likely to continue in the post-pandemic future.

It is critical, therefore, to understand the breadth and depth of potential impacts of working from home on activity-travel behavior. In this direction, the goal of this study was to investigate to what extent did working from home contribute to the reduction in work and non-work activities and overall travel, more specifically person-miles traveled, for different geographical areas during the pandemic. To address these questions, we developed a Structural Regression (SR) model to assess the interrelationships between county-level COVID-19 severity, working from home proportions, changes in workplace and non-workplace visits compared to the pre-pandemic period, average person-miles traveled, and a range of socio-economic and location characteristics. To conduct the necessary analysis, we considered an 8-week span of cross-sectional data from April 15 to June 9, 2020. This time period appeared to best capture the "flattening the curve" period of COVID-19 infection rates and an expectation of relative stability in average activity-travel behavior. The findings of this preliminary study will aid policymakers in understanding the potential impacts of working from home on travel if this work arrangement is maintained in the future as a tool for achieving sustainability goals (Beck and Hensher, 2020b).

The next section describes data sources, study timeframe, and data preparation process, followed by an overview of the methodology. The methodology section includes the conceptual framework of the Structural Regression model, exogenous and endogenous variables, model estimation technique, and goodness-of-fit statistics. Model results are then presented and discussed. Major findings, policy implications, and limitations are presented in the last section.

2. Data sources and time frame

This section describes the data sources, study time frame, and sample sizes used in the model.

2.1. Data sources and data preparation

The datasets used for this study were drawn from the following sources:

- MTI COVID-19 Impact Analysis Platform (Maryland Transportation Institute, 2020)
- Google COVID-19 Community Mobility reports (Google LLC, 2020)
- U.S. Census Bureau, 2018
- U.S. EPA Smart Location Database (U.S. EPA, 2014)
- State-level COVID-19 policies (Hale et al., 2021)

The MTI platform provides data on four major categories at the state- and county-level for each day from January 1 to April 20, 2021. These four categories include mobility and social distancing (e.g., staying at home, person-miles traveled), COVID and health (e.g., new daily cases, contact tracing), economic impact (e.g., unemployment rates, change in consumption), and vulnerable population (e.g., people over 60, ethnicity). MTI collected privacy-protected location data from cellphones and vehicles, then processed the data to identify trip origins, destinations, and stay-home devices. After applying the imputation algorithm, data are inferred on trip purpose, mode, and socio-demographic information. A rigorous multi-level weighting and validation of the imputed data based on the observed data are then integrated with the COVID data, and finally, data are made available to the online platform. For details, readers are referred to MTI's web portal (https://data.covid.umd.edu/). The list of variables collected from the MTI portal, their definitions, and

Table 1
Summary Statistics (N = 2,366).

Variable	Source	Description	Min	Max	Mean	Std. dev
Socio-economic characteristics and ICT usage						
Black	U.S. Census Bureau (2018)	Percentage of Black population	0.00	83.70	9.86	14.27
Male	U.S. Census Bureau (2018)	Percentage of male population	43.98	66.29	49.81	1.96
Median household income	U.S. Census Bureau (2018)	Median annual household income (In 2019 inflation adjusted dollars). Based on it, counties are grouped into 3 categories:	21,504	142,299	54,727	14,827
		low (income <$45 K)	0	1	0.25	0.43
		middle (>=$45 K & <$125 K)	0	1	0.75	0.43
		high (income >=$125 K)	0	1	0.001	0.03
Average commute time	U.S. Census Bureau (2018)	Population weighted average commute time (in minutes). Commute time refers to time to travel to workplace. Based on it, counties are grouped into 3 categories:	12.69	54.95	23.74	4.17
		low (commute time < 20 min)	0	1	0.16	0.37
		middle commute time >=20 & <40 min)	0	1	0.83	0.37
		high (commute time >= 40 min)	0	1	0.005	0.37
Commute mode: driving	U.S. Census Bureau (2018)	Percentage of commuters using car to travel to work	7.95	98.55	90.51	5.76
Internet access	U.S. Census Bureau (2018)	Percentage of households with internet connection	31.58	97.20	78.49	8.30
Location characteristics						
Population density	U.S. EPA (2014)	Population density is represented as the total number of people per square mile	1	48,341	293	1457
Activity density	U.S. EPA (2014)	Activity density is represented as the total number of jobs and housing units per square mile	0.02	207.42	2.13	5.34
Road network density	U.S. EPA (2014)	Facility miles of links per square mile. Facility categories include auto-oriented links, multi-modal links, and pedestrian-oriented links.	0.42	282.59	8.23	8.01
Metropolitan status	Ingram and Franco (2013)	Metropolitan status indicator based on 2013 NCHS urban–rural classification scheme; 1 = metro, 0 = nonmetro	0	1	0.46	0.50
No. of points of interests	Maryland Transportation Institute (2020)	Number of points of interests for crowd gathering per 1000 people	8	389	127	33
Transit performance score	AllTransitTM (2021)	Transit performance score ranges between 0 and 10. It refers to the weighted sum of transit connectivity, access to land area and jobs, and frequency of service, where the higher the number the better the transit service.	0.00	9.90	0.78	1.52
Presence of airport	Federal Aviation Administration (2021)	Presence of an airport in a county: yes = 1, no = 0	0	1	0.19	0.39
COVID-19 policies						
Stringency index	Hale et al. (2021)	This index ranges between 0 and 100, which reflects the measure of how many of the containment and closure policies a government has acted upon and to what degree.	53.40	89.71	72.90	5.88
Containment and health index	Hale et al. (2021)	This index ranges between 0 and 100, which reflects the measure of how many of the containment and closure and health policies a government has acted upon and to what degree.	48.30	76.21	64.16	5.09
Degree of COVID-19 severity						
Death rate	Maryland Transportation Institute (2020)	Percentage of deaths out of total COVID-19 cases	1.98	22.47	10.14	4.05
Hospital bed utilization		Percentage of hospital beds utilized by COVID-19 patients	29.32	91.91	52.62	10.04
ICU utilization		Percentage of ICUs utilized by COVID-19 patients	0.01	71.69	12.92	12.73
Telecommuting						
Working from home (during-COVID)	Maryland Transportation Institute (2020)	Percentage of workforce working from home during COVID-19 pandemic	1.08	89.71	31.47	13.21
Working from home (pre-COVID)	U.S. U.S. Census Bureau, 2018	Percentage of workers working from home before COVID-19 pandemic	0.17	18.44	4.36	2.06
Activity participation						
Percentage change in workplace visits	Google LLC (2020)	Percentage change in visits to workplace with respect to the baseline.	−72.77	−15.27	−29.82	7.11
Percentage change in non-workplace visits	Google LLC (2020)	Percentage change in visits to non-workplace (retail, recreation, grocery and pharmacy) with respect to the baseline.	−124.99	79.09	−19.44	24.49
Travel behavior						
Person-miles traveled	Maryland Transportation Institute (2020)	Average person-miles traveled per person per day on all modes (car, train, bus, plane, bike, walk, etc.)	11.90	86.70	37.03	8.10

summary statistics are listed in Table 1 along with other variables used in this study.

The Google COVID-19 Community Mobility report provided traveler locations for geographic areas worldwide, including the U.S. The report categorized activity places by several land-use types, including workplaces, groceries and pharmacies, retail and recreation, parks, transit stations, and residences. The dataset provided the relative change in visits to categorized places compared to pre-pandemic baseline values for each day since February 15, 2020. These baseline values represented a computed value for each day of the week, which was the median value from the 5-week period from January 3 to February 6, 2020. Therefore, Monday is compared to Monday, Tuesday is compared to Tuesday, and so on (Google LLC, 2020). In this study, we used the percentage change in workplace and non-workplace visits as a measure of work and non-work activity participation. The non-work activities include retail and recreation (e.g., restaurants, cafes, shopping centers, movie theaters) and grocery and pharmacy (e.g., grocery markets, food warehouses, farmers markets, pharmacies).

The state-level COVID-related policies were extracted from the Oxford COVID-19 Government Response Tracker (OxCGRT) project from the Blavatnik School of Government, University of Oxford (Hale et al., 2021). This database provided a systematic set of cross-national and longitudinal measures of government responses throughout the pandemic. The project tracked and recorded national and subnational government policies and interventions across a standardized series of indicators for each day since January 1, 2020. The COVID-19 policies were grouped into four broad indicators: (a) eight policy indicators (C1-C8) record information on containment and closure policies, such as school closures and restrictions in movement, (b) four of the indicators (E1-E4) record economic policies, such as income support to citizens or provision of foreign aid, (c) eight indicators (H1-H8) record health system policies, such as facial/mask coverings and COVID-19 testing facility, and (d) three indicators (V1-V3) record vaccination policies. In addition, four composite indices were created out of the individual indicators to aggregate data into a single index to assess the extent of policy responses. These four indices were a holistic government response index (GRI) [all indicators], a containment and health index (CHI) [all C and H indicators], a stringency index (SI) [all C indicators and public information campaigns], and an economic support index (ESI) [all E indicators]. Each of these indices ranges between 0 and 100, which indicates the level of the governments' response along certain dimensions. These indices, however, cannot confirm whether a government's policy has been implemented effectively. More details can be found in Hale et al. (2021).

In this study, we considered state-level stringency index (SI) and the containment and health index (CHI) since our goal was to identify the effect of state-level closure policies (SI) and a combined effect of closure and health-related policies (CHI) on the proportion of the workforce working from home in a county during the pandemic. First, this dataset allowed quantitative analysis of the degree of government responses. Second, the indicators were aggregated into a composite index providing a snapshot of the number and degree of policies in place in a given area. Third, the indicators were recorded for each day, providing an opportunity to track the policy across study windows when the policy was in effect or not.

The socio-economic, ICT (Information and Communication Technology) usage and location attributes of counties were obtained from the U.S. Census Bureau, 2018 and U.S. EPA Smart Location database 2014. The variables used, data sources, and summary statistics are provided in Table 1. This processing from multiple heterogeneous sources is part of the variety category of Big Data analysis (IBM infographics, 2020).

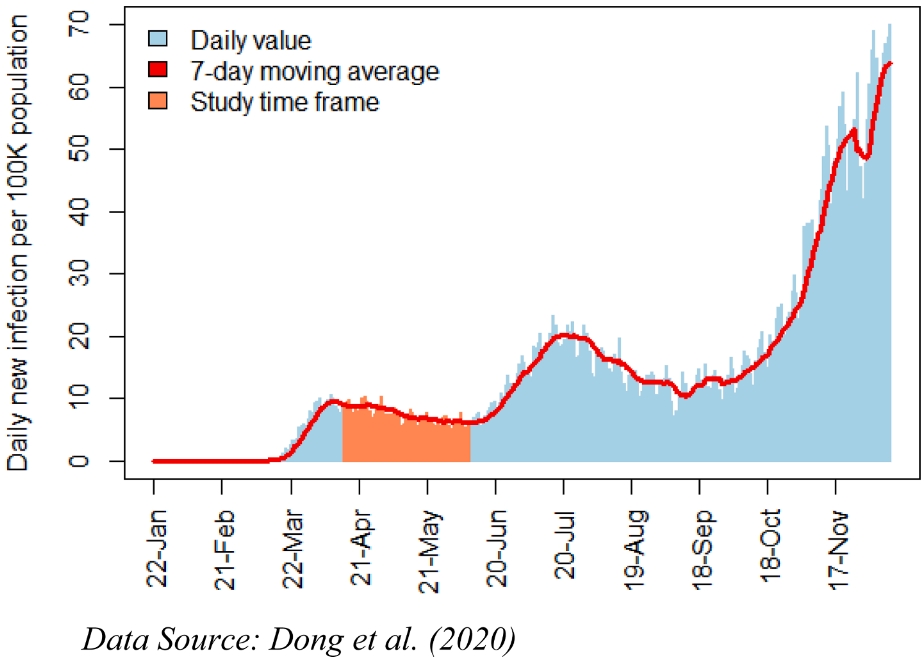


Fig. 1. Daily new domestic COVID-19 cases from January to November 2020. (See above-mentioned references for further information.)

For this initial analysis, we considered an 8-week span of cross-sectional data at the county-level from April 15 to June 9, 2020 (the rationale for this choice is described in the next section). Daily data for each variable collected from the MTI dataset and Google mobility report were collapsed into a single day value within the study time window, one value for each county, to generate an *average* value per day, thus forming the cross-sectional data for that time window. For COVID-policy variables, we extracted data on the two composite indices (SI and CHI) for each day of the study window. For each state, we then collapse each day's values into a single value (one for each index) by taking the average over all days. Note that the socio-economic and location variables are not specific to the study time window because these data are neither available at a monthly time interval nor are they available for the year 2020 when the study was conducted. Aggregate population data should not vary significantly over a short time span, and thus, we used the most recent available data for these variables (2018 for U.S. Census Bureau and 2014 for U.S. EPA data). Based on anonymity thresholds and our time frame, the Google mobility reports yielded a total 2,366 counties comprising our dataset.

2.2. Study time frame and rationale for selection

To ensure meaningful and statistically significant analysis, a span of time was identified over which the initial changes due to the pandemic had reached some degree of stability. The time window from April 15 to June 9, 2020 appeared to best meet the expectation for the following reasons. *First*, Fig. 1 shows the progress of the pandemic in the U.S. from January to December, and we observed that our selected period was the first and perhaps the least varying period with respect to the COVID-19 infection rate, following the "first wave" chaotic growth in March 2020 and prior to the summer "second wave." *Second*, this is the time window when the U.S. was well into the first phase of the pandemic, when infection rates became steady and when many response policies had been developed and implemented (stay in place and/or travel restrictions enactment started in mid-March). *Third*, in this time window, most citizens and businesses appeared to accept the reality and to support public health guidelines. Finally, during the study window, activity-travel behavior reflected a fairly steady return to normal following the drastic changes observed during the pandemic's initial shock. After this period, adherence to policy began to weaken at the beginning of the summer holidays, ultimately leading to the pandemic's second wave.

Although this window appears stable at the aggregate level, it may not be the case in all counties in the U.S. A considerable degree of variation may well exist across counties and the county-level data indeed exhibited a discernable variation to enable establishing and estimating the postulated structural relationships between working from home and activity-travel behavior during the pandemic.

Fig. 2 shows the relative changes in work and non-workplace visits during the study time window (April 15 – June 9) compared to the pre-pandemic period in the U.S. obtained from the Google COVID-19 Mobility Report (Google LLC, 2020). Note that the percentage changes in work, grocery and pharmacy, and retail and recreational place visits were considerably lower relative to the baseline. We observed a steadily rising trend in activity participation throughout the study period indicating that people slowly started to resume their activity participation over time. For example, the percentage change in grocery and pharmacy visits (blue line) was 20 percent lower than the baseline on April 15, 2020, but this change approached zero percent of the baseline by June 9, 2020. Similar trends were observed in the other two activity types. The weekly variation of work visits depicted the expected variations by days of a week. The greater change from the baseline during weekdays compared to weekends suggests a greater reduction in workplace visits during weekdays than on weekends. There was a sharp decline in workplace visits due to the Memorial Day holiday on May 25, 2020 (Fig. 2). Reductions in workplace visits were far greater than reductions in non-workplace visits.

3. Model specifications

This study developed an aggregate model by conceptualizing interrelationships among a set of socio-economic and location

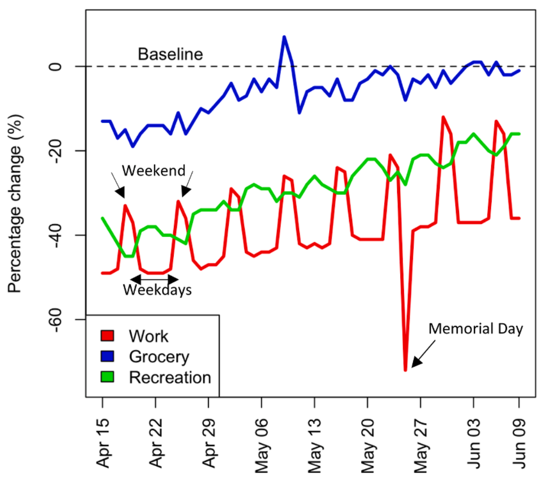


Fig. 2. Percentage changes in work and non-workplace visits during the pandemic (April 15 – June 9).

characteristics, the severity of the pandemic, working from home proportions, and activity-travel participation during the pandemic by using Structural Equation Modeling (SEM). SEM is a regression-based statistical modeling framework that can simultaneously estimate the statistical relationships among a set of observed variables, as well as unobserved variables represented as latent factors, based on a specified theoretical model (Kaplan, 2008; Schumacker and Lomax, 2004). SEM enables testing and evaluation of different models by specifying, estimating, and statistically testing hypothesized relationships among variables (Bentler, 1995; Zhang, 2018). This model can simultaneously capture the causal influences of independent variables on dependent variables (regression effects) and the causal influences of dependent variables on each other. In addition, it allows for examining the relationships among latent variables. The structural model also allows the provision of error-term covariances (Golob, 2003). The strength of the SEM is that in addition to identifying the direct effect of one variable on another, it also can capture the indirect effects through other mediating variables. The summation of direct and indirect effects represents the total effect that provides valuable insights into the interrelationships between variables.

The advantages of SEM methodology and the wide propagation of computer software packages that can estimate SEM models (in Stata, R, or MPlus) have made this method a popular one for testing theories in non-experimental research (Byrne, 2006). Correlation, multiple regression, and analysis of variance (ANOVA) are other popular statistical techniques to analyze relationships between observed variables, but none of these techniques can estimate relationships between latent variables or capture endogeneity issues that SEM can do (Hoyle, 1995; Kline, 2016). SEM is widely used in travel behavior research: Golob (2003) outlined a comprehensive review of the application of SEM in various travel behavior research. Several notable studies have used SEM to analyze relationships between telecommuting, travel behavior, and socio-economic characteristics. For example, Choo and Mokhtarian (2007) explored relationships between telecommuting and travel at the aggregate level (U.S. states) by using an SEM path model. Also, Kim (2016) applied SEM to investigate the complex relationships between telecommuting, residential or job locations, and household travel.

In this study, we used the *Structural Regression (SR)* model, which is considered the most general kind of model in SEM (Kline, 2016). It has two components: the *structural* component of the model represents hypotheses about direct and indirect effects among latent (unobserved) and observed variables, and the *measurement* component denotes the relationships between the latent variable and its indicators (Kline, 2016). The conceptualized structure, list of latent and observed variables used in our model, and the model equations are described next.

3.1. The conceptual model and variables

Analyses with structural regression models usually entail two steps: (1) the construction of a conceptual graphical structural model and (2) the estimation of model parameters or coefficients. The construction of the model involves conceptualizing relationships among a set of variables in a graphical manner where variables are represented as vertices and the relationship between a pair of variables is denoted as directed links or arrows. Each of these arrows postulates a certain degree of effect from one variable to the other and the degree of these effects is determined by respective coefficients (in their sizes, signs, and statistical significance). Given a graphical model, these model coefficients are estimated from data. Fig. 3 depicts the conceptual structure of our proposed structural regression model for investigating the impacts of working from home and related characteristics on activity-travel behavior during the

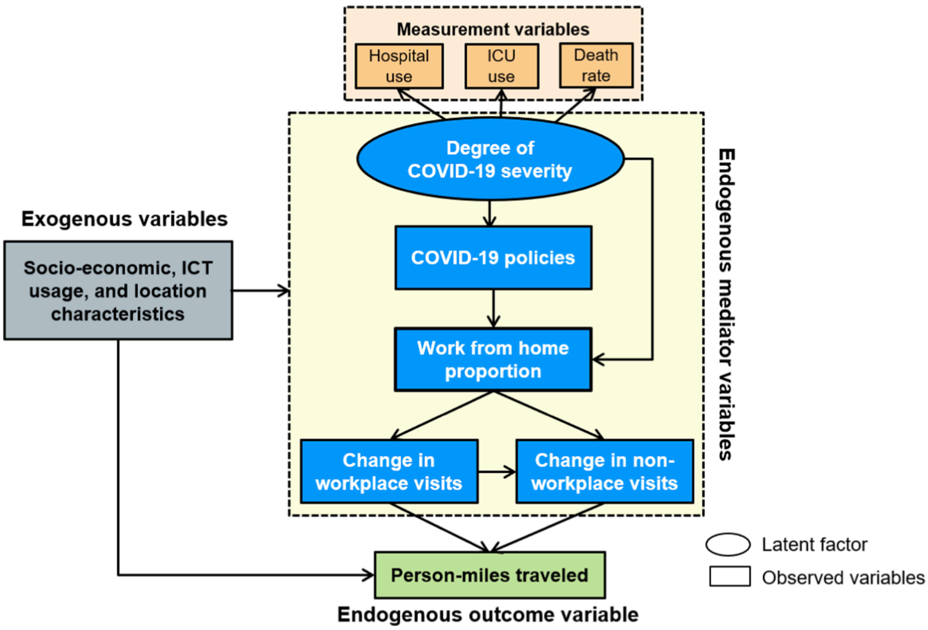


Fig. 3. Conceptual structural regression model.

pandemic using county-level data.

We used three broad categories of variables in our model: exogenous, endogenous mediator, and endogenous outcome variables. Exogenous variables are not causally dependent on any other variables in the model, whereas an endogenous outcome variable is a dependent variable with respect to all other variables used in the model. An endogenous mediator variable is independent with respect to some variables and dependent with respect to other variables in the model (Acock, 2013). The basic concepts and theories of the conceptual model are:

- The outbreak of the COVID-19 pandemic caused massive changes in our daily activity- travel schedules. Due to social distance policies and activity-travel restrictions imposed by the pandemic, working from home quickly became a widespread reaction, with significant increases during 2020 compared to prior years. We thus conceptualized both direct and indirect effects (via COVID-19 policies) of the degree of COVID-19 severity to working from home (WFH) proportions. The degree of COVID-19 severity was expressed as a *latent* factor in the model characterized by three measurement variables: hospital bed utilization, ICU utilization, and death rate.
- A county's WFH proportion was, in turn, conceptualized to affect the travel behavior of the county. The effect of WFH on travel was addressed via the core concept of the activity-based approach that travel is primarily a derived demand, implying that the demand for out-of-home activity participation creates the demand for travel (McNally and Rindt, 2008). More specifically, we conceptualized the indirect effects of WFH on travel via out-of-home work and non-work activity participation.
- Finally, a set of socio-economic, ICT (Information and Communication Technology) usage, and location characteristics for a county were hypothesized to influence the degree of severity of the pandemic, adoption of relevant policies, the extent of working from home, out-of-home activity participation, and travel behavior for that county.

As shown in Fig. 3, in our model, socio-economic, ICT usage, and location characteristics represented the exogenous variables, whereas travel, measured as person-miles traveled, was the final endogenous outcome variable. Five endogenous mediator variables considered in this study were: (1) degree of COVID-19 severity, (2) COVID-19 policies, (3) proportion of workforce working from home (WFH), (4) work participation, and (5) non-work participation. The latter variables were represented as the changes in workplace and non-workplace visits, respectively, during the pandemic with respect to baseline values (Google LLC, 2020). Fig. 4 presents the details of the conceptual model, where the rectangular boxes represent the observed exogenous and endogenous model variables, the oval-shaped box denotes the latent factor, e indicates error terms, and the arrows represent postulated non-zero direct effects.

As shown in Fig. 4, "socio-economic, ICT usage, and location characteristics" represent a collection of variables. When an arrow is directed from this collection of variables to another variable, it means that some but not necessarily all the variables in the list are directly connected to that particular variable (those exogenous variables that are directly connected to a particular variable are provided in the corresponding tables in the result section). Note that model variables were selected based on relevant prior work and data availability. The full list of all these variables with the associated data sources and relevant summary statistics is presented in Table 1. We next discuss the hypothesized connections between exogenous, endogenous, and outcome variables in detail.

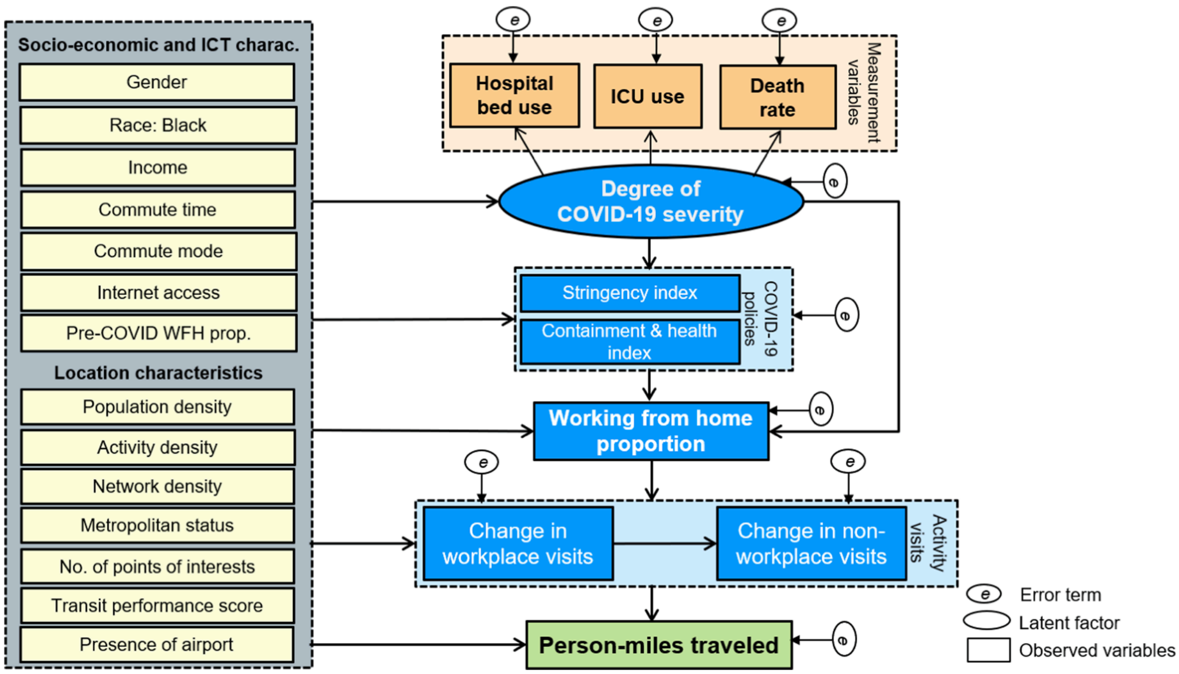


Fig. 4. Conceptual structural regression model with detailed model variables.

3.1.1. Latent measure of severity of the pandemic

In the model, the severity of the pandemic was conceptualized as a latent factor termed as the "degree of COVID-19 severity". Initially, four indicators, including infection rate, hospital bed utilization, ICU (intensive care unit) bed utilization, and death rate, were hypothesized to estimate this latent factor. But later, we omitted infection rate (daily new cases per 100 K population) from the final estimated model due to its very low factor loading value. Detailed discussion on this is provided in Section 4.1. Here, hospital bed utilization and ICU bed utilization represent the percentage of hospital beds and the percentage of ICU beds occupied with COVID-19 patients, respectively. The other indicator, named death rate, represents the percentage of deaths among all COVID-19 cases. This one is calculated by MTI based on the number of deaths and estimated total COVID-19 cases, including confirmed and untested cases (Maryland Transportation Institute, 2020). Positive effects were hypothesized between the COVID-19 severity factor and all the three observed indicators.

3.1.2. Interactions between severity of the pandemic, policies, and working from home

To measure the extent of the relationship between the severity of the pandemic and the adoption of WFH in a county, we hypothesized a direct effect from the latent factor "degree of COVID-19 severity" to the WFH proportion. To prevent local COVID-19 transmission and to reduce its severity, community mitigation strategies or policies such as social distancing, stay-at-home orders, gathering restrictions, non-essential business and school closure, and face-covering were implemented. Thus, we postulated COVID-19 policy variables as endogenous variables by considering them as a function of the degree of COVID-19 severity. In this study, as a measure of COVID-19 policies, we used two state-level indices, including a stringency index and a containment and health index (see description in Section 2.1) obtained from Hale et al. (2021). The severity of the pandemic led to various policies being enacted and these policies, in turn, affected travel, including staying at home and working from home. That is why in addition to a direct effect, we hypothesized an indirect effect of the degree of COVID-19 severity on the WFH proportion via COVID-19 policies. Both the direct and indirect effects were postulated positive. It implies that with the increase of the severity of the pandemic, more people would work from home. In addition, the higher the level of government's response towards policies, the higher the proportion of WFH would be.

3.1.3. Effects of working from home on activity-travel behavior

A county's WFH proportion was conceptualized to affect the changes in work and non-workplace visits (compared to the baseline pre-pandemic values) in that county in a negative way since a higher level of WFH should result in lower workplace and non-workplace visits. Changes in workplace visits could produce changes in non-workplace visits associated with work trips, so we hypothesized a positive connection between them. Moreover, changes in work and nonwork activity visits in a county were associated with socio-economics and location characteristics in that county. Last, we postulated indirect negative effects from WFH to travel via work and non-work activity visits in consideration that a higher WFH proportion would reduce work and non-workplace visits and consequently reduce travel. In our model, travel is represented by person-miles traveled — average miles traveled on all modes (car, train, bus, plane, bike, walk, etc.) per person per day.

3.1.4. Effects of socio-economic, ICT usage, and location characteristics

The model was expanded to consider a set of socio-economic, ICT usage, and location characteristics as exogenous variables. Model variables were selected based on relevant prior work and data availability. The list of the model variables and data sources are provided in Table 1. Socio-economic characteristics, expressed as proportions of the total population, included the number of males, the number of Blacks, and the number of commuters who drive to work. Other socio-economic characteristics considered in this study were median household income by three binary variables: low income (<$45 K), middle income (>=$45 K to <$125 K), and high income (>= $125 K) and average commute time of workers by three binary variables: low (<20 min), medium (>=20 to < 40 min), and high (>=40 min). These data were extracted from the U.S. Census Bureau, 2018 data. Note that in that dataset, commute time refers to a journey to the workplace and represents a categorical variable that denotes the percentage of workers with a particular commute time range. In our model, we calculated the population-weighted average commute time by multiplying the middle values of each category with the corresponding number of workers and factored by the total number of workers in a county. Each county was tagged with a particular category within the commute time groups (low, medium, and high) based on their average commute time.

Several location characteristics were considered in this study, including population density, activity density (jobs and housing units), road network density, metropolitan status of counties, the total number of points of interest, transit performance score, and presence of airport in a county. A detailed description of the location variables, data sources, and summary statistics are presented in Table 1. This study also considered two variables representing the ICT usage, such as the percentage of households with internet connections and the percentage of workers who worked from home during the pre-pandemic period as potential determinants of the during-pandemic working from home proportion (more details on this in the results section).

All the exogenous variables were not provided in each of the structural regression model equations instead, a sub-set of variables was conceptualized for a particular equation. For example, we considered the effects of race, gender, median household income, average commute time, and population density on the degree of COVID-19 severity. We hypothesized that counties having a higher fraction of Black people might be positively associated with a higher degree of COVID-19 severity because of their higher risk of COVID-19 exposure (CDC, 2021a). Since CDC (2021b) reported higher death cases among males compared to females, we postulated a positive effect from the proportion of males to COVID-19 severity. A positive association was anticipated between population density and COVID-19 severity as higher density areas might pose a greater possibility of close human interactions, which significantly increase the risk of COVID-19 exposure.

The exogenous variables that were considered to regress county-level WFH proportion included the proportion of Black people, males, median household income, average commute time, pre-COVID WFH proportion, the proportion of households with internet connections, population density, and network density. A similar set of exogenous variables was conceptualized to regress the changes in workplace visits. Since a higher fraction of Black people were part of the essential workers and commuter groups during the pandemic (Rafiq et al., 2022; Centers for Disease Control and Prevention (CDC), 2021a), we postulated a negative association of the proportion of Black people with WFH proportion and a positive association with workplace visits. Similarly, we assumed a negative effect from male proportion on WFH proportion and a positive effect on workplace visits because recent studies (Beck and Hensher, 2020a; Brynjolfsson et al., 2020; Rafiq et al., 2022) reported that the commuter group consisted of a higher fraction of male workers during the pandemic.

A higher proportion of households with internet access and a higher proportion of workers doing WFH prior to the pandemic would associate with more working from home (positive effect) and fewer workplace visits (negative effect). Recent research found that during the pandemic, telecommuters were predominantly from higher-income households, whereas commuters mostly belonged to low to medium-income households (Beck and Hensher, 2020a; Rafiq et al., 2022). Thus, we hypothesized a negative association of low-income counties with WFH proportion and conversely, a positive association with workplace visits. Prior studies found commuting distance as one of the determinants of telecommuting adoption (Yen and Mahmassani, 1997; Ory and Mokhtarian, 2006). In this study, we used commuting time instead of commuting distance to measure the effect on WFH due to the unavailability of distance data. We believe, however, that the effect of commute time is more direct since travelers are typically more aware of travel time due to experience or use of wayfinding apps than they are capable of assessing travel distance. We hypothesized that counties having longer commutes on average corresponds to a higher WFH proportion (positive effect), anticipating that longer commutes may lead to less frequent travel to workplaces and greater adoption of telecommuting.

Regarding location characteristics, a positive effect was conceptualized from population density to WFH proportion anticipating that denser areas might have a higher fraction of households with internet access and workers in telecommutable jobs, and thus can better accommodate stay-at-home orders by substituting in-person work with telework. Based on this hypothesis, a negative association between population density and workplace visits were postulated. The exogenous variables that were conceptualized for non-workplace visits and person-miles traveled mostly constituted location variables (detailed discussion in the results section).

3.1.5. Error-term covariances

Some error-term covariances among a similar set of variables, such as between hospital bed utilization and death rate and between ICU utilization and hospital bed utilization, between working from home and changes in work and non-workplace visits, and between two policy variables were added to the model.

3.2. The structural regression (SR) model

The conceptualized structural regression model can be mathematically represented by a set of simultaneous equations for the measurement model and the structural model. In the measurement model of degree of COVID-19 severity ($\boldsymbol{\eta}_C$), the set of equations for the three indicators is given by Eqn. (1).

$$\boldsymbol{Z}_i = \Lambda_i \boldsymbol{\eta}_C + \epsilon_i \tag{1}$$

where,

$\boldsymbol{Z}_i$	vector of indicator i for the latent variable degree of COVID-19 severity ($\boldsymbol{\eta}_C$);
Λ_i	matrix of pattern coefficients representing the loading of latent variable ($\boldsymbol{\eta}_C$) on indicator i;
ϵ_i	vector of measurement error terms for indicator i of the latent variable.

For the structural model, the following six equations provide the specification for the five endogenous mediator variables (Eqn. (2) to Eqn. (6)), representing degree of COVID-19 severity, COVID-19 policies, work from home proportion, change in workplace visits and change in non-workplace visits, and the one endogenous outcome variable (Eqn. (7)) representing person-miles traveled.

$$\boldsymbol{\eta}_C = \Gamma_C \boldsymbol{X} + \boldsymbol{\delta}_C \tag{2}$$

$$\boldsymbol{Y}_P = \mathrm{B}_P \boldsymbol{\eta}_C + \Gamma_P \boldsymbol{X} + \boldsymbol{\delta}_P \tag{3}$$

$$\boldsymbol{Y}_H = \mathrm{B}_H \boldsymbol{\eta}_C + \mathrm{B}_H \boldsymbol{Y}_P + \Gamma_H \boldsymbol{X} + \boldsymbol{\delta}_H \tag{4}$$

$$\boldsymbol{Y}_W = \mathrm{B}_W \boldsymbol{Y}_H + \Gamma_W \boldsymbol{X} + \boldsymbol{\delta}_W \tag{5}$$

$$\boldsymbol{Y}_{NW} = \mathrm{B}_{NW} \boldsymbol{Y}_H + \mathrm{B}_{NW} \boldsymbol{Y}_W + \Gamma_{NW} \boldsymbol{X} + \boldsymbol{\delta}_{NW} \tag{6}$$

$$Y_M = B_M Y_W + B_M Y_{NW} + \Gamma_M X + \delta_M \quad (7)$$

where,

η_C	vector of latent endogenous variables for degree of COVID-19 severity;
Y	vector of observed endogenous variables for COVID-19 policies (Y_P), work from home proportion (Y_H), change in workplace visits (Y_W), change in non-workplace visits (Y_{NW}) and person-miles traveled (Y_M);
X	vector of observed exogenous variables representing socio-demographic characteristics, ICT usage and location characteristics, which varies across the six equations;
B	matrix of coefficients representing direct effects from the latent endogenous variable (η_C) or observed endogenous variables (Y) to observed endogenous variables (Y);
Γ	matrix of coefficient representing direct effects from the observed exogenous variables to the latent endogenous variable (η_C) and observed endogenous variables (Y);
δ	vector of error terms for the respective endogenous variables.

Other parameter matrices include the covariance matrix of the measured exogenous factors $\mathbf{\Phi}$, the covariance matrix of for the disturbances of endogenous factors on each other $\mathbf{\Psi}$, the covariance matrix of error terms of the indicators Θ_ϵ, and the covariance matrix of error terms for the six endogenous variables Θ_δ.

The estimation of the model parameters involves minimizing a fitting function consisting of a population covariance matrix, $\mathbf{\Sigma}$, and a sample covariance matrix, $\boldsymbol{S}$. The population covariance matrix is a function of the model parameters ($\boldsymbol{B}, \Gamma, \Theta_\epsilon, \Theta_\delta, \Lambda_i, \Phi, \text{and}\Psi$), represented by $\boldsymbol{\theta}$ in Eqn. (8) (Lu and Pas, 1999).

$$\mathbf{\Sigma} = \mathbf{\Sigma}(\boldsymbol{\theta}) \quad (8)$$

3.3. Estimation of the model and Goodness-of-Fit statistics

After developing the conceptual model (as shown in Fig. 4), we estimated the model coefficients using U.S. county-level data. Before estimating the model, a Cronbach's alpha or score reliability check was made for the latent construct that measures the internal consistency reliability or the degree to which responses are consistent across the indicators of a latent measure. If internal consistency is low, then the responses may be so heterogeneous that the total score is not the best possible unit of analysis. In contrast, if internal consistency reliability is higher, then it represents the consistency among the responses. From the unstandardized solution, Cronbach's alpha value was computed as 0.76, which is considered adequate by Kline (2016). We also performed a separate confirmatory factor analysis (CFA) to check the overall fitness of the latent construct– degree of COVID-19 severity. Model statistics yielded satisfactory results (RMSEA = 0.00, CFI = 1.0, and TLI = 1.0).

Based on our conceptual structure (Fig. 4) and the best possible combination of exogenous variables, we estimated the structural regression model using the Maximum Likelihood (ML) estimation method. This method works best under the normality assumption and is fairly robust, even with some violation of normality (Acock, 2013). Note that the county-level data for the United States from April 15 – June 9 (8 weeks) in 2020 is used for this study. We checked the distribution of model variables and attempted to reduce the non-normality in selected variables by log transformations, including population density, activity density, and network density. We also conducted Variance Inflation Factor (VIF) test to check for multicollinearity among variables and found that multicollinearity was not present since the largest VIF was computed less than a value of 4.

Several goodness-of-fit measures are reported in Table 2. The chi-squared statistic ($\chi 2$) tests whether the observed covariance matrix and the model implied covariance matrix are equal. Smaller χ^2 value with high p-value (p-value > 0.05) indicates better model fit. However, with the increase in sample size χ^2 value tends to increase, and as a result, models with larger sample sizes might show larger χ^2 value and may lead to rejection of an otherwise good model (Van Acker and Witlox, 2011; Acock, 2013; Kline, 2016). For this reason, χ^2 value is not considered an appropriate measure of fit. Nevertheless, as the basis of other goodness-of-fit measures, it is always reported anyway (Byrne, 2001; Cao et al., 2007). With a sample size of 2,366, we obtained a larger χ^2 value (1602 at the degree of freedom 110) with a lower *p-value* (0.000).

Another fit measure called Root Mean Square Error Approximation (RMSEA) is also reported. This statistic measures the estimated discrepancy between the model implied and true population covariance matrix controlling for sample size (Cao et al., 2007). In other words, it measures the amount of error for each degree of freedom. A complex model may fit better as it capitalizes on chance, but RMSEA adjusts for this (Acock, 2013). Therefore, RMSEA is often considered as a robust goodness-of-fit measure in covariance structure modeling (Byrne, 1998). The recommended cut-off value for RMSEA is 0.05 for a good fit and<0.08 for a reasonably close fit

Table 2
Model goodness-of-fit indices.

Model fit indices	Cut-off value	Model-based value
Chi-squared, χ^2 (df)	$p > 0.05$	1602 (110), $p = 0.00$
RMSEA	< 0.05 (good fit), < 0.08 (reasonable fit)	0.076
CFI	> 0.90	0.91
TLI	> 0.90	0.86
SRMR	< 0.08	0.031

Acock (2013), Kline (2016), Hu and Bentler (1999).

(Acock, 2013). We obtained an RMSEA value of 0.076 for our model, which indicates a reasonably satisfactory model fit.

In addition, two incremental fit indices termed Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are reported. These are the assessment of the improvement of the hypothesized model compared to the independence model with unrelated variables (Kline, 2016; Hu and Bentler, 1999). The acceptable threshold values for CFI and TLI are>0.9 (Acock, 2013; Van Acker and Witlox, 2011), and we obtained 0.91 and 0.86, respectively for our model. Another fit index is Standardized Root Mean Squared Residual (SRMR), which measures how close the model fits in reproducing each correlation on average (Acock, 2013). In other words, it is a measure of the mean absolute correlation residual, the overall difference between the observed and predicted correlations (Kline, 2016). The recommended SRMR value is<0.08 (Acock, 2013; Kline, 2016) and we got 0.031 for our model. Based on the RMSEA, CFI, and SRMR fit statistics, it can be concluded that our postulated model of causal structure fits reasonably well with the data and represents a close approximation of the population.

4. Results and discussions

Model results are discussed in four broad sections: (a) latent measures of COVID-19 severity, (b) impact of COVID-19 severity on state-level policies, (c) impact of COVID-19 severity on working from home (WFH), and (d) impact of WFH on activity-travel behavior. The unstandardized coefficients of *direct* and *total* effects are presented, except that standardized coefficients are presented for measurement models to compare the influence of estimated factor loadings. If not otherwise stated, the effects mentioned represent direct effects.

4.1. Latent measure of COVID-19 severity

The measurement model estimated county-level COVID severity based on indicators including hospital bed utilization, ICU utilization, and death rate. The estimated factor loadings from the measurement model, standardized and unstandardized, are shown in Table 3.

An unstandardized coefficient for a variable pair represents the number of units of changes in the indicator variable due to one unit of change in the latent variable. In the study, the unstandardized coefficients of ICU utilization and death rate were scaled with respect to the hospital bed utilization (called the fixed-parameter). In unstandardized solution, since the coefficients are not normalized, they can be interpreted as regression coefficients (Kline, 2016). For example, for the indicator “ICU utilization”, the coefficient value of 1.11 indicates a 1.11 point increase in this indicator for every one-point increase in the “degree of COVID-19 severity” factor. As anticipated, each of the indicators had a positive association with the severity of the pandemic and was statistically significant at the 1% level of significance.

The standardized coefficients represent the same effect as that produced by the unstandardized coefficients, but in the units of standard deviations — change in the number of standard deviations in the indicator variables due to one standard deviation change in the latent variable (Kline, 2016). Since standardized coefficients treat all variables as having a variance of one, they become independent of the scales of both indicator and latent variables, which means that standardized coefficients can be used to directly compare the relative strengths of the factor loadings (Kwan and Chan, 2011). For example, the standardized coefficient for the variable “hospital bed utilization” in the measurement model indicates that there is a 0.99 standard deviation change in hospital bed utilization when the “degree of COVID-19 severity” latent factor changes by one standard deviation.

Among the three measurement variables, hospital bed utilization was observed to be the strongest measure of COVID-19 severity with a standardized coefficient of 0.99 (Table 3), which indicates that the latent factor, COVID-19 severity, explained 0.99^2 or 98 percent of the observed variance of hospital bed utilization (the square of standardized coefficients are the proportion of explained variance (Kline, 2016)). Note that initially, we conceptualized a measurement model in a combination of four indicators by adding the COVID-19 infection rate (daily new cases per 100 K population) with the existing three indicators. But the standardized factor loading value of this indicator appeared close to 0.1, which can be considered as very low compared to the generally cited empirical cut-off value of 0.4 or 0.5 as suggested in Acock (2013). For this reason, we did not consider the infection rate in our final model.

The latent COVID-19 severity factor was regressed based on socio-economic and location characteristics (exogenous variables) to provide insight on the factors that had associations with the severity of the pandemic. The corresponding unstandardized coefficients of the direct effects of exogenous variables on the degree of COVID-19 severity are presented in Table 4. This table also shows the total effects of exogenous variables on each of the indicators of the latent factor.

As anticipated, the percentages of Black and male populations were positively associated with the severity of the pandemic. Since a

Table 3
Estimated factor loadings of the latent degree of COVID-19 severity (N = 2,366).

Measurement model	Standardized coefficient	Unstandardized coefficient
Latent factor: Degree of COVID-19 severity		
Indicators		
Hospital bed utilization	0.992***	1***
ICU utilization	0.868***	1.114***
Death rate	0.739***	0.300***

Note: **, and *** indicate that coefficients are significant at 5% and 1% level of significance, respectively.

Table 4
Effects on the degree of COVID-19 severity (N = 2,366).

Structural model	Unstandardized coefficient			
Outcome variables	COVID severity	Hospital bed utilization	ICU utilization	Death rate
	Direct effect	Total effect	Total effect	Total effect
Predictors				
Socioeconomic characteristics				
Black	0.031**	0.031**	0.035**	0.009**
Male	0.200**	0.200**	0.222**	0.060**
Median HH Income (Base = Middle & High)				−0.399***
Low	−1.327***	−1.327***	−1.479***	
Average commute time (Base = Medium)				
Low	−5.459***	−5.459***	−6.081***	−1.640***
High	7.125***	7.125***	7.937***	2.141***
Location characteristics				
Population density (in log)	1.935***	1.935***	2.155***	0.581***

Note: **, and *** indicate that coefficients are significant at 5% and 1% level of significance, respectively.

higher percentage of Black people were employed in low-wage essential jobs (e.g., grocery stores, public transit, and health care facilities) during the pandemic, they were at a higher risk of COVID-19 exposure (Reyes, 2020). Other factors that might also increase their risk of exposure were crowded housing, lower access to healthcare facilities, and reliance on public transportation (CDC, 2021a; Kullar et al., 2020; Kemp et al., 2020). For these reasons, counties having a higher fraction of Black people might correspond to a higher degree of severity of the pandemic. The result is consistent with another concurrent study by Rafiq et al. (2022). Similarly, as hypothesized, counties with a higher percentage of male population had a higher degree of COVID-19 severity. This result is consistent with the CDC COVID-19 data tracker (CDC, 2021b), which reported that the severity of the pandemic was higher among males compared to females (percentage of death cases was 54.3% vs. 45.7%). Other socio-demographic characteristics such as counties' low median income and low average commute time demonstrated negative connections with COVID-19 severity. Regarding location characteristics, denser counties corresponded to higher severity of the pandemic. A similar finding was found in CDC (2020). They reported that between March and May 2020, the COVID-19 pandemic was highest among the residents of large metropolitan areas and the infection then shifted to a rapid surge to small metropolitan and non-metropolitan areas. Rafiq et al. (2022) also reported a similar finding for May 2020.

4.2. Effects of COVID-19 severity on State-level policies

Table 5 represents the effects of COVID-19 severity on the levels of enactment of community mitigation policies at the state level. Note that as a measure of COVID-19 policies, we considered two indices: a stringency index reflecting containment and closure policies and a containment and health index representing containment and health-related policies.

We did not conceptualize direct effects from county-level socio-economic characteristics to the policy indices; instead, we considered direct effects for the degree of COVID-19 severity and locational attributes. As anticipated, a higher degree of the severity of the pandemic corresponded to a higher level of government response towards various policies to combat the severity of the pandemic.

Table 5
Effects on COVID-19 policies (N = 2,366).

Structural model	Unstandardized coefficients			
Outcome variables	Stringency index		Containment & health index	
	Direct effect	Total effect	Direct effect	Total effect
Predictors				
Degree of COVID-19 severity (latent)	0.030***	0.030***	0.027***	0.027***
Socio-economic characteristics				
Black	—	0.001**	—	0.001**
Male	—	0.006**	—	0.005**
Median HH Income (Base = Middle&High)				
Low	—	−0.040***	—	−0.035***
Average commute time (Base = Medium)				
Low	—	−0.165***	—	−0.146***
High	—	0.214***	—	0.190***
Location characteristics				
Population density (in log)	0.028***	0.087***	0.014*	0.066***
Road network density (in log)	−0.086***	−0.086***	−0.082***	−0.082***
No. of points of interests	0.001***	0.001***	—	—
Presence of airport	—	—	0.056***	0.056***

Note: *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Since counties with higher population density experienced a greater surge of the pandemic during the study period compared to the counties with low density, those higher density counties responded with policies to a greater degree than their counterparts (positive effect between population density and policy indices).

4.3. Effects of COVID-19 severity on working from home (WFH)

The unstandardized coefficients of the direct and total effects of socio-economic, ICT usage, location, COVID-19 severity, and COVID-19 policy variables on WFH proportion are shown in Table 6. The degree of COVID-19 severity significantly positively influenced the adoption of WFH (with a direct effect of 0.16, Table 6). The positive effect indicated that people living in counties that experienced higher severity of the pandemic had a higher adoption of WFH.

The ICT usage indicators, such as the availability of internet connections and of desktop and mobile phones, had a strong influence on WFH. In this connection, we posited that two factors expedite selecting the option of WFH during the pandemic: (a) the availability of an internet connection in the household, and (b) an existing accommodation of WFH (experience with some degree of WFH prior to the pandemic). We selected ICT usage and WFH rates from the year 2018 (U.S. Census Bureau, 2018) to test how these two factors may influence WFH in the current pandemic. To capture and estimate their joint influence, an *interaction* term was defined as a product of these variables, which was linked with WFH variable as an exogenous variable. Model estimation indicated that this interaction variable indeed had a high influence on WFH (with a positive coefficient of 6.22, Table 6). This suggests that counties with a higher fraction of people having an internet connection and prior WFH experiences were more likely to adopt work-from-home during the pandemic. It indicates that WFH (even if temporarily) is dependent on the availability of resources and some degree of familiarity with the technologies needed. An element of a "digital divide" was noticed: about 78 percent of U.S. households had an internet connection, implying that the other 22 percent did not (even in such a technological age). Rural areas, in particular, lagged behind (25 percent of households in non-metro areas did not have internet connections compared to 15 percent in metro areas). Kong et al. (2020) documented similar findings.

Other socio-economic characteristics, such as the percentage of the male population, median household income, and average commute time had significant effects on WFH proportion. More specifically, counties with a higher fraction of males demonstrated a lower fraction of people working from home. Similarly, counties with a low median income tended to have a lower WFH proportion compared to middle and high median income counties. Similar findings were reported in Su et al. (2021) for the pre-pandemic period and in Rafiq et al. (2020) and Beck and Hensher (2020a) for the during-pandemic period. As anticipated, counties having a longer commute time on average had a higher WFH proportion compared to medium commute time (positive effect). Similarly, counties with a shorter commute time demonstrated a lower WFH proportion than medium commute time (negative effect). Prior studies also found that longer commute distances (i.e., longer commute time) encourage telecommuting (Yen and Mahmassani, 1997; Ory and Mokhtarian, 2006).

Regarding location characteristics, population density had a positive direct effect on the WFH proportion. Denser counties usually have a higher fraction of households with internet access and workers in telecommutable jobs, and thus, they can better accommodate stay-at-home orders imposed during the pandemic by substituting in-person work with work-from-home. Jin and Wu (2011) observed similar findings in their pre-COVID telecommuting study. Similarly, denser areas where there is a higher chance of having places with

Table 6
Effects on working from home proportion (N = 2,366).

Structural model	Unstandardized coefficients	
Outcome: WFH proportion	Direct effect	Total effect
Predictors		
Degree of COVID-19 severity (latent)	0.161***	0.189***
Socio-economic characteristics and ICT usage		
Black	−0.009	−0.003
Male	−0.118*	−0.080
Median HH Income (Base = Middle, High)		
Low	—	−0.251 ***
Average commute time (Base = Medium)		
Low	−0.333	−1.367***
High	4.274**	5.623***
Pre-COVID WFH proportion × HH fraction with internet access	6.219***	6.219***
Location characteristics		
Population density (in log)	0.331**	0.721***
Road network density (in log)	−2.662***	−2.745***
No. of points of interests	—	0.001**
Presence of airport	—	0.015
COVID-19 policies		
Stringency index	0.703**	0.703**
Containment & health index	0.275	0.275

Note: WFH refers to working from home, — denotes no direct connections, and *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

more points of crowd gatherings had a similar positive association with WFH (total effect). Unlike population density, road network density had a negative association with WFH proportion.

As expected, COVID-19 policy indices such as the stringency index positively affected the WFH proportion, which implies that the higher the level of state government response towards containment and closure policies (e.g., stay-at-home order, gathering restrictions, nonessential business closure, school closure), the higher the proportion of WFH in a county. On the other hand, the combined effect of containment and health policies did not show any significant effect on WFH.

4.4. *Effects of COVID-19 severity and working from home on Activity-Travel behavior*

Due to travel and activity restrictions imposed by the COVID-19 pandemic, working from home (WFH) significantly increased during 2020 compared to other years (Beck and Hensher, 2020a, 2020b; Hensher, 2020; Conway, 2020). The higher level of WFH consequently influenced both work and non-work activity participation as well as the associated travel. The next four sections discuss the effects of the severity of the pandemic, working from home, and socio-economic and location characteristics on the activity-travel behavior of people across U.S. counties. Work and non-work activity participation during the pandemic were denoted as the percentage changes in work and non-workplace visits compared to the pre-pandemic period. Travel was represented as average person-miles traveled by all modes. Table 7 shows the unstandardized direct and total effects of exogenous and endogenous variables on the activity participation and travel variables.

4.4.1. *Effects of COVID-19 severity on activity-travel behavior*

With the increase in the degree of COVID-19 severity, the tendency of visiting work and non-work places was significantly reduced (total effect: −0.103 for work and −0.159 for non-work, Table 7) due in part to activity-travel restrictions (negative effects from COVID-19 policy indices to change in work and non-workplace visits, Table 7). After comparing the standardized coefficients of the effects of the COVID-19 severity on workplace and non-workplace visits, it can be concluded that COVID-19 severity had a greater impact on workplace visits than non-workplace visits (standardized coefficients of −0.15 vs. −0.06). Such a reduction in the demand for out-of-home work and non-work activity would correspond with a decrease in overall travel demand as well (standardized coefficient of the total effect of COVID-19 severity on person-miles traveled is −0.01).

The summary statistics presented in Table 8 support model results. For example, about one-third of workers did WFH during the

Table 7
Effects on change in workplace and non-workplace visits and person-miles traveled (N = 2,366).

Structural model	**Unstandardized coefficients**					
Outcome variables	Change in workplace visits (%)		Change in non-workplace visits (%)		Person-miles traveled	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
Predictors						
Degree of COVID-19 severity (latent)	—	−0.103***	—	−0.159***	—	−0.008***
WFH proportion	−0.548 ***	−0.548***	0.018	−0.838***	—	−0.041***
Change in workplace visits (%)	—	—	1.561***	1.561***	0.098***	0.074***
Change in nonworkplace visits (%)	—	—	—	—	−0.015***	−0.015***
Socio-economic characteristics						
Black	0.015***	0.016**	−0.133***	−0.107***	—	0.003***
Male	—	0.044	—	0.067	0.413***	0.416***
Median HH Income (Base = Middle)						
Low	0.848***	0.986***	—	1.535***	—	0.074**
High	−16.052***	−16.052***	—	−25.053***	—	−1.195***
Average commute time (Base = Medium)		1.735***		2.683***		
Low	0.985***	2.845	—	4.541	—	0.130***
High	5.930***		—		—	0.210
Commute mode: driving	0.232***	0.232***	0.601***	0.964***	—	0.008
Pre-COVID WFH proportion × HH fraction with internet access	2.833***	−0.578***	—	−0.791**	—	−0.045***
Location characteristics						
Population density (in log)	−0.938***	−1.334***	6.186***	4.117***	−2.617***	−2.811***
Activity density (in log)	−1.036***	−1.036***	—	−1.617***	—	−0.077***
Network density (in log)	—	1.506***	3.055***	5.356***	−2.683***	−2.617***
Metropolitan status	−2.015***	−2.015***	−2.706**	−5.850***	—	−0.108**
No. of points of interests	—	−0.0004*	−0.057***	−0.058***	−0.022***	−0.021***
Transit performance score	−0.964***	−0.964***	−3.515***	−5.020***	—	−0.018
Presence of airport	—	−0.008	—	−0.013	−1.131***	−1.131***
COVID-19 policies						
Stringency index	—	−0.386**	—	−0.589**	—	−0.029**
Containment & health index	—	−0.151	—	−0.230	—	−0.011

Note: WFH refers to working from home, — denotes no direct connections, and *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 8
Percentage change in activity-travel participation during the pandemic (N = 2,366).

Variables	Metropolitan status	Pre-COVID (Jan 15 – Mar 10)	During-COVID (Apr 15 – May 9)	Change (%)
Working from home (WFH) (%)	Metro	4.64	33.06	612.50
	Non-metro	4.35	30.14	592.87
	Total	4.48	31.47	602.46
Change in workplace visits (%)	Metro	NA	NA	–33.58
	Non-metro			−26.68
	Total			−29.82
Change in non-workplace visits (%)	Metro	NA	NA	–23.39
	Non-metro			−16.21
	Total			−19.44
Person-miles traveled	Metro	40.74	33.43	−17.94
	Non-metro	45.27	40.04	−11.55
	Total	43.21	37.03	−14.30

pandemic, a level six times higher than the pre-pandemic period. There was about a 30 percent reduction in work visits and a 20 percent reduction in non-work visits compared to the pre-pandemic baseline. Consequently, the average distance traveled per person decreased by about 6 person-miles.

4.4.2. Indirect effects of working from home on travel via work participation

The percentage of the county population working from home negatively affected the percentage change in workplace visits (direct effect: −0.548). This suggests that with more people working from home, workplace visits declined. Again, the greater the reduction in workplace visits, the lower the average distance traveled per person per day in a county (a positive effect). We also observed such a proportional relationship between changes in workplace visits and person-miles traveled (see Fig. 5, where the dotted lines represent median values of the axes).

4.4.3. Indirect effects of working from home on travel via non-work participation

Unlike changes in workplace visits, the changes in non-workplace visits were positively associated with the WFH proportion. This implies that with more people working from home, non-workplace visits tended to increase. Although this positive effect would have been consistent with earlier results from the pre-COVID era (Kim, 2016; Kim et al., 2015; Zhu, 2012), we found this effect to be *insignificant* in our model. We indeed obtained a significant effect from WFH to the percentage change in non-workplace visits but only indirectly via workplace visits. Consequently, the total effect turns out to be negative (total effect: −0.838, Table 7). This might be associated with increased WFH reducing workplace visits which in turn reduced associated non-workplace visits that might have occurred as part of work tours.

Moreover, the lower the changes in non-workplace visits, the higher the average person-miles traveled in a county (negative effect). This finding was contrary to our hypothesis. We, therefore, further investigated the underlying relationship between these two variables as well as their relationships to other variables that might help explain this counter-intuitive effect. Fig. 6 shows the distribution of counties in terms of changes in non-workplace (x-axis) and workplace visits (y-axis), color-coded by the degree of person-miles traveled (PMT) in both metropolitan and non-metropolitan areas. Green implies a PMT lower than the median value, whereas red denotes a PMT higher than the median. Also, for each of the figure's quadrants, the distribution of counties with high and low PMT is reported. Each of the quadrants in Fig. 6b shows that non-metro counties contained a larger fraction of high PMT values, unlike metropolitan counties (Fig. 6a). This may be due to non-metropolitan areas typically being less dense, so activity locations are more spread spatially. In contrast, in metropolitan areas, activity locations are more often located in close proximity, so fewer non-work visit results in lower miles-per person (a positive correlation).

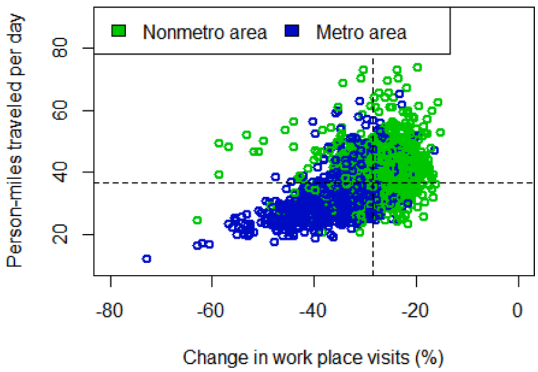
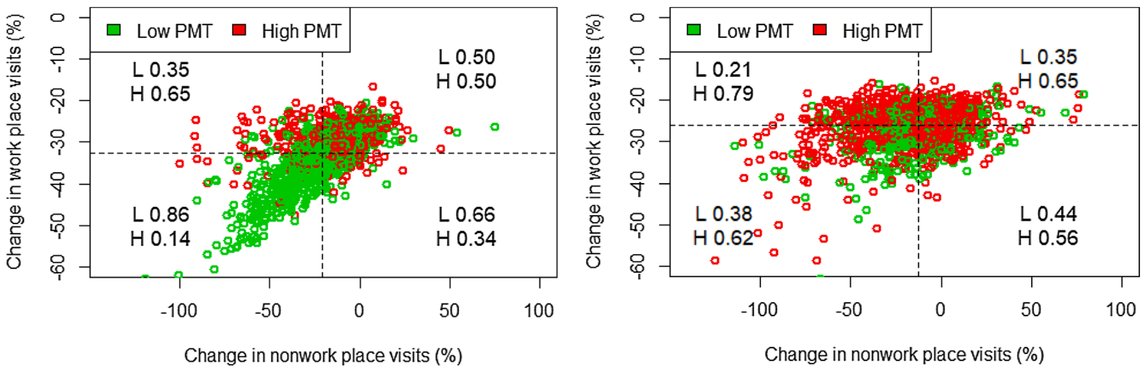


Fig. 5. Distribution of person-miles traveled due to changes in workplace visits by metropolitan status.



a. Metropolitan counties b. Non-metropolitan counties

Note: L and H reports the fraction of counties with low and high PMT in the corresponding quadrant

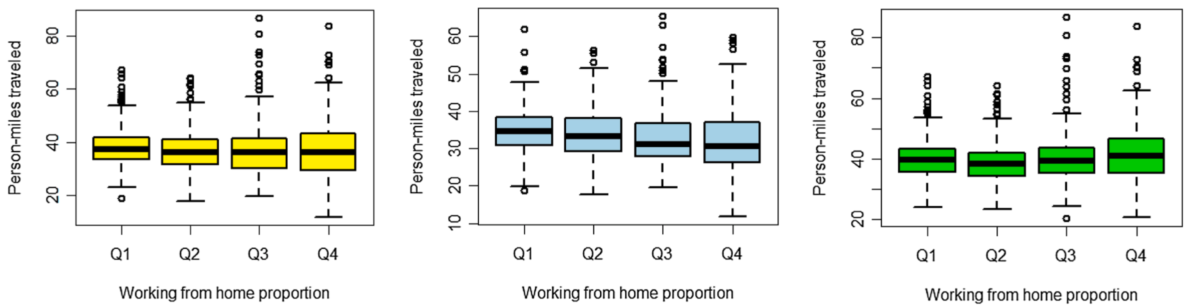
Fig. 6. County distribution based on changes in non-workplace and workplace visits by person-miles traveled.

Counties considered metropolitan areas showed a notably different relationship between work, non-work, and PMT than non-metropolitan areas. In metro areas, the lower work and non-work participation (lower-left quadrant in Fig. 6a), the lower the PMT (86 percent of counties have a low PMT). In non-metro areas, a lower work and non-work participation corresponded to higher PMT values (in the lower-left quadrant, 62 percent of counties have a high PMT, Fig. 6b). Lower non-work participation and higher work participation contributed to higher PMT values (upper-left quadrant in Fig. 6b). This implies that lower non-work participation was associated with a higher PMT value. It also implies that the reduction in non-workplace visits did not reduce the average distance traveled per person in a county unless the work or non-work trips that were made were associated with a shorter commuting distance.

We also observed a positive correlation (0.321) between non-work participation and the average distance traveled per person in metropolitan areas, whereas the correlation between the same two variables is negative (-0.199) for non-metropolitan areas. Our model results may show this effect at an aggregated level favoring the behavior observed in non-metro areas over their metro counterparts. The higher level of person-miles traveled resulting from a greater reduction in non-workplace visits during the pandemic may be due to longer driving distances of commercial delivery drivers (this could not be captured due to data anonymity and thus, needs further study).

4.4.4. Total effects of working from home on travel

We found a *negative* total effect for the WFH proportion on person-miles traveled during the pandemic. Studies conducted before the pandemic, however, found both complementary (Choo and Mokhtarian, 2007; Kim, 2016; Kim et al., 2015; Zhu, 2012) and substitutive relations (Lari, 2012; Mokhtarian et al., 1995, 2004; Vora and Mahmassani, 2002) between WFH and distance traveled. To examine this effect, we construct quantile boxplots (Fig. 7) depicting the corresponding person-miles traveled in counties within a specified range of the WFH proportion. Here the counties are split into groups based on quartile values, with Q1 denoting counties having below a 25-percentile value of the WFH proportion, Q2 denoting counties above the 25-percentile but below a 50-percentile, and so on. It was observed that counties with a larger share of WFH indeed had lower PMT values, as the median values (the central line inside the box) declined in higher quartile boxes (Fig. 7a). However, this relationship varied between metropolitan and non-metropolitan counties. In metropolitan counties, PMT declined (Fig. 7b), whereas in non-metropolitan areas, PMT increased (Fig. 7c) for higher quantile values of WFH.



a. All counties b. Metropolitan counties c. Non-metropolitan counties

Fig. 7. Relationship between working from home proportion and person-miles traveled.

4.4.5. Effects of socio-economic characteristics on activity-travel behavior

The county-level socio-economic and location characteristics significantly affected work and non-work activity participation and average PMT by county. The corresponding unstandardized coefficients are shown in Table 7. Counties with low median household income and a higher percentage of Blacks had more workplace visits, and as a result, more person-miles traveled. Counties with a higher percentage of workers driving to work (thus, a lower fraction of commuters commuting by other modes) before the pandemic experienced higher workplace and non-workplace visits during the pandemic. This, in part, might be a choice to avoid the risk of exposure to the virus while traveling with strangers in shared commuting modes.

Metropolitan counties with a greater number of jobs and housing units (activity density) and points of interest for crowd gathering and a higher transit performance score were associated with fewer workplace visits (c.f. Table 7). A possible rationale is that metropolitan counties experienced a higher share of COVID-19 spread during the first few months of the pandemic (Hamidi et al., 2020; Carozzi, 2020); consequently, those counties experienced a higher degree of activity-travel restrictions causing workers not to make their regular out-of-home workplace visits. This would lower both the non-workplace visits and the average PMT in metropolitan counties (c.f. Table 7). Regarding the impacts of the state-level policies, a higher degree of government response to containment and closure policies corresponded to a higher reduction in the workplace and non-workplace visits and overall person-miles traveled.

5. Conclusions and policy implications

The ongoing COVID-19 pandemic has created significant disruption in our daily lives and has triggered massive changes in how we schedule and perform activities and travel. Among other impacts, policies that restricted activity and travel resulted in significant growth in working from home (WFH). This study found that about one-third of workers worked from home during the initial months of the pandemic, a level which was six times higher than prior to the pandemic. The rapidity in which this WFH shift was implemented has created a range of impacts on daily activity participation and travel arrangements. This study explored the aggregate impacts of WFH on activity participation and travel behavior during the pandemic across U.S. counties. We developed a Structural Regression (SR) model by conceptualizing interrelationships between county-level WFH proportion, changes in workplace and non-workplace visits compared to pre-pandemic levels, average person-miles traveled, and a range of socio-economic and location characteristics. We considered an 8-week period (April 15 to June 9, 2020) of cross-sectional data during the early phase of the pandemic. The major study findings, their policy implications, and limitations of our study are discussed below.

5.1. Major findings

The major findings of this study are summarized as:

- Counties that had a larger fraction of households with internet access and a greater proportion of people with some degree of working from home before the pandemic had significant increases in the proportion working from home during the pandemic.
- The greater a county's working from home (WFH) proportion, the greater the reduction in *workplace visits* and consequently the lower the average person-miles traveled (PMT).
- The relationship between WFH and PMT was complex via non-work participation. WFH negatively affected *non-workplace visits* only indirectly via workplace visits. This, in turn, led to a reduction in average PMT, but only for metropolitan counties.
- The greater a county's WFH population, the greater the reduction in average *person-miles traveled*, a negative total effect.
- A higher degree of government response to various containment and closure policies, such as school closing, workplace closing, and stay-at-home orders, corresponded to a higher reduction in the work and non-workplace visits and person-miles traveled.

5.2. Policy implications

The preliminary ideas, analysis, and findings of this study provide important insights on working from home (WFH) practice, differences in impacts of WFH between metropolitan and non-metropolitan counties, and its overall impacts on activity-travel behavior at an aggregate scale. The policy implications of our findings are discussed below. Note that to make a broader connection of our study findings to relevant policies, we interchangeably used the term WFH and telecommuting in this section.

(a) Revisit the relationships between telecommuting and travel in the context of the pandemic

Telecommuting has long been considered by planners and policymakers an effective travel demand management and environmental management tool to reduce overall travel and greenhouse gas emissions. However, there is conflicting empirical evidence between the relationship of telecommuting and travel. Some studies suggested a complementary relationship between telecommuting and travel (Choo and Mokhtarian, 2007; Kim, 2016; Kim et al., 2015; Zhu, 2012) and found that the practice of telecommuting induced new travel and thus increased vehicle-miles traveled. In contrast, other studies found a substitutive relationship suggesting that telecommuting practice could be a travel reduction tool (Lari, 2012; Mokhtarian et al., 1995, 2004; Vora and Mahmassani, 2002).

The ongoing COVID-19 pandemic, despite creating immense disruption, has offered a unique opportunity to experiment with a large fraction of the workforce telecommuting, providing some understanding of potential ramifications of telecommuting on travel, one that likely could not have been tested otherwise. In this context, our county-level findings suggested that during the early phase of the pandemic, when infection rates were stabilized and activity-travel behavior began to approach pre-pandemic levels, a greater level of working from home (telecommuting) corresponded to a greater reduction in average person-miles traveled. These results can guide policymakers in evaluating county-level changes in greenhouse gas emissions and air quality associated with increases (or decreases) in the workforce proportion working from home and the corresponding changes in person-miles traveled. However, relationships between WFH and travel likely vary over the temporal evolution of the pandemic. Examining the changes in the degree of adoption of WFH and associated changes in travel behavior as the pandemic continues, is a focus of future research.

(b) Prospects of telecommuting and its potential impacts

It is unclear whether the changes in telecommuting and activity-travel behavior that were observed during the pandemic will continue after the pandemic ebbs. There have been numerous media reports of both employers and employees preferring telecommuting over commuting, at least some of the time. A recent poll from the American Institute of Architects revealed that 56 percent of firms expected to have their employees work from the office (down from 74 percent pre-pandemic) and suggested that future workplaces may reflect a hybrid mixing of in-person and telework (Keller, 2021). The Society for Human Resource Management surveyed U.S. employees about their work preferences when the pandemic ebbs and found that 31 percent of workers preferred to work fully remote, whereas 31 percent preferred fully in-person. In addition, 22 percent wanted remote work most of the time and 16 percent preferred in-person some of the time (Vincent, 2021). Other studies suggest that telecommuting practice is likely to continue and, in some cases, may even increase in the post-pandemic future (Conway et al., 2020; Beck and Hensher, 2020a; Amekudzi-Kennedy et al., 2020). However, whether some portion of the workforce can and will adopt some degree of telecommuting as a new norm will depend on the relative weight of advantages and challenges that need to be addressed by transportation, land use, and economic policies.

We observed that telecommuting contributed to reductions in work trips, which has important policy implications for transportation. A reduction in work trips will likely reduce peak hour traffic since work trips are a primary contributor, especially in the morning peak. It could consequently contribute to a reduction in miles traveled and emissions and indirectly could provide a better level of service. However, a reduction in commuting could have negative impacts on public transit ridership and thus service. If peak hour traffic is reduced and traffic flows are spread out throughout the day, transit operators may need to restructure their service or introduce new technologies to meet peak and off-peak demands.

The consequences of telecommuting on non-work trips are complicated. We found that telecommuting did not have a significant direct influence on aggregate changes in non-work trips, but it indirectly led to reductions in non-work trips that were associated with the work commute. This indicates that telecommuting may impact businesses located in or near business centers that depend on worker patronage. Policies could provide incentives to such businesses to compensate for negative impacts. Alternative options could involve changing business modalities (e.g., online delivery) or relocating businesses to residential areas.

(c) Geographical variations in telecommuting and travel

COVID-19 severity, telecommuting adoption, and changes in activity-travel behavior varied across metropolitan and non-metropolitan counties. Metropolitan counties experienced a higher rate of COVID-19 infections during the initial phase of the pandemic compared to non-metropolitan counties. The adoption of work-from-home and the reduction in work and non-work activity visits, and in person-miles traveled in metropolitan areas were greater than in non-metropolitan counties. Metropolitan areas showed notably different relationships between working from home and activity-travel behavior than non-metropolitan areas, thus, policies related to work-from-home arrangement and transportation need to take this geographical variation into consideration.

(d) Telecommuting adoption and equity considerations

There are likely equity issues in the adoption of work from home policies. First, not all workers are employed in telecommutable jobs. The level of opportunities associated with working from home will not be equal, whether it be savings in commuting costs or even reduced advancement at work. Second, while reduced congestion might benefit those who still commute, there could be service changes in public transit that might not be beneficial. Third, the pre-pandemic land use pattern could change fundamentally if significant people working from home become the new normal. Service businesses located in major employment centers may no longer be economically viable with reduced commuting. Changes in residential location may also have equity impacts since those that can telecommute may have more locations opportunities and thus reduced housing costs than those who must still commute. Consequently, land-use and transportation policies may need to be re-considered.

5.3. Study limitations and future research

There are some limitations in this study. Several other possible variables and interconnections could be added to the conceptual framework of the structural regression model estimated in this study. For example, transportation infrastructure level characteristics and detailed spatial attributes in a county might affect the WFH proportion and activity participation in that county. But we did not include these variables in our model due to the unavailability of data or to avoid further complexity into the model. In addition, due to the unavailability of county-level vehicle-miles traveled (VMT) data, this study was limited to analysis of the influence of telecommuting on person-miles traveled. Nevertheless, the conceptual structure and the findings will provide directions for further analysis to investigate similar relationships between telecommuting and VMT at both aggregate and disaggregate levels.

We conducted a structural analysis using an 8-week span of cross-sectional data from the early phase of the pandemic (Spring 2020). This static analysis for a specific time frame can be extended for the other time periods, for example, Summer 2020, Fall 2020, and post-vaccination period which can provide valuable insights on how the relationships between the degree of COVID-19 severity and working from home adoption evolved throughout the year. In addition to this, time-series analysis can be done to portray the dynamic relationship between COVID, WFH, and travel along with the various policy measures and vaccination data, which is one of our future research interests.

In addition, we recognize that the structural equation model (SEM) cannot strongly infer causation between variables even with time-series data. This is because we never know whether we have been able to include all the relevant variables in our model and any missing variable may actually cause the endogeneity outcome (Acock, 2013). That is why throughout the paper, we avoided using the term "X causes Y", instead used "X influences Y" or "X is associated with Y". This is a classical issue in SEM and has been widely recognized in the literature (Bollen and Pearl, 2013; Kline, 2016).

The findings of this preliminary study can aid policymakers in understanding the potential impacts of working from home and thus can guide the development of work-from-home and transportation-related policies that can make work-from-home a more effective travel demand and environmental management tool.

CRediT authorship contribution statement

Rezwana Rafiq: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Michael G. McNally:** Conceptualization, Methodology, Investigation, Supervision, Writing – review & editing. **Yusuf Sarwar Uddin:** Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Tanjeeb Ahmed:** Data curation, Methodology, Software, Writing – review & editing.

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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