The Effect of Remote Job Opportunities on Internal Migration in USA

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Abstract

This paper examines how remote job opportunities (RJOs) influence internal migration patterns in the United States. Motivated by migration theory, which emphasizes job search costs as a major factor behind relocation, the paper considers two opposing effects. RJOs can make migration easier for individuals who were previously discouraged by the risk of not finding a job in a new location. At the same time, they may reduce the need for moves that are solely motivated by the search for better career opportunities. Leveraging a nationally representative dataset of 11.5 million individuals, the study applies a shift-share IV and recursive bivariate probit model to ensure credible identification. The results show that working remotely reduces the probability of interstate migration by 34.9%, while increasing moves between local labor market areas by 26.7% and moves within the same area by 52.9%, relative to the mean. These findings suggest that remote work reduces long-distance migration but encourages medium and short distance moves, reshaping the geography of labor market adjustment.

Keywords: remote work, urban economics, economic development, internal migration

JEL Codes: R1,R23, J61, O18

1 Introduction

The COVID-19 pandemic accelerated a dramatic shift in how people work, turning remote work from a limited option into a regular part of everyday life. In the first quarter of 2024, 35.5 million people in the United States worked from home, representing a fourfold increase from 9 million in 2019 (U.S. Bureau of Labor Statistics 2025, March; U.S. Census Bureau 2022b, September). This trend has major implications for migration choices, as migration theory argues that job search at the destination is one of the most important factors people consider when determining whether they want to move. Furthermore, having a remote job

practically eliminates the need to search for a new job, as people can keep their job while moving to a different location. Figure 1 illustrates this by comparing migration patterns across two different groups, while also displaying the share of remote workers over time to clarify how changes in remote work prevalence may have influenced these trends. The migration rate was higher among office workers until 2019 compared to the migration rate among remote workers. However, after 2019, this pattern reversed and the gap between two groups reached 3 % in 2021. This shift overlaps with a sharp rise in the share of remote workers, suggesting that the expansion of remote job opportunities may have contributed to the change in patters of migration. The combination of rising remote work trends and established insights from migration theory motivates a central question that this article seeks to address: How do remote job opportunities (RJO,hereafter) affect internal migration patterns in USA?

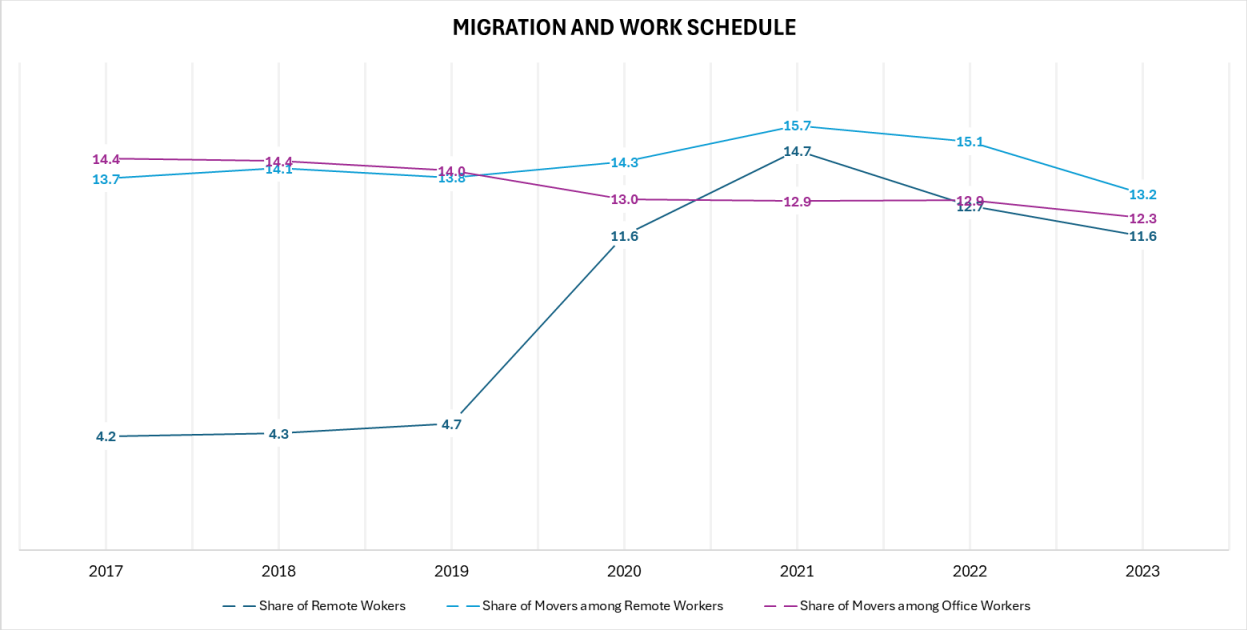


Figure 1: Migration and Work Schedule, 2017–2023

Note: This figure shows trends in remote work and migration rates for remote and office workers between 2017 and 2023. The data are from IPUMS USA. The y-axis shows the share of remote workers and the share of individuals who migrated between or within states in each group. Migration shares are calculated separately for remote and office workers. Between-state and within-state moves are combined in each migration share. All values are unweighted annual averages.

This relationship has important implications that extend beyond individual labor market decisions and location preferences.As remote work expands geographic flexibility, it is reshaping migration patterns in ways that affect regional labor markets, housing demand, tax revenues, and infrastructure planning. These changes create new policy challenges, requiring governments to revisit zoning regulations, transportation systems, and investment strategies. Understanding the role of remote work in shaping relocation decisions is essential

for anticipating the spatial and economic contours of the post-pandemic labor market. Despite its growing relevance, the effect of remote work on migration remains theoretically ambiguous, operating through two opposing channels. On one hand, remote work may facilitate migration by reducing the risks associated with finding a job at the destination. For instance, someone hesitant to leave a landlocked state for a coastal area due to job uncertainty can relocate without changing employers. On the other hand, remote work may discourage migration by removing the need to move for better career opportunities. A recent graduate, for example, may prefer to stay near family while pursuing a remote position that offers career advancement elsewhere. The net effect of remote work on migration depends on which of the two theoretical channels dominates. A positive coefficient indicates that the first channel is dominant, while a negative coefficient indicates that the second channel is more influential. Since internal migration is the outcome of interest, it is important to account for its multiple types. The dataset distinguishes eight types of migration, which are used as separate outcomes in the analysis. These types differ by distance, and distance matters because the composition of individuals likely varies across migration types. For example, among those making long-distance moves, are most people relocating primarily for job search, or are they individuals who had long wanted to move but were restricted by job location? If the answer is that the first group dominates, meaning individuals who move primarily for job search, then the coefficient will be negative, since the second channel reduces unnecessary moves and lowers migration of this type. If the second group is more prevalent, referring to those who wish to move but were constrained by job location, the coefficient will be positive, as remote work enables them to relocate.The same question applies to medium- and short-distance moves.

Analyzing the relationship between RJOs and migration outcomes requires addressing the endogeneity of remote work through an appropriate empirical strategy. To address endogeneity and estimate causal effects, a recursive bivariate probit model is combined with the shift-share instrumental variable approach. To implement this framework, individual-level data from IPUMS USA (Ruggles et al.(2025)), which harmonizes microdata from the American Community Survey (ACS), is used. The dataset provides nationally representative information on work schedules, migration decisions, and socioeconomic characteristics. The sample includes approximately 11.5 million individuals from 2017 to 2023, restricted to working-age adults with complete information on employment and residential location.

The results show that remote job opportunities significantly affect internal migration patterns, with the direction and magnitude of the effects varying by distance. Long-distance migration decreases substantially, with individuals working remotely being 34.9% less likely to move between states relative to the sample mean. In contrast, medium-distance migration increases by 26.7%, and short-distance relocation rises by 52.9% relative to the mean. Heterogeneity analysis reveals that the reduction in long-distance migration is primarily driven by younger individuals. Robustness checks separate the effect of remote work from that

of the COVID-19 pandemic, showing that the influence of remote jobs on migration behavior existed even before the pandemic and persists in the post-pandemic period.

This paper makes several contributions to the literature on remote work and migration. It offers one of the first causal estimates of how remote job opportunities affect internal migration using a shift-share IV combined with a recursive bivariate probit model, introduces a conceptual framework that clarifies two distinct channels through which remote work influences mobility, utilizes a nationally representative dataset of 11.5 million individuals to enhance generalizability, and uncovers substantial heterogeneity by distinguishing eight migration types rather than treating migration as a single outcome.

The paper is structured as follows. Section 2 reviews the literature on remote work and migration. Section 3 outlines the data, variables, methodology, and descriptive analysis. Section 4 presents the main findings. Section 5 discusses robustness checks, and Section 6 concludes.

2 Literature Review

The COVID-19 pandemic brought major shifts across society, including a rapid expansion of remote work, which has become a major focus of recent research. A large body of literature examined its consequences, such as work-life balance, productivity, and relocation preferences. This review focuses on studies related to migration and housing, as they are most relevant to the questions addressed in this paper.

The first group of studies includes theoretical models and descriptive studies that examine how remote work affects cities, housing costs, and migration. Theoretical models predict both intra- and inter-city migration shifts in response to the rise of remote work (Brueckner et al. (2023); Delventhal et al. (2022); Bond-Smith and McCann (2022)). A common implication across these studies is the outmigration from urban centers to suburban or lower-cost regions, accompanied by declines in housing prices in areas experiencing population outflows. Davis et al. (2024) similarly show that remote work increases spatial flexibility, enabling workers to relocate to more affordable areas. While these theoretical models provide a foundation for understanding potential mechanisms, several studies have taken a descriptive approach to document how migration behavior has evolved alongside remote work adoption. Using survey data, Ozimek (2020) estimates that between 14 and 23 million Americans intended to relocate due to expanded remote work opportunities, with over half planning to move more than two hours away. In follow-up work, Ozimek (2022) finds that areas with both high costs of living and high shares of remote work experienced the greatest out-migration. Similarly, Bohm (2023) report that nearly 30% of surveyed individuals cited remote work as their main reason for relocating, with many expressing preferences for larger homes and greater distance from their workplace.

The second group of studies empirically examines how remote job opportunities (RJOs) influence migration patterns, especially the shift away from dense urban centers toward suburban and rural areas. Ramani and Bloom (2021) introduced the term "donut effect" to describe the population and business outflows from major city centers. Their analysis shows that during the first two years of the pandemic, approximately 9% of the population and 16% of business establishments moved out of central urban ZIP codes. This effect was especially strong in areas with a high share of jobs that can be done remotely. Supporting evidence is provided by Correa (2023), who finds that in Sweden, remote work increased the probability of leaving large cities by 12.5% and the probability of relocating to rural areas by 11.5%, compared to pre-pandemic trends. Similarly, Haslag and Weagley (2021) analyze data on over 360,000 interstate moves and report that individuals increasingly relocated to less dense, lower-rent areas with more desirable amenities. In the third quarter of 2020, around 13% of movers influenced by the pandemic cited remote work as a factor. This share remained between 15% and 22% through the end of 2021.

The third strand of the literature examines how remote work influences housing demand and its consequences for housing prices and rents. Su and Liu (2020) find that housing demand declined more in densely populated areas with greater remote work potential compared to less dense areas. In particular, zip codes with high work-from-home potential saw slower growth in both housing prices and rents.Kim and Long (2024) confirm this pattern by showing that remote work has flattened intracity house price gradients by reducing the premium placed on proximity to job centers. Interestingly, approximately 20% of this effect operates indirectly through decreased traffic congestion. In contrast, Mondragon and Wieland (2022) find that remote work increased aggregate U.S. house prices by 15.1%, with the strongest effects occurring in suburban and peripheral areas, confirming the prediction that working from home reduces the value of central proximity.

The existing literature leaves several important questions unanswered. Firstly, there is a tendency to focus on COVID-19's migration impact without fully exploring the role of remote work as a contributing factor. Second, even when remote work is considered, many studies rely on correlational evidence or strong assumptions, with limited attention to its potential endogeneity. Third, researchers often focus on specific demographic or occupational groups, such as high-income families and tech workers, which limits the ability to capture broader migration trends.Fourth, most existing studies offer limited theoretical discussion of the mechanisms through which RJOs affect migration, and do not develop a clear theoretical framework to interpret their results. Finally, migration is frequently measured as a single outcome, often interstate migration, despite the fact that remote work is likely to influence short, medium, and long distance moves in different ways.

This paper addresses these gaps by offering one of the first causal estimates of the effect of RJOs on migration using a nationally representative dataset of 11.5 million individuals. It uses a shift-share

instrumental variable and a recursive bivariate probit model to correct for endogeneity in the presence of binary outcomes. The paper also introduces a dual-channel theoretical framework, explaining how RJOs can both encourage and discourage migration depending on underlying motivations. Finally, it distinguishes among eight types of migration, thereby providing a richer picture of how remote work is reshaping the geography of labor mobility. The next section describes the data and key variables used in the analysis.

3 Data and Methodology

3.1 Model Specification

To estimate the effect of (RJOs) on migration while addressing potential endogeneity concerns, this study employs a recursive bivariate probit model. This approach is appropriate given that both the treatment variable and the outcome variable are binary, and may be jointly influenced by unobserved factors. Migration, the dependent variable, is expected to be affected by an endogenous binary variable, working from home. Since the decision to work from home is endogenous or unobserved variables affecting work schedule preferences are associated with those affecting migration, a basic univariate probit model would produce biased and inconsistent estimates. Likewise, for several reasons, estimating this relationship with a linear probability model (LPM) and instrumental variables (IV), such as two-stage least squares (2SLS), is also not optimal (Greene 2018, Section 17.2.6; Wooldridge 2010). First, linear models have constant marginal effects and can give projected probabilities outside the [0,1] range, making them unsuitable for binary outcomes. Second, when both the dependent and endogenous variables are binary, linear IV models can exhibit significant functional form misspecification, resulting in biased and inconsistent results even when correct instruments are utilized. Therefore, to address these limitations, endogeneity, and the binary character of both variables, the recursive bivariate probit (RBP) model is used. The RBP model is developed by Greene 2018 (Section 17.9.5), and is used to model two binary dependent variables where one is endogenous. The model consists of two equations. The first equation models the unobserved propensity to work from home, denoted WFH^*, as a function of a shift-share instrument ShiftShare_{ost}, individual-level characteristics X_{indiv}, and fixed effects for year (X_{year}), occupation (X_{occ}), and state (X_{state}):

$$\text{WFH}^* = \delta \cdot \text{ShiftShare}_{ost} + X_{\text{indiv}} \cdot \alpha + X_{\text{year}} \cdot \eta + X_{\text{occ}} \cdot \theta + X_{\text{state}} \cdot \lambda + \varepsilon_1 \tag{1}$$

The second equation models the unobserved propensity to migrate, Migrate^*, as a function of the same covariates, along with the observed work-from-home status WFH:

$$\text{Migrate}^* = X_{\text{indiv}} \cdot \beta + X_{\text{year}} \cdot \mu + \gamma \cdot \text{WFH} + X_{\text{occ}} \cdot \theta + X_{\text{state}} \cdot \lambda + \varepsilon_2 \tag{2}$$

The observed binary outcomes are defined as:

$$\text{WFH} = \begin{cases} 1, & \text{if WFH}^* > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$\text{Migrate} = \begin{cases} 1, & \text{if Migrate}^* > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The error terms ε_1 and ε_2 are assumed to follow a bivariate normal distribution:

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right) \tag{5}$$

Equation (1) models the probability of working from home as a function of a shift-share instrument at the state occupation level, along with individual characteristics and fixed effects (year, occupation and state). The resulting binary indicator, Y_2, then enters Equation (1) as an explanatory variable to estimate its effect on migration. This reflects the structural effect of remote work on migration, while also accounting for the potential that unobserved factors influence both the likelihood of working from home and migration outcomes. To account for this possible endogeneity, the model assumes that the error components ϵ_1 and ϵ_1 follow a bivariate normal distribution, as defined in Equation (5). Here, ρ represents the correlation between the error terms, and a statistically significant ρ provides evidence of endogeneity, in which case standard univariate probit estimation would be inconsistent. Estimating the two equations jointly via full information maximum likelihood corrects for this endogeneity. Therefore, the parameter γ in Equation (**??**) captures the causal effect of Y_1 on Y_2.

The Average Treatment Effect (ATE) measures the mean change in the probability of the outcome variable resulting from the treatment. In a binary treatment setting, the ATE can be computed as the average difference between the predicted probabilities under treatment and non-treatment conditions across all observations. Formally, the ATE is given by:

$$\text{ATE} = \frac{1}{n} \sum_{i=1}^{n} \left[\Phi(x_i'\beta + \alpha) - \Phi(x_i'\beta) \right] \tag{6}$$

In this expression, n denotes the total number of observations. The term $x_i'\beta$ represents the linear predictor

for observation i, capturing the probability of the outcome in the absence of treatment. The parameter α reflects the treatment effect, i.e., the shift in the latent index due to the treatment. The function $\Phi(\cdot)$ denotes the cumulative distribution function (CDF) of the standard normal distribution, which translates the latent index into a probability in the context of a probit model.

Under this framework, $\Phi(x_i'\beta + \alpha)$ gives the predicted probability of the outcome for individual i under treatment, while $\Phi(x_i'\beta)$ gives the corresponding probability without treatment. The ATE is obtained by averaging the difference between these two predicted probabilities across the entire sample. This method captures the marginal effect of treatment on the likelihood of the outcome and is particularly suited to binary dependent variables modeled through a probit specification. The resulting ATE reflects the expected change in the probability of the outcome due to the treatment across the population.

While the recursive bivariate probit model is theoretically identified through its nonlinear structure, assuming the data matrix meets the necessary full rank condition (as discussed in Heckman 1978; Wilde 2000), an exclusion restriction is additionally introduced to enhance the credibility of causal inference (Maddala 1983; Monfardini and Radice 2008). Specifically, the probability of working remotely is instrumented using a state-level shift share variable (Bartik IV), which varies exogenously across regions and is not expected to directly affect the migration decision. The shift share instrument used in this study is similar to the one constructed by Cortes (2008) and consists of two main components: a share component and a shift component. As mentioned earlier, it is built using the occupation variable, and is defined in Equation 7 as:

$$S_{ost} = \frac{R_{os2012}}{X_{os2012}} \cdot (X_{ost}) \tag{7}$$

In this expression, ShiftShare_{ost} denotes the value of the shift-share instrument for occupation o, in state s, at time t. The term R_{os2012} represents the number of remote workers in occupation o in state s in the year 2012, while X_{os2012} is the total number of workers in occupation o in state s in the same year. The ratio $\frac{R_{os2012}}{X_{os2012}}$ therefore reflects the baseline remote-work share for that occupation and state in 2012. The shift component, X_{ost}, is the number of individuals working in occupation o in state s at time t, capturing the current occupational distribution in the local labor market. The year 2012 is chosen as the base period for constructing the share component due to both data consistency and identification concerns. It is the earliest year in which occupational classifications are consistent with those used throughout the study period, making it suitable for constructing the share component of the instrument. Relying on an earlier reference point also strengthens the case for exogeneity, as it reduces the risk that the instrument is influenced by contemporary migration patterns.

The share of individuals in state **s** with a given occupation who work remotely serves as a proxy for

the probability that an individual with the same occupation and residing in the same state works remotely today. The shift component is X_{ost}, the number of individuals in occupation o in state s at time t. This reflects the current local distribution of occupations, that is, how many workers in the state are employed in that occupation. Areas more concentrated in remote-friendly occupations will receive higher instrument values. This interaction produces cross-sectional and temporal variation in the instrument that is predictive of the endogenous variable (working from home) but uncorrelated with unobserved shocks to migration, as long as the historical shift component is exogenous and the occupational distribution was not endogenously chosen in response to future migration decision.

3.2 Data and Summary Statistics

This study utilizes the IPUMS ACS dataset (Ruggles et al.(2025)) for the main analysis. The sample covers the period from 2017 to 2023 and includes approximately 11.5 million observations. IPUMS ACS 2012 is used to construct the initial shares for the instrument, while IPUMS CPS (Ruggles et al. (2024)) is employed for robustness checks.As is standard in the literature, the sample is restricted to individuals aged 16 to 65 to capture the working age population. The dependent variable is a dummy variable that indicates whether the individual moved within the past year. As mentioned earlier, this study examines eight distinct types of moves, each of which is used as a separate dependent variable: (1) interstate migration, (2) intrastate migration, (3) migration between PUMAs, (4) relocation within PUMAs, (5) moving back to the birth state, (6) moving from the birth state, (7) migration between contiguous states, and (8) migration between non-contiguous states. Public Use Microdata Areas (PUMAs) are non-overlapping, statistical geographic areas that partition each state or equivalent entity into geographic areas containing no fewer than 100,000 people each (U.S. Census Bureau (2022a)). The main independent variable, which is also a dummy variable, indicates whether the person works remotely. It is obtained from the question of how long it typically takes for the person to get to work. The response has two options: Respondents can indicate that they worked remotely or how long it took to travel to work. The shift share instrumental variable is constructed using the occupation variable, where it is aggregated into 26 different groups using broader definitions of census. There are also 4 groups of control variables which are gradually added in the corresponding models to see how each group will affect the results. These include individual characteristics, year fixed effects, occupation fixed effects, and state fixed effects.

Table 1: Summary Statistics by Work Type and COVID Period

	Before Covid		During Covid		After Covid	
	Remote	**Office**	**Remote**	**Office**	**Remote**	**Office**
Migration						
Between States	3.99	2.41	3.86	2.34	4.1	2.45
Within State	9.23	11.45	10.85	10.23	9.51	9.6
Between PUMA	2.9	3.01	3.43	2.94	3.38	3.02
Within PUMA	6.33	8.44	7.42	7.29	6.13	6.58
To Birth State	0.76	0.57	0.84	0.56	0.8	0.59
From Birth State	1.17	0.68	0.97	0.69	1.07	0.69
Between Non-Cont States	2.97	1.66	2.77	1.6	3.05	1.7
Between Cont States	1.01	0.76	1.09	0.75	1.05	0.75
Average Age	44.53	41.29	42.54	41.14	42.72	42.62
Gender						
Male	47.37	52.29	47.99	52.95	46.98	52.77
Female	52.63	47.71	52.01	47.05	53.02	47.23
Race						
White	83.4	77.36	70.12	67.33	69.24	65.72
Black/African American	5.57	8.87	6.53	8.48	6.81	8.15
Asian	5.83	6.31	10.25	6.27	9.82	6.84
Others	5.2	7.46	13.1	17.92	14.13	19.29
Nationality						
Hispanic	9.71	14.83	10.44	16.3	11.34	17.33
Marital Status						
Married	63.11	53.02	60.05	51.6	60.17	50.96
Work Schedule						
Works from Home	4.39		13.35		12.15	
Education						
College Graduate	50.81	36.3	64.74	34.56	62.62	36.45
Observations	220195	3889286	402751	1999955	421366	2424585

Note: This table presents summary statistics for remote and office workers across three periods: Before COVID (2017–2019), During COVID (2020–2021), and After COVID (2022–2023). Values represent percentages unless indicated otherwise. Age is reported as the average in years. "Works from Home" reports the overall share of remote workers. Migration variables refer to the percentage of individuals experiencing each migration type within the corresponding period. Observations refer to the number of person-year records in each group. Sample sizes differ across columns due to variation in the number of observations available in each period.

In Table 1, the summary statistics for the main specification are provided. The table sheds light on the demographics and migration patterns of two groups, remote workers and office workers, over three periods: before, during, and after the COVID-19 pandemic. First and foremost, as expected, the percentage of remote workers has increased threefold since the epidemic. The average age of remote workers is greater than that of office workers in all periods, but the gap narrows in the post-COVID period as the number of younger people in the remote worker category increases. The gender distribution remains stable over time, with women consistently making up a larger share of remote workers compared to office workers. This is

consistent with previous studies, which indicate that women, particularly mothers, prefer to work remotely because it allows them to balance work and family life responsibilities (Chung, Seo, et al. 2020, Chung and Van der Lippe 2020). Therefore, it is also not surprising that compared to office workers, a higher percentage of remote workers are married. The same rationale applies here: remote work offers a higher degree of freedom in terms of time, which can better support work-life balance and family obligations, both of which are valued by married people. The share of college graduates is always higher among remote workers. This is a predictable result, consistent with earlier findings (Bloom 2020, Cowan 2024, and Dingel 2020) that employees with a college degree are significantly more likely to work in positions that can be done from home. Across all racial classifications, White people make up the majority in all groups and periods. Compared to office workers, a slightly higher share of White individuals work remotely, whereas all other racial groups were more likely to work on-site across all years, with the exception of Asians in the post-COVID period. The data suggests that more Asians began to work remotely following the pandemic.

The table reveals several noteworthy patterns in migration behavior. In general, across short- and medium-distance relocations, office workers had a higher rate of migration than remote workers during the pre-COVID period. However, this pattern reversed following the COVID pandemic. As shown in the table, short- and medium-distance migration increased among remote workers in the post-COVID period relative to the pre-COVID period, whereas it declined among office workers. This implies that the expansion of remote work may be enabling greater geographic flexibility for workers. On the other hand, long distance migration parameters show little variation over time, specifically for office workers. These results highlight how remote work affects migration patterns and how it can help employees be more flexible with their location.

Although college graduation status is helpful in explaining the preference to work from home, it is mostly due to differences in the types of jobs available to college graduates compared to non-college graduates. This is supported by Figure 2, which illustrates remote work rates by occupation, showing substantial variation even before the pandemic. In the post-pandemic period, this variation becomes more pronounced, with increasingly distinct gaps emerging across occupations.

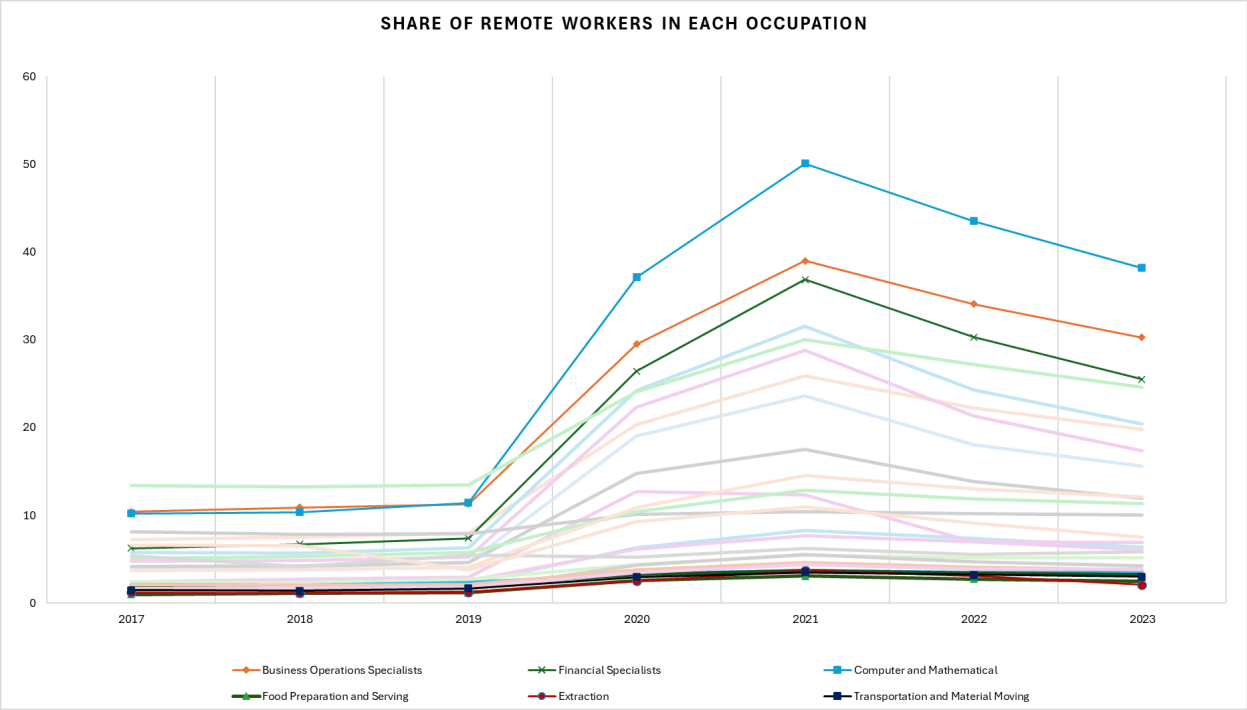


Figure 2: Share of Remote Workers by Occupation, 2017–2023

Note: The figure shows the share of remote workers by occupation from 2017 to 2023. Remote work is defined as working primarily from home. Occupational groups follow IPUMS standardized categories. Data are unweighted and reflect annual averages. The figure highlights substantial variation in remote work adoption across occupations, both before and after the COVID-19 pandemic.

In 2017, the occupations with the highest and lowest remote work rate were "Art, Design, Entertainment, Sports and Media" and "Transportation and Material Moving" with a corresponding rate of 13.4% and 1.5%. Following the pandemic, the share of remote workers increased in nearly all occupations. Nevertheless, as might be expected, the occupation with the highest share of remote workers in 2023 is "Computer and Mathematics" with a rate of 38.2%.

Since occupation is treated as a choice variable, it may be subject to endogeneity concerns. To address this, the second specification serves as a robustness check by constructing the shift share IV using the field of degree variable instead of occupation. It includes 38 broad categories used in the analysis rather than a more detailed version. As these two specifications differ based on the variable used to construct the shift share IV, each specification has a different sample set. Everyone is included in the primary specification, except those who have not worked in the previous five years because their occupation cannot be determined. On the other hand, the second specification, used as a robustness check, includes only individuals with at least a bachelor's degree, as the field of degree is not defined for those without a college education. This is also the primary reason for using occupation instead of field of degree to build IV for the main specification, as the latter does not represent the general population. Appendix table 7 contains summary data for the

second specification, which includes only college graduates in the sample, and is used only for the robustness check. When comparing the pre- and post-COVID eras, almost all patterns are consistent with the main sample. It is worth noting that the proportion of remote workers is larger in all three periods than in the main specification. This is not surprising, given that the dataset only includes college graduates.

4 Results

To assess the strength and validity of the shift-share instrument, a first-stage probit regression is estimated, where the endogenous variable, working from home, is regressed on the instrument and control variables. The results are reported in Table 2 where the first column reports the results from the baseline specification, which includes individual characteristics, year fixed effects, and occupation fixed effects as controls. In the second column, state fixed effects are added to account for time-invariant differences across states.

Table 2: First Stage Regression Results

	Working From Home	
	(1)	(2)
Shift Share IV	0.0002***	0.0001***
	(2.42e-06)	(3.73e-06)
Age	0.003***	0.003***
	(5.00e-05)	(5.00e-05)
Female	0.071***	0.072***
	(0.0012)	(0.0012)
Fixed Effects	Year, Occupation	Year, Occupation, State
Observations	11,495,961	11,495,961

Note: This table reports coefficient estimates from first-stage probit regressions where the dependent variable is working from home. Column (1) includes year and occupation fixed effects; Column (2) additionally includes state fixed effects. The shift-share instrument is constructed using 2012 occupational employment shares interacted with contemporaneous national trends. Full control variables are included in both specifications but are omitted for brevity. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The coefficient of shift share IV is difficult to interpret directly, as the variable captures changes that depend jointly on initial shares from 2012 and the number of individuals in occupation o at time t in state s. Although the coefficient on the instrument is relatively small, this reflects the measurement scale of the variable. A one-unit change in the instrument is not meaningful on its own, as the variable spans a wide range. To illustrate its practical significance, a one-standard-deviation increase in the instrument is equivalent to a 6.9% increase in the probability of working from home relative to its value at the sample mean. This effect remains statistically significant even after controlling for state fixed effects in the second

specification.

To assess instrument strength, a linear first-stage regression is also estimated for diagnostic purposes, as the RBP model does not directly support traditional weak-instrument tests. The resulting F-statistic is 2516.36, far exceeding the conventional threshold of 10 recommended by Staiger and Stock 1997, providing strong evidence of instrument relevance. An `ivprobit` model is also estimated for diagnostic purposes, not as a primary specification. The Wald test of exogeneity strongly rejects the null hypothesis $\left(\chi^2(1) = 234.84,\ p < 0.001\right)$, indicating that working from home is endogenous and confirms the need for an instrumental variable approach. The Anderson-Rubin (AR) test, developed by Anderson and Rubin (1949), and the robust Wald test are also conducted to address concerns about weak instruments. The AR test rejects the null hypothesis that the coefficient on working from home is zero ($\chi^2(1) = 234.40$, $p < 0.001$), indicating that indicating a strong first-stage relationship. The robust Wald test confirms this result ($\chi^2(1) = 214.39$, $p < 0.001$), further supporting the instrument's relevance.

Table 3: Regression Results (Part 1)

	Between States		**Within State**		**Between PUMAs**		**Within PUMAs**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATE	-0.0217***	-0.009***	0.0576***	0.051***	0.0133***	0.010***	0.0429***	0.041***
	(0.0008)	(0.001)	(0.0026)	(0.003)	(0.0014)	(0.001)	(0.0023)	(0.002)
Rho(ρ)	0.331***	0.168***	-0.143***	-0.131***	-0.068***	-0.049***	-0.1424***	-0.140***
	(0.0127)	(0.009)	(0.0056)	(0.006)	(0.0075)	(0.008)	(0.00623)	(0.006)
Test for endogeneity of Treatment ($\rho = 0$)								
χ^2 (1)	580.929***	308.068***	621.004***	521.780***	82.20***	40.459***	507.858***	501.763***
Log Likelihood	-4423334	-4391750.5	-6834050.9	-6811403.0	-4722303.5	-4694494.4	-5988920.1	-5964929.0
Sample Mean	2.95		11.5		3.75		7.75	
Relative Change	-73.6%	-30.5%	50.1%	44.3%	35.5%	26.7%	55.4%	52.9%

Note: Each specification includes individual characteristics, year fixed effects, and occupation fixed effects. Columns (2), (4), (6), and (8) additionally include state fixed effects. All models are estimated using 11,495,961 observations from the IPUMS USA dataset (2017–2023). Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATE values represent percentage point changes. Relative change is calculated as ATE divided by the sample mean of the migration outcome. All control variables are included in the regression but are omitted from the table for brevity.

A recursive bivariate probit model is estimated using 11.5 million observations from the 2017–2023 IPUMS USA dataset to examine the relationship between remote work and various migration outcomes. Table 3 and Table 4 present the main regression results across eight different specifications, each corresponding to a distinct type of migration, including moves between states, within states, between and within PUMAs, to and from birth state, and between contiguous and non-contiguous states. In each specification, the first column reports results from the baseline model, which includes individual characteristics, year fixed effects,

and occupation fixed effects. The second column extends the baseline by adding state fixed effects to account for time-invariant differences across states.

Each table includes four primary statistics. The Average Treatment Effect (ATE) describes the estimated change in the probability of migration caused by working from home. ATE values are expressed as percentage point changes. Relative change is also reported, calculated as the ATE divided by the sample mean of the corresponding migration type, providing a sense of the effect's size in proportion to the baseline rate. The parameter rho (ρ) measures the correlation between the error terms of the treatment and the outcome equations. A statistically significant ρ suggests endogeneity and justifies the use of the recursive bivariate probit model. The log likelihood provides a measure of overall model fit, where higher values indicate better fit. The χ^2 test checks whether ρ equals zero; rejection of this null implies that the treatment variable is endogenous.

The results suggest that remote job opportunities significantly influence internal migration. The coefficients remain highly significant after accounting for state fixed effects, with the exception of moves between contiguous states. Moreover, the magnitude of the estimated effects is considerable across most types of migration. There are consistent patterns in the direction of the coefficients. RJOs reduce long-distance migration, while they are associated with an increase in short- and medium-distance migration. The probability of moving within a state increases by 5.1 percentage points for individuals with a remote job, which corresponds to a 44.3% increase relative to the sample mean in a specification that includes state fixed effects. Migration between PUMAs, often reflecting shifts within metro-area subregions, rises by 1 percentage point, representing a 26.7% increase relative to the sample mean. The estimated effect of RJOs on within-PUMA moves is 4.1 percentage points, corresponding to a 52.9% increase over the sample average of 7.75%.

Table 4: Regression Results (Part 2)

	To Birth State		**From Birth State**		**Between Non-Cont States**		**Between Cont States**	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ATE	-0.0017***	-0.002***	-0.006***	-0.002***	-0.0115***	-0.010***	-0.039***	0.001
	(0.00045)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.001)	(0.0005)	(0.001)
Rho(ρ)	0.110***	0.137***	0.248***	0.119***	0.2587***	0.233***	0.874***	0.035***
	(0.016)	(0.017)	(0.0180)	(0.014)	(0.0120)	(0.012)	(0.0033)	(0.013)
Test for endogeneity of Treatment ($\rho = 0$)								
χ^2 (1)	42.51***	63.520***	175.091***	74.148***	416.887***	380.236***	9054***	6.846***
Log Likelihood	-3446417.6	-3433630.7	-3548369.9	-3526597.9	-4061915.4	-4032266.6	-3576867.0	-3545586.6
Sample Mean	0.67		0.93		2.02		0.93	
Relative Change	-25.4%	-29.9%	-64.5%	-21.5%	-56.9%	-49.5%	-419.4%	10.8%

Note: Each specification includes individual characteristics, year fixed effects, and occupation fixed effects. Columns (10), (12), (14), and (16) additionally include state fixed effects. All models are estimated using 11,495,961 observations from the IPUMS USA dataset (2017–2023). Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATE values represent percentage point changes. Relative change is calculated as ATE divided by the sample mean of the migration outcome. All control variables are included in the regression but are omitted from the table for brevity.

In contrast to their positive effects on short- and medium-distance relocations, remote job opportunities appear to reduce long-distance migration as stated above. After controlling for state fixed effects, working from home is associated with a 0.9 percentage point decrease in migration between states, a 34.9% decline relative to the sample mean of 2.58%. Interestingly, both the probability of returning to one's birth state and the probability of leaving it decrease by 0.2 percentage points for individuals with a remote job. Despite this identical absolute change, the relative changes differ: a 33.3% drop for returning to one's birth state and a 27.4% drop for leaving it.

Migration between contiguous states declines by 1 percentage point in response to remote job opportunities. This represents a 55.6% reduction relative to the sample mean of 1.8%. A noticeable exception is the specification for migration between non-contiguous states. In the baseline model without state fixed effects, the estimated effect of remote work is –3.9 percentage points, an unrealistically large decline, nearly five times the sample mean of 0.79%. This suggests that the estimate was partly capturing unobserved, state-specific factors correlated with both remote work and the migration between non-contiguous states. Once state fixed effects are introduced, the coefficient shrinks substantially and changes the sign, becoming statistically insignificant. This change highlights the importance of accounting for unobserved heterogeneity across states to avoid overstating the effect of remote work.

As mentioned earlier, the effect of remote jobs on migration is assumed to depend on which of the two main channels is more dominant. The first channel encourages migration by freeing individuals from the need to live near their workplace, leading to a positive effect of remote jobs on mobility. In contrast, the second

channel discourages migration by reducing job-search-related relocations, resulting in a negative effect. The findings suggest that medium-distance migration is primarily driven by the first channel, consistent with the existing literature. The second channel appears to be more dominant in long-distance migration, which in this context primarily consists of interstate moves. The primary reason for this stems from the fact that individuals often have to travel farther to search for a job. This is supported by evidence from the statistics about the IPUMS CPS "Reason to Move" variable, which captures individuals' stated motivations for relocation. Among those who moved between states, nearly 37% cited job-related reasons as their primary motivation. In contrast, only 4.7% of the individuals who moved within the county borders did so for job-related reasons. Notably, 15.4% of the within-state movers reported employment-related motivations. Based on these patterns, share of individuals that move purely for job search among between-state movers is high, lending support to the idea that if they find remote job they are more likely to stay. Additionally, the financial and social costs (separation from family and friends, loss of social networks) are higher for long distance migration. However, it is quite opposite for medium distance movers. Individuals who previously relocated closer to their workplace may now opt to move medium distance (e.g., moving to another PUMA), as the shift to remote work eliminates the necessity of living near their job location. This allows them to pursue more affordable housing, access better schools, and enhance their overall quality of life, while still maintaining connections with family, friends, and their social network.

Short-distance relocation is unlikely to be strongly driven by work schedule preferences, as individuals can typically move locally without leaving their jobs. Therefore, the effect of remote work on short-distance moves is less clear, especially when considering the relative importance of two channels discussed here. A key reason individuals move within a short distance after transitioning to remote work is the desire for improved amenities and additional living space, particularly to accommodate a home office, given the increased time spent at home.

The parameter ρ, which reflects the correlation between unobserved determinants of remote work and migration, is statistically different from zero in all cases. This supports the use of the recursive bivariate probit model, as it confirms that unobservable factors simultaneously influence both decisions. The χ^2 tests reinforce this finding by strongly rejecting the null hypothesis of no endogeneity in almost every specification. Although ρ varies in sign across specifications, its primary role here is to signal the presence of endogeneity rather than to identify the direction of selection. Improvements in log likelihood values with the inclusion of state fixed effects suggest a better model fit.

5 Sensitivity And Robustness Checks

In order to address potential threats to the methodology used in this study, several tests and robustness checks are conducted. First, as stated before, due to potential endogeneity of the occupation variable, the shift-share variable is also constructed using the field of degree variable, which is considered more exogenous. The structure of this alternative instrument mirrors that used in the main analysis.

Specifically, the instrument is calculated by first taking the number of remote workers in field of degree f residing in state s in 2012, denoted R_{fs2012}, and dividing it by the total number of individuals in that field and state in the same year, X_{fs2012}. This share is then multiplied by the number of individuals with field f living in state s at time t, denoted X_{fst}, scaled by one thousand. Formally, the variable is defined as:

$$\text{ShiftShare}_{fst} = \left(\frac{R_{fs2012}}{X_{fs2012}}\right) \cdot X_{fst} \tag{8}$$

This construction leverages variation in the geographic distribution of educational fields and their historical tendency toward remote work. Because field of degree is less likely to be endogenously determined with respect to local labor market conditions and migration patterns, this version of the instrument provides a useful robustness check for the main results based on occupation-driven variation.

The second stage results are reported in appendix tables 6, and 7. Notably, both the significance level and the direction of the treatment effect are nearly identical to those in the main specification. The average treatment effects are highly consistent with the main specification, showing only minor differences. Summary statistics from the field-of-degree specification indicate that mean migration rates differ slightly from those in the occupation-based sample. As a result, calculating relative probability changes using mean values from the field-of-degree specification yields results that closely match those of the main specification. Appendix Table 14 presents the first-stage results for this specification, which are again highly similar to those in the main model.

Another concern is that migration outcomes may vary significantly by age, particularly for long-distance moves. As discussed in the introduction, individuals often cite job search as the primary motivation for interstate migration. It is reasonable to assume that younger individuals—such as recent college graduates—are more likely to migrate for job opportunities, whereas older individuals typically have a more established career path and are less mobile (Plane and Jurjevich 2009). As a result, the effect of remote job opportunities—particularly through the second channel that reduces job-search-related moves—may differ substantially across age groups. Appendix Tables 8 and 9 present regression results by age group for each specification. In each migration type, the first column reports estimates for individuals aged 40 or younger, and the second

column for those over 40. The findings reveal substantial heterogeneity in migration responses to remote work across different age cohorts. Across multiple migration types, younger individuals exhibit significantly stronger responses to remote job opportunities than their older counterparts. For younger individuals, working from home reduces the probability of moving to another state by 1.4 percentage points, equivalent to a 31% decrease relative to the sample mean. In contrast, the average treatment effect is positive but statistically insignificant for older cohorts. For other types of interstate migration, a similar pattern emerges. However, for short- and medium-distance moves, the direction of the effect is consistent across age groups, although the magnitudes vary slightly. These patterns confirm the hypothesis that age-related heterogeneity plays an important role in shaping migration outcomes, particularly for long-distance migration, as the influence of the second channel differs significantly by age group.

It is also worth noting that the treatment effect may capture the impact of the COVID-19 pandemic rather than the effect of remote work arrangements, indicating that the observed changes in migration patterns may be driven more by the pandemic itself than by remote work. To check this, dummy variables for 3 separate time periods are added to the main regression together with their interaction with the remote work variable. The three periods are defined as follows: the pre-COVID period (2017–2019), the COVID period (2020–2021), and the post-pandemic period (2022–2023). The results are presented in Appendix Tables 10 and 11. For 5 out of 8 migration types, the effect of remote job opportunities is statistically significant both before and after the pandemic. For 3 of these types, the effect is also significant during the pandemic period. In contrast, the effects on migration between contiguous states and migration from the birth state are not statistically significant in either the pre- or post-pandemic period. For within-PUMA migration, the effect is significant only during and after the pandemic. The effect of RJOs is larger in the post-pandemic period for short- and medium-distance migration. In contrast, the effect on long-distance migration types is generally smaller after the pandemic compared to the pre-pandemic period. Taken together, these findings confirm that although the pandemic influenced migration behavior, the effect of remote job opportunities was present and substantial even before the onset of COVID-19. The last concern that this paper addresses is whether the relationship between the shift-share IV and remote work has changed over time. In other words, the instrument may not adequately explain remote work preferences prior to the pandemic, since the main variation in remote work preferences across occupations emerged after the pandemic. To test this, the first-stage probit regression is run separately for the three periods discussed earlier. Table 12 presents the results, showing that the coefficients on the shift-share IV are statistically significant and nearly identical across all three periods. This suggests that the shift-share variable could explain remote work preferences even before the pandemic.

6 Conclusion

This study offers important insights into the relationship between remote work and migration patterns through the application of a recursive bivariate probit model and the shift-share instrumental variable technique. Drawing on 11,495,961 observations from the IPUMS ACS dataset, the analysis focuses on eight distinct migration types. The results show that remote work significantly reduces long-distance moves while increasing the likelihood of medium- and short-distance relocations. These patterns reflect two primary mechanisms: first, remote work enables individuals to live farther from job centers, encouraging some mobility; second, it reduces the need to relocate for employment, particularly for younger individuals seeking jobs across state lines. In addition to these two channels, the increased demand for larger housing and better amenities, especially for setting up home offices, drives much of the short-distance migration.

Robustness checks confirm that these effects are not driven solely by the COVID-19 pandemic. The interaction terms show that the impact of remote work on migration was already present before 2020 and remains significant in the post-pandemic period. Analysis by age groups further confirms that younger individuals are more responsive to remote job opportunities, especially in long-distance contexts, likely because remote work reduces the need for job-related relocation, something younger workers are more likely to pursue. The strength and relevance of the instrumental variable are supported by large first-stage F-statistics and consistent AR and Wald test results, reinforcing the validity of the causal claims. These findings highlight the need to reassess traditional models of migration in the context of changing work patterns. As remote work becomes more common, the traditional assumption that people move mainly to be closer to jobs may require reconsideration. Instead, factors such as flexibility in job location, the transformation of the home into a workspace, and lifestyle preferences such as access to space and amenities are becoming central considerations in residential choices.

Beyond the academic contribution, the results have practical relevance. As more people work from home and seek housing that aligns with remote work needs, local governments and urban planners may need to anticipate increased local and regional mobility. This shift may also prompt real estate developers and policymakers to review zoning regulations, housing supply, and infrastructure planning to better support workers no longer tied to a central office.

Beyond the academic contribution, the results have practical relevance. As more people work from home and seek housing that aligns with remote work needs, local governments and urban planners may need to anticipate increased local and regional mobility. This shift may also prompt real estate developers and policymakers to review zoning regulations, housing supply, and infrastructure planning to better support

workers no longer tied to a central office. On the methodological side, this study shows that combining a shift-share instrument with a recursive bivariate probit model can be an effective way to address endogeneity in studies of remote work and migration. This approach may also be useful in other research areas that examine how geographic factors influence individual decisions, particularly in contexts where endogeneity limits the use of standard causal inference techniques. Taken together, these findings contribute to the literature on labor mobility and remote work by demonstrating how increasing remote work is reshaping relocation decisions. Future research could extend this work by incorporating hybrid work arrangements and panel data to better capture dynamic migration behavior over time.

7 Appendix

Table 5: Summary Statistics (Field of Degree Sample)

	Before Covid		During Covid		After Covid	
	Remote	**Office**	**Remote**	**Office**	**Remote**	**Office**
Average Age	45.45	42.24	42.54	42.36	42.82	42.24
Gender						
Male	47.91	48.22	49.27	47.49	48.28	47.19
Female	52.09	51.78	50.73	52.51	51.72	52.81
Race						
White	84.7	79.03	71.26	72.19	70.66	70.1
Black/African American	4.09	6.49	5.17	6.34	5.36	6.26
Asian	7.94	10.13	13.14	9.85	12.88	10.78
Others	3.27	4.35	10.43	11.62	11.1	12.86
Nationality						
Hispanic	5.84	8.12	7.54	9.41	8.03	10.39
Marital Status						
Married	70.74	62.3	64.48	61.58	65.04	61.18
Work Schedule						
Works from Home	6.07		22.4		19.17	
Migration						
Between States	4.45	3.18	4.1	2.94	4.53	3.08
Within State	8.87	11.37	11.18	10.32	9.67	9.5
Between PUMA	2.66	3.2	3.39	2.98	3.3	3.07
General Definition	13.96	15.13	15.74	13.7	14.72	13.26
Within PUMA	6.21	8.17	7.79	7.34	6.37	6.43
To Birth State	0.88	0.66	0.9	0.66	0.86	0.67
From Birth State	0.94	0.74	0.84	0.67	1.01	0.69
Between Non-Cont States	3.41	2.25	2.94	2.05	3.38	2.17
Between Cont States	1.04	0.93	1.16	0.89	1.15	0.91
Observations	111876	1411768	260756	691088	263873	883663

Note: This table presents summary statistics for remote and office workers across three periods: Before COVID (2017–2019), During COVID (2020–2021), and After COVID (2022–2023), based on the Field of Degree specification used as a robustness check. Values represent percentages unless otherwise indicated. Age is reported as the average in years. "Works from Home" reflects the overall share of remote workers. Migration variables refer to the percentage of individuals experiencing each migration type within the corresponding period. Observations refer to the number of person-year records in each group, and differ from the main specification due to the restriction to college graduates. Sample sizes vary across columns due to differences in the number of observations available in each period.

Table 6: Regression Results for Field of Degree Specification (Part 1)

	Between States		**Within State**		**Between PUMAs**		**Within PUMAs**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATE	-0.039***	-0.014***	0.069***	0.048***	0.0227***	0.015***	0.047***	0.034***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
Rho(ρ)	0.481***	0.208***	-0.180***	-0.128***	-0.130***	-0.084***	-0.161***	-0.124***
	(0.036)	(0.018)	(0.010)	(0.011)	(0.013)	(0.015)	(0.011)	(0.012)
Test for endogeneity of Treatment ($\rho = 0$)								
χ^2 (1)	122.068***	127.261***	293.135***	135.825***	86.651***	31.298***	176.96***	99.050***
Log Likelihood	-2278820.7	-2260719.7	-2994312.8	-2981208.7	-2235072.1	-2219613.7	-2710993.9	-2697040.7
Sample Mean	3.31		10.50		3.13		7.37	
Relative Change	-117.8%	-42.3%	65.7%	45.7%	72.5%	47.9%	63.8%	46.1%

Note: This table reports results from recursive bivariate probit regressions conducted as a robustness check, using an alternative shift-share instrument constructed with Field of Degree instead of Occupation. The dependent variables are migration outcomes. All specifications include individual characteristics, year fixed effects, and field of degree fixed effects. Columns (2), (4), (6), and (8) additionally include state fixed effects. The models are estimated using 4,383,841 observations from the IPUMS USA dataset (2017–2023), restricted to college graduates, resulting in a smaller sample than in the main specification. Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATE values represent percentage point changes. Relative change is calculated as ATE divided by the sample mean of the corresponding migration outcome. All control variables are included in the regression but omitted from the table for brevity.

Table 7: Regression Results for Field of Degree Specification (Part 2)

	To Birth State		**From Birth State**		**Between Non-Cont States**		**Between Cont States**	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ATE	-0.0056***	-0.005***	-0.0037***	-0.001***	-0.013***	-0.014***	-0.052***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Rho(ρ)	0.262***	0.227***	0.191***	0.087***	0.245***	0.249***	0.858***	0.090***
	(0.047)	(0.037)	(0.038)	(0.028)	(0.022)	(0.021)	(0.006)	(0.028)
Test for endogeneity of Treatment ($\rho = 0$)								
χ^2 (1)	28.299***	35.817***	23.414***	9.713***	112.46***	124.630***	2666.06***	10.313***
Log Likelihood	-1840034.3	-1830193.3	-1843422.5	-1830783.7	-2142659.0	-2124842.5	-1887691.3	-1870031.0
Sample Mean	0.70		0.74		2.36		0.95	
Relative Change	-80.0%	-71.4%	-50.0%	-13.5%	-55.1%	-59.3%	-547.4%	-10.5%

Note: This table reports results from recursive bivariate probit regressions conducted as a robustness check, using an alternative shift-share instrument constructed with Field of Degree instead of Occupation. The dependent variables are migration outcomes. All specifications include individual characteristics, year fixed effects, and field of degree fixed effects. Columns (10), (12), (14), and (16) additionally include state fixed effects. The models are estimated using 4,383,841 observations from the IPUMS USA dataset (2017–2023), restricted to college graduates, resulting in a smaller sample than in the main specification. Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATE values represent percentage point changes. Relative change is calculated as ATE divided by the sample mean of the corresponding migration outcome. All control variables are included in the regression but omitted from the table for brevity.

Table 8: Regression Results by Age Group (Part 1)

	Between States		**Within State**		**Between PUMAs**		**Within PUMAs**	
	Age ≤ 40	Age > 40	Age ≤ 40	Age > 40	Age ≤ 40	Age > 40	Age ≤ 40	Age > 40
ATE	-0.014***	0.001	0.052***	0.012***	0.002	0.003***	0.051***	0.009***
	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Rho(ρ)	0.186***	0.064***	-0.101***	-0.055***	0.001	-0.019***	-0.130***	-0.066***
	(0.011)	(0.015)	(0.007)	(0.008)	(0.009)	(0.013)	(0.007)	(0.010)
Test for endogeneity of Treatment ($\rho = 0$)								
χ^2 (1)	294.781***	17.478***	214.992***	41.611***	0.015	2.177***	322.520***	45.749***
Log Likelihood	-2289567.5	-2082904.4	-3830871.1	-2950471.2	-2519494.3	-2158840.4	-3273592.5	-2664534.0
Sample Mean	4.5	1.47	17	6.18	5.77	1.81	11.25	4.37
Relative Change	-31.1%	6.8%	30.6%	19.4%	3.5%	16.6%	45.3%	20.6%

Note: This table reports results from recursive bivariate probit regressions conducted as a robustness check to examine heterogeneity in the effect of remote work by age group. The dependent variables are migration outcomes. Regressions are estimated separately for individuals aged 40 and below, and those above 40. All specifications include individual characteristics, year fixed effects, occupation fixed effects, state fixed effects, and the full set of control variables. Models for the Age ≤ 40 group are estimated using 5,640,903 observations; models for the Age > 40 group use 5,855,058 observations. Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATE values represent percentage point changes. Relative change is calculated as ATE divided by the sample mean of the corresponding migration outcome. All control variables are included in the regressions but omitted from the table for brevity.

Table 9: Regression Results by Age Group (Part 2)

	To Birth State		**From Birth State**		**Between Non-Cont States**		**Between Cont States**	
	Age ≤ 40	Age > 40	Age ≤ 40	Age > 40	Age ≤ 40	Age > 40	Age ≤ 40	Age > 40
ATE	-0.004***	0.00007	-0.004***	0.002***	-0.014***	-0.001	-0.001	0.002**
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rho(ρ)	0.155***	0.046*	0.142***	-0.021	0.231***	0.107***	0.064***	-0.008
	(0.019)	(0.025)	(0.015)	(0.026)	(0.013)	(0.019)	(0.016)	(0.023)
Test for endogeneity of Treatment ($\rho = 0$)								
χ^2 (1)	65.481***	3.429*	88.236***	0.651	326.095***	31.884***	16.492***	0.115
Log Likelihood	-1636609.6	-1784630.3	-1732993.4	-1776099.2	-2043466.0	-1971965.1	-1718496.0	-1813584.4
Sample Mean	1	0.34	1.55	0.32	3	1	1.43	0.45
Relative Change	-40.0%	2.1%	-25.8%	62.5%	-46.7%	-10.0%	-7.0%	44.4%

Note: This table reports results from recursive bivariate probit regressions conducted as a robustness check to examine heterogeneity in the effect of remote work by age group. The dependent variables are migration outcomes. Regressions are estimated separately for individuals aged 40 and below, and those above 40. All specifications include individual characteristics, year fixed effects, occupation fixed effects, state fixed effects, and the full set of control variables. Models for the Age ≤ 40 group are estimated using 5,640,903 observations; models for the Age > 40 group use 5,855,058 observations. Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATE values represent percentage point changes. Relative change is calculated as ATE divided by the sample mean of the corresponding migration outcome. All control variables are included in the regressions but omitted from the table for brevity.

Table 10: Heterogeneous Effects of Remote Work by COVID Period (Part 1)

	Between States	**Within State**	**Between PUMAs**	**Within PUMAs**
	(1)	(2)	(3)	(4)
RW	-.201***	.075***	.031	.080***
	(.023)	(.017)	(.025)	(.019)
RW × During	-.004	.082***	.035***	.089***
	(.008)	(.006)	(.008)	(.007)
RW × After	.030***	.052***	.033***	.050***
	(.007)	(.006)	(.008)	(.006)
During COVID	.029***	-.072***	-.003	-.093***
	(.003)	(.002)	(.002)	(.002)
After COVID	.019***	-.119***	-.006**	-.152***
	(.003)	(.001)	(.002)	(.002)
Rho (ρ)	.185***	-.067***	-.017*	-.078***
	(.011)	(.007)	(.009)	(.008)
Test for endogeneity of Treatment ($\rho = 0$)				
χ^2 (1)	267.802***	82.463***	3.395*	94.010***
Log Likelihood	-4395225.1	-6815122.8	-4698001.5	-5968540.3

Note: This table reports results from recursive bivariate probit (RBP) regressions conducted as a robustness check to assess whether the effect of remote work varies across time and to examine potential pre-COVID effects. Time period dummies (During COVID and After COVID) and their interactions with the remote work (RW) dummy variable are included in each specification; the omitted category is the pre-COVID period and its interaction with RW. Year fixed effects are not included due to the inclusion of these time dummies. All regressions include individual characteristics, occupation fixed effects, state fixed effects, and the full set of control variables. Reported values are coefficient estimates from the outcome equation. Standard errors are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All control variables are included but omitted from the table for brevity.

Table 11: Heterogeneous Effects of Remote Work by COVID Period (Part 2)

	To Birth State	**From Birth State**	**Between Non-Cont States**	**Between Cont States**
	(5)	(6)	(7)	(8)
RW	-.287***	-.039	-.321***	.005
	(.042)	(.035)	(.026)	(.035)
RW × During	.058***	-.063***	.003	-.005
	(.013)	(.012)	(.008)	(.013)
RW × After	.053***	-.010	.040***	.008
	(.013)	(.012)	(.008)	(.012)
During COVID	.035***	.031***	.046***	.003
	(.006)	(.004)	(.004)	(.004)
After COVID	.028***	.019***	.038***	-.010**
	(.005)	(.004)	(.003)	(.004)
Rho (ρ)	.190***	.099***	.256***	.0439***
	(.021)	(.016)	(.013)	(.016)
Test for endogeneity of Treatment ($\rho = 0$)				
χ^2 (1)	78.794***	38.088***	334.9***	7.522***
Log Likelihood	-3437040.5	-3530035.0	-4035722.5	-3549026.6

Note: This table reports RBP regression results from a robustness check examining whether the effect of remote work (RW) varies across COVID periods. Time dummies (During and After COVID) and their interactions with RW are included; the omitted category is the pre-COVID period and its interaction. Year fixed effects are excluded due to these time indicators. All models include individual characteristics, occupation and state fixed effects, and the full set of controls. Models are estimated on 11,495,961 person-level observations from the IPUMS USA dataset (2017–2023). Reported values are coefficient estimates from the outcome equation. Standard errors are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All control variables are included but omitted from the table for brevity.

Table 12: First-Stage Regression Results by COVID Period

	Before COVID		**During COVID**		**After COVID**	
	(1)	(2)	(3)	(4)	(5)	(6)
Shift-Share IV	.0002***	.0001***	.0002***	.0001***	.0002***	.0001***
	(4.36e-06)	(7.05e-06)	(4.50e-06)	(7.11e-06)	(3.46e-06)	(5.82e-06)
Age	.001***	.007***	.001***	.001***	.0016***	.0015***
	(9.26e-05)	(9.81e-05)	(9.28e-05)	(9.34e-05)	(8.82e-05)	(.0001)
Female	.0678***	.0499***	.0671***	.0676***	.0946***	.0948***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Constant	-1.36***	-2.13***	-1.36***	-1.58***	-1.37***	-1.57***
	(.009)	(.014)	(.009)	(.013)	(.008)	(.012)
Observations	5,010,419	5,010,420	3,017,810	3,017,811	3,467,729	3,467,730

Note: This table reports coefficient estimates from first-stage probit regressions, estimated separately for the periods Before COVID (2017–2019), During COVID (2020–2021), and After COVID (2022–2023). The dependent variable is a binary indicator for remote work. Each specification includes individual characteristics, occupation fixed effects, and year fixed effects. Columns (2), (4), and (6) additionally include state fixed effects. The shift-share instrument is constructed using 2012 occupational employment shares interacted with contemporaneous national trends. Standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: First Stage Regression Results for Degree of Field Specification

	Working From Home	
	(1)	(2)
shift share IV	0.0003***	0.00003***
	(5.66e-06)	(8.58e-06)
Age	-.0007***	-.0007***
	(7.53e-05)	(7.58e-05)
Female	0.013***	0.012***
	(0.0012)	(0.0016)
Constant	-1.66***	-1.95***
	(0.011)	(0.0136)

Note: This table reports coefficient estimates from first-stage probit regressions conducted as a robustness check, using an alternative shift-share instrument constructed with Field of Degree instead of Occupation. Column (1) includes year and occupation fixed effects; Column (2) additionally includes state fixed effects. Full control variables are included in both specifications but are omitted for brevity. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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