THE CONTRIBUTION OF BROADBAND INTERNET TO REMOTE WORKING AND RELATED EFFECTS BEFORE AND DURING THE PANDEMIC

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EXECUTIVE SUMMARY

Industrialization since the mid-1800s combined with the accelerated rate of urbanization that took place in the twentieth century have been the defining factors driving an increase of commuting to work. Since household migration to the suburbs did not evolve in parallel with employment decentralization, commuting became a fixture of the American workforce, especially in the service sector. According to the Census Bureau, the average worker in 2019 in the United States spent 55 minutes a day commuting to work, while 9.8 percent reported daily commutes of at least 2 hours.¹ In this context, by reducing commuting time, remote working enabled by fast broadband became an option to improve quality of life. The COVID-19 pandemic accelerated this trend. Especially before the launch of COVID vaccinations, governments enacted massive social distancing measures, including severe restrictions with abrupt falls in physical interactions.

According to the Census Bureau, the average worker in 2019 in the United States spent 55 minutes a day commuting to work, while 9.8 percent reported daily commutes of at least 2 hours.

1 Burd et al (2021)



Following the pandemic-related restrictions imposed in 2020, strong anecdotal evidence has emerged suggesting that a robust ICT infrastructure has contributed to counteract some of the isolation measures, allowing economic systems to continue operating, at least partially. A great deal of that resilience is linked to the remote working capabilities enabled by broadband infrastructure. The goal of this study is to analyze specifically the contribution of broadband, as part of a robust ICT infrastructure, to remote working and its related effects in the United States under normal, pre-pandemic circumstances and in the context of the pandemic.

In 2020 during the pandemic, on average, every worker that started to work from home (rather than commuting) enjoyed 24 additional daily minutes of family time.

Existing literature suggests that remote working reduces commuting time, with the consequent increase in quality of life, productivity, and overall wellbeing. However, there is not a clear consensus regarding the net effects on carbon emissions due to remote work: remote working naturally reduces work-related transport; however, with more time available, telecommuters may increase non-working travel. One of the main aims of this study was to disentangle these opposite effects and estimate the net outcome.

The estimation is based on a model linking broadband adoption and remote working. This effect is expected, in turn, to yield savings in travel time, which would flow into an improvement of quality of life, and savings in carbon emissions (see Figure A).



Figure A. Causal chain to assess the contribution of broadband to remote working and related effects



Source: Telecom Advisory Services

The estimates of causality were calculated through Structural Equation Modelling (SEM) for two different periods: before the pandemic and during the pandemic, factoring the impact of social restrictions on work routines. The data used was extracted from the American Time Use Survey conducted by the Bureau of Labor Statistics.

Since high-speed broadband is inseparably linked to remote working, and the latter appears to have become a social fixture of the future, the government needs to close the digital divide.

The results of the empirical models provide two relevant insights:

• Remote working, enabled by broadband, was found to significantly increase workers' quality time, defined as the time spent with family members. This is an important result in terms of well-being, and can be associated, in turn, to increased happiness and a better life balance. In 2020 during the pandemic, on average, every worker that started to work from home (rather than commuting) enjoyed 24 additional daily minutes of family time.



Remote working is also associated with a reduction in carbon emissions resulting from less travel time to work, although part of this decrease is offset by an increase in emissions as a result of non-work-related travel. When remote working is less frequent, such as in the pre-pandemic situation (2017 and 2018) both effects cancel each other out, and the net result is negligible. However, when remote working is more frequent, as during the COVID-19 pandemic, the net reduction in emissions prevails. This means that during the pandemic the reduction in travel time to work is higher than the increase in non-work-related travel. In 2020, on average, every worker that started to work from home (rather than commuting) contributed to reduce emissions in 0.045 metric tons.² This result is naturally influenced by the mobility restrictions during that time.

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Given the net impact of hybrid work patterns on carbon emissions, remote working enabled by broadband is a key contributor to environmental sustainability.

The implications of these findings are critical going-forward. Eighty-two percent of U.S. workers want to work remotely at least once a week when the pandemic is over. Of these, fifty-five percent would prefer to work according to a hybrid-remote schedule, while nineteen percent said they would like to telecommute full-time. Only eight percent do not want to work from home at all.³ However, employee preferences will be naturally conditioned by the



² Since the commuting data does not differentiate between individual travel by car and public transportation, the total impact might be somewhat less, although it could vary by community.

³ Global Work from Home Experience Survey, Global Workplace Analytics & Iometrics, 2020 – based on 1,100 U.S. respondents

employer's criteria. This data implies that the post-pandemic situation of remote working could be somewhat between the 2017-2018 and 2020 conditions.

The policy implications of these findings are key:

- Since high-speed broadband is inextricably linked to remote working, and the latter appears to have become a social fixture of the future, the government needs to close the digital divide and ensure everyone can adopt a high-quality internet connection in the United States. Today, wide penetration rate disparities exist between states. To mention a specific example, less than 40% of households had a broadband connection of at least 25 Mbps downstream speed in Arkansas in 2020. In contrast, that figure was 91.4% for the case of Delaware.⁴ This means that not all Americans have the same resources needed to work remotely.⁵ Because of this, public authorities should focus on creating policy frameworks that allow operators to spur infrastructure deployments, to find the optimal technological mixes to deliver the highest performance to the users and to help increase levels of adoption among households who have access to broadband but have chosen not to use it at home.
- Given the net impact of hybrid work patterns on carbon emissions, remote working enabled by broadband is a key contributor to environmental sustainability. Therefore, even considering that close to 60% of US occupations cannot be done remotely, governments and the private sector should consider how remote work can help make a significant impact on reducing emissions.⁶



⁴ Source: Federal Communications Commission (FCC)

⁵ Naturally, not all jobs can be performed remotely because they are either considered "essential" (health care, police) or due to the nature of the occupation; this limits the benefits of telecommuting.

⁶ Dingel, J. and Neiman, B. (2020). How many jobs can be done at home? University of Chicago and NBER

1. INTRODUCTION

The COVID-19 pandemic has brought to the fore a social trend that was already under development for some years since the gradual migration of workers to the periphery of metropolitan areas: remote working. Before the pandemic, twenty-six percent of workers reported working at home three or more days per week.⁷ This trend accelerated during the pandemic. Before the launch of vaccination campaigns, the federal, state, and local governments enacted social distancing measures, including severe work restrictions limiting many physical work interactions. As of June 2020, sixty-six percent of US respondents to Nielsen had started to work from home since the Coronavirus outbreak.⁸

Following this trend, strong anecdotal evidence has emerged suggesting that a robust ICT infrastructure has contributed to counteract some of the isolation measures, allowing economic systems to continue operating, at least partially. In a previous study, we demonstrated that broadband adoption was essential in building structural resiliency to face the economic disruption generated by the pandemic in the United States.⁹ In fact, a great deal of resilience is linked to the remote working capabilities enabled by a robust broadband infrastructure.¹⁰

The goal of this study is to analyze specifically the contribution of broadband, as part of a robust ICT

infrastructure, to remote working and its related effects, particularly quality of life and carbon emissions. The impact of broadband on remote working has been studied for some time, although, as expected, it has accelerated since the beginning of the pandemic. Therefore, this study becomes critical based on two reasons:

- Since the "new normal" of the post-pandemic world will include remote working as an important social feature, it is important to understand the role of broadband as an enabler to ensure that as many workers as possible can benefit from the technology.
- Since the massive migration to telecommuting is expected to have generated additional contributions to an improvement in quality of life and a reduction in carbon emissions, broadband is a key lever for attaining these effects.

The purpose of this study is to estimate the magnitude of these effects in the United States. The estimation is based on a model linking broadband adoption and remote working. This effect is expected, in turn, to yield savings in travel time, which would flow into an improvement of quality of life, and reductions in carbon emissions (see Figure 1).



⁷ Source: 2017 and 2018 American Time Use Survey – Leave Module, U.S. Bureau of Labor Statistics

⁸ See Nielsen (2020)

⁹ See Katz and Jung (2022)

¹⁰ Other enabling effects include the virtualization of supply chain processes, massification of e-commerce, and even the support for socialization resulting from videoconferencing and social networks.

Figure 1. Causal chain to assess the contribution of broadband to remote working and related effects



Source: Telecom Advisory Services

The analysis will be conducted for two different periods: before the pandemic, and during the pandemic, factoring in the latter case the impact of COVID-19 social restrictions on work routines. The analysis before the pandemic is particularly relevant since it might shed some light on the effects of broadband on remote working in the absence of mobility restrictions, and because it serves as a benchmark that gives a sense of how much things have changed after COVID. The study of the impact of these variables during the pandemic will add a deeper understanding of how the technology can help buttress social and economic resilience in the eventuality of future disruptions and also provide a sense of what the "new normal" might be. The next section of this study reviews the research literature on the issue of the effects generated by remote working. Section 3 presents an exploratory analysis on remote working statistics before and during the pandemic in the United States. Section 4 presents the theoretical underpinnings of an empirical model to study the link between remote working, quality of life and environmental conditions. Section 5 describes the methodology and dataset selected for the empirical analysis. Section 6 presents the results of the empirical estimations before and after the pandemic. Based on the evidence presented in the previous section, section 7 draws conclusions, derives some policy implications, and outlines potential future research directions.



2. RESEARCH LITERATURE REVIEW

The development of remote working is inseparably linked to the diffusion of fast internet networks. The accelerated rate of urbanization that took place in the twentieth century was the defining factor driving an increase of commuting to work. From 1830 to 1930, the share of the population living in an urban area increased six-fold to 60 percent. With the gradual shift from agriculture to manufacturing and later to services, cities became the centers of economic activity. As reported by Boustan et al. (2013), by 1920, 69 percent of manufacturing employment occurred in a metropolitan setting.

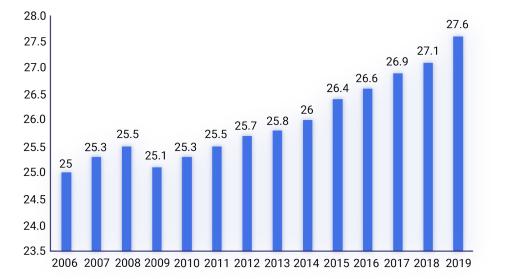
With the shift in economic activity to urban centers, population deployment progressed in parallel, although following specific patterns. Over the twentieth century, the share of households in central metropolitan areas declined substantially. As reported by Boustan and Shertzer (2013), over the second half of the twentieth century, the share of metropolitan residents living in a central city fell from 58 percent to 36 percent. Researchers do not agree on the driving factors of the spatial relocation to the suburbs but point to a series of variables ranging from transportation improvements reducing the time cost of travel (Rhode and Strumpf (2003), to an increase in demand for land and housing and, finally, an increase in real incomes (Margo, 1992).

Household migration to the suburbs did not evolve in parallel with employment decentralization. While, as reported by Glaser and Kahn (2001), most jobs were located in the suburbs, information-intense sectors, the dominant driver of occupational growth in the US (Porat, 1975), have not decentralized. Therefore, metropolitan areas with heavy information-based industries (New York, San Francisco, Philadelphia, Chicago, and Washington DC) indicate that firm relocation did not follow industry redeployment: offices and certain manufacturing establishments remained located in metropolitan areas while workers migrated to the peripheries. This resulted in an increase in commuting times, as tracked by the American Community Survey (see Graphic 1).



Graphic 1. Average Travel Time to Work in the United States: 2006-2019 (in minutes)

(Workers 16 years and above who did not work from home)



Source: Burd et al. (2021)

According to the Census Bureau, the duration of the average one-way commute in the United States in 2019 increased to 27.6 minutes, while 9.8 percent of commuters reported daily one-way commutes of at least 1 hour.¹¹

In this context, research literature has emerged analyzing the potential benefits that remote work can provide. The advantages identified range from increasing employee happiness, productivity, and pollution reduction derived from reduced travel to work.¹²

2.1 Remote work and well-being

Remote working has been associated to enhanced well-being, although the dependent variable, which is intrinsically subjective, has been measured in different ways. For example, Kazekami (2020) found that remote work increases life satisfaction (a variable that in turn improves labor productivity).¹³ He also determined remote work to increase happiness and work satisfaction.



¹¹ Burd et al (2021)

¹² As detailed below, the variable "happiness" is a subjective metric defined differently in each study.

^{13 &}quot;Life satisfaction" is measured in a survey where individuals filled up a value for (1) Happiness: scale where very happy = 1, unhappy = 5; (2) Life satisfaction: scale where very satisfied = 1, unsatisfied = 5; and (3) Work Satisfaction: scale where very satisfied = 1, unsatisfied = 5.

Other authors have also analyzed the link between remote working and well-being. Anderson et al (2015) analyzed a sample of 102 employees from a large US government agency, employing within-person approach to test the relationship between remote working and affective wellbeing.¹⁴ Their results showed that employees experience more job-related positive affective well-being and less job-related negative affective well-being on days when they were working remotely compared to days they were working in the office.

Similarly, Gimenez-Nadal et al (2018) analyzed time allocation decisions of remote workers, comparing them with their commuter counterparts. The authors relied on the American Time Use Survey for the years 2003 to 2015, which leads to conclude that a higher percentage of teleworkers than commuters are engaged in leisure and non-market work at the central hours of the day. They found that male telecommuters were happier in their job tasks than commuters, which may lead to a higher productivity of the former and explains why teleworkers are able to work fewer hours per day.^{15, 16}

2.2 Remote work and productivity

In a recent paper, Pabilonia and Vernon (2022) analyzed the wage differentials for remote workers and compared how workers allocate their time when they work from home rather than the office. The authors used the 2017–2018 American Time Use Survey Leave and Job Flexibilities Module. Their results suggest that some remote workers earn a wage premium, although this varies by gender, parental status, and remote working intensity. The wage premium can be associated with increased productivity, according to the authors. They argue that working from home makes people happier and allows them more concentration as they are now not being interrupted by coworkers. Time reassignment for sleeping and relaxing leisure activities can also be important for workers to be happier and more productive.

Similarly, Kazekami (2020) investigated the effects of remote working on labor productivity in Japan. The author found that appropriate remote working hours can increase labor productivity; however, as expected, when remote work hours are too long, it decreases productivity.



¹⁴ Participants in this survey were asked to complete 10 items from a five-point scale. Five items measured Positive Affective Well Being (at ease, grateful, enthusiastic, happy, and proud) and five items measured Negative Affective Well Being (bored, frustrated, angry, anxious, and fatigued). The items read "My job made me feel...." The response scale ranged from strongly disagree (1) to strongly agree (5).

¹⁵ Surveyed participants answered (i) Minutes of leisure, (2) Life satisfaction indicates how respondents personally feel about where they stand in the present regarding the best/worst possible life for them and takes values from 0 ("worst possible life") to 10 ("best possible life"). Happiness, Sadness, Stress, Pain, and Tiredness measure how much happiness/sadness/stress/pain/tiredness respondents felt during the correspondent activity and take values from 0 ("not at all") to 6 ("very").

¹⁶ The study does report significant difference in this regard for female teleworkers and commuters.

2.3 Remote work and mobility

Other authors focused on the potential effects of remote working in reducing mobility. In that respect, the literature of reference is diverse and still inconclusive. The first wave of studies dates from the late nineties, when remote workers used to carry out their duties in telecenters, rather than at home. One of the first contributions was that of Henderson et al (1996), who analyzed commuting distance and emissions reduction by cutting down on need for daily commutes. The authors concluded that on non-remote working days, telecenter-based workers have 91% higher total annual vehicle miles traveled, suggesting that they live further from work than regular commuters. On the opposite end, Koenig et al (1996) found that remote workers had an overall daily travel of 10.2 miles on remote working days compared with 32.7 miles for non-remote workers. In addition, Balepur et al (1998) studied the vehicle distance and person distance avoided in working at a telecenter instead of travelling to work. They concluded that a telecenter commuting frequency of one day a week led total weekly person travel to be reduced by 19%, compared with regular commuters who travel to the office every day. Likewise, Choo et al (2005) studied vehicle distance travel avoided by working from home. They concluded that remote working once a week by 12% of the workforce has reduced total annual vehicle miles travelled in the United States by 0.8%.

More recently, Asgari and Jin (2018) analyzed, using survey data from the New York metropolitan area, whether flexible

commutes (such as part-time remote working) led to reduced congestion. They concluded that remote working during peak travel times could potentially reduce travel and congestion at those times by 20%.

In addition, Chakrabarti (2018) analyzed the annual miles driven per person in the United States, finding that frequent remote workers travelled more by car each year than nonremote workers. They explain these results as longer commutes of remote workers on days they travel to work more than offset savings made on remote working days.

2.4 Remote work and carbon emissions

Other studies focused specifically in estimating the impact of remote working on carbon emissions. A relevant review of studies is provided by Hook et al (2020), who explored the extent to which remote working reduces the need to travel to work and the consequent impact on economywide energy consumption. They reviewed the results of 39 empirical studies, with most of them suggesting that remote working reduces energy use, although eight surveyed papers suggest that remote working increases or has a neutral impact on energy use. An increase of energy consumption may arise from non-work travel and home energy use that can potentially outweigh the gains from reduced work travel. The main source of savings is naturally the reduced distance traveled to work, although lower office energy consumption may also play a role. The authors also mention that those studies that appear to be more rigorous generally find smaller savings.



That being said, most researchers found remote working to reduce emissions. That is the case of Fuhr and Pociask (2011), who examined the link between greenhouse gas emissions in the United States with the widespread availability of broadband services and the expansion of telecommuting. They found that telecommuting can reduce greenhouse gas emissions over a period of 10 years by approximately 588.2 tons of which 247.7 million tons is due to less driving, 28.1 million tons is due to reduced office construction, and 312.4 million tons because of less energy usage by businesses. Similarly, Atkyns et al (2002) analyzed the distance travelling avoided by working from home in the United States. They found that having one fifth of AT&T employees working one day a week from home could reduce vehicle distance travelled by 110,000 miles, reduce gasoline use by 5.1 million gallons, and reduce carbon emissions by 48,450 tons. In turn, Kitou and Horvath (2003) analyzed emissions reduced through remote working. They found that remote working between one, three and five times a week decreases CO2 emissions by between 2%-80%. As a counterpoint, Zhu and Mason (2014) report that remote workers have more vehicle miles traveled than non-remote workers, estimating that a telecommuter on average travels 38 vehicle miles more on a daily basis in 2001 and 45 vehicle miles more in 2009 compared with a non-telecommuter. The reason that explains this pattern is that telecommuters have more free time, which can be used to pursue other activities that require driving.

Finally, Belzunegui-Eraso and Erro-Garcés (2020) analyzed the implementation of remote working as a security practice to face the crisis resulting from the COVID-19 pandemic. The study argued about environmental, safety, and legal factors that explain remote work. They reported that the pandemic demonstrated how remote working has been used by companies to ensure their employees' safety and to provide continuity to economic activity.

To sum up, the research literature can be summarized as follows:

- Remote working naturally reduces commuting time, with the consequent increase in quality of life, productivity, and overall well-being. As expected, most of the prior empirical evidence was generated before the pandemic, which makes it relevant to understand how these effects materialize under COVID-19.
- Most evidence suggests that remote working can have positive environmental effects, although some studies point in the opposite direction. This may be related to the following compensatory effects: remote working naturally reduces work-related transport; however, with more time available, telecommuters may increase non-working travel. If that is the case, remote working can result in two opposite effects over emissions, with the net result being inconclusive. Disentangling this opposite-effects and estimating the net outcomes in terms of emissions for the case of the United States is another focus and contribution of this study.



3. EXPLORATORY DATA ANALYSIS

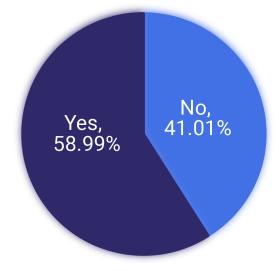
In this section we explore the evidence of remote working in the United States. First, we explore the main indicators before COVID-19. Next, we analyze the main changes occurred since the arrival of the pandemic.

3.1 Trends of remote working before the pandemic

Already before the COVID-19 pandemic, partly as a response to the tension between job deployment and

household relocation, remote working was, as mentioned above, already a common practice in the United States. According to the American Time Use Survey - Leave Module conducted by the Bureau of Labor Statistics during 2017 and 2018, most of the individuals' surveyed declared to work at home "some days" (Graphic 2). After data-cleaning, from the total 2,858 surveyed workers 1,686 declare to work at home "some days".

Graphic 2. Working at home at least "some days" (2017-18)

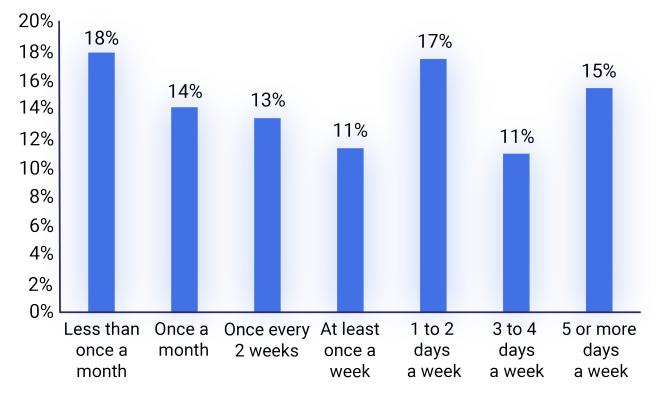


Source: 2017 and 2018 American Time Use Survey - Leave Module, U.S. Bureau of Labor Statistics



However, according to the same survey, "intensive" remote workers were only a minority. In fact, most of those that declared to work at home "some days" should not be considered frequent remote workers. Only 45% of those did so with a frequency of at most, once every two weeks. On the other hand, only 15% of those that declared to work at home "some days", did so every day. Graphic 3 presents the frequency detail for those that declared to remote work before the pandemic.

Graphic 3. Frequency of working at home for those who declared occasional remote working before the pandemic (2017-2018)

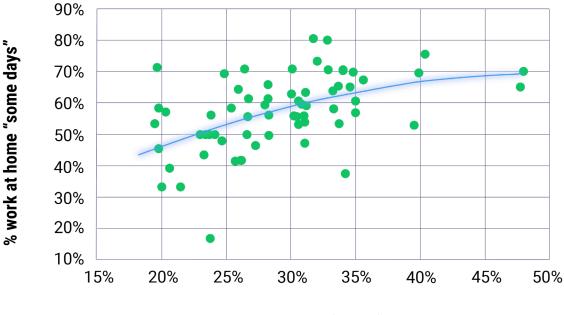


Source: 2017 and 2018 American Time Use Survey - Leave Module, U.S. Bureau of Labor Statistics



Naturally, the degree of remote working before the pandemic was associated to the sector composition of each state. To illustrate this point, we plot in Graphic 4 the stateaverage percentage of those declaring working at home at least "some days" next to the share of GDP of each state in Service Industries that are more likely to have the ability to be performed remotely. ¹⁷





Services (%GDP)

Source: 2017 and 2018 American Time Use Survey - Leave Module, U.S. Bureau of Labor Statistics and Bureau of Economic; Telecom Advisory Services analysis



¹⁷ To account for services, we considered education, information, professional and business services, financial activities, and wholesale trade, discarding other services that are more prone to be done face-to-face (e.g.: health or accommodation services).

Graphic 4 clearly indicates a positive relationship between geographies with larger percentages of output in service sectors where work can be performed remotely and the propensity of the population to work remotely.

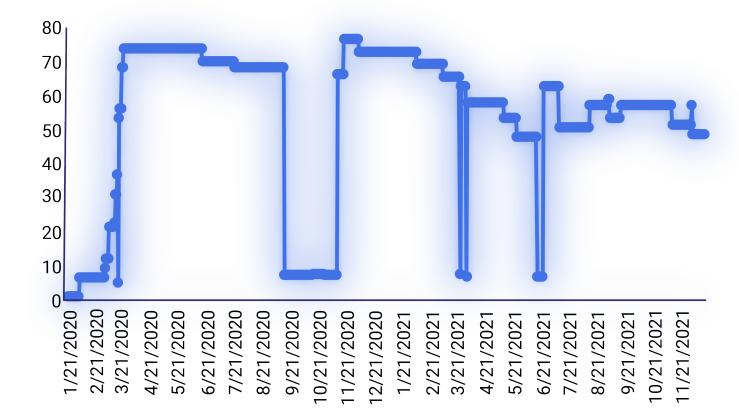
In short, the pre-pandemic indicators point to a gradual increase in the practice of remote working, although with low intensity and associated primarily to sectoral characteristics and to the process of household migration to the suburbs.

3.2 Changes after the start of COVID-19

Once the pandemic began, governments enacted strict social distancing measures, including severe restrictions that led to abrupt falls in travelling, tourism, and many physical work interactions. For the United States, the Stringency Index published by Our World in Data, which measures the level of closure of economic activity in response to the pandemic, including school and office closures, travel bans, among other measures, shows that the severity of restrictions during 2020 was concentrated in the period from March to September of that year, while another period of strong restrictions was imposed from November 2020 until November of 2021.¹⁸ Graphic 5 shows the daily evolution of the Stringency Index.



¹⁸ The COVID-19 Stringency Index is a composite index based on six measures adopted by nations facing the pandemic, including school closures, workplace closures, travel bans, among others. Each indicator is measured between 0-100. The data source comes from the Oxford COVID-19 Government Response Tracker. Blavatnik School of Government, University of Oxford.



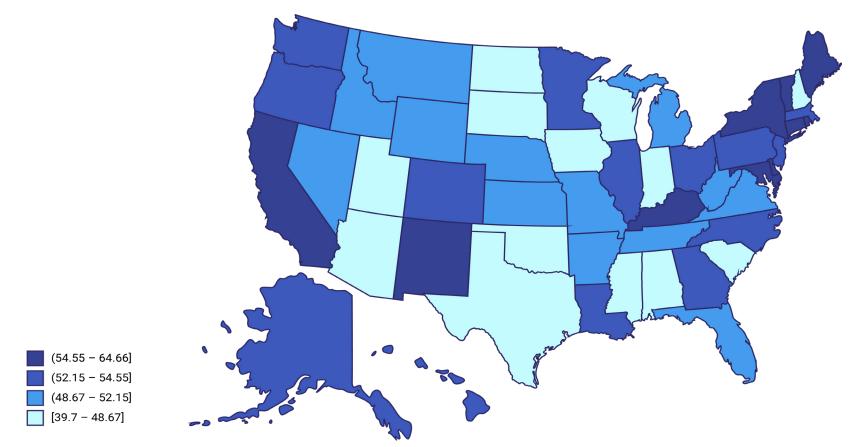
Graphic 5. United States: Stringency Index

Source: Our World in Data

The average national Stringency Index masks important regional differences. Figure 2 displays the index by state, indicating that the more severe restrictions were imposed by the northeastern states, as well as Maryland, Delaware, Kentucky, New Mexico, and California.





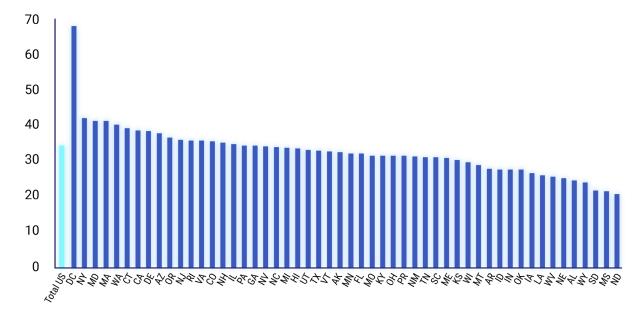


Source: Our World in Data

On average, 35 percent of surveyed firms by the US Bureau of Labor Statistics for the Business Response to the Coronavirus Pandemic survey declare to have increased remote working since the beginning of COVID-19. However, considering the cross-state variation in restrictions imposed, it is not surprising to find that there are some potentially important differences by state (Graphic 6).







Source: 2021 U.S. Business Response to the Coronavirus Pandemic, U.S. Bureau of Labor Statistics

The District of Columbia (DC) is the region with the largest remote working, with 68 percent of establishments having declared to increase this practice since the start of the pandemic. After the District of Columbia, the states attain much lower values, although New York, Maryland, Massachusetts, and Washington still depict roughly 40 percent of establishments reported increased amounts of teleworking. North Dakota is the state in which the lowest share of establishments declared to have increased remote working since the start of the pandemic: only 21 percent. After more than a year since the start of the pandemic (mid 2021), remote working was still very much extended in the US, with 10 percent of establishments declaring that all of their employees worked remotely all the time, while 30 percent declared that some of their employees were still working remote. Again, differences arise by state, highlighting again the case of DC, where nearly 76 percent of establishments declared to continue practicing at least some remote working (Table 1).



Table 1. Establishment reaction to COVID-19 (July-Sept 2021)

(% of establishments)

State	All of their employees working remote all of the time	Some of their employees working remote	All of their employees working remote rarely or never
Total US, private sector	10.3%	29.8%	60.1%
Alabama	7.4%	21.3%	71.5%
Alaska	6.2%	30.5%	63.3%
Arizona	15.1%	34.7%	50.2%
Arkansas	5.7%	24.7%	69.5%
California	14%	32.8%	53.3%
Colorado	14.2%	32.2%	53.8%
Connecticut	12.2%	30.2%	58.7%
Delaware	11.7%	32.3%	56%
District of Columbia	29.1%	46.5%	24.9%
Florida	9.8%	28.4%	61.8%
Georgia	9.9%	28.6%	61.5%
Hawaii	7.4%	30.7%	61.9%
Idaho	10.9%	25.7%	63.5%
Illinois	12.7%	28.9%	58.4%
Indiana	8.1%	27.4%	64.5%



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Louisiana4.7%23.7%71.7%Maine7.8%27.3%65%Maryland13.9%32.9%53.2%Massachusetts11.5%36%52.5%Michigan9.6%28.4%62.1%Minnesota9.6%29.9%60.8%Mississippi31%21%76%Missouri9.3%26.1%65.3%Nontana8.9%26.1%57.3%Nev Hampshire1.1%31%57.5%New Hampshire21.%31%57.5%New Hampshire21.%31.2%60.6%	Kansas	10.5%	25%	64.5%
Maine7.8%27.3%65%Maryland13.9%32.9%53.2%Massachusetts11.5%36%52.5%Michigan9.6%28.4%62.1%Minnesota9.6%29.9%60.8%Mississippi3.1%21%76%Missouri3.3%21%55%Nethana6.2%21.3%65%Nethana1.5%31.8%57%New Hampshire21%31%57.5%New Hampshire8.3%31.2%6.0%	Kentucky	9%	28.4%	62.6%
Maryland13.9%32.9%53.2%Massachusetts1.5%36%52.5%Michigan9.6%28.4%62.1%Minnesota9.6%29.9%60.8%Mississippi3.1%21%60.8%Missouri7.3%27.8%65%Nontana8.9%26.1%65.3%Nebraska6.2%21.2%71.6%New Hampshire1.5%31.8%57%New Jersey3.4%31.2%60.6%	Louisiana	4.7%	23.7%	71.7%
Massachusetts1.5%36%52.5%Michigan9.6%28.4%62.1%Minnesota9.6%29.9%60.8%Mississippi3.1%21%76%Missouri7.3%27.8%65%Montana8.9%26.1%65.3%Nebraska6.2%31.8%57%New Hampshire12.1%31%57.5%New Jersey8.3%31.2%60.6%	Maine	7.8%	27.3%	65%
Michigan9.6%28.4%62.1%Minesota9.6%29.9%6.0.8%Mississippi3.1%21%7.6%Missouri7.3%27.8%65.3%Montana8.9%26.1%65.3%Nevada1.5%31.8%57%New Hampshire1.21%31%57.5%New Jersey8.3%31.2%6.0%	Maryland	13.9%	32.9%	53.2%
Minesota9.6%29.9%60.8%Mississippi3.1%21%76%Missouri7.3%27.8%65%Montana8.9%26.1%65.3%Nebraska6.2%22.2%71.6%Nevada1.5%31.8%57%New Jersey8.3%31.2%6.6%	Massachusetts	11.5%	36%	52.5%
Missispi3.%21%76%Missouri7.3%27.8%65%Montana8.9%26.1%65.3%Nebraska6.2%22.2%71.6%New dat1.5%31.8%57%New Jersey8.3%31.2%60.6%	Michigan	9.6%	28.4%	62.1%
Missouri7.3%27.8%65%Montana8.9%26.1%65.3%Nebraska6.2%22.2%71.6%Nevada11.5%31.8%57%New Hampshire12.1%31%57.5%New Jersey8.3%31.2%60.6%	Minnesota	9.6%	29.9%	60.8%
Montana8.9%26.1%65.3%Nebraska6.2%22.2%71.6%Nevada11.5%31.8%57%New Hampshire12.1%31%57.5%New Jersey8.3%31.2%60.6%	Mississippi	3.1%	21%	76%
Nebraska 6.2% 22.2% 71.6% Nevada 11.5% 31.8% 57% New Hampshire 12.1% 31% 57.5% New Jersey 8.3% 31.2% 60.6%	Missouri	7.3%	27.8%	65%
Nevada 11.5% 31.8% 57% New Hampshire 12.1% 31% 57.5% New Jersey 8.3% 31.2% 60.6%	Montana	8.9%	26.1%	65.3%
New Hampshire 12.1% 31% 57.5% New Jersey 8.3% 31.2% 60.6%	Nebraska	6.2%	22.2%	71.6%
New Jersey 8.3% 31.2% 60.6%	Nevada	11.5%	31.8%	57%
	New Hampshire	12.1%	31%	57.5%
New Mexico 8.8% 27.6% 63.8%	New Jersey	8.3%	31.2%	60.6%
	New Mexico	8.8%	27.6%	63.8%
New York 7.3% 35% 57.8%	New York	7.3%	35%	57.8%



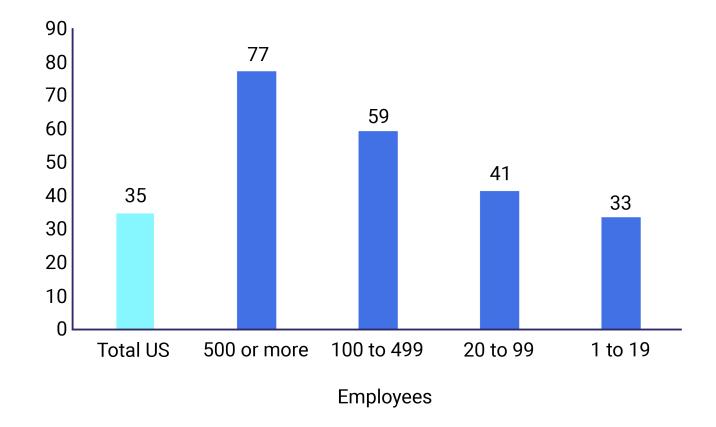
North Carolina	14.4%	27.6%	58.1%
North Dakota	4.1%	20.6%	75.3%
Ohio	7.4%	28.6%	64.2%
Oklahoma	8%	22.1%	70%
Oregon	12.3%	32.5%	55.3%
Pennsylvania	8.7%	27.4%	64.1%
Rhode Island	14%	28.6%	57.4%
South Carolina	12.3%	27.5%	60.3%
South Dakota	7.6%	20.7%	72.2%
Tennessee	8.6%	28.4%	63.1%
Texas	8%	29.9%	62.5%
Utah	10.3%	31.6%	58.1%
Vermont	9%	29.9%	61.2%
Virginia	9.4%	34%	56.6%
Washington	14.7%	32%	53.7%
West Virginia	6.7%	22.1%	71.1%
Wisconsin	8.7%	27.3%	64.1%
Wyoming	8.3%	23.7%	68.1%

Source: 2021 U.S. Business Response to the Coronavirus Pandemic, U.S. Bureau of Labor Statistics



Another important pattern to explain differences is related by the size of the establishments: larger establishments are more likely to have increased remote working during the pandemic (Graphic 7).

Graphic 7. Establishments that increased remote work since the start of the pandemic, by size (% of establishments)



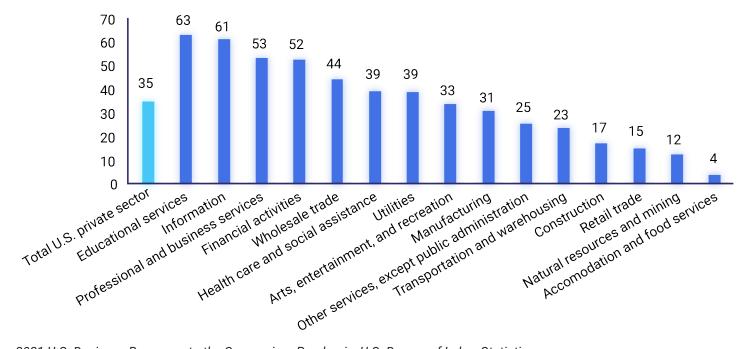
Source: 2021 U.S. Business Response to the Coronavirus Pandemic, U.S. Bureau of Labor Statistics



While the American average is 35 percent of establishments having increased remote working during COVID-19, that figure increases to 77 percent for establishments with 500 employees or more, and 59 percent for those with 100 to 499 workers.

In turn, as expected, there are relevant differences by industrial sector. Confirming the evidence above, those more likely to remote work are employees in services related to education, information, professional, business, and financial; in all those cases more than the half of the firms have declared to increase remote working. Naturally, it is very difficult in other sectors to continue operating without physical presence. Such is the case of essential services (hospitals, safety, and the like), natural resources and mining or accommodation services (Graphic 8).





Source: 2021 U.S. Business Response to the Coronavirus Pandemic, U.S. Bureau of Labor Statistics



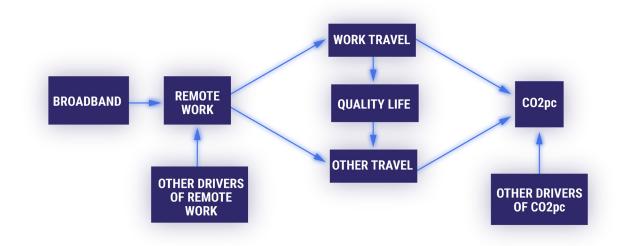
Considering this important expansion of remote working, it is worth studying its effects in terms of wellbeing and environmental impact. We will conduct the analysis before and after the pandemic to understand the contribution of broadband to remote working before and during the emergency period, and to find out which lessons can be gained for the future.

4. THEORETICAL MODEL TO EVALUATE THE IMPACT OF BROADBAND INTERNET ON REMOTE WORKING AND RELATED ENVIORNMENTAL EFFECTS

4.1 Theoretical framework

Based on the effects identified by the previous research literature, we propose a baseline model as depicted in Figure 3, to be estimated at the individual level.

Figure 3. Model to estimate the impact of Broadband on remote working and associated effects



Source: Telecom Advisory Services



The terms in Figure 3 are defined as follows:

- BROADBAND refers to the degree of access and quality of broadband in the county where the individual lives
- REMOTE WORK refers to individuals working at home in the county
- WORK TRAVEL refers to the time spent travelling for work
- OTHER TRAVEL refers to the time spent travelling for other purposes beyond work
- QUALITY LIFE refers to the time spent with family members
- CO2pc refers to emissions generated per person in the location where the individual lives

The concepts underlying Figure 3 are as follows:

- Better access and quality of BROADBAND can help people to engage in REMOTE WORK. Naturally, an internet connection can be assumed as a necessary condition, but this BROADBAND construct measures adoption by quality level, an important variable to consider as not every connection is suitable to successfully support videoconferencing and other data-intensive applications. This has been argued, for instance, by Belzunegui-Eraso and Erro-Garcés (2020), referring to how internet and device evolution offers new possibilities for remote working.
- In addition, REMOTE WORK is expected to have an impact on the time individuals spent travelling. Naturally, working at home is expected to reduce WORK TRAVEL. This has been analyzed by the research by Henderson et al (1996), Balepur et al (1998), Atkyns et al (2002), Choo et al (2005), Kitou and Horvath

(2008), Fuhr and Pociask (2011), Zhu and Mason (2014), Asgari and Jin (2018), Hook et al (2020), among others. However, REMOTE WORK may also generate nonwork-related travel (OTHER TRAVEL), as people now have more free time for leisure or to conduct other activities. The link between REMOTE WORK and nonwork-related travelling has been addressed in Zhu and Mason (2014), Chakrabarti (2018) and Hook et al (2020).

- There is a potential link between remote working, and reduced time travelling, with QUALITY LIFE, as people now have more time to spend with the family. This has been argued, for instance, in Pabilonia and Vernon (2022). In addition, more family-time may be related to more travelling for leisure in normal conditions, although this may not have been the case during the pandemic due to mobility restrictions. The link between family related trips and travelling has been addressed by Zhu and Mason (2014).
- Finally, all work and non-work travelling should be positively related with emissions. The link between travelling and emissions has been addressed by Henderson et al (1996), Atkyns et al (2002), Kitou and Horvath (2008), Fuhr and Pociask (2011), Zhu and Mason (2014), and Hook et al (2020). Therefore, we expect REMOTE WORK to indirectly generate opposite effects on emissions: reduced WORK TRAVEL is expected to decrease CO2pc, while on the other hand, increased OTHER TRAVEL should contribute to larger CO2pc. Again, it is important to remind that during the pandemic years this relation may not have been clear, at least in comparison to the pre-COVID period.



4.2 Hypotheses

According to the framework presented above, we sketch out a set of hypotheses:

- H1: There is a direct and positive impact of <u>BROADBAND</u> on <u>REMOTE WORK</u>.
- H2a: There is a direct and negative effect from REMOTE WORK to WORK TRAVEL.
- H2b: There is a direct and positive effect from <u>REMOTE</u> WORK to <u>OTHER TRAVEL</u>.
- H3a: There is a direct and negative effect of <u>WORK</u> <u>TRAVEL</u> on <u>QUALITY LIFE</u>.
- H3b: There is a direct and positive effect of <u>QUALITY</u> LIFE on <u>OTHER TRAVEL</u>.
- H4a: There is a direct and positive effect of <u>WORK</u> TRAVEL on <u>CO2pc</u>

5. METHODOLOGY AND DATASET

5.1 Methodological approach

We use structural equation modelling (SEM) to estimate the effects of remote working on CO2 emissions. SEM models are suitable for validating hypothesis with empirical data, involving multiple linkages and mediating relations, conforming a group of direct and indirect effects among two or more variables or constructs. The hypotheses can then be tested statistically in a simultaneous analysis of the entire system of variables to determine if it is consistent with the data (Pearl, 2012). Among the advantages of SEM,

- H4b: There is a direct and positive effect of <u>OTHER</u> <u>TRAVEL</u> on <u>CO2pc</u>
- H5: The overall effect of <u>BROADBAND</u> and <u>REMOTE</u> WORK on <u>QUALITY LIFE</u> is positive
- H6: The overall effect of <u>BROADBAND</u> and <u>REMOTE</u> <u>WORK</u> on <u>CO2pc</u> is negative

As reviewed in the research literature, the net effect on emissions (H6) remains the main unknown because work and other travel may partially cancel out. In that respect, one of the main contributions of this paper is to find out which effect prevails over the other (H2a*H4a vs. H2b*H4b+H2a*H3a*H3b*H4b), if any. These hypotheses will be tested empirically with a dataset from US individuals surveyed before and during the pandemic.

all these measurements and tests are done simultaneously in one statistical estimation procedure, where the model errors are calculated using all information available from the model. As a result, the estimated errors are more accurate than those resulting from calculating each part of the model separately. To estimate and test our conceptual model we will use the two-step method checking for the measurement and the structural model, additionally computing indirect and total effects. The constructs to be built must follow certain properties. For instance, convergent validity tests that items conforming



constructs are effectively related as assumed. In addition, discriminant validity must be verified, as this test measures whether constructs that theoretically should not be related to each other are, in fact, unrelated.

The SEM model will be estimated through the Maximum Likelihood approach, that offers asymptotically efficient results under the assumption of multivariate normality.

5.2 Sample and survey administration

The sample used in this study has been extracted from the American Time Use Survey (ATUS) sponsored by the Bureau of Labor Statistics and conducted by the US Census Bureau. This dataset has already been used to analyze the effects of remote working in several research papers, such as Pabilonia and Vernon (2022), Gimenez-Nadal et al (2018) and Song and Gao (2020), to name a few. The survey measures the amount of time people spend conducting various activities, such as work, childcare, housework, travelling, and socializing. Households that have completed their final (8th) month of the Current Population Survey are eligible for the ATUS. Among those, households are selected based on a range of demographic characteristics. One person aged 15 or over is randomly chosen from each household to answer the questions. Respondents are distributed across 279 counties in 40 states (see Appendix for full detail).

The main part of the ATUS interview is used to collect a detailed account of the respondent's activities, starting at 4 a.m. the previous day and ending at 4 a.m. on the interview day. For each activity, the interviewer asks how

long the activity lasted. This is essential information for our analysis, since it is based on how much time everyone spends travelling or with family. Considering the purpose of this work, we excluded from the sample those individuals not currently employed, and those who were surveyed about their activities over weekends. We also excluded those observations where there was not a countylocation identified as the living place, as this information is essential in the context of the model because broadband and emission variables are collected on a county-level.

To perform the estimate before the start of the pandemic, we relied on the microdata for the 2017 and 2018 surveys. The reason to consider those years, and not 2019 instead, is that the ATUS Leave Module, containing information related to working at home, among other job flexibilities and work schedules was only conducted during 2017 and 2018. To estimate the model in the context of the pandemic, we considered the 2020 survey that specifically introduced questions of remote working because of the pandemic.

The ATUS survey provides data for the REMOTE WORK, WORK TRAVEL, OTHER TRAVEL and QUALITY LIFE indicators. Other data sources are also used: Federal Communications Commission (FCC) for Broadband penetration at county-level, National Renewable Energy Laboratory for emissions by county, and Bureau of Economic Analysis (BEA) for economic county-level control variables.



5.3 Measures

Two constructs were built from observed data.

The BROADBAND construct intends to be a proxy measure of the level of broadband access for every individual considered in the sample. It was measured with four items, each of them represented as an ordinal scale according to the number of connections per 1,000 Housing Units at the county where the respondent lives, for the following downstream speed tiers: i) at least 200 Kbps; ii) at least 10 Mbps; iii) at least 25 Mbps; and iv) at least 100 Mbps. Data for the 2017-18 sample is from those specific years, while for the 2020 sample we had to rely on 2019 data as this is, to date, the latest information provided by the FCC. The scale reliability was good (Cronbach's alpha is 0.863 for the 2017-18 sample, and 0.874 for the 2020 sample), much larger than the minimum thresholds required according to Hair et al (2006). This BROADBAND construct gives a measure of expansion and quality of broadband connections where each individual lives.

The QUALITY LIFE construct was measured with two items: "Total time respondents spent with family members" and "Total time respondents spent with household family members", in both cases measured in minutes. The scale reliability was also good (Cronbach's alpha = 0.703 for the 2017-18 sample, and 0.967 for 2020). REMOTE WORK is a dummy variable taking values 1 or 0, depending on whether the respondent worked from home. However, the question in the survey is not exactly the same for the 2017-18 and 2020 surveys. In the first case, the question is simply: "Are there days when you work only at home?", while during 2020, it was formulated as "At any time in the last 4 weeks, did you telework or work at home for pay because of the pandemic?".

WORK TRAVEL is defined as the quantity of minutes the respondent has spent in "travel related to working" or "travel related to work-related activities". OTHER TRAVEL is the sum of all minutes incurred to other travel purposes reviewed in the sample, including personal care, housework, household management and related activities, animal or family care, job search, education, grocery, financial services or banking, eating and drinking, socialization, leisure, sports, etc.

CO2pc emissions is defined as the average level of travelrelated emissions per person in the county where the individual lives. As the most recent data of county-level emissions, to the best of our knowledge, dates from 2016, we made some extrapolations of this data based on different sources available. The starting point is the on-road transportation (either Gasoline or Diesel) GHG emissions in metric tons CO2e for 2016, dataset developed by the National Renewable Energy Laboratory.¹⁹ However, as we need data for years 2017, 2018 and 2020, we had to make some extrapolations to extend county-level emission



¹⁹ https://data.openei.org/files/149/2016cityandcountyenergyprofiles.xlsb

data towards those years. First, we extrapolated the data to 2019 by using the growth rates of the transportation sector fossil CO2 emissions in the state where each county is located (data provided by the US Energy Information Administration up to 2019). Considering that we still needed to expand the series to 2020, the growth rate to project the data to 2020 was taken from the total CO2 emissions by state from the United States Environmental Protection Agency.

Finally, as shown in Figure 4, we also introduce control variables to account for other factors that may influence the decision to work remotely and on the emissions level. As drivers of remote work beyond the BROADBAND construct, we consider dummy variables accounting for the nature of the occupation, which are also provided in the ATUS survey, that should be easier to be conducted at home: professional or management activities, sales, or other service-related activities. Unfortunately, the data does not provide more detailed information within those groups in order to split the specific tasks between those occupations that are more prone to be conducted at home, and those that do not In the case of CO2 emissions, we control for county size (GDP, population, and area extension in square miles), development (GDP per capita), and sector composition for those industries more prone to generate pollution (share of GDP attributable to energy and mining, transportation, and manufacturing industry).

5.4 Descriptive statistics

Descriptive statistics, reliability estimates (Cronbach's alpha, in brackets) and correlations are presented in Table 2 (for the 2017-18 sample) and Table 3 (for the 2020 sample).²⁰



²⁰ As most of our data is cross-sectional and self-reported, we followed Conway and Lance (2010) to provide evidence of the construct discriminant validity in the results section. Our constructs (BROADBAND and QUALITY LIFE) are distinct both conceptually and in terms of their underlying factors, reducing any risk attributable to common method variance. Nonetheless, a Harman's one factor test (an un-rotated factor analysis on all items used in the model) was conducted to ensure this is the case. This analysis showed that the explained variance by the first factor was under half of the total variance; thus, common method bias is unlikely to be a risk.

Table 2. Descriptive statistics (2017-2018)

	Mean [Std. Dv.]		Correlations			
		BROADBAND	QUALITY LIFE	REMOTE WORK	WORK TRAVEL	OTHER TRAVEL
BROADBAND	0.000 [1.700]					
QUALITY LIFE	0.000 [1.387]	0.000				
REMOTE WORK	0.590 [0.491]	0.070**	0.032*			
WORK TRAVEL	12.504 [31.312]	0.034**	-0.260***	-0.027		
OTHER TRAVEL	57.727 [77.237]	0.012	0.191***	0.007	-0.127***	
CO2pc	5.292 [1.511]	-0.200***	0.057***	-0.033	-0.048***	-0.003

Notes: Correlation coefficients presented. *p<10%, **p<5%, ***p<1%.

Source: Telecom Advisory Services analysis



Table 3. Descriptive statistics (2020)

	Mean	Correlations				
	[Std. Dv.]	BROADBAND	QUALITY LIFE	REMOTE WORK	WORK TRAVEL	OTHER TRAVEL
BROADBAND	0.000 [1.708]					
QUALITY LIFE	0.000 [1.392]	0.048***				
REMOTE WORK	0.323 [0.468]	0.104***	0.079***			
WORK TRAVEL	8.539 [25.457]	0.015	-0.166***	-0.150***		
OTHER TRAVEL	41.486 [66.806]	-0.007	0.166***	-0.015	-0.098***	
CO2pc	4.931 [1.413]	-0.163***	0.035**	-0.093***	-0.007	0.004

Notes: Correlation coefficients presented. **p<5%, ***p<1%.

Source: Telecom Advisory Services analysis

Both constructs (BROADBAND and QUALITY LIFE) are not correlated, something required to ensure the desired properties of the model.²¹ BROADBAND and REMOTE WORK are positively correlated, as expected. Due to the factor analysis conducted, all constructs were built with a mean of zero. Correlation between BROADBAND and REMOTE WORK on QUALITY LIFE is insignificant or weak for 2017-18, and much stronger for the 2020 sample. As for the correlation between BROADBAND and emissions, it is negative and significant in both samples, while



²¹ This support to the hypothesis of the construct discriminant validity

correlation between REMOTE WORK and emissions is negative although only significant in 2020. This suggests, preliminarily, that the effect we want to analyze has possibly been stronger during the pandemic. WORK TRAVEL is naturally negatively correlated with REMOTE WORK, although both travel variables are not significantly correlated to emissions. This can be explained as there are several other factors that have an influence on emissions, reinforcing the necessity of considering further control variables to emissions to account for local-level heterogeneities.²²

6. ESTIMATION RESULTS AND DISCUSSION

6.1 Effects before the pandemic: Estimation for the 2017-18 sample

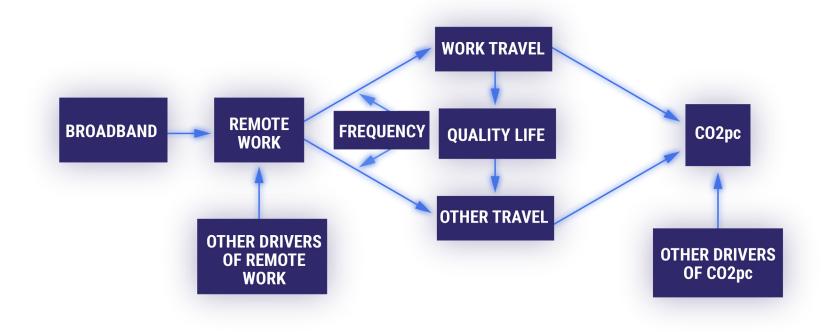
For the 2017-18 sample, we will first estimate the baseline model as depicted in Figure 3. As a second estimation, we will introduce remote working frequency as moderator between REMOTE WORK and TRAVEL TIME (Figure 4). This is important because most remote workers in 2017-18 were not intensive ones, as shown above in Graphic 2. In total, the 2017-18 dataset is composed by 4,367 observations, although nearly three quarters of the observations exhibit missing data.²³



²² Divergent validity was tested by comparing the squared root of the Average Variance Extracted (AVE) with respect to correlation indices of each construct with the other ones. BROADBAND presents a squared root of AVE equal to 0.786 and 0.802 (2017-18 and 2020 samples, respectively), while for QUALITY LIFE the value for both samples is 0.978. In both cases, these metrics are well above the largest correlation identified in Tables 5 and 6, providing support to the divergent validity.

²³ In section 6.3 we conduct a robustness check including only the observations with non-missings

Figure 4. Model to estimate the role of Broadband and remote working



Source: Telecom Advisory Services

The measurement model yielded an acceptable fit (NFI = 0.898; IFI = 0.900; CFI = 0.900; RMSEA =0.046).²⁴ The standardized regression weights (SRW) for the items of

each construct were all significant (p<0.05), all of them over 0.5. $^{\scriptscriptstyle 25}$

We ran the structural model as described in Figures 3 and 4. Table 4 presents the standardized direct effects.



²⁴ When adding frequency as moderator, these values turn into NFI=0.891; IFI=0.893; CFI=0.893; RMSEA=0.042

²⁵ This evidence brings support to the convergent validity of the scales used.

Table 4. Standardized Direct Effects for period 2017-2018

Path	2017-18 baseline	2017-18 with frequency
BROADBAND → REMOTE WORK	0.077**	0.080**
REMOTE WORK → WORK TRAVEL	-0.037**	-0.012
REMOTE WORK → OTHER TRAVEL	0.035**	0.026
WORK TRAVEL → QUALITY LIFE	-0.216***	-0.216***
QUALITY LIFE → OTHER TRAVEL	0.227***	0.227***
WORK TRAVEL → CO2pc	0.051***	0.051***
OTHER TRAVEL → CO2pc	0.094***	0.094***
REMOTE WORK*ALL DAYS → WORK TRAVEL		-0.112***
REMOTE WORK*ALL DAYS → OTHER TRAVEL		0.014
REMOTE WORK*3-4DAYS → WORK TRAVEL		-0.038**
REMOTE WORK*3-4DAYS → OTHER TRAVEL		-0.006

Notes: Standard errors estimated for significance analysis. **p<5%, ***p<1%.

Source: Telecom Advisory Services analysis

We start first with the analysis of the baseline model. Coefficients must be interpreted as the effect on the outcome variable after an increase of one standard deviation on the explanatory variable. Regarding the relationship among outcomes, as expected, we found a significant and positive effect of BROADBAND on REMOTE WORK. In addition, again as expected, there is a negative and significant effect of REMOTE WORK on WORK TRAVEL. Moreover, REMOTE WORK, through reduced WORK TRAVEL, has a positive impact on QUALITY LIFE, measured as time with the family. This is an important result in terms of wellbeing, in line with previous research of Gimenez-Nadal et



al (2018), Kazekami (2020) and Anderson et al (2015). Having more family time can be associated, in turn, to increased happiness and a better life balance. However, a positive effect of REMOTE WORK on OTHER TRAVEL emerges, something that materializes both directly and indirectly, through QUALITY LIFE. This confirms that, with more free time due to working at home, people tend to travel more for other purposes. In turn, both travel variables impact positively on CO2pc emissions, as expected.

In the right-column of Table 4 we introduce the moderating effects from remote working frequency, measure in terms of ALL DAYS and 3-4 DAYS. The purpose is to determine if there are significant differences in the impact generated on travel decisions from remote working frequency. For that purpose, we introduce as determinants of the travel variables two interactions of remote work: a dummy indicating if the respondent declares to work remotely all days (we call this, "intensive remote workers") and another one identifying those who work remote 3 or 4 days a week (following a hybrid working scheme). Interestingly, the REMOTE WORK variable is no longer significant to explain WORK TRAVEL, while those interactions with intensive and hybrid remote workers are negative and significant. This means that frequency is a relevant variable, something that is reinforced by comparing the coefficients and significance levels between both moderating variables. pointing to a much larger impact from every-day remote workers. On the other hand, the non-significance of the REMOTE WORK variable to explain WORK TRAVEL can be interpreted as the absence of significant effects from those

that work remote with a frequency lower than 3 days a week.

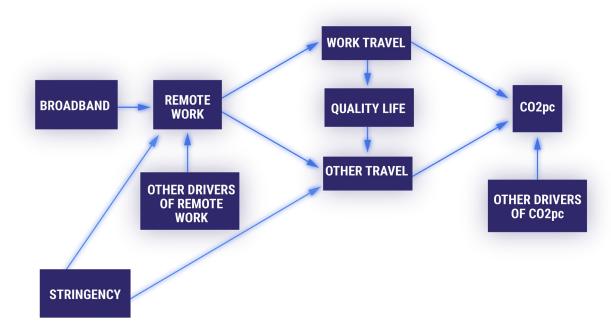
While these results are in line with most of the hypotheses presented above, they are still inconclusive regarding H6. BROADBAND and REMOTE WORK indirect positive and negative effects on emissions, since the net result appears to be negligible, although to confirm this we need to estimate the standard errors of the total effects, something that will be done in the robustness check (6.3) as it requires to have a reduced sample with non-missing values.

6.2 Effects during the pandemic: Estimation for the 2020 sample

For the 2020 sample, we will first estimate the baseline model as depicted in Figure 3. Unfortunately, we are not able to introduce frequency as a moderator in this case, as it was not asked in the 2020 survey. However, and considering the emergency faced in the pandemic, we can expect most of the 2020 remote workers to be intensive. As a second estimation, we will consider as control for remote work and travel decisions the lockdown policies carried out in the state where each respondent resides. As seen above in Figure 2, states differed in their lockdown policies. Therefore, this is expected to explain remote working and travel patterns across individuals living in different locations, and indirectly, on emissions. For this purpose, we introduce the state-level Stringency Index as a driver of business closure (thus impacting on REMOTE WORK) and directly on OTHER TRAVEL (Figure 5). For the 2020 sample, the dataset is composed of 3,790 observations.



Figure 5. Model to estimate the role of Broadband and remote working



Source: Telecom Advisory Services

The measurement model for the 2020 sample yielded a very good fit (NFI = 0.916; IFI = 0.918; CFI = 0.918; RMSEA =0.046).²⁶ The standardized regression weights (SRW) for the items of each construct were all significant (p<0.01), all of them over $0.6.^{27}$

Table 5 presents the standardized direct effects. Again, the effect of BROADBAND on REMOTE WORK, and from REMOTE WORK on WORK TRAVEL exhibits the expected sign and significance levels. This supports the key relevance of REMOTE WORK on OTHER TRAVEL during the pandemic. An important difference with respect to the estimate for



²⁶ When adding the Stringency Index in the model these values turn into NFI=0.904; IFI=0.906; CFI=0.906; RMSEA=0.047

²⁷ Supporting again the convergent validity of the scales.

2017-18 is that now there is not a significant effect from REMOTE WORK on other travel, possibly because most movements were restricted during the pandemic. However, REMOTE WORK still impacts positively OTHER TRAVEL, indirectly, through reduced WORK TRAVEL and improved QUALITY LIFE that in turn makes people to increase

Table 5. Standardized Direct Effects for 2020

leisure travelling. This suggests that, despite mobility restrictions, some travelling still took place. Finally, as in the previous sample, both travel variables affect emissions with a positive sign. This means that both positive and negative effects of BROADBAND and REMOTE WORK on emissions are still present in the 2020 sample.



Path	2020 baseline	2020 with Stringency
BROADBAND → REMOTE WORK	0.084***	0.074**
REMOTE WORK → WORK TRAVEL	-0.046***	-0.046***
REMOTE WORK → OTHER TRAVEL	0.001	0.002
WORK TRAVEL → QUALITY LIFE	-0.148***	-0.148***
QUALITY LIFE → OTHER TRAVEL	0.189***	0.189***
WORK TRAVEL → CO2pc	0.035***	0.035***
OTHER TRAVEL → CO2pc	0.073***	0.073***
STRINGENCY → REMOTE WORK		0.052***
STRINGENCY → OTHER TRAVEL		-0.004

Notes: Standard errors estimated for significance analysis. **p<5%, ***p<1%.

Source: Telecom Advisory Services analysis



When introducing the Stringency Index, the results are very similar as in the previous estimate. The only difference is that after adding the Stringency Index as a driver of REMOTE WORK, the direct effect of BROADBAND on this variable is slightly smaller in magnitude, although it remains positive and significant at 5 percent level. This means that the decision to REMOTE WORK during the pandemic is not only dependent on policy measures: it still depends critically on the expansion and quality of broadband.

6.3 Robustness check: bootstrapping

To check the robustness of the previous results, we reestimate them using bootstrapping 95 percent confidence intervals through the percentile method.²⁸ This was not possible before as we had missing observations. Therefore, considering that to perform bootstrap we need a complete dataset, we now eliminate incomplete observations, reducing our samples (now we will have 1,174 and 920 observations for 2017-18 and 2020, respectively).

We group all estimates with reduced sample and bootstrapped standard errors in Table 6. In general terms, the previous results stand, verifying their robustness. By relying on the reduced but complete sample we can estimate standard errors for the total effects (the sum of both direct and indirect effects). Total effects are reported at the bottom of Table 6.



²⁸ Bootstrapping is any test or metric that uses random sampling with replacement and falls under the broader class of resampling methods. Bootstrapping assigns measures of accuracy to sample estimates. This technique allows estimation of the sampling distribution of almost any statistic using random sampling methods. This process allows for the calculation of standard errors, confidence intervals, and hypothesis testing.

	Path	2017-18 baseline	2017-18 with frequency	2020 baseline	2020 with Stringency
Direct Effect	BROADBAND → REMOTE WORK	0.053**	0.053**	0.106***	0.104***
	REMOTE WORK → WORK TRAVEL	-0.052*	-0.005	-0.190***	-0.190***
	REMOTE WORK \rightarrow OTHER TRAVEL	0.023	0.027	-0.011	-0.011
	WORK TRAVEL \rightarrow QUALITY LIFE	-0.295***	-0.295***	-0.197***	-0.197***
	QUALITY LIFE \rightarrow OTHER TRAVEL	0.232***	0.231***	0.233***	0.233***
	WORK TRAVEL \rightarrow CO2pc	0.094***	0.095***	0.055**	0.055**
	OTHER TRAVEL → CO2pc	0.103***	0.103***	0.092**	0.092**
	REMOTE WORK*ALL DAYS \rightarrow WORK TRAVEL		-0.135***		
	REMOTE WORK*ALL DAYS \rightarrow OTHER TRAVEL		-0.004		
	REMOTE WORK*3-4DAYS → WORK TRAVEL		-0.057*		
	REMOTE WORK*3-4DAYS → OTHER TRAVEL		-0.015		
	STRINGENCY → REMOTE WORK				0.008
	STRINGENCY → OTHER TRAVEL				-0.003
Total Effect	BROADBAND → QUALITY LIFE	0.001*	0.000	0.004***	0.004***
	REMOTE WORK \rightarrow QUALITY LIFE	0.015*	0.002	0.037***	0.037***
	REMOTE WORK*ALL DAYS \rightarrow QUALITY LIFE		0.040***		

Table 6. Standardized Effects for reduced sample with bootstrapped standard errors



REMOTE WORK*3-4DAYS → QUALITY LIFE		0.017*		
BROADBAND → CO2pc	0.000	0.000	-0.001**	-0.001**
REMOTE WORK → CO2pc	-0.002	0.002	-0.011**	-0.011**
REMOTE WORK*ALL DAYS → CO2pc		-0.012***		
REMOTE WORK*3-4DAYS → CO2pc		-0.006**		

Notes: Bootstrapped Standard errors estimated for significance analysis. *p<10%, **p<5%, ***p<1%.

Source: Telecom Advisory Services analysis

First, we analyze total effects on BROADBAND and REMOTE WORK on QUALITY LIFE. For the baseline 2017-18 estimate, results are positive although significantly at 10 percent. This is related to low frequency of remote working during those years, because in the estimate with frequency as moderator, clearly the more intensive remote workers are those that increased family time the most. In both 2020 estimates, BROADBAND and REMOTE total effect on QUALITY LIFE is strong and highly significant.

In addition, total effects are essential to understand the overall effect on BROADBAND and REMOTE WORK on emissions, because as seen above, both "positive" and "negative" effects take place simultaneously. In this sense, the total effects provide very important results:

 Starting with the 2017-18 baseline model, BROADBAND and REMOTE WORK do not have, in overall, a significant effect on emissions. This means that during 2017 and 2018 both positive and negative effects generated by REMOTE WORK on emissions compensated each other, with the net result being negligible. This can be explained, on the one hand, because most remote workers were not intensive ones during those years, and on the other hand, as OTHER TRAVEL increases were enough to offset the work travel variation.

- When introducing frequency as a moderating effect, there is, again, an insignificant effect of REMOTE WORK on emissions, but if we consider only those intensive remote workers (all days) and hybrid (3-4 days), there is a negative and significant effect: these remote workers reduced emissions.
- Finally, for the 2020 sample the results are also confirmed. During the pandemic year, BROADBAND and REMOTE WORK generated an overall a negative and significant effect on emissions. Based on the results from Table 6, on average, every worker that started to work from home during the pandemic



(rather than commuting) contributed to reduce emissions in 0.045 metric tons.

6.4 Discussion of results

With the previous results, we are now prepared to analyze all the sketched hypotheses. The summary is presented in Table 7.

Table 7. Hypotheses validation of direct effects

Hypothesis	Path	Sign	Findings
H1	BROADBAND → REMOTE WORK	+	Validated
H2a	REMOTE WORK → WORK TRAVEL	-	Validated
H2b	REMOTE WORK → OTHER TRAVEL	+	Not validated (only in 2017-18 baseline model)
НЗа	WORK TRAVEL \rightarrow QUALITY LIFE	-	Validated
НЗЬ	QUALITY LIFE → OTHER TRAVEL	+	Validated
H4a	WORK TRAVEL \rightarrow CO2pc	+	Validated
H4b	OTHER TRAVEL → CO2pc	+	Validated
H5	BROADBAND/REMOTE WORK \rightarrow QUALITY LIFE	+	Validated
H6	BROADBAND/REMOTE WORK → CO2pc	-	Validated depending on frequency in 2017-18, and overall, in the 2020 sample

Source: Telecom Advisory Services analysis



Most hypotheses are clearly validated (H1, H2a, H3a, H3b, H4a, H4b, H5). However, there are two cases that are worth discussing:

• The direct link between REMOTE WORK and OTHER TRAVEL has only been found to be significant in one estimate (the baseline 2017-18 model). In the 2020 sample, this link is not significant. This can be related to overall mobility reduction during the pandemic. In any case, it is important to mention that this does not mean that remote working does not increase nonworking travelling, as there is a positive indirect effect between REMOTE WORK and OTHER TRAVEL that materializes through increased family time. This indirect effect is robust as was found to be significant in all estimates.

7. CONCLUSIONS

The purpose of this study was to analyze the role of remote working enabled by a robust broadband infrastructure. The objective was to find out the effects of remote working on quality of life and in reducing emissions before and during the pandemic.

The most relevant contributions of this paper are two:

• We found broadband-enabled remote working to significantly increase the quality time of workers, defined as the time spent with family members. This is an important result in terms of well-being, and • The significance of the total effect from BROADBAND and REMOTE WORK to CO2pc. was verified through the reduced sample estimate as we required a complete dataset for calculating the necessary standard errors to assess statistical significance. The total effect on emissions is not significant for 2017-18, but it is negative and significant for 2020. From this, we conclude that there was not a significant effect before the pandemic, which was related to low frequency of working at home at that time. When we analyze the effects for frequency before the pandemic, and in the context of the pandemic (characterized by intensive remote working) there is a significant effect from remote work on reducing emissions.

can be associated, in turn, to increased happiness and a better life balance. In 2020, on average, every worker that started to work from home (rather than commuting) enjoyed 24 additional daily minutes of family time.

 We have successfully disentangled both positive and negative effects associated with broadband-enabled remote working on carbon emissions by being able to estimate the net results. When remote working is less intensive in frequency, both effects compensate each other, and the net result is negligible. When higher remote working frequency occurs (three working



days and more), the net reduction in emissions seems to prevail. During 2020, on average, every worker that started to work from home (rather than commuting) contributed to reduce emissions in 0.045 metric tons.

Recent trends in the United States point to a future with more flexible working schemes. According to the Global Work From Home Experience Survey conducted in 2020 by Global Workplace Analytics & Iometrics, 82% of U.S. employees want to work remotely some days when the pandemic is over. On average, they would prefer to do so half of the time, while 19% said they would like to telecommute full-time.

From these results, it seems clear that the preference is towards a hybrid-remote schedule, as the most preferred option of American workers is to work at home half of the time. However, it is important to remind us that not all jobs can be conducted remotely, creating this a limit to the teleworking benefits. According to our results, this hybrid working scheme would increase guality time and contribute to reduce carbon emissions. Moreover, this can bring significant benefits for both employers and employees. Global Workplace Analytics' estimates that a typical U.S. employer can save an average of \$11,000 per half-time telecommuter per year, because of increased productivity, lower real estate costs, reduced absenteeism and turnover, and better disaster preparedness. Similarly, employees can save between \$600 and \$6,000 per year by working at home half the time, due to reduced costs for travel, parking, and food, net of additional energy costs and home food costs. A half-time telecommuter can save

the equivalent of 11 workdays per year in time they would have otherwise spent commuting. Given the importance of broadband as an enabler of remote working, these economic effects underline broadband's criticality.

Lastly, these results highlight the need to close the digital divide and to ensure everyone can adopt a highquality internet connection in the United States. Today, wide penetration rate disparities exist between states. To mention a specific example, less than 40% of households had a broadband connection of 25 Mbps downstream speed in Arkansas in 2020. In contrast, that figure was 91.4% for the case of Delaware. This means that not all Americans have the same resources needed to work remotely. Because of this, public authorities should focus on creating policy frameworks that allow operators to spur infrastructure deployments and to find the optimal technological mixes to deliver the highest performance to the users. Likewise, as sometimes the bottlenecks arise from the demandside, policies should be designed to stimulate adoption of broadband services, particularly for low-income families.



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APPENDIX. COUNTIES INCLUDED IN THE SAMPLE

Baldwin, AL	Brevard, FL	Johnson, KS	Washtenaw, MI	Suffolk, NY	Florence, SC
Lee, AL	Broward, FL	Sedgwick, KS	Wayne, MI	Westchester, NY	Horry, SC
Mobile, AL	Clay, FL	Boone, KY	Anoka, MN	Alamance, NC	Spartanburg, SC
Maricopa, AZ	Collier, FL	Fayette, KY	Ramsey, MN	Buncombe, NC	York, SC
Pima, AZ	Escambia, FL	Jefferson, KY	Scott, MN	Davidson, NC	Blount, TN
Pinal, AZ	Hernando, FL	Kenton, KY	Washington, MN	Forsyth, NC	Knox, TN
Yavapai, AZ	Hillsborough, FL	Ascension, LA	Wright, MN	Mecklenburg, NC	Montgomery, TN
Yuma, AZ	Lake, FL	East Baton Rouge, LA	Franklin, MO	Onslow, NC	Sumner, TN
Alameda, CA	Lee, FL	Jefferson, LA	Jefferson, MO	Pitt, NC	Wilson, TN
Butte, CA	Marion, FL	Livingston, LA	St. Louis, MO	Robeson, NC	Brazos, TX
El Dorado, CA	Martin, FL	Orleans, LA	Yellowstone, MT	Rowan, NC	Cameron, TX
Fresno, CA	Miami-Dade, FL	Ouachita, LA	Douglas, NE	Union, NC	Ector, TX
Kern, CA	Orange, FL	St. Tammany, LA	Clark, NV	Wayne, NC	Ellis, TX
Kings, CA	Palm Beach, FL	Androscoggin, ME	Hillsborough, NH	Clermont, OH	Grayson, TX
Los Angeles, CA	Pasco, FL	Cumberland, ME	Merrimack, NH	Greene, OH	Hidalgo, TX
Monterey, CA	Pinellas, FL	Kennebec, ME	Rockingham, NH	Lake, OH	Johnson, TX
Orange, CA	Polk, FL	Penobscot, ME	Strafford, NH	Licking, OH	McLennan, TX
Placer, CA	St. Johns, FL	Anne Arundel, MD	Bergen, NJ	Lucas, OH	Smith, TX
Sacramento, CA	St. Lucie, FL	Carroll, MD	Burlington, NJ	Medina, OH	Tarrant, TX
San Diego, CA	Santa Rosa, FL	Cecil, MD	Camden, NJ	Miami, OH	Taylor, TX
San Francisco, CA	Bartow, GA	Charles, MD	Cumberland, NJ	Montgomery, OH	Webb, TX



San Joaquin, CACarroll, GAHarford, MDEssex, NJPortage, OHWichita, TXSan Luis Obispo, CACherokee, GAMontgomery, MDHudson, NJSummit, OHWeshington, UTSan Mateo, CAClayton, GAPrince George's, MDHutterdon, NJBeschutes, ORAlfington, VASanta Babrar, CADouglas, GABaltimore, MDMercier, NJJackson, ORHenrico, VASanta Gruz, CADouglas, GABistol, MAMorris, NJLane, ORHenrico, VASanta Cruz, CAForsyth, GAEssex, MAPassaic, NJBeever, PADouglas, GASolono, CAGwinert, GAHampelm, MASomerset, NJBeever, PAPrince Willian, VASolono, CAGwinert, GAHampelm, MASomerset, NJBucks, PAStafford, VAStarlislaus, CAHall, GAHampelm, MASomerset, NJBucks, PAStafford, VATuler, CAHauding, GAMiddlesex, MAInion, NJBucks, PANorfolk, VAYolo, CALake, ILPiymouth, MADona, Ana, NMChester, PANorfolk, VABouder, COMadison, ILSoffolk, MASanta Fe, NMDaware, PANorfolk, VALinner, COMadison, ILSoffolk, MASanta Fe, NMDelaware, PANorfolk, VABouder, COMadison, ILSoffolk, MASanta Fe, NMDaware, PANorfolk, VALinner, COLidean, MIGono, MISinsa, NYFandin, PASanta, NAVeld, COLark, ILGeree, MINorce, NYS						
San Mateo, CAClayton, GAPrince George's, MDHunterdon, NJDeschutes, ORArlington, VASanta Barbara, CACoweta, GABaltimore, MDMercer, NJJackson, ORChesterfield, VASanta Gruz, CADouglas, GABarnstable, MAMiddlesex, NJLane, ORHenrico, VAShasta, CAFayette, GABiristol, MAMorris, NJAllegheny, PALoudoun, VASolano, CAForsyth, GAEssex, MAPassaic, NJBeaver, PAPrince William, VASonoma, CAGwinnett, GAHampden, MASomerset, NJBerks, PASpotsylvania, VAStanislaus, CAHall, GAHampshire, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJBuller, PAChesapeake, VAVentura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANevport News, VAYolo, CALake, ILPiymouth, MADoña Ana, NMChester, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASanta Fe, NMDalaware, PAWingina Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErice, PAKing, WAVeld, COTazewell, ILBerrien, MIKings, NYErice, PASnohomish, WALairiner, COIskhart, INGenesee, MINassu, NYLencester, PASnohomish, WALairiner, COIskhart, INGenesee, MINassu, NYLencester, PASnohomish, WA <trr>Lairiner, CTIskhart, INGe</trr>	San Joaquin, CA	Carroll, GA	Harford, MD	Essex, NJ	Portage, OH	Wichita, TX
Santa Barbara, CACoweta, GABaltimore, MDMercer, NJJackson, ORChesterfield, VASanta Cruz, CADouglas, GABarnstable, MAMiddlesex, NJLane, ORHenrico, VAShata, CAFayette, GABristol, MAMorris, NJAllegheny, PALoudoun, VASolano, CAForsyth, GAEssex, MAPassaic, NJBeaver, PAPrince William, VASonoma, CAGwinnett, GAHampden, MASomerset, NJBerks, PASotsytvania, VAStanislaus, CAHail, GAHampshire, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJButler, PAChesspeake, VAVontura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASan Juan, NMDauphin, PARichmond, VABoulder, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALariner, COTazewell, ILBernien, MIKings, NYFranklin, PASkagit, WAVeid, COClark, INGalboun, MIMonroe, NYLancaster, PASonhomish, WAFairfield, CTElkhart, INGenesee, MINassau, NYLucaster, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKanawha, WINerder, DEJohnson, INKent, MIOn	San Luis Obispo, CA	Cherokee, GA	Montgomery, MD	Hudson, NJ	Summit, OH	Washington, UT
Santa Cruz, CADouglas, GABarnstable, MAMiddlesex, NJLane, ORHenrico, VAShasta, CAFayette, GABristol, MAMorris, NJAllegheny, PALoudoun, VASolano, CAForsyth, GAEssex, MAPassaic, NJBeaver, PAPrince William, VASonoma, CAGwinnett, GAHampden, MASomerset, NJBerks, PASpotsylvania, VAStanislaus, CAHall, GAHampden, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJButler, PAChesapeake, VAVontura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANewport News, VAYolo, CALake, ILPiymouth, MADoña Ana, NMDauphin, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASant Fe, NMDalaphin, PANichmond, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAVeld, COClark, INCalhoun, MIMonroe, NYLancaster, PAShohomish, WAFairfield, CTElkhart, INGenesee, MINassau, NYLucoming, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINew York, NYMorce, PAMarathon, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMontogenzy, PARacine, WINerd, DEMonroe, INMacomb, MIOrange, NYPhi	San Mateo, CA	Clayton, GA	Prince George's, MD	Hunterdon, NJ	Deschutes, OR	Arlington, VA
Shasta, CAFayette, GABristol, MAMorris, NJAllegheny, PALoudoun, VASolano, CAForsyth, GAEssex, MAPassaic, NJBeaver, PAPrince William, VASonoma, CAGwinnett, GAHampden, MASomerset, NJBerks, PASpotsylvania, VAStanislaus, CAHall, GAHampshire, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJButler, PAChesspeake, VAVentura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANewport News, VAVolo, CALake, ILPlymouth, MADoña Ana, NMChester, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASant Jaan, NMDauphin, PARichmond, VABerver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VALarimer, COSt. Clair, ILAllegan, MIBronx, NYFrie, PAKing, WAVeld, COClark, INCalhoun, MIMonroe, NYLancaster, PAShohomish, WAVeld, COLake, ILMorroit, MASasu, NYLucoming, PAKanawha, WYVeld, COLake, INGenesee, MINassau, NYMorroe, PAKanawha, WIVerthfield, CTHendricks, INJackson, MINew York, NYMorroe, PAKanawha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarthon, WINerd, DEMonroe, INMonroe, MIOntario, NYMontgomery, PA </td <td>Santa Barbara, CA</td> <td>Coweta, GA</td> <td>Baltimore, MD</td> <td>Mercer, NJ</td> <td>Jackson, OR</td> <td>Chesterfield, VA</td>	Santa Barbara, CA	Coweta, GA	Baltimore, MD	Mercer, NJ	Jackson, OR	Chesterfield, VA
Solano, CAForsyth, GAEssex, MAPassaic, NJBeaver, PAPrince William, VASonoma, CAGwinnett, GAHampden, MASomerset, NJBerks, PASpotsylvania, VAStanislaus, CAHall, GAHampshire, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJButler, PAChessapeake, VAVentura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANewport News, VAYolo, CALake, ILPlymouth, MADoña Ana, NMChester, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASan Juan, NMDauphin, PARichmond, VADenver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronz, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PAShaohish, WAYeiffeld, CTElkhart, INGenesee, MINosroe, NYLancaster, PAMonohish, WAYeiffeld, CTJohnon, INKent, MIOnondaga, NYMorce, PAKenosha, WINew Haven, CTJohnon, INKent, MIOnondaga, NYMortgomery, PARacine, WIWindham, CTLake, INLivingston, MIOntario, NYMortgomery, PARacine, WINerd, DEJohnon, INMacomb, MIOntario, NYMortgomery, PARacine, WIWend, DEJohnon, IAMonroe, MIQueens, NYS	Santa Cruz, CA	Douglas, GA	Barnstable, MA	Middlesex, NJ	Lane, OR	Henrico, VA
Sonoma, CAGwinnett, GAHampden, MASomerset, NJBerks, PASpotsylvania, VAStanislaus, CAHall, GAHampshire, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJButler, PAChesapeake, VAVentura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANewport News, VAYolo, CALake, ILPiymouth, MADoña Ana, NMChester, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASan Juan, NMDauphin, PARichmond, VADenver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBrons, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAWeld, COClark, INGenesee, MIMonroe, NYLancaster, PASnohmish, WAFairfield, CTHendricks, INJackson, MINew York, NYMorroe, PAKenosha, WILitchfield, CTHendricks, INJackson, MIOntario, NYMorroe, PAMarathon, WIWindham, CTLake, INKent, MIOntario, NYMorroe, PAMarathon, WIKent, DEMonroe, INMacomb, MIOrnadga, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrnadga, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrnadga, NYMontgomery,	Shasta, CA	Fayette, GA	Bristol, MA	Morris, NJ	Allegheny, PA	Loudoun, VA
Stanislaus, CAHall, GAHampshire, MASussex, NJBucks, PAStafford, VATulare, CAHenry, GAMiddlesex, MAUnion, NJButler, PAChesapeake, VAVentura, CAPaulding, GANorfolk, MABernalillo, NMCambria, PANewport News, VAYolo, CALake, ILPlymouth, MADoña Ana, NMChester, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASan Juan, NMDauphin, PARichmond, VADenver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAVeld, COClark, INCalhoun, MIMonroe, NYLancaster, PASnohomish, WALitchfield, CTElkhart, INGenesee, MINassau, NYLycoming, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINonroe, NYMarathon, WIWindham, CTLake, INLivingston, MINonroe, NYMarathon, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PALivingston, MISchuylkill, PASussex, DEJohnson, IAMaklad, MIRockland, NYWash	Solano, CA	Forsyth, GA	Essex, MA	Passaic, NJ	Beaver, PA	Prince William, VA
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Yolo, CALake, ILPlymouth, MADoña Ana, NMChester, PANorfolk, VABoulder, COMcHenry, ILSuffolk, MASan Juan, NMDauphin, PARichmond, VADenver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAWeld, COClark, INCalhoun, MIMonroe, NYLancaster, PASnohomish, WAFairfield, CTElkhart, INGenesee, MINassau, NYLycoming, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKenosha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PALitchfield, CHNew Castle, DEJohnson, IAMosegon, MIRichmond, NYWashington, PALitchfield, CHNew Castle, DEJohnson, IAMonroe, MIRock, NYWashington, PALitchfield, CHNew Castle, DEJohnson, IAMosegon, MI <td>Tulare, CA</td> <td>Henry, GA</td> <td>Middlesex, MA</td> <td>Union, NJ</td> <td>Butler, PA</td> <td>Chesapeake, VA</td>	Tulare, CA	Henry, GA	Middlesex, MA	Union, NJ	Butler, PA	Chesapeake, VA
Boulder, COMcHenry, ILSuffolk, MASan Juan, NMDauphin, PARichmond, VADenver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAWeld, COClark, INCalhoun, MIMonroe, NYLancaster, PASnohomish, WAFairfield, CTElkhart, INGenesee, MINassau, NYLycoming, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKenosha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PALivinebago, WI	Ventura, CA	Paulding, GA	Norfolk, MA	Bernalillo, NM	Cambria, PA	Newport News, VA
Denver, COMadison, ILWorcester, MASanta Fe, NMDelaware, PAVirginia Beach, VAJefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAVeld, COClark, INCalhoun, MIMonroe, NYLancaster, PASnohomish, WAFairfield, CTElkhart, INGenesee, MINassau, NYLycoming, PAKenosha, WILitchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKenosha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontogenery, PARacine, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PAVirginabago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PAVirginabago, WI	Yolo, CA	Lake, IL	Plymouth, MA	Doña Ana, NM	Chester, PA	Norfolk, VA
Jefferson, COSt. Clair, ILAllegan, MIBronx, NYErie, PAKing, WALarimer, COTazewell, ILBerrien, MIKings, NYFranklin, PASkagit, WAWeld, COClark, INCalhoun, MIMonroe, NYLancaster, PASnohomish, WAFairfield, CTElkhart, INGenesee, MINassau, NYLycoming, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKenosha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PAWinnebago, WISussex, DELinn, IAOakland, MIRockland, NYWestmoreland, PAKentoreland, PA	Boulder, CO	McHenry, IL	Suffolk, MA	San Juan, NM	Dauphin, PA	Richmond, VA
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Fairfield, CTElkhart, INGenesee, MINassau, NYLycoming, PAKanawha, WVLitchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKenosha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRockland, MYWestmoreInd, PAVestmoreInd, PA	Larimer, CO	Tazewell, IL	Berrien, MI	Kings, NY	Franklin, PA	Skagit, WA
Litchfield, CTHendricks, INJackson, MINew York, NYMercer, PAKenosha, WINew Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PADistrict of Columbia, DCLinn, IAOakland, MIRockland, NYWestmoreland, PA	Weld, CO	Clark, IN	Calhoun, MI	Monroe, NY	Lancaster, PA	Snohomish, WA
New Haven, CTJohnson, INKent, MIOnondaga, NYMonroe, PAMarathon, WIWindham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PAYestmoreland, PADistrict of Columbia, DCLinn, IAOakland, MIRockland, NYWestmoreland, PA	Fairfield, CT	Elkhart, IN	Genesee, MI	Nassau, NY	Lycoming, PA	Kanawha, WV
Windham, CTLake, INLivingston, MIOntario, NYMontgomery, PARacine, WIKent, DEMonroe, INMacomb, MIOrange, NYPhiladelphia, PARock, WINew Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PATerritory ConstraintsDistrict of Columbia, DCLinn, IAOakland, MIRockland, NYWestmoreland, PA	Litchfield, CT	Hendricks, IN	Jackson, MI	New York, NY	Mercer, PA	Kenosha, WI
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New Castle, DESt. Joseph, INMonroe, MIQueens, NYSchuylkill, PAWinnebago, WISussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PADistrict of Columbia, DCLinn, IAOakland, MIRockland, NYWestmoreland, PA	Windham, CT	Lake, IN	Livingston, MI	Ontario, NY	Montgomery, PA	Racine, WI
Sussex, DEJohnson, IAMuskegon, MIRichmond, NYWashington, PADistrict of Columbia, DCLinn, IAOakland, MIRockland, NYWestmoreland, PA	Kent, DE	Monroe, IN	Macomb, MI	Orange, NY	Philadelphia, PA	Rock, WI
District of Columbia, DC Linn, IA Oakland, MI Rockland, NY Westmoreland, PA	New Castle, DE	St. Joseph, IN	Monroe, MI	Queens, NY	Schuylkill, PA	Winnebago, WI
	Sussex, DE	Johnson, IA	Muskegon, MI	Richmond, NY	Washington, PA	
Bay, FL Scott, IA Saginaw, MI Saratoga, NY York, PA	District of Columbia, DC	Linn, IA	Oakland, MI	Rockland, NY	Westmoreland, PA	
	Bay, FL	Scott, IA	Saginaw, MI	Saratoga, NY	York, PA	





