Teleworkability: The Weakened Tie Between Office Place and Residential Place

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Abstract

Since the Industrial Revolution, workers have tended to live close to their workplaces due to the need for physical commuting, driving the formation of factory towns and contributing to agglomeration economies. However, advancements in information technology and communication tools have enabled many jobs to be performed remotely. While flexible work arrangements were not widely adopted before 2020, the COVID-19 pandemic accelerated the shift, particularly for teleworkable jobs, granting workers in these roles greater flexibility regarding workplace location. This paper examines the impact of teleworkability on migration patterns, focusing on the likelihood of moving, interstate migration, relocation distances, and the distance between home and workplace. Using data from the American Community Survey (2013–2022) and employing an instrumented difference-in-differences approach, the study reveals that, relative to non-teleworkable workers, teleworkable workers are 6% more likely to migrate overall, experience an 10% increase in interstate migration, and move an average of 24 miles farther. The analysis also shows that teleworkable workers are more willing to accept longer commutes and live farther from their workplaces, reflecting a weakened link between home and office locations. These effects are particularly pronounced among women, married couples, and dual-career households. Furthermore, county-pair analysis demonstrates a notable shift in migration preferences, with workers moving out of counties with higher shares of teleworkable workers and larger population. This study underscores the significant implications of telework for individual lifestyle choices and broader economic and urban structures, offering valuable insights for policymakers and urban planners navigating the post-pandemic labor market.

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1 Introduction

The spatial relationship between residential areas and workplaces has long been a defining feature of labor markets and urban development. Since the Industrial Revolution, geographic proximity between home and work has been essential for minimizing commuting costs and maximizing productivity, as evidenced by the emergence of factory towns and urban centers centered around specific industries. Throughout the 20th century, economic factors such as agglomeration economies reinforced this connection, shaping urban structures and influencing labor mobility patterns.

However, the rise of telework has begun to disrupt this traditional linkage, particularly for workers whose jobs can be performed remotely. Advancements in information technology and communication tools have enabled remote work arrangements, offering workers in teleworkable jobs greater flexibility in balancing their job and living arrangements. In contrast, workers in non-teleworkable jobs continue to face the need for physical commuting. The COVID-19 pandemic served as a significant catalyst for this shift, compelling many industries to adopt remote or hybrid work models where feasible. Empirical evidence from the pandemic period indicates that approximately half of workers previously employed in non-remote roles transitioned to telework, with 35.2% of these individuals being prior commuters (Brynjolfsson et al., 2020).

As telework has become a widespread work arrangement for certain occupations, the traditional relationship between home and work is being redefined. This raises key questions about how teleworkability affects migration patterns, labor mobility, and household location decisions. Workers in teleworkable jobs now enjoy the greater freedom to live farther from their workplaces, enabling them to prioritize factors such as housing affordability, lifestyle preferences, and family needs over proximity to job centers. This shift makes it crucial to understand how increased workplace flexibility among teleworkable workers influences geographic mobility, particularly in light of the pandemic-driven acceleration of remote work. The shift towards telework among teleworkable jobs represents a fundamental change in the structure of labor markets and urban economies. As remote work becomes more widespread in these occupations, it challenges long-standing assumptions about the necessity of geographic proximity to workplaces and its influence on housing markets, commuting behavior, and migration. Understanding these shifts is crucial for policymakers, urban planners, and businesses, as telework has the potential to reshape cities, reduce congestion, and alter the demand for infrastructure and housing. By decoupling work from location for a subset of the workforce, telework raises important questions about regional economic disparities, as teleworkable workers are increasingly able to move away from high-cost urban centers to more affordable areas without sacrificing employment opportunities. Workers in non-teleworkable jobs, however, continue to face the traditional constraints imposed by physical commuting requirements. The implications of this shift for social and economic equity are complex. On one hand, teleworkable jobs are more prevalent among higher-educated, higher-paid occupations, potentially exacerbating existing inequalities by benefiting those already in more privileged positions. On the other hand, increased demand for services and housing in residential areas could stimulate local economies, potentially alleviating some disparities by redistributing economic activity outside of traditional job centers. Moreover, the rise in teleworkability offers the potential to expand opportunities for underrepresented or marginalized groups who have historically faced geographic constraints. Women balancing caregiving responsibilities, dual-career households struggling with co-location challenges, and individuals living in regions with fewer job opportunities may now have greater flexibility to pursue careers without being tied to specific locations. Telework could thus play a role in increasing labor mobility and supporting more inclusive economic participation for these groups.

This paper investigates how the rise in teleworkability, accelerated by the COVID-19 pandemic, has impacted workers' migration patterns and geographic choices. Specifically, the study examines how increased workplace flexibility among teleworkable workers after the pandemic influences the likelihood of moving, interstate migration, the distance of relocations, and the relationship between home and office locations. Utilizing data from the American Community Survey (ACS) spanning 2013 to 2022, we employ an instrumented difference-in-differences (IV-DiD) approach to estimate the causal effects of teleworkability on migration decisions. Workers in non-teleworkable jobs serve as the control group in this analysis, allowing for a comparison of migration patterns between teleworkable and non-teleworkable workers. The instrument for teleworkability is based on the share of teleworkable jobs by field of degree in 2013, capturing the long-term alignment between educational choices and job teleworkability.

Our findings suggest that workers in teleworkable jobs are more likely to move post-pandemic by approximately 6%, with an increased likelihood of interstate migration by 10% and greater relocation distances, averaging an increase of 24 miles. These changes highlight the substantial impact of telework on mobility patterns among teleworkable workers, as the traditional geographic constraints of work and residence become less relevant. Additionally, the analysis of home-office distance shows that teleworkable workers are more willing to accept longer commutes and, for those living in different PUMAs, are residing significantly farther from their workplaces, reflecting the weakened link between work and home locations. These effects are more pronounced among specific demographic groups, particularly women, married couples, and dual-earner households. For these groups, the flexibility afforded by telework enables a more nuanced balance between job location and family needs, allowing them to navigate the complexities of co-locating careers and household responsibilities more effectively.

The results on migration preferences, based on county pair analysis using a gravity model, reveal that counties with a higher share of teleworkable workers experienced increased out-migration post-pandemic. Contiguous county pairs are seeing a decrease in migration post-pandemic, indicating that movers are migrating over longer distances. Additionally, migration flows have shifted away from more densely populated counties and counties with lower education quality. Migrants are moving into locations with higher median household income and lower gross rent. Interestingly, there is no significant difference in destination preferences across teleworkability, suggesting that teleworkable and non-teleworkable workers value similar characteristics in destination counties.

This study makes several contributions to the existing literature on telework, labor market flexibility, migration, and dual-career households. First, it extends the literature on telework and labor market flexibility by shifting the focus from job characteristics and productivity impacts to the broader spatial implications of teleworkability, specifically for workers in teleworkable jobs. Previous studies have primarily described the characteristics of jobs that can be performed remotely, such as those by Dingel and Neiman (2020), which classified jobs based on their potential for remote work, and Adams-Prassl et al. (2022), which explored the heterogeneity in the ability to work from home across occupations and industries, revealing systematic differences in teleworkability by gender and employment stability. Studies like Brynjolfsson et al. (2020) analyzed the sudden shift to telework during the COVID-19 pandemic, while others such as Bloom et al. (2015) and Pabilonia and Vernon (2022) have focused on estimating telework's effects on productivity, wages, and time use. However, these works have generally overlooked the spatial dimension of telework and how it reshapes workers' geographic mobility. By examining how increased teleworkability influences migration patterns, home-office distance, and relocation preferences, this study fills a critical gap in the literature by linking labor market flexibility with relocation decisions and geographic mobility.

Second, this paper contributes to the literature on migration and labor mobility, which has often focused on urban structure and residential choices but has not fully addressed how job characteristics—such as teleworkability—shape relocation decisions. Traditional migration studies, such as Glaeser, Kolko, and Saiz (2001); Rappaport (2007); Diamond (2016), have analyzed the determinants of geographic mobility and the role of housing costs, amenities, and job opportunities in urban and regional migration. More recent works, such as Delventhal, Kwon, and Parkhomenko (2022); Delventhal and Parkhomenko (2023), have developed spatial equilibrium models to explore how telework impacts urban structure, housing prices, and suburbanization trends. Brueckner, Kahn, and Lin (2023) demonstrated the downward pressure on housing prices in high-productivity areas due to WFH, while Gupta et al. (2022) showed the flattening of the bid-rent curve. Despite these advances, empirical evidence on how teleworkability directly influences migration behavior remains scarce. This paper addresses this gap by providing evidence that teleworkability significantly impacts migration patterns, including migration rates, interstate moves, relocation distances, and preferences for origin and destination counties.

Third, this study contributes to the literature on dual-career households and co-location challenges. The literature on dual-career households has highlighted the challenges faced by couples in balancing career opportunities and residential locations, particularly the trailing spouse problem and gender differences in commuting patterns (Costa and Kahn, 2000; Guler, Guvenen, and Violante, 2012; Venator, 2020). By analyzing migration decisions across subgroups, including gender, marital status, and spousal employment status, this study provides new insights into how telework flexibility mitigates the co-location challenges faced by dual-earner couples. Telework allows for a more flexible geographic arrangement, reducing the trade-offs between job location and family needs, which has significant implications for gender equity in labor market participation and the household division of labor.

The remainder of this paper is structured as follows: Section 2 describes the data and presents descriptive statistics. Section 3 outlines the empirical strategy and identification assumptions. Section 4 presents the baseline results on migration patterns and home-office relationship, and discusses robustness checks and heterogeneity analysis. Section 5 shows the results on migration preference. Section 6 concludes the paper and offers directions for future research.

2 Data and Descriptive Analysis

This section outlines the primary data sources used in the study and provides a descriptive analysis of the data.

2.1 Data

2.1.1 American Community Survey

This study utilizes data from the American Community Survey (ACS), accessed through the Integrated Public Use Microdata Series (IPUMS-USA) database (Ruggles et al., 2024). The ACS is a nationally representative, ongoing survey that provides detailed demographic, social, and economic information on the United States population. It is well-suited for examining migration patterns at a granular level due to its comprehensive geographic and household-level information.

For this analysis, ACS data from 2013 to 2022 are used, excluding the year 2020 due to significant disruptions in data collection during the COVID-19 pandemic. The focus is on employed workers aged 25 to 55, capturing prime-age individuals and excluding those more likely to be affected by labor market entry or exit decisions, such as students or retirees. Additionally, the sample is restricted to individuals with at least a bachelor's degree. This restriction is motivated by two factors: first, teleworkable jobs are more prevalent among higher-educated workers, making the analysis more relevant and comparable; second, the instrumental variable (IV) strategy used in this study relies on workers' field of degree, which is only available for those with a college education.

The primary independent variable is *teleworkability*, defined at the occupation level using the classification from Dingel and Neiman (2020). Occupations are classified based on whether their tasks and work environment allow for remote work. However, using current occupation to measure teleworkability may introduce endogeneity, as workers might select into teleworkable jobs after the pandemic to enjoy flexible work arrangements. To address this issue, an IV approach is employed, using the percentage of teleworkable jobs by field of degree in 2013 as an instrument for teleworkability. This instrument assumes that a worker's field of study influences their occupational outcomes and thus teleworkability, while remaining exogenous to migration decisions made after entering the labor market. Due to the construction of IV using 2013 data, the analyses are based on ACS 2014-2022 (excluding 2020) observations.

Migration patterns are captured through two main variables. First, *migration status* identifies whether an individual has moved within the last year. Second, *migration distance* measures the distance moved by individuals who have changed their place of residence. This distance is calculated based on the centroids of the Public Use Microdata Areas (PUMAs) of their current and previous residences. For individuals who moved within the same PUMA, the distance is proxied using the radius of that PUMA. PUMAs are the smallest geographic units in the ACS, each containing a population of at least 100,000 residents, allowing for a meaningful analysis of geographic mobility.

To examine the impact of teleworkability on commuting patterns, the study analyzes the distance between workers' residential locations and their places of work. The *office-home distance* is calculated using the distance between the centroids of the residence PUMA and the place-of-work PUMA, as reported in the ACS. For individuals who work within the same PUMA as their residence, the distance is approximated using the radius of that PUMA. This method accounts for the lack of more precise geographic identifiers due to privacy restrictions but still provides a reasonable proxy for commuting distance.

Standard demographic variables are incorporated into the analysis. These include age, sex, education level, marital status, and family structure, such as the presence of young children and spousal employment status. These variables provide additional insights into the characteristics that may influence migration behavior across different demographic groups.

2.1.2 Location Characteristics

To analyze how migration decisions are influenced by characteristics of both origin and destination counties[1] and to examine the impact of the origin county's share of teleworkable workers, data from multiple sources are combined.

The migrant flows between pairs of counties are derived from the main ACS data analysis. To understand how increased teleworkability has changed migration preferences, the *lagged share of teleworkable workers* in the destination and origin county is included. This variable, calculated using ACS data from 2014 onwards, reflects the percentage of teleworkable jobs in each county in the previous year. This approach allows us to capture how the teleworkable job composition influences subsequent migration behavior, with the data for this analysis spanning from 2014 to 2022.

To better understand the drivers of migration decisions, a variety of county-level characteristics are considered. First, to account for the potential impact of the COVID-19 pandemic on migration preferences, I incorporate county-level COVID-19 severity data from The New York Times. Using data from June 2020, I calculate two specific measures: the infection rate, defined as the total number of COVID-19 cases divided by the 2019 population (to avoid any COVID-induced population shifts); and the death rate, calculated as the total number of COVID-19 deaths in June 2020 per the 2019 population. These

[1] 2022 observations for counties in Connecticut are excluded due to the change from county to planning regions as county-equivalent geographic units.

metrics provide insight into the initial severity of the pandemic across counties, offering a perspective on whether health risks influenced migration patterns.

Second, to understand whether individuals prefer relocating within nearby areas or moving further, I include *county adjacency* data from the U.S. Census Bureau. This dataset identifies whether pairs of counties are geographically contiguous, helping to capture the extent of moves between neighboring versus non-neighboring counties. In addition, to distinguish migration trends between urban and rural areas, *metropolitan status* is included. This information is derived from the 2023 Rural-Urban Continuum Codes, provided by the U.S. Department of Agriculture's Economic Research Service. These codes classify counties based on their level of urbanization and proximity to metropolitan areas, allowing for an analysis of whether workers prefer to move towards more urban, suburban, or rural regions.

Third, to capture the overall economic and demographic environment, I use county-level socioeconomic data from the ACS 5-year estimates. Variables such as *population*, *median household income*, *unemployment rate*, and *median gross rent* help to understand the economic landscape that might attract or repel migrants. For example, the unemployment rate and population density provide insights into both economic opportunities and urbanization levels, which are key determinants of migration decisions.

Fourth, health and quality-of-life considerations are also essential factors in relocation decisions. Therefore, I incorporate additional data from the County Health Rankings & Roadmaps program. This dataset includes the *Primary Care Physicians Rate* (as a measure of healthcare access), the percentage of households with *severe housing problems* (indicative of housing quality), the *injury death rate* (as a community safety indicator), and the *average daily* $PM_{2.5}$ concentration (to measure environmental quality). These metrics help to capture the attractiveness of counties based on safety, healthcare, and living conditions.

Finally, to capture workers' preferences over education quality, particularly for households with young children, I include the *average test scores* from the Stanford Education Data Archive (SEDA). These scores are derived from standardized math and Reading Language Arts (RLA) tests, which were administered annually by each state to all public-school students in grades 3–8 from the 2008–09 through 2018–19 school years. The scores indicate the quality of educational opportunities, which often plays a critical role in migration decisions for families.

By integrating these diverse data sources, this study captures a comprehensive set of county-level characteristics that may influence migration preferences and decisions. This allows for a detailed analysis of how teleworkability affects not only the likelihood of migration but also the types of locations individuals choose when moving, considering multiple aspects of quality of life, urbanization, economic opportunity, and community resources.

2.2 Descriptive Analysis

Table 1: Summary Statistics of American Community Survey

Variable	Teleworkable	Non-teleworkable	Total
Age	39.68	40.47	40.23
	(8.87)	(8.69)	(8.75)
Sex (female = 1)	0.53	0.52	0.52
	(0.50)	(0.50)	(0.50)
Citizen	0.94	0.94	0.94
	(0.24)	(0.24)	(0.24)
White	0.75	0.78	0.77
	(0.43)	(0.42)	(0.42)
Married	0.64	0.68	0.67
	(0.48)	(0.47)	(0.47)
number of own family members in household	3.02	2.99	3.00
	(1.49)	(1.42)	(1.44)
Has child under age 5	0.19	0.18	0.18
	(0.39)	(0.39)	(0.39)
N	834,135	2,004,186	2,838,321

Note: This table presents the summary statistics by the teleworkability status of workers. The ACS data is from 2014 to 2022, excluding 2020. Standard deviations in parentheses.

2.2.1 Summary Statistics

Table 1 presents summary statistics of key demographic and household characteristics for workers in teleworkable and non-teleworkable occupations. The sample comprises employed individuals aged 25 to 55 with at least a bachelor's degree, totaling 2,838,321 observations—834,135 in teleworkable jobs and 2,004,186 in non-teleworkable jobs. Overall, teleworkable and non-teleworkable workers exhibit similar demographic profiles, which is crucial for isolating the impact of teleworkability on migration behaviors without confounding demographic factors. The average age is slightly lower among teleworkable workers (39.68 years) compared to non-teleworkable workers (40.47 years), though this difference is minimal. The gender distribution is nearly identical, with females comprising 53% of teleworkable workers and 52% of non-teleworkable workers. Citizenship status is consistent across both groups, with 94% being U.S. citizens. Some differences emerge in racial composition and marital status. Teleworkable workers are slightly less likely to be White (75%) compared to non-teleworkable workers (78%). Additionally, a smaller proportion of teleworkable workers are married (64%) compared to non-teleworkable workers

Table 2: Teleworkability by Main Occupations

Main Occupation	Teleworkability	Share in the Full Sample
Architecture and Engineering	66.69	4.00
Arts, Design, Entertainment, Sports, and Media	82.15	3.60
Building and Grounds Cleaning and Maintenance	0.00	0.56
Business and Financial Operations	92.97	11.06
Community and Social Service	37.79	3.46
Computer and Mathematical	100.00	6.72
Construction and Extraction	1.79	0.82
Educational Instruction and Library	97.99	12.81
Farming, Fishing, and Forestry	2.64	0.15
Food Preparation and Serving	2.50	1.06
Healthcare Practitioners and Technical occ.	8.43	10.50
Healthcare Support	4.37	0.88
Installation, Maintenance, and Repair	0.90	0.63
Legal	100.00	2.69
Life, Physical, and Social Science	75.97	2.32
Management	85.22	18.06
Office and Administrative Support	81.91	7.17
Personal Care and Service	50.29	1.16
Production	1.89	1.37
Protective Service	14.98	1.69
Sales and Related Occupations	52.98	7.72
Transportation and Material Moving	7.40	1.57

(68%). Household size is similar across groups, averaging around three family members. The proportion of workers with children under age five is also comparable, at 19% for teleworkable workers and 18% for non-teleworkable workers. These similarities suggest that, while minor demographic differences exist, the two groups are largely comparable in terms of age, gender, household composition, and family responsibilities. This comparability strengthens our empirical strategy by reducing concerns that any observed differences in migration behavior are driven by underlying demographic disparities rather than differences in teleworkability.

Table 2 displays the percentage of teleworkable jobs and the share of each occupation in the full sample across major occupational categories. Occupations such as *Computer and Mathematical* and *Legal* are classified as fully teleworkable, with 100% of workers in these fields having the option to work remotely. High levels of teleworkability are also observed in occupations like *Educational Instruction and Library* (98%), *Business and Financial Operations* (93%), and *Management* (85%). These occupations typically involve cognitive, analytical, or managerial tasks that can be performed independently of a specific location, aligning with the capacity for remote work. Conversely, occupations requiring physical presence or manual labor exhibit low teleworkability. For instance, *Construction and Extraction*

(1.79%), *Food Preparation and Serving* (2.50%), and *Building and Grounds Cleaning and Maintenance* (0%) have minimal teleworkability. Even in sectors like *Healthcare Practitioners and Technical Occupations*, teleworkability remains low (8.43%) due to the necessity of direct patient care. This distribution underscores the significant variation in teleworkability across occupations, reflecting inherent differences in job tasks and requirements.

2.2.2 Trends in Teleworkable Jobs Over Time

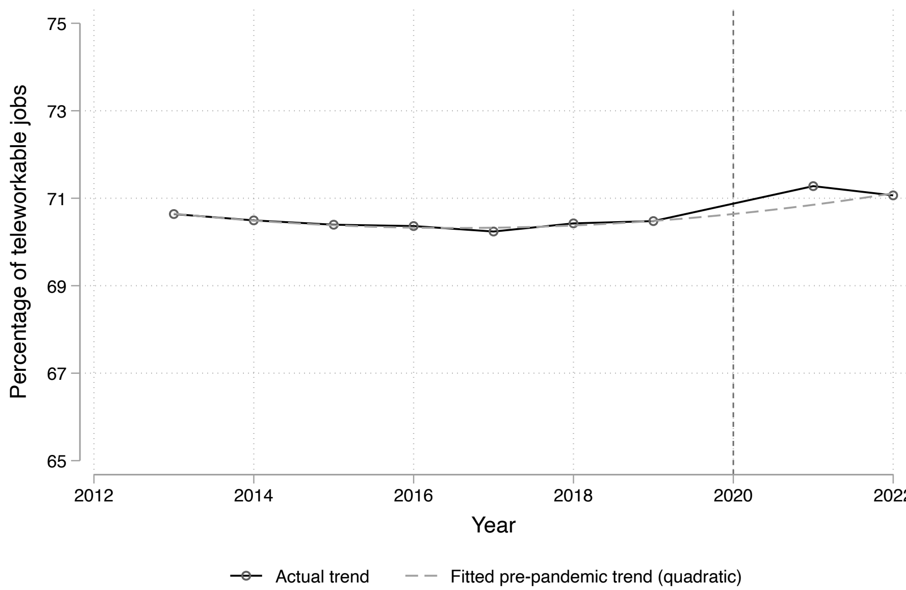


Figure 1: Share of Teleworkable Jobs over Time

Note: The solid line represents the actual trend in teleworkable jobs from 2013 to 2022, while the dashed line represents the fitted quadratic trend based on pre-pandemic data (2013-2019). The vertical line at 2020 marks the onset of the COVID-19 pandemic.

Figure 1 displays the share of teleworkable jobs over time from 2013 to 2022, comparing the actual observed trend (solid line) with the pre-pandemic fitted quadratic trend (dashed line) based on data from 2013 to 2019. Prior to the COVID-19 pandemic, the percentage of teleworkable jobs remained relatively stable, experiencing a slight decline from 2013 to 2017, followed by a modest upward trend in 2018 and 2019. After the onset of the pandemic in 2020, a noticeable deviation from the pre-pandemic trend emerges. However, the magnitude of this change is modest; the proportion of teleworkable jobs increased by less than one percentage point in 2021 compared to 2019. This suggests that there was not a substantial shift in workers changing occupations to teleworkable jobs post-pandemic, mitigating concerns about endogeneity arising from occupation switching.

2.2.3 Demographic Trends by Teleworkability

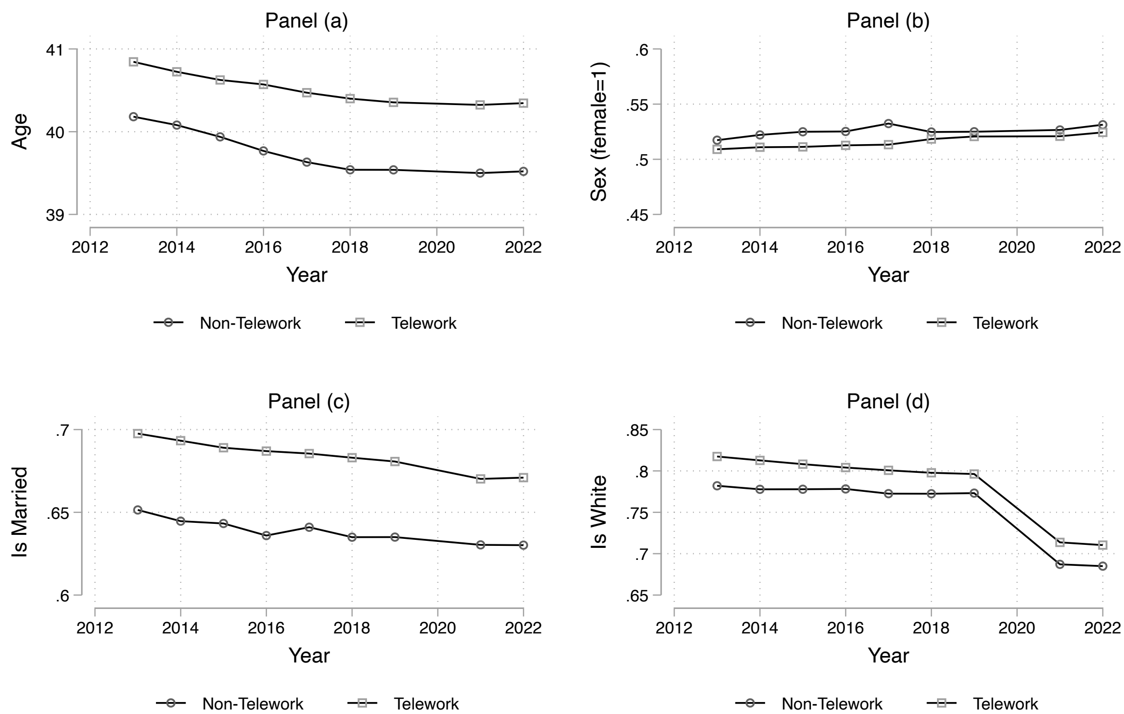


Figure 2: Demographic Trend by Teleworkability Status

Note: The figure shows demographic trends for teleworkable and non-teleworkable workers between 2013 and 2022. Panel (a) presents the average age, Panel (b) shows the proportion of female workers, Panel (c) represents the marital status (proportion married), and Panel (d) displays the proportion of White workers.

The demographic trends presented in Figure 2 indicate a high level of stability in the composition of teleworkable and non-teleworkable groups throughout the study period. Panel (a) shows that the average age of workers in both groups has slightly declined over time, with teleworkable workers consistently being older than their non-teleworkable counterparts. However, the gap in average age remains small and relatively constant, providing assurance that age is not driving the differential migration behavior between these groups. Panel (b) suggests that the proportion of female workers increased steadily and the difference between teleworkable workers and non-teleworkable workers is small. Panel (c) shows marital status trends, where teleworkable workers are consistently more likely to be married than their non-teleworkable peers. Despite a gradual decline in the proportion of married workers in both groups, there are no dramatic shifts that would suggest significant demographic changes within the sample. Finally, panel (d) reports racial composition, with a consistent gap in the share of White workers between the two groups. However, the trends in racial composition follow similar trajectories, particularly after 2017, indicating no marked compositional change post-pandemic that could interfere with the analysis. Overall, these demographic trends suggest that the teleworkable and non-teleworkable groups remained comparable in key characteristics throughout the study period. As a result, we can reasonably attribute differences in migration patterns to the shock of teleworkability brought on by the COVID-19 pandemic, rather than to any significant changes in worker demographics.

2.2.4 Migration Patterns Over Time

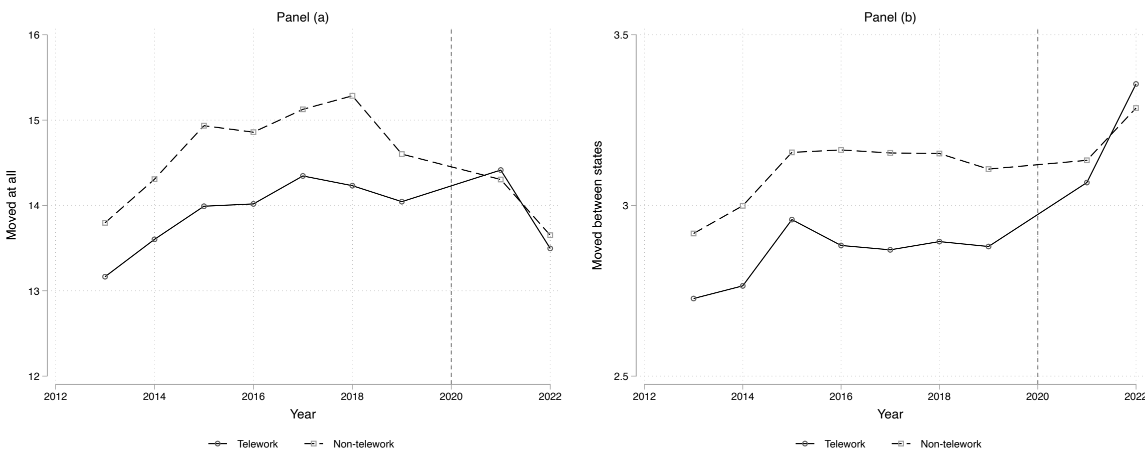


Figure 3: Likelihood of Move by Teleworkability Status over Time

Note: Trends in migration rates and interstate migration rates by teleworkability status from 2013 to 2022. Panel (a) presents the proportion of workers who moved in the last year, and Panel (b) depicts the proportion of workers who moved across state lines. The vertical dashed line indicates the start of the COVID-19 pandemic in 2020.

Figure 3 illustrates the migration patterns by teleworkability status for two key measures: the likelihood of moving at all (Panel a) and the likelihood of interstate migration (Panel b). The solid lines correspond to workers in teleworkable jobs, while the dashed lines represent workers in non-teleworkable jobs. Before the pandemic, both groups exhibit relatively stable trends in their migration behaviors, providing initial support for the parallel trends assumption in a difference-in-differences framework. In both panels, the trends for teleworkable and non-teleworkable workers appear similar, with only minor differences over time. For example, the overall likelihood of moving at all fluctuates within a small range, with non-teleworkable workers consistently showing a slightly higher migration rate before 2020. Post-2020, a clear divergence emerges between the two groups. The proportion of teleworkable workers moving in any given year drops significantly, while the rate for non-teleworkable workers declines more sharply. Similarly, the interstate migration rate for teleworkable workers rises dramatically after the pandemic, while non-teleworkable workers experience only a modest increase. These post-pandemic trends suggest that the ability to telework may have afforded workers greater flexibility to relocate, particularly across state lines, while those in non-teleworkable jobs may have been less mobile due to employment constraints or other factors. The pre-pandemic stability and post-pandemic divergence highlight the importance of teleworkability in shaping migration behaviors, reinforcing the validity of the empirical strategy that leverages the COVID-19 pandemic as an exogenous shock to teleworkability.

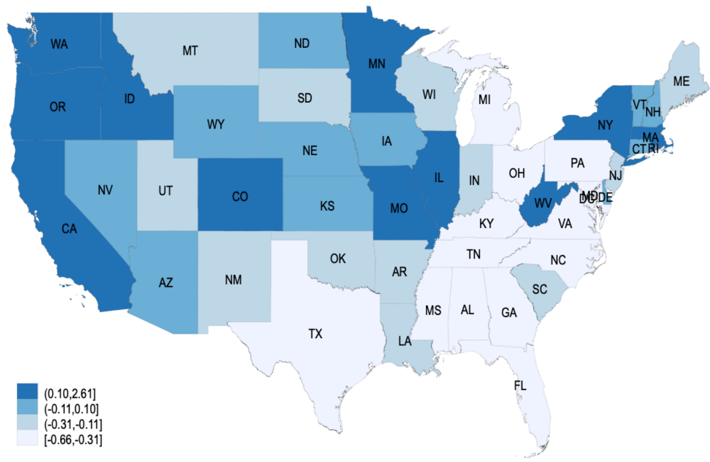
2.2.5 Migration Flows

Figure 4 illustrates the changes in interstate migration patterns from 2019 to 2021, focusing on the proportion of interstate migrants moving from and to each state as a share of total number of interstate movers. 4a shows the change in the proportion of migrants originating from each state, while 4b depicts the change in the proportion of migrants arriving in each state. These maps provide insight into how migration trends shifted during this period, potentially influenced by the increased prevalence of remote work and other factors following the COVID-19 pandemic.

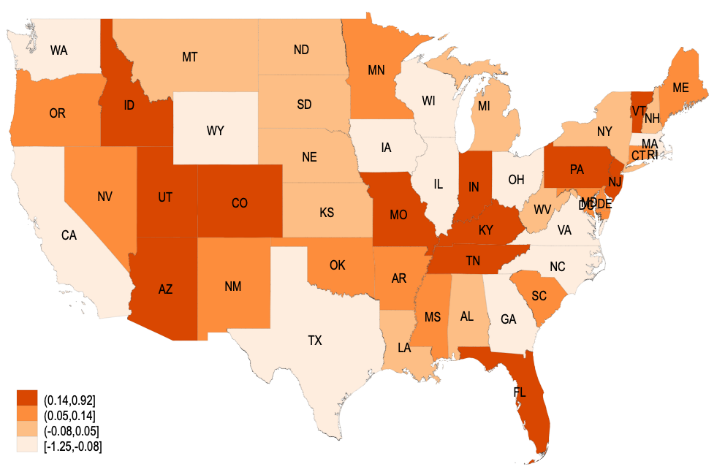
4a shows the change in the proportion of interstate migrants leaving each state between 2019 and 2021. Darker shades of blue indicate a greater increase in the share of migrants coming from a state, while lighter shades represent smaller changes. One of the key observations is the *increased out-migration from coastal states.* States on the west coast, such as California, Washington, and Oregon, as well as states on the east coast, including New York and Massachusett, experienced the largest increases in the proportion of out-migrants. This pattern aligns with the narrative of workers leaving densely populated urban areas, which became less attractive due to high living costs, and the necessity of living near major metropolitan job centers is weakened by the growing flexibility of remote work.

4b highlights the change in the proportion of migrants moving into each state during the same period. Darker shades of orange indicate a larger increase in the share of inbound migrants. A notable trend is the *increased in-migration to neighboring inland states.* States contiguous to the coastal areas experiencing high out-migration, such as Nevada, Idaho, Utah, and Arizona in the west, and states like Vermont, Pennsylvania, New Jersey, Tennessee in the east, saw an increase in their share of inbound migrants. These states likely attracted migrants due to more affordable housing, lower population densities, and better community amenities, while still being relatively close to the major job hubs on the coasts.

Overall, the analysis of these figures suggests that the pandemic led to a significant reshuffling of interstate migration patterns, characterized by out-migration from large coastal states and in-migration to



(a) The Proportion Change in Origin State



(b) The Proportion Change in Destination State

Figure 4: Change in Interstate Migration Flows 2019 to 2021

Note: The figure illustrates changes in interstate migration flows across U.S. states between 2019 and 2021. Alaska and Hawaii are not included in the map. Panel 4a shows the change in the outmigration rate, which measures the proportion of people moving out of a state relative to the total number of interstate movers in a given year. A positive value for a state indicates that the proportion of people moving out of that state increased in 2021 compared to 2019. Panel 4b presents the change in the inmigration rate, which represents the proportion of people moving into a state as a share of the total number of interstate movers in a given year. A positive value for a state indicates that the proportion of people moving into that state increased in 2021 compared to 2019.

more affordable, less densely populated states, particularly those in close proximity to the major coastal job hubs. This shift likely reflects a combination of factors, including the increased flexibility brought by telework, changing preferences for housing affordability and space, and local economic conditions. These maps, combined with the earlier regression results showing the positive effect of teleworkability on migration patterns, reinforce the idea that increased workplace flexibility is reshaping traditional migration dynamics. Workers are moving away from densely populated and expensive urban areas to more affordable regions while still maintaining access to their jobs remotely.

3 Empirical Strategy

3.1 Instrumented Difference-in-Differences

To estimate the causal effect of teleworkability on migration outcomes, I employ an instrumented difference-in-differences (IV-DiD) approach. The COVID-19 pandemic serves as an exogenous shock that altered the feasibility and prevalence of remote work, providing a natural experiment to identify the impact of increased teleworkability. Prior to the pandemic, most workers were required to commute to their workplaces due to company policies and the nature of their work. However, following the outbreak of COVID-19, many companies adopted remote work policies for jobs that can be performed remotely. Consequently, workers in teleworkable occupations experienced an increase in workplace flexibility, while those in non-teleworkable occupations continued to work on-site.

A key challenge in implementing a difference-in-differences analysis is the potential endogeneity of the teleworkability variable. The pandemic-induced shift toward remote work may have prompted individuals to switch into teleworkable occupations to obtain flexible work arrangements. This occupational switching introduces bias, as current occupation teleworkability may be endogenous to migration decisions. To address this issue, I employ an instrumental variable (IV) strategy.

The instrument used is the share of teleworkable jobs in 2013 by field of degree (FoD). This approach relies on the notion that an individual's field of study, chosen before entering the labor market, strongly influences their occupational choice and, consequently, their teleworkability. The key advantage of this instrument is that it captures predetermined variation in the propensity to work in teleworkable occupations, which remains relatively stable over time and is unaffected by the pandemic-induced shift toward telework. Specifically, individuals with degrees in fields that lead to teleworkable occupations are more likely to hold teleworkable jobs. For example, graduates in computer science are more likely to enter teleworkable occupations such as software development, whereas those with degrees in health-care or construction are more likely to work in non-teleworkable occupations. Therefore, the share of teleworkable jobs by field of degree serves as a relevant instrument for individual teleworkability.

The IV-DiD framework is formally specified in two stages:

$$
\begin{aligned}
Tele_{it} = \alpha_0 + \alpha_1 z_i + \lambda X_{it} + \eta_{ct} + \delta_p + \xi_{qt} + u_{it} \\
y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 \widehat{Tele_{it}} + \beta_3 Post_t \cdot \widehat{Tele_{it}} + \gamma X_{it} + \eta_{ct} + \delta_p + \xi_q + \varepsilon_{it}
\end{aligned}
\tag{1}
$$

where $Tele_{it}$ is a binary indicator equal to 1 if worker i's job is teleworkable in year t, and 0 otherwise; z_i is the share of teleworkable jobs in 2013 by the individual's field of degree; $Post_t$ is a binary indicator for the post-pandemic period (equal to 1 for years after 2020, and 0 otherwise); $\widehat{Tele}_{it}$ is the fitted value of teleworkability from the first-stage regression; y_{it} is the outcome variable of interest for individual i in time period t; X_{it} is a vector of individual characteristics that control for demographic factors (such as age, gender, race, marital status, and presence of child), η_{ct} represents county-year fixed effects[2]; δ_p represents major occupation fixed effects; ξ_q represents major industry fixed effects; and u_{it} and ε_{it} are error terms. The standard errors are clustered at the location-year level to account for correlations between individuals within the same location and time period.

The key coefficient of interest is β_3, which captures the differential effect of the pandemic on migration outcomes for workers in teleworkable occupations compared to those in non-teleworkable occupations. A positive and significant β_3 would indicate that teleworkable workers experienced a greater change in migration outcomes post-pandemic relative to non-teleworkable workers.

Including major occupation and major industry fixed effects (δ_p and ξ_q) helps control for unobserved heterogeneity and shocks at the occupation and industry levels that could affect migration decisions and are correlated with teleworkability. For instance, some industries such as tourism may have faced greater spatial mobility while some occupations such as doctors and nurses may have preference living closer to their workplace. By controlling for these fixed effects, we isolate the impact of teleworkability from other occupation-specific or industry-specific factors. I have also consider the inclusion of major industry-year fixed effects. The COVID-19 pandemic had disparate impacts across different industries, with some sectors experiencing severe disruptions while others adapted more readily to remote work or even expanded. By incorporating industry-year fixed effects, we control for time-varying shocks at the

[2]For identifiable counties only. For those unidentifiable counties, county-year fixed effects are at the state-PUMA-year level (comprise of 30% of total observations).

industry level that could influence both teleworkability and migration decisions. However, this inclusion would absorb the variation of interest. More discussion can be found in Chapter 4 and the results including major industry-year fixed effects are presented in Appendix.

County-year fixed effects (η_{ct}) absorb time-varying shocks at the county level that could influence migration decisions, such as COVID-19 serverity, changes in local economic conditions, housing markets, or regional pandemic responses. These fixed effects control for any unobserved factors that are common to all individuals within a specific location and year, ensuring that the estimated effects are not driven by regional trends or policies. The vector of individual control variables (X_{it}) includes demographic characteristics that may influence migration decisions and could be correlated with teleworkability. These controls typically encompass age, gender, race, marital status, family size, and the presence of young children. Including these variables helps to account for individual-level factors that could affect both teleworkability and the propensity to migrate.

The validity of the instrument relies on two key assumptions: relevance and the exclusion restriction. The instrument is relevant if the share of teleworkable jobs by field of degree in 2013 is strongly correlated with individual teleworkability during the study period. This is expected, as individuals with degrees in fields that lead to teleworkable occupations are more likely to hold teleworkable jobs. The field of degree affects migration outcomes only through its impact on teleworkability and not through other channels. A potential concern is that different fields of degree may be associated with unobserved characteristics or preferences that directly affect migration decisions, independent of teleworkability. For example, individuals in certain fields may have a greater propensity to migrate due to industry norms or career opportunities. To mitigate this concern, the inclusion of major occupation and industry fixed effects helps control for occupation-specific and industry-specific factors that could influence migration decisions. By accounting for these fixed effects, we mitigate the possibility that the instrument is correlated with unobserved variables affecting migration.

The identification of the causal effect also relies on the parallel trends assumption. In the absence of the pandemic, migration outcomes for teleworkable and non-teleworkable workers would have followed similar trends over time. This assumption is examined by inspecting pre-pandemic trends in migration outcomes between the two groups. Placebo tests using pre-pandemic data are conducted to verify that there were no differential trends prior to the pandemic, supporting the validity of the parallel trends assumption.

3.2 Heckman Selection Model

When analyzing home-office distances, potential selection bias arises because this distance is only observed for workers who do not work exclusively from home. Ignoring this selection process could lead to biased estimates, as workers who work entirely from home may differ systematically from those who commute, in ways not captured by observable characteristics. To address this issue, I employ a Heckman selection model.

The Heckman Selection Model consists of two stages. The first stage models the probability that a worker does not work exclusively from home (i.e., has an observable home-office distance) as a function of observable characteristics and unobserved factors. The selection equation is specified as a Probit model:

$$s^*_{it} = \gamma_0 + \gamma_1 AccessBroadband_{it} + \gamma_2 Post_t \times z_i + \gamma_3 z_i + \delta X_{it} + \eta_{st} + \delta_p + \xi_q + \epsilon_{it} \tag{2}$$

where s^*_{it} is the latent propensity for worker i at time t to not work exclusively from home (i.e., to have an observable home-office distance). $AccessBroadband_{it}$ is an exogenous variable representing the worker's access to broadband internet, which is relevant for the decision to work from home but assumed uncorrelated with the error term in the outcome equation. The term $Post_t \times z_i$ captures the interaction between the post-pandemic period and the field-of-degree teleworkability measure, following the IV strategy. X_{it} is a vector of individual characteristics, including age, age squared, sex, citizenship status, marital status, race, family size, and the presence of children under age 5 or over age 5. η_{st} represents state-year fixed effects[3] , δ_p represents major occupation fixed effects, and ξ_q represents major industry fixed effects. The error term is ϵ_{it}. The standard errors are clustered at the location-year level. The selection equation estimates the probability that the home-office distance is observed.

The second stage models the home-office distance (or one-way commuting time to work) using an instrumented difference-in-differences framework as in 1, incorporating the Inverse Mills Ratio from the selection stage to correct for selection bias.

The identification relies on the exclusion restriction that the variable $AccessBroadband_{it}$ affects the

[3] Location-year fixed effects were initially considered in the first stage of the Heckman Selection Model. However, the inclusion of location-year fixed effects in a Probit model can be problematic due to the model's structure and computational limitations. Unlike linear models, the Probit model is less flexible with a high-dimensional fixed effects structure, often resulting in issues such as convergence failure or biased estimates. For this reason, I instead use state-year fixed effects in the first stage to control for broader geographic and temporal variation while preserving model feasibility. In the second stage, I include location-year fixed effects to control for localized shocks that could impact migration decisions.

selection equation but does not directly affect the outcome equation, except through its influence on the selection. This variable is relevant for the decision to work from home, as access to reliable internet is a prerequisite for remote work, but it is assumed not to directly impact the commuting distance for those who do commute.

3.3 Poisson Pseudo-Maximum Likelihood Gravity Model

To analyze migration flows between county pairs and examine how these flows change in relation to county-level characteristics, I employ a gravity model estimated using the Poisson Pseudo-Maximum Likelihood (PPML) estimator. This approach is well-suited for modeling migration flows, where the dependent variable is the count of migrants from origin county o to destination county d. The PPML estimator accommodates the non-negative integer nature of migration flow data, including zero flows between certain county pairs. It is robust to heteroskedasticity and provides consistent estimates even when the variance is not proportional to the mean.

The empirical specification of the gravity model is as follows:

$$\begin{aligned} M_{odt} = \exp(&\varphi_0 + \varphi_1(Post_t \times TeleShare_o) + \varphi_2(Post_t \times TeleShare_d) \\ &+ \varphi_3 \ln Pop_o + \varphi_4 \ln Pop_d + \rho X_{ot} + \tau X_{dt} + \eta_{od} + \delta_{ijt} + \mu_{odt}) \end{aligned} \tag{3}$$

where M_{odt} is the number of migrants moving from origin county o to destination county d in year t. $Post_t$ is a post-pandemic indicator variable. $TeleShare_o$ and $TeleShare_d$ are the share of teleworkable workers in the origin county and destination county respectively, capturing the potential for increased out-migration from areas with higher teleworkability after the pandemic. $\ln Pop_o$ and $\ln Pop_d$ are the natural logs of the populations of the origin and destination counties, respectively. X_{ot} and X_{dt} represent a set of county-level characteristics in origin and destination, such as median household income, unemployment rates, median gross rents, population densities, educational quality, healthcare access, environmental quality, and adjacency indicators. η_{od} represents origin-destination fixed effects, controlling for time-invariant factors specific to each county pair. δ_{ijt} represents origin state-to-destination state-by-year fixed effects, capturing time-varying factors at the state-to-state level. The error term is μ_{odt}.

The interaction term $(Post_t \times TeleShare_o)$ allows us to examine how the relationship between the origin county's share of teleworkable workers and migration flows changes after the pandemic. A positive coefficient on φ_1 would indicate that counties with higher shares of teleworkable workers experienced greater out-migration after the pandemic, consistent with the hypothesis that increased teleworkability weakens the tie between office and home locations. I also interact the county-level features (X_{ot} and X_{dt}) with post-pandemic indicator to see the change in migration preferences have shifted in the post-pandemic period. And by further interacting with county's share of teleworkable workers, I investigate the disparate preference change.

The inclusion of origin state-destination state-by-year fixed effects (δ_{ijt}) controls for unobserved, time-varying factors affecting migration preferences between states. For example, changes in state-level policies, economic conditions, or major corporate relocations (e.g., the relocation of Tesla's headquarters) could influence migration flows between specific state pairs. By accounting for these factors, we reduce potential biases arising from state-level shocks that could confound the relationship between teleworkability and migration flows.

By employing the PPML gravity model with comprehensive fixed effects and detailed county-level characteristics, we can analyze how teleworkability and regional attributes shape inter-county migration flows in the post-pandemic context. This analysis provides insights into the changing preferences of migrants and the broader impact of teleworkability on residential mobility and urban structure.

4 Impact of Teleworkability on Location Decisions

4.1 Migration Pattern

Table 3 presents the estimated impact of increased teleworkability on the likelihood of moving, using both difference-in-differences (Panel A) and instrumented difference-in-differences (Panel B) approaches. The dependent variable in all specifications is a binary indicator equal to one if the individual moved in the past year and zero otherwise.

In Panel A, the basic DiD results indicate that the interaction term between the post-pandemic period and teleworkability is positive and statistically significant across all specifications. The coefficients on *post* $\times$ *Teleworkability* range from 0.006 to 0.007, suggesting that teleworkable workers were 0.6 to 0.7 percentage points more likely to move after the pandemic compared to non-teleworkable workers. Given the baseline migration rate of 14.2%, these estimates represent an increase of approximately 4.2% to 4.9% in the likelihood of moving for teleworkable workers post-pandemic. As we progressively add controls and fixed effects across columns (1) to (4), the estimated coefficients remain relatively stable, indicating the robustness of the results. Column (1) includes individual characteristics and state fixed effects and year fixed effects. In column (2), we add major occupation and industry fixed effects to control for occupation-specific and industry-specific factors that may influence migration decisions. Column (3) incorporates state-year fixed effects, capturing local shocks and time-varying regional characteristics at the state level. Finally, column (4) includes county-by-year fixed effects to account for county-specific shocks over time, such as those induced by the pandemic.

In Panel B, the IV-DiD results account for the potential endogeneity of teleworkability by instrumenting it with the share of teleworkable jobs in 2013 by field of degree. The coefficients on $post \times Teleworkability$ are larger than in the DiD estimates, ranging from 0.009 to 0.012 and statistically significant at the 1% levels. These coefficients imply that teleworkable workers were 0.9 to 1.2 percentage points more likely to move after the pandemic compared to non-teleworkable workers. This corresponds to an approximate 6.3% to 8.5% increase in the likelihood of moving for teleworkable workers post-pandemic. The first-stage F-statistics are substantial across all IV specifications (ranging from 6,346 to 38,830), indicating a strong correlation between the instrument and teleworkability, and alleviating concerns about weak instrument bias. The inclusion of major county-by-year fixed effects in column (4) addresses potential concerns regarding county-specific shocks due to the pandemic, further strengthening the credibility of the results. These findings are consistent with the hypothesis that increased teleworkability, accelerated by the pandemic, has enabled workers to relocate more freely due to reduced constraints tied to workplace location. The significant and positive impact of teleworkability on migration likelihood suggests that the weakening of the tie between home and office has had a meaningful effect on individuals' mobility decisions in the post-pandemic period.

Table 4 presents the estimated impact of increased teleworkability on the likelihood of interstate migration, using both difference-in-differences (Panel A) and instrumented difference-in-differences (Panel B) approaches. The dependent variable in all specifications is a binary indicator equal to one if the individual moved across state lines in the past year and zero otherwise.

In Panel A, the DiD estimates suggest a 0.2 to 0.3 percentage point increase in the likelihood of moving across state lines for teleworkable workers post-pandemic, relative to non-teleworkable workers. With a baseline interstate migration rate of 3%, this implies a 7-10% increase in interstate migration for teleworkable workers. The magnitude of this effect suggests that teleworkability has not only enabled workers to move but has also encouraged more long-distance moves, including interstate relocations.

In Panel B, the instrumented difference-in-differences results account for the potential endogeneity of teleworkability. The coefficients on $Post \times Teleworkability$ remain positive and statistically significant, ranging from 0.003 to 0.004. This implies that teleworkable workers were 0.3 to 0.4 percentage points more likely to move across state lines post-pandemic, corresponding to an approximate 10% to 13% increase in interstate migration likelihood.

Table 3: The Impact of Increased Teleworkability on the Likelihood of Move

	(1) Move	(2) Move	(3) Move	(4) Move
Panel A: diff-in-diffs				
post # Teleworkability	0.007***	0.007***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Teleworkability	-0.001	0.002**	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Instrumented diff-in-diffs				
post # Teleworkability	0.012***	0.012***	0.011***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Teleworkability	-0.005***	0.045***	0.045***	0.030***
	(0.001)	(0.010)	(0.010)	(0.010)
Individual Characteristics	X	X	X	X
State FE	X	X	X	X
Year FE	X	X	X	X
Main industry and occupation FE		X	X	X
State-Year FE			X	X
County-Year FE				X
Dependent variable mean	0.142	0.142	0.142	0.142
Observations	2838321	2838321	2838321	2838321
First-stage F-stat	38830.490	6546.511	6549.088	6346.732

Note: Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

The effect of increased teleworkability on the distance moved is detailed in Table 5. Here, the outcome variable is the natural logarithm of the distance moved, restricted to movers only. Therefore, unlike Table 3 and Table 4, which focus on the extensive margin of mobility, this analysis concentrates on the intensive margin—examining, for individuals who moved, the effect of teleworkability on the distance they decided to move.

In Panel A, the DiD estimates suggest a 2.7 to 4.5% increase in the distance moved for teleworkable workers post-pandemic. These results indicate that teleworkability, enabled by the pandemic, encouraged teleworkable workers to relocate farther from their workplaces compared to non-teleworkable workers. The increase in distance suggests that remote work flexibility allowed workers to prioritize factors other than proximity to work, such as housing affordability, quality of life, or access to amenities. The IV-DiD estimates in Panel B show an even larger effect, with the interaction term between post-pandemic and teleworkability indicating an 8.9 to 10.8% increase in the distance moved by teleworkable workers

Table 4: The Impact of Increased Teleworkability on Interstate Migration

	(1) Interstate Move	(2) Interstate Move	(3) Interstate Move	(4) Interstate Move
Panel A: diff-in-diffs				
post # Teleworkability	0.002***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Teleworkability	-0.001***	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Instrumented diff-in-diffs				
post # Teleworkability	0.004**	0.004**	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Teleworkability	-0.004***	0.020***	0.020***	0.013***
	(0.001)	(0.005)	(0.005)	(0.005)
Individual Characteristics	X	X	X	X
State FE	X	X	X	X
Year FE	X	X	X	X
Main industry and occupation FE		X	X	X
State-Year FE			X	X
County-Year FE				X
Dependent variable mean	0.030	0.030	0.030	0.030
Observations	2838321	2838321	2838321	2838321
First-stage F-stat	38830.490	6546.511	6549.088	6346.732

Note: Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

Table 5: The Impact of Increased Teleworkability on the Distance of Move

	(1) Log Moving Distance	(2) Log Moving Distance	(3) Log Moving Distance	(4) Log Moving Distance
Panel A: diff-in-diffs				
post # Teleworkability	0.027*	0.035**	0.043***	0.045***
	(0.015)	(0.015)	(0.014)	(0.013)
Teleworkability	-0.072***	-0.030***	-0.032***	-0.016*
	(0.007)	(0.009)	(0.009)	(0.009)
Panel B: Instrumented diff-in-diffs				
post # Teleworkability	0.089**	0.090**	0.103***	0.108***
	(0.041)	(0.041)	(0.038)	(0.037)
Teleworkability	-0.233***	-0.417***	-0.417***	0.015
	(0.018)	(0.116)	(0.115)	(0.114)
Individual Characteristics	X	X	X	X
State FE	X	X	X	X
Year FE	X	X	X	X
Main industry and occupation FE		X	X	X
State-Year FE			X	X
County-Year FE				X
Dependent variable mean	3.787	3.787	3.787	3.787
Observations	402870	402870	402870	402801
First-stage F-stat	14105.198	978.221	975.301	903.299

Note: Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

post-pandemic. Given that the average migration distance for movers is approximately 217.2 miles, this translates to an additional 19 to 24 miles moved by teleworkable workers after the pandemic. This stronger effect in the IV-DiD specification suggests that once we account for potential endogeneity in occupation choice, the flexibility offered by teleworkability has an even more pronounced impact on migration distance. These results are consistent with the hypothesis that teleworkability has significantly reduced the importance of proximity to the workplace, allowing workers to move farther away from high-density urban centers or regions with high living costs, to areas offering better amenities, lower housing prices, or improved quality of life. The pandemic accelerated these trends by decoupling residential location from workplace location for teleworkable jobs.

To better understand the role of industry-specific trends, I further explored whether the disparate impacts of the pandemic across industries might explain changes in migration patterns. Certain industries have high concentrations of teleworkable workers, and if industry-by-year shocks have a direct impact on migration decisions, excluding them could result in omitted variable bias.

While the inclusion of industry-year fixed effects does not change our findings regarding the likelihood of moving (as shown in Appendix Table B.1), I find that it absorbs much of the variation in interstate migration and migration distance associated with teleworkability over time. Specifically, once industry-year fixed effects are included, the interaction term between post-pandemic and teleworkability for interstate migration and moving distance becomes statistically insignificant (see Appendix Tables B.2 and B.3). This suggests that much of the variation driving interstate migration among teleworkable workers can be attributed to industry-specific factors, which are absorbed by the fixed effects. However, by running separate regressions with interaction terms between each major industry and the post-pandemic indicator (Appendix Table B.4), I find that the positive and significant impact of teleworkability on interstate migration is primarily driven by workers in the Information and Communication and Professional Activities industries. These industries are highly teleworkable and saw significant change in work arrangement during the pandemic, leading to greater flexibility in location choices for workers. For instance, the Information and Communication industry shows a 0.007 coefficient at the 5% significance level, while the Professional Activities industry shows a 0.005 coefficient at the 10% significance level.

Overall, the main results suggest that teleworkability has had a significant and positive impact on the likelihood of moving, the likelihood of interstate migration, and the migration distance post-pandemic. However, the impact is not uniform across industries. The pandemic amplified migration patterns in sectors with high concentrations of teleworkable jobs, such as Information and Communication and

Professional Activities. Given the role industry plays in shaping these patterns, I opted not to include industry-year fixed effects in the main specification, as they absorb key variations related to teleworkability. Excluding these fixed effects allows us to capture the overall effect of teleworkability on migration without over-controlling for industry-specific trends that are inherently linked to teleworkability itself.

4.2 Home-Office Distance

Table 6 presents the results from the Heckman Selection Model, estimating the impact of increased teleworkability on home-office distance, which serves as a proxy for labor market mobility. The key idea here is that as teleworkability increases, workers may also become more mobile in the labor market, choosing jobs farther from their residential location due to the reduced need for daily commuting. The first two columns show the results for workers who do not work exclusively from home, using two outcome measures: home-office distance (column 1) and one-way commute time to work (column 2). Column 3 restricts the sample to those who live and work in different PUMAs, where the distance between home and work is measured more precisely.

In column (1), the coefficient on the interaction term, *post* × *teleworkability*, is negative but statistically insignificant, suggesting that increased teleworkability did not lead to detectable changes in home-office distance for workers who do not work from home. This lack of significance could be due to noise in the home-office distance measure, especially for workers living and working in the same PUMA. In such cases, the distance is approximated using the PUMA radius, which may not capture the full extent of mobility in the labor market.

In contrast, column (2) shows a positive and highly significant coefficient on *post* × *teleworkability* for the one-way commute time to work. The estimated coefficient of 1.677, which suggests that, for workers who do not work from home, increased teleworkability post-pandemic is associated with longer commute times, indicating that workers are willing to accept jobs located farther away from their residential locations. Comparing the estimate (1.677 minutes) to the dependent mean of 28.541 minutes, this translates to a 5.88% increase in one-way commute time. The results imply that teleworkable workers, who likely commute less frequently due to hybrid or remote work arrangements, are more flexible in choosing jobs that are farther from their homes, further reinforcing the notion of increased labor market mobility.

Column (3) focuses on workers who live and work in different PUMAs, providing a more accurate measure of home-office distance. Here, the interaction term *post* × *teleworkability* is positive and highly significant, with a coefficient of 65.010. This indicates that, for workers living and working in different PUMAs, increased teleworkability post-pandemic is associated with a substantial increase in home-office distance. Given a dependent mean of 54.487 miles, this corresponds to an approximately 119.31% increase in home-office distance. This result demonstrates a substantial shift in workers' job location choices, supporting the hypothesis that teleworkable workers are not only more mobile in the housing market but also more mobile in the labor market. Workers with teleworkable jobs are more likely to choose jobs that are farther from their residential locations, reflecting the weakened geographic tie between their home and office.

These findings provide strong evidence that increased teleworkability has reshaped the labor market by reducing the constraints of job location proximity. As workers gain more flexibility in how often they need to be physically present at their workplace, they are more likely to choose jobs that are farther away, resulting in longer distance between home location and office location. This shift has broader implications for regional labor markets, as teleworkable workers may now consider a wider array of job opportunities that were previously constrained by commuting limitations. The results, particularly in column (3), highlight a clear trend: teleworkability enables workers to expand their job search geographically, choosing work locations that might offer better wages, career opportunities, or amenities, despite being farther from their homes.

Table 6: The Impact of Increased Teleworkability on Home-Office Distance (Heckman Model)

	(1)	(2)	(3)
	Not WFH		Home-office in diff. PUMA
	Home-Work Distance	One-Way Time to Work	Home-Work Distance
post # Teleworkability	-0.526	1.677***	65.010***
	(1.372)	(0.383)	(19.627)
Teleworkability	-38.589***	-19.452***	57.755
	(2.907)	(0.701)	(42.415)
Dependent mean	33.544	28.541	54.487
Observations	2472359	2472359	740704
First-stage F-stat	5101.368	5090.155	69.380

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Demographic controls include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

4.3 Robustness Checks

4.3.1 Placebo Test

To assess the validity of the parallel trends assumption, a placebo test is conducted using pre-pandemic data. The sample is restricted to the years 2014-2018, and I artificially define 2017-2018 as the "post" period. Since there was no significant increase in teleworkability during this period and workers were still required to commute, this pseudo-treatment should have no effect on migration outcomes if the parallel trends assumption holds. In other words, we expect no significant difference in migration patterns between teleworkable and non-teleworkable workers before and after this false treatment.

The results, presented in Table 7, confirm this expectation. The interaction term between the pseudo-post period and teleworkability is close to zero and statistically insignificant across all specifications, including the likelihood of moving, interstate migration, migration distance, home-office distance, and one-way commute time. These findings suggest that there were no significant changes in migration behavior between teleworkable and non-teleworkable occupations before the pandemic, which reinforces the validity of the parallel trends assumption in the difference-in-differences framework. The observed effects in the main analysis are therefore likely attributable to the exogenous shock of the pandemic, rather than pre-existing trends in migration patterns.

It is important to note that the last two columns in the table, which examine home-office distance and one-way commute time, use the IV-DiD approach instead of the Heckman selection model. Since the placebo test focuses on the pre-pandemic period, there is no issue of selection into working from home, allowing us to estimate these outcomes directly without requiring the Heckman correction. The results remain consistent, showing no significant effects, further reinforcing the validity of the baseline results.

Table 7: Placebo Test Using a Pseudo Treatment

	(1) Moved	(2) Interstate Move	(3) Log Moving Distance	(4) Home-Office Distance	(5) One-Way Time to Work
post # Teleworkability	-0.001	0.000	0.003	-0.250	-0.481
	(0.003)	(0.002)	(0.037)	(0.809)	(0.299)
Teleworkability	0.006	0.010	-0.020	-43.571***	-18.641***
	(0.013)	(0.007)	(0.152)	(3.866)	(0.957)
Dependent variable mean	0.143	0.029	3.762	33.719	28.839
Observations	1680294	1680294	240333	1567928	1567928
First-stage F-stat	3741.630	3741.630	528.246	3618.896	3618.896

Note: The regression limits the observations to 2014-2018 only, and define a pseudo treatment indicator as years in and after 2017. As there is no shock to teleworkability during this period, the interaction term is expected to have no impact on the outcomes of interest. All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Notice column (4) and (5) are estimation results from instrumented diff-in-diffs regression instead of Heckman selection model as there is no selection issue before the pandemic. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

4.3.2 Falsification Test

To further ensure that the observed effects are driven by increased teleworkability rather than other confounding factors, a falsification test is performed using health outcomes as the dependent variables. Three health outcomes are examined: cognitive difficulty, independent living difficulty, and self-care difficulty. The rationale behind this test is straightforward—if teleworkability is indeed affecting migration decisions, it should not have any direct effect on unrelated outcomes, such as health. Therefore, any significant effect of teleworkability on these health outcomes would suggest that the observed relationships in the main analysis could be driven by unobserved factors, rather than by teleworkability itself. The results in Table 8 show no significant effect of teleworkability on any of the health outcomes examined. The interaction term between the post-pandemic period and teleworkability is near zero and statistically insignificant for all health measures. These results provide further support for the validity of the main analysis, indicating that the effects observed in migration outcomes are not driven by spurious correlations or omitted variables that might also influence unrelated outcomes, such as health.

Table 8: Falsification Test: Health Outcomes

	(1) Cognitive difficulty	(2) Independent living difficulty	(3) Self-care difficulty
post # Teleworkability	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.000)
Teleworkability	-0.000	0.001	-0.001
	(0.003)	(0.002)	(0.001)
Dependent variable mean	0.009	0.004	0.002
Observations	2838321	2838321	2838321
First-stage F-stat	6346.732	6346.732	6346.732

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

4.3.3 Sensitivity in Teleworkability Measure

To assess whether the results are sensitive to the specific measure of teleworkability used, I re-estimate the main models using an alternative measure from Adams-Prassl et al. (2022). This continuous measure captures the share of tasks that can be performed remotely by occupation-industry groups, providing a more granular perspective on teleworkability.

The results, presented in Table 9, remain consistent with the primary analysis. The alternative teleworkability measure shows a significant positive impact on the likelihood of moving, interstate migration, and the distance of moves. The robustness of the results across different teleworkability measures suggests

Table 9: Sensitivity of Teleworkability Measure: Alternative Measure

	(1) Move	(2) Interstate	(3) Log Mig. Dist.	(4) HO Dist.	(5) Time to Work	(6) HO Dist. (diff. PUMA)
post # Teleworkability (AP2022)	0.021***	0.008**	0.293***	-49.191	44.876	151.428***
	(0.006)	(0.003)	(0.085)	(103.948)	(37.456)	(29.696)
Teleworkability (AP2022)	0.139	0.670***	18.102***	-578.969	227.156	-719.570***
	(0.151)	(0.080)	(2.687)	(522.575)	(197.995)	(175.602)
Dependent variable mean	0.142	0.030	3.787	33.544	28.541	54.487
Observations	2838321	2838321	402801	2472359	2472359	740704
First-stage F-stat	910.454	910.454	83.449	1.672	1.557	209.301

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. The dependent variables are as follows: (1) Moved in the past year; (2) Moved across state lines in the past year; (3) Natural logarithm of migration distance (movers only); (4) Home-office distance for those not completely working from home; (5) One-way commute time to work for those not completely working from home; (6) Home-office distance for those living and working in different PUMAs. Column (1)-(3) are from IV-DiD results, column (4)-(6) are from Heckman Selection model. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

that the findings are not sensitive to the exact definition of the key independent variable. The positive and significant effect on migration outcomes persists, reinforcing the conclusion that teleworkability plays an important role in workers' location and labor market decisions.

Table 10: Heterogeneous Effect across Gender and Marital Status

Subgoups	(1) Move	(2) Interstate	(3) Log Mig. Dist.	(4) HO Dist. (diff. PUMA)	(5) Time to Work
Male	0.006	0.003	0.149**	-15.084	2.085**
	(0.005)	(0.003)	(0.064)	(56.355)	(0.902)
Female	0.011***	0.004***	0.100**	46.702**	1.357***
	(0.003)	(0.002)	(0.042)	(20.689)	(0.372)
Single	0.009	0.004	0.114**	72.448*	1.570**
	(0.006)	(0.003)	(0.053)	(37.158)	(0.652)
Married	0.009***	0.003**	0.098*	75.295***	2.505***
	(0.003)	(0.002)	(0.050)	(24.040)	(0.406)

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Demographic controls include age, age square, citizen status, race, family size, having child under age 5, having child greater than age 5, sex or marital status. The dependent variables are as follows: (1) Moved in the past year; (2) Moved across state lines in the past year; (3) Natural logarithm of migration distance (movers only); (4) Home-office distance for those living and working in different PUMAs; (5) One-way commute time to work for those not completely working from home. Column (1)-(3) are from IV-DiD results, column (4) and (5) are from Heckman Selection model. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

4.4 Heterogeneity

4.4.1 Demographics

Table 10 reveals significant variation in the impact of teleworkability on migration outcomes across gender and marital status. The results demonstrate that women and married individuals are more responsive to increased teleworkability in terms of migration decisions, home-office distance, and commute time.

For women, increased teleworkability has a significant and positive impact on all mobility outcomes. Women are 1.1 percentage points more likely to move post-pandemic due to increased teleworkability, a statistically significant effect at the 1% level. In terms of interstate migration, the likelihood of moving across state lines increases by 0.4 percentage points for women, also significant at the 1% level. Women also move approximately 10% farther, as indicated by a significant increase in the log of migration distance. Additionally, home-office distance for women increases by 46.7 miles (significant at the 5% level) when living and working in different PUMAs. Finally, women experience a significant increase of 1.36 minutes in one-way commute time. These findings suggest that women are taking greater advantage of the flexibility offered by teleworkable jobs, likely because of the ability to balance household and caregiving responsibilities more effectively.

In contrast, for men, the effects are generally smaller and less consistently significant. While the likelihood of moving shows a positive increase of 0.6 percentage points, this result is not statistically significant. Similarly, the increase in interstate migration is positive but insignificant. However, men do move approximately 14.9% farther, with a statistically significant result. Interestingly, home-office distance for men decreases by 15.1 miles, but this result is not significant. Men also experience a significant increase of 2.09 minutes in one-way commute time.

These findings align with the literature indicating that women tend to have stronger preferences for shorter commutes. (Le Barbanchon, Rathelot, and Roulet, 2021) find that women are more averse to commuting than men. Telework reduces the necessity of daily commuting, potentially making longer distances more acceptable for women. The increased teleworkability may alleviate commuting constraints, allowing women to relocate further from their workplaces or to accept job offers from a distant employer. This shift may explain women's greater responsiveness to teleworkability in migration decisions.

When examining marital status, the effects are larger and statistically significant for married individuals. Married individuals are 0.9 percentage points more likely to move, significant at the 1% level. In terms of interstate migration, married individuals are 0.3 percentage points more likely to move across state lines, significant at the 5% level. Married individuals also move approximately 10.3% farther, and their home-office distance increases by 75.3 miles (significant at the 1% level). One-way commute time for married individuals increases by 2.5 minutes, also significant at the 1% level.

The demographic heterogeneity highlights that teleworkability's impact on migration is not uniform across all groups. Women, in particular, appear to respond more to the increased flexibility of telework, potentially due to their adverse to commute. Married households might take greater advantage of teleworkability to relocate to areas that better suit their overall household needs, such as larger homes or regions with better schools or quality of life.

When we further disaggregate the results by both gender and marital status, shown in Appendix Table B.5, we still observe that single women respond more strongly to teleworkability than single men. Single women are 2.0 percentage points more likely to move, while single men show no statistically significant effect. Married women also display higher responsiveness compared to their male counterparts, with a 0.8 percentage point increase in likelihood to move and a 14.1% increase in migration distance, compared to married men who show no significant effect on interstate migration and migration distance. This gender-marital status interaction highlights that the flexibility of telework may provide greater benefits to women, particularly those in single or dual-earner households.

Table 11: Heterogeneous Effect by Family Structure and Spousal Characteristics

Subgroup	(1) Move	(2) Interstate	(3) Log Mig. distance	(4) Home-Office Distance	(5) Time to Work
No child presence	0.027*	0.012	0.159	78.657	3.475
	(0.015)	(0.008)	(0.189)	(65.902)	(3.195)
Young children only	-0.011	0.002	0.524*	-14.989	16.475***
	(0.024)	(0.011)	(0.297)	(118.527)	(5.716)
Older children only	0.021**	-0.001	-0.620**	-11.856	14.668**
	(0.008)	(0.004)	(0.304)	(39.537)	(5.736)
Spouse is unemployed	0.012	0.004	-0.041	34.336	3.075
	(0.016)	(0.009)	(0.314)	(85.461)	(7.049)
Spouse is employed	0.024***	0.006	0.052	25.095	7.862***
	(0.008)	(0.004)	(0.132)	(32.844)	(2.681)

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Individual characteristics include age, age square, sex, citizen status, race, family size. Standard errors are clustered at the county-year level. Young children are defined as children below age 5. Older children are children aged 5 and above. * p<0.1 ** p<0.05 *** p<0.01

4.4.2 Family Structure

Restrict the sample to households[4],table 11 presents the heterogeneity analysis of the impact of teleworkability on migration outcomes by family structure and spousal employment status. The results highlight how the presence and age of children, as well as the employment status of a spouse, influence the relationship between teleworkability and migration behavior.

For households with no children, increased teleworkability has a positive and statistically significant ef-

[4]Married individuals with spouse present, and the head is defined as the one with the higher income.

fect on the likelihood of moving. Specifically, teleworkable workers without children are 2.7 percentage points more likely to move post-pandemic, significant at the 10% level. While the coefficients for interstate migration and migration distance are positive, they are not statistically significant. The increase in home-office distance is 78.7 miles, and one-way commute time increases by 3.48 minutes, but these effects are not statistically significant. These findings suggest that households without children may find it easier to leverage the flexibility offered by telework to relocate, without being constrained by considerations related to childrearing or schooling.

In contrast, households with young children only (defined as children under age 5) do not exhibit significant changes in the likelihood of moving or interstate migration due to increased teleworkability. However, one-way commute time increases significantly by 16.48 minutes (significant at the 1% level). These results suggest that while households with young children are not more likely to move overall, but they tend to accept longer commutes. This could indicate that teleworkability enables these households to consider job opportunities that were previously impractical due to commuting constraints.

For households with older children only (defined as children aged 5 and above), teleworkability increases the likelihood of moving by 2.1 percentage points, significant at the 5% level. However, the log of migration distance decreases by 0.620 (significant at the 5% level). One-way commute time increases by 14.67 minutes (significant at the 5% level). These findings suggest that households with older children are more likely to move but prefer shorter-distance relocations. The negative effect on migration distance may reflect a preference for remaining within certain school districts or proximity to educational resources, while the increased commute time could be due to relocating to suburban areas or taking a job farther away from residences.

The employment status of a spouse also plays a critical role in migration decisions. For households where the spouse is employed, increased teleworkability has a significant positive impact on the likelihood of moving. Specifically, these households are 2.4 percentage points more likely to move (significant at the 1% level). One-way commute time increases by 7.86 minutes (significant at the 1% level). While the coefficients for interstate migration, migration distance, and home-office distance are positive, they are not statistically significant. These findings suggest that dual-earner households are more responsive to increased teleworkability, likely because remote work reduces the co-location challenges that often constrain residential choices in dual-career couples.

In contrast, for households where the spouse is unemployed, none of the migration outcomes show a statistically significant effect in response to increased teleworkability. This indicates that households with a non-working spouse may have fewer constraints related to spousal employment and thus are less influenced by teleworkability in their migration decisions. The lack of significant effects suggests that the flexibility offered by telework is particularly valuable for dual-earner households facing co-location challenges.

These findings are consistent with the literature on dual-career households and the challenges of co-location decisions. (Costa and Kahn, 2000) discuss the "power couple" phenomenon, highlighting how dual-career households face difficulties in finding optimal locations that satisfy both partners' career aspirations. The trailing spouse problem, where one partner (often the woman) sacrifices career opportunities for the other's job, is well-documented (Guler, Guvenen, and Violante, 2012; Venator, 2020). Increased teleworkability can mitigate these challenges by allowing one or both partners to work remotely, reducing the need for both partners to find suitable employment in the same geographic area. This increased flexibility may explain why households with an employed spouse are more likely to move and accept longer commute times.

Table 12: The Impact of Teleworkability on Migration in Dual-Career Households

	(1) Move	(2) Interstate Migration	(3) Log Migration Distance
post # Male Teleworkability	0.023**	0.001	-0.009
	(0.009)	(0.004)	(0.146)
post # Female Teleworkability	0.006	0.001	-0.015
	(0.005)	(0.003)	(0.098)
Dependent variable mean	0.109	0.022	3.698
Observations	519914	519914	54440
First-stage F-stat	4548.845	4548.845	436.082

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Demographic controls include age, age square, citizen status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

4.4.3 Dual-Career Households

The Table 12 presents the analysis of the impact of increased teleworkability on migration outcomes within dual-career households, where both spouses are employed. In this context, teleworkability is measured separately for the male and female partners to assess their individual contributions to household migration decisions, and the migration outcomes include the likelihood of moving, interstate migration, and the distance moved.

The results indicate that within dual-career households, the teleworkability of the male spouse has a significant and positive effect on the likelihood of moving. Specifically, male teleworkability increases the probability of moving by 2.3 percentage points post-pandemic (significant at the 5% level). This effect is notable given the baseline moving rate of 10.9% among dual-career households, representing an approximate 21% increase in the likelihood of moving due to male teleworkability. In contrast, the teleworkability of the female spouse does not have a statistically significant effect on the likelihood of moving, with a coefficient of 0.006. For other migration outcomes, neither male nor female teleworkability shows significant effects on interstate migration or the log of migration distance. The coefficients for both spouses are close to zero and statistically insignificant, suggesting that teleworkability does not significantly influence the likelihood of long-distance moves within dual-career households.

Overall, these findings indicate that within dual-career households, male teleworkability plays a more prominent role in influencing whether a household decides to move, while female teleworkability's effect is less clear in this context.

5 Inter-County Migration Preferences

This section presents an empirical analysis of migration preferences in the post-pandemic period, utilizing a Poisson Pseudo-Maximum Likelihood (PPML) gravity model framework.

5.1 Location Preferences Post-Pandemic

Table 13 displays the results of the baseline PPML gravity model estimating the impact of various county-level characteristics on migration flows post-pandemic. The model includes interaction terms between the post-pandemic indicator and key origin and destination county characteristics, controlling for county characteristics, county-pair fixed effects and state-pair-by-year fixed effects. Standard errors are clustered at the county-pair level.

The interaction terms between health risk variables (infection and death rates) and the post-pandemic indicator are not statistically significant. Specifically, the coefficients for infection rate dest#post and infection rate orig#post are -0.016 and -0.095, respectively, with large standard errors. Similarly, the coefficients for death rate dest#post and death rate orig#post are 1.054 and 2.727, respectively, but not statistically significant. These results suggest that health risks, as measured by COVID-19 infection and death rates, did not have a significant differential impact on migration flows in the post-pandemic period when controlling for other factors.

The coefficient on lag tele pct orig#post is positive and statistically significant at the 5% level, indi-

Table 13: The Change in Migration Preference Post-Pandemic

Variable Set	Interaction Term	Coefficient
Health Risk	infection rate dest # post	-0.016
		(0.189)
	infection rate orig # post	-0.095
		(0.194)
	death rate dest # post	1.054
		(2.427)
	death rate orig # post	2.727
		(2.401)
Teleworkability	lag tele pct dest # post	-0.002
		(0.002)
	lag tele pct orig # post	0.005**
		(0.002)
Contiguous County Pair	contiguous cnty # post	-0.241***
		(0.023)
Metro	metro dest # post	-0.035
		(0.099)
	metro orig # post	0.015
		(0.100)
Population	log population dest # post	0.030
		(0.021)
	log population orig # post	0.079***
		(0.020)
Economic Factors	median household income dest # post	0.009***
		(0.003)
	median household income orig # post	0.003
		(0.003)
	gini dest # post	0.348
		(0.489)
	gini orig # post	0.624
		(0.489)
Education Quality	education quality dest # post	0.011
		(0.028)
	education quality orig # post	-0.070***
		(0.027)
Housing Costs	median gross rent dest # post	-0.593***
		(0.180)
	median gross rent orig # post	-0.193
		(0.170)
Environmental Quality	air quality dest # post	-0.018*
		(0.011)
	air quality orig # post	-0.019*
		(0.011)
N		166813
Pseudo R-squared		0.858

Note: The regression includes location characteristics, state-pair-year fixed effects, and county pair fixed effects. Location characteristics include infection rate, death rate, lag share of teleworkable workers, log population, median household income, median gross rent, Gini index, air quality in both origin county and destination county. Standard errors are clustered at the county pair level. * p<0.1 ** p<0.05 *** p<0.01

cating that origin counties with a higher share of teleworkable jobs experienced increased out-migration post-pandemic. Specifically, a one-percentage point increase in the teleworkable share in the origin county is associated with a 0.5% increase in out-migration flows ($(\exp(0.005) - 1) \times 100 \approx 0.5\%$). This finding aligns with the hypothesis that teleworkability reduces the dependency on physical workplaces, granting workers greater flexibility to relocate. The coefficient on lag tele pct dest#post is negative but not significant, suggesting that the share of teleworkable jobs in destination counties did not significantly influence migration inflows.

The negative and highly significant coefficient (-0.241***) on the interaction between contiguous county pair indicator and post-pandemic indictor, contiguous cnty#post, indicates a decline in migration between contiguous counties post-pandemic. This suggests that individuals were more likely to migrate over longer distances, potentially facilitated by the increased feasibility of remote work.

The coefficient on log population orig#post is positive and significant at the 1% level (0.079***), implying that larger origin counties experienced higher out-migration post-pandemic. A 1% increase in population is associated with an 8.2% increase in the expected number of migrants ($(\exp(0.079) - 1) \times 100 \approx 8.2\%$). Conversely, the coefficient for log population dest#post is positive but not significant, suggesting that destination county population size did not significantly influence migration inflows.

The interaction term median household income dest#post is positive and significant (0.009***), indicating that destination counties with higher median household incomes attracted more migrants post-pandemic. This suggests a preference for relocating to economically prosperous areas. The corresponding coefficient for origin counties is positive but not significant, implying that origin county income levels did not significantly affect out-migration.

The coefficient on education quality orig#post is negative and significant (-0.070***), indicating that origin counties with lower educational quality experienced increased out-migration post-pandemic. This suggests that educational resources are an important factor influencing migration decisions. The coefficients for housing costs (median gross rent dest#post and median gross rent orig#post show that higher housing costs in destination counties deterred in-migration (-0.593***), while the effect in origin counties is negative but not significant. This implies that affordability considerations played a role in destination choice.

The negative and marginally significant coefficients on air quality dest# post (-0.018*) and air quality orig# post (-0.019*) suggest that poorer air quality in both origin and destination counties influenced migration decisions, with individuals moving away from areas with lower environmental quality and avoiding such areas as destinations.

Table 14: Placebo Test on Change in Migration Preferences

Variable Set	Interaction Term	Coefficient
Health Risk	infection rate dest # post	0.006
		(0.131)
	infection rate orig # post	-0.087
		(0.130)
	death rate dest # post	-0.746
		(1.577)
	death rate orig # post	0.759
		(1.580)
Teleworkability	lag tele pct dest # post	0.003
		(0.002)
	lag tele pct orig # post	-0.004*
		(0.002)
Contiguous County Pair	contiguous cnty # post	0.038
		(0.024)
Metro	metro dest # post	0.040
		(0.103)
	metro orig # post	-0.008
		(0.100)
Population	log population dest # post	-0.010
		(0.015)
	log population orig # post	0.003
		(0.015)
Economic Factors	median household income dest # post	0.001
		(0.002)
	median household income orig # post	-0.001
		(0.002)
	gini dest # post	-0.418
		(0.404)
	gini orig # post	-0.173
		(0.398)
Education Quality	education quality dest # post	-0.014
		(0.026)
	education quality orig # post	-0.025
		(0.025)
Housing Costs	median gross rent dest # post	-0.088
		(0.134)
	median gross rent orig # post	0.152
		(0.137)
Environmental Quality	air quality dest # post	0.032*
		(0.018)
	air quality orig # post	-0.015
		(0.019)
N		73678
Pseudo R-squared		0.864

Note: The regression includes location characteristics, state-pair-year fixed effects, and county-pair fixed effects. Location characteristics include infection rate, death rate, lag share of teleworkable workers, log population, median household income, median gross rent, Gini index, air quality in both origin county and destination county. The standard errors are clustered at the county-pair level. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

5.2 Placebo Test

To validate the identification strategy and ensure that the observed effects are attributable to the pandemic rather than pre-existing trends, a placebo test is conducted using data from 2014 to 2018. A pseudo-treatment period is defined for the years 2017-2018. Table 14 presents the results of this placebo test, mirroring the specifications of the baseline model.

The interaction terms between county-level characteristics and the pseudo-post period are generally insignificant, indicating no systematic changes in migration preferences during this period. The coefficient on lag tele pct orig# post is negative and marginally significant (-0.004*), which is contrary to the positive effect observed in the baseline model. However, this effect is small in magnitude and may be attributed to random variation.

Overall, the placebo test results support the validity of the main findings by demonstrating that the significant effects observed in the baseline model are not driven by underlying trends prior to the pandemic.

Table 15: The Change in Migration Preference by Teleworkability

	(1)	(2)	(3)	(4)	(5)
			Number of Mingrants		
death rate dest#lag tele pct dest#post	0.085				
	(0.054)				
death rate orig#lag tele pct orig#post	-0.173***				
	(0.050)				
log population dest#lag tele pct dest#post		0.002			
		(0.002)			
log population orig#lag tele pct orig#post		0.001			
		(0.001)			
median household income dest#lag tele pct dest#post			-0.000		
			(0.000)		
median household income orig#lag tele pct orig#post			0.000		
			(0.000)		
education quality dest#lag tele pct dest#post				-0.000	
				(0.002)	
education quality orig#lag tele pct orig#post				0.001	
				(0.002)	
median gross rent dest#lag tele pct dest#post					0.001
					(0.003)
median gross rent orig#lag tele pct orig#post					-0.003
					(0.003)
N	166813	166813	166813	166813	166813
Pseudo R-squared	0.858	0.858	0.858	0.858	0.858

Note: All regressions include the interaction terms as in Table 13, location characteristics, state-pair-year fixed effects, and county pair fixed effects. Location characteristics include infection rate, death rate, lag share of teleworkable workers, log population, median household income, median gross rent, Gini index, air quality in both origin county and destination county. Standard errors are clustered at the county pair level. * p<0.1 ** p<0.05 *** p<0.01

5.3 Heterogeneity in Migration Preferences by Teleworkability

Table 15 explores the heterogeneity in migration preferences by teleworkability, introducing triple interaction terms between the post-pandemic indicator, lagged share of teleworkable workers, and specific county-level characteristics. Each column adds one triple interaction term to the baseline model to isolate the effect.

In Column (1), the triple interaction involving the death rate in the origin county is negative and significant (-0.173***), suggesting that teleworkable workers in counties with higher COVID-19 death rates were less likely to migrate compared to non-teleworkable workers. This could indicate that teleworkable workers chose to stay in place, leveraging remote work to minimize exposure risks. The interaction term for the destination county is positive but not significant, indicating no differential effect for teleworkable workers regarding health risks in destination counties.

Column (2) examines the interaction with population size. The triple interaction terms for both origin and destination counties are positive but not significant, indicating that teleworkable workers do not exhibit significantly different migration responses based on population size compared to non-teleworkable workers.

In Column (3), the triple interaction terms involving median household income are effectively zero and not significant. This suggests that teleworkable workers do not have different migration preferences based on income levels in origin or destination counties relative to non-teleworkable workers.

Column (4) introduces interactions with education quality. The triple interaction terms are not significant, indicating that teleworkable workers do not have distinct preferences regarding educational resources in their migration decisions compared to non-teleworkable workers.

Column (5) focuses on housing costs. The triple interaction terms are not significant, suggesting that differences in housing costs do not differentially influence the migration decisions of teleworkable workers post-pandemic.

The results indicate that while teleworkable workers are generally more mobile post-pandemic, their migration preferences concerning destination county characteristics such as population size, income levels, education quality, and housing costs do not differ significantly from those of non-teleworkable workers. The notable exception is the response to health risks in the origin county, where teleworkable workers appear less inclined to move away from high-risk areas, possibly due to their ability to mitigate exposure through remote work.

6 Conclusion

This study investigates how increased teleworkability, accelerated by the COVID-19 pandemic, has impacted migration patterns and location decisions among U.S. workers. Using an instrumented difference-in-differences (IV-DiD) approach with American Community Survey data (2013–2022), the analysis examines shifts in mobility and migration preferences for teleworkable versus non-teleworkable occupations, focusing on several aspects: migration likelihood, relocation distance, interstate migration rates, and the decoupling of home and workplace locations.

The findings indicate that workers in teleworkable jobs demonstrate a heightened propensity for mobility following the pandemic. This is reflected in a 6% increased likelihood of moving, a 10% rise in interstate migration, and an approximate 24-mile increase in relocation distance. The analysis of home-office distance further supports the divided trend; teleworkable workers show an increased tolerance for longer commutes and, for those relocating to different PUMAs, a notable expansion in the distance from home to office. This weakening of the traditional home-office link suggests that teleworkability affords workers greater flexibility to prioritize factors such as affordability and lifestyle quality over proximity to the workplace.

A closer examination of demographic variation reveals significant heterogeneity in response to teleworkability across gender, marital status, and spousal employment. Female workers, married couples, and dual-earner households exhibit higher responsiveness to teleworkability, suggesting that the flexibility provided by flexible work arrangements supports more diverse family and career considerations. These findings contribute to a deeper understanding of how household and individual factors influence the migration decisions of teleworkable workers.

The study also explores migration preferences at the county-pair level, identifying a shift toward less densely populated areas and regions with higher income and educational quality, and lower housing costs. Counties with a higher proportion of teleworkable workers experienced increased out-migration post-pandemic, while contiguous county pairs saw a decline in migration, indicating a preference for longer-distance moves. These shifts suggest that teleworkable workers are relocating toward regions with favorable economic and living conditions, facilitated by reduced dependency on proximity to job centers. However, no significant preference differences emerge for teleworkable workers compared to non-teleworkable workers in destination characteristics, indicating that the drivers for destination choice remain consistent across worker types.

The implications of these shifts for policymakers, urban planners, and local governments are substantial.

Regions experiencing an influx of teleworkable workers may face new demands on infrastructure, public services, and educational systems. Specifically, regions that are traditionally less densely populated may face increased pressure to expand infrastructure, including housing, schools, and healthcare facilities, to accommodate new residents. This growth in population could lead to urban sprawl and necessitate proactive investments in sustainable infrastructure. The migration to areas with better educational quality and higher household incomes could amplify disparities in school demand and local resource allocation. Policymakers in high-demand areas should consider investing in educational infrastructure to ensure capacity meets the needs of new families relocating to these regions. The demand for affordable housing in destination regions underscores the need for thoughtful zoning policies and housing incentives to prevent cost-of-living spikes. Finally, the weakened home-office tie also suggests a rethinking of labor market policies. Employers might expand recruitment to remote workers, offering more flexible and inclusive hiring practices.

The findings in this paper point toward the need for further research into the long-term sustainability of telework-driven migration patterns and their broader implications. Future studies could examine whether these changes represent enduring shifts or temporary adjustments driven by pandemic-related disruptions, or explore the potential for teleworkability to exacerbate or alleviate regional economic disparities, particularly in areas where migration inflows increase demand on local infrastructure and resources.

The rise of teleworkable jobs, catalyzed by the pandemic, is reshaping residential and work mobility patterns across the United States. The findings show that teleworkable workers, enabled by workplace flexibility, are prioritizing lifestyle factors, housing affordability, and quality of life over traditional commuting concerns, leading to a reconfiguration of urban and rural landscapes. As these trends continue, they have the potential to shape the labor market, urban planning, and housing policies for years to come, underscoring the need for adaptive, forward-looking policy frameworks that balance economic growth, resource distribution, and social equity in a rapidly evolving labor environment.

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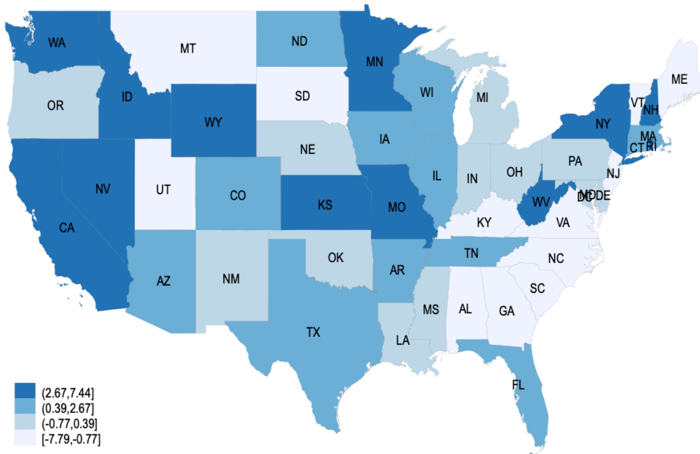
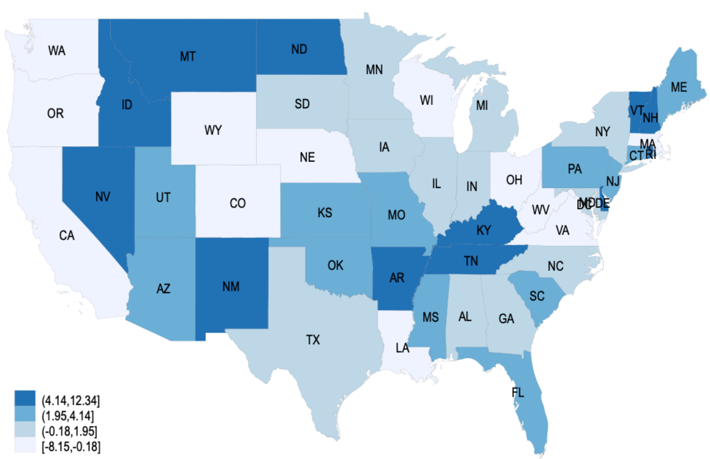
A Figures



(a) The Change in Outmigration Rate



(b) The Change in Inmigration Rate

Figure A.1: Change in Interstate Migration Flows 2019 to 2021

Note: The figure illustrates changes in interstate migration flows across U.S. states between 2019 and 2021. Alaska and Hawaii are not included in the map. Panel A.1a shows the change in the outmigration rate, which defined as the proportion of individuals moving out of a state relative to the state's total number of movers. A positive value for a state indicates that the proportion of people moving out of that state increased in 2021 compared to 2019. Panel A.1b presents the change in the inmigration rate, which depicts changes in the inmigration rate, which measures the proportion of individuals moving into a given state as a share of that state's total number of movers. A positive value for a state indicates that the proportion of people moving into that state increased in 2021 compared to 2019.

B Tables

Table B.1: The Impact of Increased Teleworkability on the Likelihood of Move

	(1) Move	(2) Move	(3) Move	(4) Move
Panel A: diff-in-diffs				
post # Teleworkability	0.007***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Teleworkability	-0.001	0.002**	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Instrumented diff-in-diffs				
post # Teleworkability	0.011***	0.011***	0.009***	0.011**
	(0.003)	(0.003)	(0.003)	(0.005)
Teleworkability	-0.005***	0.045***	0.030***	0.029***
	(0.001)	(0.010)	(0.010)	(0.010)
Individual Characteristics	X	X	X	X
State-Year FE	X	X	X	X
Occupation FE		X	X	X
Industry FE		X	X	X
County-Year FE			X	X
Industry-Year FE				X
Dependent variable mean	0.142	0.142	0.142	0.142
Observations	2838321	2838321	2838321	2838321
First-stage F-stat	37025.411	6549.088	6346.732	6349.134

Note: Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

Table B.2: The Impact of Increased Teleworkability on Interstate Migration

	(1) Interstate Move	(2) Interstate Move	(3) Interstate Move	(4) Interstate Move
Panel A: diff-in-diffs				
post # Teleworkability	0.002***	0.003***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Teleworkability	-0.001***	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Instrumented diff-in-diffs				
post # Teleworkability	0.004**	0.004***	0.003**	0.003
	(0.001)	(0.001)	(0.001)	(0.002)
Teleworkability	-0.005***	0.020***	0.013***	0.014***
	(0.001)	(0.005)	(0.005)	(0.005)
Individual Characteristics	X	X	X	X
State-Year FE	X	X	X	X
Occupation FE		X	X	X
Industry FE		X	X	X
County-Year FE			X	X
Industry-Year FE				X
Dependent variable mean	0.030	0.030	0.030	0.030
Observations	2838321	2838321	2838321	2838321
First-stage F-stat	37025.411	6549.088	6346.732	6349.134

Note: Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

Table B.3: The Impact of Increased Teleworkability on the Distance of Move

	(1) Log Moving Distance	(2) Log Moving Distance	(3) Log Moving Distance	(4) Log Moving Distance
Panel A: diff-in-diffs				
post # Teleworkability	0.034**	0.043***	0.045***	0.025*
	(0.014)	(0.014)	(0.013)	(0.014)
Teleworkability	-0.074***	-0.032***	-0.016*	-0.011
	(0.006)	(0.009)	(0.009)	(0.009)
Panel B: Instrumented diff-in-diffs				
post # Teleworkability	0.101***	0.103***	0.108***	0.097
	(0.038)	(0.038)	(0.037)	(0.064)
Teleworkability	-0.236***	-0.417***	0.015	0.016
	(0.018)	(0.115)	(0.114)	(0.115)
Individual Characteristics	X	X	X	X
State-Year FE	X	X	X	X
Occupation FE		X	X	X
Industry FE		X	X	X
County-Year FE			X	X
Industry-Year FE				X
Dependent variable mean	3.787	3.787	3.787	3.787
Observations	402870	402870	402801	402801
First-stage F-stat	6463.510	975.301	903.299	907.861

Note: Individual characteristics include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

Table B.4: The Heterogeneity in Migration Patterns Across Industries

	(1)	(2)	(3)
	Moved	Interstate Move	Log Distance
Teleworkability	0.029***	0.014***	0.018
	(0.010)	(0.005)	(0.115)
post # Teleworkability	0.011**	0.003	0.096
	(0.005)	(0.002)	(0.064)
Accommodation and Food Service Activities # post	0.000	0.000	0.000
	(.)	(.)	(.)
Activities of Households as Employers # post	-0.022	-0.003	-0.006
	(0.016)	(0.008)	(0.143)
Administrative and Support Services # post	-0.003	0.003	0.037
	(0.005)	(0.003)	(0.059)
Agriculture Forestry and Fishing # post	0.007	0.003	0.044
	(0.006)	(0.003)	(0.082)
Arts, Entertainment and Recreation	-0.000	-0.000	-0.062
	(0.005)	(0.003)	(0.058)
Construction # post	0.004	0.001	-0.047
	(0.005)	(0.002)	(0.051)
Education # post	-0.004	-0.001	-0.068
	(0.005)	(0.003)	(0.059)
Electricity, Gas, Steam etc.	0.000	0.002	0.018
	(0.007)	(0.003)	(0.084)
Finacial and Insurance Activities # post	0.005	0.003	-0.035
	(0.005)	(0.003)	(0.059)
Human Health and Social Work # post	0.004	0.001	-0.025
	(0.004)	(0.002)	(0.040)
Information and Communication # post	0.006	0.007**	0.057
	(0.005)	(0.003)	(0.061)
Manufacturing # post	0.004	0.002	-0.025
	(0.005)	(0.002)	(0.051)
Mining and Quarrying # post	0.003	0.006	0.063
	(0.009)	(0.006)	(0.126)
Other Service Activities # post	-0.000	0.002	0.010
	(0.005)	(0.003)	(0.061)
Professional Activities # post	0.008	0.005*	0.001
	(0.005)	(0.003)	(0.057)
Public Administration and Defence # post	0.003	0.001	-0.060
	(0.005)	(0.002)	(0.049)
Real Estate Activities # post	0.007	0.001	-0.079
	(0.006)	(0.003)	(0.071)
Transportation and Storage # post	0.000	-0.001	-0.041
	(0.005)	(0.003)	(0.056)
Water Supply etc. # post	-0.006	-0.003	-0.029
	(0.009)	(0.004)	(0.108)
Wholesale and Retail Trade # post	0.007	0.003	-0.018
	(0.004)	(0.002)	(0.045)
Observations	2838321	2838321	402801
KP Wald F-stat	6334.563	6334.563	902.472

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Demographic controls include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01

Table B.5: Heterogeneous Effect across Gender and Marital Status

Subgoups	(1) Move	(2) Interstate Migration	(3) Log Migration Distance
Single Male	-0.010	0.009	0.302***
	(0.012)	(0.006)	(0.094)
Single Female	0.020***	0.003	0.047
	(0.006)	(0.004)	(0.063)
Married Male	0.012**	0.001	0.046
	(0.006)	(0.003)	(0.088)
Married Female	0.008**	0.005***	0.141**
	(0.003)	(0.002)	(0.058)

Note: All regressions include demographic controls, industry fixed effects, occupation fixed effects, and county-year fixed effects. Demographic controls include age, age square, sex, citizen status, marital status, race, family size, having child under age 5, having child greater than age 5. The dependent variables are as follows: (1) Moved in the past year; (2) Moved across state lines in the past year; (3) Natural logarithm of migration distance (movers only). Results are from IV-DiD regressions. Home-office relationship outcomes are not included due to insufficient observations. Standard errors are clustered at the county-year level. * p<0.1 ** p<0.05 *** p<0.01