# Impacts of remote work on vehicle miles traveled and transit ridership in the United States

Yunhan Zheng[1], Shenhao Wang[2,*], Lun Liu[3], Jim Aloisi[4], Jinhua Zhao[4]

**1** Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

**2** Department of Urban and Regional Planning, University of Florida, Gainesville, FL 32611, USA

**3** School of Government, Peking University, Beijing 100871, China

**4** Department of Urban Studies and Planning, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

***** To whom correspondence should be addressed. E-mail: shenhaowang@ufl.edu

# Abstract

Remote work's potential as a sustainable mobility solution has garnered attention, particularly due to its widespread adoption during the COVID-19 pandemic. Our study systematically examines the impacts of remote work on vehicle-miles traveled (VMT) and transit ridership in the United States from April 2020 to October 2022. We find that using the pre-pandemic levels as the baselines, a mere 1% decrease in on-site workers corresponds to a 0.99% reduction in state-level VMT and a 2.26% drop in Metropolitan Statistical Area (MSA)-level transit ridership. Notably, a 10% decrease in on-site workers compared to the pre-pandemic level could yield a consequential annual reduction of 191.8 million metric tons (10%) in $CO_2$ emissions from the transportation sector, alongside a substantial \$3.7 billion (26.7%) annual loss in transit fare revenues within the contiguous US. These findings offer policymakers crucial insights into how different remote work policies can impact urban transport and environmental sustainability as remote work continues to persist.

Decarbonizing the transportation sector is critical for mitigating climate change, as transportation accounts for 35.9% of energy-related carbon dioxide emissions in the United States [1]. To cut transportation-related greenhouse gas (GHG) emissions, studies acknowledge the need to promote both technological innovations and sustainable behavior changes [2, 3, 4, 5]. Among demand-side solutions, remote work has gained attention as a sustainable mobility tool in the past decades. By allowing employees to work from home, in satellite telecenters, or other locations, remote work was initially proposed to provide more flexibility to employees regarding work locations and work hours [6, 7, 8]. Advocates for the remote work arrangement usually highlight its utilities of cutting carbon emissions by reducing the number of commuting trips [9, 10, 8], saving travel time through alleviating traffic congestion [11, 12], and in some cases promoting the usage of sustainable travel modes such as public transit [13, 14].

Despite theoretical advantages, the actual impact of remote work on urban mobility remains uncertain and sometimes contradictory in existing literature. Previous studies have shown a wide range of estimated impacts on vehicle-miles traveled (VMT) associated with remote work, ranging from a 20% reduction to a 3.9% increase when teleworking one day a week in pre-pandemic settings [6]. These disparities can be attributed to variations in measuring remote work, utilizing diverse datasets, and the intricate mechanisms through which remote work influences motorized travel.

Regarding the mechanisms, on one hand, remote work has the potential to reduce VMT by eliminating or reducing employees' commuting needs and by cutting down vehicle travel time, particularly during peak hours, thus reducing carbon emissions [9, 10, 15]. On the other hand, it can also potentially lead to an increase in VMT [16, 17]. For instance, remote workers may engage in more non-work travel due to the flexibility of their work schedule and location [18, 19]. Additionally, they may choose to live further away from their workplace, resulting in longer commutes on non-remote working days [9, 20].

The effect of remote work on public transit is also uncertain: though some literature suggested that remote work can increase public transit usage [13, 14], others found that remote work actually reduced transit usage through reducing the commuting needs [21, 22]. Despite the controversy in previous research findings, we need to note that identifying the pre-pandemic impacts of remote work on urban mobility itself was challenging, because remote work was a very limited practice at that time. In 2017-2018, just 8% of Americans worked from home for at least one day per week, as reported by the American Time Use Survey [23, 24]. In 2019, the American Community Survey revealed that only about 5.7% of workers in the United States primarily worked from home [25]. As a result, the impacts remote work imposed on the overall urban transport system were marginal and unstable, making them difficult to identify in practice.

The COVID-19 pandemic has had a profound impact on remote work trends [26]. It has compelled millions of Americans to adapt to working from home (WFH), with a significant 37% of the population working remotely full-time as of April 2020 [27]. While the pandemic health emergency is reaching its conclusion [28], many companies have recognized the benefits and and are embracing remote work policies for the long term. This decision allows employees the flexibility to work remotely either part-time or full-time. Data from May 2023 indicates that approximately 20.1% of employed Americans WFH for at least one day per week [29]. With remote work likely to remain a popular working arrangement in the post-pandemic era, it becomes crucial to systematically evaluate the effects of remote work on urban mobility. Such an analysis can provide valuable insights for governments seeking to reduce VMT, alleviate congestion, and mitigate air pollution in the long run. It will also help employers and employees understand how their remote work policies and preferences collectively influence the urban transport system and environmental sustainability in the future.

Using a combination of anonymized and aggregated workplace visitation data along with nationwide panel data on VMT and public transit, we conducted a comprehensive analysis to investigate the impacts of remote work on VMT and transit ridership across the United States following the COVID-19 pandemic. To address concerns of endogeneity, we employed an instrumental variable (IV) approach and investigated how these effects varied across different spatial and temporal dimensions. Furthermore, based on the estimated effects of remote work on VMT and transit ridership, we quantified the corresponding reductions in carbon dioxide ($CO_2$) emissions and transit fare revenues at both national and regional levels. By doing so, our study aims to provide valuable insights into the environmental implications of advocating remote work as a strategy for mitigating on-road GHG emissions. It is noteworthy that our analysis spans the period from April 2020 to October 2022, during which the effects of remote work on VMT and transit ridership may have been uniquely shaped by the COVID-19 pandemic. During the pandemic period, the induced trips may have been restricted, potentially introducing an upward bias in estimating the net impact of remote work on VMT and transit ridership. Hence, we recognize the need to further examine the impacts of remote work on urban mobility in the post-pandemic era.

# Results

To examine the impact of remote work on VMT and transit ridership in the United States from April 2020 to October 2022, we adopt a unique identification strategy based on the heterogeneity in the recovery rate of onsite workers. The recovery rate of onsite workers serves as a proxy for the inverse of remote work prevalence, which is measured by the percentage of onsite workers compared to pre-pandemic levels. In this study, we examine the impact of remote work on two key urban mobility measures: (1) VMT in 48 states and the District of Columbia, and (2) transit ridership in 217 Metropolitan Statistical Areas (MSAs).

Based on the panel datasets that offer broad spatiotemporal coverage, we first employ the fixed-effect regressions, where the dependent variables are the recovery rates of VMT and transit ridership, measured by the percentage of VMT and transit ridership compared to their respective values in the same month of 2019. By including the regional and month fixed effects in the models, we can effectively control for the region- and time-specific variations. In addition to the fixed effects, we account for other relevant covariates, including GDP per capita, unemployment rate, the recovery rate of transit services, transit fares, population size, net migration rate, reopening status, reported COVID cases per capita, and vaccination rate. These covariates help to control for various factors that could potentially impact the fluctuations in VMT and transit ridership throughout the duration of the study. The primary independent variable of focus is the recovery rate of onsite workers.

However, fixed-effects models have limitations, such as omitted variable bias and reverse causality. Furthermore, using the percentage of onsite workers as a proxy for remote work may not accurately capture the full extent of remote work, particularly for individuals who may remain offsite due to job loss. To address these issues simultaneously and refine our analysis, we adopted an instrumental variable approach using two-stage least squares (2SLS) estimation. Specifically, we used the percentage of suitable remote workers in each state/MSA for each month as our instrument. This instrument was derived by considering industry-specific percentages of suitable remote workers and variations in employment levels across different industries in each state/MSA. By employing this instrument, we effectively removed variations in the endogenous predictor (i.e., the percentage of onsite workers compared to pre-pandemic levels) unrelated to remote work, including changes due to shifts in unemployment rates. Additionally, we examine the spatial heterogeneity and temporal evolution of the causal effects, and estimate the corresponding marginal effect of remote work on the $CO_2$ emissions in each state and that on transit fare revenues in each MSA, yielding the following major findings:

1. Compared to pre-pandemic levels, a 1% increase in the number of onsite workers is associated with a 0.99% increase in state-level VMT and a 2.26% increase in MSA-level transit ridership. On a regional scale, when a state or an MSA has a higher percentage of transit commuters, the impact of remote work on VMT tends to be smaller, while its effect on transit ridership tends to be larger.

2. A 10% decrease in the number of onsite workers compared to pre-pandemic levels could lead to a reduction of 191.8 million metric tons of $CO_2$ emissions related to VMT, which represents a 10% annual reduction in $CO_2$ emissions from the transportation sector in the contiguous US. Additionally, this decrease in onsite workers may result in a \$3.7 billion or 26.7% annual loss in transit fare revenues.

3. Temporally, the impacts of remote work on the recovery rates of VMT and transit ridership display remarkable temporal consistency over the entire study period.

## Remote work highly correlated with VMT and transit ridership

We begin by examining the non-causal correlations between remote work and both VMT and transit ridership, which provide suggestive evidence of the negative impact of remote work on the recovery of these two mobility indicators. We present recovery rates of VMT and transit ridership in relation to the recovery rate of onsite workers, as shown in Figure 1(a)-(d). These figures depict aggregated samples at state/MSA and month-year levels.

These four subfigures reveal significantly positive correlation coefficients between the recovery rate of onsite workers and the recovery rates of VMT and transit ridership. Figures 1(a) and (b) clearly illustrate positive associations between onsite workers' recovery rates and both VMT and transit ridership at the state/MSA level. Furthermore, these figures suggest that states and MSAs with a higher percentage of transit commuters tend to show a lower recovery rate of onsite workers.

The month-year level aggregation in Figures 1(c) and (d) reveals even more pronounced correlations between the recovery rate of remote work and the recovery rates of VMT and transit ridership. The slopes of the best-fit lines in these figures exceed 1, indicating stronger relationships at the month-year level. Additionally, as the pandemic progressed, we observed simultaneous increases in the recovery rates of onsite workers, VMT, and transit ridership.

To further our analysis, we employ a set of fixed-effect models and 2SLS models to estimate the causal effects of remote work on VMT and transit ridership, with the results presented in the following sections.

## Causal effect of remote work on VMT

Columns (1) and (2) of Table 1 present results using ordinary least square (OLS) and fixed-effect modeling to investigate the influence of remote work on VMT. Both models reveal a positive correlation between the recovery rate of onsite workers and VMT recovery, confirming the trends observed in Fig. 1. The fixed-effect models reveal a more pronounced impact of remote work, with a 1-percentage-point increase in onsite worker recovery rate associated with a substantial 0.82-percentage-point increase in the VMT recovery rate. Furthermore, the fixed-effect model (Column 2), after accounting for state fixed effects and month fixed effects, identifies covariates like state reopening status, transit service recovery rate, vaccination rate, and population size as positively correlated with VMT recovery, while unemployment rate and COVID-19 cases show negative correlations. These findings remain robust across alternative specifications, as confirmed by our sensitivity tests, which show that excluding GDP per capita or unemployment rate does not qualitatively affect the inference (Supplementary Section 2.1 and 2.2).

Next, in Table 2, we present the results of the 2SLS estimation, with the model statistics used to assess the model's validity presented in Supplementary Section 2.3. The 2SLS results suggest that a 1-percentage-point increase in the recovery rate of onsite workers is associated with a 0.99-percentage-point increase in the VMT recovery rate (Column 1). This estimate is slightly larger than that derived from the fixed-effect model (0.82-percentage-point increase, as indicated in Column 2 of Table 1). The smaller estimate in the fixed-effect model may be attributed to the issue of reverse causality, as an increase in VMT and road congestion may lead people to opt for remote work as a means to avoid commuting [30], thereby attenuating the estimated effect of remote work on VMT reduction.

Given that the graphical findings in Fig. 1 suggest that the percentage of transit commuters can influence the relationship between the recovery rate of onsite workers and the recovery rates of VMT and transit ridership, we introduce an interaction term between the recovery rate of onsite workers and the log-transformed percentage of transit commuters. Our analysis reveals that the magnitude of the causal effect of remote work on VMT is diminished in states with higher percentages of transit commuters (Column 2 of Table 2). Furthermore, we examine regional heterogeneity in the causal effect across states (*Methods*). Column 3 of Table 2 illustrates the causal effect of the recovery rate of onsite workers by geographical division. The result shows that the effect is consistently significant across all geographical divisions, with variations in magnitude, such as Pacific and Mountain regions exhibiting effects below the average, and others exhibiting effects above the average.

Our study's findings align with the majority of pre-pandemic research on remote work and VMT which generally indicates a negative association, signifying reduced VMT. Notably, the effect sizes observed in our study tend to be larger than those in previous research [6], likely because the impact on VMT was weak and unstable due to the limited adoption of remote work before the pandemic. However, our results differ from certain pre-pandemic studies that reported a net increase in VMT associated with remote work [31, 32, 14]. This net increase occurs because the travel-reduction effect is outweighed by the travel-inducing effect, where remote workers may engage in more non-work-related trips due to schedule flexibility or opt for longer commutes due to workplace relocation. [31, 32, 14]. It's essential to highlight that our study does not distinguish between the travel reduction and travel-inducing effects of remote work; instead, it quantifies the net impact that considers both aspects. Our 2SLS analysis demonstrates a significant negative net effect, suggesting that, during our study period, the reduction in travel associated with remote work outweighs any travel-inducing effects.

## Causal effect of remote work on transit ridership

Among the 217 MSAs included in the transit ridership estimations, our 2SLS results (Column 4 in Table 2) indicate that a 1-percentage-point increase in the recovery rate of onsite workers corresponds to a 2.26-percentage-point increase in transit ridership. In comparison, the fixed-effect model yields a smaller estimate (i.e., 0.54 as indicated by Column 4 in Table 1), suggesting that there might be omitted variables exerting a directional impact on transit ridership that differs from the effect of the recovery rates of onsite workers. One possible omitted variable is the demand for ride-hailing services. Notably, both the number of ride-hailing users and the number of onsite workers exhibit increasing trends during our study period [33, 34]. Since the rising demand for ride-hailing services is likely to partially offset the transit demand resulting from people's return to the workplace, the omission of ride-hailing demand in our fixed-effect models might underestimate the effect of onsite workers on transit ridership. In contrast to the VMT estimation result, we observe that the effect of remote work on transit ridership recovery increases with the percentage of transit commuters (Column 5 in Table 2). Across geographical divisions, the effect remains significant in all nine geographical divisions. Notably, the West North Central and New England regions exhibit the most substantial marginal effects, surpassing the average marginal effect of 2.259, while other divisions are associated with effects below the average marginal impact.

Our finding of remote work reducing transit ridership aligns with certain pre-pandemic studies [22, 21, 35], while contradicting others [14, 20, 15]. This discrepancy may be attributed to differences in how remote work is measured, variations in data structures, and modeling techniques. However, our fixed-effect and 2SLS results are directionally consistent with a pre-pandemic study that utilized a dataset with a similar structure and geographical coverage to ours. The aforementioned study found that an additional percentage of remote workers was associated with a 0.76% reduction in transit ridership in the U.S. between 2012 and 2018 using fixed-effect estimation [21].

## Determinants of onsite workers' recovery rate

Table 3 presents the first-stage results of the IV regression, where the recovery rate of onsite workers is regressed on the percentage of suitable remote workers (the IV), along with the covariates and fixed effects. The significantly negative coefficients of the IV indicate that a higher percentage of suitable remote workers is associated with a lower recovery rate of onsite workers, even after accounting for factors such as reopening stimulus effects, GDP per capita, unemployment rate, transit service recovery trends, transit fares, vaccination rates, and population changes. Specifically, a 1-percentage-point increase in the percentage of suitable remote workers is associated with a decrease of 2.28 percentage points in the recovery rate of onsite workers across the 48 states and District of Columbia, and a decrease of 0.24 percentage points across the 217 MSAs. This disparity can be attributed to the larger geographic area and population coverage of states compared to the specific urban focus of MSAs. State-level analysis combines remote work behavior across diverse MSAs, resulting in a more homogeneous effect, while MSA-level analysis captures localized dynamics, leading to greater heterogeneity in the effects of the IV on the recovery rate of onsite workers. Following the main 2SLS estimations, we conducted robustness tests on our 2SLS models, including falsification tests, variations in the study period, and the use of an alternative metric for remote work (detailed in Supplementary Section 3). The results not only confirm the validity of our results but also strengthen the robustness of our conclusions.

## Temporal variation of the effect of remote work

To analyze the temporal evolution of the causal relationship between the recovery rate of onsite workers and urban mobility, we estimate the quarterly effects for each mobility measure. As depicted in Figure 2, our results reveal that the effects on the recovery rates of VMT and transit ridership remain not only statistically significant but also remarkably stable throughout the study period (detailed results in Supplementary Tables S10 and S11).

Specifically, the effect on transit ridership exhibits a consistent stability with a slight increasing trend over time. Meanwhile, the effect on VMT recovery displays some seasonal fluctuations. However, after accounting for these seasonal trends, the effect on VMT remains overall stable with a slight upward trajectory. These persistent patterns in both transit ridership and VMT underscore the robustness of the observed effect over time and suggest its potential for long-term significance.

## Effects on on-road $CO_2$ emissions and transit fare revenues

To contextualize the effects of remote work on VMT and transit, we estimate the reduction in $CO_2$ emissions associated with the effect of remote work on VMT and the reduction in transit fare revenue associated with the effect of remote work on transit ridership. On a national basis, we estimate that a 10% decrease in the number of onsite workers compared to pre-pandemic levels will reduce the annual total VMT-related $CO_2$ emission by 191.8 million metric tons. For reference, the annual energy-related $CO_2$ emissions from the transportation sector in the contiguous U.S. is 1915.26 million metric tons in 2019 [1]. Therefore, our finding suggests that a 10% decrease in the number of onsite workers compared to pre-pandemic levels could potentially result in a 10% reduction in $CO_2$ emissions from the transportation sector in the contiguous U.S., using the 2019 level as the baseline (*Methods*). We also find that the marginal effect of remote work on VMT-related $CO_2$ reductions varies substantially across states (Fig. 3a). For example, a 1% decrease in the number of onsite workers compared to pre-pandemic levels would lead to monthly reductions of 176.1 thousand metric tons versus 47.5 thousand metric tons in $CO_2$ emissions in Texas versus New York State. The difference in $CO_2$ emissions across states is due to three factors: the marginal effect of remote work on VMT varying with the percentage of transit commuters in each state (the effect for each state is reported in Supplementary Fig. S5), the pre-pandemic (2019) VMT levels of each state, and the state-specific emission factors in 2020-2021 (*Methods*).

Increasing the remote working level would also lead to a considerable loss in public transit fare revenues, which may impact the financial sustainability of the transit agencies and thus poses a challenge for transit agencies to deliver transit services that are responsive to people's travel needs. Across the 217 MSAs, we estimate that a 10% decrease in the number of onsite workers compared to pre-pandemic levels would lead to an annual loss of 2.4 billion transit trips and \$3.7 billion in fare revenue, which are roughly 26.7% of the annual transit ridership and fare revenue in 2019 (*Methods*). Regionally, the marginal effects of remote work on transit fare revenue vary widely across MSAs (Fig. 3b). The majority of the transit fare revenue loss occurs in the New York MSA, where a 1-percentage-point decrease in the recovery rate of onsite workers would result in \$18.16 million loss in transit fare revenue per month, which accounts for 59.46% of the total monthly transit fare revenue loss in all 217 MSAs.

# Discussion

The advent of remote work has brought about transformative changes in work and lifestyle, with profound implications for urban mobility. Our research has shown that remote work has led to significant reductions in VMT and transit ridership since the onset of the COVID-19 pandemic. These findings are consistent with numerous pre-pandemic studies [6, 9, 10, 8, 11, 12]. Importantly, the impact of remote work on VMT and transit ridership persisted from April 2020 to October 2022, with the magnitude of these effects showing relative stability over the course of the study. This enduring pattern underscores the robustness of our estimated impact and suggests their potential long-term implications.

The widespread adoption of remote work offers significant benefits in terms of on-road carbon emissions. Our research emphasizes the effectiveness of remote work policies in mitigating on-road $CO_2$ emissions, complementing existing measures such as carbon tax and road pricing. Notably, organizations worldwide have embraced remote work and are committed to maintaining these options in the future [36, 37]. This persistent trend is poised to generate enduring reductions in on-road carbon emissions, underscoring the need for companies and policymakers to recognize the environmental advantages of remote work and for governments to consider the incorporation of remote work strategies into their initiatives for transportation decarbonization.

However, despite the positive impact of remote work on on-road $CO_2$ emissions, our research also reveals a significant challenge related to transit fare revenue loss due to reduced transit ridership. Although transit agencies have received assistance through federal funding since March 2020 [38, 39, 40], persistently low ridership poses financial difficulties for transit agencies. This situation raises concerns about their long-term financial sustainability and their ability to operate independently from federal subsidies [41, 42, 43]. To address this challenge, transit agencies must focus on enhancing customer attraction and revenue generation while promoting sustainable urban growth through viable alternatives to car-centric and fuel-inefficient development. Given that remote work often involves home-based flexible trips, transit agencies can invest in on-demand services, flexible routing, and non-commuting trips in residential areas, thereby diversifying their service offerings beyond traditional fixed-route services primarily designed for regular commuting in the pre-pandemic era.

This study also paves the way for future research endeavors. Firstly, while our analysis covers the period from April 2020 to October 2022 due to data availability, further research is necessary to assess the long-term impacts of remote work on urban mobility, considering potential behavioral changes and evolving work dynamics in the post-pandemic era. Secondly, previous studies have highlighted that work-related travel savings resulting from remote work may stimulate other types of travel, potentially offsetting the reductions achieved by avoiding commuting [18, 19, 16, 17]. While our study measures the net effect of remote work on overall travel, additional investigations are needed to quantify the impacts of remote work on work-related travel and other types of travel separately. Lastly, although our study indirectly measures the extent of remote work using the recovery rate of onsite workers from Google Community Mobility Reports, future research should consider direct measurements of remote work. Additionally, it's crucial to acknowledge that Google Community Mobility Reports rely on data from users who have enabled Location History, possibly introducing bias toward individuals with access to smartphones and technology. While our data robustly represents remote work based on a comparison with a national remote work survey dataset (Supplementary Section 1.3), exploring other datasets with greater representativeness is advisable for future research.

# Methods

**Data.**

The recovery rate of onsite workers is determined using data obtained from the Google Community Mobility Reports [44]. These reports provide information on the percentage change in visitors to workplaces compared to a baseline, which we consider as the recovery rate of onsite workers, at the county level. The baseline represents the median value observed during the 5-week period from January 3 to February 6, 2020, specifically for the corresponding day of the week. It's important to note that this data is collected by Google from users who have enabled Location History, which may introduce limitations in representativeness as it does not account for individuals who are not Google users or Google users who did not enable Location History during the study period. To assess data representativeness, we conducted a comparison of our data with the remote working indicator obtained from a national remote work survey dataset, specifically the monthly U.S. Survey of Working Arrangements and Attitudes (SWAA). The results reveal a strong negative correlation between the recovery rate of onsite workers in our sample and the remote work measure in the SWAA data when aggregated to the state and month-year level, with correlation coefficients of -0.83 and -0.88, respectively. Our data validation results affirm the robust representation of our indicator regarding the extent of remote work (details in Supplementary Section 1.3).

To calculate the monthly recovery rate of onsite workers for a state or MSA, we average the recovery rates of all counties within that state/MSA. The averaging is weighted by the employment level in each county for the corresponding month, which is obtained from the US Bureau of Labor Statistics [45]. The available data spans from April 2020 to October 2022, which serves as our study period.

The monthly state-level VMT data are collected from the U.S. Federal Highway Administrations (FHWA) [46], which report the vehicle miles traveled on all roads for 50 US states and the District of Columbia. We focus on the contiguous U.S. which includes 48 states and the District of Columbia from April 2020 to October 2022.

Public transit data comes from the National Transit Database [47], which contains panel data of transit profiles and summaries at an agency-month level, reported separately by mode. We include only "full reporters" that regularly report their ridership monthly, and exclude "reduced reporters"/"small systems reporters" (agencies operating fewer than 30 vehicles in maximum service) and "rural reporters" (agencies not reporting data to the monthly ridership module). For each agency, we include bus modes (bus, bus rapid transit, commuter bus, and trolleybus) and rail modes (light rail, heavy rail, commuter rail, etc.), and exclude demand-responsive transit and all other modes. We retained only agencies that provided continuous service from January 2019 to October 2022, covering 97.5% of all transit vehicle revenue miles provided by agencies that operated throughout 2019. The resulting data covers 217 MSAs from April 2020 to October 2022.

Transit ridership and transit service supply are calculated as the total number of unlinked passenger trips and the total vehicle revenue miles (VRM) for all operators within an MSA, respectively. The recovery rates for transit ridership and service supply are calculated by comparing the transit ridership and service supply in a specific month to the values in the same month of 2019. Yearly average transit fare data is also sourced from the National Transit Database. To calculate this average fare, we first sum the annual unlinked passenger trips (i.e., transit ridership) and the annual fare revenue for all operators within an MSA. Subsequently, we compute the average fare by dividing the annual fare revenue by the annual unlinked passenger trips.

Data on the percentage of suitable remote workers ($SW$), serving as the instrumental variable (IV) in our two-stage least squares (2SLS) regressions, is sourced from the US Bureau of Labor Statistics. This variable is derived using two statistics: 1) the industry-specific percentage of suitable remote workers obtained from a national employment survey dataset, and 2) the time-varying employment by industry in each state/MSA.

To calculate $SW_{it}$, which represents the percentage of suitable remote workers for state or MSA $i$ at time $t$, we take the weighted average across all industries in that region. More specifically, we use the formula $SW_{it} = \sum_j e_{ij}^t p_{ij} / \sum_{ij} e_{ij}^t$. Here, $p_{ij}$ refers to the estimated percentage of suitable remote workers for industry type $j$ in region $i$, which is obtained from the May 2019 Occupational Employment Statistics survey [48]. $e_{ij}^t$ represents the employment level in region $i$ for industry $j$ at time $t$, which is extracted from the quarterly census of employment and wages published by the US Bureau of Labor Statistics [45].

The reopening status of a state refers to the lifting of social distancing measures, such as imposing mandatory stay-at-home orders, closing or limiting capacity at non-essential businesses, restaurants, and bars, as well as limiting large gatherings [49]. A value of 1 is assigned if the state had reopened by the end of the month, and 0 if it had not. This information is sourced from the Kaiser Family Foundation [49], which has been tracking the reopening status of each state on a weekly basis since the beginning of the pandemic. Each MSA is mapped to a state which has the most population of that MSA.

The GDP data utilized in this study are sourced from the Bureau of Economic Analysis. As the GDP data is reported on a quarterly basis, we calculate the average monthly GDP data per quarter per capita, which serves as our independent variable. For the MSA-based analysis, since the quarterly data is available only at the state level, we represent each MSA by the state with the highest population within that MSA. To capture the monthly unemployment rates, data for each state and MSA are collected from the U.S. Bureau of Labor Statistics and retrieved from Federal Reserve Economic Data (FRED).

Previous research has indicated that individuals may opt to relocate to more distant locations when engaging in remote work, leading to potential changes in their travel patterns [9, 20]. To address this phenomenon, we incorporate the net migration rate as an independent variable in our analysis. The net migration rate for region (state or MSA) $i$ during month-year $t$ is calculated as:

$$Net\ migration\ rate_i^t = (Gross\ inflow_i^t - Gross\ outflow_i^t)/Population_i \quad [1]$$

Gross in- and outflows refer to the total number of individuals moving in and out of the region $i$ during month-year $t$. The raw data is sourced from change-of-address records provided by the United States Postal Service (USPS)[50], which document these migrations at the ZIP code level on a monthly basis. We then aggregate this data to the state or MSA level. $Population_i$ refers to the total population in region $i$.

The daily number of new COVID-19 cases at the county level was sourced from the New York Times [51], and we aggregated this data to the region-month level for our analysis. To account for population differences, we utilized the number of new cases per capita as an independent variable in our regressions. Information on vaccination rates for each state was obtained from the Centers for Disease Control and Prevention (CDC) [52]. It is worth noting that vaccine effectiveness diminishes over time. A meta-analysis of studies on COVID-19 vaccination effectiveness [53] found that after any primary vaccination cycle, the effectiveness against symptomatic disease dropped to less than 10% for Omicron and less than 50% for Delta. To capture the temporal variations in vaccine effects, we incorporated three variables: vaccinations per person in the past 3 months, vaccinations over the past 3-6 months, and vaccinations over the past 6-9 months.

The annual population data for the years 2020 to 2022 for each state and MSA is derived from the U.S. Census Bureau [54, 55]. Information on the percentage of transit commuters in each state and MSA is sourced from the 2021 American Community Survey 5-year estimates.

We have compiled the essential information on key variables, including their measurement units, sources, and original spatiotemporal granularity, in Supplementary Section 1.1. Descriptive statistics of the variables are provided in Supplementary Section 1.2. Data processing utilized Python version 3.7.4 and R version 3.6.3, while modeling was performed using R version 3.6.3.

**Fixed-effect model specification.** The main goal of this study is to analyze how the recovery rate of onsite workers impacts the recovery of VMT and transit ridership. To achieve this goal, we first apply the following fixed-effect models:

$$Y_{it} = \beta_0 + \beta_1 RW_{it} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + \upsilon_{it} \quad [2]$$

where $Y_{it}$ denotes the recovery rate of VMT for state $i$ at time $t$ or the recovery rate of transit ridership for MSA $i$ at time $t$, which are calculated as the percentages of VMT and transit ridership compared to the values in the same month of 2019. $RW_{it}$ denotes the recovery rate of onsite workers for state/MSA $i$ at time $t$, which is calculated as the percentage of the number of workplace visitors at time $t$ compared with its pre-pandemic level. $Controls_{it}$ is a set of control variables corresponding to state/MSA $i$ and time $t$, including GDP per capita, unemployment rate, the recovery rate of transit services, transit fares, population size, net migration rate, reopening status, reported COVID cases per capita, and vaccination rate. Most variables can be aggregated to the monthly level. However, transit fares and population size are reported annually, thus we employ data from the corresponding year. For GDP per capita, which is reported quarterly, we calculate and employ the average monthly GDP per capita for the corresponding quarter. $\beta_0$ denotes the intercept, $\beta_1$ is the coefficient of $RW_{it}$, and $\beta_2$ represents the coefficients for the control variables. $\alpha_{1i}$ denotes the regional fixed effects that control for time-invariant characteristics at the state or MSA level. $\alpha_{1m}$ denotes the month fixed effects that account for the variation by month. $\upsilon_{it}$ is the error term.

**2SLS specification.** To solve the endogeneity problem of $RW_{it}$ and estimate the causal effect of the recovery rate of onsite workers on transit ridership recovery, we apply a 2SLS estimation. In the first stage of the 2SLS model, we estimate the recovery rate of onsite workers using the following formula:

$$RW_{it} = \gamma_0 + \gamma_1 SW_{it} + \gamma_2 Controls_{it} + \alpha_{2i} + \alpha_{2m} + \epsilon_{it} \quad [3]$$

where $SW_{it}$ represents the percentage of suitable remote workers in region $i$ at time $t$. $\gamma_0$ denotes the intercept, $\gamma_1$ is the coefficient of $SW_{it}$, and $\gamma_2$ represents the coefficients for the control variables. $\alpha_{2i}$ and $\alpha_{2m}$ are the regional fixed effects and the month fixed effects, and $\epsilon_{it}$ is the error term. We include the same set of control variables, regional and month fixed effects as in the fixed-effect model (equation 2). The second stage of the 2SLS follows the formula:

$$Y_{it} = \beta_0 + \beta_1 \widehat{RW_{it}} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + \upsilon_{it} \quad [4]$$

where $\widehat{RW_{it}}$ is the predicted value of the recovery rate of onsite workers estimated from Equation 3. $Controls_{it}$ is the same set of control variables as in Equation 2. $\alpha_{1i}$ and $\alpha_{1m}$ denote the regional fixed effects and the month fixed effects, and $\upsilon_{it}$ is the error term. For all the 2SLS regressions, we conduct robustness tests in Supplementary Section 3.

**Heterogeneity of the causal effect by geographical divisions** To estimate the heterogeneity of the effect across geographical divisions, we re-estimate the second stage model using the following formula:

$$Y_{it} = \beta_0 + \sum_m \theta_m * \mathbf{I}\{i \in D_m\} * \widehat{RW_{it}} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + \upsilon_{it} \quad [5]$$

where $D_m$ indicates a specific geographical divisions. There are nine divisions in the United States, namely New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific [56]. $\mathbf{I}\{i \in D_m\}$ takes value 1 if $i$ is in $D_m$ and 0 if not. $\theta_m$ denotes the division-specific effect. Other parts of the model remain the same as in Equation 4.

**Effects by the percentage of transit commuters.** Theoretically, the influence of remote work on both VMT and transit ridership depends on the interplay between its impact on people's travel needs and the distribution of residents' travel modes within a region. To account for these variations, we explore how the marginal effect of remote work varies by the percentage of transit commuters using the following specification:

$$Y_{it} = \beta_0 + \omega_1 * \widehat{RW_{it}} + \omega_2 * \widehat{RW_{it}} * log(Z_i) + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + \upsilon_{it} \quad [6]$$

where $Z_i$ is a key socio-demographic variable for region $i$. It denotes both the percentage of transit commuters in state $i$ for the VMT estimation and the percentage of transit commuters in MSA $i$ for the transit ridership estimation. The region-specific effect of the recovery rate of remote workers on $Y_{it}$ in region $i$ is thus represented by $\omega_1 + \omega_2 * log(Z_i)$. It's worth mentioning that the state-specific percentage of transit commuters is obtained from the 2021 American Community Survey 5-Year data, and given that this dataset is cross-sectional and lacks temporal variation, it does not reflect the evolving regional travel mode dynamics over our study period. Other parts of the model remain the same as in Equation 4.

**Temporal heterogeneity of the causal effect.** To explore the temporal change in the effect of the recovery rate of onsite workers on urban mobility, we estimate the following model:

$$Y_{it} = \beta_0 + \sum_k \gamma_k * \mathbf{I}\{t \in T_k\} * \widehat{RW_{it}} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + \upsilon_{it} \qquad [7]$$

where $T_k$ indicates the $k^{th}$ year-quarter in the study period, ranging from 2020 Q2 to 2022 Q3, with October 2022 categorized into 2022 Q3. $\mathbf{I}\{t \in T_k\}$ takes value 1 if $t$ is in $T_k$ and 0 if not. $\gamma_k$ denotes the year-quarter-specific effect. Other parts of the model remain the same as in Equation 4.

**Measuring the marginal effect of remote work on the VMT-related carbon emissions.** To quantify the impact of remote work on carbon emissions related to VMT, we begin by calculating the state-specific marginal effect of remote work on VMT based on the results of our 2SLS modeling (as shown in Equation 6):

$$\beta_i = \hat{\omega_1} + \hat{\omega_2} * log(Z_i) \qquad [8]$$

Here, $\beta_i$ represents the marginal effect for state $i$, and $Z_i$ represents the percentage of transit commuters in state $i$. We incorporate $Z_i$ to determine state-specific marginal effects for two key reasons: firstly, in theory, the effects of remote work on VMT and transit ridership in a region depend on the interplay between its impact on people's travel needs and the region's travel mode distribution, with the percentage of transit commuters being a crucial indicator of this distribution. Second, our 2SLS modeling results (as demonstrated in Column 2 and 5 of Table 2) indicate significant variations in the marginal impacts of remote work on VMT and transit ridership with respect to $Z_i$, and the inclusion of $Z_i$ improves the model's $R^2$. Given these considerations, we employ Equation 4 to represent region-specific marginal effects.

Subsequently, we compute $CO_2$ emissions per VMT in each state ($EF_i$). This is defined as:

$$EF_i = E_i / V_i \qquad [9]$$

where $E_i$ represents the total on-road $CO_2$ emissions during 2020 and 2021 in state $i$, and $V_i$ represents the total VMT in state $i$ during the same period. The choice of the 2020 and 2021 time period is due to the unavailability of 2022 data on $E_i$. To obtain the data for $E_i$, we first collected information on the total motor gasoline and diesel fuel consumption for each state during 2020 and 2021 from the Federal Highway Administration's annual Highway Statistics Series Table MF-21 [57]. Subsequently, we converted this fuel consumption data into $CO_2$ emissions using the following conversion factors: 8.887 kg of $CO_2$ emissions per gallon of gasoline consumed and 10.180 kg of $CO_2$ emissions per gallon of diesel consumed [58]. Data for $V_i$ was obtained from FHWA's annual Highway Statistics Series Table VM-2 [59], which tracks traffic involving six vehicle types: motorcycles, passenger cars, light-duty trucks, buses, single-unit trucks, and multi-unit combination trucks [60].

Finally, we compute the marginal effect of remote work on VMT-related carbon emissions ($ME_{it}$) by multiplying the state-specific marginal effect on VMT by the pre-pandemic (2019) average monthly VMT ($V_i^{19}$) and the emission factor:

$$ME_{it} = \beta_i * V_i^{19} * EF_i \qquad [10]$$

It is important to note that fuel consumption per mile traveled varies depending on the type of vehicle. In this analysis, due to data limitations, we could only assess the impact of remote work on total VMT and apply the average emission factor, without distinguishing the effect on VMT related to different types of vehicles. Therefore, the accuracy of our estimated marginal impacts on on-road $CO_2$ emissions relies on the assumption that the change in VMT due to remote work maintains a similar vehicle type composition as the VMT in 2020 and 2021 for each state. Given that remote work could affect the travel of different types of vehicles differently, further analysis could enhance accuracy by estimating the marginal effect of remote work on various VMT types and calculating the total $CO_2$ impacts using different emission factors for each vehicle type. Additionally, emission factors may change over time, so caution should be exercised when applying these results to infer the $CO_2$ impact from 2022 onward.

**Measuring the marginal effect of remote work on transit fare revenues.** We compute the marginal effect of remote work on transit revenue fare for each MSA $i$, $F_i$, based on the equation: $F_i = \beta_i * P_i$. $\beta_i$ represents the marginal effect of remote work on transit ridership estimated from the transit ridership 2SLS model (Equation 6): $\beta_i = \hat{\omega_1} + \hat{\omega_2} * log(Z_i)$, where $Z_i$ denotes the percentage of transit commuters in MSA $i$. $P_i$ denotes the average fare per passenger trip in MSA $i$, which is obtained from the National Transit Database [47].

# Data availability

The data used for this study are sourced from publicly available databases, and detailed information about each variable's source can be found in the Data section of the Methods. The compiled datasets can be accessed on GitHub at `https://github.com/zhengyunhan/remote_work_mobility`.

# Code availability

The code used for conducting the analysis is accessible on GitHub at `https://github.com/zhengyunhan/remote_work_mobility`.

## Acknowledgements

This work is funded by the MIT Energy Initiative and the Barr Foundation. S.W. acknowledges the support from the Research Opportunity Seed Fund 2023 (ROSF) from the University of Florida. L.L. acknowledges the support from Beijing Social Science Foundation (20GLA003).

## Author contributions

Y.Z. contributes to conceptualization, methodology, data curation, modeling, visualization, formal analysis, result interpretation, writing - original draft, writing - review and editing; S.W. contributes to formal analysis, result interpretation, writing - review and editing; L.L. contributes to formal analysis, result interpretation; J.A. contributes to result interpretation, supervision, project administration, funding acquisition; J.Z. contributes to formal analysis, result interpretation, supervision, project administration, funding acquisition.

## Competing interests

The authors declare no competing interests.

## Tables

Table 1: Impacts of onsite workers' recovery rate on VMT and transit ridership: OLS and fixed-effect results

| | The recovery rates of: | | | |
|---|---|---|---|---|
| | VMT | | Transit ridership | |
| | (1) | (2) | (3) | (4) |
| Recovery rate of onsite workers | 0.652*** | 0.818*** | 0.441*** | 0.544*** |
| | (0.057) | (0.068) | (0.032) | (0.047) |
| | p = 0.000 | p = 0.000 | p = 0.000 | p = 0.000 |
| Reopening status | 1.363** | 1.236** | 8.882*** | 5.448*** |
| | (0.667) | (0.558) | (0.652) | (0.533) |
| | p = 0.042 | p = 0.027 | p = 0.000 | p = 0.000 |
| GDP per capita (in thousand dollars) | 0.360* | −0.774 | −0.318 | 12.473*** |
| | (0.216) | (1.892) | (0.200) | (1.479) |
| | p = 0.096 | p = 0.683 | p = 0.113 | p = 0.000 |
| Unemployment rate | −1.010*** | −0.550*** | −0.442*** | 0.064 |
| | (0.138) | (0.156) | (0.071) | (0.119) |
| | p = 0.000 | p = 0.0005 | p = 0.000 | p = 0.592 |
| Transit service recovery rate | 0.151*** | 0.078** | 0.410*** | 0.426*** |
| | (0.022) | (0.031) | (0.013) | (0.020) |
| | p = 0.000 | p = 0.012 | p = 0.000 | p = 0.000 |
| Transit fare | −0.540*** | 0.949 | −5.303*** | −3.970*** |
| | (0.173) | (0.904) | (0.358) | (0.712) |
| | p = 0.002 | p = 0.294 | p = 0.000 | p = 0.00000 |
| COVID cases per 1000 people | −0.039 | −0.105*** | −0.057*** | 0.022 |
| | (0.025) | (0.031) | (0.014) | (0.016) |
| | p = 0.112 | p = 0.001 | p = 0.0001 | p = 0.169 |
| Vaccinations per person in the past 3 months | 3.544*** | 9.631*** | −10.753*** | −10.404*** |
| | (1.006) | (1.027) | (0.905) | (0.739) |
| | p = 0.0005 | p = 0.000 | p = 0.000 | p = 0.000 |
| Vaccinations per person over the past 3-6 months | 0.796 | 0.388 | −4.524*** | −8.131*** |
| | (1.064) | (0.921) | (1.116) | (0.900) |
| | p = 0.455 | p = 0.674 | p = 0.0001 | p = 0.000 |
| Vaccinations per person over the past 6-9 months | 3.373*** | 2.810*** | 2.928*** | 3.408*** |
| | (1.154) | (1.051) | (1.066) | (0.882) |
| | p = 0.004 | p = 0.008 | p = 0.007 | p = 0.0002 |
| Net migration rate | 0.096 | −0.112 | 1.095*** | −0.005 |
| | (0.407) | (0.397) | (0.243) | (0.183) |
| | p = 0.815 | p = 0.779 | p = 0.00001 | p = 0.977 |
| ln (population in millions) | 2.128*** | 112.127*** | 0.934*** | 40.523*** |
| | (0.234) | (30.602) | (0.173) | (15.607) |
| | p = 0.000 | p = 0.0003 | p = 0.00000 | p = 0.010 |
| State FE | NO | YES | / | / |
| MSA FE | / | / | NO | YES |
| Month FE | NO | YES | NO | YES |
| Observations | 1,519 | 1,519 | 6,727 | 6,727 |
| Adjusted $R^2$ | 0.570 | 0.739 | 0.388 | 0.697 |

*Note:* Robust standard errors reported in parentheses, and p-values from two-sided t-tests are listed under standard errors. *p<0.1; **p<0.05; ***p<0.01

Table 2: Impacts of onsite workers' recovery rate on VMT and transit ridership: 2SLS results

| | The recovery rates of: | | | | | |
|---|---|---|---|---|---|---|
| | VMT | | | Transit ridership | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Recovery rate of onsite workers | 0.987$^{***}$ | 1.161$^{***}$ | | 2.259$^{***}$ | 2.025$^{***}$ | |
| | (0.192) | (0.195) | | (0.374) | (0.374) | |
| | p = 0.00000 | p = 0.000 | | p = 0.000 | p = 0.00000 | |
| Recovery rate of onsite workers × log (percentage of transit commuters) | | $-0.113^{***}$ | | | 0.259$^{***}$ | |
| | | (0.035) | | | (0.028) | |
| | | p = 0.002 | | | p = 0.000 | |
| *Marginal effects of "the recovery rate of onsite workers" by geographical division:* | | | | | | |
| New England | | | 1.126$^{***}$ | | | 2.582$^{***}$ |
| | | | (0.207) | | | (0.387) |
| | | | p = 0.00000 | | | p = 0.000 |
| Middle Atlantic | | | 1.009$^{***}$ | | | 2.238$^{***}$ |
| | | | (0.226) | | | (0.386) |
| | | | p = 0.00001 | | | p = 0.000 |
| East North Central | | | 1.099$^{***}$ | | | 1.928$^{***}$ |
| | | | (0.232) | | | (0.381) |
| | | | p = 0.00001 | | | p = 0.00000 |
| West North Central | | | 1.151$^{***}$ | | | 2.616$^{***}$ |
| | | | (0.206) | | | (0.385) |
| | | | p = 0.00000 | | | p = 0.000 |
| South Atlantic | | | 1.066$^{***}$ | | | 1.826$^{***}$ |
| | | | (0.243) | | | (0.383) |
| | | | p = 0.00002 | | | p = 0.00001 |
| East South Central | | | 1.104$^{***}$ | | | 1.656$^{***}$ |
| | | | (0.245) | | | (0.382) |
| | | | p = 0.00001 | | | p = 0.00002 |
| West South Central | | | 1.305$^{***}$ | | | 2.172$^{***}$ |
| | | | (0.274) | | | (0.381) |
| | | | p = 0.00001 | | | p = 0.000 |
| Mountain | | | 0.973$^{***}$ | | | 1.634$^{***}$ |
| | | | (0.232) | | | (0.385) |
| | | | p = 0.00003 | | | p = 0.00003 |
| Pacific | | | 0.750$^{***}$ | | | 2.116$^{***}$ |
| | | | (0.205) | | | (0.381) |
| | | | p = 0.0003 | | | p = 0.00000 |
| Controls | YES | YES | YES | YES | YES | YES |
| State FE | YES | YES | YES | / | / | / |
| MSA FE | / | / | / | YES | YES | YES |
| Month FE | YES | YES | YES | YES | YES | YES |
| Observations | 1,519 | 1,519 | 1,519 | 6,727 | 6,727 | 6,727 |
| Adjusted $R^2$ | 0.715 | 0.717 | 0.716 | 0.691 | 0.695 | 0.696 |
| First stage F-test | 144.72$^{***}$ | | | 90.74$^{***}$ | | |
| Wu–Hausman test | 1.5 | | | 30.26$^{***}$ | | |

*Notes:* Robust standard errors reported in parentheses, and p-values from two-sided t-tests are listed under standard errors ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.). The definition of geographical divisions can be found in the U.S. Census Bureau [56]. Coefficient for each region corresponds to the coefficient for the interaction term between "recovery rate of onsite workers" and that region. All models include the same set of control variables and fixed effects as presented in Columns (2) and (4) of Table 1. The full results are reported in Supplementary Table S8 and S9.

Table 3: First-stage results of IV regression: estimating the effect of percentage of suitable remote workers on the recovery rate of onsite workers

| | *Dependent variable: recovery rate of onsite workers* | |
|---|---|---|
| | State-month | MSA-month |
| | (1) | (2) |
| Percentage of suitable remote workers | $-2.279^{***}$ | $-0.240^{***}$ |
| | (0.189) | (0.025) |
| | p = 0.000 | p = 0.000 |
| Reopening status | $-0.201$ | $1.000^{***}$ |
| | (0.232) | (0.148) |
| | p = 0.388 | p = 0.000 |
| GDP per capita (in thousand dollars) | $-1.013$ | $2.064^{***}$ |
| | (1.048) | (0.660) |
| | p = 0.335 | p = 0.002 |
| Unemployment rate | $-0.962^{***}$ | $-1.240^{***}$ |
| | (0.080) | (0.048) |
| | p = 0.000 | p = 0.000 |
| Transit service recovery rate | $0.107^{***}$ | $0.034^{***}$ |
| | (0.016) | (0.005) |
| | p = 0.000 | p = 0.000 |
| Transit fare | $1.422^{***}$ | $0.557^{***}$ |
| | (0.397) | (0.152) |
| | p = 0.0004 | p = 0.0003 |
| COVID cases per 1000 people | $-0.083^{***}$ | $-0.035^{***}$ |
| | (0.008) | (0.004) |
| | p = 0.000 | p = 0.000 |
| Vaccinations per person in the past 3 months | $2.728^{***}$ | $-0.929^{***}$ |
| | (0.523) | (0.248) |
| | p = 0.00000 | p = 0.0002 |
| Vaccinations per person over the past 3-6 months | $2.617^{***}$ | $1.263^{***}$ |
| | (0.368) | (0.222) |
| | p = 0.000 | p = 0.000 |
| Vaccinations per person over the past 6-9 months | $2.090^{***}$ | $0.641^{***}$ |
| | (0.349) | (0.236) |
| | p = 0.000 | p = 0.007 |
| Net migration rate | 0.227 | 0.045 |
| | (0.170) | (0.073) |
| | p = 0.181 | p = 0.538 |
| ln (population in millions) | $59.337^{***}$ | $53.086^{***}$ |
| | (12.673) | (6.162) |
| | p = 0.00001 | p = 0.000 |
| State FE | YES | / |
| MSA FE | / | YES |
| Month FE | YES | YES |
| Observations | 1,519 | 6,727 |
| Adjusted $R^2$ | 0.908 | 0.842 |

*Note:* Robust standard errors reported in parentheses, and p-values from two-sided t-tests are listed under standard errors. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

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Figure 1: **Relationships between the recovery rate of onsite workers and the recovery rates of VMT and transit ridership. a** and **b**, Recovery rates of onsite workers plotted against VMT and transit ridership, respectively, with samples aggregated at the state level (for VMT) and the MSA level (for transit ridership). The correlation coefficient $r$ and the slope of the best-fit line $\beta$ are provided, along with the significance level from two-sided t-tests. The p-values from two-sided t-tests are smaller than 0.01 for $r$ and $\beta$ in all plots (*p<0.1; **p<0.05; ***p<0.01). The color represents the percentage of transit commuters, while the size of each point is proportional to the population of the state or MSA. Notably, regions with a higher percentage of transit commuters generally exhibit a lower recovery rate of onsite workers. **c** and **d**, Recovery rates of onsite workers plotted against VMT and transit ridership, respectively, with samples aggregated at the month-year level. Colors represent different time periods, illustrating that later time periods tend to have higher recovery rates of onsite workers, VMT, and transit ridership. The significantly positive values of $r$ and $\beta$ in all plots indicate a positive correlation between the recovery rate of onsite workers and the recovery rates of VMT and transit ridership, both spatially and temporally.

Figure 2: **Effects of the recovery of onsite workers on the recovery rates of VMT and transit ridership over time.** The markers denote the coefficient of onsite worker recovery for predicting VMT (red squares) and transit ridership (green circles) across various year-quarters (see Methods for model details). The error bars represent the 90% confidence intervals. The dashed lines represent the trends of the effects. $N$ = 1,519 (VMT) and 6,727 (transit ridership). The model includes the same set of control variables and fixed effects as presented in Columns (2) and (4) of Table 1. The full results are reported in Supplementary Tables S10 and S11.

Figure 3: **Marginal effect of remote work on the reduction of on-road $CO_2$ emissions by state and that on the reduction of transit fare revenues by MSA.** These two graphs show the reduction in monthly on-road $CO_2$ emissions by state (**a**) and the reduction in monthly transit fare revenues by 50 most populated MSAs (**b**) caused by a 1-percentage-point increase in the number of onsite workers. These estimates are calculated based on the effects of remote work on VMT and transit ridership, as estimated from the 2SLS models with sample sizes of $N$ =1,519 (VMT) and 6,727 (transit ridership). The bars represent the point estimates, while the orange lines denote the 95% confidence intervals.

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