How working from home and migration can affect income? Evidence from the United States

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Resumo: A pandemia COVID-19 mudou a forma como trabalhamos. Nos Estados Unidos, por exemplo, cerca de 20 a 30% de todas as horas pagas agora são realizadas de forma remota. O aumento do trabalho remoto (WFH) está associado a um novo padrão de migração, com as pessoas deixando os centros urbanos para as áreas da periferia. A monografia explora a relação entre esses fluxos de migração, exposição ao trabalho remoto e renda média dos lares em um determinado código postal. Os resultados mostram uma correlação fraca e positiva entre o fluxo líquido de migração e a renda e uma relação negativa entre a exposição ao trabalho remoto e a renda. A pesquisa apresenta as implicações das novas tendências do trabalho remoto nos padrões de renda e fornece evidências para uma literatura mais ampla e ainda incipiente sobre o tema.

Palavras-chave: trabalho remoto; migração; renda.

Abstract: The COVID-19 pandemic has dramatically altered the way we work. In the United States, approximately 20-30% of all paid work hours are now conducted remotely. The rise of remote work (WFH) has initiated a new migration pattern, with individuals relocating from urban centers to suburban areas. This paper explores the relationship between these migration flows, WFH exposure, and median household income in specific zip codes. The results indicate a weakly positive correlation between net migration flow and income, as well as a negative relationship between WFH exposure and income. This research elucidates the implications of the WFH trend for income patterns and contributes to the burgeoning literature on this topic.

Keywords: working from home; migration; income.

JEL Codes: J21; J22; R12; R41.

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Introduction

The work-from-home (WFH) model has significantly increased in response to social distancing measures against COVID-19 worldwide, particularly in the USA. Current literature suggests a lasting shift in WFH adoption in the labor market, especially among high-income and well-educated workers. Various authors, including Bick et al. (2020), Dalton and Groen (2022), and Barrero et al. (2021), conducted surveys between 2020 and 2021 to measure employers' and employees' willingness to work temporarily or permanently with the WFH model and their perspectives on its future. The results indicate that both WFH-Only (remote work 5 days a week) and WFH-Hybrid (remote work at least once a week) have become significantly more popular and even vital in certain economic sectors.

Beyond this uptake in remote work, new implications for urban and interurban geography have emerged. Althoff et al. (2022) and Delventhal and Parkhomenko (2021) constructed spatial models to analyze migration patterns related to the new WFH model. Their findings suggest that since the remote work shift in the labor market, workers may opt not to commute to their workplaces at all (WFH-Only) or at least once a week (WFH-Hybrid). This reduces the necessity to live near their workplaces, thereby opening up various new housing pattern possibilities. The models suggest that to be closer to areas with more amenities, people are moving further from city centers to the periphery.

According to these authors, this contributes to a new scenario in the labor market. Assuming a permanent shift to remote work, the implications of this popularized model could be profound, including new migration patterns, changes in the housing market, increased workers' bargaining power, new spatial distributions within cities, new work relationships, and changes in preferences. Considering that migration movements by telecommuters predominantly involve high-income and well-educated workers (Althoff et al., 2022), they bring their earnings to these new areas, potentially boosting the local economies.

These new migration flows among telecommuters raise important questions: do they constitute a significant share of total migration flows? If so, is their economic influence substantial? Is this influence different between intra-county and inter-county migration? This paper investigates the relationship between migration associated with remote work and its potential economic impact on the destinations of these teleworkers.

The paper presents a regression analysis of median household income (sourced from the American Community Survey) in relation to WFH exposure (constructed using the Dingel and Neiman (2020) classification system and job distribution from the US Census Bureau) and net population flow (sourced from the United States Postal Service) at the zip code level, along with other controls. The paper follows the methodology of Ramani and Bloom (2021), which calculates the arc-percentage change of income pre- and post-2020. The ultimate goal of the model is to test the hypothesis that WFH and migration can affect income in a given location.

The results suggest a non-robust positive relationship between in-migration and income and a negative relationship between pre-COVID WFH exposure and income. If corroborated by other studies, the results may support the hypothesis that zip codes with a high number of workers capable of teleworking experience out-migration, thereby lowering the income in those zip codes, while the destinations of these individuals experience income growth. However, this explanation must be cautiously interpreted, as some results do not hold under robustness tests.

The paper is structured as follows: a literature review of recent publications on remote work and its relationships with migration and economic activity; a section detailing the data and methods used in the regression analysis; a presentation of the results, possible interpretations, and a robustness check; and finally, the conclusion.

1. Theoretical framework

With the popularization of remote work across the United States, researchers such as Ramani and Bloom (2021), Bick et al. (2021), and Althoff et al. (2022) have been examining the implications of this phenomenon. One area of focus is how migration patterns change when there is no requirement to work onsite and how such migration can influence economic activity in specific locations, measured by county GDP, consumer spending, and tax revenue. This section reviews the literature related to these three aspects—remote work, migration, and economic activity—and elucidates the mechanisms linking them.

1.1 The current literature on remote work

In the literature related to the increase in WFH levels, termed Zoomshock by De Fraja et al. (2021), most authors provide data—either primary or secondary sources—to demonstrate that after the onset of the pandemic, there was a significant shift in remote work adoption. Although the exact figures vary depending on the source, the time series trends are consistently clear. The papers offer various explanations for this phenomenon and generally concur that WFH is likely to remain a permanent feature of the US labor market.

Aksoy et al. (2022) conducted a survey across 27 countries, targeting full-time workers who had completed primary school, to understand the effects of WFH in each country after the initial stages of the pandemic (the survey was conducted 16 to 23 months after the pandemic's onset). Their findings provide strong evidence of a long-term and sustained increase in WFH. Moreover, they attribute this phenomenon to the pandemic-induced reorganization and re-optimization of work arrangements, which created an environment conducive to social experimentation.

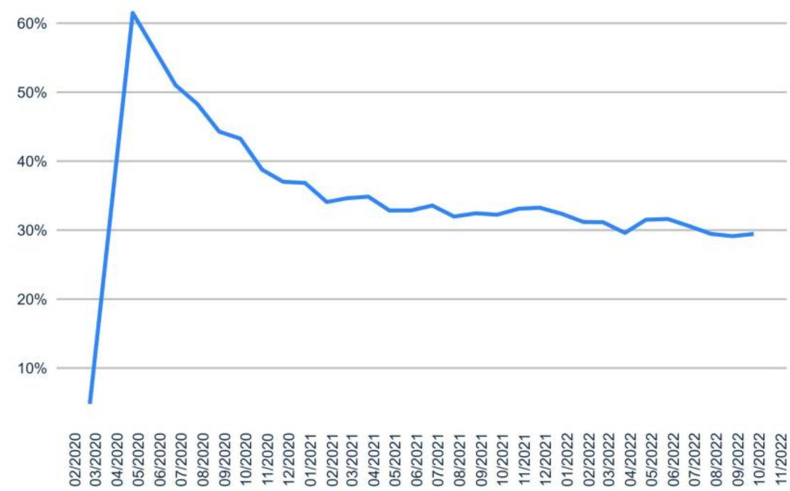
In 2019, when WFH was not prevalent, 82% of employed people did all or some of their work at the workplace, while 24% worked from home. By 2021, these numbers shifted to 68% and 38%, respectively. This indicates that firms were compelled to adopt the WFH model indiscriminately to comply with social distancing measures and that the newly introduced model continues to be utilized by the workforce. This argument is supported by a 39% increase in social acceptance of WFH in the US, as evidenced by survey data showing an increase in WFH social acceptance and a rise from an average of 1.6 WFH days to a planned average of 2.1 days in the future.

When asked about their productivity compared to their expectations before COVID-19, over 87% of respondents believed they were as productive or more productive, indicating a shift in workers' preferences towards the new work arrangement. According to the authors, this shift was only possible because the pandemic forced WFH across various occupations, resulting in a learn-by-doing experiment.

> The simultaneity of large-scale experimentation is important in this regard. A law firm, for example, could have experimented with WFH before the pandemic. What it could not have done was experiment with WFH when the courts and other firms - including clients, rival law firms, consultants, and suppliers - also worked remotely. Had the COVID-19 pandemic not occurred, our evidence suggests that the big shift to WFH would have taken place much more slowly over many years (AKSOY et al.; 2022, page 17).

Barrero et al. (2021) designed the Survey of Working Arrangements and Attitudes (SWAA) to gather cross-sectional data on workers' and employers' perceptions of WFH. The survey has been conducted monthly since May 2020 and is released on the 5th day of each month. The authors argue that the COVID-19 pandemic initiated a massive WFH experiment across the United States, leading to a long-term increase in WFH levels. Prior to the pandemic, only 4.8% of full paid working days were conducted from home. This figure peaked at 61.5% in May 2020. Since then, WFH levels have declined and stabilized at approximately 30%.

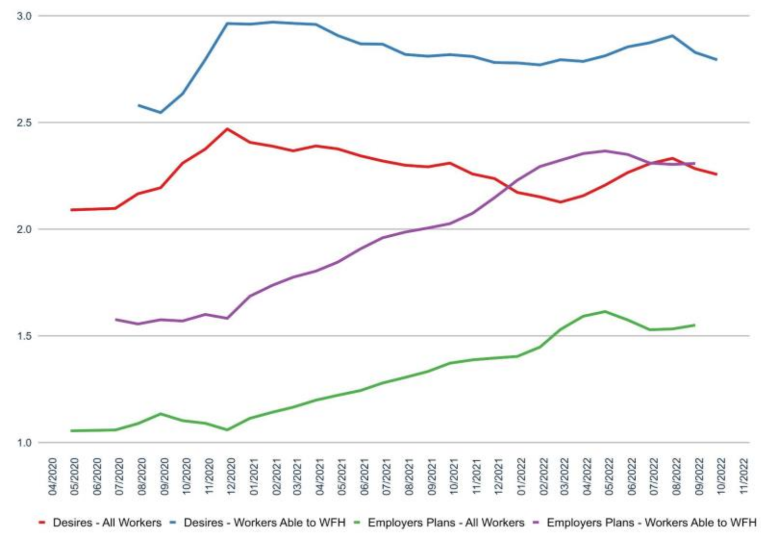
Figure 1 – WFH as % of full paid working days



Source: prepared by the authors based on Barrero et al. (2021).

The desires of workers and plans of employers regarding WFH also support the thesis of a long-term shift towards WFH in the US. Since the inception of the survey, employers have increasingly shown a willingness to adopt WFH within their firms. From an employee's perspective, the desired levels of WFH have been high since early 2021, as illustrated in Figure 2. The gap between worker desires (below 50%) and employer plans (about 20%) suggests that the actual WFH level should be somewhere in between, as it currently stands at 30%.

Figure 2 – WFH days



Source: prepared by the authors based on Barrero et al. (2021).

The authors developed a framework to explain these structural changes. First, the pandemic's WFH experiment, driven by government-imposed social distancing measures, eliminated the social cost of experimentation for individuals and firms by compelling economic agents to adopt WFH who otherwise would not have done so. Consequently, the average worker invested $561 in home equipment to better meet their WFH needs. Additionally, US patent applications for WFH technologies doubled in 2020, enhancing the efficiency and quality of remote work and enabling industries less likely to adopt WFH to participate in this new work model.

This experimentation and new investment allowed agents to update their beliefs about WFH, reassessing their productivity in remote work more favorably compared to their views before the pandemic. This led to greater acceptance of remote work, as suggested by Figure 2. Reduced commuting time is highly valued by qualified workers, whose opportunity cost per unit of time is greater than average, as discussed in other papers.

Bick et al. (2021) developed the Real-Time Population Survey (RPS) to track changes in the labor market due to the pandemic. The survey was designed to differentiate WFH adoption among demographic groups—such as age, gender, income, education, and residence—and its impacts. Notably, they found that commuting time significantly decreased since early 2020 and recovered after the first COVID-19 wave. The authors also argue that the bulk of the WFH increase was driven by WFH-Only workers, who work entirely remotely. They estimate that at the end of 2020, 20.4% of all employed individuals still worked entirely from home. However, the paper's most important contribution is described by the authors as follows:

> […] we develop a stylized model of WFH employment that leads to a clear distinction between two main channels through which a pandemic can cause large numbers of commuters to start WFH. The first is an intuitive WFH substitution channel. Because of the increased health risks of working away from home, workers substitute on-site work for working at home within working arrangements that already included the option to WFH before the pandemic. A key aspect of this channel is that, for those that switched to WFH in the pandemic, by revealed preference home-based work is less efficient than on-site work in a normal health situation; if it were not, those workers would have already worked from home before the pandemic. The second channel is a WFH adoption channel. In this channel, the increased health risks of on-site work in the pandemic force changes to work arrangements through the adoption of a WFH option and/or of new technologies that enable WFH. A key aspect of this channel is that many of those that switched to WFH in the pandemic could in principle already have worked more productively from home before the start of the pandemic, for instance because of advances in information and communication technology. However, because of adoption lags, social norms or general inertia, employers did not provide the option to WFH until the pandemic. (BICK et al.; 2021, pages 2-3)

The adoption channel, according to the authors, explains the differences in the WFH transition across certain labor markets. They find that, after the pandemic, the ability to WFH is strongly correlated with the WFH level in different occupations. However, this correlation was much smaller before the pandemic, and there were not significant differences across occupations. To explain why high WFH-ability sectors were not already working remotely before the pandemic, the authors suggest that these sectors must have experienced larger costs associated with working onsite, which would imply a greater job loss in those sectors. Nonetheless, these were the occupations with lower job loss rates. In this sense, the adoption channel enabled them to break inertia and adopt WFH.

Brynjolfsson et al. (2020) were among the first to develop a survey to track COVID-19's impact on the labor market. Their findings indicate that, around May 2020, 35.2% of people who were commuting transitioned to the WFH model. They also found that, in the early stages of the pandemic, the share of workers WFH could be predicted by the incidence of COVID-19, supporting the thesis that the pandemic drove a massive social experiment in WFH. They also identified differences in WFH adoption according to workers' occupations and industries.

Dalton and Groen (2022) analyzed the 2021 Business Response Survey to present estimates of telework patterns during the pandemic. Consistent with other authors, they found that 12.6% of jobs involved full-time teleworking, while 21.8% involved part-time teleworking. They also provided information on WFH adoption categorized by various characteristics, such as flexibility, changes in payment, changes in onsite square footage, independent contractor status, freelancer status, voluntary status, and industry.

Regarding occupations and the incidence of remote work, the results align with the Dingel and Neiman (2020) classification model of teleworkability. Sectors such as Information, Financial Activities, and Professional and Business Services are all characterized by a high propensity for WFH and are among the top three sectors with the largest percentage of remote work jobs.

Dey et al. (2021) used data from the Current Population Survey, which added questions about remote work post-pandemic, to measure WFH incidence in the United States and the overall impact of COVID-19 on the labor market. From May to June 2020, roughly one-third of the workforce teleworked due to the COVID-19 pandemic. This number declined in the following months, reaching 22.3% by the last quarter, consistent with Barrero et al. (2021)'s SWAA. The authors also advocate for a permanent shift in WFH, as follows:

> It seems likely that some of the increase in teleworking will be permanent as workers and employers gain experience with teleworking arrangements and with the information technology that helps facilitate teleworking. (DEY et al.; 2021)

The authors also present a revised classification of teleworkability according to the North American Industry Classification System, as introduced by Dingel and Neiman (2020), to improve certain aspects of the categorization.

1.2 The current literature on remote work and migration

Since the COVID-19 outbreak, several papers have attempted to model the relationship between remote work and the spatial distribution of workers [Delventhal et al. (2021), Althoff et al. (2022), Delventhal and Parkhomenko (2020), Correa (2022), Ramani and Bloom (2021), Liu and Su (2021), De Fraja et al. (2021), Haslag and Weagley (2021)]. For these authors, this is an important implication of remote work because the Zoomshock alleviated the historical constraint that workers prefer to live near their work sites. Less commuting time leads to greater welfare and, as stated by Aksoy et al. (2022), to a reallocation of resources, including in the real estate market.

Delventhal et al. (2021, page 1) study the urban structure of Los Angeles using "a quantitative model featuring local agglomeration externalities and endogenous traffic congestion." Their contribution to the remote work literature lies in their findings on changes in wages and real estate prices, commuting patterns, and an increase in welfare due to more widespread telecommuting. Delventhal and Parkhomenko (2020, 2022) expand the analysis to a national level, differentiating by education and industry. The authors build a model that robustly predicts migration patterns in the US between 2020 and 2021.

Using cell phone data from SafeGraph, Althoff et al. (2022) identify a positive correlation between the likelihood of remote work and out-migration. They found that areas with a high share of business service workers experienced more significant outflows of workers. They adopted Eckert et al.'s (2020) definition of these workers' industries as skilled scalable services (SSS), consisting of North American Industry Classification System (NAICS) industries 51, 52, 54, or 55. The authors then used Dingel and Neiman's (2022) classification of the potential for remote work (Table 1, left panel) to categorize industries by their likelihood of telecommuting. By this definition, SSS workers are the group with the highest incidence of remote work (Table 1, right panel), demonstrating that WFH is correlated with out-migration.

Table 1 – WFH exposure by Industry

	Unweighted	Weighted by wage
Educational Services	0.83	0.71
Professional, Scientific, and Technical Services	0.80	0.86
Management of Companies and Enterprises	0.79	0.86
Finance and Insurance	0.76	0.85
Information	0.72	0.80
Wholesale Trade	0.52	0.67
Real Estate and Rental and Leasing	0.42	0.54
Federal, State. and Local Government	0.41	0.47
Utilities	0.37	0.41
Other Services (except Public Administration)	0.31	0.43
Administrative and Support and Waste Management and Remediation Services	0.31	0.43
Arts. Entertainment, and Recreation	0.30	0.36
Mining, Quarrying, and Oil and Gas Extraction	0.25	0.37
Health Care and Social Assistance	0.25	0.24
Manufacturing	0.22	0.36
Transportation and Warehousing	0.19	0.25
Construction	0.19	0.22
Retail Trade	0.14	0.22
Agriculture Forestry, Fishing and Hunting	0.08	0.13
Accommodation and Food Services	0.04	0.07

	Annual Income (USD)	Remote Work Potential (%)
Skilled Scalable Services (SSS)	84,000	79.6
Resources + Construction	54,900	19.7
Manufacturing	60,900	32.1
Trade + Transport	40,300	22.5
Education + Medical	48,500	50.6
Arts + Hospitality	22,600	14.4
Other Services	39,400	33.9

Source: prepared by the authors based on Dingel and Neiman (2020) and Althoff et al. (2022)

Furthermore, the authors found that large, high-density cities—which concentrated SSS workers and had the greatest share of the workforce working from home—were the primary targets of the migration outflow of high-income service workers. This migration has led to a decline in consumer spending in consumer service industries, which typically employ lower-skilled workers. Althoff et al. (2022) support this idea by demonstrating that the decline in weekly hours of non-SSS workers in high-density areas is greater than in low-density areas. This dynamic can be explained as follows:

> With improvements in technology and high-speed internet, many business service jobs can now be done remotely, so that big cities' specialization in business services has translated into a specialization in remote work jobs. [...] the recent COVID-19 pandemic has accelerated the transition [...].
>
> Such a transition is likely to affect business and consumer service workers differently due to the differences in markets served. As high-skill service workers transition to remote work, they become more mobile, and may leave big city centers with high rents for regions with lower costs of living or more favorable amenities. When they depart big cities, they take their demand for consumer services with them. As a result, the transition to remote work is likely to hurt less-mobile consumer service workers in big cities the most (ALTHOFF et al., 2022, page 1).

It is also important to note that regardless of the density, SSS workers are almost equally affected by changes in hours worked across the entire time series, indicating that remote work mitigates regional shocks to the labor market. These papers use data from the ACS and CPS to obtain economic, social, housing, demographic, and migration data for the US, along with data from private companies to gather information about migration flows and real estate prices.

Ramani and Bloom (2021) study the new migration patterns related to WFH post-pandemic. They discovered what they call a donut effect, where people and businesses move further away from the center—defined as central business districts (CBD)—populating more peripheral areas, thus forming a donut-like shape. Their second finding is that migration across metropolitan areas is much smaller than within metropolitan areas.

To achieve these results, they built an analytical spatial equilibrium model consisting of two metro areas, one larger and one smaller, each with a center and suburb. Using real estate price data from Zillow, WFH exposure data constructed from Dingel and Neiman's (2020) classification method, LODES data, and migration data from USPS, the authors estimated the relationship between the pandemic, WFH exposure, and new migration patterns. Quantitatively, monthly population outflows from CBDs increased by almost 2% compared to pre-pandemic levels in the 12 largest metro areas in the US.

For this work's purpose, the paper's findings about between-metro migration raise intriguing questions. First, they show that the outflows of people and businesses from the center across cities are proportionally weaker than within-metro reallocation. Second, they show a positive relationship between population density and real estate prices when comparing different cities, suggesting that "real estate markets expect denser metros to perform well in the longer term" (Ramani and Bloom, 2021). In this context, the WFH-Hybrid model could play an important role: people move further away from CBDs to enjoy the benefits of suburban living but cannot live too far from their workplace since they are required to work onsite one or more days per week.

From another perspective, Correa (2022) examines how the ability to WFH contributes to the out-migration decision from large cities in Sweden. In contrast to previous studies, he finds that people more likely to WFH are less likely to migrate. The author uses a European-based index (based on Sostero et al., 2020) to build his model and emphasizes that whether his results generalize to other countries remains a topic for further discussion, but it aligns with Ramani and Bloom (2021). Both studies found significant movement of workers from the centers to the suburbs, but not across cities. The results are explained by hybrid work, where workers commute one or more days per week, binding them to the city where they work and consequently diminishing the role of remote work in the new geography of work.

Liu and Su (2021), in line with Ramani and Bloom (2021), use real estate data and the Dingel and Neiman (2020) classification system to find a "shift in housing demand from central cities and dense neighborhoods to the suburbs." They conjecture about the reasons for this movement. First, denser neighborhoods are close to center jobs, which concentrate high-skilled workers who are more likely to WFH and thus would experience the largest drop in housing demand. Second, these areas tend to have consumption amenities, such as bars and restaurants, which were closed at the pandemic's peak and would not be a premium to those living nearby at that moment. Third, these areas have higher costs, and as the need to live in these locations diminishes, people would not value paying those costs.

Haslag and Weagley (2021) find that "households are moving more for non-work-related reasons, and they are moving to lower rent, lower tax, and less populous areas after the onset of the pandemic." It is important to note that this change in behavior varies across demographic and income groups; lower-income households still tend to move for job-related reasons and are less likely to move for non-work reasons. In contrast, high-income households—defined as SSS workers—are the group with the greatest change in behavior. The authors also highlight the role that WFH plays in the decision to move:

> "[...] our results support many of the theoretical predictions and corroborate survey evidence that remote work is having a significant impact on the migration of workers and is likely to continue to play a role in migration decisions in the future as well". (HASLAG and WEAGLEY; 2021, pages 7-8)

The paper focuses on interstate migration flows, which are not representative of the entire moving population and may not capture broader migration trends. However, the authors used CPS migration data at the interstate level to address this issue by comparing changes in behavior in their original database (UniGroup) with CPS data before and after the pandemic. Moreover, supporting the thesis that remote work is now established in the labor market, their results of migration as a consequence of COVID-19 extend through the end of 2021. This indicates that temporary causes, such as the pandemic itself and social distancing measures, play a lesser role compared to permanent causes like the Zoomshock.

Furthermore, given that SSS workers have a greater share of income and are more likely to WFH, their relocation to smaller suburbs and towns is likely to impact local economies, following Moretti's (2010) argument. This supports the general concern among researchers that the Zoomshock has economic impacts that need to be better addressed in future research.

Brueckner et al. (2021) explore how the WFH option affects spatial hedonic equilibrium. They highlight two possible types of migration due to the introduction of remote work. Workers can either move from high-productive, expensive areas to low-productive, cheaper neighborhoods, or they can relocate to high-amenity places without losing their high-productive jobs. The authors develop a spatial equilibrium model to highlight these new possibilities. The major difference between the two scenarios is that housing prices move inversely: while prices tend to rise in high-amenity places, they tend to fall in high-productive areas, and vice versa. However, there are some features present in both effects:

> "Underlying both outcomes are two key features of the new hedonic equilibrium: wage equalization across cities, which must occur when people can work anywhere; and a disconnect between a city's population and employment levels, which are no longer equal." (BRUECKNER et al.; 2021, page 2)

Within a city, the migration outcomes may differ from intercity moves. For workers in the hybrid WFH model, they still have to commute to their offices, thereby maintaining some physical connection to them. Nonetheless, the value of proximity to the central business district (CBD) is reduced, implying "a reduction in the city's housing-price gradient, with prices under WFH falling more slowly than before moving away from the CBD (the job-access premium thus falls)" (Brueckner et al., 2021, p. 2).

1.3 The current literature on remote work and economic activity

Since the migration patterns due to remote work are concentrated in the Donut Effect (Ramani and Bloom, 2021), there is a major concern about changes in economic activity around these areas. Ramani and Bloom (2021, p. 13) state that since SSS workers are more likely to WFH, the reallocation of these workers is "likely to make the drop in consumption spending on services especially large." This is particularly important to understand because it may lead to a significant drop in tax revenue for county governments.

Althoff et al. (2022) observe that this drop in consumption affects non-SSS workers, as their income generally depends on spending by SSS workers. Therefore, non-SSS workers within large metro areas experienced the largest revenue declines compared to those living in other cities.

De Fraja et al. (2021) address the issue of how increased WFH levels impact local economies and employment, arguing that non-SSS workers—particularly those providing locally-consumed services (LS) such as retail and hospitality—are more likely to be negatively affected by the new migration flows caused by the Zoomshock. They use a survey conducted in the United Kingdom to find that the impacts of remote work depend on demographic characteristics, income, and education—similar to findings by Ramani and Bloom (2021) and Althoff et al. (2022)—and that around 1.5% of total spending is estimated to relocate away from urban centers to residential areas.

In other words, they estimate that “approximately 77,000 jobs in retail and hospitality will either need to similarly relocate or be lost altogether” (De Fraja et al., 2021, p. 2). They further argue that the demand for office space may fall as remote work becomes more prominent, though the total extent of this impact depends on “how firms adapt their use of space given increased remote work” (De Fraja et al., 2021, p. 31). This leads to two possible outcomes: first, a need to repurpose this extra space in city centers, potentially driving new implications in the geography of remote work; and second, reduced economic externalities that benefit LS workers.

2. Data and methods

To investigate how remote workers who have moved since the onset of the pandemic have economically affected the regions to which they migrated, we rely on the model analysis by Ramani and Bloom (2021). The authors examine whether WFH exposure, density, and distance from the city center in a given zip code affect rent prices and net migration flows. Their results show a significant link between these variables, using a regression model.

To expand on their findings, we model the relationship between the median household income of a zip code after the pandemic and the net flow of migrants, incorporating the same regressors used by the authors, as mentioned above.

2.1 Dependent and control variables

We use the **median household income** from the American Community Survey (ACS) as the economic variable of interest. This measure represents the average income of households in a given geographic area, specifically at the zip code level. The data is collected annually by the U.S. Census Bureau, which conducts the largest household survey in the United States, gathering information from over 3 million households each year.

The data used spans from 2018 to 2021, the most recent release, and is taken from the 5-year estimates of the ACS. This comprehensive dataset addresses income earnings for almost all U.S. zip codes, serving as a proxy for economic activity over the years in a given location.

To calculate the percentage difference in median income across all U.S. zip codes, we use the arc-percentage methodology. This method, introduced by Davis, Haltiwanger, and Schuh (1996), is employed to calculate the percentage difference of a variable over time or across different geographic regions. This methodology is particularly useful when changes in the variable of interest are non-linear, as is often the case with changes in income, compared to traditional linear methods.

To track **migration flows**, we use the dataset provided by the United States Postal Service (USPS) through the National Change of Address (NCOA). This dataset contains monthly data on the net migration flow of families, households, businesses, and total migration at the zip code level. We apply the same treatment used by Ramani and Bloom (2021), as described by them:

> [...] we multiply the number of household change-of-address requests by 1.7, the mean household size of moving families in the US and add the number of individual change-of-address requests. The data also bottom-codes zip code-month flow counts to 0 if the value is less than or equal to 10 due to privacy concerns. We impute such values with the midpoint, 5 [...] (RAMANI and BLOOM; 2021, pages. 6-7)

To measure the **WFH incidence** in a given zip code, we use the Ramani and Bloom (2021) index of the share of employment and share of income that can be done through remote work (**WFH exposure**). To build this measure, they used the job industry distribution for residents across U.S. zip codes from the LEHD Origin-Destination Employment Statistics (LODES) at the U.S. Census Bureau. They then merged this data with the Dingel and Neiman classification of remote work probability to find the WFH exposure of income and employment. This dataset is built using 2019 LODES data to obtain the exposure before the Zoomshock triggered by the COVID-19 pandemic.

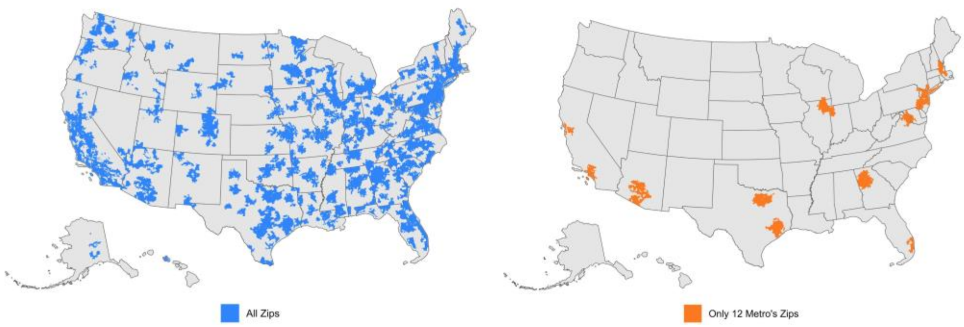
The mapping of zip codes to their **corresponding metro area's Central Business District (CBD)** is based on data from Holian (2019). The study evaluates various sources and techniques for determining CBD coordinates and concludes that the 1982 Census of Retail Trade's official coordinates accurately reflect the city's center of concentration. Since the 1982 Census only defines CBD coordinates for 268 metro areas, the CBD for the remaining areas is defined using the city's City Hall. In cases where both the 1982 Census and City Hall data exist, the City Hall coordinates usually align with the 1982 Census CBD coordinates. The CBD area is defined as all zip codes whose centroids are within 2 kilometers of the CBD coordinates. We used the Ramani and Bloom (2021) measure of the distance of each zip code to the nearest CBD.

Other zip code characteristics are used as control variables. **Population density** is calculated using the 2015-2019 American Community Survey (ACS) pooled estimates from IPUMS (Manson et al., 2020). **Land area** data is from the Census Bureau's Zip Code Tabulation Area files. Zip codes with fewer than 100 people or less than 0.1 square miles of area are filtered out in the analysis. Zip code coordinates are obtained from the Census Bureau's Gazetteer files and used to determine **distance from the CBD**. **Business establishment data** is from the 2018 Zip Code Business Patterns dataset.

The final dataset used as input for the model was built using the data sources described above. We adopted the Ramani and Bloom (2021) treatment for the data, adding the median household income from the American Community Survey as the dependent variable. This results in a dataset with six determinant independent variables used as covariates: WFH exposure, net flow of migration, population density, distance of the zip code from the nearest CBD and which CBD it is, and the arc-percentage change of income before the pandemic (the change after the pandemic is used as the dependent variable).

Given that, there are two rounds of models to be considered: one with zip codes from all over the United States (All-zips) and another with 12 selected metropolitan areas (12-Metro). From the 33,120 different zip codes in the United States, we used roughly 44.1% of them (14,631) in the All-zips models and 10.9% of them (3,622) in the 12-Metro models. Figure 3 shows which ones are used.

Figure 3 – Maps with the zip-codes considered in the analysis



Source: prepared by the authors based on US Census.

When weighted by total area, the zip codes considered in the All-zips models represent 26.4% of the total area in the US, while the 12-Metro models account for only 2.7%. However, the zip codes in the All-zips models represent 82.6% of the total US population in 2019, whereas the 12-Metro zip codes encompass 28.8% of the total population. Consistent with Ramani and Bloom (2021), we have filtered out all zip codes with fewer than 100 people or less than 0.1 square mile of area. Tables 2.1 and 2.2 present descriptive statistics for the most relevant variables used in the analysis for both the All-zips and 12-Metro models.

Tables 2.1 and 2.2 – Descriptive Statistics of the variables used in All-zips model (up) and 12-Metro model (down)

All-zips model								
Variable	**N**	**Mean**	**Std. Dev.**	**Min.**	**Pctl.25**	**Pctl.50**	**Pctl.75**	**Max.**
post_inc_pct_change	14,626	5.57	7.66	-78.15	2.58	5.45	8.62	85.25
pre_inc_pct_change	14,587	7.43	10.66	-85.04	2.31	7.20	12.47	102.35
wfh_emp	14,631	0.35	0.05	0.16	0.31	0.34	0.37	0.60
net_pop_20	14,608	-0.09	3.85	-172.32	-1.26	-0.05	1.03	77.35
density_2019	14,631	2,542	6,947	0.15	105.01	593.61	2,744	149,036
dist_to_cbd	14,631	31,661	24,724	60,545	13,721	25,885	43,453	447,262
2019_population	14,631	18,522	17,499	56	4,376	12,998	28,301	128,294
12-Metro model								
Variable	**N**	**Mean**	**Std. Dev.**	**Min.**	**Pctl.25**	**Pctl.50**	**Pctl.75**	**Max.**
post_inc_pct_change	3,562	5.69	6.23	-53.42	3.10	5.47	8.41	58.39
pre_inc_pct_change	3,553	8.24	9.18	-54.79	3.55	7.84	12.64	85.76
wfh_emp	3,564	0.38	0.05	0.19	0.34	0.37	0.41	0.60
net_pop_20	3,562	-0.26	4.12	-52.34	-1.51	-0.27	1.03	77.35
density_2019	3,564	6,367	12,248	2.29	869.21	2,922	6,423	148,862
dist_to_cbd	3,564	39,622	28,422	226.53	17,762	33,157	55,570	174,203
2019_population	3,564	26,489	20,342	157	10,069	23,076	37.874	128,294

Source: prepared by the authors based on ACS, USPS NCOA, LODES and Dingel and Neiman (2020)

2.2 Model Specification

The goal of the model is to address changes in median income as a result of WFH exposure and migration flow across US zip codes. To achieve this, we use a multiple linear regression, which models the response variable's— in this case, the change in income— relationship to its explanatory variables. Using the ordinary least squares method, one can calculate the predictors of the independent variables, leading to the following equation (WOOLDRIDGE, 2012):

$$\%\Delta income_{i,t} = \alpha + \beta_1 \%\Delta income_{i,t-1} + \beta_2 pop_i + \beta_3 ln\ density_i + \beta_4 ln\ dist\_CBD_i + \beta_5 ln\ WFH\_exp_i + \boldsymbol{\psi} + \epsilon_i$$

Where i stands for the zip code index, ψ is a vector of dummy variables, each indicating one Metro Area (for the two rounds of models), $\%\Delta income_t$ is the arc-percentage change of the median household income from 2020 to 2021, and $\%\Delta income_{t-1}$ is the arc-percentage change from 2018 to 2019. The model also includes the control variables used by Ramani and Bloom (2021): the density in 2019, the distance from the Central Business District to the zip code, the WFH employment exposure in 2019, and the net population flow in 2020 as a percent of the total population, all at the zip code level. Furthermore, as mentioned above, the models are weighted by the total zip code population, meaning that a zip code with a larger population has a greater impact compared to one with a smaller population.

Even though the regression analysis has some interesting characteristics, such as predicting the conditional mean of the response variable given certain values in the explanatory variables or the coefficient of determination, which is the proportion of the variation of the dependent variable explained by the model, these are not the main focus of this paper. Instead, we are interested in the values of the coefficients in the equation, particularly their signs and significance.

The significance of a predictor variable indicates whether its value is due to chance or if it is indeed significant, meaning whether the null hypothesis is rejected. The commonly considered significance levels are 5%, 1%, and 0.01%, each represented by one, two, or three stars in the results table, respectively. For this paper, a significant predictor means that the variable is important in the model context to explain the variation of the response variable. However, this should not be interpreted as a causal effect of one variable on another, as certain assumptions must be considered, and more robust modeling techniques should be used.

Therefore, the coefficients indicate how the independent variables relate to the dependent variable, whether the relationship is positive or negative. In the case of a numerical explanatory variable X, if X has a positive coefficient, on average, more of X results in more of Y (the response variable). If the coefficient is negative, more of X results in less of Y. The numerical variables in the model can be percentages or log-transformed variables, which affects the interpretation of how much Y increases or decreases, but this is not the main focus of the analysis and is therefore not considered in detail. The categorical variable used is the dummy variable for the nearest CBD to the zip code. If a dummy variable is significant, then being near that specific CBD can change the income arc-percentage change independently.

3. Results and discussion

It is important to consider the distribution of variables used in the model, notably the pre- and post-COVID-19 arc-percentage income change, the net population flow, and the WFH exposure. Since the variables in the models are weighted by the zip codes' total population, the distribution of the variables is also explored, weighting them by population.

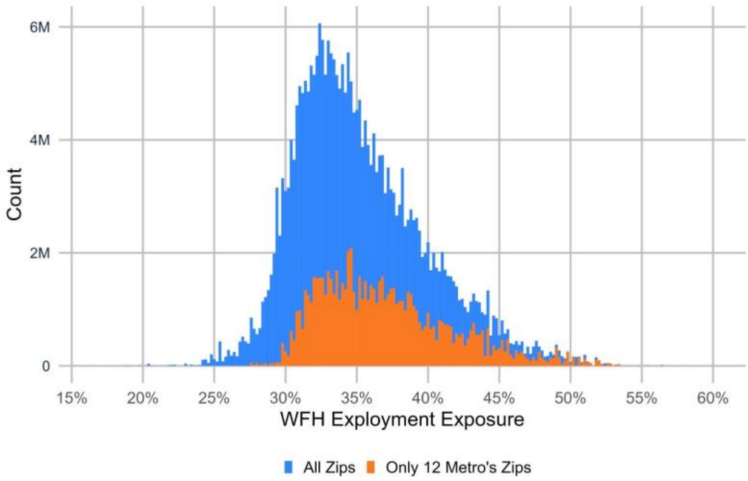
The distribution of net population flow in 2020 shows a skewness towards emigration from the zip codes. This indicates that, on average, more people are out-migrating from both the All-zips and 12-Metro models' zip codes than immigrating. Although the NCOA dataset has limited information about migration—with about one-quarter of the total zip codes not included—there is no complete tracking of the flows. However, given that highly populated zip codes experienced between 0% and 2% population loss, it is possible to hypothesize that people are moving away from city centers towards suburbs. This hypothesis aligns with the discussions in the literature review (Ramani and Bloom, 2021; Althoff et al., 2022). However, verifying this hypothesis is beyond the scope of this paper.

Figure 4 - Distribution of net population flow, weighted by zips' population

Source: prepared by the authors based on USPS NCOA.

Figure 5 shows the distribution of the WFH exposure index of employment, created by Ramani and Bloom (2021), weighted by population. The histogram suggests that most zip codes are located between 30% and 45% of WFH exposure, with the 12-Metro zip codes being skewed towards higher exposure compared to the All-zips zip codes. As discussed by Barrero et al. (2021), by the end of 2022, roughly 30% of all paid hours in the US were worked in the remote work model, which aligns well with the index.

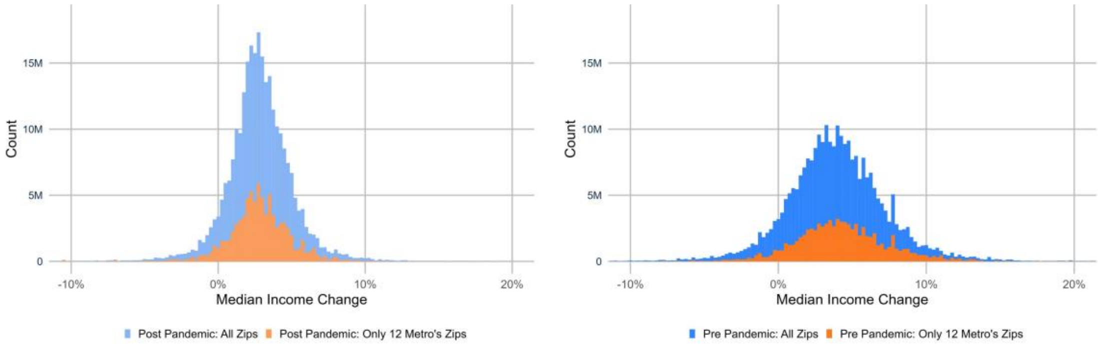
Figure 5 - Distribution of WFH exposure, weighted by zips' population



Source: prepared by the authors based on Ramani and Bloom (2021).

Finally, Figures 6.1 and 6.2 show the distribution of the arc-percentage change in income before and after the pandemic (2019 to 2020 and 2020 to 2021, respectively). The post-pandemic change is much more concentrated than the pre-pandemic change, as the COVID-19 pandemic impacted the economy uniformly, leading different locations to experience similar changes in income levels.

Figures 6.1 and 6.2 - Distribution of pre and post pandemic median household arc-percentage income change, weighted by population



Source: prepared by the authors based on American Community Survey.

3.1 General results

Table 3 shows the results of the regression analysis for four different model specifications. In models (1) and (2), all zip codes with available data are used as observations, but model (2) includes dummy variables for the nearest metropolitan areas, whereas model (1) does not. Models (3) and (4) include only zip codes from the 12 largest metropolitan areas in the US. Similarly, model (4) incorporates dummy variables for the nearest metropolitan areas, while model (3) does not.

Table 3 – Regression results

	Dependent variable:			
	post_inc_pct_change			
	(1)	(2)	(3)	(4)
pre_inc_pct_change	-0.039***	-0.070***	0.002	-0.025**
	(0.006)	(0.006)	(0.011)	(0.012)
net_pop_20	0.076***	0.057***	0.038	0.080*
	(0.018)	(0.020)	(0.044)	(0.045)
log(density2019)	0.148***	-0.200***	-0.020	-0.200**
	(0.029)	(0.047)	(0.079)	(0.093)
log(dist_to_cbd)	-0.029	-0.454***	-0.251**	-0.461***
	(0.050)	(0.069)	(0.125)	(0.135)
log(wfh_emp)	-1.973***	-3.171***	-3.187***	-3.955***
	(0.322)	(0.398)	(0.611)	(0.640)
Constant	3.092***	7.547***	5.224***	8.391***
	(0.750)	(1.754)	(1.745)	(1.921)
Observations	14,587	14,587	3,553	3,553
R^2	0.007	0.070	0.008	0.041
Note:				*p**p***p<0.01

Source: prepared by the authors based on ACS, USPS NCOA, LODES and Dingel and Neiman (2020).

The regression models indicate a negative relationship between income growth before and after the pandemic. Specifically, zip codes that experienced increasing earnings prior to the pandemic now show slower income growth. Additionally, WFH exposure before the pandemic is negatively correlated with income growth. These results combined suggest that zip codes with a high concentration of workers capable of telecommuting and earning high incomes – as Althoff et al. (2022) note, high income is positively correlated with the probability of telecommuting – have experienced out-migration of these workers. These workers have relocated with their incomes, resulting in diminished income growth in their original locations following the Zoomshock. Notably, the effect of WFH exposure is significant across all four models.

Furthermore, net population flow in 2020 is positively correlated with income, indicating that zip codes with positive net migration experienced income growth. This suggests that migration, in general, leads to increased earnings. Combining this with the previous findings, and assuming the interpretation is correct, it implies that migration motivated by remote work-related reasons is positively associated with income growth.

The distance between the zip code and the Central Business District (CBD) is negatively correlated with income growth in models that include metropolitan area dummy variables. This means that zip codes further from the CBD experience lower income growth. Despite the Donut Effect, where people move away from city centers to suburbs (Ramani and Bloom, 2021), being in a city center still correlates with higher earnings.

The effect of zip code density in 2019 on income growth varies. In model (3), where the coefficient is not significant, density is positively correlated with income when not combined with metropolitan area dummies. However, it is negatively correlated when metropolitan area dummies are included. This suggests that the variation in density's impact is explained by the inclusion of metropolitan area dummies, which alters the coefficient's sign.

In conclusion, the hypothesis that remote work and migration affect income is supported by the results. The findings suggest that workers capable of WFH moved and brought their income to their new locations, thereby increasing the median income of those areas. However, this paper aims to provide evidence for this phenomenon and acknowledges that more robust modeling is needed to establish a causal relationship between remote work migration and income growth. The following section discusses how the results hold when certain assumptions are violated.

3.2 Diagnostic tests

To verify the reliability of the results, diagnostic tests are necessary to ensure that the overall interpretation of the model remains valid even when potential violations of underlying assumptions, such as linearity, normality, and homoscedasticity, are present. Diagnostic tests help mitigate the impact of these violations by employing more robust estimation methods.

In this analysis, we adopt the same approach used by Ramani and Bloom (2021), which involves employing robust standard errors to ensure the coefficients remain significant. Robust standard errors are particularly useful in protecting against the effects of outliers, which can substantially impact ordinary standard errors.

Additionally, diagnostic tests provide a check on the model's validity, ensuring that the results are not solely driven by outliers or a particular subset of the data. By conducting these tests, analysts can be more confident in the validity of the results and the conclusions drawn from the analysis.

Robust standard errors are calculated using the sandwich estimator method, which accounts for the data's covariance structure. This method provides a more accurate representation of the estimators' variability, leading to more reliable hypothesis tests and confidence intervals, while maintaining the same interpretation of the model. Table 4 presents the results using robust standard errors.

Table 4 – Regression results with robust standard errors

	Dependent variable:			
	post_inc_pct_change			
	(1)	(2)	(3)	(4)
pre_inc_pct_change	-0.039***	-0.070***	0.002	-0.025
	(0.011)	(0.011)	(0.025)	(0.025)
net_pop_20	0.076**	0.057	0.038	0.080
	(0.034)	(0.035)	(0.064)	(0.075)
log(density2019)	0.148***	-0.200***	-0.020	-0.200
	(0.044)	(0.076)	(0.124)	(0.147)
log(dist_to_cbd)	-0.029	-0.454***	-0.251	-0.461**
	(0.087)	(0.127)	(0.200)	(0.229)
log(wfh_emp)	-1.973***	-3.171***	-3.187***	-3.955***
	(0.536)	(0.680)	(0.866)	(0.947)
Constant	3.092**	7.547***	5.224*	8.391***
	(1.261)	(2.684)	(2.746)	(3.216)
Observations	14,587	14,587	3,553	3,553
R^2	0.007	0.070	0.008	0.041
Note:				*p**p***p<0.01

Source: prepared by the authors based on ACS, USPS NCOA, LODES and Dingel and Neiman (2020)

With the updated standard errors, some of the coefficients lose significance, indicating that the model's predictive power for median income should be interpreted with caution. Notably, the WFH exposure variable remains significant, affirming its substantial explanatory power over income. However, the other critical covariate, net population flow, loses significance in models (2) and (4), remaining significant only in model (1). This suggests that migration positively affects income across all zip codes when not accounting for nearest CBD dummy variables, while the effect becomes null in the other models.

The pre-pandemic arc-percentage change of median household income and the zip code density remain significant only in the All-zips models, whereas they do not hold in the 12-Metro models. Additionally, the distance from the nearest CBD of each zip code is significant only in the models that include metro dummies.

Given these results, it appears that the analysis inspired by Ramani and Bloom (2021) for the 12 largest metropolitan areas is less robust compared to the analysis conducted nationwide. As several coefficients lose significance with robust standard errors, the overall explanatory power of the model diminishes.

To address these issues and better determine whether migration motivated by remote work directly influences income, as suggested by Ramani and Bloom (2021) and Althoff et al. (2022), further research is necessary. Future studies should aim to expand the pool of evidence, employing additional exercises to enhance the robustness of the findings.

Final Remarks

Working from home has become an integral part of our daily lives. While it is still too early to fully measure its long-term impacts on markets and society, the increased attention and growing body of literature since 2020 provide new insights into its effects. This paper aims to contribute to the ongoing debate by presenting evidence that remote work and the associated new migration flows can influence income growth, thereby altering the economy.

Existing literature indicates a new migration flow driven by the possibility of working from home (Ramani and Bloom, 2021; Althoff et al., 2022). The consensus is that individuals who can work from home tend to migrate with their incomes to new locations. On average, these individuals, who perform skilled, scalable service jobs, have higher incomes and can move to areas with more amenities without leaving their jobs. In contrast, non-SSS workers, who generally do not work from home, remain near their onsite workplaces and lose revenue from migrating workers who no longer consume locally. However, non-SSS workers in the destination areas of these movers benefit from the increase in local spending.

This paper provides further evidence for this explanation using a multiple linear regression model to analyze the arc-percentage change in income after the pandemic, explained by WFH exposure before the pandemic and net population flow after it. The findings suggest that areas with higher pre-pandemic WFH exposure experienced a decline in income post-shock due to the migration of SSS workers. Conversely, areas with a high inflow of people saw significant income gains. This dynamic is examined both between and within cities, as the analysis is conducted at the zip code level.

The paper addresses a relatively unexplored aspect of WFH and migration in the current literature, specifically how local economies respond to newcomers who migrate due to remote work. It also provides a comprehensive and updated literature review summarizing the main data sources and methods used in WFH research.

However, the debate is far from settled. The evidence provided by the model results is not causal and lacks sufficient robustness to be conclusive. Future research should incorporate new data to enhance the model's explanatory power and update the dataset beyond the current four-year period. Additional robustness tests and alternative modeling strategies are necessary to ensure the reliability of the results and to draw causal inferences from the findings. Future studies should aim to address these gaps to further our understanding of the economic impacts of remote work and migration.

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