

Impacts of remote work on vehicle miles traveled and transit ridership in the USA

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1 Abstract

2 Remote work's potential as a sustainable mobility solution has garnered attention, particularly due
3 to its widespread adoption during the COVID-19 pandemic. Our study systematically examines the
4 impacts of remote work on vehicle-miles traveled (VMT) and transit ridership in the United States
5 from April 2020 to October 2022. We find that using the pre-pandemic levels as the baselines, a
6 mere 1% decrease in on-site workers corresponds to a 0.99% reduction in state-level VMT and a
7 2.26% drop in Metropolitan Statistical Area (MSA)-level transit ridership. Notably, a 10% decrease
8 in on-site workers compared to the pre-pandemic level could yield a consequential annual reduction
9 of 191.8 million metric tons (10%) in CO₂ emissions from the transportation sector, alongside a
10 substantial \$3.7 billion (26.7%) annual loss in transit fare revenues within the contiguous US. These
11 findings offer policymakers crucial insights into how different remote work policies can impact urban
12 transport and environmental sustainability as remote work continues to persist.

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

24 Despite theoretical advantages, the actual impact of remote work on urban mobility remains
25 uncertain and sometimes contradictory in existing literature. Previous studies have shown a wide
26 range of estimated impacts on vehicle-miles traveled (VMT) associated with remote work, ranging
27 from a 20% reduction to a 3.9% increase when teleworking one day a week in pre-pandemic settings
28 [6]. These disparities can be attributed to variations in measuring remote work, utilizing diverse
29 datasets, and the intricate mechanisms through which remote work influences motorized travel.

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

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

47 The coronavirus disease 2019 (COVID-19) pandemic has had a profound impact on remote work
48 trends [26]. It has compelled millions of Americans to adapt to working from home (WFH), with
49 a substantial 37% of the population working remotely full-time as of April 2020 [27]. While the
50 pandemic health emergency is reaching its conclusion [28], many companies have recognized the
51 benefits and are embracing remote work policies for the long term. This decision allows employees
52 the flexibility to work remotely either part-time or full-time. Data from May 2023 indicates that

53 approximately 20.1% of employed Americans WFH for at least one day per week [29]. With remote
54 work likely to remain a popular working arrangement in the post-pandemic era, it becomes crucial to
55 systematically evaluate the effects of remote work on urban mobility. Such an analysis can provide
56 valuable insights for governments seeking to reduce VMT, alleviate congestion, and mitigate air
57 pollution in the long run. It will also help employers and employees understand how their remote
58 work policies and preferences collectively influence the urban transport system and environmental
59 sustainability in the future.

60 Using a combination of anonymized and aggregated workplace visitation data along with nation-
61 wide panel data on VMT and public transit, we conducted a comprehensive analysis to investigate
62 the impacts of remote work on VMT and transit ridership across the United States following the
63 COVID-19 pandemic. To address concerns of endogeneity, we employed an instrumental variable
64 (IV) approach and investigated how these effects varied across different spatial and temporal dimen-
65 sions. Furthermore, based on the estimated effects of remote work on VMT and transit ridership,
66 we quantified the corresponding reductions in carbon dioxide (CO₂) emissions and transit fare rev-
67 enues at both national and regional levels. By doing so, our study aims to provide valuable insights
68 into the environmental implications of advocating remote work as a strategy for mitigating on-road
69 GHG emissions. It is noteworthy that our analysis spans the period from April 2020 to October
70 2022, during which the effects of remote work on VMT and transit ridership may have been uniquely
71 shaped by the COVID-19 pandemic. During the pandemic period, the induced trips may have been
72 restricted, potentially introducing an upward bias in estimating the net impact of remote work on
73 VMT and transit ridership. Hence, we recognize the need to further examine the impacts of remote
74 work on urban mobility in the post-pandemic era.

75 Results

76 To examine the impact of remote work on VMT and transit ridership in the United States from
77 April 2020 to October 2022, we adopt a unique identification strategy based on the heterogeneity
78 in the recovery rate of onsite workers. The recovery rate of onsite workers serves as a proxy for the
79 inverse of remote work prevalence, which is measured by the percentage of onsite workers compared
80 to pre-pandemic levels. In this study, we examine the impact of remote work on two key urban
81 mobility measures: (1) VMT in 48 states and the District of Columbia, and (2) transit ridership in
82 217 Metropolitan Statistical Areas (MSAs).

83 Based on the panel datasets that offer broad spatiotemporal coverage, we first employ the fixed-
84 effect regressions, where the dependent variables are the recovery rates of VMT and transit ridership,
85 measured by the percentage of VMT and transit ridership compared to their respective values in
86 the same month of 2019. By including the regional and month fixed effects in the models, we can
87 effectively control for the region- and time-specific variations. In addition to the fixed effects, we
88 account for other relevant covariates, including GDP per capita, unemployment rate, the recovery
89 rate of transit services, transit fares, population size, net migration rate, reopening status, reported
90 COVID cases per capita, and vaccination rate. These covariates help to control for various factors

91 that could potentially impact the fluctuations in VMT and transit ridership throughout the duration
92 of the study. The primary independent variable of focus is the recovery rate of onsite workers.

93 However, fixed-effects models have limitations, such as omitted variable bias and reverse causal-
94 ity. Furthermore, using the percentage of onsite workers as a proxy for remote work may not
95 accurately capture the full extent of remote work, particularly for individuals who may remain
96 offsite due to job loss. To address these issues simultaneously and refine our analysis, we adopted
97 an instrumental variable approach using two-stage least squares (2SLS) estimation. Specifically, we
98 used the percentage of suitable remote workers in each state/MSA for each month as our instrument.
99 This instrument was derived by considering industry-specific percentages of suitable remote workers
100 and variations in employment levels across different industries in each state/MSA. By employing
101 this instrument, we effectively removed variations in the endogenous predictor (i.e., the percentage
102 of onsite workers compared to pre-pandemic levels) unrelated to remote work, including changes due
103 to shifts in unemployment rates. Additionally, we examine the spatial heterogeneity and temporal
104 evolution of the causal effects, and estimate the corresponding marginal effect of remote work on the
105 CO₂ emissions in each state and that on transit fare revenues in each MSA, yielding the following
106 major findings:

- 107 1. Compared to pre-pandemic levels, a 1% increase in the number of onsite workers is associated
108 with a 0.99% increase in state-level VMT and a 2.26% increase in MSA-level transit ridership.
109 On a regional scale, when a state or an MSA has a higher percentage of transit commuters,
110 the impact of remote work on VMT tends to be smaller, while its effect on transit ridership
111 tends to be larger.
- 112 2. A 10% decrease in the number of onsite workers compared to pre-pandemic levels could lead
113 to a reduction of 191.8 million metric tons of CO₂ emissions related to VMT, which represents
114 a 10% annual reduction in CO₂ emissions from the transportation sector in the contiguous
115 US. Additionally, this decrease in onsite workers may result in a \$3.7 billion or 26.7% annual
116 loss in transit fare revenues.
- 117 3. Temporally, the impacts of remote work on the recovery rates of VMT and transit ridership
118 display remarkable temporal consistency over the entire study period.

119 **Remote work highly correlated with VMT and transit ridership**

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

125 These four subfigures reveal significantly positive correlation coefficients between the recovery
126 rate of onsite workers and the recovery rates of VMT and transit ridership. Figures 1(a) and (b)
127 clearly illustrate positive associations between onsite workers' recovery rates and both VMT and

128 transit ridership at the state/MSA level. Furthermore, these figures suggest that states and MSAs
129 with a higher percentage of transit commuters tend to show a lower recovery rate of onsite workers.

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

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

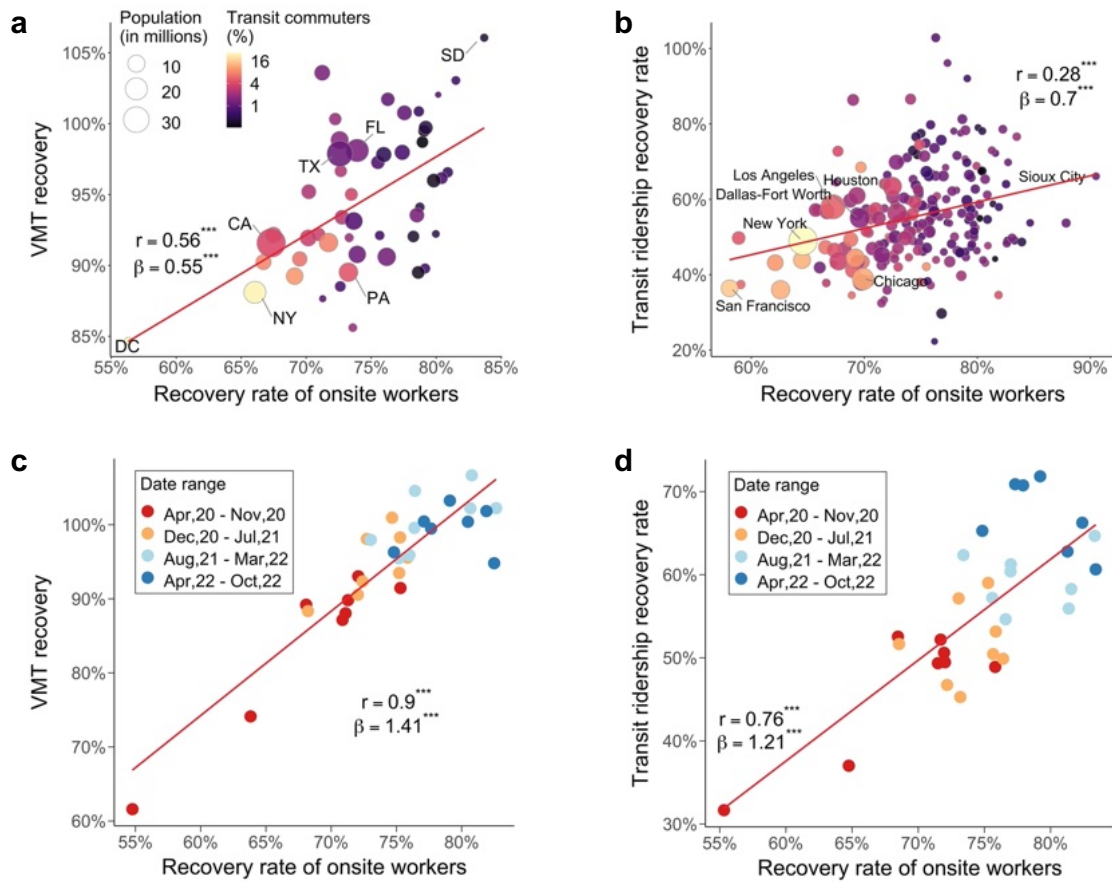


Figure 1: **Relationships between the recovery rate of onsite workers and the recovery rates of VMT and transit ridership.** **a** and **b**, Recovery rates of onsite workers plotted against VMT and transit ridership, respectively, with samples aggregated at the state level (for VMT) and the MSA level (for transit ridership). The correlation coefficient r and the slope of the best-fit line β 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 β 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 β 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.

138 Causal effect of remote work on VMT

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

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

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

170 Our study’s findings align with the majority of pre-pandemic research on remote work and VMT
171 which generally indicates a negative association, signifying reduced VMT. Notably, the effect sizes
172 observed in our study tend to be larger than those in previous research [6], likely because the impact
173 on VMT was weak and unstable due to the limited adoption of remote work before the pandemic.
174 However, our results differ from certain pre-pandemic studies that reported a net increase in VMT
175 associated with remote work [31, 32, 14]. This net increase occurs because the travel-reduction effect
176 is outweighed by the travel-inducing effect, where remote workers may engage in more non-work-

177 related trips due to schedule flexibility or opt for longer commutes due to workplace relocation.
178 [31, 32, 14]. It's essential to highlight that our study does not distinguish between the travel
179 reduction and travel-inducing effects of remote work; instead, it quantifies the net impact that
180 considers both aspects. Our 2SLS analysis demonstrates a significant negative net effect, suggesting
181 that, during our study period, the reduction in travel associated with remote work outweighs any
182 travel-inducing effects.

183 **Causal effect of remote work on transit ridership**

184 Among the 217 MSAs included in the transit ridership estimations, our 2SLS results (Column
185 4 in Table 2) indicate that a 1-percentage-point increase in the recovery rate of onsite workers
186 corresponds to a 2.26-percentage-point increase in transit ridership. In comparison, the fixed-effect
187 model yields a smaller estimate (i.e., 0.54 as indicated by Column 4 in Table 1), suggesting that
188 there might be omitted variables exerting a directional impact on transit ridership that differs from
189 the effect of the recovery rates of onsite workers. One possible omitted variable is the demand
190 for ride-hailing services. Notably, both the number of ride-hailing users and the number of onsite
191 workers exhibit increasing trends during our study period [34, 35]. Since the rising demand for ride-
192 hailing services is likely to partially offset the transit demand resulting from people's return to the
193 workplace, the omission of ride-hailing demand in our fixed-effect models might underestimate the
194 effect of onsite workers on transit ridership. In contrast to the VMT estimation result, we observe
195 that the effect of remote work on transit ridership recovery increases with the percentage of transit
196 commuters (Column 5 in Table 2). Across geographical divisions, the effect remains significant in
197 all nine geographical divisions. Notably, the West North Central and New England regions exhibit
198 the most substantial marginal effects, surpassing the average marginal effect of 2.259, while other
199 divisions are associated with effects below the average marginal impact.

200 Our finding of remote work reducing transit ridership aligns with certain pre-pandemic studies
201 [22, 21, 36], while contradicting others [14, 20, 15]. This discrepancy may be attributed to differences
202 in how remote work is measured, variations in data structures, and modeling techniques. However,
203 our fixed-effect and 2SLS results are directionally consistent with a pre-pandemic study that utilized
204 a dataset with a similar structure and geographical coverage to ours. The aforementioned study
205 found that an additional percentage of remote workers was associated with a 0.76% reduction in
206 transit ridership in the U.S. between 2012 and 2018 using fixed-effect estimation [21].

207 **Determinants of onsite workers' recovery rate**

208 Table 3 presents the first-stage results of the IV regression, where the recovery rate of onsite workers
209 is regressed on the percentage of suitable remote workers (the IV), along with the covariates and
210 fixed effects. The significantly negative coefficients of the IV indicate that a higher percentage of
211 suitable remote workers is associated with a lower recovery rate of onsite workers, even after ac-

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*** (0.057) p = 0.000	0.818*** (0.068) p = 0.000	0.441*** (0.032) p = 0.000	0.544*** (0.047) p = 0.000
Reopening status	1.363** (0.667) p = 0.042	1.236** (0.558) p = 0.027	8.882*** (0.652) p = 0.000	5.448*** (0.533) p = 0.000
GDP per capita (in thousand dollars)	0.360* (0.216) p = 0.096	-0.774 (1.892) p = 0.683	-0.318 (0.200) p = 0.113	12.473*** (1.479) p = 0.000
Unemployment rate	-1.010*** (0.138) p = 0.000	-0.550*** (0.156) p = 0.0005	-0.442*** (0.071) p = 0.000	0.064 (0.119) p = 0.592
Transit service recovery rate	0.151*** (0.022) p = 0.000	0.078** (0.031) p = 0.012	0.410*** (0.013) p = 0.000	0.426*** (0.020) p = 0.000
Transit fare	-0.540*** (0.173) p = 0.002	0.949 (0.904) p = 0.294	-5.303*** (0.358) p = 0.000	-3.970*** (0.712) p = 0.00000
COVID cases per 1000 people	-0.039 (0.025) p = 0.112	-0.105*** (0.031) p = 0.001	-0.057*** (0.014) p = 0.0001	0.022 (0.016) p = 0.169
Vaccinations per person in the past 3 months	3.544*** (1.006) p = 0.0005	9.631*** (1.027) p = 0.000	-10.753*** (0.905) p = 0.000	-10.404*** (0.739) p = 0.000
Vaccinations per person over the past 3-6 months	0.796 (1.064) p = 0.455	0.388 (0.921) p = 0.674	-4.524*** (1.116) p = 0.0001	-8.131*** (0.900) p = 0.000
Vaccinations per person over the past 6-9 months	3.373*** (1.154) p = 0.004	2.810*** (1.051) p = 0.008	2.928*** (1.066) p = 0.007	3.408*** (0.882) p = 0.0002
Net migration rate	0.096 (0.407) p = 0.815	-0.112 (0.397) p = 0.779	1.095*** (0.243) p = 0.00001	-0.005 (0.183) p = 0.977
ln (population in millions)	2.128*** (0.234) p = 0.000	112.127*** (30.602) p = 0.0003	0.934*** (0.173) p = 0.00000	40.523*** (15.607) 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*** (0.192) p = 0.00000	1.161*** (0.195) p = 0.000		2.259*** (0.374) p = 0.000	2.025*** (0.374) p = 0.00000	
Recovery rate of onsite workers \times log (percentage of transit commuters)		-0.113*** (0.035) p = 0.002			0.259*** (0.028) p = 0.000	
<i>Marginal effects of "the recovery rate of onsite workers" by geographical division:</i>						
New England			1.126*** (0.207) p = 0.00000			2.582*** (0.387) p = 0.000
Middle Atlantic			1.009*** (0.226) p = 0.00001			2.238*** (0.386) p = 0.000
East North Central			1.099*** (0.232) p = 0.00001			1.928*** (0.381) p = 0.00000
West North Central			1.151*** (0.206) p = 0.00000			2.616*** (0.385) p = 0.000
South Atlantic			1.066*** (0.243) p = 0.00002			1.826*** (0.383) p = 0.00001
East South Central			1.104*** (0.245) p = 0.00001			1.656*** (0.382) p = 0.00002
West South Central			1.305*** (0.274) p = 0.00001			2.172*** (0.381) p = 0.000
Mountain			0.973*** (0.232) p = 0.00003			1.634*** (0.385) p = 0.00003
Pacific			0.750*** (0.205) p = 0.00003			2.116*** (0.381) 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 [33]. 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.

212 counting for factors such as reopening stimulus effects, GDP per capita, unemployment rate, transit
213 service recovery trends, transit fares, vaccination rates, and population changes. Specifically, a 1-
214 percentage-point increase in the percentage of suitable remote workers is associated with a decrease
215 of 2.28 percentage points in the recovery rate of onsite workers across the 48 states and District of
216 Columbia, and a decrease of 0.24 percentage points across the 217 MSAs. This disparity can be
217 attributed to the larger geographic area and population coverage of states compared to the specific
218 urban focus of MSAs. State-level analysis combines remote work behavior across diverse MSAs, re-
219 sulting in a more homogeneous effect, while MSA-level analysis captures localized dynamics, leading
220 to greater heterogeneity in the effects of the IV on the recovery rate of onsite workers.

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

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

221 Following the main 2SLS estimations, we conducted robustness tests on our 2SLS models, in-
222 cluding falsification tests, variations in the study period, and the use of an alternative metric for
223 remote work (detailed in Supplementary Section 3). The results not only confirm the validity of
224 our results but also strengthen the robustness of our conclusions.

225 **Temporal variation of the effect of remote work**

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

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

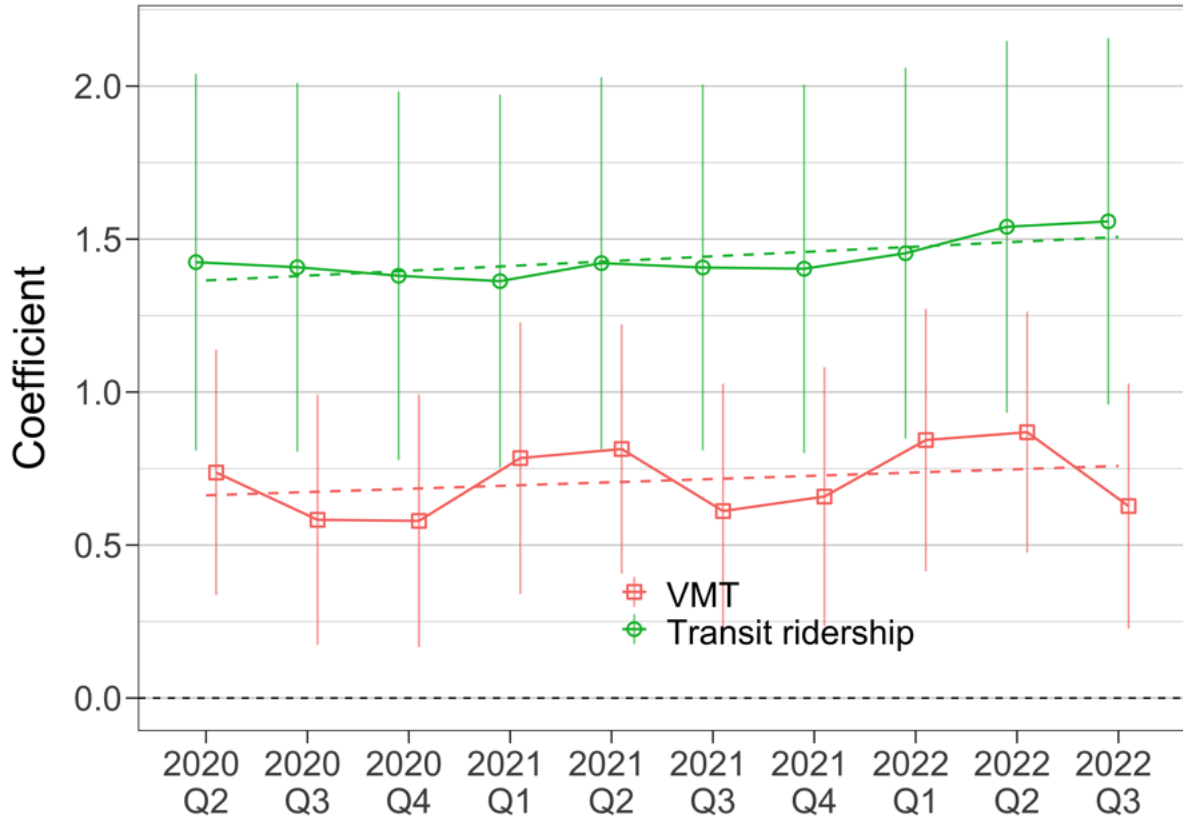


Figure 2: **Effects of the recovery of onsite workers on the recovery rates of VMT and transit ridership over time.** The markers denote the coefficient of onsite worker recovery for predicting VMT (red squares) and transit ridership (green circles) across various year-quarters (see Methods for model 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.

236 **Effects on on-road CO₂ emissions and transit fare revenues**

237 To contextualize the effects of remote work on VMT and transit, we estimate the reduction in
238 CO₂ emissions associated with the effect of remote work on VMT and the reduction in transit fare
239 revenue associated with the effect of remote work on transit ridership. On a national basis, we
240 estimate that a 10% decrease in the number of onsite workers compared to pre-pandemic levels will
241 reduce the annual total VMT-related CO₂ emission by 191.8 million metric tons. For reference,
242 the annual energy-related CO₂ emissions from the transportation sector in the contiguous U.S. is
243 1915.26 million metric tons in 2019 [1]. Therefore, our finding suggests that a 10% decrease in
244 the number of onsite workers compared to pre-pandemic levels could potentially result in a 10%
245 reduction in CO₂ emissions from the transportation sector in the contiguous U.S., using the 2019
246 level as the baseline (*Methods*). We also find that the marginal effect of remote work on VMT-
247 related CO₂ reductions varies substantially across states (Fig. 3a). For example, a 1% decrease in
248 the number of onsite workers compared to pre-pandemic levels would lead to monthly reductions
249 of 176.1 thousand metric tons versus 47.5 thousand metric tons in CO₂ emissions in Texas versus
250 New York State. The difference in CO₂ emissions across states is due to three factors: the marginal
251 effect of remote work on VMT varying with the percentage of transit commuters in each state (the
252 effect for each state is reported in Supplementary Fig. S5), the pre-pandemic (2019) VMT levels of
253 each state, and the state-specific emission factors in 2020-2021 (*Methods*).

254 Increasing the remote working level would also lead to a considerable loss in public transit fare
255 revenues, which may impact the financial sustainability of the transit agencies and thus poses a
256 challenge for transit agencies to deliver transit services that are responsive to people’s travel needs.
257 Across the 217 MSAs, we estimate that a 10% decrease in the number of onsite workers compared
258 to pre-pandemic levels would lead to an annual loss of 2.4 billion transit trips and \$3.7 billion in fare
259 revenue, which are roughly 26.7% of the annual transit ridership and fare revenue in 2019 (*Methods*).
260 Regionally, the marginal effects of remote work on transit fare revenue vary widely across MSAs
261 (Fig. 3b). The majority of the transit fare revenue loss occurs in the New York MSA, where a
262 1-percentage-point decrease in the recovery rate of onsite workers would result in \$18.16 million
263 loss in transit fare revenue per month, which accounts for 59.46% of the total monthly transit fare
264 revenue loss in all 217 MSAs.

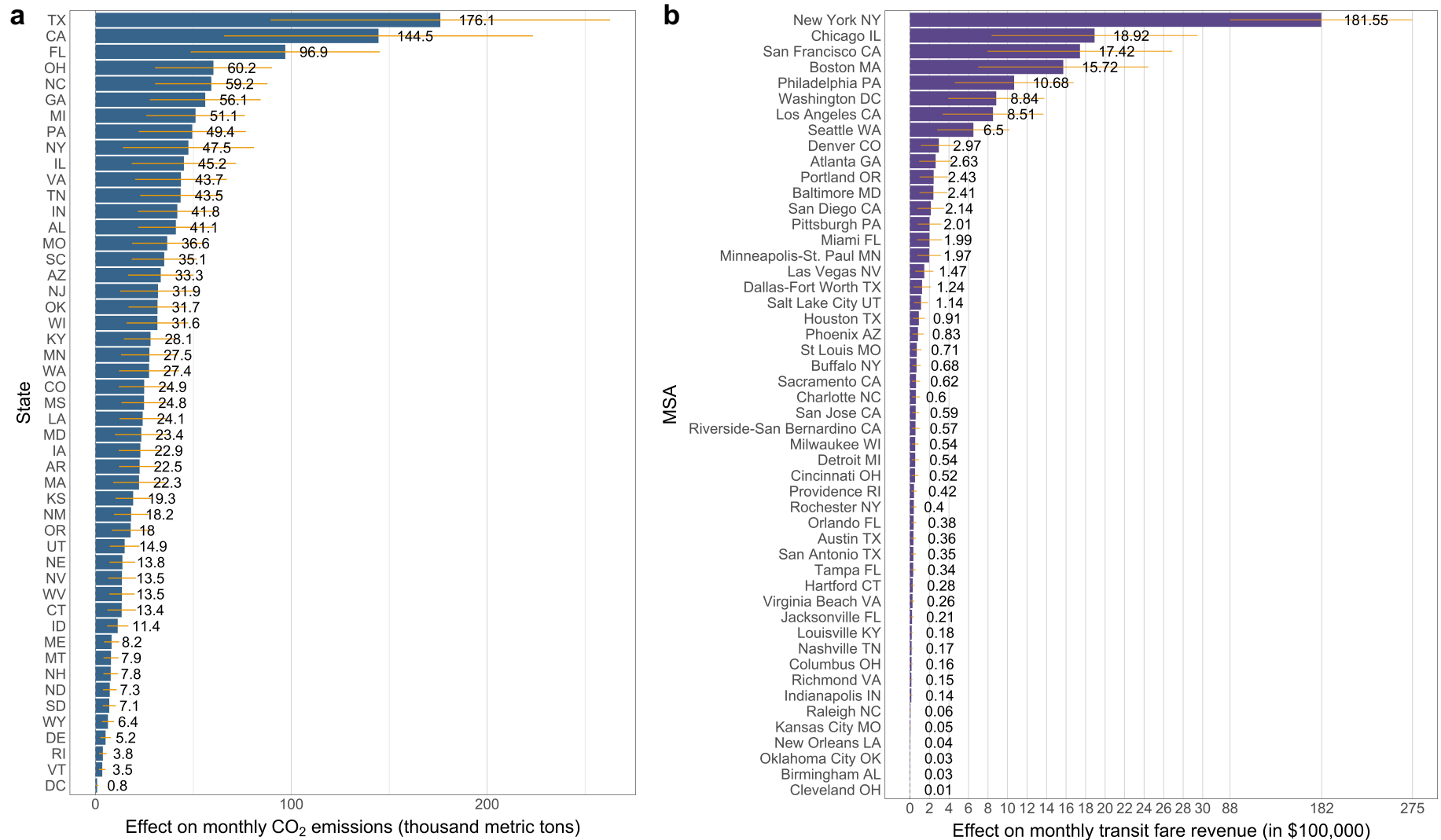


Figure 3: Marginal effect of remote work on the reduction of on-road CO₂ emissions by state and that on the reduction of transit fare revenues by MSA. These two graphs show the reduction in monthly on-road CO₂ emissions by state (a) and the reduction in monthly transit fare revenues by 50 most populated 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.

265 Discussion

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

274 The widespread adoption of remote work offers significant benefits in terms of on-road carbon
275 emissions. Our research emphasizes the effectiveness of remote work policies in mitigating on-road
276 CO₂ emissions, complementing existing measures such as carbon tax and road pricing. Notably, or-
277 ganizations worldwide have embraced remote work and are committed to maintaining these options
278 in the future [37, 38]. This persistent trend is poised to generate enduring reductions in on-road
279 carbon emissions, underscoring the need for companies and policymakers to recognize the environ-
280 mental advantages of remote work and for governments to consider the incorporation of remote
281 work strategies into their initiatives for transportation decarbonization.

282 However, despite the positive impact of remote work on on-road CO₂ emissions, our research
283 also reveals a significant challenge related to transit fare revenue loss due to reduced transit rider-
284 ship. Although transit agencies have received assistance through federal funding since March 2020
285 [39, 40, 41], persistently low ridership poses financial difficulties for transit agencies. This situation
286 raises concerns about their long-term financial sustainability and their ability to operate indepen-
287 dently from federal subsidies [42, 43, 44]. To address this challenge, transit agencies must focus on
288 enhancing customer attraction and revenue generation while promoting sustainable urban growth
289 through viable alternatives to car-centric and fuel-inefficient development. Given that remote work
290 often involves home-based flexible trips, transit agencies can invest in on-demand services, flexible
291 routing, and non-commuting trips in residential areas, thereby diversifying their service offerings be-
292 yond traditional fixed-route services primarily designed for regular commuting in the pre-pandemic
293 era.

294 This study also paves the way for future research endeavors. Firstly, while our analysis covers
295 the period from April 2020 to October 2022 due to data availability, further research is necessary
296 to assess the long-term impacts of remote work on urban mobility, considering potential behavioral
297 changes and evolving work dynamics in the post-pandemic era. Secondly, previous studies have
298 highlighted that work-related travel savings resulting from remote work may stimulate other types
299 of travel, potentially offsetting the reductions achieved by avoiding commuting [18, 19, 16, 17].
300 While our study measures the net effect of remote work on overall travel, additional investigations
301 are needed to quantify the impacts of remote work on work-related travel and other types of travel
302 separately. Lastly, although our study indirectly measures the extent of remote work using the
303 recovery rate of onsite workers from Google Community Mobility Reports, future research should

304 consider direct measurements of remote work. Additionally, it's crucial to acknowledge that Google
305 Community Mobility Reports rely on data from users who have enabled Location History, possibly
306 introducing bias toward individuals with access to smartphones and technology. While our data
307 robustly represents remote work based on a comparison with a national remote work survey dataset
308 (Supplementary Section 1.3), exploring other datasets with greater representativeness is advisable
309 for future research.

310 **Methods**

311 **Data.**

312 The recovery rate of onsite workers is determined using data obtained from the Google Commu-
313 nity Mobility Reports [45]. These reports provide information on the percentage change in visitors
314 to workplaces compared to a baseline, which we consider as the recovery rate of onsite workers, at
315 the county level. The baseline represents the median value observed during the 5-week period from
316 January 3 to February 6, 2020, specifically for the corresponding day of the week. It's important to
317 note that this data is collected by Google from users who have enabled Location History, which may
318 introduce limitations in representativeness as it does not account for individuals who are not Google
319 users or Google users who did not enable Location History during the study period. To assess data
320 representativeness, we conducted a comparison of our data with the remote working indicator ob-
321 tained from a national remote work survey dataset, specifically the monthly U.S. Survey of Working
322 Arrangements and Attitudes (SWAA). The results reveal a strong negative correlation between the
323 recovery rate of onsite workers in our sample and the remote work measure in the SWAA data
324 when aggregated to the state and month-year level, with correlation coefficients of -0.83 and -0.88,
325 respectively. Our data validation results affirm the robust representation of our indicator regarding
326 the extent of remote work (details in Supplementary Section 1.3).

327 To calculate the monthly recovery rate of onsite workers for a state or MSA, we average the
328 recovery rates of all counties within that state/MSA. The averaging is weighted by the employment
329 level in each county for the corresponding month, which is obtained from the US Bureau of Labor
330 Statistics [46]. The available data spans from April 2020 to October 2022, which serves as our study
331 period.

332 The monthly state-level VMT data are collected from the U.S. Federal Highway Administrations
333 (FHWA) [47], which report the vehicle miles traveled on all roads for 50 US states and the District
334 of Columbia. We focus on the contiguous U.S. which includes 48 states and the District of Columbia
335 from April 2020 to October 2022.

336 Public transit data comes from the National Transit Database [48], which contains panel data
337 of transit profiles and summaries at an agency-month level, reported separately by mode. We
338 include only "full reporters" that regularly report their ridership monthly, and exclude "reduced
339 reporters"/"small systems reporters" (agencies operating fewer than 30 vehicles in maximum service)
340 and "rural reporters" (agencies not reporting data to the monthly ridership module). For each
341 agency, we include bus modes (bus, bus rapid transit, commuter bus, and trolleybus) and rail

342 modes (light rail, heavy rail, commuter rail, etc.), and exclude demand-responsive transit and
343 all other modes. We retained only agencies that provided continuous service from January 2019 to
344 October 2022, covering 97.5% of all transit vehicle revenue miles provided by agencies that operated
345 throughout 2019. The resulting data covers 217 MSAs from April 2020 to October 2022.

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

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

359 To calculate SW_{it} , which represents the percentage of suitable remote workers for state or MSA
360 i at time t , we take the weighted average across all industries in that region. More specifically, we
361 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
362 remote workers for industry type j in region i , which is obtained from the May 2019 Occupational
363 Employment Statistics survey [49]. e_{ij}^t represents the employment level in region i for industry j at
364 time t , which is extracted from the quarterly census of employment and wages published by the US
365 Bureau of Labor Statistics [46].

366 The reopening status of a state refers to the lifting of social distancing measures, such as imposing
367 mandatory stay-at-home orders, closing or limiting capacity at non-essential businesses, restaurants,
368 and bars, as well as limiting large gatherings [50]. A value of 1 is assigned if the state had reopened
369 by the end of the month, and 0 if it had not. This information is sourced from the Kaiser Family
370 Foundation [50], which has been tracking the reopening status of each state on a weekly basis since
371 the beginning of the pandemic. Each MSA is mapped to a state which has the most population of
372 that MSA.

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

380 Previous research has indicated that individuals may opt to relocate to more distant locations
381 when engaging in remote work, leading to potential changes in their travel patterns [9, 20]. To

382 address this phenomenon, we incorporate the net migration rate as an independent variable in our
 383 analysis. The net migration rate for region (state or MSA) i during month-year t is calculated as:

$$384 \quad \text{Net migration rate}_i^t = (\text{Gross inflow}_i^t - \text{Gross outflow}_i^t) / \text{Population}_i \quad [1]$$

385 Gross in- and outflows refer to the total number of individuals moving in and out of the region
 386 i during month-year t . The raw data is sourced from change-of-address records provided by the
 387 United States Postal Service (USPS)[51], which document these migrations at the ZIP code level
 388 on a monthly basis. We then aggregate this data to the state or MSA level. Population_i refers to
 389 the total population in region i .

390 The daily number of new COVID-19 cases at the county level was sourced from the New York
 391 Times [52], and we aggregated this data to the region-month level for our analysis. To account for
 392 population differences, we utilized the number of new cases per capita as an independent variable in
 393 our regressions. Information on vaccination rates for each state was obtained from the Centers for
 394 Disease Control and Prevention (CDC) [53]. It is worth noting that vaccine effectiveness diminishes
 395 over time. A meta-analysis of studies on COVID-19 vaccination effectiveness [54] found that after
 396 any primary vaccination cycle, the effectiveness against symptomatic disease dropped to less than
 397 10% for Omicron and less than 50% for Delta. To capture the temporal variations in vaccine effects,
 398 we incorporated three variables: vaccinations per person in the past 3 months, vaccinations over
 399 the past 3-6 months, and vaccinations over the past 6-9 months.

400 The annual population data for the years 2020 to 2022 for each state and MSA is derived from
 401 the U.S. Census Bureau [55, 56]. Information on the percentage of transit commuters in each state
 402 and MSA is sourced from the 2021 American Community Survey 5-year estimates.

403 We have compiled the essential information on key variables, including their measurement units,
 404 sources, and original spatiotemporal granularity, in Supplementary Section 1.1. Descriptive statistics
 405 of the variables are provided in Supplementary Section 1.2. Data processing utilized Python version
 406 3.7.4 and R version 3.6.3, while modeling was performed using R version 3.6.3.

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

$$410 \quad Y_{it} = \beta_0 + \beta_1 RW_{it} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + v_{it} \quad [2]$$

411 where Y_{it} denotes the recovery rate of VMT for state i at time t or the recovery rate of transit
 412 ridership for MSA i at time t , which are calculated as the percentages of VMT and transit rider-
 413 ship compared to the values in the same month of 2019. RW_{it} denotes the recovery rate of onsite
 414 workers for state/MSA i at time t , which is calculated as the percentage of the number of workplace
 415 visitors at time t compared with its pre-pandemic level. $Controls_{it}$ is a set of control variables cor-
 416 responding to state/MSA i and time t , including GDP per capita, unemployment rate, the recovery
 417 rate of transit services, transit fares, population size, net migration rate, reopening status, reported
 418 COVID cases per capita, and vaccination rate. Most variables can be aggregated to the monthly

419 level. However, transit fares and population size are reported annually, thus we employ data from
 420 the corresponding year. For GDP per capita, which is reported quarterly, we calculate and employ
 421 the average monthly GDP per capita for the corresponding quarter. β_0 denotes the intercept, β_1 is
 422 the coefficient of RW_{it} , and β_2 represents the coefficients for the control variables. α_{1i} denotes the
 423 regional fixed effects that control for time-invariant characteristics at the state or MSA level. α_{1m}
 424 denotes the month fixed effects that account for the variation by month. v_{it} is the error term.

425

426 **2SLS specification.** To solve the endogeneity problem of RW_{it} and estimate the causal effect of
 427 the recovery rate of onsite workers on transit ridership recovery, we apply a 2SLS estimation. In the
 428 first stage of the 2SLS model, we estimate the recovery rate of onsite workers using the following
 429 formula:

$$430 \quad RW_{it} = \gamma_0 + \gamma_1 SW_{it} + \gamma_2 Controls_{it} + \alpha_{2i} + \alpha_{2m} + \epsilon_{it} \quad [3]$$

431 where SW_{it} represents the percentage of suitable remote workers in region i at time t . γ_0 denotes
 432 the intercept, γ_1 is the coefficient of SW_{it} , and γ_2 represents the coefficients for the control variables.
 433 α_{2i} and α_{2m} are the regional fixed effects and the month fixed effects, and ϵ_{it} is the error term.
 434 We include the same set of control variables, regional and month fixed effects as in the fixed-effect
 435 model (equation 2). The second stage of the 2SLS follows the formula:

$$436 \quad Y_{it} = \beta_0 + \beta_1 \widehat{RW}_{it} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + v_{it} \quad [4]$$

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

441

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

$$445 \quad Y_{it} = \beta_0 + \sum_m \theta_m * \mathbf{I}\{i \in D_m\} * \widehat{RW}_{it} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + v_{it} \quad [5]$$

446 where D_m indicates a specific geographical divisions. There are nine divisions in the United States,
 447 namely New England, Middle Atlantic, East North Central, West North Central, South Atlantic,
 448 East South Central, West South Central, Mountain, and Pacific [33]. $\mathbf{I}\{i \in D_m\}$ takes value 1 if i
 449 is in D_m and 0 if not. θ_m denotes the division-specific effect. Other parts of the model remain the
 450 same as in Equation 4.

451

452 **Effects by the percentage of transit commuters.** Theoretically, the influence of remote work
 453 on both VMT and transit ridership depends on the interplay between its impact on people's travel

454 needs and the distribution of residents' travel modes within a region. To account for these variations,
 455 we explore how the marginal effect of remote work varies by the percentage of transit commuters
 456 using the following specification:

$$457 \quad Y_{it} = \beta_0 + \omega_1 * \widehat{RW}_{it} + \omega_2 * \widehat{RW}_{it} * \log(Z_i) + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + v_{it} \quad [6]$$

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

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

$$469 \quad Y_{it} = \beta_0 + \sum_k \gamma_k * \mathbf{I}\{t \in T_k\} * \widehat{RW}_{it} + \beta_2 Controls_{it} + \alpha_{1i} + \alpha_{1m} + v_{it} \quad [7]$$

470 where T_k indicates the k^{th} year-quarter in the study period, ranging from 2020 Q2 to 2022 Q3, with
 471 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. γ_k denotes
 472 the year-quarter-specific effect. Other parts of the model remain the same as in Equation 4.

473 **Measuring the marginal effect of remote work on the VMT-related carbon emissions.**

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

$$477 \quad \beta_i = \hat{\omega}_1 + \hat{\omega}_2 * \log(Z_i) \quad [8]$$

478 Here, β_i represents the marginal effect for state i , and Z_i represents the percentage of transit com-
 479 muters in state i . We incorporate Z_i to determine state-specific marginal effects for two key reasons:
 480 firstly, in theory, the effects of remote work on VMT and transit ridership in a region depend on
 481 the interplay between its impact on people's travel needs and the region's travel mode distribution,
 482 with the percentage of transit commuters being a crucial indicator of this distribution. Second,
 483 our 2SLS modeling results (as demonstrated in Column 2 and 5 of Table 2) indicate significant
 484 variations in the marginal impacts of remote work on VMT and transit ridership with respect to Z_i ,
 485 and the inclusion of Z_i improves the model's R^2 . Given these considerations, we employ Equation
 486 4 to represent region-specific marginal effects.

487 Subsequently, we compute CO₂ emissions per VMT in each state (EF_i). This is defined as:

$$488 \quad EF_i = E_i/V_i \quad [9]$$

489 where E_i represents the total on-road CO₂ emissions during 2020 and 2021 in state i , and V_i
490 represents the total VMT in state i during the same period. The choice of the 2020 and 2021
491 time period is due to the unavailability of 2022 data on E_i . To obtain the data for E_i , we first
492 collected information on the total motor gasoline and diesel fuel consumption for each state during
493 2020 and 2021 from the Federal Highway Administration’s annual Highway Statistics Series Table
494 MF-21 [57]. Subsequently, we converted this fuel consumption data into CO₂ emissions using the
495 following conversion factors: 8.887 kg of CO₂ emissions per gallon of gasoline consumed and 10.180
496 kg of CO₂ emissions per gallon of diesel consumed [58]. Data for V_i was obtained from FHWA’s
497 annual Highway Statistics Series Table VM-2 [59], which tracks traffic involving six vehicle types:
498 motorcycles, passenger cars, light-duty trucks, buses, single-unit trucks, and multi-unit combination
499 trucks [60].

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

$$503 \quad ME_{it} = \beta_i * V_i^{19} * EF_i \quad [10]$$

504 It is important to note that fuel consumption per mile traveled varies depending on the type of
505 vehicle. In this analysis, due to data limitations, we could only assess the impact of remote work on
506 total VMT and apply the average emission factor, without distinguishing the effect on VMT related
507 to different types of vehicles. Therefore, the accuracy of our estimated marginal impacts on on-road
508 CO₂ emissions relies on the assumption that the change in VMT due to remote work maintains a
509 similar vehicle type composition as the VMT in 2020 and 2021 for each state. Given that remote
510 work could affect the travel of different types of vehicles differently, further analysis could enhance
511 accuracy by estimating the marginal effect of remote work on various VMT types and calculating
512 the total CO₂ impacts using different emission factors for each vehicle type. Additionally, emission
513 factors may change over time, so caution should be exercised when applying these results to infer
514 the CO₂ impact from 2022 onward.

515 **Measuring the marginal effect of remote work on transit fare revenues.** We compute the
516 marginal effect of remote work on transit fare revenue for each MSA i , F_i , based on the equation:
517 $F_i = \beta_i * R_i^{19} * P_i$. β_i represents the marginal effect of remote work on transit ridership estimated
518 from the transit ridership 2SLS model (Equation 6): $\beta_i = \hat{\omega}_1 + \hat{\omega}_2 * \log(Z_i)$, where Z_i denotes the
519 percentage of transit commuters in MSA i . R_i^{19} denotes the prepandemic (2019) average monthly
520 transit ridership. P_i denotes the average fare per passenger trip in MSA i , which is obtained from
521 the National Transit Database [48].

522 Data availability

523 The data used for this study are sourced from publicly available databases, and detailed information
524 about each variable’s source can be found in the Data section of the Methods. The compiled datasets

525 can be accessed on GitHub at https://github.com/zhengyunhan/remote_work_mobility.

526 **Code availability**

527 The code used for conducting the analysis is accessible on GitHub at [https://github.com/zhengyunhan/](https://github.com/zhengyunhan/remote_work_mobility)
528 `remote_work_mobility`.

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537 **Author contributions**

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

544 **Competing interests**

545 The authors declare no competing interests.

546 **References**

- 547 [1] EIA. State carbon dioxide emissions data, 2020. [https://www.eia.gov/environment/](https://www.eia.gov/environment/emissions/state/)
548 `emissions/state/`, last accessed on 2022-11-26.
- 549 [2] Felix Creutzig, Joyashree Roy, William F Lamb, Inês ML Azevedo, Wändi Bruine de Bruin,
550 Holger Dalkmann, Oreane Y Edelenbosch, Frank W Geels, Arnulf Grubler, Cameron Hepburn,
551 et al. Towards demand-side solutions for mitigating climate change. *Nature Climate Change*,
552 8(4):260–263, 2018.

- 553 [3] Ghislain Dubois, Benjamin Sovacool, Carlo Aall, Maria Nilsson, Carine Barbier, Alina Her-
554 rmann, Sébastien Bruyère, Camilla Andersson, Bore Skold, Franck Nadaud, et al. It starts at
555 home? climate policies targeting household consumption and behavioral decisions are key to
556 low-carbon futures. *Energy Research & Social Science*, 52:144–158, 2019.
- 557 [4] Jonn Aksen, Patrick Plötz, and Michael Wolinetz. Crafting strong, integrated policy mixes for
558 deep co2 mitigation in road transport. *Nature Climate Change*, 10(9):809–818, 2020.
- 559 [5] John ET Bistline, Geoffrey Blanford, John Grant, Eladio Knipping, David L McCollum, Uar-
560 porn Nopmongcol, Heidi Scarth, Tejas Shah, and Greg Yarwood. Economy-wide evaluation of
561 co2 and air quality impacts of electrification in the united states. *Nature communications*, 13
562 (1):1–12, 2022.
- 563 [6] Andrew Hook, Benjamin K Sovacool, Steve Sorrell, et al. A systematic review of the energy
564 and climate impacts of teleworking. *Environmental Research Letters*, 15(9):093003, 2020.
- 565 [7] Mei-Po Kwan. Mobile communications, social networks, and urban travel: Hypertext as a new
566 metaphor for conceptualizing spatial interaction. *The Professional Geographer*, 59(4):434–446,
567 2007.
- 568 [8] Paul O’keefe, Brian Caulfield, William Brazil, and Peter White. The impacts of telecommuting
569 in dublin. *Research in Transportation Economics*, 57:13–20, 2016.
- 570 [9] Prashant N Balepur, Krishna V Varma, and Patricia L Mokhtarian. Transportation impacts
571 of center-based telecommuting: Interim findings from the neighborhood telecenters project.
572 *Transportation*, 25(3):287–306, 1998.
- 573 [10] Sangho Choo, Patricia L Mokhtarian, and Ilan Salomon. Does telecommuting reduce vehicle-
574 miles traveled? an aggregate time series analysis for the us. *Transportation*, 32(1):37–64, 2005.
- 575 [11] John S Niles. Beyond telecommuting: a new paradigm for the effect of telecommunications on
576 travel. Technical report, USDOE Office of Energy Research, Washington, DC (United States),
577 1994.
- 578 [12] Hamidreza Asgari and Xia Jin. An evaluation of part-day telecommute impacts on work trip
579 departure times. *Travel Behaviour and Society*, 12:84–92, 2018.
- 580 [13] Somitra Saxena and Patricia L Mokhtarian. The impact of telecommuting on the activity
581 spaces of participants. *Geographical analysis*, 29(2):124–144, 1997.
- 582 [14] João de Abreu e Silva and Patrícia C Melo. Does home-based telework reduce household total
583 travel? a path analysis using single and two worker british households. *Journal of Transport
584 Geography*, 73:148–162, 2018.

- 585 [15] Ugo Lachapelle, Georges A Tanguay, and Léa Neumark-Gaudet. Telecommuting and sustain-
586 able travel: reduction of overall travel time, increases in non-motorised travel and congestion
587 relief? *Urban Studies*, 55(10):2226–2244, 2018.
- 588 [16] Nathaniel C Horner, Arman Shehabi, and Inês L Azevedo. Known unknowns: Indirect energy
589 effects of information and communication technology. *Environmental Research Letters*, 11(10):
590 103001, 2016.
- 591 [17] Piet Rietveld. Telework and the transition to lower energy use in transport: On the relevance
592 of rebound effects. *Environmental Innovation and Societal Transitions*, 1(1):146–151, 2011.
- 593 [18] Pengyu Zhu. Are telecommuting and personal travel complements or substitutes? *The Annals*
594 *of Regional Science*, 48(2):619–639, 2012.
- 595 [19] Seung-Nam Kim, Sangho Choo, and Patricia L Mokhtarian. Home-based telecommuting and
596 intra-household interactions in work and non-work travel: A seemingly unrelated censored
597 regression approach. *Transportation Research Part A: Policy and Practice*, 80:197–214, 2015.
- 598 [20] Sandip Chakrabarti. Does telecommuting promote sustainable travel and physical activity?
599 *Journal of Transport & Health*, 9:19–33, 2018.
- 600 [21] Gregory D Erhardt, Jawad Mahmud Hoque, Vedant Goyal, Simon Berrebi, Candace Brake-
601 wood, and Kari E Watkins. Why has public transit ridership declined in the united states?
602 *Transportation Research Part A: Policy and Practice*, 161:68–87, 2022.
- 603 [22] Patricia L Mokhtarian and Krishna V Varma. The trade-off between trips and distance traveled
604 in analyzing the emissions impacts of center-based telecommuting. *Transportation research part*
605 *D: Transport and Environment*, 3(6):419–428, 1998.
- 606 [23] U.S. Bureau of Labor Statistics. Job flexibilities and work schedules summary, 2019. [https:](https://www.bls.gov/news.release/flex2.nr0.htm)
607 [//www.bls.gov/news.release/flex2.nr0.htm](https://www.bls.gov/news.release/flex2.nr0.htm), last accessed on 2023-07-05.
- 608 [24] U.S. Bureau of Labor Statistics. Workers who worked at home and how often they worked
609 exclusively at home by selected characteristics, averages for the period 2017-2018, 2019. [https:](https://www.bls.gov/news.release/flex2.t03.htm)
610 [//www.bls.gov/news.release/flex2.t03.htm](https://www.bls.gov/news.release/flex2.t03.htm), last accessed on 2023-10-25.
- 611 [25] Michael Burrows, Charlynn Burd, and Brian McKenzie. Home-based workers and the covid-19
612 pandemic, 2023. [https://www.census.gov/content/dam/Census/library/publications/](https://www.census.gov/content/dam/Census/library/publications/2023/acs/acs-52.pdf)
613 [2023/acs/acs-52.pdf](https://www.census.gov/content/dam/Census/library/publications/2023/acs/acs-52.pdf), last accessed on 2023-10-25.
- 614 [26] Susan Lund, Anu Madgavkar, James Manyika, Sven Smit, Kweilin Ellingrud, Mary Meaney,
615 and Olivia Robinson. The future of work after covid-19. *McKinsey Global Institute*, 18, 2021.
- 616 [27] Jose Maria Barrero, Nicholas Bloom, and Steven J Davis. 60 million fewer commuting hours
617 per day: How americans use time saved by working from home. *University of Chicago, Becker*
618 *Friedman Institute for Economics Working Paper*, (2020-132), 2020.

- 619 [28] New York Times. White house will end most covid vaccine mandates, 2023.
- 620 [29] U.S. Census Bureau. Household pulse survey microdata, 2023. [https://www.census.gov/](https://www.census.gov/programs-surveys/household-pulse-survey/data.html)
621 [programs-surveys/household-pulse-survey/data.html](https://www.census.gov/programs-surveys/household-pulse-survey/data.html), last accessed on 2023-07-03.
- 622 [30] Gilmore M Rioveros, Ethel Reyes-Chua, Noel R Navigar, Alfe M Solina, Maryann H
623 Lanuza, and Marc Sylvester G Garcia. The impact of work from home set-up during
624 the covid-19 pandemic. *Worldwide Journal of Multidisciplinary Research and Develop-*
625 *ment*. [http://wujmrd.com/upload/the-impact-of-work-from-home-set-up-during-the-covid-19-](http://wujmrd.com/upload/the-impact-of-work-from-home-set-up-during-the-covid-19-pandemic_1631623804.pdf)
626 [pandemic_1631623804.pdf](http://wujmrd.com/upload/the-impact-of-work-from-home-set-up-during-the-covid-19-pandemic_1631623804.pdf), 2021.
- 627 [31] Seung-Nam Kim. Is telecommuting sustainable? an alternative approach to estimating the
628 impact of home-based telecommuting on household travel. *International Journal of Sustainable*
629 *Transportation*, 11(2):72–85, 2017.
- 630 [32] Pengyu Zhu and Susan G Mason. The impact of telecommuting on personal vehicle usage and
631 environmental sustainability. *International Journal of Environmental Science and Technology*,
632 11(8):2185–2200, 2014.
- 633 [33] United States Census Bureau. Census regions and divisions of the united states. https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf, last accessed on
634 https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf, last accessed on
635 2023-10-18.
- 636 [34] Mansoor Iqbal. Uber revenue and usage statistics (2022). *Business of apps*, 2022.
- 637 [35] Mansoor Iqbal. Lyft revenue and usage statistics (2022). *Business of apps*, 2022.
- 638 [36] Simon J Berrebi and Kari E Watkins. Who’s ditching the bus? *Transportation Research Part*
639 *A: Policy and Practice*, 136:21–34, 2020.
- 640 [37] André Dua, Kweilin Ellingrud, Phil Kirschner, Adrian Kwok, Ryan Luby, Rob Palter, and
641 Sarah Pemberton. Americans are embracing flexible work—and they want more of it. *McKinsey*
642 *research*, 2022.
- 643 [38] New York Times. The return to office revolt, 2022. [https://www.nytimes.com/2022/06/17/](https://www.nytimes.com/2022/06/17/briefing/the-return-to-office-revolt.html)
644 [briefing/the-return-to-office-revolt.html](https://www.nytimes.com/2022/06/17/briefing/the-return-to-office-revolt.html), last accessed on 2022-09-12.
- 645 [39] Federal Transit Administration. U.s. department of transporta-
646 tion announces increased flexibility to help transit agencies respond
647 to coronavirus, 2020. [https://www.transit.dot.gov/about/news/](https://www.transit.dot.gov/about/news/us-department-transportation-announces-increased-flexibility-help-transit-agencies)
648 [us-department-transportation-announces-increased-flexibility-help-transit-agencies](https://www.transit.dot.gov/about/news/us-department-transportation-announces-increased-flexibility-help-transit-agencies),
649 last accessed on 2022-09-12.
- 650 [40] Federal Transit Administration. U.s. department of transportation announces the
651 availability of \$2.2 billion in american rescue plan funding to help transit agencies

652 with additional service needs, 2021. [https://www.transit.dot.gov/about/news/
653 us-department-transportation-announces-availability-22-billion-american-rescue-plan,](https://www.transit.dot.gov/about/news/us-department-transportation-announces-availability-22-billion-american-rescue-plan)
654 last accessed on 2022-09-12.

655 [41] Federal Transit Administration. President Biden, USDOT announce
656 more than \$20 billion for communities of all sizes to support tran-
657 sit this year, 2022. [https://www.transit.dot.gov/about/news/
658 president-biden-usdot-announce-more-20-billion-communities-all-sizes-support-transit,](https://www.transit.dot.gov/about/news/president-biden-usdot-announce-more-20-billion-communities-all-sizes-support-transit)
659 last accessed on 2022-09-12.

660 [42] New York Times. The pandemic wasn't supposed to hurt New York transit this
661 much, 2022. [https://www.nytimes.com/2022/08/15/nyregion/mta-nyc-budget.html?
662 smid=tw-share,](https://www.nytimes.com/2022/08/15/nyregion/mta-nyc-budget.html?smid=tw-share) last accessed on 2022-10-14.

663 [43] Bloomberg. Without commuters, US transit agencies are running out of
664 options, 2022. [https://www.bloomberg.com/news/articles/2022-06-16/
665 public-transportation-braces-for-fewer-commuters-amid-work-from-home,](https://www.bloomberg.com/news/articles/2022-06-16/public-transportation-braces-for-fewer-commuters-amid-work-from-home) last
666 accessed on 2022-10-14.

667 [44] Governing. For mass transit agencies, a fiscal cliff looms, 2022. [https://www.governing.com/
668 nw/for-mass-transit-agencies-a-fiscal-cliff-looms,](https://www.governing.com/nw/for-mass-transit-agencies-a-fiscal-cliff-looms) last accessed on 2022-10-14.

669 [45] Google LLC. COVID-19 Community Mobility Reports, 2022. [https://www.google.com/
670 covid19/mobility/,](https://www.google.com/covid19/mobility/) last accessed on 2022-10-14.

671 [46] U.S. Bureau of Labor Statistics. Quarterly census of employment and wages, 2021.

672 [47] FHWA. Traffic volume trends, 2022. [https://www.fhwa.dot.gov/policyinformation/
673 travel_monitoring/tvt.cfm,](https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm) last accessed on 2022-11-26.

674 [48] Federal Transit Administration. NTD data, 2022. [https://www.transit.dot.gov/ntd/
675 ntd-data,](https://www.transit.dot.gov/ntd/ntd-data) last accessed on 2022-11-26.

676 [49] U.S. Bureau of Labor Statistics. Teleworking and lost work during the pandemic:
677 new evidence from the CPS, 2021. [https://www.bls.gov/opub/mlr/2021/article/
678 teleworking-and-lost-work-during-the-pandemic-new-evidence-from-the-cps.htm#
679 BLStable_2021_7_6_15_1_footnotes,](https://www.bls.gov/opub/mlr/2021/article/teleworking-and-lost-work-during-the-pandemic-new-evidence-from-the-cps.htm#BLStable_2021_7_6_15_1_footnotes) last accessed on 2022-09-12.

680 [50] Kaiser Family Foundation. State COVID-19 data and policy actions. *KFF State Vaccine Rollout*,
681 2021.

682 [51] The United States Postal Service. Change of Address Stats, 2022. [https://about.usps.com/
683 who/legal/foia/library.htm,](https://about.usps.com/who/legal/foia/library.htm) last accessed on 2022-09-12.

684 [52] The New York Times. We're sharing coronavirus case data for every US county, 2022. [https:
685 //github.com/nytimes/covid-19-data,](https://github.com/nytimes/covid-19-data) last accessed on 2022-09-12.

Supplementary Information: impacts of remote work on vehicle miles traveled and transit ridership in the United States

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1 S1 Data

2 S1.1 Data variables and sources

3 Table [S1](#) presents a summary of the key variables involved in this study, including their measurement units, sources, and original spatiotemporal granularity.

Table S1: Summary of key variables with measurement units, sources, and original spatiotemporal granularity

Variable	Unit of measurement	Source	Spatial unit	Time unit
Recovery rate of onsite workers	Percentage	Google Community Mobility Reports [1]	County	Daily
Vehicle-miles travelled (VMT)	Million miles	U.S. Federal Highway Administrations [2]	State	Monthly
Transit ridership	Number of unlinked passenger trips	National Transit Database [3]	Urbanized Area (UZA)	Monthly
Transit vehicle revenue miles (VRM)	Mile	National Transit Database [3]	UZA	Monthly
Transit fare	Dollar	National Transit Database [3]	UZA	Yearly
Percentage of suitable remote workers	Percentage	Occupational Employment Statistics survey, U.S. BLS [4]	County	Monthly
Net migration rate	Individuals per 1 million population	Change of Address Stats, USPS [5]	ZIP Code	Monthly
COVID cases per 1000 people	Case number per 1000 people	The New York Times [6]	County	Daily
Vaccinations per person	Vaccinations per person	Centers for Disease Control and Prevention (CDC) [7]	State	Daily
Reopening status	Dummy variable	Kaiser Family Foundation [8]	State	Monthly
Population	Million people	U.S. Census Bureau [9] [10]	State, MSA	Yearly
Percentage of transit commuters	Percentage	2021 American Community Survey 5-year estimates	County	2021
Per capita GDP	Thousand dollars	U.S. Bureau of Economic Analysis [11]	State	Quarterly
Unemployment rate	Percentage	Federal Reserve Economic Data [12]	State, MSA	Monthly
Per capita income, annual rate	Thousand dollars	U.S. Bureau of Economic Analysis [13]	State	Quarterly
Percentage of remote working days (SWAA data)	Percentage	U.S. Survey of Working Arrangements and Attitudes [14]	State	Monthly

Note: "Recovery rate of onsite workers" is measured by the number of workplace visitors compared to the pre-pandemic level.

5 **S1.2 Descriptive statistics**

Table S2: Descriptive statistics

Variable	N	Mean	Std.dev	Min	Max
Vehicle-miles travelled (VMT) (in million miles)	1519	5247.75	5369.27	186.00	30293.00
VMT compared to the 2019 level (%)	1519	94.62	11.64	41.10	144.43
Number of workplace visitors compared to the pre-pandemic level (%)	1519	74.46	7.73	36.07	93.56
Percentage of suitable remote workers (%)	1519	30.88	2.73	23.79	40.95
Net migration rate (individuals per 1 million population)	1519	-0.21	0.56	-3.88	2.75
ln (monthly transit VRM)	1519	13.58	1.72	10.60	17.81
Transit VRM compared to the 2019 level (%)	1519	88.84	10.32	45.71	118.75
Transit fare (\$)	1519	0.96	1.15	0.00	7.47
COVID cases per 1000 people	1519	9.38	11.26	0.06	92.92
Vaccinations per person in the past 3 months	1519	0.18	0.20	0.00	0.96
Vaccinations per person over the past 3-6 months	1519	0.17	0.21	0.00	0.96
Vaccinations per person over the past 6-9 months	1519	0.16	0.21	0.00	0.96
Reopening status (0/1)	1519	0.64	0.48	0.00	1.00
Population (in millions)	1519	6.74	7.40	0.58	39.50
Percentage of transit commuters (%)	1519	3.01	5.21	0.26	27.11
Per capita GDP (in thousand dollars)	1519	4.81	1.79	2.62	16.45
Per capita GDP compared to the 2019 level (%)	1519	101.36	5.20	84.91	114.39
Annual per capita income (in thousand dollars)	1519	61.42	10.23	41.84	98.26
Per capita income compared to the 2019 level (%)	1519	112.59	4.87	100.40	125.91
Unemployment rate (%)	1519	5.40	2.97	1.90	30.60
Percentage of remote working days in SWAA data (%)	1162	36.11	13.62	0.00	100.00
Part 2: Public transit ridership					
ln (monthly transit ridership)	6727	11.89	1.80	6.48	19.37
Transit ridership compared to the 2019 level (%)	6727	55.75	19.09	0.90	259.35
Number of workplace visitors compared to the pre-pandemic level (%)	6727	74.96	7.96	33.20	103.97
Percentage of suitable remote workers (%)	6727	29.65	5.87	14.11	54.14
Net migration rate (individuals per 1 million population)	6727	-0.24	0.89	-8.99	8.66
ln (monthly transit VRM)	6727	12.19	1.46	7.62	18.02
Transit VRM compared to the 2019 level (%)	6727	89.26	16.59	1.95	177.77
Transit fare (\$)	6727	0.95	0.66	0.00	6.14
COVID cases per 1000 people	6727	9.39	11.80	-88.35	108.77
Vaccinations per person in the past 3 months	6727	0.18	0.20	0.00	0.93
Vaccinations per person over the past 3-6 months	6727	0.17	0.21	0.00	0.93
Vaccinations per person over the past 6-9 months	6727	0.16	0.21	0.00	0.93
Reopening status (0/1)	6727	0.62	0.48	0.00	1.00
Population (in millions)	6727	1.16	2.11	0.08	20.05
Percentage of transit commuters (%)	6727	1.72	2.56	0.14	27.01
Per capita GDP (in thousand dollars)	6727	4.81	0.90	2.62	6.86
Per capita GDP compared to the 2019 level (%)	6727	101.80	5.04	84.91	114.39
Annual per capita income (in thousand dollars)	6727	62.53	9.06	41.84	87.66
Per capita income compared to the 2019 level (%)	6727	112.94	4.92	100.85	125.91
Unemployment rate (%)	6727	5.90	3.40	1.30	34.00

Note: "VRM" stands for vehicle revenue miles.

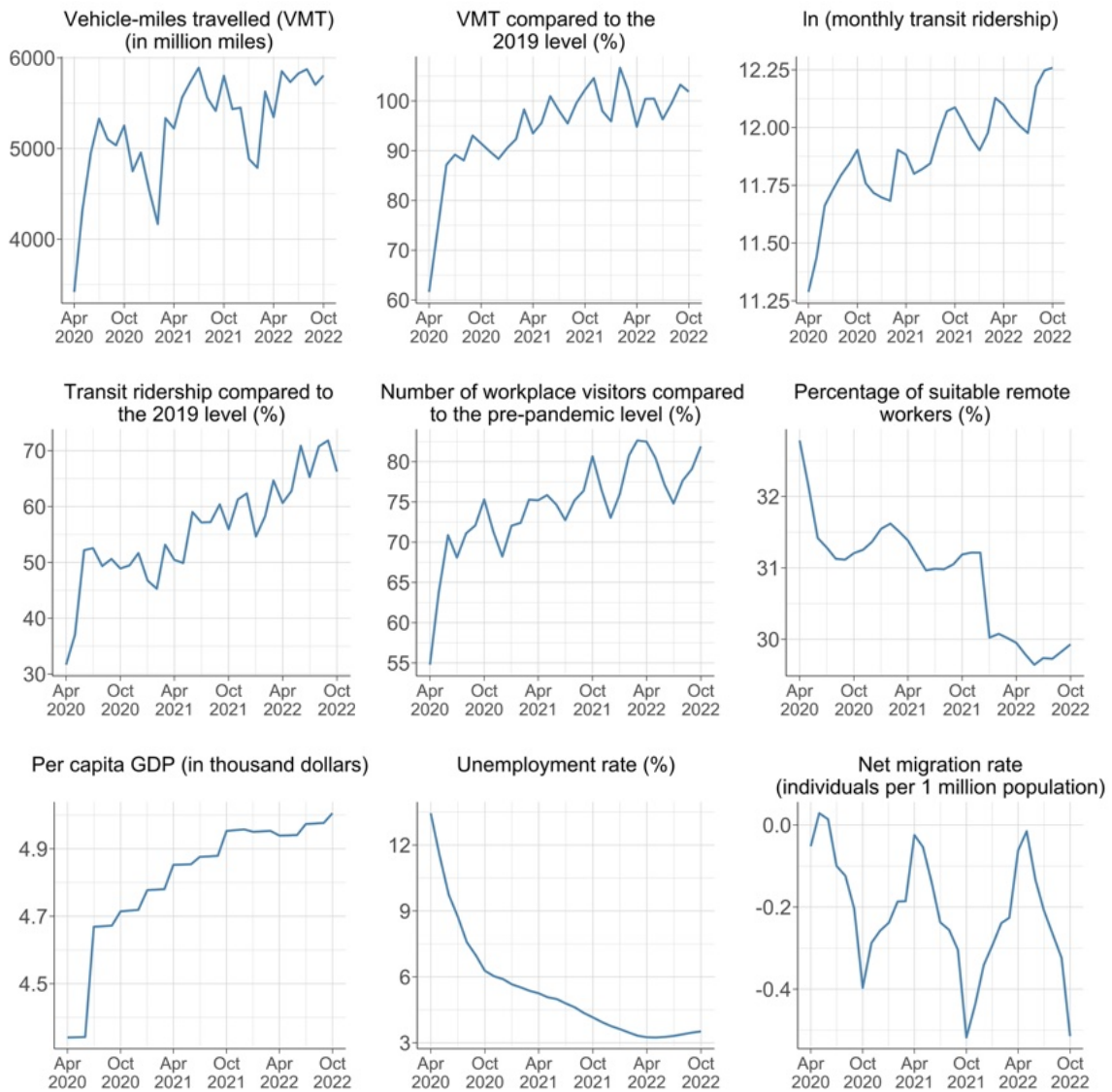


Figure S1: **Time Series of Key Variables.** These figures illustrate the temporal trends in the average values of important variables. Transit ridership, transit vehicle miles traveled (VRM), and transit fares are averaged at the MSA level, while the others represent state-averaged values. Transit fare and state-level population are yearly data, per capita GDP is quarterly data, while others are monthly data.



Figure S2: (Cont.) Time Series of Key Variables.

6 **S1.3 Data representativeness**

7 **S1.3.1 Google Community Mobility Reports data**

8 The primary explanatory variable in our study, which we refer to as the "recovery rate of onsite
9 workers", is represented by the "Workplaces" variable in Google Community Mobility Reports [1].
10 The "Workplaces" variable quantifies the percentage change in workplace visitors compared to a
11 baseline at the county-day level. We define this metric as the recovery rate of onsite workers.
12 The baseline corresponds to the median value observed during a 5-week period from January 3 to
13 February 6, 2020, for the respective day of the week. To aggregate the county-day level recovery
14 rate of onsite workers to the state-month and MSA-month levels, we first sum the figures to the
15 county-month level. Subsequently, we calculate the weighted average of the figures for all counties
16 within a specific state or MSA, with weights based on the employment level in each county for the
17 corresponding month, as obtained from the US Bureau of Labor Statistics [4].

18 It's important to note that the data for "Workplaces" is collected by Google from users with
19 enabled Location History [15]. Consequently, it may have representativeness limitations, as it
20 doesn't account for individuals who are not Google users or Google users who did not enable
21 Location History during the study period. This could potentially introduce bias toward certain
22 populations or regions.

23 **S1.3.2 SWAA data**

24 To assess data representativeness, we conducted a comparison with the remote working indicator
25 obtained from a national remote work survey dataset, specifically the monthly U.S. Survey of
26 Working Arrangements and Attitudes (SWAA). The SWAA survey, which has been conducted
27 monthly since May 2020, gathered information on the working arrangements about Americans'
28 working arrangements, including the amount of time people spent working from home. As of
29 October 2022, a total of 184,772 responses had been collected. A detailed description of the data
30 collection process can be found in Barrero et al. (2021) [16].

31 Using the SWAA survey data, we calculate the percentage of remote working days at the state-
32 month level between May 2020 and October 2022. We start by excluding those who do not work,
33 resulting in a total sample of 145,034 respondents. We focus on two key questions: "How many full
34 days are you working this week (whether at home or on business premises)?" and "How many full
35 paid working days are you working from home this week?". By dividing the number of days reported
36 in the second question by the number reported in the first question, we derive the percentage of
37 paid full days spent working from home (i.e., the percentage of remote working days) for each
38 respondent. We then calculate the weighted average of this remote work measure at the state-
39 month level. These sample weights were designed by Barrero et al. (2021) [16] to align with the
40 joint distribution of individuals across age, sex, education, and earnings categories from the Current
41 Population Survey (CPS) data spanning 2010 to 2019. To ensure that the results are representative
42 of the state population, we exclude state-month pairs with fewer than 10 samples. For detailed

43 descriptive statistics on this measure, please refer to Table [S2](#) and Figure [S2](#). Previous research has
44 demonstrated that the extent of remote work derived from the SWAA data aligns with measures
45 from the American Community Survey and the Household Pulse Survey regarding remote work
46 [17](#). Moreover, the comprehensiveness of the SWAA data exceeds that of the latter two datasets.
47 Consequently, we have chosen to use the SWAA data as our benchmark dataset for validating our
48 data measure.

49 **S1.3.3 Comparison between Google Community Mobility Reports data and SWAA** 50 **data**

51 In Supplementary Figure [S3](#), we present a comparison between the recovery rate of onsite workers in
52 our data and the percentage of remote working days derived from the SWAA survey. Figure [S3\(a\)](#)
53 represent the heatmap reflecting the count of state-month pairs across these two dimensions, showing
54 that the correlation between the metric in our sample and the metric in SWAA is moderately high,
55 with coefficients of $r = -0.62$. Realizing that individual state-month pairs may have suffer from
56 instability and uncertainties given the potentially small respondent count of SWAA survey in a pair,
57 we then aggregate samples to the state level in Figure [S3\(b\)](#), and to the month-year level in Figure
58 [S3\(c\)](#). These two subfigures indicate that the recovery rate of onsite workers in our sample and the
59 remote work measure in the SWAA data has strong negative correlations when aggregated to the
60 state and month-year level, with the r being -0.83 and -0.88 , respectively. These data validation
61 results underscore the robust representation of our indicator on the extent of remote work.

62 Nonetheless, it is crucial to acknowledge that the remote work measure in SWAA has its own set
63 of limitations. This measure is not selected as the primary explanatory variable in our main analyses
64 for the following reasons: 1) The number of valid state-month pairs (pairs with equal to or more
65 than 10 responses) in SWAA decreases from 1519 to 1162 over the study period. And the potential
66 limited number of responses in the remaining state-month pairs may introduce some bias into the
67 results. 2) Additionally, due to the constraints imposed by the sample size, conducting MSA-level
68 analyses becomes impractical, as many MSAs will have insufficient samples to draw meaningful
69 conclusions.

70 However, we do undertake fixed-effects and instrumental variable approaches utilizing this re-
71 mote work measure to estimate the recovery rate of VMT. The results are reported in Supplementary
72 Section [S3](#), Table [S16](#), as a robustness check. Notably, these results reveal that the impact of remote
73 work on the recovery rate of VMT remains significant, both in the fixed-effects model and using the
74 instrumental variable approach. This underscores the robustness of our findings.

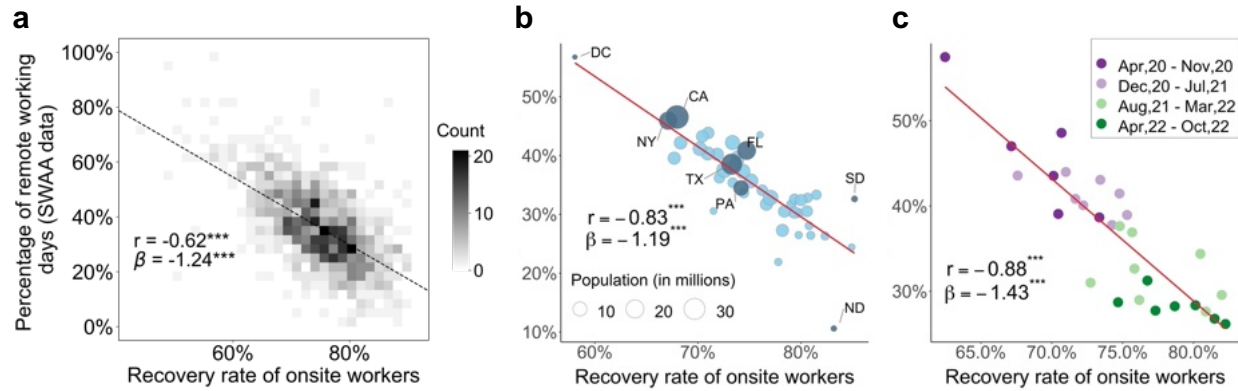


Figure S3: **Data Representativeness.** (a) Heatmaps comparing the recovery rates of onsite workers in our primary analysis with the percentage of remote working days obtained from SWAA data using the state-month level data. (b) and (c) illustrate the aggregated data at the state and month-year levels, respectively. The correlation coefficient r and the slope of the best-fit line β 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 β in all plots (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

75 **S1.4 List of MSAs**

Table S3: List of MSAs

MSA Name	Population (in millions)	MSA Name	Population (in millions)
New York-Newark-Jersey City, NY-NJ-PA	19.714	Omaha-Council Bluffs, NE-IA	0.926
Los Angeles-Long Beach-Anaheim, CA	13.136	Albuquerque, NM	0.912
Chicago-Naperville-Elgin, IL-IN-WI	9.451	Greenville-Anderson-Mauldin, SC	0.899
Dallas-Fort Worth-Arlington, TX	7.406	Bakersfield, CA	0.886
Houston-The Woodlands-Sugar Land, TX	6.897	Knoxville, TN	0.879
Washington-Arlington-Alexandria, DC-VA-MD-WV	6.142	Albany-Schenectady-Troy, NY	0.878
Miami-Fort Lauderdale-West Palm Beach, FL	6.066	New Haven-Milford, CT	0.857
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6.065	McAllen-Edinburg-Mission, TX	0.856
Atlanta-Sandy Springs-Roswell, GA	5.873	Oxnard-Thousand Oaks-Ventura, CA	0.847
Boston-Cambridge-Newton, MA-NH	4.786	El Paso, TX	0.839
Phoenix-Mesa-Scottsdale, AZ	4.781	Allentown-Bethlehem-Easton, PA-NJ	0.837
San Francisco-Oakland-Hayward, CA	4.621	Columbia, SC	0.824
Riverside-San Bernardino-Ontario, CA	4.569	North Port-Sarasota-Bradenton, FL	0.818
Detroit-Warren-Dearborn, MI	4.303	Dayton, OH	0.803
Seattle-Tacoma-Bellevue, WA	3.853	Charleston-North Charleston, SC	0.776
Minneapolis-St. Paul-Bloomington, MN-WI	3.567	Greensboro-High Point, NC	0.759
San Diego-Carlsbad, CA	3.300	Cape Coral-Fort Myers, FL	0.751
Tampa-St. Petersburg-Clearwater, FL	3.110	Stockton-Lodi, CA	0.743
Denver-Aurora-Lakewood, CO	2.885	Little Rock-North Little Rock-Conway, AR	0.735
St. Louis, MO-IL	2.799	Colorado Springs, CO	0.722
Baltimore-Columbia-Towson, MD	2.793	Boise City, ID	0.715
Charlotte-Concord-Gastonia, NC-SC	2.533	Akron, OH	0.703
Orlando-Kissimmee-Sanford, FL	2.500	Lakeland-Winter Haven, FL	0.695
San Antonio-New Braunfels, TX	2.474	Winston-Salem, NC	0.667
Portland-Vancouver-Hillsboro, OR-WA	2.441	Deltona-Daytona Beach-Ormond Beach, FL	0.654
Pittsburgh, PA	2.321	Syracuse, NY	0.649
Sacramento-Roseville-Arden-Arcade, CA	2.316	Des Moines-West Des Moines, IA	0.643
Las Vegas-Henderson-Paradise, NV	2.189	Springfield, MA	0.625
Cincinnati, OH-KY-IN	2.176	Augusta-Richmond County, GA-SC	0.601
Austin-Round Rock, TX	2.124	Toledo, OH	0.599
Columbus, OH	2.073	Palm Bay-Melbourne-Titusville, FL	0.591
Cleveland-Elyria, OH	2.053	Jackson, MS	0.578
Indianapolis-Carmel-Anderson, IN	2.027	Harrisburg-Carlisle, PA	0.571
San Jose-Sunnyvale-Santa Clara, CA	1.965	Durham-Chapel Hill, NC	0.567
Nashville-Davidson-Murfreesboro-Franklin, TN	1.897	Spokane-Spokane Valley, WA	0.564
Virginia Beach-Norfolk-Newport News, VA-NC	1.721	Chattanooga, TN-GA	0.557
Providence-Warwick, RI-MA	1.620	Scranton-Wilkes-Barre-Hazleton, PA	0.555
Milwaukee-Waukesha-West Allis, WI	1.565	Youngstown-Warren-Boardman, OH-PA	0.541
Jacksonville, FL	1.513	Modesto, CA	0.541
Oklahoma City, OK	1.381	Lancaster, PA	0.539
Raleigh, NC	1.340	Portland-South Portland, ME	0.537
Richmond, VA	1.295	Lexington-Fayette, KY	0.508
Louisville/Jefferson County, KY-IN	1.285	Santa Rosa, CA	0.500
New Orleans-Metairie, LA	1.261	Pensacola-Ferry Pass-Brent, FL	0.489
Kansas City, MO-KS	1.243	Port St. Lucie, FL	0.479
Hartford-West Hartford-East Hartford, CT	1.207	Reno, NV	0.462
Salt Lake City, UT	1.195	Visalia-Porterville, CA	0.461
Birmingham-Hoover, AL	1.148	Springfield, MO	0.460
Buffalo-Cheektowaga-Niagara Falls, NY	1.126	Huntsville, AL	0.459
Rochester, NY	1.069	Asheville, NC	0.458
Grand Rapids-Wyoming, MI	1.051	Corpus Christi, TX	0.452
Tulsa, OK	0.990	York-Hanover, PA	0.445
Fresno, CA	0.981	Killeen-Temple, TX	0.445
Bridgeport-Stamford-Norwalk, CT	0.948	Santa Maria-Santa Barbara, CA	0.442
Worcester, MA-CT	0.939	Vallejo-Fairfield, CA	0.441

Table S4: (Cont.) List of MSAs

MSA Name	Population (in millions)	MSA Name	Population (in millions)
Shreveport-Bossier City, LA	0.437	Medford, OR	0.216
Salinas, CA	0.432	Lafayette-West Lafayette, IN	0.214
Fort Wayne, IN	0.432	Charleston, WV	0.214
Brownsville-Harlingen, TX	0.422	Yuma, AZ	0.211
Salem, OR	0.419	Springfield, IL	0.208
Mobile, AL	0.413	Athens-Clarke County, GA	0.206
Salisbury, MD-DE	0.409	Elkhart-Goshen, IN	0.202
Beaumont-Port Arthur, TX	0.407	St. Cloud, MN	0.198
Flint, MI	0.406	Racine, WI	0.195
Canton-Massillon, OH	0.398	Bend-Redmond, OR	0.189
Gulfport-Biloxi-Pascagoula, MS	0.394	El Centro, CA	0.180
Savannah, GA	0.386	Blacksburg-Christiansburg-Radford, VA	0.179
Fayetteville, NC	0.383	Columbia, MO	0.175
Tallahassee, FL	0.380	Yuba City, CA	0.172
Davenport-Moline-Rock Island, IA-IL	0.378	Billings, MT	0.170
Montgomery, AL	0.372	Terre Haute, IN	0.169
Eugene, OR	0.370	East Stroudsburg, PA	0.168
Peoria, IL	0.369	Sioux City, IA-NE-SD	0.168
Hickory-Lenoir-Morganton, NC	0.368	Iowa City, IA	0.167
Ann Arbor, MI	0.361	Eau Claire, WI	0.165
Huntington-Ashland, WV-KY-OH	0.355	Bloomington, IN	0.162
Fort Collins, CO	0.342	State College, PA	0.160
Rockford, IL	0.336	Jackson, MI	0.158
Kalamazoo-Portage, MI	0.333	Sebastian-Vero Beach, FL	0.156
Lincoln, NE	0.325	Albany, GA	0.151
South Bend-Mishawaka, IN-MI	0.319	Hanford-Corcoran, CA	0.150
Green Bay, WI	0.317	Wheeling, WV-OH	0.141
Lubbock, TX	0.314	Lebanon, PA	0.140
Evansville, IN-KY	0.314	Napa, CA	0.139
Roanoke, VA	0.313	Flagstaff, AZ	0.139
Kennewick-Richland, WA	0.290	La Crosse-Onalaska, WI-MN	0.135
Wilmington, NC	0.290	Logan, UT-ID	0.133
San Luis Obispo-Paso Robles-Arroyo Grande, CA	0.282	Johnstown, PA	0.133
Gainesville, FL	0.280	Harrisonburg, VA	0.133
Duluth, MN-WI	0.277	Jackson, TN	0.129
Crestview-Fort Walton Beach-Destin, FL	0.275	Pittsfield, MA	0.128
Laredo, TX	0.274	Carbondale-Marion, IL	0.123
Erie, PA	0.272	Altoona, PA	0.123
Merced, CA	0.272	San Angelo, TX	0.119
Santa Cruz-Watsonville, CA	0.271	Wenatchee, WA	0.119
Norwich-New London, CT	0.268	Missoula, MT	0.117
Waco, TX	0.267	Muncie, IN	0.114
Bremerton-Silverdale, WA	0.266	Williamsport, PA	0.114
Lynchburg, VA	0.262	Kankakee, IL	0.110
Sioux Falls, SD	0.259	Lewiston-Auburn, ME	0.107
College Station-Bryan, TX	0.255	Sumter, SC	0.107
Yakima, WA	0.248	Longview, WA	0.107
Binghamton, NY	0.240	Ithaca, NY	0.101
Champaign-Urbana, IL	0.236	Grand Forks, ND-MN	0.099
Fargo, ND-MN	0.236	Rome, GA	0.097
Appleton, WI	0.235	Ames, IA	0.094
Chico, CA	0.224	Kokomo, IN	0.079
Bellingham, WA	0.220		
Barnstable Town, MA	0.219		
Rochester, MN	0.218		

76 S1.5 Correlation between the main predictor and IV

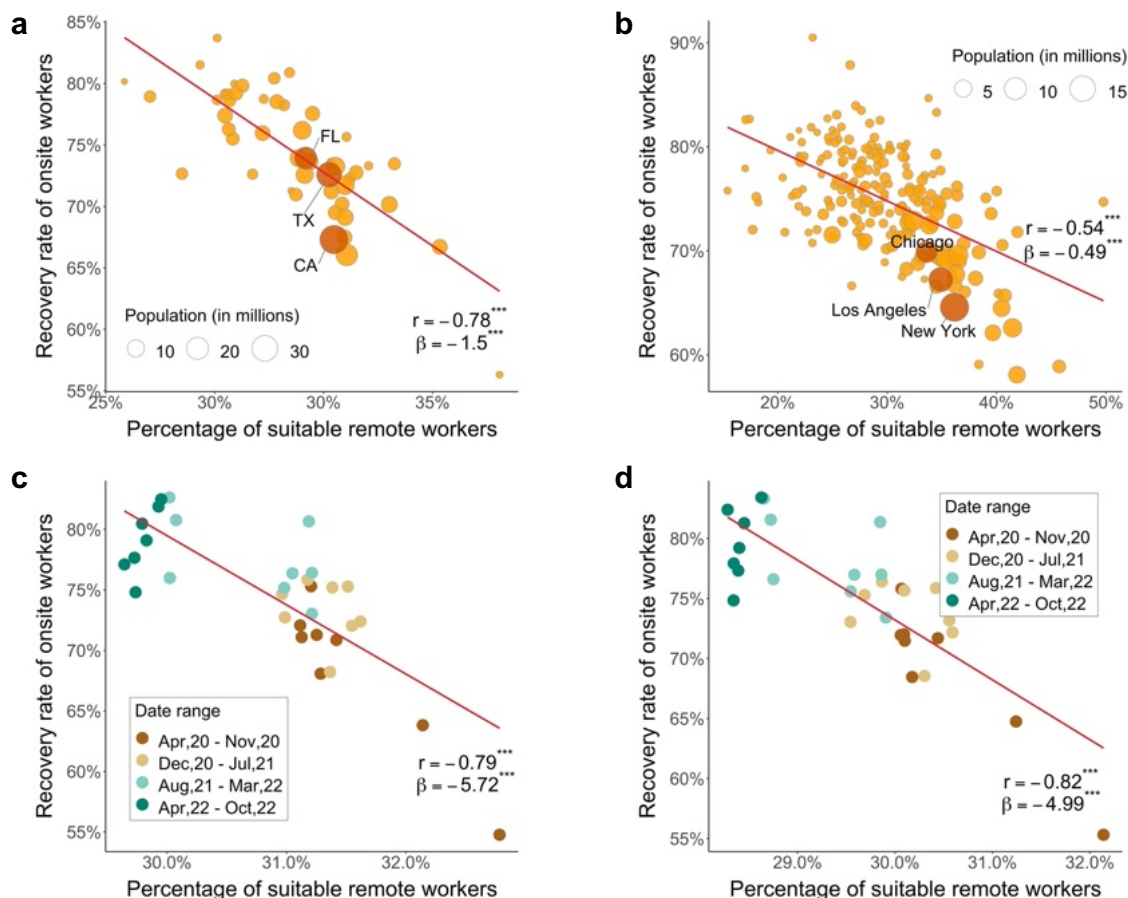


Figure S4: **Correlation between the recovery rate of onsite workers and the percentage of suitable remote workers (IV).** Percentage of suitable remote workers (x-axis) vs. recovery rate of onsite workers (y-axis) in 48 states and District of Columbia (**a**: samples aggregated to the state level; **c**: samples aggregated to the month-year level) and in 217 MSAs (**b**: samples aggregated to the MSA level, **d**: samples aggregated to the month-year level). The correlation coefficient r and the slope of the best-fit line β 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 β in all plots (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). The presence of statistically significant negative values of β in all these figures provides evidence of robust negative correlations between the recovery rate of onsite workers and the instrumental variable across both space and time.

77 S2 Modeling results

78 S2.1 Multicollinearity test

79 To assess the extent of multicollinearity among the explanatory variables in our OLS and fixed-effect
80 models, as presented in Table 1, we computed the Variance Inflation Factor (VIF) for each variable.
81 The VIF results, displayed in Table S5, indicate that all VIFs are below 10, which aligns with the
82 commonly used rule of thumb for evaluating severe multicollinearity [18, 19]. This suggests that
83 there is no significant multicollinearity present in our OLS and fixed-effect models.

84 It's noteworthy that some researchers have also suggested considering VIF values exceeding 5 as
85 potential indicators of problematic collinearity [20, 21]. In model (4), the VIFs of GDP per capita
86 and the unemployment rate slightly surpass this threshold (5.66 and 5.50, respectively), suggesting
87 that these two variables might offer redundant information. Therefore, we considered the option of
88 removing one of them.

89 To evaluate the robustness of our fixed-effect modeling results, we conducted sensitivity tests by
90 excluding one of these two variables (and both of them), as shown in Tables S6 and S7. Notably,
91 columns (2) - (4) in both tables reveal that the estimated coefficients of the recovery rate of onsite
92 workers remain remarkably stable even when either GDP per capita or the unemployment rate is
93 removed. These coefficients consistently demonstrate statistical significance, with magnitudes rang-
94 ing from 0.812 to 0.953 in VMT estimations and from 0.533 to 0.566 in transit ridership estimations.
95 This further underscores the robustness of our findings.

Table S5: Variance Inflation Factor (VIF) in OLS and fixed-effect models

	VMT		Transit ridership	
	OLS (1)	Fixed-Effect (2)	OLS (3)	Fixed-Effect (4)
Recovery rate of onsite workers	3.60	4.41	1.96	3.14
Reopening status	3.04	3.49	2.99	3.80
GDP per capita (in thousand dollars)	2.04	3.93	1.13	5.66
Unemployment rate	3.23	4.97	1.93	5.50
Transit service recovery rate	1.20	1.51	1.13	1.20
Transit fare (\$)	1.39	1.16	1.04	1.03
COVID cases per 1000 people	1.15	1.16	1.09	1.13
Vaccinations per person in the past 3 months	1.19	1.45	1.20	1.48
Vaccinations per person over the past 3-6 months	1.61	1.70	1.70	1.79
Vaccinations per person over the past 6-9 months	1.60	1.87	1.71	1.94
Net migration rate	1.39	1.13	1.06	1.02
ln (population in millions)	1.49	1.28	1.29	1.16

Note: Column (1) - (4) present VIF of variables corresponding to the models (1) - (4) in Table ???. In the computation of VIFs for fixed-effect models, we first standardize each independent variable by removing entity-specific effects at both the state/MSA level and the month level, and subsequently calculate the VIF for each variable.

Table S6: Sensitivity of fixed-effects model in VMT prediction to GDP and unemployment rate

	<i>Dependent variable:</i>				
	The recovery rate of VMT				
	(1)	(2)	(3)	(4)	(5)
Recovery rate of onsite workers	0.652*** (0.057) p = 0.000	0.818*** (0.068) p = 0.000	0.812*** (0.069) p = 0.000	0.953*** (0.052) p = 0.000	0.978*** (0.046) p = 0.000
Reopening status	1.363** (0.667) p = 0.042	1.236** (0.558) p = 0.027	1.179** (0.545) p = 0.031	1.647*** (0.563) p = 0.004	1.812*** (0.546) p = 0.001
GDP per capita (in thousand dollars)	0.360* (0.216) p = 0.096	-0.774 (1.892) p = 0.683		1.462 (1.710) p = 0.393	
Unemployment rate	-1.010*** (0.138) p = 0.000	-0.550*** (0.156) p = 0.0005	-0.525*** (0.137) p = 0.0002		
Transit service recovery rate	0.151*** (0.022) p = 0.000	0.078** (0.031) p = 0.012	0.076** (0.030) p = 0.011	0.084*** (0.031) p = 0.007	0.088*** (0.030) p = 0.004
Transit fare (\$)	-0.540*** (0.173) p = 0.002	0.949 (0.904) p = 0.294	0.975 (0.898) p = 0.278	0.907 (0.924) p = 0.327	0.845 (0.918) p = 0.358
COVID cases per 1000 people	-0.039 (0.025) p = 0.112	-0.105*** (0.031) p = 0.001	-0.105*** (0.030) p = 0.001	-0.095*** (0.031) p = 0.002	-0.096*** (0.031) p = 0.002
Vaccinations per person in the past 3 months	3.544*** (1.006) p = 0.0005	9.631*** (1.027) p = 0.000	9.527*** (1.007) p = 0.000	9.806*** (1.032) p = 0.000	10.051*** (1.003) p = 0.000
Vaccinations per person over the past 3-6 months	0.796 (1.064) p = 0.455	0.388 (0.921) p = 0.674	0.393 (0.920) p = 0.670	0.293 (0.926) p = 0.753	0.272 (0.931) p = 0.771
Vaccinations per person over the past 6-9 months	3.373*** (1.154) p = 0.004	2.810*** (1.051) p = 0.008	2.746*** (1.032) p = 0.008	2.599** (1.059) p = 0.015	2.717*** (1.040) p = 0.010
Net migration rate	0.096 (0.407) p = 0.815	-0.112 (0.397) p = 0.779	-0.166 (0.411) p = 0.688	-0.313 (0.410) p = 0.447	-0.215 (0.418) p = 0.607
ln (population in millions)	2.128*** (0.234) p = 0.000	112.127*** (30.602) p = 0.0003	110.240*** (30.353) p = 0.0003	103.365*** (30.624) p = 0.001	106.601*** (30.432) p = 0.0005
State FE	NO	YES	YES	YES	YES
Month FE	NO	YES	YES	YES	YES
Observations	1,519	1,519	1,519	1,519	1,519
Adjusted R ²	0.570	0.739	0.739	0.736	0.736

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 S7: Sensitivity of fixed-effects model in transit ridership prediction to GDP and unemployment rate

	<i>Dependent variable:</i>				
	The recovery rate of transit ridership				
	(1)	(2)	(3)	(4)	(5)
Recovery rate of onsite workers	0.441*** (0.032) p = 0.000	0.544*** (0.047) p = 0.000	0.566*** (0.047) p = 0.000	0.533*** (0.040) p = 0.000	0.693*** (0.037) p = 0.000
Reopening status	8.882*** (0.652) p = 0.000	5.448*** (0.533) p = 0.000	6.546*** (0.543) p = 0.000	5.420*** (0.527) p = 0.000	7.324*** (0.514) p = 0.000
GDP per capita (in thousand dollars)	-0.318 (0.200) p = 0.113	12.473*** (1.479) p = 0.000		11.976*** (1.167) p = 0.000	
Unemployment rate	-0.442*** (0.071) p = 0.000	0.064 (0.119) p = 0.592	-0.462*** (0.100) p = 0.00001		
Transit service recovery rate	0.410*** (0.013) p = 0.000	0.426*** (0.020) p = 0.000	0.432*** (0.020) p = 0.000	0.426*** (0.020) p = 0.000	0.440*** (0.020) p = 0.000
Transit fare (\$)	-5.303*** (0.358) p = 0.000	-3.970*** (0.712) p = 0.00000	-4.041*** (0.713) p = 0.00000	-3.974*** (0.713) p = 0.00000	-4.029*** (0.714) p = 0.00000
COVID cases per 1000 people	-0.057*** (0.014) p = 0.0001	0.022 (0.016) p = 0.169	0.008 (0.016) p = 0.606	0.021 (0.016) p = 0.187	0.013 (0.016) p = 0.408
Vaccinations per person in the past 3 months	-10.753*** (0.905) p = 0.000	-10.404*** (0.739) p = 0.000	-8.403*** (0.699) p = 0.000	-10.398*** (0.739) p = 0.000	-7.609*** (0.679) p = 0.000
Vaccinations per person over the past 3-6 months	-4.524*** (1.116) p = 0.0001	-8.131*** (0.900) p = 0.000	-8.343*** (0.906) p = 0.000	-8.114*** (0.898) p = 0.000	-8.619*** (0.908) p = 0.000
Vaccinations per person over the past 6-9 months	2.928*** (1.066) p = 0.007	3.408*** (0.882) p = 0.0002	4.562*** (0.876) p = 0.00000	3.454*** (0.873) p = 0.0001	4.557*** (0.879) p = 0.00000
Net migration rate	1.095*** (0.243) p = 0.00001	-0.005 (0.183) p = 0.977	-0.046 (0.186) p = 0.805	-0.005 (0.183) p = 0.980	-0.069 (0.189) p = 0.714
ln (population in millions)	0.934*** (0.173) p = 0.00000	40.523*** (15.607) p = 0.010	61.225*** (15.997) p = 0.0002	41.527*** (15.724) p = 0.009	59.282*** (15.975) p = 0.0003
MSA FE	NO	YES	YES	YES	YES
Month FE	NO	YES	YES	YES	YES
Observations	6,727	6,727	6,727	6,727	6,727
Adjusted R ²	0.385	0.696	0.693	0.696	0.692

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

97 **S2.3 Validity of 2SLS models**

98 The validity of our 2SLS models is rigorously assessed using multiple model statistics. Notably,
99 the first-stage F-statistics in the 2SLS regressions are 144.72 (for VMT estimation) and 90.74 (for
100 transit ridership estimation), significantly exceeding the threshold of 10. This finding suggests that
101 the percentage of suitable remote workers serves as a robust instrument for the recovery rate of
102 onsite workers, even after accounting for numerous covariates and fixed effects at the regional and
103 monthly levels (Table 2, column (1) and (4)). To further validate the strong instrument assumption,
104 we depict the correlation between the instrumental variable and the recovery rate of onsite workers in
105 Supplementary Fig. S4. Additionally, the Wu-Hausman test statistics for the transit ridership model
106 is statistically significant, suggesting the presence of endogeneity and supporting the preference for
107 the 2SLS over the fixed-effect model (Column 4 of Table 2). It's worth noting that this statistic is
108 not statistically significant in the VMT model (Column 1 of Table 2), suggesting that the coefficient
109 estimates for the recovery rate of onsite workers are similar between the fixed-effect and 2SLS
110 models. Nevertheless, considering the theoretical reasons to suspect endogeneity, we continue to
111 rely on the 2SLS modeling results as our primary estimate for the VMT model.

112 **S2.4 Full 2SLS modeling results**

113 Table S8 and S9 present the complete second-stage results of the 2SLS regressions.

Table S8: 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)
RR_OW	0.987*** (0.192) p = 0.00000	1.161*** (0.195) p = 0.000		2.259*** (0.374) p = 0.000	2.025*** (0.374) p = 0.00000	
RR_OW × log (% of transit commuters)		-0.113*** (0.035) p = 0.002			0.259*** (0.028) p = 0.000	
<i>Marginal effects of "the recovery rate of onsite workers" by geographical division:</i>						
New England			1.126*** (0.207) p = 0.00000			2.582*** (0.387) p = 0.000
Middle Atlantic			1.009*** (0.226) p = 0.00001			2.238*** (0.386) p = 0.000
East North Central			1.099*** (0.232) p = 0.00001			1.928*** (0.381) p = 0.00000
West North Central			1.151*** (0.206) p = 0.00000			2.616*** (0.385) p = 0.000
South Atlantic			1.066*** (0.243) p = 0.00002			1.826*** (0.383) p = 0.00001
East South Central			1.104*** (0.245) p = 0.00001			1.656*** (0.382) p = 0.00002
West South Central			1.305*** (0.274) p = 0.00001			2.172*** (0.381) p = 0.000
Mountain			0.973*** (0.232) p = 0.00003			1.634*** (0.385) p = 0.00003
Pacific			0.750*** (0.205) p = 0.0003			2.116*** (0.381) p = 0.00000

Note: "RR_OW" stands for "the recovery rate of onsite workers". Robust standard errors reported in parentheses, and p-values from two-sided t-tests are listed under standard errors. The definition of geographical divisions can be found in the U.S. Census Bureau [22]. Coefficient for each region corresponds to the coefficient for the interaction term between "recovery rate of onsite workers" and that region. *p<0.1; **p<0.05; ***p<0.01

Table S9: (Cont.) 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)
<i>Control variables:</i>						
Reopening status	1.099*	0.793	1.006*	3.555***	4.038***	4.127***
	(0.591)	(0.597)	(0.601)	(0.708)	(0.709)	(0.705)
	p = 0.064	p = 0.185	p = 0.095	p = 0.00000	p = 0.000	p = 0.000
GDP per capita (in thousand dollars)	-1.502	0.978	-1.127	8.254***	5.802***	6.210***
	(2.238)	(2.398)	(2.271)	(1.791)	(1.834)	(1.852)
	p = 0.503	p = 0.684	p = 0.620	p = 0.00001	p = 0.002	p = 0.001
Unemployment rate	-0.347	-0.141	-0.258	2.271***	1.873***	1.830***
	(0.299)	(0.297)	(0.321)	(0.486)	(0.492)	(0.490)
	p = 0.247	p = 0.634	p = 0.422	p = 0.00001	p = 0.0002	p = 0.0002
Transit service recovery rate	0.058	0.031	0.042	0.369***	0.371***	0.369***
	(0.041)	(0.042)	(0.043)	(0.024)	(0.024)	(0.024)
	p = 0.161	p = 0.452	p = 0.328	p = 0.000	p = 0.000	p = 0.000
Transit fare	0.657	0.359	-0.183	-4.826***	-4.487***	-4.579***
	(0.989)	(0.987)	(1.135)	(0.751)	(0.752)	(0.757)
	p = 0.507	p = 0.716	p = 0.872	p = 0.000	p = 0.000	p = 0.000
COVID cases per 1000 people	-0.098***	-0.090***	-0.089***	0.074***	0.059***	0.064***
	(0.031)	(0.031)	(0.032)	(0.018)	(0.018)	(0.018)
	p = 0.002	p = 0.005	p = 0.006	p = 0.00005	p = 0.002	p = 0.0004
Vaccinations per person in the past 3 months	9.809***	9.346***	9.539***	-8.128***	-7.746***	-8.010***
	(1.086)	(1.092)	(1.102)	(0.899)	(0.897)	(0.915)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Vaccinations per person over the past 3-6 months	0.211	0.154	0.034	-10.085***	-10.096***	-10.323***
	(0.975)	(0.970)	(0.977)	(1.020)	(1.014)	(1.015)
	p = 0.829	p = 0.875	p = 0.972	p = 0.000	p = 0.000	p = 0.000
Vaccinations per person over the past 6-9 months	2.628**	2.426**	2.332**	2.505***	2.552***	2.211**
	(1.080)	(1.076)	(1.077)	(0.888)	(0.879)	(0.882)
	p = 0.016	p = 0.025	p = 0.031	p = 0.005	p = 0.004	p = 0.013
Net migration rate	-0.158	-0.150	-0.204	-0.102	-0.110	0.041
	(0.399)	(0.394)	(0.409)	(0.184)	(0.183)	(0.178)
	p = 0.692	p = 0.705	p = 0.619	p = 0.581	p = 0.549	p = 0.820
ln (population in millions)	103.884***	54.055	98.488**	-52.214**	2.594	-12.193
	(33.511)	(38.461)	(40.787)	(25.852)	(26.592)	(27.165)
	p = 0.002	p = 0.161	p = 0.016	p = 0.044	p = 0.923	p = 0.654
<i>Fixed effects:</i>						
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***		

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

114 **S2.5 Time variation modeling results**

Table S10: Time variation modeling results

	The recovery rates of:	
	VMT	transit ridership
	(1)	(2)
<i>Marginal effects of "the recovery rate of onsite workers" by time periods:</i>		
April 2020 - June 2020	0.737*** (0.244) p = 0.003	1.425*** (0.374) p = 0.0002
July 2020 - September 2020	0.583** (0.249) p = 0.020	1.408*** (0.366) p = 0.0002
October 2020 - December 2020	0.579** (0.251) p = 0.022	1.380*** (0.366) p = 0.0002
January 2021 - March 2021	0.784*** (0.270) p = 0.004	1.362*** (0.371) p = 0.0003
April 2021 - June 2021	0.814*** (0.248) p = 0.002	1.421*** (0.370) p = 0.0002
July 2021 - September 2021	0.611** (0.253) p = 0.016	1.407*** (0.363) p = 0.0002
October 2021 - December 2021	0.659** (0.257) p = 0.011	1.403*** (0.366) p = 0.0002
January 2022 - March 2022	0.843*** (0.261) p = 0.002	1.454*** (0.368) p = 0.0001
April 2022 - June 2022	0.869*** (0.239) p = 0.0003	1.540*** (0.369) p = 0.00004
July 2022 - October 2022	0.627*** (0.243) p = 0.011	1.558*** (0.364) p = 0.00002

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 S11: (Cont.) Time variation modeling results

	The recovery rates of:	
	VMT (1)	transit ridership (2)
<i>Control variables:</i>		
Reopening status	0.523 (0.663) p = 0.431	-0.693 (0.751) p = 0.357
GDP per capita (in thousand dollars)	-3.005 (2.409) p = 0.213	-1.603 (2.033) p = 0.431
Unemployment rate	-0.231 (0.332) p = 0.488	1.432*** (0.474) p = 0.003
Transit service recovery rate	0.057 (0.048) p = 0.237	0.411*** (0.024) p = 0.000
Transit fare	0.262 (0.999) p = 0.794	-4.939*** (0.748) p = 0.000
COVID cases per 1000 people	-0.114** (0.046) p = 0.014	-0.020 (0.023) p = 0.382
Vaccinations per person in the past 3 months	10.926*** (2.738) p = 0.0001	3.116* (1.771) p = 0.079
Vaccinations per person over the past 3-6 months	-0.412 (2.384) p = 0.863	0.584 (1.828) p = 0.750
Vaccinations per person over the past 6-9 months	-1.364 (2.501) p = 0.586	5.273*** (1.852) p = 0.005
Net migration rate	-0.117 (0.394) p = 0.767	-0.211 (0.181) p = 0.245
ln (population in millions)	74.891** (34.083) p = 0.029	-61.462** (25.297) p = 0.016
State FE	YES	/
MSA FE	/	YES
Month FE	YES	YES
Observations	1,519	6,727
Adjusted R ²	0.727	0.705

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

115 **S2.6 Regional-specific marginal effect**

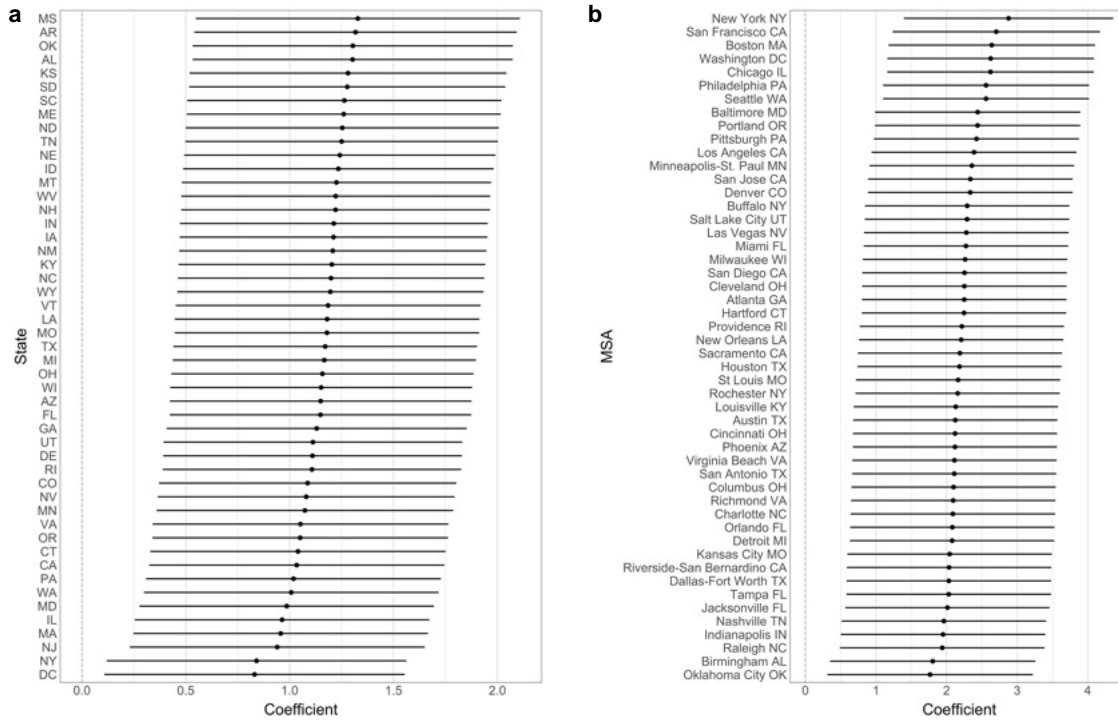


Figure S5: **Regional-specific marginal effect of the recovery rate of onsite workers on the recovery rates of VMT (a), and transit ridership (b) in the 2SLS regressions.** The points depict the point estimates of the marginal effects, corresponding to the coefficients of the recovery rate of onsite workers in two 2SLS models with sample sizes of $N = 1,519$ (VMT) and $6,727$ (transit ridership). The error bars denote the 95% confidence intervals. For transit ridership, only the results for the top 50 most populated MSAs are reported. The method for calculating the marginal effect can be found in the *Methods* section.

116 **S3 Robustness tests**

117 We conduct a series of robustness tests. First, the exclusion restriction assumption of the IV
 118 approach requires that the percentage of suitable remote workers can only affect the transit ridership
 119 recovery rate through its effect on the recovery rate of onsite workers. One may argue that the IV
 120 can directly affect the outcome through other channels. For instance, it could be that regions with
 121 a higher share of suitable remote workers happen to be more car-dependent, thus witnessing a lower
 122 recovery in transit ridership and a higher recovery in VMT. In such case, our 2SLS estimation
 123 might pick up not only the effect of return-to-workplace but also the levels of car-dependency or
 124 transit-dependency of the states or MSAs. To address this concern, we conduct a falsification test
 125 based on a reduced form regression. We first calculate the average values of the IV and all the
 126 control variables between April 2020 and October 2022 for each MSA and each state. Then, we

127 regress the percentage of transit commuters and the percentage of no-vehicle households on the IV
128 and control variables. Table S12 shows that the estimated coefficients of the IV are insignificant,
129 suggesting that it is unlikely that our IV picks up the level of car-dependency or transit-dependency
130 of states/MSAs in our 2SLS estimations.

131 Secondly, we conducted additional analyses focusing specifically on the post-June 2020 sample,
132 with the intention of excluding the circumstances related to the initial lockdown phase characterized
133 by stay-at-home orders and restrictions on economic activities. These measures were implemented
134 to control the spread of COVID-19 in the United States. Furthermore, we examined the modeling
135 results after excluding the entire year of 2020, along with further excluding the winter of 2021. The
136 pervasive impact of the pandemic in the US significantly influenced the entirety of 2020, while the
137 winter of 2021 witnessed a surge in COVID-19 cases, as illustrated in Figure S2. Consequently,
138 people’s travel behavior might have undergone some unusual changes during these periods.

139 The results of the fixed-effect and 2SLS analyses using these refined subsamples are presented
140 in Table S13, S14, and S15. Both fixed-effect and 2SLS models consistently indicate significant
141 impacts of remote work on VMT and transit ridership, suggesting that the significant impacts of
142 remote work on VMT and transit ridership are not simply artifacts of the enforced stay-at-home
143 orders associated with the COVID-19 pandemic or people’s risk-aversion behaviors in response to
144 virus surges. While the magnitudes of the impacts generally remain consistent in fixed-effect models,
145 they diminish in 2SLS estimations within the refined samples. Specifically, in 2SLS estimations, the
146 marginal effect of remote work on the VMT recovery rate decreases from 1.013 to 0.849, and on the
147 transit ridership recovery rate, it decreases from 2.604 to 2.052 when both the entire year of 2020
148 and the winter of 2021 are excluded (Table S14). These results suggest that remote work might
149 have a lesser influence on the recovery rates of VMT and transit ridership during relatively normal
150 periods compared to these special periods.

151 Thirdly, we adopt an alternative metric to gauge the prevalence of remote work at the state
152 level. Specifically, we utilize the percentage of paid full days spent working from home, as derived
153 from SWAA data, to assess remote work at the state-month level, instead of relying on the recovery
154 rate of onsite workers from Google Community Mobility Reports. The results are presented in Table
155 S16. Our findings consistently align with our primary results: in model (1), we observe a significant
156 negative correlation between the percentage of remote working days and the recovery rate of VMT
157 within the fixed-effects model. Model (2), based on 2SLS results, indicates that remote work exerts
158 a substantial negative impact on the recovery rate of VMT. Specifically, for every 1% increase in the
159 percentage of remote working days, the recovery rate of VMT experiences a 0.39% decrease. Model
160 (3) suggests that the absolute magnitude of the remote work effect diminishes as the percentage
161 of transit commuters increases, consistent with our primary results outlined in Table 2. Model (4)
162 validates the significant correlation between the IV and the primary predictor (i.e. the percentage
163 of remote working days).

164 It is important to acknowledge that the measures of remote work differ between the Google Com-
165 munity Mobility data and the SWAA data, rendering a direct comparison of effect sizes challenging.
166 However, when considered together, the significance and direction of the coefficients utilizing both

167 measures collectively underscore the robustness of our principal finding: remote work exerts a neg-
 168 ative impact on the recovery of VMT, and this effect holds statistical significance.

Table S12: Falsification tests

	State-level		MSA-level	
	Percentage of no-vehicle households	Percentage of transit commuters	Percentage of no-vehicle households	Percentage of transit commuters
Percentage of suitable remote workers	0.166 (0.358) p = 0.646	0.297 (0.483) p = 0.543	0.056 (0.037) p = 0.129	0.053 (0.040) p = 0.184
Reopening status	0.887 (3.757) p = 0.815	1.437 (4.614) p = 0.758	-0.778 (1.397) p = 0.579	-4.777*** (1.329) p = 0.0005
Per capita GDP (in thousand dollars)	1.317 (0.817) p = 0.116	1.089 (1.972) p = 0.585	0.092 (0.202) p = 0.649	-0.380 (0.242) p = 0.118
Unemployment rate	0.988* (0.535) p = 0.073	1.433* (0.749) p = 0.064	0.148 (0.104) p = 0.158	0.362*** (0.106) p = 0.001
COVID cases per 1000 people	-0.952 (0.764) p = 0.221	-0.918 (0.864) p = 0.295	-0.360** (0.156) p = 0.022	-0.209 (0.154) p = 0.177
Vaccines per 1000 people	-0.029 (0.074) p = 0.699	-0.064 (0.105) p = 0.548	0.056*** (0.017) p = 0.002	0.052** (0.022) p = 0.020
Transit service recovery rate	0.054 (0.045) p = 0.235	0.082 (0.054) p = 0.138	-0.004 (0.009) p = 0.673	0.010 (0.014) p = 0.478
Transit fare (\$)	1.126 (0.722) p = 0.128	0.663 (0.860) p = 0.446	0.420 (0.304) p = 0.169	0.503* (0.300) p = 0.096
Net migration rate	-3.242 (2.560) p = 0.214	-4.477 (3.207) p = 0.171	-1.878*** (0.461) p = 0.0001	-1.962*** (0.489) p = 0.0001
ln (population in millions)	-0.311 (0.893) p = 0.730	-0.728 (1.207) p = 0.551	0.898** (0.373) p = 0.017	0.408 (0.380) p = 0.284
Per capita income compared to the 2019 level (%)	0.127 (0.211) p = 0.550	0.151 (0.349) p = 0.668	-0.125 (0.084) p = 0.139	-0.407*** (0.084) p = 0.00001
Constant	-24.143 (26.072) p = 0.361	-27.763 (44.950) p = 0.541	13.240 (10.090) p = 0.191	51.036*** (10.357) p = 0.00001
Observations	49	49	217	217
Adjusted R ²	0.766	0.691	0.423	0.293

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 S13: Samples excluding periods significantly affected by the pandemic: Fixed-effect modeling results

	Post-June 2020		Post-2020		Post-2020 and excluding 2021 winter	
	<i>VMT</i>	<i>Transit ridership</i>	<i>VMT</i>	<i>Transit ridership</i>	<i>VMT</i>	<i>Transit ridership</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Recovery rate of onsite workers	0.598*** (0.117) p = 0.00000	0.790*** (0.059) p = 0.000	0.580*** (0.145) p = 0.0001	0.695*** (0.071) p = 0.000	0.544*** (0.144) p = 0.0002	0.692*** (0.074) p = 0.000
Reopening status	1.995*** (0.652) p = 0.003	2.055*** (0.601) p = 0.001	1.704* (0.885) p = 0.055	2.448*** (0.751) p = 0.002	2.284** (0.885) p = 0.011	2.433*** (0.757) p = 0.002
GDP per capita (in thousand dollars)	-3.792 (2.632) p = 0.150	20.429*** (1.938) p = 0.000	-8.211* (4.628) p = 0.077	14.168*** (2.803) p = 0.00000	-6.059 (4.899) p = 0.217	12.407*** (3.037) p = 0.00005
Unemployment rate	-0.670*** (0.228) p = 0.004	-0.632*** (0.151) p = 0.00004	-1.790*** (0.513) p = 0.001	-1.171*** (0.235) p = 0.00000	-1.734*** (0.518) p = 0.001	-1.156*** (0.246) p = 0.00001
Transit service recovery rate	0.075* (0.039) p = 0.053	0.438*** (0.026) p = 0.000	0.099** (0.048) p = 0.042	0.456*** (0.031) p = 0.000	0.099** (0.050) p = 0.049	0.460*** (0.034) p = 0.000
Transit fare (\$)	1.594 (0.969) p = 0.101	-4.194*** (0.745) p = 0.00000	1.908 (1.412) p = 0.177	-4.979*** (0.839) p = 0.000	1.961 (1.383) p = 0.157	-5.758*** (0.948) p = 0.000
COVID cases per 1000 people	-0.105*** (0.030) p = 0.001	0.018 (0.016) p = 0.263	-0.115** (0.046) p = 0.012	0.083*** (0.021) p = 0.0001	-0.143*** (0.052) p = 0.006	0.097** (0.041) p = 0.018
Vaccinations per person in the past 3 months	7.910*** (1.134) p = 0.000	-7.396*** (0.790) p = 0.000	9.355*** (1.943) p = 0.00001	-10.811*** (1.035) p = 0.000	10.534*** (2.199) p = 0.00001	-12.069*** (1.217) p = 0.000
Vaccinations per person over the past 3-6 months	0.719 (0.950) p = 0.449	-8.563*** (0.893) p = 0.000	1.542 (1.166) p = 0.187	-8.962*** (0.960) p = 0.000	1.284 (1.163) p = 0.271	-9.194*** (0.978) p = 0.000
Vaccinations per person over the past 6-9 months	4.246*** (1.111) p = 0.0002	-0.334 (0.883) p = 0.706	1.814 (1.581) p = 0.252	-6.432*** (0.972) p = 0.000	2.782* (1.655) p = 0.094	-7.218*** (1.117) p = 0.000
Net migration rate	0.045 (0.434) p = 0.918	-0.086 (0.187) p = 0.647	-0.199 (0.531) p = 0.708	-0.047 (0.190) p = 0.807	-0.155 (0.575) p = 0.789	-0.143 (0.219) p = 0.515
ln (population in millions)	111.207*** (33.935) p = 0.002	14.685 (18.084) p = 0.417	97.015 (62.335) p = 0.120	37.364 (24.942) p = 0.135	130.517* (67.264) p = 0.053	58.179** (28.217) p = 0.040
State FE	YES	/	YES	/	YES	/
MSA FE	/	YES	/	YES	/	YES
Month FE	YES	YES	YES	YES	YES	YES
Observations	1,372	6,076	1,078	4,774	931	4,123
R ²	0.591	0.696	0.546	0.732	0.559	0.733
Adjusted R ²	0.568	0.684	0.514	0.718	0.524	0.716

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 S14: Samples excluding periods significantly affected by the pandemic: Second-stage results of 2SLS

	Post-June 2020		Post-2020		Post-2020 and excluding 2021 winter	
	<i>VMT</i>	<i>Transit ridership</i>	<i>VMT</i>	<i>Transit ridership</i>	<i>VMT</i>	<i>Transit ridership</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Recovery rate of onsite workers	1.013*** (0.289) p = 0.0005	2.604*** (0.542) p = 0.00001	0.881* (0.499) p = 0.078	2.057** (0.863) p = 0.018	0.849** (0.424) p = 0.046	2.052** (0.814) p = 0.012
Reopening status	1.300* (0.772) p = 0.093	-2.045 (1.414) p = 0.149	1.282 (1.081) p = 0.236	0.134 (1.699) p = 0.937	1.843* (1.032) p = 0.075	0.118 (1.621) p = 0.942
GDP per capita (in thousand dollars)	-5.777** (2.804) p = 0.040	15.675*** (2.365) p = 0.000	-10.111* (5.336) p = 0.059	6.701 (5.350) p = 0.211	-8.023 (5.613) p = 0.154	4.177 (5.570) p = 0.454
Unemployment rate	-0.378 (0.313) p = 0.228	0.587 (0.393) p = 0.136	-1.334 (0.898) p = 0.138	0.686 (1.197) p = 0.567	-1.238 (0.813) p = 0.129	0.765 (1.174) p = 0.515
Transit service recovery rate	0.056 (0.043) p = 0.189	0.417*** (0.027) p = 0.000	0.084 (0.056) p = 0.139	0.432*** (0.035) p = 0.000	0.085 (0.056) p = 0.128	0.434*** (0.038) p = 0.000
Transit fare (\$)	0.944 (1.054) p = 0.371	-5.021*** (0.818) p = 0.000	1.875 (1.419) p = 0.187	-4.966*** (0.838) p = 0.000	1.923 (1.384) p = 0.166	-5.636*** (0.939) p = 0.000
COVID cases per 1000 people	-0.094*** (0.031) p = 0.003	0.051*** (0.018) p = 0.005	-0.102** (0.047) p = 0.030	0.125*** (0.032) p = 0.0002	-0.129** (0.057) p = 0.024	0.156*** (0.047) p = 0.001
Vaccinations per person in the past 3 months	9.212*** (1.381) p = 0.000	-0.763 (2.123) p = 0.720	9.650*** (2.050) p = 0.00001	-8.681*** (1.707) p = 0.00000	10.629*** (2.239) p = 0.00001	-10.583*** (1.522) p = 0.000
Vaccinations per person over the past 3-6 months	-0.023 (1.060) p = 0.983	-12.082*** (1.412) p = 0.000	0.777 (1.678) p = 0.644	-13.012*** (2.723) p = 0.00001	0.476 (1.538) p = 0.758	-13.238*** (2.640) p = 0.00000
Vaccinations per person over the past 6-9 months	3.459*** (1.190) p = 0.004	-3.373*** (1.213) p = 0.006	1.569 (1.584) p = 0.323	-7.075*** (1.038) p = 0.000	2.526 (1.681) p = 0.134	-8.174*** (1.187) p = 0.000
Net migration rate	-0.036 (0.432) p = 0.934	-0.220 (0.196) p = 0.264	-0.235 (0.525) p = 0.655	-0.050 (0.200) p = 0.802	-0.163 (0.567) p = 0.774	-0.022 (0.234) p = 0.926
ln (population in millions)	91.745*** (35.501) p = 0.010	-73.250** (32.079) p = 0.023	75.511 (69.840) p = 0.280	-30.364 (49.667) p = 0.541	106.843 (72.848) p = 0.143	-14.404 (52.293) p = 0.783
State FE	YES	/	YES	/	YES	/
MSA FE	/	YES	/	YES	/	YES
Month FE	YES	YES	YES	YES	YES	YES
Observations	1,372	6,076	1,078	4,774	931	4,123
R ²	0.583	0.687	0.537	0.726	0.551	0.727
Adjusted R ²	0.560	0.674	0.504	0.712	0.515	0.710

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 S15: Samples excluding periods significantly affected by the pandemic: First-stage results of 2SLS

	Post-June 2020		Post-2020		Post-2020 and excluding 2021 winter	
	<i>VMT</i>	<i>Transit ridership</i>	<i>VMT</i>	<i>Transit ridership</i>	<i>VMT</i>	<i>Transit ridership</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Percentage of suitable remote workers	-1.599*** (0.122) p = 0.000	-0.169*** (0.020) p = 0.000	-1.172*** (0.138) p = 0.000	-0.126*** (0.021) p = 0.000	-1.392*** (0.155) p = 0.000	-0.139*** (0.024) p = 0.000
Reopening status	1.059*** (0.224) p = 0.00001	2.230*** (0.156) p = 0.000	0.905*** (0.316) p = 0.005	1.654*** (0.185) p = 0.000	0.938*** (0.328) p = 0.005	1.659*** (0.193) p = 0.000
GDP per capita (in thousand dollars)	0.796 (0.720) p = 0.269	2.265*** (0.529) p = 0.00002	3.012** (1.329) p = 0.024	5.172*** (0.699) p = 0.000	2.130 (1.399) p = 0.129	5.715*** (0.771) p = 0.000
Unemployment rate	-0.467*** (0.071) p = 0.000	-0.629*** (0.042) p = 0.000	-1.121*** (0.140) p = 0.000	-1.312*** (0.062) p = 0.000	-1.234*** (0.150) p = 0.000	-1.356*** (0.066) p = 0.000
Transit service recovery rate	0.046*** (0.015) p = 0.003	0.012** (0.005) p = 0.012	0.053*** (0.020) p = 0.008	0.018*** (0.006) p = 0.002	0.050** (0.022) p = 0.025	0.019*** (0.006) p = 0.003
Transit fare (\$)	1.263*** (0.273) p = 0.00001	0.489*** (0.123) p = 0.0001	0.036 (0.365) p = 0.922	0.047 (0.142) p = 0.738	0.060 (0.403) p = 0.883	-0.025 (0.156) p = 0.872
COVID cases per 1000 people	-0.056*** (0.007) p = 0.000	-0.021*** (0.004) p = 0.00000	-0.056*** (0.010) p = 0.00000	-0.033*** (0.005) p = 0.000	-0.053*** (0.015) p = 0.0004	-0.045*** (0.009) p = 0.00001
Vaccinations per person in the past 3 months	-0.488 (0.355) p = 0.171	-3.383*** (0.196) p = 0.000	0.203 (0.524) p = 0.699	-1.433*** (0.290) p = 0.00000	1.514** (0.623) p = 0.016	-0.924*** (0.342) p = 0.007
Vaccinations per person over the past 3-6 months	2.927*** (0.303) p = 0.000	2.012*** (0.195) p = 0.000	3.262*** (0.327) p = 0.000	3.017*** (0.200) p = 0.000	3.585*** (0.348) p = 0.000	3.026*** (0.203) p = 0.000
Vaccinations per person over the past 6-9 months	2.877*** (0.301) p = 0.000	1.779*** (0.228) p = 0.000	1.618*** (0.395) p = 0.00005	0.595** (0.267) p = 0.026	1.701*** (0.416) p = 0.00005	0.839*** (0.292) p = 0.005
Net migration rate	0.059 (0.125) p = 0.638	0.062 (0.062) p = 0.314	0.061 (0.139) p = 0.661	-0.003 (0.063) p = 0.965	-0.008 (0.158) p = 0.959	-0.092 (0.071) p = 0.195
ln (population in millions)	52.849*** (8.633) p = 0.000	47.911*** (4.929) p = 0.000	68.208*** (14.831) p = 0.00001	48.583*** (8.026) p = 0.000	79.240*** (17.223) p = 0.00001	52.308*** (8.824) p = 0.000
State FE	YES	/	YES	/	YES	/
MSA FE	/	YES	/	YES	/	YES
Month FE	YES	YES	YES	YES	YES	YES
Observations	1,372	6,076	1,078	4,774	931	4,123
R ²	0.937	0.880	0.935	0.898	0.935	0.896
Adjusted R ²	0.933	0.875	0.931	0.892	0.930	0.890

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 S16: SWAA modeling results

	<i>Dependent variable:</i>			
	Recovery rate of VMT			% of remote working days
	(1)	(2)	(3)	(4)
	Fixed-effects	2SLS-2 stage	2SLS-2 stage	2SLS-1 stage
Percentage of remote working days	-0.037** (0.019) p = 0.047	-0.392*** (0.117) p = 0.001	-0.486*** (0.123)	
Percentage of remote working days × log (% of transit commuters)			0.053* (0.028) p = 0.055	
Percentage of suitable remote workers				3.679*** (0.683) p = 0.00000
Reopening status	2.413*** (0.590) p = 0.00005	1.631*** (0.599) p = 0.007	1.447** (0.597) p = 0.016	-0.493 (1.374) p = 0.720
GDP per capita (in thousand dollars)	1.443 (2.585) p = 0.577	-1.178 (2.713) p = 0.665	0.140 (2.660) p = 0.959	1.970 (4.804) p = 0.682
Unemployment rate	-1.320*** (0.185) p = 0.000	-0.625** (0.311) p = 0.045	-0.488 (0.312) p = 0.118	1.541*** (0.328) p = 0.00001
Transit service recovery rate	0.150*** (0.038) p = 0.0001	0.107*** (0.040) p = 0.008	0.091** (0.039) p = 0.021	-0.121* (0.070) p = 0.085
Transit fare (\$)	2.583*** (0.986) p = 0.009	2.999*** (1.004) p = 0.003	3.023*** (1.004) p = 0.003	1.667 (1.512) p = 0.271
COVID cases per 1000 people	-0.154*** (0.025) p = 0.000	-0.154*** (0.025) p = 0.000	-0.150*** (0.026) p = 0.000	0.082* (0.047) p = 0.079
Vaccinations per person in the past 3 months	6.850*** (1.079) p = 0.000	9.017*** (1.267) p = 0.000	9.033*** (1.268) p = 0.000	-0.620 (2.389) p = 0.796
Vaccinations per person over the past 3-6 months	1.725* (1.005) p = 0.087	2.730** (1.063) p = 0.011	2.876*** (1.067) p = 0.008	0.030 (2.081) p = 0.989
Vaccinations per person over the past 6-9 months	2.791*** (1.023) p = 0.007	0.931 (1.197) p = 0.437	0.412 (1.206) p = 0.733	-7.687*** (2.305) p = 0.001
Net migration rate	0.633 (0.453) p = 0.163	1.370*** (0.524) p = 0.010	1.473*** (0.525) p = 0.006	2.242** (0.901) p = 0.014
ln (population in millions)	116.186*** (36.188) p = 0.002	64.650* (38.691) p = 0.096	22.960 (45.555) p = 0.615	-163.688*** (55.508) p = 0.004
State FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Observations	1,162	1,162	1,162	1,162
Adjusted R ²	0.622	0.625	0.625	0.462

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

References

- [1] G. LLC, COVID-19 Community Mobility Reports, <https://www.google.com/covid19/mobility/>, last accessed on 2022-10-14 (2022).
- [2] FHWA, Traffic volume trends, https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm, last accessed on 2022-11-26 (2022).
- [3] Federal Transit Administration, Ntd data, <https://www.transit.dot.gov/ntd/ntd-data>, last accessed on 2022-11-26 (2022).
- [4] U.S. Bureau of Labor Statistics, Quarterly census of employment and wages (2021).
- [5] The United States Postal Service, Change of Address Stats, <https://about.usps.com/who/legal/foia/library.htm>, last accessed on 2022-09-12 (2022).
- [6] T. N. Y. Times, We're sharing coronavirus case data for every us county, <https://github.com/nytimes/covid-19-data>, last accessed on 2022-09-12 (2022).
- [7] The Centers for Disease Control and Prevention, Covid-19 vaccinations in the united states, <https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-United-States-Jurisd/uns-k-b7fc>, last accessed on 2022-09-12 (2022).
- [8] K. F. Foundation, State covid-19 data and policy actions, KFF State Vaccine Rollout (2021).
- [9] U.S. Census Bureau., State population totals and components of change: 2020-2022, <https://www.census.gov/data/tables/time-series/demo/popest/2020s-state-total.html>, last accessed on 2023-10-18 (2023).
- [10] U.S. Census Bureau., Metropolitan and micropolitan statistical areas population totals: 2020-2022, <https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-metro-and-micro-statistical-areas.html>, last accessed on 2023-10-18 (2023).
- [11] U.S. Bureau of Economic Analysis, Bea data: Gross domestic product (2023).
- [12] Federal Reserve Economic, Federal reserve economic data: Unemployment rate (2023).
- [13] U.S. Bureau of Economic Analysis, Bea data: Personal income (2023).
- [14] WFH Research, U.s. survey of working arrangements and attitudes (swaa), <https://wfhresearch.com/>, last accessed on 2024-02-03 (2023).
- [15] Google, Mobility Report CSV Documentation, https://www.google.com/covid19/mobility/data_documentation.html?hl=en#about-this-data, last accessed on 2022-10-14 (2022).

- 200 [16] J. M. Barrero, N. Bloom, S. J. Davis, Why working from home will stick, Tech. rep., National
201 Bureau of Economic Research (2021).
- 202 [17] J. M. Barrero, N. Bloom, S. Buckman, S. J. Davis, Benchmarking swaa estimates of the preva-
203 lence of working from home (2023).
- 204 [18] M. H. Kutner, C. J. Nachtsheim, J. Neter, W. Li, Applied linear statistical models, McGraw-
205 hill, 2005.
- 206 [19] R. M. O'brien, A caution regarding rules of thumb for variance inflation factors, Quality &
207 quantity 41 (2007) 673–690.
- 208 [20] S. Sheather, A modern approach to regression with R, Springer Science & Business Media,
209 2009.
- 210 [21] G. James, D. Witten, T. Hastie, R. Tibshirani, et al., An introduction to statistical learning,
211 Vol. 112, Springer, 2013.
- 212 [22] United States Census Bureau, Census regions and divisions of the united states, [https:](https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf)
213 [//www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf](https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf), last accessed on
214 2023-10-18.

- 686 [53] The Centers for Disease Control and Prevention. Covid-19 vaccina-
687 tions in the united states, 2022. [https://data.cdc.gov/Vaccinations/
688 COVID-19-Vaccinations-in-the-United-States-Jurisdi/uns-k-b7fc](https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-United-States-Jurisdi/uns-k-b7fc), last accessed on
689 2022-09-12.
- 690 [54] Francesco Menegale, Mattia Manica, Agnese Zardini, Giorgio Guzzetta, Valentina Marziano,
691 Valeria d'Andrea, Filippo Trentini, Marco Ajelli, Piero Poletti, and Stefano Merler. Evaluation
692 of waning of sars-cov-2 vaccine-induced immunity: A systematic review and meta-analysis.
693 *JAMA Network Open*, 6(5):e2310650–e2310650, 2023.
- 694 [55] U.S. Census Bureau. State population totals and components of change: 2020-2022, 2023.
695 [https://www.census.gov/data/tables/time-series/demo/popest/2020s-state-total.
696 html](https://www.census.gov/data/tables/time-series/demo/popest/2020s-state-total.html), last accessed on 2023-10-18.
- 697 [56] U.S. Census Bureau. Metropolitan and micropolitan statistical areas population to-
698 tals: 2020-2022, 2023. [https://www.census.gov/data/tables/time-series/demo/popest/
699 2020s-total-metro-and-micro-statistical-areas.html](https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-metro-and-micro-statistical-areas.html), last accessed on 2023-10-18.
- 700 [57] FHWA. Highway statistics series, table mf-21, 2020-2021. [https://www.fhwa.dot.gov/
701 policyinformation/statistics.cfm](https://www.fhwa.dot.gov/policyinformation/statistics.cfm), last accessed on 2023-10-18.
- 702 [58] EPA. Greenhouse gases equivalencies calculator - calcula-
703 tions and references, 2023. [https://www.epa.gov/energy/
704 greenhouse-gases-equivalencies-calculator-calculations-and-references](https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references), last
705 accessed on 2023-10-18.
- 706 [59] FHWA. Highway statistics series, table vm-2, 2020-2021. [https://www.fhwa.dot.gov/
707 policyinformation/statistics.cfm](https://www.fhwa.dot.gov/policyinformation/statistics.cfm), last accessed on 2023-10-18.
- 708 [60] FHWA. 2022 traffic monitoring guide, 2022. [https://www.fhwa.dot.gov/
709 policyinformation/tmguides/2022_TMG_Final_Report.pdf](https://www.fhwa.dot.gov/policyinformation/tmguides/2022_TMG_Final_Report.pdf), last accessed on 2023-10-18.