Fully Remote Work and Interstate Migration: Causal Evidence from the American Community Survey

by

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Abstract

This paper confirms that the results of Bick, Blandin, Mertons and Rubinton (2024), who use proprietary survey data to show a positive causal effect of fully remote work on interstate migration, also hold using the publicly available data from the American Community Survey. Together, the two studies provide formal confirmation of post-pandemic anecdotal evidence in the media showing how workers took advantage of fully remote employment to relocate to different metro areas while keeping their original jobs. More generally, the results show that the WFH revolution has not only altered intracity locational incentives, which now favor greater suburbanzation, but has also made intercity relocation more likely.

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1. Introduction

Following the explosion of work-from-home (WFH) during the pandemic, the media offered many anecdotal stories describing how fully remote workers could escape high housing prices in places like San Francisco by relocating to cheaper locales while working at their well-paid jobs remotely.[1] While some academic papers have confirmed the implied population flows,[2] only more recently has causal evidence emerged suggesting that fully remote work does indeed foster interstate migration. Using proprietary survey data, Bick, Blandin, Mertons and Rubinton (2024) show that, following the pandemic, workers with fully remote employment were more likely to have recently moved to a different state, a finding consistent with the anecdotal media evidence. To produce a causal estimate, the paper relies on individual questions capturing recent liberalization of the WFH policy of the respondent's employer, using the answers as instruments for the endogenous remote-work indicator on the right-hand-side of their regression.

One purpose of present short paper is repeat the exercise of Bick et al. (2024) (hereafter BBMR) using a different, publicly available data source: micro data from the American Community Survey (ACS). Like their survey data, the ACS micro dataset contains a variable indicating that the individual's employment is fully remote, and it also contains a variable indicating an interstate or within-state move in the previous year. While the ACS has no

‡ I thank David Agrawal for helpful comments. The usual disclaimer applies.

1 See, for example, Bindley (2020, 2021), Coy (2021), Dillon (2021), Kamp (2021).

2 For example, using US postal service data, Brueckner, Kahn and Lin (2023) show that relocation early in the pandemic was greater out of such cities (and downward pressure on housing prices also stronger). Ramani and Bloom (2022), again using USPS data, document movement from larger to smaller metro areas, while Li and Su (2026) similarly show intercity relocation toward lower-density cities using different data. Haslag and Weagley (2021) use client survey data from an interstate moving company to document that WFH was the second-most important factor underlying clients' "COVID-related" moves.

counterpart to BBMR's indicator of WFH liberalization by the employer, the present analysis relies on a related instrument for fully remote employment: a variable indicating whether the respondent's job occupation is "teleworkable," with its tasks capable of being done remotely. This variable relies on the work of Dingel and Neiman (2020), who produced a teleworkable indicator for hundreds of different occupations. A regression relying on this instrument and containing a set of control variables replicates BBMR's conclusion: fully remote work makes interstate relocation more likely.

As a prelude to these empirical results, a second contribution of the paper is to use a formal WFH model to show how the ability to work in fully remote fashion work can incentivize interstate migration. This discussion makes use of the stylized framework of Brueckner, Kahn and Lin (2023) (hereafter BKL), and it shows that flight from a city like San Francisco to cheaper locales by fully remote workers is indeed one prediction of a theoretical framework. Taken together, this demonstration along with the paper's empirical exercise extending the results of BBMR helps to highlight the important role of WFH in altering locational incentives in today's economy.

Some previous empirical work on WFH has focused on how it changes *intracity*, as opposed to intercity, locational incentives. Lower commuting costs under hybrid WFH, where workers stay in the same city but go to the office less frequently, create a suburbanization incentive that flattens the intracity house-price gradient, an effect documented by Gupta et al. (2022), BKL, Bloom and Ramani (2022) and Akan et al. (2025). While other empirical work explores WFH's depressing (stimulating) effect on the demand for commercial (home) office-space and its harm to downtown service workers,[3] the WFH literature has also burgeoned in the theoretical direction.[4]

[3] See Gupta, Mittal and Van Nieuwerburgh (2022) for the commercial side; Stanton and Tiwari (2021), Mondragon and Wieland (2022), and Gamber, Graham and Yadav (2023) for housing-demand changes due to home-office effects; and Gokan et al. (2024) for impacts on service workers.

[4] BKL's theoretical focus on fully remote work is shared by Brueckner and Sayantani (2023) and to some extent by the models of Delventhal, Kwon and Parkhomenko (2022), Delventhal and Parkhomenko (2024), Lee (2024), and Gokan et al. (2024), which allow a mixture of hybrid and fully remote work. Other theoretical papers focusing solely on hybrid WFH include Kyriakopoulou and Picard (2023), Behrens, Kickho and Thisse (2024), Davis, Ghent and Gregory (2024), and Brueckner (2025). For surveys of the WFH literature, see Duranton and Handbury (2023) and Van Nieuwerburgh (2024).

The next section of the paper presents a sketch of the BKL model and its implications, and section 3 discusses the data. Section 4 presents the empirical results, and section 5 offers conclusions.

2. BKL model

In the stylized model of Brueckner, Kahn and Lin (2023),[5] the economy has just two cities, which can be viewed as located in different states. The cities have fixed unitary residential land areas and endogenous populations N_c, $c = 1, 2$, where $N_1 + N_2 = \overline{N}$, the fixed total population. The cities' endogenous employment levels are L_c, $c = 1, 2$, which must also sum to the total population: $L_1 + L_2 = \overline{N}$. When fully remote work is possible, a city's population need not equal its employment level, but otherwise $L_c = N_c$ must hold.

Workers are all employed in the same occupation and industry and earn a wage of $w_c(L_c)$ in city c, with $w_c' < 0$. The wage (and hence productivity) is assumed to be the same for resident and remote workers,[6] and for a common L, $w_1(L) \geq w_2(L)$. The strict inequality would reflect higher productivity in city 1, possibly due to a better endowment of an immobile fixed factor. Along with a productivity difference, the cities also differ in amenity levels, which are denoted A_c, with $A_1 \geq A_2$. Intercity relocation is costless, a standard assumption in models with multiple jurisdictions.

The workers' common utility function is quasi-linear and depends on land consumption q, nonland consumption e, and amenities, being given by $U(e, q, A) = A + e + v(q)$, where v is strictly concave. The budget constraint in city c is $e_c = w_c(L_c) - r_c q_c$, with the land price r_c increasing in the city population N_c via a market-clearing condition. With a few extra steps, utility can be written $A_c + w_c(L_c) + H(N_c)$, where H gives net housing utility $(v(q_c) - r_c q_c)$, a decreasing function of N_c given the resulting increase in r_c.[7]

[5] This sketch of BKL's model is similar to one in Agrawal and Brueckner (2026).

[6] The evidence on WFH productivity is mixed, with some studies showing lower productivity at home and some showing no difference. See Bloom et al. (2015), Gibbs Mengel and Siemroth (2023), Harrington and Emanuel (2024), and Bloom, Han and Liang (2024).

[7] Using q_c's first-order condition $v'(q_c) = r_c$ along with the land-market-clearing condition $N_c q_c = 1$, which implies $q_c = 1/N_c$, net housing utility, equal to $v(q_c) - r_c q_c$, can be written as $v(1/N_c) - v'(1/N_c)(1/N_c) \equiv H(N_c)$, with differentiation yielding $H' < 0$.

If fully remote work is infeasible, then a city's employment level must equal its population, with $L_c = N_c$. Then, the equilibrium populations of the two cities are determined by equalization of utilities between them, or

$$A_1 + w_1(N_1) + H(N_1) = A_2 + w_2(N_2) + H(N_2), \tag{1}$$

along with the population constraint $N_1+N_2 = \overline{N}$. The population difference between the cities in equilibrium depends on the intercity productivity and amenity differences. An equilibrium condition like (1) is familiar from Roback (1982) and Rosen (1979).

When fully remote work becomes possible, residential and work locations are decoupled, and a city's population and employment no longer need to be equal. Two equilibrium conditions must then hold. First, since workers can work in either city regardless of their place of residence, they must be indifferent between workplaces in an equilibrium where both cities have jobs. This indifference requires equal wages in the two cities, or

$$w_1(L_1) = w_2(L_2). \tag{2}$$

Satisfaction of this equilibrium condition is achieved by shifts in employment, with workers switching to jobs in the initially high-wage city until wages under WFH are equalized.

In addition, workers must be indifferent to their place of residence, which requires satisfaction of a modified version of (1), with the employment levels L_c replacing populations N_c in the wage functions. Since the wages cancel from this equation given the wage equalization in (2), the residential-indifference condition reduces to

$$A_1 + H(N_1) = A_2 + H(N_2). \tag{3}$$

Satisfaction of this condition is achieved by reallocation of the population between the cities. Along with the adding-up conditions $N_1 + N_2 = \overline{N}$ and $L_1 + L_2 = \overline{N}$, (2) and (3) determine employment levels (and hence wages) and populations (and hence land prices) in the two cities.

The pre-WFH equilibrium and the adjustment to the WFH equilibrium depend on whether the cities differ in productivity or amenities. Derivation of unambiguous conclusions requires a difference in only one of these characteristics, not both.

If the cities have the same amenities while productivity is higher in city 1, $w_1(L) > w_2(L)$ holds for a common L. BKL then show that pre-WFH wages satisfy $w_1(N_1) > w_2(N_2)$ even though N_1 is larger than N_2, with city 1's larger population also yielding $r_1 > r_2$. In response to the wage differential, some city-2 residents shift their employment to city 1 (the high-w city), while continuing to live in city 2, until wages are equalized. In response to the land price differential, some city-1 workers move to city 2 (the low-r city) until land prices are equalized, with the migrants now working remotely at their original city-1 jobs.[8] *Thus, interstate migration under WFH in the differential-productivity case has fully remote workers relocating from the high-productivity city to the low-productivity city.*

The direction of interstate migration in this case is the one envisioned in the media reports cited in the introduction, which focus on people leaving high-productivity places like San Francisco for lower-productivity (and cheaper) cities elsewhere in the country. The prediction of negative effects on housing (land) prices is supported by BKL's empirical work, which shows downward pressure under WFH on prices in high-productivity counties.[9]

If amenities differ and productivities are the same in the two cities, then $A_1 > A_2$ holds and the c subscript disappears from the wage function. In this case, BKL show that the pre-WFH wage is lower in the high-amenity city, with $w_1 = w(N_1) < w_2 = w(N_2)$, a consequence of $N_1 > N_2$, which also yields $r_1 > r_2$ (the usual Rosen-Roback wage-price pattern with differential amenities). In response to the wage differential, employment shifts to city 2 (the high-w city), with some city-1 residents shifting their jobs to city 2 until wages are equalized. With its previous wage disadvantage disappearing, city 1's higher amenity makes it more residentially attractive. Some original city-2 residents then move in, keeping their city-2 jobs and thus

[8] Note that city-1 workers who do not move are now fully remote even though they work and live and city 1.

[9] BKL also present evidence based on postal-service data showing that relocation out of high-productivity cities was higher than out of low-productivity cities, indirectly supporting the interstate-migration prediction. Agrawal and Brueckner (2026) test the wage-equalization prediction of the theory by showing that inter-MSA wage dispersion narrowed in teleworkable occupations relative to dispersion in non-teleworkable occupations after the pandemic.

working alongside the original city-1 residents now employed in city 2.[10] *Thus, interstate migration under WFH in the differential-amenity case has fully remote workers relocating from the low-amenity city to the high-amenity city.* This change would correspond to migration *into* a high-amenity city like San Francisco in a situation where productivity in that city is the same as anywhere else. Thus, depending on the nature of city 1's advantage (productivity vs. amenities), WFH can generate migration in opposite directions, away from (toward) city 1 when the advantage is productivity (amenities).

This theoretical motivation shows that, starting in a pre-WFH world, the emergence of fully remote work leads to migration between cities. The remainder of the paper tests this prediction by asking whether an individual's fully remote employment in the post-pandemic years of 2022-2023 indeed increased the likelihood of migration, either interstate or within a state.

3. Data

The data for the empirical analysis consists of ACS microdata for the post-pandemic years 2022-2023. The ACS microdata are not a panel data set, with the yearly observations consisting of different individuals. Following BBMR, observations where the respondent's age is outside the 18-64 year range are dropped, as are self-employed individuals, those working less than 20 hours per week, and those living in group quarters (which may include members of the military). The ACS variable that captures fully remote work is called "tranwork," and the response indicates which of a variety of different transportation modes the individual used to commute to work in the previous week. One of the possible responses is "worked at home," indicating that the individual did not visit the worksite in the previous week. Although this response may indicate a temporary disruption of normal commuting, it is also likely to indicate that the individual's employment is fully remote. Buckman et al. (2025) provide evidence supporting this interpretation by comparing the ACS data to data from their Survey of Working Arrangements and Attitudes (SWAA), which asks the precise location of work for each day in the past week, showing a close match between the SWAA and the tranwork

[10] The population increase in city 1 raises its land price, widening the previous price gap between the cities. With wages now equalized, this wider gap is needed to offset city 1's amenity advantage.

response from the ACS. This response is thus used to create a binary variable *fully_remote* that proxies fully remote employment.

The other crucial ACS variable is "migrate," which indicates whether, in the previous year, the individual moved between states, moved within a state, or was residing abroad. Observations with the last response are dropped, and two binary dependent variables are created using the remaining data: *moved_inter* and *moved*, indicating an interstate move and either an interstate or within-state move, respectively. Note that when *move_inter* takes a value of 1, the cases of no move and a within-state move receive a zero value, thus being treated as indistinguishable. A dependent variable *moved_within*, indicating a within-state move, is also created, and when it is used as a dependent variable, observations with interstate moves are dropped, so that the outcomes are no move versus a within-state move. This regression is less informative that the other two, but it is included for completeness.

Note that within-state moves are of interest, justifying being combined with interstate moves when *moved* is used as dependent variable, because they may involve migration to a different metro area in the state, thus being similar in reach to an interstate move. Such moves, of course, may involve much shorter distances, perhaps occurring with the same metro area.

The control variables for the regression are *age*, the respondent's age in years; *male*, a gender indicator; *married*, an indicator of married status with the spouse present; *white*, a race indicator; *hs_less*, a variable indicating as high-school education or less; and *yr_2023*, an indicator for the second of the two sample years. The data set contains 2,032,426 observations.[11]

As in BBMR, the basic regression using *moved_inter* as dependent variable takes the following form:

$$moved\_inter_{it} \;=\; \alpha \;+\; \beta\, fully\_remote_{it} \;+\; X_{it}\delta \;+\; \epsilon_{it}, \qquad (4)$$

[11] Different sampled workers in the ACS data may belong to the same household. While all workers in a multiple-worker household that moves between states may be fully remote, thus retaining their pre-move jobs, some workers may need to find new jobs after relocating. These workers are thus seen to be migrating without fully remote status, even though another household member may be fully remote. This possibility suggests the need for clustering of the coefficient standard errors by household, but Stata automatically takes this step when the `svyset` command is invoked using the proper parameters.

where i is the respondent within a given year, t is the year, X_{it} is the vector of control variables, and ϵ_{it} is the error term. Initially, this equation is estimated by OLS as a linear probability model.

Before discussing instrumental-variable estimation and a separate bivariate-probit approach to estimation, it is useful to review patterns in the ACS data that are highlighted by BBMR. They thoroughly explore what the ACS data reveal about interstate migration and fully remote work prior to turning to their proprietary survey data to generate causal estimates. First, BBMR show that, after falling between 2005 and 2010, the interstate migration rate among ACS respondents rose gradually up to 2019 and then notably jumped starting in 2020, almost returning to its 2005 level by 2022. Next, they show that, over the years since 2015, interstate migration by fully remote workers (indicated by the current *moved_inter* measure) was higher than for workers who commuted, with the divergence widening after 2020. Finally, they show the increase in fully remote work after 2020 accounted for most of the increase in interstate migration after that year. Agrawal and Chen (2026) provide similar results using the ACS data, and they also show that, while all interstate movers saw a reduction in their average state income tax rate after moving, fully remote workers saw a larger reduction than commuters, suggesting that their footloose status allowed tax incentives to play a bigger role in relocation choices (Akan et al. 2005 report similar results).[12]

While these patterns strongly suggest a causal relationship between fully remote work and interstate migration, BBMR turn to their survey data, where the respondents also indicate fully remote status as well as interstate relocation, for causal estimates. As explained earlier, they use survey responses indicating relaxation of the WFH policy of the respondent's employer (as well as whether this relaxation applied to them personally) as instruments for fully remote status. With such responses not available in the ACS data, an alternative approach is to use ACS information on the occupation of the respondent along with Dingel and Neiman's (2021) pre-pandemic categorization of occupations into teleworkable and non-teleworkable groups. This approach leads to a variable *teleworkable* that indicates whether the ACS respondent's

[12] See Agrawal and Brueckner (2025) for an analysis of how state income taxation affects the economy's adjustments to WFH.

occupation, of which the sample contains 458, can be carried out remotely.[13] This variable is used as an instrument for the *fully_remote* variable in the regression dataset.

Note that possible reverse causality points to the need for an IV approach. In particular, while fully remote employment may ease interstate migration (which is the underlying hypothesis), a desire to move to another state may lead an individual to adopt fully remote work, yielding a causal effect in the other direction. As a result, the estimated coefficient from an OLS linear probability model is likely to be biased, not yielding a causal estimate of the effect of fully remote employment on interstate migration. Bias may also be caused by possible omission of migration determinants correlated with *fully_remote*. The variable *teleworkable* is a suitable instrument for remedying these potential biases because it is strongly correlated with *fully_remote* while appearing to have no influence on migration aside from the influence operating through *fully_remote*.

The resulting correlation between the *fully_remote* variable on the RHS of the regression and error term can be tackled more directly by estimating a bivariate probit model, which is also appropriate given the binary nature of the key variables. Following Maddala (1983, pp. 122-124) and suppressing the previous i and t subscripts for simplicity, this model for the present context can be written using the latent versions of *moved_inter* and *fully_remote*, denoted $moved\_inter^*$ and $fully\_remote^*$, as follows:

$$moved\_inter^* = \alpha + \beta fully\_remote + X\delta + \epsilon; \quad moved\_inter = 1 \text{ if } moved\_inter^* > 0 \quad (5)$$

$$fully\_remote^* = \theta + X\delta + \gamma\, teleworkable + \phi; \quad fully\_remote = 1 \text{ if } fully\_remote^* > 0. (6)$$

In (5)-(6), (ϵ, ϕ) are bivariate normal error terms with mean zero, unit variance and covariance

[13] Creation of the instrument starts with the use of the Dingel-Neiman-based teleworkable variable from Agrawal and Brueckner (2026), which relies on occupation codes from the Bureau of Labor Statistics. Since these codes do exactly align with those used by Dingel and Neiman (2001), a few BLS codes embrace several different Dingel-Neiman occupations, which sometimes have different values of the 0-1 teleworkable indicator. Agrawal and Brueckner treated the BLS occupation as teleworkable if *any* of the corresponding Dingel-Neiman occupations are denoted as teleworkable. A further issue is that the ACS uses different occupational codes than the BLS. Fortunately, a crosswalk between the codes is available at `https://www.bls.gov/emp/documentation/crosswalks.htm`, which is contained in the spreadsheet `nem-occcode-acs-crosswalk.xlsx`. The crosswalk is not perfect, however, since several ACS occupational codes correspond to multiple BLS codes. In such cases, the ACS occupation was assigned the average of 0-1 teleworkable values for the corresponding BLS occupations. The resulting *teleworkable* variable is thus not strictly binary, instead taking a fractional value for 29 out of the 458 ACS occupations.

ρ, with (6) containing the *teleworkable* instrument. The model is estimated using Stata's seemingly unrelated bivariate probit routine.

Eqs. (5)-(6) have a recursive structure, with (6) determining *fully_remote* and (5) then determining *moved_inter*. To understand this recursive structure, note that (6) can be viewed as analogous to one of the reduced-form equations from a standard simultaneous system determining *moved_inter* and *fully_remote*, which captures two-way causation between these variables. That system would consist of one structural equation giving *moved_inter* as a function of *fully_remote*, X, and an error term ϵ (as in (4)) and a second structural equation giving *fully_remote* as a function of *moved_inter*, X, *teleworkable*, and an error term ϕ. The second-reduced form equation from this system would give *fully_remote* as a function of X, *teleworkable*, and an error term ν that depends on both ϵ and ϕ, and (6) can be viewed as the latent-variable version of that reduced-form equation.

Moreover, it can be shown that the sign of the correlation between the reduced-form error term ν and the error term ϵ in (4) is ambiguous in general. As a result, the correlation between *fully_remote* and ϵ in (4) can take either sign, implying that the OLS bias in the estimation of β, the *fully_remote* coefficient, can be in either direction. Turning to the latent-variable setup, this discussion would suggest that the sign of the correlation ρ between the error terms ϵ and ϕ in (5)-(6) is also ambiguous (ϕ is analogous to ν). Estimation of the bivariate probit mobile will reveal this sign, which will in turn help to explain the direction of coefficient bias when (5) is instead estimated by OLS using the linear-probability model in (4).

The summary statistics for the regression dataset are shown in Table 1. Among the individuals in the sample, 2.6% moved between states and 9.7% moved within a state, with 12.2% thus exhibiting either type of move. Work is fully remote for 12.9% of the sample workers, a value that aligns with survey evidence (including the SWAA) cited by Agrawal and Brueckner (2026). Average age in the sample is almost 42 years, 52% of the sample individuals are male, 53% are married, 67% are white, 34% have a high-school education or less, and 50% of the observations (which cover 2022-2023) are from 2023. The mean value of *teleworkable* is 0.39. But recalling from footnote 13 that this variable takes a fractional value for a handful of observations, the share with positive values (indicating some degree of teleworkability in the

ACS occupation code) is smaller at 34%.

4. Empirical findings

4.1. Linear probability model

Recall that the regression in (4) is estimated using a linear probability model. Table 2 presents the OLS and 2SLS versions these results, with *moved_inter* being the dependent variable in columns 1 and 2, *moved_within* the dependent variable in columns 3 and 4, and *moved* (indicating either interstate or within-state move) the dependent variable in columns 5 and 6. All the columns of Table 2 show significantly positive coefficients for *fully_remote*, indicating that fully remote employment is associated with a greater likelihood of moving between or within states. Focusing on the interstate-move regressions in columns 1-2, the 2SLS *fully_remote* coefficient, which has a causal interpretation, is much larger than the OLS coefficient. This pattern suggests negative correlation between *fully_remote* and the error term in the OLS regression, which leads to a downward-biased estimate (a possible outcome given the previous discussion). The same pattern exists in columns 5-6, which combine interstate and within-state moves via the *move* dependent variable.

Columns 3 and 4 show the results when interstate-move observations are dropped from the sample and the variable *move_within* is used as dependent variable. Interestingly, the *fully_remote* coefficients are smaller than those in columns 1-2 and 5-6, with the 2SLS coefficient again being the larger of the two. A possible explanation is that, since some within-state moves may occur inside the same metro area, fully remote employment is not a necessary condition for such moves, diluting the influence of this variable.

The coefficients of the control variables are mostly as expected. Older individuals are less likely to move, as are those who are married and have a high-school education or less. White males are more likely to move, while moves are less likely in 2023 than in the default year of 2022, possibly indicating that those WFH-related moves that occurred did so closer to the pandemic.

Table A.1 in the appendix shows the results from the first-stage regression of 2SLS using the larger sample from columns 1-2 and 4-6 of Table 2. The coefficient of *teleworkable* is positive as expected, and its enormous t-statistic (over 200) indicates that the instrument is not weak. The results also show that fully remote work is more likely for older, married, white individuals and in the year 2023, and less likely for males with low education.

The results from the 2SLS linear probability model thus show a positive causal effect of fully remote work on the likelihood of interstate migration, matching the results of BBMR. They also show a positive causal effect on the broader migration measure (*move*) that captures both interstate and within-state migration.

4.2. Bivariate probit model

The results from the bivariable probit model from equations (5) and (6) are shown in Table 3. Columns 1-2 show results using the *moved_inter* migration variable, with column 1 showing the estimated coefficients from (5) and column 2 showing the coefficients from (6), the equation determining *fully_remote*. Columns 3-4 show the analogous results using *moved* as the migration variable. As can be seen, sign pattern of the coefficients in columns 1 and 3 matches that of the linear-probability 2SLS results in columns 2 and 6 of Table 2. In addition, the sign pattern of the coefficients in columns 2 and 4 matches that of the first-stage linear probability coefficents in Table A.1.

While the qualitative results are thus the same as under the linear probability model, a quantitative comparison comes from the reported marginal effects of *fully_remote* on the migration variables, as shown at the bottom of columns 1 and 3. The values give the marginal effect on the migration variable of changing *fully_remote* from 0 to 1, with first number showing the effect evaluated at the sample-mean values of the control variables and the second number using the marginal effects for each observation, with the sample average then computed. In each column, the two different marginal effects are close to one another in magnitude, with the values in column 1 showing that fully remote work raises the probability of interstate migration by about 5 percentage points. Since interstate movers constitute only about 2.5% of the sample from Table 1, this marginal effect, though modest in size, is double the average incidence of interstate moves. Also, the magnitude of the marginal effects in columns 1 and 3 are also similar to the corresponding 2SLS *fully_remote* coefficients in columns 2 and 6 of Table 2. Therefore, the quantitative migration effects of fully remote work are closely matched under the linear-probability and bivariate probit approaches, adding credence to the existence of a positive causal impact.

Providing further insight into the results of Table 2, the ρ covariance estimate shown in columns 1 and 3 of Table 3 is negative, a possibility discussed above. By indicating that the error term ϕ in the *fully_remote* equation (6) is negatively correlated with the error term ϵ in the migration equation (5), this finding helps to explain the downward bias seen in the OLS linear-probability estimate of the *fully_remote* coefficient in Table 2, as discussed above.

5. Conclusion

This paper has confirmed that the results of Bick, Blandin, Mertons and Rubinton (2024), who use proprietary survey data to show a positive causal effect of fully remote work on interstate migration, also hold using the publicly available data from the American Community Survey. The paper relies on a different but related identification strategy, using the teleworkable status of the ACS respondent's occupation as an instrument for fully remote work, in contrast to their use of survey responses indicating liberalization of the employer's work-from-home policy. Together, the two studies provide formal confirmation of post-pandemic anecdotal evidence in the media showing how workers took advantage of fully remote employment to relocate to different metro areas while keeping their original jobs. More generally, the results show that the WFH revolution has not only altered intracity locational incentives, which now favor greater suburbanzation, but has also made intercity relocation more likely.

Table 1: Summary statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
moved_inter	.0258128	.1585765	0	1
moved_within	.096678	.2955189	0	1
moved	.1224908	.3278519	0	1
fully_remote	.129311	.335544	0	1
age	41.58164	12.814	18	64
male	.5189945	.4996392	0	1
married	.5330091	.4989093	0	1
white	.6705016	.4700312	0	1
hs_less	.3370616	.4727062	0	1
yr_2023	.5023789	.4999945	0	1
teleworkable	.3905407	.465098	0	1

Observations = 2,032,426

Table 2: Regressions using linear probability model

VARIABLES	(1) moved_inter OLS	(2) moved_inter 2SLS	(3) moved_within OLS	(4) moved_within 2SLS	(5) moved OLS	(6) moved 2SLS
fully_remote	0.0188**	0.0494**	0.00923**	0.0283**	0.0274**	0.0777**
	(0.000403)	(0.00223)	(0.000918)	(0.00632)	(0.000705)	(0.00446)
age	-0.000903**	-0.000915**	-0.00419**	-0.00420**	-0.00453**	-0.00455**
	(9.37e-06)	(9.45e-06)	(2.65e-05)	(2.67e-05)	(1.93e-05)	(1.94e-05)
male	0.00185**	0.00286**	-0.00167**	-0.00101	0.000491	0.00215**
	(0.000217)	(0.000235)	(0.000624)	(0.000667)	(0.000448)	(0.000477)
married	-0.00746**	-0.00820**	-0.0432**	-0.0436**	-0.0468**	-0.0480**
	(0.000233)	(0.000241)	(0.000647)	(0.000664)	(0.000484)	(0.000497)
white	0.00424**	0.00398**	0.00824**	0.00801**	0.00850**	0.00807**
	(0.000228)	(0.000230)	(0.000664)	(0.000670)	(0.000484)	(0.000487)
hs_less	-0.0102**	-0.00739**	-0.0113**	-0.00963**	-0.0191**	-0.0145**
	(0.000215)	(0.000288)	(0.000672)	(0.000860)	(0.000473)	(0.000620)
yr_2023	-0.00184**	-0.00141**	-0.00391**	-0.00367**	-0.00801**	-0.00730**
	(0.000214)	(0.000217)	(0.000616)	(0.000621)	(0.000443)	(0.000447)
Constant	0.0640**	0.0594**	0.303**	0.300**	0.334**	0.327**
	(0.000487)	(0.000577)	(0.00138)	(0.00163)	(0.000995)	(0.00119)
Observations	2,032,426	2,032,426	1,983,398	1,983,398	2,032,426	2,032,426
R^2	0.010	0.006	0.040	0.040	0.046	0.043

Instrument for *fully_remote* in 2SLS estimation is *teleworkable*.
Standard errors clustered by household in parentheses
** p<0.01, * p<0.05

Table 3: Bivariate probit estimates

VARIABLES	(1) moved_inter	(2) fully_remote	(3) moved	(4) fully_remote
fully_remote	0.612**	–	0.323**	–
	(0.0297)		(0.0245)	
age	-0.0173**	0.00111**	-0.0243**	0.00108**
	(0.000186)	(9.67e-05)	(0.000108)	(9.74e-05)
male	0.0457**	-0.101**	0.0102**	-0.100**
	(0.00401)	(0.00237)	(0.00251)	(0.00238)
married	-0.131**	0.0862**	-0.241**	0.0861**
	(0.00442)	(0.00251)	(0.00267)	(0.00251)
white	0.0690**	0.0144**	0.0303**	0.0143**
	(0.00427)	(0.00252)	(0.00256)	(0.00252)
hs_less	-0.184**	-0.383**	-0.0977**	-0.383**
	(0.00504)	(0.00286)	(0.00332)	(0.00286)
yr_2023	-0.0279**	-0.0699**	-0.0410**	-0.0702**
	(0.00391)	(0.00231)	(0.00239)	(0.00232)
teleworkable	–	0.531**	–	0.531**
		(0.00254)		(0.00254)
Constant	-1.320**	-1.303**	-0.127**	-1.301**
	(0.00834)	(0.00478)	(0.00578)	(0.00480)
ρ	-0.173**		-0.095**	
	(0.00152)		(0.00132)	
marginal effect of fully_remote:				
-at sample mns.	0.0487		0.0674	
-average effect	0.0521		0.0683	
Observations	2,032,426	2,032,426	2,032,426	2,032,426

Standard errors clustered by household in parentheses

** p<0.01, * p<0.05

Appendix

Table A1: First-stage regression

VARIABLES	(1) fully_remote
age	0.000141**
	(1.82e-05)
male	-0.0167**
	(0.000479)
married	0.0171**
	(0.000498)
white	0.00284**
	(0.000483)
hs_less	-0.0630**
	(0.000446)
yr_2023	-0.0141**
	(0.000460)
teleworkable	0.115**
	(0.000566)
Constant	0.104**
	(0.000896)
Observations	2,032,426
R^2	0.047

This is the first-stage regression for the 2SLS regressions in columns 2 and 6 of Table 2.

Standard errors clustered by household in parentheses

** p<0.01, * p<0.05

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