Understanding the temporal and spatial trend of work-at-home in the United States

Sicheng Wang[a]* and Mohammed Iddrisu Kambala[b]

Abstract

Technology-enabled work-at-home (WAH) has been widely adopted and accelerated by the COVID-19 pandemic. The rapid growth of WAH is likely to transform the modern workplace and people's behaviors regarding work, housing, and transportation. This study presents a comprehensive analysis of the temporal and spatial trends of WAH in the U.S. between 2013 and 2022 at both the county and census tract levels. We combined multi-year and multi-scale American Community Survey data to illustrate the trend. Two different regression models were performed to evaluate various factors associated with the WAH rate and the change in the WAH rate, respectively. After accounting for the fixed effects of years and states, our panel model indicated that the WAH rate was negatively associated with population density, car-driving commuters, long-distance commuters, and bedrooms per capita. It was positively associated with high socio-economic status, middle-aged populations, married people, the presence of children, and house size. The model focusing on the change of WAH was largely consistent with the panel model but highlighted the potential impact of WAH in aggravating spatial disparities regarding race and ethnicity, income, education, and age. It may also reduce car driving and increase the demand for single-family houses. We discussed the policy implications relevant to our results, including issues of suburbanization, social equity, an age-friendly and family-friendly society, and transportation and housing choices.

Keywords: *geography of jobs; social disparity; telework; workplace; work-at-home*.

[a]*Department of Geography, University of South Carolina, Columbia, South Carolina, USA;*

[b]*Department of Economics, University of South Carolina, Columbia, South Carolina, USA*

*Corresponding author:

Sicheng Wang, Ph.D.
Assistant Professor
Department of Geography, University of South Carolina
Address: Callcott 213, 709 Bull Street, Columbia, South Carolina, USA 29208
Email: sichengw@mailbox.sc.edu

Introduction

Traditional workplace dynamics have been rapidly transformed with the advancement of information and communication technologies (ICTs), which enable people to complete many work tasks virtually (Ellison 2004). An increasing number of workers in a wide variety of occupations have adopted work-at-home (WAH) as a common workplace arrangement in the recent decade (Althoff et al. 2022). This trend has been accelerated by the COVID-19 pandemic, which forced many employers and workers to transition from office-based work to telework (Belzunegui-Eraso and Erro-Garcés 2020). Although concerns about virus infection diminished over time, WAH remains ubiquitous after the pandemic (Sostero et al. 2020). People may benefit from the flexibility and cost saving offered by WAH (He and Hu 2015; Parra-Lokhorst 2021), but they are also exposed to the risks of social isolation, overwork, and lack of accessibility (Beckel and Fisher 2022). A rich body of literature has explored the impacts of WAH on individuals, including work-life balance, health and well-being, productivity, accessibility, and social equity. However, little has been done to uncover the aggregate impacts of WAH on a region or local community from a geographic perspective.

We are motived to investigate the most recent temporal and spatial trend of WAH in the U.S. As WAH becomes the new normal in workplace settings, understanding its pattern of spatial distribution and the factors associated with this pattern is essential for preparing for its potential impacts and implications. These impacts and implications are relevant to policies concerning population and economic growth, social equity, age-friendly and family-friendly societies, housing demand, and transportation behavior. Therefore, there is a need for an analysis of the recent WAH trend with high geographic resolution throughout the U.S., examining a variety of factors associated with the spatial distribution of WAH. This study contributes to this literature gap by answering the following four research questions: (1) How is the prevalence of WAH distributed across the country? (2) How has the prevalence of WAH changed over the last ten years? (3) What factors are associated with the prevalence of WAH? and (4) What factors are associated with the change in the prevalence of WAH?

A challenge in answering these questions is the lack of sufficient datasets that provide information about WAH at a fine-grained geographic level and cover the entire country. We utilized an instrument about transportation modes for travel to work in the American Community Survey (ACS), which included the choice of “work at home,” to extract the proxy variable for our analysis. As a large-scale national dataset based on an ongoing household survey program, ACS has good temporal frequency and spatial coverage, enabling us to unveil the temporal and spatial trends of WAH with high geographic resolution. It also provides rich information about sociodemographic characteristics, family structure, transportation behavior, and housing, which can be linked to the trend of WAH.

Our results are informative for decision-makers in the government and industry to plan for the potential transformation driven by the widespread adoption of WAH. The study will be particularly relevant to housing development, community and transportation planning, workforce development, and social welfare.

Prior works and research gaps

We reviewed studies on three topics: (1) the trends in WAH before and after the COVID-19 pandemic, (2) factors associated with WAH, and (3) potential implications of WAH. After reviewing the important prior works, we summarized the research gaps that we filled in this study.

Trends in WAH before and after the pandemic

WAH began during the oil crisis of the 1970s when workers increasingly became mindful of the rising fuel prices, traffic congestion, and long commuting, especially in dense metropolitan areas

(Bailey and Kurland 2002). Despite this increasing awareness, WAH did not record a marked increase. Even at the beginning of the age of widespread use of computers and the internet in the early 2000s, the share of WAH workers had not visibly increased (Pratt 2002). The slow diffusion of WAH in the early age was highly concentrated in limited industries, such as ICT (Pyöriä 2011; Hynes 2016). WAH was constrained because some organizations and managers were not willing to provide such flexibility due to the perceived negative effects of remoteness such as isolation, lack of direct control, and shirking of work (Bailey and Kurland 2002; Illegems and Verbeke 2004; Ton et al. 2022).

Beginning from the early 2010s, the growth in telework was dramatic. Part of this was related to the emergence and massive diffusion of the knowledge economy that births occupations and jobs that are inherently suited for remote work. Dey et al. (2020) estimated that about 45% of U.S. employments were in occupations eligible for WAH. Another study showed that 37% of jobs in the U.S. can be performed entirely from home. Worldwide, about 20% of jobs are work-from-home feasible, as the percentage is significantly lower in developing countries than developed countries (Garrote Sanchez et al. 2021).

Another reason behind the accelerated growth of WAH is the increasing awareness and attention drawn to the twin factors of work-life balance and family-friendly policies (Felstead et al. 2002). Historically, the excessive loads and demands of work and the lack of opportunities to balance work and multiple nonwork responsibilities led to deleterious effects on workers' wellbeing and performance outcomes (Kalliath and Brough 2008; Yuile et al. 2012). This concern compelled governments to enact various policies that provide avenues for workers, particularly parents, to undertake childcare responsibilities or other nonwork activities such as study, sports, and travel (Cho 2020). The flexibility of engaging in other nonwork activities partly increased the desire and growth of telework (Biron, Casper, and Raghuram 2022).

WAH has become even more diffusive since the Covid-19 Pandemic. The 2023 WAH rate in the U.S., for example, was four times its 2019 level (Barrero, Bloom, and Davis 2023). During the lockdown period in the U.S. work-from-home rate rose dramatically - in just about four months it increased by about 330% from February to May 2020 (Bick, Blandin, and Mertens 2023). 72% of workers whose job allowed a degree of virtual work eventually worked from home in May of 2020 (Bick, Blandin, and Mertens 2023). About half of the pre-pandemic workers started working from home during the pandemic (Brynjolfsson et al. 2020). And WAH remains ubiquitous in many occupations in the post-pandemic era, despite the decreasing concern over infection recently (Golden 2022; Semuels 2022).

Factors associated with WAH

The literature has examined various factors associated with the recent trend in WAH, including sociodemographic characteristics, housing, and transportation. However, many factors showed contradictory effects in different studies. For instance, researchers found significant associations between WAH and several household arrangement characteristics, such as presence of children in the house and marital status. Some studies indicated that working parents are more likely to value the opportunity to work from home highly due to their childcare responsibility, and therefore, having children has been shown to have a positive association with the likelihood of WAH (Sweet and Scott 2022; Barrero, Bloom, and Davis 2023). However, a representative German sample suggested parents were less likely to WAH compared to those without children. Marital status also showed ambiguous effects (Zhang et al. 2020). Dey et al., (2020) found that compared to married couples, unmarried people were more likely to work in jobs ineligible for WAH. However, the same German study demonstrated that single individuals were more likely to WAH than married people (Zhang et al. 2020). Nevertheless, partnered parents were more likely to WAH than single parents (Zhang et al. 2020). In addition, Baruch (2000) unveiled that telework improved family relationships.

Education and income show more consistent associations. Researchers revealed that education level had a significantly positive correlation with the likelihood of WAH (Saltiel 2020; Bick, Blandin, and Mertens 2023). Well-educated people were more likely to work in knowledge-based jobs that require less manual tasks or physical presence at workplace (Saltiel 2020; Bick, Blandin, and Mertens 2023). Income has also been found to have a positive association with WAH. Low-income workers were less likely to WAH, whereas high-income counterparts had more possibility to WAH (He and Hu 2015; Garrote Sanchez et al. 2021).

Three other common demographic variables that may be associated with WAH are gender, race and ethnicity, and age. The effect of gender is mixed. Some studies reported that females were more likely to WAH because it makes it easier to simultaneously undertake caring responsibilities (Maruyama and Tietze 2012). However, such an explanation may confuse gender with motherhood. Absent the motherhood component, no compelling evidence explains why one gender should prefer WAH more than the other. In the aforementioned German sample, for single individuals without children, males were more likely to WAH than females, while single mothers were more likely to WAH than single fathers (Zhang et al. 2020). The difference between the genders may partially be due to other factors such as job type and work hours. Bailey & Kurland (2002), for instance, found that male professionals and female clerical workers dominated the WAH trend.

In terms of race and ethnicity, non-Whites were found significantly less likely to WAH than Whites in some studies (Dey et al. 2020; Bick, Blandin, and Mertens 2023). In a context of the U.S., Black and Hispanic workers were found less likely to WAH during the pandemic, implying a structural racial disparity (Brynjolfsson et al. 2020).

Age has been found to be associated with the possibility of WAH. Some studies suggested a positive correlation between age and WAH, especially during the pandemic (Dey et al. 2020; Yasenov 2020; Garrote Sanchez et al. 2021; Barrero, Bloom, and Davis 2023). However, a European study found that compared to younger workers, older workers intended to not WAH after the pandemic (Sostero et al. 2020). A U.S. study also showed that younger people were more like than the older population to choose WAH during the pandemic (Brynjolfsson et al. 2020). Use of computers and ICTs needed for telework may be the barrier for older workers (Arvola et al. 2017).

Transportation and commuting are also associated with the likelihood of WAH. Caulfield (2015) and Ton et al. (2022) both found that WAH was correlated with the access and usage of public transit. The former found that WAH was more popular in areas with less access to public transit in the Dublin Area, Ireland (Caulfield 2015). The latter, however, showed that transit commuters were more likely to WAH during the pandemic (Ton et al. 2022). Additionally, a U.K.-based survey suggested long-distance commuters tended to WAH more frequently as it may be strategy to mitigate the travel costs (de Abreu e Silva and Melo 2018).

Implications of WAH

There have been mixed concerns and research findings about the implications and/or impacts of WAH. This study focuses on the implications that are more likely to concern geographers in various fields, that is, how WAH would affect the environment, economy, and society across space.

First, WAH has essential implications for both the natural and built environment of the world. WAH may help combat climate change by reducing commuting travel and transportation-related emissions. However, the literature has highlighted that the environmental impacts of WAH may be complicated as the ability to WAH also changes peoples' travel and housing decisions. On the one hand, Shabanpour et al. (2018) found that telecommuting significantly decreases both daily vehicles miles and hours traveled, an effect with the potential to reduce greenhouse gas (GHG) and particulate matter emissions. Chakrabarti (2018) also showed that WAH increased non-motorized travels and walking and biking distance. A recent U.S. study showed that WAH reduced GHG emissions by 29% compared to traveling to office (Wu, Chang, and Chen 2024). On the other hand, a trade-off effect on emission has been found for WAH as teleworkers tended to make longer trips for both work and non-work travel (Cerqueira et al. 2020). Fewer trips or shorter commuting distances may lead to using less fuel-efficient vehicles that emit greater amount of greenhouse gases over short periods. This may be worse in the long run when savings on driving cost induce households to move to locations with longer commuting and cheaper housing (Marz and Şen 2022).

WAH also has critical impacts on regional and local economic structure and growth. Galardo and Whitacre (2018) found the percentage of WAH had a positive impact of median household income, and more importantly, spillover effects of WAH existed in neighboring communities. Therefore, the authors stressed the need to modify local economic and workforce development policies to increase. WAH could improve national savings and hence income through cost savings on transportation (Mitomo and Jitsuzumi 1999). However, the widespread WAH may also exacerbate spatial disparities. In Metropolitan Lima in Peru, research observed spatial disparities in unemployment and Internet data usage that were related to the prevalence of WAH during the pandemic, and therefore, a new labor structure was shaped by WAH (Palomino Pichihua and Ruiz Sánchez 2023). More importantly, as high-skilled well-paid jobs adapted more easily to WAH, less-skilled, low-paid jobs became less productive and were left behind due to the dissemination of WAH (Palomino Pichihua and Ruiz Sánchez 2023). WAH could also alter the real estate market and change real estate assets' prices (Bergeaud and Ray 2020). Uzun (2021) found that WAH was likely to lead to the decentralization of offices and reduce the demand for office space. Furthermore, people who can WAH tended to relocate to remote, lower-priced neighborhoods, transforming the local housing market (Bunting 2017).

Relatedly, WAH also has multidimensional effects on modern society. Switching from office work to WAH alters the people's workplace environment and lifestyle. Some studies found that WAH led to reduced physical activity, increased screen time, unhealthy diets, and substance use (Brusaca et al. 2021; Abed Alah et al. 2022). WAH also presented challenges for workers who did not have adequate equipment and home space for teleworking, causing mental and physical health issues. While the flexibility offered by WAH may benefit work-life balance, it could also increase risks of overwork, social isolation, and less access to healthcare services (Buomprisco et al. 2021; Beckel and Fisher 2022). Also, WAH was found to be positively associated with online food purchases, potentially generating food insecurity and food access inequality for disadvantaged populations (Music et al. 2022). Moreover, the growth of WAH may create a new form of digital divide as some workers lack adequate digital skills required for teleworking (Sostero et al. 2020). More attention needs to be paid to disparities and inequalities for older worker populations (Arvola et al. 2017).

Data and methodology

Data source and processing

We extracted consecutive 1-year and 5-year estimates of ACS datasets for a 10-year period between 2013 and 2022 from Social Explorer, a web-based platform that re-organizes U.S. demographic datasets (Social Explorer n.d.). ACS is an ongoing survey conducted by the U.S. Census Bureau, providing detailed demographic, social, economic, employment, and housing data for a large-size representative sample of housing units and people in the U.S. population very year (US Census Bureau 2024b). Currently, ACS produces two types of population estimates datasets based on the survey: 1-year estimates and 5-year estimates. The former record data for the current year, whereas the latter are considered as moving average for a 5-year period (Missouri Census Data Center 2021). However, 1-year estimates are only available for geographic areas with populations of 65,000 or more, which cover only part of the country down to the county level, whereas 5-year estimates cover all geographic areas down to the census tract and block group levels (US Census Bureau 2018).

We examined both 1-year and 5-year estimates as they complement each other regarding temporal and spatial granularity. The 1-year datasets capture changes in WAH on an annual basis but have coarser and incomplete geographic coverage. The 5-year datasets miss the nuanced variations between each year but provide full and finer geographic coverage. In our analysis, we linked the counties available in the 1-year data to metropolitan statistical areas (MSAs) and found all these counties can be matched with an MSA. Therefore, our results for the 1-year data can be considered as findings for metropolitan areas of the U.S.

We selected 2013-2022 as the period of our analysis, which covers consecutive 10-year datasets including the most recently published data as of the time this paper was written. It should be noted that the Census Bureau did not release the 1-year estimates for 2020 as the pandemic disrupted the ACS data collection for that year, while the 5-year estimates containing 2020 (i.e., 2016-2020, 2017-2021, 2018-2022) are available, despite a delay of the data release (US Census Bureau 2022, 2024a). In sum, we extracted nine ACS 1-year datasets (2013, 2014, 2015, 2016, 2017, 2018, 2019, 2021, 2022) and six ACS 5-year datasets (2013-2017, 2014-2018, 2015-2019, 2016-2020, 2017-2021, 2018-2022). The data were cleaned and combined into two integrated tables: 1-year and 5-year data.

Analysis strategy

To address the research questions, we performed two types of regression analyses: (1) the fixed-effects panel regression model for the WAH rate throughout the 10 years and (2) the robust linear regression model for the net change in the WAH rate between 2013 and 2022. The two models had the same specifications that were derived from the same set of ACS variables, ensuring consistency and comparability across samples and models.

Model specifications

The dependent variable of our analysis was the WAH rate, i.e., percentage of workers that worked at home. It was derived from the variable Means of Transportation to Work for Workers 16 Years and Over, which records the number of workers who reported to WAH in the ACS survey (Census Reporter n.d.). This WAH number was divided by the total number of people 16 years and over who participated in the labor force in the survey (variable: Labor Force for Population 16 Years and Over).

Based on the literature we have reviewed, we selected five categories of independent variables that may be associated with the WAH rate, namely density, demographics, family structure, transportation, and housing. We exhausted the variables available in ACS that could fit into the five categories. Then, we dropped variables that contained substantial missing values (e.g., housing price). Variables with significantly high correlations with other variables were also dropped to minimize multicollinearity in the analysis. For example, we eliminated the poverty variable “Poverty Status in the Past 12 Months” because of its high association with educational attainment and median household income.

The finalized set of independent variables was determined to indicate population density, race and ethnicity (percentage of non-White population), income (median household income), educational attainment (percentage of a college degree or above), age (percentage of age 35-64 and percentage of age 65 or older), marital status (percentage of married people), presence of children (percentage of households with a child under age 18), number of workers commuting by car, number of long-distance commuters (travel time was equal to or longer than 60 minutes), number of bedrooms (percentage of 5 or more bedrooms), types of housing units (single house attached, single house detached), and rooms per capita in the house (percentage of 2 or more persons per room). Except for population density (1000/mile^2) and median household income ($1000), all variables indicating the number of individuals or households were converted to percentages, using the total population or total households as the denominator, respectively. Median household income in different years were all adjusted to the 2022 U.S. dollars using the Bureau of Labor Statistics' inflation calculator (US Bureau of Labor Statistics n.d.).

Table 1 presents the full list of the variables and their descriptive statistics, for both the 1-year and 5-year datasets, respectively. It displays the number of observations (N), minimum value, maximum value, and mean value for the dependent variable (the WAH rate) and each independent variable. As shown by the table, the mean WAH rate was similar across the two datasets, with about 7% within the 10-year period. All independent variables for both the 1-year and 5-year data showed similar statistics. However, population density and median household income showed greater differences between the 1-year and 5-year data.

Multicollinearity has been minimized for the regression analysis as the Pearson correlation coefficients between each independent variable were assessed and found acceptable (see Appendix Tables 1 and 2). We also assessed the Variance Inflation Factors of the variables (see Appendix Table 3), which confirmed the acceptable multicollinearity.

Table 1. Descriptive Statistics

	1-year estimates County-level				5-year estimates Tract-level			
	N	min	max	mean	N	min	max	mean
% WAH	3,385	0.682	48.78	7.198	472,725	0	100	7.093
Density								
Population density	7,473	0.00387	73.48	0.881	472,857	0	311.1	5.397
Demographics								

% Non-Hispanic White	4,156	0.437	94.38	62.91	473,487	0	100	60.22
Median household income	7,473	11.94	167.5	61.11	470,188	2.499	250.0	69.58
% college degree or above	7,466	7.269	78.22	30.15	473,379	0	100	31.29
% age 35-64	7,473	22.08	47.81	38.28	473,487	0	100	38.43
% age 65 or older	7,473	6.558	59.50	16.32	473,487	0	100	16.56
Family structure								
% married	7,473	24.94	69.21	48.67	473,487	0	100	46.99
% have own children under 18 in house	7,473	3.113	51.57	27.22	472,178	0	100	27.21
Transportation								
% drive car to work	3,385	6.991	97.37	84.53	472,725	0	100	83.44
% long commute	7,473	0.805	40.61	7.563	472,695	0	100	9.097
Housing characteristics								
% single houses attached	6,498	0	41.62	6.867	470,972	0	100	6.715
% single houses detached	6,498	0.225	73.10	31.18	470,972	0	100	39.42
% 5 plus bedrooms	7,472	0.131	32.15	4.684	472,178	0	100	4.731
% 2 plus persons per room	5,351	0	4.975	0.225	472,178	0	100	0.293

Two types of regression models

In the first model, we used the WAH rate as the dependent variable. For the 1-year and 5-year estimates, the WAH rate for a geographic unit (i.e., a county or a census tract) appeared repetitively in different survey years. Therefore, these datasets were considered as panel data, which track the WAH rate in the same geographic units over the 10 years. For 1-year data, variables for a county were recorded 9 times (values of 2020 were missing). For the 5-year data, variables for a tract were reported 6 times.

Since the datasets had the temporal dimension, it is suitable to use fix-effects panel regression to account for unobserved heterogeneity across time (Baltagi 2021). Moreover, in the U.S. each state has different economic and sociodemographic characteristics. Fix-effects panel regression also enables us to control for characteristics that may be constant within a state but vary across different states (Baltagi 2021). With the given specification, the equation of the model can be expressed as:

$$\mathbf{WAH_{cst} = \alpha + \beta_1 Density_{cst} + \beta_2 Demographic_{cst} + \beta_3 Living\ Arrangement_{cst} + \beta_4 Transportation_{cst} + \beta_5 Housing_{cst} + \gamma_t + \delta_s + \varepsilon_{cst}} \quad (1)$$

where c denotes county in the one-year estimates but represents tracts in the five-year estimates, and s denotes state while t is time. WAH_{cst}, for example, refers to the WAH rate in County (or Tract) c in State s in Year t. γ_t and δ_s are time and state fixed effects, respectively. Under each broad category of factors, we included independent variables associated with the WAH rate, as described in the previous section.

In the second model, we examined the factors that may be associated with the net change in the WAH rate from 2013 to 2022. The robust linear regression was used to deal with outliers and heteroskedasticity. In this analysis, we focused on the start and end points of the period, that is, t = 2013 and t = 2022. We calculated the net changes in the dependent variable and all independent variables for these two time points. The model can be expressed as:

$$\mathbf{\Delta WAH_{cst} = \beta_1 \Delta Density_{cst} + \beta_2 \Delta Demographic_{cst} + \beta_3 \Delta Living\ Arrangement_{cst} + \beta_4 \Delta Transportation_{cst} + \beta_5 \Delta Housing_{cst} + \Delta\gamma_t + \Delta\varepsilon_{cst}} \quad (2)$$

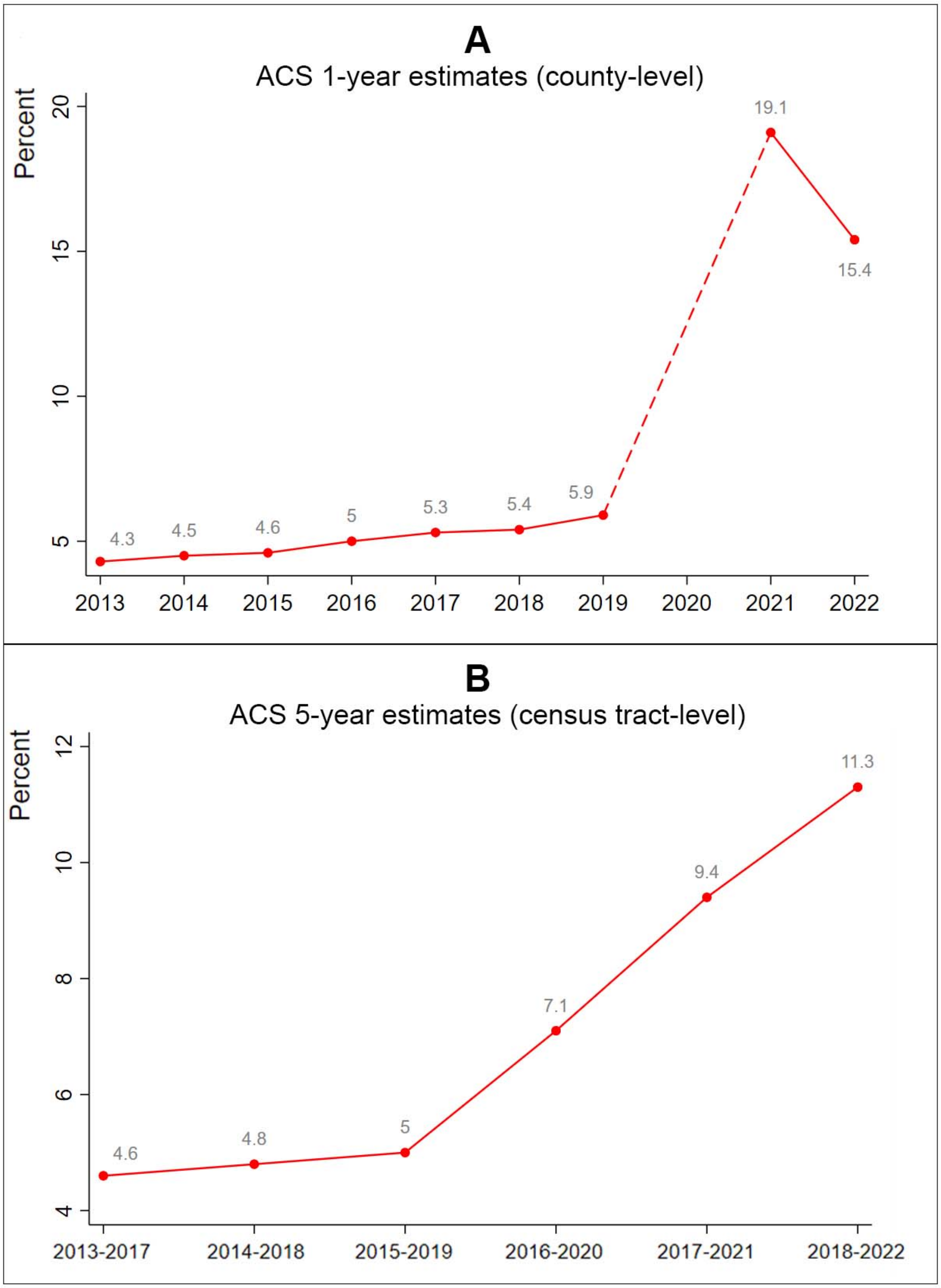
In this "change model," all time-constant factors disappeared as the data were not a panel anymore. Therefore, the model became a linear model, which is OLS in the analysis.

Results and discussions

Temporal and Spatial Trend in WAH

In this section, we first present the temporal trend of WAH across the U.S. Figure 1 displays the temporal trend in the WAH rate in the 1-year and 5-year ACS estimates at the county and tract levels, as the lines shown in Figures 1A and 2B, respectively. Two plots both recorded a turning point occurring in 2020. The WAH rate increased stably and slowly between 2013 and 2019 in the 1-year data and between the survey samples 2013-2017 and 2015-2019 in the 5-year data. Figure 1A shows that the WAH rate constantly increased from 4.3% to 5.9% from 2013 to 2019 on average at the county level. Similarly, Figure 1B shows that it increased from 4.6% to 5.0%

on average at the tract level from the years 2013-2017 to 2015-2019. If this trend was not disrupted, the WAH rate would be around 6% by 2022.



Data from American Community Survey, U.S. Census Bureau

Figure 1. Trend in the WAH rate in the 1-year and 5-year ACS data

However, the sudden jump in the WAH rate was obviously caused by the pandemic that started in early 2020. As aforementioned, the 1-year data missed the year 2020, but in 2021, the WAH rate reached 19.1%, increasing by 223.7% compared to the rate in 2019. According to other studies, such as Pew Research Center's survey (Parker, Horowitz, and Minkin 2020), the WAH rate in 2020 was likely higher than in 2021 because of lockdown enforced by the governments and telework policies widely adopted by employers at the beginning of the pandemic (Huang et al. 2021). While the infection of COVID-19 continued to be severe in 2021, most coercive lockdown policies were no longer active. Moreover, vaccinations against the COVID-19 virus became available in 2021. These factors might have driven a decline in WAH in 2021 (Parker, Horowitz, and Minkin 2020). Such an inference is reasonable since we observed a significant decline in WAH in 2022, which dropped to 15.4%. Nevertheless, the WAH rate remained high compared to the trend before the pandemic.

The 5-year data, on the other hand, presented a steeper increasing trend after 2016-2020. Given the nature of moving averages, the potential fluctuations related to COVID-19 lockdowns were smoothed out. The average tract-level WAH rate reached 7.1% in the years 2016-2020, 9.4% in the years 2017-2021, and then 11.3% in the years 2018-2022, increasing by 126% compared to the pre-COVID WAH rate.

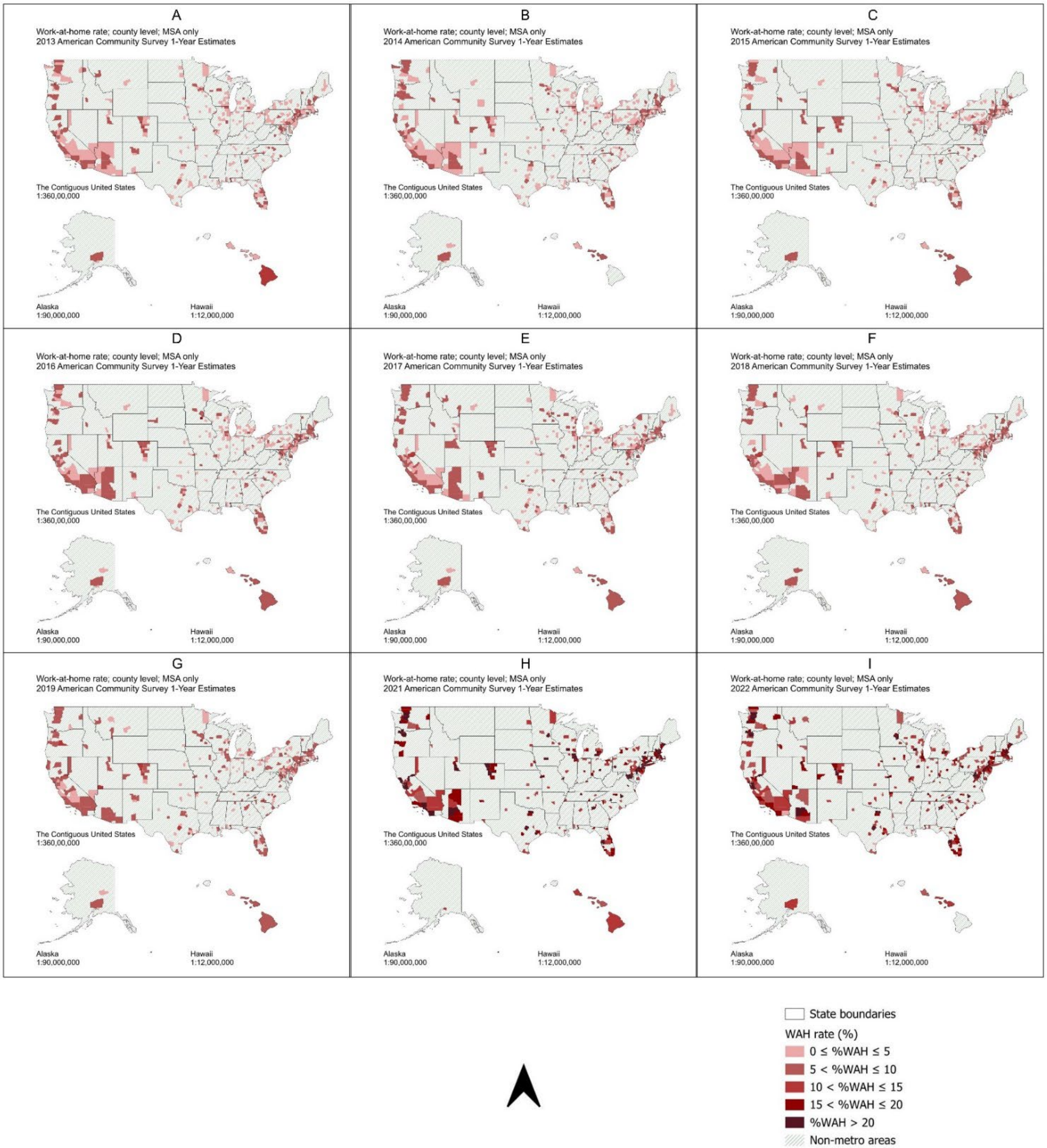


Figure 2. Trend in the WAH rate at the county level (MSA only)
Data source: ACS 1-year estimates

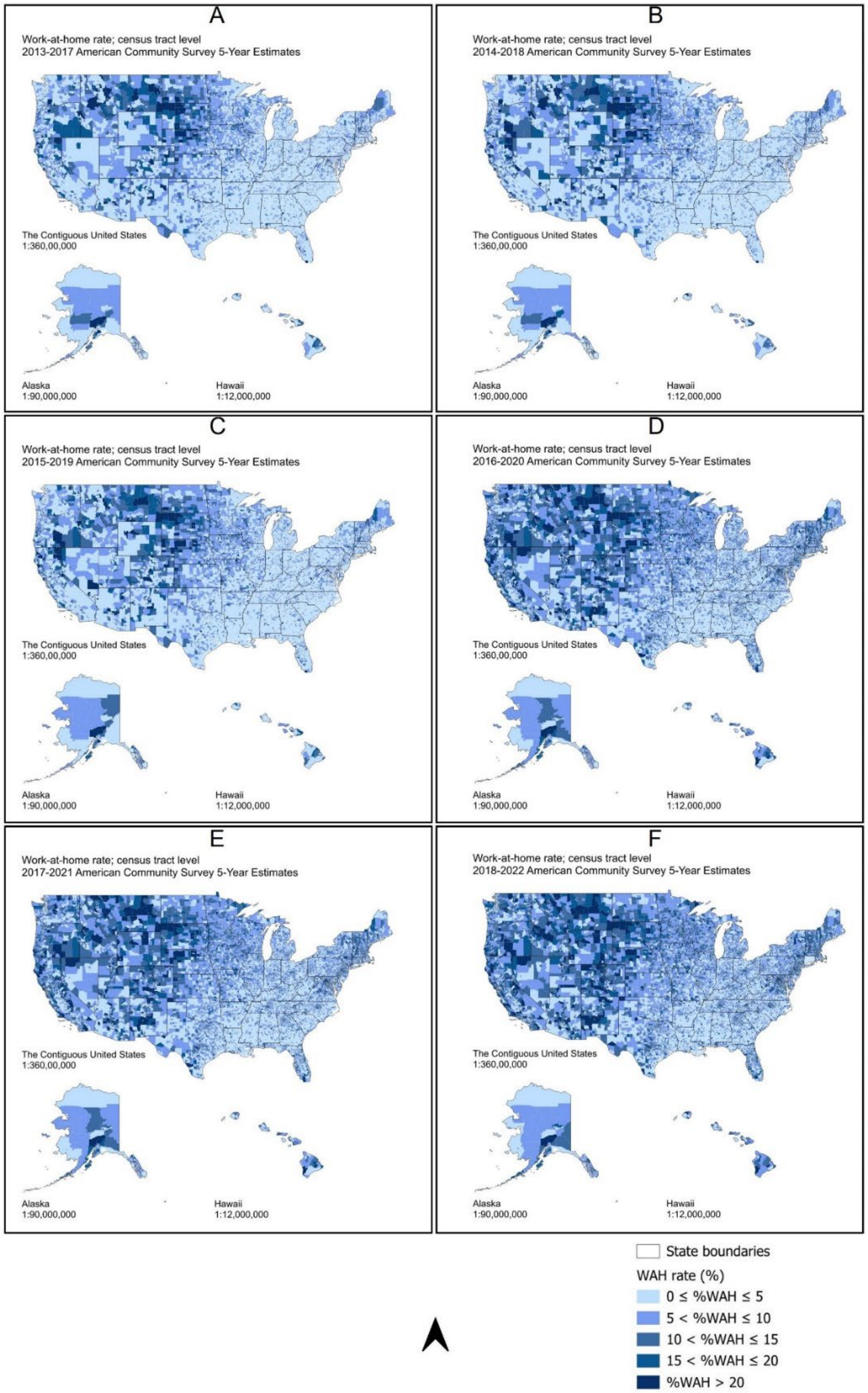


Figure 3. Trend in the WAH rate at the census tract level
Data source: ACS 5-year estimates

Figures 2 and 3 present maps of the WAH rate at the county (MSA only) and tract levels between 2013 and 2022, based on the ACS 1-year and 5-year estimates, respectively.

The two figures provide different pictures of the spatial pattern of WAH. Figure 2 shows that counties on the northeastern coast (from southern Maine to Washington, D.C.) and the western coast (from the Seattle area to southern California) had high WAH rates at the beginning of the 10-year study period. These two coastlines are well known for their high density of traditional megacities and metropolitan areas, including Boston, New York, Philadelphia, Baltimore, Washington, D.C., Seattle, Portland, San Francisco, Los Angeles, and San Diego. Some other emerging big metropolitan areas, such as those on the Florida coast, Denver, and Phoenix, also presented high WAH rates. Moreover, most of these cities are well-known for their advantage in high-technology industries. This phenomenon is consistent with prior studies such as Pyöriä (2011) and Hynes (2016). However, the spatial pattern displayed in Figure 2 ignored the less populous non-metropolitan areas. By contrast, Figure 3 shows that the Midwest and West regions initially had high WAH rates at the beginning of the period, particularly in North Dakota, South Dakota, Nebraska, Iowa, Missouri, Minnesota, Montana, and Idaho. The tracts with high WAH rates in the early years typically had large sizes, indicating that they were in less populous rural areas, usually dominated by agricultural workers. In sum, WAH was more prevalent in both high-tech hubs and remote agricultural areas in the early 2010s.

After 10 years, almost all areas experienced significant increases in WAH. In Figure 2, we have seen that the dispersed smaller metropolitan areas in the Great Lakes region, the Southeast, and the Gulf Coast of Mexico, which had lower WAH rates at the beginning, also gained high values in 2021 and 2022. In Figure 3, we have also identified obvious increases in these regions, especially in Illinois, Michigan, the upper state of New York, Virginia, North Carolina, Georgia, and Texas. Figure 3 also shows that most increases in WAH occurred in populous urban areas (smaller-sized tracts), while many rural areas in the east and southeast remained relatively lower WAH rates.

Factors associated with the WAH rate

We now present the results of the fix-effects panel regression models that examined the factors associated with the WAH rate. Table 2 combines the results from the 1-year and 5-year data. Column 1 shows the results from the 1-year data at the county level, and Column 2 reports those from the 5-year data at the tract level. Both models included the state and year fixed effects. The values represent the estimated coefficients. We also report heteroskedasticity-robust standard errors in the parentheses following each coefficient. For most variables, the results are consistent across the 1-year and 5-year data models in terms of statistical significance and the direction of the coefficients, while the magnitudes are different.

Table 2. Results of fix-effects panel regression models

Dependent Variable: % WAH	(1) 1-year estimates County-level	(1) 5-year estimates Tract-level
Density		
Population density	-0.330***	-0.141***
	(0.043)	(0.002)
Demographic		
% Non-Hispanic White	0.031***	0.019***
	(0.006)	(0.000)
Median household income	0.036***	0.021***
	(0.011)	(0.001)
% having a college degree or above	0.028*	0.056***
	(0.014)	(0.001)
% age 35-64	0.361***	0.075***
	(0.029)	(0.002)
% age 65 or older	0.084***	0.093***
	(0.030)	(0.002)
Family structure		
% Married	-0.040	0.022***
	(0.025)	(0.001)
% Having own children under 18 in house	0.143***	0.042***
	(0.029)	(0.001)
Transportation		
% Driving car to work	-0.372***	-0.270***
	(0.023)	(0.001)
% Long commuters	-0.240***	-0.066***
	(0.017)	(0.001)
Housing characteristics		
% Single houses attached	0.030**	0.008***
	(0.013)	(0.001)
% Single houses detached	0.052***	0.008***
	(0.007)	(0.000)
% 5 plus bedrooms	0.054	0.022***
	(0.034)	(0.002)
% 2 plus persons per room	-0.694***	-0.098***
	(0.216)	(0.007)
Observations	2,757	466,193
Adjusted R-squared	0.864	0.619
STATE F.E.	YES	YES
YEAR F.E.	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

After controlling the year and state fixed effects and holding all other variables constant, population density was negatively associated with the WAH rate. The magnitude of the coefficient was greater in the county-level model than the tract-level model (b=-0.330 vs. -0.141). This indicated that WAH tended to be higher in lower density areas, and this factor was much more impactful at the county level. This results is consistent with previous studies such as Bunting (2017) which found that WAH people tended to relocate to remote neighborhoods for lower housing costs.

All variables in the demographics category, including race, household income, educational attainment, and age, were statistically significant. The percentage of non-Hispanic White, representing the more privileged racial group, were positively associated with the WAH rate. Also, median household income had a positive association with the WAH rate. The percentage of having a college degree or higher, representing the share of the highest educated group, was also positively associated with the WAH rate. The results for these three variables confirmed that WAH workers had relatively higher socioeconomic status: whiter, higher income, and better educated (He and Hu 2015; Dey et al. 2020; Saltiel 2020; Yasenov 2020; Garrote Sanchez et al. 2021; Bick, Blandin, and Mertens 2023). Workers in this privileged group usually have a job with more WAH flexibility, while people with lower socioeconomic status are more likely to work in jobs that require physical presence (e.g., in-person production and service).

The shares of the two age groups (i.e., 35-64, 65 or older) were both positively associated with the WAH rate compared to the share of younger populations. These two age groups are more likely to have administrative roles in their organizations than younger workers, and the literature suggested that managerial and administrative positions are more adaptive to telework (Hajal 2022). In the county-level model, the magnitude of the coefficient for the share of the middle-aged group (35-64) was much larger than that for the older group (65 or older) (b=0.361 vs. 0.084), indicating that middle-aged workers are more impactful on the prevalence of WAH than older workers. The result is consistent with previous studies suggesting older adults were less likely to choose WAH, especially during non-pandemic times (Sostero et al. 2020). However, the tract-level model shows similar coefficients for the two age groups, with the magnitude for the older group slightly greater than that for the middle-aged group (b=0.075 vs. 0.093). A plausible reason for this is the smoothing effect of the 5-year average in the tract-level data, which included the pandemic years (2020, 2021) multiple times. This may augment the impact of the older worker group, as older people were more concerned about the health risks during the pandemic (Brynjolfsson et al. 2020).

Family structure plays an essential role in the WAH behavior. The percentage of married individuals had no significant effect in the county-level model but was positively associated with the WAH rate in the tract-level model (b=0.022). In the literature, the correlation between marital status and WAH was also mixed. On the one hand, some studies found that single people were more likely to WAH compared to married people (Caulfield 2015; Zhang et al. 2020). On the other hand, other studies suggested that married people tended to favor WAH more than single individuals (Lim and Teo 2000). Additionally, couples with children also preferred WAH compared to single parents (Caulfield 2015; Zhang et al. 2020). The mechanisms behind these controversial results are complicated. For single individuals, WAH may be attractive because of its flexibility and cost-saving benefits. For couple parents, the primary consideration for WAH may be their childcare duties. The non-significant coefficient in our county-level model may reflect the complexity of these relationships. However, the results of the tract-level model may be impacted by the pandemic since married couples generally had more family responsibilities, such as domestic work and childcare. The results for the percentage of households with children under age 18 strongly supported our speculation. In both the county-level and tract-level models, this variable presented a positive association with the WAH rate, and its effect was stronger in the county-level model. It is not surprising that workers who have more family responsibilities are motivated to make use of WAH to balance their work and life.

Transportation is another essential factor since WAH can significantly reduce travel costs (Parra-Lokhorst 2021). We found that the percentage of car-driving commuters consistently had a strong negative association with the WAH rate. There might be multiple reasons for this. First, car commuters (especially medium-income workers) face higher transportation expenditure and affordability problems compared to people using other transportation modes (Venter 2011). The costs of driving include car purchasing, taxes, insurance, car maintenance and repair, energy, and parking. Additionally, households may not have adequate vehicles, especially for dual-earner couples. Households with limited car access usually suffered by greater transportation barriers (Schwanen 2011; Blumenberg 2016). For example, parents who drive to work may also need to drive their children to school or daycare. WAH may mitigate these problems to some extent.

The percentage of long-distance commuters (travel time > 60 min) showed a negative association with WAH. In the literature, WAH workers may relocate to remote suburbs (Bunting 2017), but this does not mean many people in these neighborhoods have long commuting distances. Additionally, although longer commuting distances (>50 km) are one of the primary motivations for WAH, extremely long distances (>100 km) may encourage people to have secondary housing near the workplace, thereby reducing their commuting distances (Helminen and Ristimäki 2007). More importantly, areas with a high percentage of long-distance commuters, which are far from major cities, may not have adequate jobs that are suitable for WAH and may also lack other amenities (grocery stores, restaurants, schools) needed by those people. Another reasonable interpretation is that long-distance commuters were reduced as many of them switched to WAH. This will be further examined in the model of the changes in WAH, described in the next section.

Parallel to transportation factors, housing also plays a critical role in WAH. As WAH saves transportation costs, people can relocate to larger houses with lower rents or prices. Unfortunately, the ACS data on housing rent and price had excessive missing values, so we included variables indicating housing types and sizes. Compared to multiunit housing, single-family houses were positively associated with the WAH rate, with detached single houses showing a stronger relationship than attached ones. Houses with five or more bedrooms were linked to higher WAH rates, whereas having two or more people per room was linked to lower rates. These findings align with previous studies (Bunting 2017; Schulz, Watson, and Wersing 2023), highlighting WAH workers' demand for larger single houses, more bedrooms, and spacious, high-quality home offices.

Overall, both models in Table 2 exhibited high adjusted R-squared values, indicating strong explanatory power. Notably, the adjusted R-squared was higher in the county-level model compared to the tract-level model (0.864 vs. 0.619). This suggests that the model specification had greater explanatory power for the 1-year county-level data. This is reasonable, as the tract-level data were based on 5-year moving average estimates, which mixed the impact of the pandemic on WAH across datasets.

Understanding the changes in WAH Between 2013-2022

In this section, we investigated changes in the WAH rate across counties and tracts. Some counties and tracts had missing values for the WAH rate in either the start or end year due to

ACS sampling variation, resulting in fewer observations than in the fixed-effect panel models. Figure 4 shows histograms of the net change in the WAH rate at the county level (Figure 4A) and the tract level (Figure 4B), both demonstrating an approximately normal distribution. The county-level data centered around 10, while the tract-level data centered around 5, due to the smoothing effect of the 5-year moving averages. The mean change in the WAH rate was 11.2 at the county level, about 5 points higher than the 6.5 at the tract level. The tract data had longer tails, indicating more variation and extremes. Only one county had a negative value, while 0.8% of tracts had zero values and 14.4% had negative values. These differences are reasonable, as population changes more dynamically in smaller census tracts than in most counties.

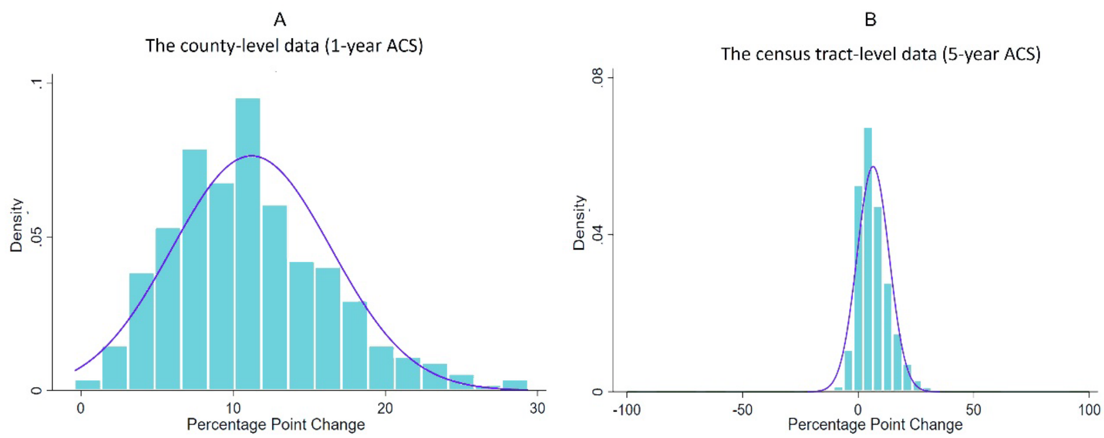


Figure 4. Histogram of the change in the WAH rate at the county and census tract levels

To further understand the mechanism behind the trend, Table 3 presents the results of two robust linear regression models examining the factors associated with the change in the WAH rate across space from 2013 to 2022, based on the 1-year and 5-year ACS data, respectively. Both models exhibited fair adjusted R-squared values (0.765 and 0.510), indicating good explanatory power. Similar to the fixed-effect panel models in the last section, the results were consistent in the two models regarding the statistical significance and direction of coefficients, while the magnitudes of coefficients were much greater in the county-level model.

Table 3. Factors associated with changes in WAH Between 2013-2022

Dependent Variable: Change in % WAH	(1)	(2)

	1-year estimates County-level	5-year estimates Tract-level
Density		
Change in Population density	-0.549	0.025
	(2.636)	(0.021)
Demographic		
Change in % Non-Hispanic White	0.344***	0.020***
	(0.116)	(0.003)
Change in median household income	0.149***	0.069***
	(0.036)	(0.002)
Change in % having a college degree or above	0.128	0.062***
	(0.099)	(0.004)
Change in % age 35-64	0.554***	0.013***
	(0.195)	(0.005)
Change in % age 65 or older	0.030	0.026***
	(0.283)	(0.007)
Family structure		
Change in % married	0.094	0.028***
	(0.101)	(0.003)
Change in % having own children under 18 in house	0.037	0.006
	(0.106)	(0.004)
Transportation		
Change in % driving car to work	-0.816***	-0.550***
	(0.061)	(0.004)
Change in % long commuters	-0.375***	-0.118***
	(0.108)	(0.005)
Housing characteristics		
Change in % single houses attached	-0.064	-0.009***
	(0.074)	(0.002)
Change in % single houses detached	0.151***	0.002
	(0.048)	(0.001)
Change in % 5 plus bedrooms	-0.636***	-0.013**
	(0.170)	(0.006)
Change in % 2 plus persons per room	0.800	0.005
	(0.853)	(0.023)
Observations	256	53,583
Adjusted R-squared	0.765	0.510

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The change in population density did not show a statistically significant relationship with the change in the WAH rate. One of the primary reasons was that density did not change significantly during the ten years for most areas. The mean population density only increased by 25 and 19 persons per square mile at the county and tract levels, respectively. Therefore, the recent trend of WAH has not affected the distribution of population density, at least in the past decade.

An increase in the three socioeconomic status variables, the percentage of non-Hispanic White, the median household income, and the percentage of people holding a college degree or higher, would expect an increase in the WAH rate. In conclusion, a growth of high-socioeconomic status populations (racially privileged, high-income, and well-educated) was associated with a growth of WAH workers.

An increase in middle-aged workers (35-64) was associated with an increase in WAH for both counties and tracts, while the change in older workers (65+) did not show a significant correlation at the county level. This result is consistent with the fixed-effect panel model. It confirms that the majority of WAH adopters are middle-aged. They are more senior than younger, entry-level workers, who are less likely to have administrative roles, and younger than older generations, who have more difficulty with the technologies needed for WAH. Additionally, compared to other age groups, middle-aged workers usually have more family responsibilities, making WAH preferable for them.

The change in the percentage of married individuals was not associated with the change in the WAH rate at the county level but was positively associated with it at the tract level. The presence of children in households did not show an association in either model. In general, these two variables are stable and do not have noticeable variations over time. Nevertheless, married people seemed to engage in WAH more than unmarried individuals, which is consistent with the panel models.

Transportation still showed a strong association with the trend in WAH in both models. The change in the percentage of people driving to work was negatively associated with the change in the WAH rate. This suggests that a growth in WAH workers may reduce the use of automobiles for commuting. The change in the percentage of long-distance commuters also showed a negative association, indicating that the increase in WAH may lead many long-distance commuters to switch to home-based work. It should be noted that the percentage of car-driving commuters dropped by 9 points in the county-level data and 5 points in the tract-level data from 2013 to 2022. The significant decline in car driving was likely due to the COVID-19 pandemic and soaring energy costs, which may motivate people to reduce automobile use and choose WAH when it was available.

Looking at the broad categories, changes in transportation and demographics have the most significant effect on changes in WAH. As discussed above, changes in transportation might have been significantly affected by the Covid-19 pandemic. Similarly, demographics such as race, income, education and age distribution are also factors likely to record considerable changes in a span of a decade. But whereas all the changes in transportation have negative effects on changes in WAH due to the drops in long commute and car driving, the changes in demographics all have positive effects on changes in WAH. Intuitively, a positive change in median household income over a decade, for example, causes a positive effect on WAH, and the reverse is true. All the other demographic variables fit similar explanation, hence the positive relationship between changes in these demographics and changes in WAH.

Changes in housing characteristics did not show strong relationships with the change in the WAH rate. The change in the percentage of attached single houses had a marginal negative association in the tract-level model. The change in the percentage of detached single houses had a positive association in the county-level model but was not statistically significant in the tract-level model. The change in the percentage of houses with 2 or more persons per room did not have an association in either model. However, the change in the percentage of houses with 5 or more bedrooms had a negative association with the change in the WAH rates. This is likely related to the downsizing trends in the U.S. real estate market over the last ten years due to increasingly constrained affordability (Dietz 2023). In our 1-year and 5-year data, the mean percentage of houses with 5 more bedrooms dropped at both the county and tract levels from 2013 to 2022.

Policy implications

Our analysis has provided valuable policy implications based on the spatial and temporal trends in WAH. In this section we discuss these implications falling into distinct categories.

Will WAH lead to suburbanization and decentralization?

There has been a long concern that the rise of WAH will lead to suburbanization and decentralization for residence (Sridhar and Sridhar 2003; Gokan et al. 2022). Our fixed effects panel model suggests that the WAH rate was negatively associated with population density at both the county and tract levels. Remember that for county-level model, we only had data in MSAs, which excluded rural areas. The result indicates that WAH tended to be more popular in lower-density areas, which are likely to be suburban communities. However, at least for now, we have not observed a suburbanization/decentralization trend driven by WAH during this past decade, because the change in population density did not show a significant relationship with the change in WAH.

It is uncertain whether WAH will reshape population density in the long run. Although low-density suburbs may be attractive due to larger spaces and lower housing costs, people still need physical access to amenities like schools, childcare, hospitals, grocery stores, parks, and cultural facilities. Activities involving these destinations are less likely to be fully virtualized. Thus, unless these amenities are also decentralized, people may hesitate to move farther out even with WAH options. Additionally, some jobs, such as food services, education, personal care, and utilities, are less suitable for WAH. Communities with high concentrations of these jobs are less likely to lose population due to WAH. Therefore, the long-term impact of WAH on population density may not be evenly distributed. However, in suburban areas with many high-tech or managerial workers, policymakers might anticipate rapid WAH growth and an increased demand for related infrastructure and amenities.

Will WAH create new social and spatial disparities?

Our analysis confirmed that WAH was more prevalent in counties and tracts with higher socioeconomic status. Moreover, WAH was growing faster in areas where we observed an increase in socioeconomically advantaged populations, namely, non-Hispanic White, high household income, and high education levels. Our results are consistent with prior works on WAH and telework concerning social equity (He and Hu 2015; Bick, Blandin, and Mertens 2023). The difference in virtualizability and WAH suitability of occupations may be a primary reason for this phenomenon (Han, Zhao, and Chen 2023). In general, many high-income, high-education jobs are more suitable for WAH than low-income, low-skilled jobs, which still require in-person presence at work (Elldér 2019).

While high-income and socially privileged workers can enjoy the benefits of WAH, such as flexibility in time use, money and time savings, and improved work-life balance, low-income and socially disadvantaged populations may still suffer the burden and costs of daily commuting. Furthermore, WAH is likely to generate new forms of spatial disparities if this trend continues in the future. The increase in the WAH rate may create some “WAH-friendly neighborhoods” where people can enjoy preferable housing features and amenities, low living costs, and the benefits of WAH simultaneously. Privileged people who can WAH may relocate to these “WAH-friendly neighborhoods,” attracting investments for infrastructure and facility improvements, including internet, education, healthcare, and public transit. Subsequently, disadvantaged populations who lack the ability to WAH may be stuck in neighborhoods that are losing these resources.

How will WAH affect age-friendly and family-friendly workforce?

The percentage of middle-aged workers (35-64) and older workers (65+) showed consistent positive associations with the work-from-home (WAH) rate, compared to younger workers (<35), at both the county and tract levels. This result aligns with previous studies, such as Brussevich et al. (2020), which found that younger workers were less likely to WAH. This suggests that many young people lack the flexibility to WAH and have to bear the burden of daily commuting, including high transportation costs and stress. Some approaches could mitigate the inequitable outcomes of WAH for younger workers, such as flexible work hours and financial support for commuting transportation (e.g., providing subsidies for public transit fares or vehicle purchase).

Older workers who are 65 or older face other challenges caused by WAH. The county-level model with 1-year ACS data indicated that middle-aged workers had a stronger association with the WAH rate than older workers did. Although older workers tended to choose WAH to avoid virus infection during the pandemic (Brynjolfsson et al. 2020), they were also more eager to return to the office in the post-COVID period (Sostero et al. 2020). One of the major barriers limiting older workers from WAH is their skill level and fluency in using computers and ICTs (Arvola et al. 2017). Therefore, there is a need for older workers to master necessary WAH skills through training provided by employers or the government.

Our results indicate that family structure characteristics, including marriage and the presence of a child, have significant associations with WAH. More specifically, the share of married people and the share of households with children under age 18 were positively associated with the WAH rate in the fixed effects panel model. This is consistent with previous studies such as Caulfield (2015), Zhang et al. (2020), and Lim and Teo (2000), which suggest that family responsibilities and maintaining work-life balance are an essential driver for some WAH workers. For these individuals, WAH may be a better option for their families but not necessarily relaxing or beneficial for them individually. Vulnerable individuals, such as single mothers with young children, could face unique challenges and stress in managing their time for both paid work and heavy family duties simultaneously at home. More attention should be paid to the well-being of these groups.

How will WAH affect people's transportation and housing choices?

Our results highlighted the association between WAH and transportation and housing behaviors. The share of car-driving commuters and the share of long-distance commuters were negatively associated with the WAH rate, and the changes in these two variables were also negatively associated with the change in the WAH rate. This result indicates that the prevalence of WAH may reduce automobile dependence for work-related travel, which is potentially beneficial for the environment by reducing GHG emissions. However, the literature indicates that WAH workers may increase car use and travel distance for non-work trips, which lead to a compensatory effect on emissions (Cerqueira et al. 2020). Moreover, as WAH workers potentially move to farther areas for lower housing costs (Bunting 2017), they may face accessibility challenges for other essential demands, such as healthcare and food. Policymakers need to facilitate more environmental-friendly and accessible transportation modes and infrastructure for WAH workers, including public transit, bicycling and walking facilities, and on-demand services.

We also observed that WAH was associated with larger-sized houses. First, the WAH rate was positively associated with the share of single-family homes, both attached and detached. Second, the WAH rate was positively associated with the share of houses with five or more bedrooms. Finally, the WAH rate was negatively associated with rooms per capita, represented by the share of households with two or more persons per room. These factors align with previous studies showing WAH workers' high demand for home office spaces (Bunting 2017). If this housing trend continues, there may be a new wave of suburbanization driven by the rise of WAH. Policymakers need to prepare for the potential housing demand and proactively plan for the impact of WAH-driven housing relocations.

Conclusion

We conducted a comprehensive analysis of the temporal and spatial trends of WAH from 2013 to 2022 at both the county and tract levels in the U.S. By combining multi-year and multi-scale ACS datasets, we illustrated these trends. We utilized two different regression models to examine factors associated with the WAH rate and its changes. After controlling for the fixed effects of years and states, our panel model revealed that the WAH rate was negatively associated with population density, car-driving commuters, long-distance commuters, and bedrooms per capita, while it was positively associated with high socio-economic status, middle-aged populations, married individuals, the presence of children, and house size. The model focusing on the change in WAH echoed the panel model while underscoring the potential for WAH to exacerbate spatial disparities related to race and ethnicity, income, education, and age. Additionally, it suggested a reduction in car driving and an increased demand for single-family houses. The policy implications of our findings may concern decision-makers regarding issues such as suburbanization, social equity, the creation of age-friendly and family-friendly societies, and transportation and housing choices.

Despite our contributions, there were several limitations in the data. First, the tract-level ACS data were 5-year averages, which lost nuanced information for each year. Second, the county-level ACS data were available only for counties in metropolitan areas, which did not cover the entire country. Additionally, the 2020 1-year estimates were missing due to the disruption of the pandemic. Finally, the ACS data did not provide more detailed information specifically about the WAH population. We need to make more efforts in instrument design and data collection for this specific population in the future.

References

Abed Alah, M., S. Abdeen, V. Kehyayan, and I. Bougmiza. 2022. The Impact of Changes in Work Arrangements During COVID-19 Pandemic on the Lifestyle of Qatar's Working Population. *Journal of Occupational and Environmental Medicine* 64 (2): e53.

de Abreu e Silva, J., and P. C. Melo. 2018. Home telework, travel behavior, and land-use patterns: A path analysis of British single-worker households. *Journal of Transport and Land Use* 11 (1):419–441.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh. 2022. The Geography of Remote Work. *Regional Science and Urban Economics* 93:103770.

Arvola, R., P. Tint, Ü. Kristjuhan, and V. Siirak. 2017. Impact of telework on the perceived work environment of older workers. *Scientific annals of economics and business* 64 (2). http://archive.sciendo.com/SAEB/saeb.2017.64.issue-2/saeb-2017-0013/saeb-2017-0013.pdf (last accessed 21 June 2024).

Bailey, D. E., and N. B. Kurland. 2002. A review of telework research: findings, new directions, and lessons for the study of modern work. *Journal of Organizational Behavior* 23 (4):383–400.

Baltagi, B. H. 2021. *Econometric Analysis of Panel Data*. Cham: Springer International Publishing. https://link.springer.com/10.1007/978-3-030-53953-5 (last accessed 25 June 2024).

Barrero, J. M., N. Bloom, and S. J. Davis. 2023. The Evolution of Work from Home. *Journal of Economic Perspectives* 37 (4):23–50.

Beckel, J. L. O., and G. G. Fisher. 2022. Telework and Worker Health and Well-Being: A Review and Recommendations for Research and Practice. *International Journal of Environmental Research and Public Health* 19 (7):3879.

Belzunegui-Eraso, A., and A. Erro-Garcés. 2020. Teleworking in the Context of the Covid-19 Crisis. *Sustainability* 12 (9):3662.

Bergeaud, A., and S. Ray. 2020. The macroeconomics of teleworking. *Economic research* 231:2.

Bick, A., A. Blandin, and K. Mertens. 2023. Work from Home before and after the COVID-19 Outbreak. *American Economic Journal: Macroeconomics* 15 (4):1–39.

Biron, M., W. J. Casper, and S. Raghuram. 2022. Crafting telework: a process model of need satisfaction to foster telework outcomes. *Personnel Review* 52 (3):671–686.

Blumenberg, E. 2016. Why low-income women in the US still need automobiles. *Town Planning Review* 87 (5):525–545.

Brusaca, L. A., D. F. Barbieri, S. E. Mathiassen, A. Holtermann, and A. B. Oliveira. 2021. Physical Behaviours in Brazilian Office Workers Working from Home during the COVID-19

Pandemic, Compared to before the Pandemic: A Compositional Data Analysis. *International Journal of Environmental Research and Public Health* 18 (12):6278.

Brussevich, M., M. E. Dabla-Norris, and S. Khalid. 2020. *Who will bear the brunt of lockdown policies? Evidence from tele-workability measures across countries*. International Monetary Fund. https://books.google.com/books?hl=zh-CN&lr=&id=EbEaEAAAQBAJ&oi=fnd&pg=PA4&dq=Who+will+Bear+the+Brunt+of+Lockdown+Policies%3F+Evidence+from+Tele-workability+Measures+Across+Countries&ots=j4JhtoG0L_&sig=sTiKp99q8q5l4U-0x4QdtXUwEK8 (last accessed 20 July 2024).

Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe. 2020. COVID-19 and Remote Work: An Early Look at US Data. https://www.nber.org/papers/w27344 (last accessed 20 June 2024).

Bunting, W. C. 2017. Unlocking the Housing-Related Benefits of Telework: A Case for Government Intervention. https://papers.ssrn.com/abstract=2994779 (last accessed 23 June 2024).

Buomprisco, G., S. Ricci, R. Perri, and S. D. Sio. 2021. Health and Telework: New Challenges after COVID-19 Pandemic. *European Journal of Environment and Public Health* 5 (2): em0073.

Caulfield, B. 2015. Does it pay to work from home? Examining the factors influencing working from home in the Greater Dublin Area. *Case Studies on Transport Policy* 3 (2):206–214.

Census Reporter. Census tabulation detail: Means of Transportation to Work. *Census Reporter*. https://censusreporter.org/tables/B08301/ (last accessed 24 June 2024).

Cerqueira, E. D. V., B. Motte-Baumvol, L. B. Chevallier, and O. Bonin. 2020. Does working from home reduce CO2 emissions? An analysis of travel patterns as dictated by workplaces. *Transportation Research Part D: Transport and Environment* 83:102338.

Chakrabarti, S. 2018. Does telecommuting promote sustainable travel and physical activity? *Journal of Transport & Health* 9:19–33.

Cho, K. 2020. Telework and Its Associations with Job Satisfaction and Turnover in the Los Angeles County Department of Public Social Services. http://scholarworks.csun.edu/bitstream/handle/10211.3/217227/Cho-Ken-thesis-2020.pdf?sequence=1 (last accessed 21 June 2024).

Dey, M., H. Frazis, M. A. Loewenstein, and H. Sun. 2020. Ability to work from home: evidence from two surveys and implications for the labor market in the COVID-19 pandemic. *Monthly Labor Review* :1–19.

Dietz, R. 2023. Single-Family Home Size Moves Lower to More than a Decade Low. https://eyeonhousing.org/2023/08/single-family-home-size-moves-lower-to-more-than-a-decade-low/ (last accessed 13 July 2024).

Elldér, E. 2019. Who Is Eligible for Telework? Exploring the Fast-Growing Acceptance of and Ability to Telework in Sweden, 2005–2006 to 2011–2014. *Social Sciences* 8 (7):200.

Ellison, N. B. 2004. *Telework and social change: How technology is reshaping the boundaries between home and work*. Bloomsbury Publishing USA. https://books.google.com/books?hl=zh-CN&lr=&id=Fn3DEAAAQBAJ&oi=fnd&pg=PP1&dq=Traditional+workplace+dynamics+have+been+rapidly+transformed+with+the+advancement+of+information+and+communication+technologies+(ICTs),+which+enable+people+to+complete+many+work+tasks+virtually.&ots=dYImYF73tC&sig=bDzFzmQtZaXFVXoYtUlhg5CKX2U (last accessed 31 July 2024).

Felstead, A., N. Jewson, A. Phizacklea, and S. Walters. 2002. Opportunities to work at home in the context of work-life balance. *Human Resource Management Journal* 12 (1):54–76.

Gallardo, R., and B. Whitacre. 2018. 21st century economic development: Telework and its impact on local income. *Regional Science Policy & Practice* 10 (2):103–124.

Garrote Sanchez, D., N. Gomez Parra, C. Ozden, B. Rijkers, M. Viollaz, and H. Winkler. 2021. Who on Earth Can Work from Home? *The World Bank Research Observer* 36 (1):67–100.

Gokan, T., S. Kichko, J. Matheson, and J.-F. Thisse. 2022. How the Rise of Teleworking Will Reshape Labor Markets and Cities. https://papers.ssrn.com/abstract=4235466 (last accessed 13 July 2024).

Golden, R. 2022. The companies that went fully remote — and never looked back. *HR Dive*. https://www.hrdive.com/news/fully-remote-work-companies/635915/ (last accessed 29 November 2023).

Hajal, G. E. 2022. Teleworking and the jobs of tomorrow. *Research in Hospitality Management* 12 (1):21–27.

Han, Z., Y. Zhao, and M. Chen. 2023. Research on the suitability of telework in the context of COVID-19. *International Journal of Manpower* 45 (4):697–713.

He, S. Y., and L. Hu. 2015. Telecommuting, income, and out-of-home activities. *Travel Behaviour and Society* 2 (3):131–147.

Helminen, V., and M. Ristimäki. 2007. Relationships between commuting distance, frequency and telework in Finland. *Journal of Transport Geography* 15 (5):331–342.

Huang, X., X. Shao, L. Xing, Y. Hu, D. D. Sin, and X. Zhang. 2021. The impact of lockdown timing on COVID-19 transmission across US counties. *eClinicalMedicine* 38. https://www.thelancet.com/journals/eclinm/article/PIIS2589-5370(21)00315-1/fulltext (last accessed 26 June 2024).

Hynes, M. 2016. Developing (tele)work? A multi-level sociotechnical perspective of telework in Ireland. *Research in Transportation Economics* 57:21–31.

Illegems, V., and A. Verbeke. 2004. Telework: What Does it Mean for Management? *Long Range Planning* 37 (4):319–334.

Kalliath, T., and P. Brough. 2008. Work–life balance: A review of the meaning of the balance construct. *Journal of Management & Organization* 14 (3):323–327.

Lim, V. K. G., and T. S. H. Teo. 2000. To work or not to work at home-An empirical investigation offactors affecting attitudes towards teleworking. *Journal of Managerial Psychology* 15 (6):560–586.

Maruyama, T., and S. Tietze. 2012. From anxiety to assurance: concerns and outcomes of telework. *Personnel Review* 41 (4):450–469.

Marz, W., and S. Şen. 2022. Does telecommuting reduce commuting emissions? *Journal of Environmental Economics and Management* 116:102746.

Missouri Census Data Center. 2021. Ten Things to Know about the American Community Survey. https://mcdc.missouri.edu/help/ten-things/ACS.html (last accessed 24 June 2024).

Mitomo, H., and T. Jitsuzumi. 1999. Impact of telecommuting on mass transit congestion: the Tokyo case. *Telecommunications Policy* 23 (10):741–751.

Music, J., S. Charlebois, V. Toole, and C. Large. 2022. Telecommuting and food E-commerce: Socially sustainable practices during the COVID-19 pandemic in Canada. *Transportation Research Interdisciplinary Perspectives* 13:100513.

Palomino Pichihua, Y. M., and J. Ruiz Sánchez. 2023. The Geography of Telework in Latin America: New Spatial Devices during the Pandemic. *Latin American Perspectives* 50 (4):103–121.

Parker, K., J. M. Horowitz, and R. Minkin. 2020. How the Coronavirus Outbreak Has – and Hasn't – Changed the Way Americans Work. *Pew Research Center*. https://www.pewresearch.org/social-trends/2020/12/09/how-the-coronavirus-outbreak-has-and-hasnt-changed-the-way-americans-work/ (last accessed 26 June 2024).

Parra-Lokhorst, M. 2021. Teleworking effects on transportation behaviour in a post-Covid-19 context: 10 case studies from Montréal, Canada. https://escholarship.mcgill.ca/concern/papers/zk51vn67d (last accessed 9 July 2024).

Pratt, J. H. 2002. Teleworkers, Trips, and Telecommunications: Technology Drives Telework—But Does It Reduce Trips? *Transportation Research Record* 1817 (1):58–66.

Pyöriä, P. 2011. Managing telework: risks, fears and rules. *Management Research Review* 34 (4):386–399.

Saltiel, F. 2020. Who can work from home in developing countries? *Covid Economics* 7 (2020):104–118.

Schulz, R., V. Watson, and M. Wersing. 2023. Teleworking and housing demand. *Regional Science and Urban Economics* 101:103915.

Schwanen, T. 2011. Car Use and Gender: The Case of Dual-Earner Families in Utrecht, The Netherlands. In *Auto Motives*, eds. K. Lucas, E. Blumenberg, and R. Weinberger, 151–171. Emerald Group Publishing Limited https://doi.org/10.1108/9780857242341-008 (last accessed 9 July 2024).

Semuels, A. 2022. The Problem with the Way We Train Truckers. *Time*. https://time.com/6144516/truck-driver-training/ (last accessed 20 January 2023).

Shabanpour, R., A. Shamshiripour, and A. Mohammadian. 2018. Modeling adoption timing of autonomous vehicles: innovation diffusion approach. *Transportation* 45 (6):1607–1621.

Social Explorer. Social Explorer. *Social Explorer*. https://www.socialexplorer.com/ (last accessed 20 June 2024).

Sostero, M., S. Milasi, J. Hurley, E. Fernandez-Macías, and M. Bisello. 2020. *Teleworkability and the COVID-19 crisis: a new digital divide?* JRC working papers series on labour, education and technology. https://www.econstor.eu/handle/10419/231337 (last accessed 21 June 2024).

Sridhar, K. S., and V. Sridhar. 2003. The effect of telecommuting on suburbanization: empirical evidence. *Journal of Regional Analysis & Policy* 33 (1):1–25.

Sweet, M., and D. M. Scott. 2022. Insights into the future of telework in Canada: Modeling the trajectory of telework across a pandemic. *Sustainable Cities and Society* 87:104175.

Ton, D., K. Arendsen, M. de Bruyn, V. Severens, M. van Hagen, N. van Oort, and D. Duives. 2022. Teleworking during COVID-19 in the Netherlands: Understanding behaviour, attitudes, and future intentions of train travellers. *Transportation Research Part A: Policy and Practice* 159:55–73.

US Bureau of Labor Statistics. CPI Inflation Calculator. *Bureau of Labor Statistics*. https://www.bls.gov/data/inflation_calculator.htm (last accessed 25 June 2024).

US Census Bureau. 2018. Understanding and Using American Community Survey Data. https://www.census.gov/content/dam/Census/library/publications/2018/acs/acs_general_handbook_2018_ch03.pdf.

———. 2022. American Community Survey 2016-2020 5-Year Data Release. *Census.gov*. https://www.census.gov/newsroom/press-kits/2021/acs-5-year.html (last accessed 24 June 2024).

———. 2024a. 2020 ACS 1-Year Experimental Data Release. *Census.gov*. https://www.census.gov/programs-surveys/acs/data/experimental-data.html (last accessed 24 June 2024).

———. 2024b. About the American Community Survey. *Census.gov*. https://www.census.gov/programs-surveys/acs/about.html (last accessed 24 June 2024).

Uzun, S. 2021. *Telework and its Effect on Office Real Estate: A Study on Telework, its Future, and How Telework can Affect the Market for Office Space*. https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-298388 (last accessed 23 June 2024).

Venter, C. 2011. Transport expenditure and affordability: The cost of being mobile. *Development Southern Africa* 28 (1):121–140.

Wu, H., Y. Chang, and Y. Chen. 2024. Greenhouse gas emissions under work from home vs. office: An activity-based individual-level accounting model. *Applied Energy* 353:122167.

Yasenov, V. I. 2020. Who Can Work from Home? https://papers.ssrn.com/abstract=3590895 (last accessed 20 June 2024).

Yuile, C., A. Chang, A. Gudmundsson, and S. Sawang. 2012. The role of life friendly policies on employees' work-life balance. *Journal of Management & Organization* 18 (1):53–63.

Zhang, S., R. Moeckel, A. T. Moreno, B. Shuai, and J. Gao. 2020. A work-life conflict perspective on telework. *Transportation Research Part A: Policy and Practice* 141:51–68.