Work from Home and Interstate Migration*

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Abstract

Interstate migration by working-age adults in the US declined substantially during the Great Recession and remained subdued through 2019. We document that interstate migration rose sharply following the 2020 Covid-19 outbreak, nearly recovering to pre-Great recession levels, and provide evidence that this reversal was primarily driven by the rise in work from home (WFH). Before the pandemic, interstate migration by WFH workers was consistently 50% higher than for commuters. Since the Covid-19 outbreak, this migration gap persisted while the WFH share tripled. Using quasi-panel data and plausibly exogenous changes in employer WFH policies, we address concerns about omitted variables or reverse causality and conclude that access to WFH induces greater interstate migration. An aggregate accounting exercise suggests that over half of the rise in interstate migration since 2019 can be accounted for by the rise in the WFH share. Moreover, both actual WFH and pre-pandemic WFH potential, based on occupation shares, can account for a sizable share of cross-state variation in migration.

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1 Introduction

Interstate migration in the US sharply fell during the Great Recession and remained subdued for a decade. In the American Community Survey (ACS), annual interstate migration among working age adults (ages 18-64) fell from 2.75% in 2005 to 2.23% in 2010, a 20% decline. Migration rose somewhat in the proceeding years, but by 2019 the migration rate was still only 2.40% per year. Because migration is an important mechanism of adjustment to local economic shocks—see, e.g., Blanchard and Katz (1992)—subdued interstate moving rates may reflect a less-dynamic economy, potentially delaying economic recoveries and slowing economic growth.

This paper documents that interstate migration rose sharply in the years after the 2020 Covid-19 outbreak. Annual interstate migration rose from 2.40% in 2019 to 2.66% in 2022, only slightly below its 2005 value (see Figure 1). Because the Covid-19 pandemic disrupted many aspects of life, it is not obvious a priori what drove the increase in interstate migration. One possibility is that unusually high rates of employer changes led to a surge in moves by workers to be near new employers (Bagga et al., 2023; Bick and Blandin, 2023). Another possibility is that rising concerns over health or crime induced many individuals to relocate. Identifying the sources of increasing interstate migration is crucial for determining whether it will persist and its broader economic implications.

While many factors likely played some role, we argue that the surge in interstate migration since 2020 was primarily driven by one particular consequence of the pandemic: the rise in work from home (WFH). We begin by documenting a set of aggregate patterns in the American Community Survey (ACS) that suggest a quantitatively important role for WFH. In the five years prior to the pandemic, from 2015-2019, the interstate migration rate was consistently about 50% higher among full-time WFH workers compared with commuters, even after controlling for a host of observable characteristics. Following the Covid-19 outbreak, the share of full-time WFH workers roughly tripled from 5% to above 15% and the WFH-commuter gap in interstate migration grew even wider. A reduced form accounting exercise based on these statistics implies that the rise in WFH can account for at least half of the rise in national interstate migration in 2022 relative to 2019. Moreover, across states, both actual WFH rates and pre-pandemic WFH capacity based on state occupation shares are predictive of cross-state variation in out-migration and net-migration.

We provide several pieces of micro evidence from quasi-panel data consistent with the notion that access to WFH increases interstate migration. Our data comes from the Real-Time Population Survey (RPS), an online nationwide survey designed to track commuting behavior.

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1The rise in interstate migration since 2020 is also apparent in IRS data. This increase was not driven by foreign-born individuals or by local moves that crossed state borders. See Section 3 for additional details and discussion.
and labor market developments before and after the Covid-19 outbreak (Bick and Blandin, 2023; Bick et al., 2023). First, while ACS data show high migration rates among workers who currently WFH, it cannot say whether this reflects rising migration rates among pre-pandemic WFH workers or high migration rates among workers who switched to WFH since the Covid-19 outbreak. Using RPS data, we show that pre-pandemic commuters who switched to WFH had much higher interstate migration rates than commuters who did not switch to WFH.

Next, we address a potential concern that the pandemic increased the desire to move across states and a large share of these moves involve WFH, but WFH itself was not necessary for those moves to happen. For example, a worker who is determined to move may request permission to WFH and remain with their employer if they receive permission, and these requests may have become more frequent since 2020. The key difference in this interpretation is that these individuals would still have moved if they could not WFH. To address this concern, we instrument for transitions to WFH using novel questions in the RPS about changes in employers’ WFH policies since the Covid-19 outbreak. Specifically, we use information on whether workers who commuted prior to the pandemic did so due to job characteristics, personal preferences, or employer requirements, and whether employer WFH policies had changed since 2020. We find that plausibly exogenous changes in employer WFH policies predict higher rates of WFH and higher rates of interstate migration. Finally, consistent with the interpretation that WFH reduces the benefit of living near a workplace, we find that (i) among workers who remain with their pre-pandemic employer, WFH workers are more likely to move states, and (ii) among workers who move states WFH workers are less likely to change employers.

Our findings connect to several papers studying declining migration since the 1980s (see reviews by Molloy et al. (2011) and Jia et al. (2023)). Molloy et al. (2017) argue that declining interstate migration is related to declining rates of job changes. Relatedly, Kaplan and Schulhofer-Wohl (2017) argue that declining interstate migration can be partially explained by declining geographic specificity of occupations. To the extent that WFH reduces the benefit of living near a workplace, WFH can be viewed as an extreme decrease in the geographic specificity of occupations. Hence, WFH should reduce job-related migration. Because we find empirically that WFH increases interstate migration, we infer that WFH must increase non-job-related migration and that this positive effect dominates the reduction in job-related migration. This is consistent with our finding in Section 5 that WFH workers are more likely to move states conditional on remaining with their employer.

We also contribute to a rapidly expanding literature on the geographic and economic implications of WFH. Delventhal et al. (2022), Monte et al. (2023), Davis et al. (2024), and Richard (2024) construct models that predict an expansion in WFH will induce some workers to relocate from city centers with high rent to more distant suburbs with lower rent or better amenities.
Brueckner et al. (2023) and Delventhal and Parkhomenko (2023) analyze models in which some full-time WFH workers move larger distances, such as across metro areas or states. Several existing papers provide indirect empirical evidence that is consistent with these predictions. Liu and Su (2021), Ramani and Bloom (2021), and Althoff et al. (2022) provide evidence that housing demand shifted away from city-center locations with high population density toward lower-density areas on the outskirts of cities. Relatedly, Mondragon and Wieland (2022) argue that the rise in remote work and the resulting demand for more space accounts for about half of the increase in home prices between 2019 and 2021. These papers show that changes in housing demand were correlated with an area’s WFH potential, proxied by the area’s occupation mix. However, none of these papers present evidence on WFH and migration at the individual level, and it is not clear the extent to which these patterns are driven by greater exposure to WFH versus other post-pandemic developments like concerns over health or crime. To our knowledge, our paper is the first to provide empirical evidence that (i) individuals who WFH move states at higher rates than commuters, (ii) commuters who switch to WFH have higher interstate migration rates, (iii) changes in employer WFH policies predict higher migration, and (iv) interstate moves by WFH workers are less likely to be accompanied by employer changes. Consistent with our findings, Haslag and Weagley (2021) provide moving company data from 2020-2021, showing that many individuals cite remote work as a motive for their interstate move.

To the extent that higher rates of WFH persist, our results suggest several important implications. Agrawal and Brueckner (2022) argue that highly mobile WFH workers can have important effects on state taxation and spending. Zabek (2024) emphasizes the importance of local ties for geographic sorting; by weakening the geographic link between a worker and their workplace, a rise in WFH may lead these forces to become even more central. Recent research has emphasized that local constraints on the supply of housing, particularly in highly productive cities, limit the number of workers who have access to the productive technology and agglomeration effects contained within these cities (Ganong and Shoag, 2017; Herkenhoff et al., 2018; Hsieh and Moretti, 2019). These studies suggest that local constraints lower aggregate output and raise income inequality between cities and states. From this perspective, WFH could impact both aggregate output and inequality if it allows a subset of workers to more easily access high-wage jobs from a long distance.

The remainder of the paper proceeds as follows. Section 2 describes our data sources and how we measure migration and WFH. Section 3 documents the aggregate trends in interstate migration and WFH. Section 4 provides plausibly exogenous variation in WFH induced by employer policies. Section 5 shows that migration and employer changes are less closely related for WFH workers than commuters. Section 6 documents cross-state variation in WFH and migration. Section 7 concludes.
2 Data Sources and Measurement

2.1 The American Community Survey

Our primary data source is the American Community Survey (ACS), an annual survey of one percent of US households. Several features of the ACS are well-suited to our analysis.

First, the ACS has information on migration. Because the ACS is mailed to a specific address, the Census Bureau knows the current residence of all household members. Then, the ACS asks of each household member: “Where did this person live 1 year ago?” and then asks to provide the relevant address. Data users observe the state and public-use-microdata area (PUMA) for current and previous-year residences for each individual.

Second, the ACS has information on WFH. For each employed individual, the ACS asks “How did this person usually get to work LAST WEEK?” along with a list of transportation options, one of which is “Worked from home.” The phrasing suggests that the ACS measure of WFH will capture workers who are primarily or fully remote. For example, a person who worked from home on one of five workdays in the previous week would not be captured, but a person who worked entirely from home would be.2

A third useful feature of the ACS is its large sample size. A one percent sample of US households yields a sample size of over two million adults each year. This is particularly helpful when studying interstate migration, which only a few percent of individuals do in a given year. A final useful feature of the ACS is that it has comparable data going back to 2005.3 This allows us to assess potential time trends in pre-pandemic migration.

We highlight one important point of caution when interpreting the ACS data. The Census Bureau reported that the 2020 ACS data collection data collection operations were significantly impacted during the Covid-19 pandemic and may have resulted in substantial non-response bias. The ACS released a set of “experimental weights” that attempt to correct for this bias. For transparency, all our time series display the 2020 ACS estimates using these experimental weights. However, when analyzing changes in migration, we largely ignore the 2020 estimates and focus our analysis on the years before and after 2020.

2The preceding question in the ACS asks “At what location did this person work LAST WEEK? If this person worked at more than one location, print where he or she worked most last week.” These directions also indicate that respondents should not be categorized as WFH unless they are primarily or fully WFH.

3Pilot data from the ACS is available going back to 2001, but Kaplan and Schulhofer-Wohl (2017) argue that occasional changes to the survey procedure before 2005 may have affected migration rates.
2.2 The Real-Time Population Survey

While the ACS contains a wealth of valuable information, an important limitation is that it is not a panel dataset. In particular, the ACS does not observe changes in a given person’s WFH behavior over time. This means we cannot directly observe whether individuals who switched to WFH since the Covid-19 pandemic had unusually high rates of migration.

To help fill in this gap, we also use the Real-Time Population Survey (RPS), an online nationwide survey of working-age adults designed to track commuting behavior and labor market developments before and after the Covid-19 outbreak (Bick and Blandin, 2023; Bick et al., 2023). The RPS is fielded online using Qualtrics, a large commercial survey provider. Qualtrics panel respondents are not recruited by traditional probability-based sampling methods such as in the CPS panel. Instead, panel members are recruited to the panel online and, in our case, can participate in exchange for 30 to 50 percent of the $7 paid per completed survey.\(^4\) The Qualtrics panel includes about 15 million members and is not a random sample of the US population, even if one would condition on the 94 percent of individuals aged 18-64 living in households with internet access according to the 2019 American Community Survey. However, researchers can direct Qualtrics to target survey invitations to desired demographic groups. In the case of the RPS, the sample was targeted to be nationally representative of the US along several broad demographic characteristics: gender, age, race and ethnicity, education, marital status, number of children in the household, Census region, and household income in 2019.

We use data from five waves of the RPS spanning February 2022 through October 2023 that contain comparable questions on migration.\(^5\) These five survey waves contain an average sample size of 3,498 respondents each. Similar to the ACS, the RPS also asks respondents to answer the same questions on behalf of spouses or any unmarried partners in the same household. This additional information expands the average number of observations to 5,717 individuals per survey wave for a total sample size of 28,586.

Even with our sampling targets, there remain some potential concerns about the representativeness of the sample for the population of US adults aged 18 to 64. First, the targets are not met exactly; second, live-in spouses and partners are not incorporated into the sampling targets; third, budget constraints limit our sample size, preventing even greater granularity in the sampling targets. To alleviate these concerns, we construct sample weights using the iterative proportional fitting (raking) algorithm of Stephan et al. (1940) so that our weight sample matches a richer array of sample targets; see Appendix A.1 for additional details. In previ-
ous work, Bick and Blandin (2023) document that the RPS closely aligns with other national data sources for a range of important labor market variables, including the share of workers paid hourly, weekly hours worked, the usual weekly earnings distribution, sectoral and industry composition, and job tenure.

Each RPS survey from 2022 and 2023 asked respondents “When did you move into this home?” Respondents were prompted to provide the year and month of their move-in date. We use this information to assess whether the respondent has moved since the pandemic. For individuals who have moved, we ask their state and zip code of residence in February 2020.

Our main information on commuting behavior comes from the following survey questions regarding the individual’s main job:

1. Last week, how many days did you [your spouse/partner] work for this job?
2. Last week, how many days did you [your spouse/partner] commute to this job?

For the first question, respondents are presented with a slider that provides a choice of integers from 1 to 7, since this question is only asked of individuals who worked in the previous week; for the second question, the integers span 0 to 7. To align with the measure of WFH in the ACS, we classify an individual as working from home if they were fully remote; i.e., they worked at least one day in the previous week but did not commute on any day. We also ask respondents to think back to February of 2020, and present them with the same questions for the main job in that month. Crucially, this allows us to identify workers who commuted pre-Covid and switched to WFH post-Covid. Bick et al. (2023) document a similar evolution of commuting trips during the Covid-19 pandemic between RPS data and Google Mobility data based on cell phones. Appendix B.1 documents very similar WFH rates in the RPS and ACS throughout our sample period.

2.3 Sample Selection

We set our sample criteria in the ACS to be consistent with the prior literature’s emphasis on working-age adults (ages 18-64) in civilian households. We exclude households in group quarters.

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6The default position for the slider is zero days commuted. The question is not recorded as “answered” until the respondent touches the slider (either with a mouse on a computer or a finger on a touchscreen). Individuals reporting that they commuted more days than worked were prompted with an error message and asked to revise their answers.

7The retrospective questions do not ask about a specific week in February 2020. Instead, they are phrased as in the following: For this question, we would like you to think back to February of this/last year (2020). In February 2020, which of the following best describes your work experience? Appendix A.3 shows that the results based on the retrospective questions remain broadly consistent across the months in our sample.
(e.g., rooming houses and military barracks) and households with an active duty member of the military. We then restrict attention to the working-age population 18 to 64 to minimize moves related to retirement. We use similar criteria for the RPS, except that we cannot exclude group quarters because we do not observe them.

3 Interstate Migration Before and After the Covid-19 Outbreak

Figure 1a displays annual residential migration rates in the US from 2005 through 2022 using ACS data. This series includes both within-state and interstate moves. Residential migration declined from 17.2% in 2005 to 14.1% in 2019, just before the Covid-19 pandemic. In March 2020, the World Health Organization declared that the Covid-19 outbreak constituted a global pandemic. Residential migration declined sharply in 2020, though, as mentioned previously, the 2020 ACS estimates should be treated with caution due to disruptions in data collection. Residential migration partially recovered in 2021 but then declined again in 2022. Figure 1b reveals qualitatively similar patterns for within-state migration.

Figure 1c shows that in the years around the Great Recession, interstate migration also declined. Interstate migration in the ACS declined from 2.75% in 2005 to 2.23% in 2010 (Kaplan and Schulhofer-Wohl, 2017; Molloy et al., 2011). During the recovery from the Great Recession, interstate migration partially recovered, and from 2015 to 2019, the interstate migration rate was roughly stable in the range of 2.40%-2.46%.

Following the Covid-19 outbreak, interstate migration declined in 2020. However, in 2021, interstate migration in the ACS increased significantly above the 2019 level to 2.51%, a 4.5% increase from 2019. In 2022, migration increased further in the ACS to 2.66%, an 11.1% increase from 2019. This is the highest measured migration rate since 2006, and reverses more than three-fourths of the decline between 2005 and 2019. Appendix B.2 documents a quantitatively similar spike in interstate migration since 2020 in IRS data. Appendix B.3 shows that the rise in interstate migration was not driven by foreign-born individuals. Appendix B.4 verifies that the rise in interstate migration was not driven by local moves across state borders; in particular, the share of interstate moves that were long-distance slightly increased over this period.

3.1 Work from Home and the Rise in Interstate Migration

An important consequence of the Covid-19 pandemic was a rise in WFH (Barrero et al., 2023; Bick et al., 2023). Initially, WFH was a short-run response by firms and workers to avoid health risks associated with the pandemic. However, despite a gradual reduction in health risks, WFH has endured, indicating that many businesses and employees value the greater
Figure 1: Annual Residential Migration Before and After the Covid-19 Outbreak

(a) Total Residential Migration: 2005-2022

(b) Within-State Migration: 2005-2022

(c) Interstate Migration: 2005-2022

Notes: American Community Survey (ACS). Panels 1a-1c display annual migration rates. The sample is working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.
flexibility of remote work arrangements. Because WFH, especially full-time WFH, reduces the need for a worker to live near their workplace, it is natural to ask whether WFH workers are more likely to move across states, and to what extent the sudden increase in the availability of WFH arrangements contributed to the increase in interstate migration.

To begin investigating this relationship, Figure 2a plots annual interstate migration in the ACS separately for three different commuting groups: non-employed individuals, employed commuters, and employed WFH workers. The figure shows that WFH workers had substantially higher rates of interstate migration prior to 2020. From 2015 to 2019, the interstate migration rate averaged 2.28% among commuters and 2.71% among non-workers on an annual basis, with a minimal time trend. By contrast, among WFH workers, the interstate migration rate was substantially higher, averaging 3.40% over the same period. Figure 2b shows that in 2019, the gap in migration between WFH and commuters was 1.20 percentage points, a 52.8% difference.

Figures 2a and 2b show that the gap in interstate migration by commuting status expanded after 2020. From 2019 to 2022, interstate migration increased by 0.11 percentage points among non-workers, by .10 percentage points among commuters, and by 0.79 percentage points among
WFH workers. As a result, the gap in annual migration rates between WFH workers and commuters increased from 1.20 percentage points in 2019 to 1.88 percentage points in 2022.

The propensity to WFH is highly heterogeneous; for example, it is correlated with age, education, industry, and occupation (Barrero et al., 2023; Bick et al., 2023; Dingel and Neiman, 2020). To verify whether WFH status has incremental explanatory power for interstate migration beyond its correlates, we run the following linear probability regression:

\[ m_i = \beta_0 + \beta_w w_i + \gamma X_i + \epsilon_i \]  

The left-hand side variable \( m_i \) is a dummy variable that is zero if the individual is living in the same state as one year ago and one if the individual is living in a different state. The variable \( X_i \) contains controls for sex, age, education, race, Hispanicity, marital status, the presence of children, log income, occupation, and industry. The key right-hand side variable is \( w_i \), which is a dummy indicator for the individual’s WFH status. Intuitively, the parameter \( \beta_w \) will say how much WFH increases the predicted probability of an interstate move, holding the other controls in \( X \) constant. We run this regression on workers in the ACS using individual sample weights. To examine whether the explanatory power of WFH status on interstate migration has changed since the Covid-19 outbreak, we run the regression separately for each year from 2015 to 2022.

Figure 2b displays the estimated coefficient \( \beta_w \) for a version of the regression with and without the controls in \( X \). Prior to 2020, the WFH effect without controls is close to \( \beta_w = 1 \), indicating that a WFH worker is one percentage point (or roughly 50%) more likely to move states in a given year. Importantly, the estimated WFH effect with the other controls included is very similar to the estimate without controls, indicating that the other variables in \( X \) are not driving the relationship between WFH and migration. After 2020, the WFH effect without controls increases, reaching 1.88 percentage points in 2022. The WFH effect with controls also increases in 2021 and 2022, but by less, reaching only 1.42 percentage points in 2022. This indicates that some of the increase in interstate migration among WFH workers can be accounted for by other observables that are correlated with WFH after 2020.

The impact that WFH workers had on aggregate interstate migration would have been muted had it not been for the substantial increase in WFH over this time period. Figure 3a shows the WFH share among workers in the ACS. From 2015 to 2019, the WFH share increased very gradually, from 4.5% in 2015 to 5.6% in 2019. Following the Covid-19 outbreak, WFH roughly tripled to 15.6% in 2020 and remained above 15% through 2022.\(^8\)

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\(^8\)The 2020 WFH rate should be interpreted with caution: in addition to survey disruptions related to the pandemic, it reflects an uncertain combination of responses from pre-pandemic months with low WFH rates and post-pandemic months with very high WFH rates.
Figure 3: Accounting Exercise: The Impact of Work from Home on Interstate Migration

(a) Share of Workers Who Work from Home

(b) Impact of WFH on Migration

Notes: American Community Survey (ACS). Left Panel: the share of workers (%) who WFH. Right Panel: the black circle is actual interstate migration; the gray diamond is the counterfactual migration path if WFH would have remained at the 2019 share; the hollow black diamond is the counterfactual migration path if WFH would remained at the 2019 share and if the migration of WFH workers would have remained at the 2019 rate (see text for details on these counterfactuals). The sample is working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.
The results thus far suggest that the post-Covid rise in WFH may have contributed to the increase in aggregate interstate migration. To gauge the quantitative potential of this channel, we conduct the following decomposition exercise. Aggregate interstate migration in year $t$, $m_t$, can be written as

$$m_t = \sum_{i=n,c,w} \theta_{i,t} m_{i,t}$$

Here, $n, c, w$ denote the non-employed, commuters, and WFH workers, respectively; $\theta_{i,t}$ denotes the population share of group $i$ in year $t$; $m_{i,t}$ denotes the interstate migration rate of group $i$ in year $t$. We now define two counterfactual aggregate interstate migration rates. Define $m^1_t$ to be the counterfactual aggregate migration in year $t$ if the group shares had remained fixed at their 2019 level $\tilde{\theta}_{i,t}$:

$$m^1_t = \sum_{i=n,c,w} \tilde{\theta}_{i,t} m_{i,t}$$

Next, define $m^2_t$ to be the counterfactual aggregate migration in year $t$ if (i) the group shares had remained fixed at their 2019 level $\tilde{\theta}_{i,t}$ as in $m^1_t$, and (ii) interstate migration among WFH workers also remained fixed at its 2019 rate $\tilde{m}_{w,t}$:

$$m^2_t = \tilde{\theta}_{n,t} m_{n,t} + \tilde{\theta}_{c,t} m_{c,t} + \tilde{\theta}_{w,t} \tilde{m}_{w,t}$$

Intuitively, the difference between $m_t$ and $m^1_t$ quantifies the effect of the jump in the share of WFH workers after 2019, while the difference between $m_t$ and $m^2_t$ also incorporates the effect of the rise in migration among WFH workers after 2019.

Figure 3b plots aggregate interstate migration, $m_t$, as well as the counterfactual series $m^1_t$ and $m^2_t$. The first takeaway is that the rise in WFH accounts for a sizable share of the increase in interstate migration since 2019. In 2021, $m_t$ is 6.6 percentage points higher than $m^1_t$. In 2022, $m_t$ is 5.5 percentage points higher than $m^1_t$, accounting for 49.7% of the increase in migration relative to trend. The second takeaway is that the rise in migration among WFH workers also accounts for some of the rise in aggregate interstate migration, though quantitatively, this effect is more modest. For example, in 2022, the higher WFH share and higher migration among WFH workers together account for 57.3% of the increase in interstate migration, compared with 49.7% explained by the share alone. If we restrict attention to the employed population, interstate migration was 13.7% higher in 2022 than in 2019. For this population, the higher WFH share alone accounts for 56.8% of the increase in migration (compared to 49.7% among all working-age adults), and higher migration among WFH workers together accounts for 69.8% of the increase (compared to 57.3% among all working-age adults); see Appendix B.5. Appendix B.6 repeats
our analysis relative to a linear time trend estimated for the five years before the Covid-19 outbreak. Allowing for a linear time trend yields very similar conclusions, and results in a slightly larger contribution of the rise in WFH to the observed increase in interstate migration.

3.2 Individual-Level Changes in WFH and Interstate Migration

The large rise in WFH after 2019 did not result in a lower migration rate among WFH workers. Because the ACS is not a panel dataset, it is not clear the extent to which this is driven by the changing behavior of people who were already WFH before the Covid-19 outbreak versus the changing behavior of people who switched to WFH since 2020. Fortunately, the RPS does contain this information.

Before analyzing the RPS, we first confirm that the RPS and ACS align on the key dimensions of interest: the WFH rate, migration rates, and the interaction between moving and WFH status. Figure B.1.10 shows similar WFH rates in both surveys throughout our sample period. Regarding migration, in the ACS, interstate moves are identified using the respondent’s residence one year prior. In the RPS, interstate moves are identified using the respondent’s residence in February 2020, just before the Covid-19 outbreak. This difference means that we cannot cleanly validate interstate migration rates in the RPS (since February 2020) with interstate migration rates in the ACS (in the past year). However, in both datasets we can observe whether the respondent has moved within the last year (but not whether they have moved states in the last year). In 2022, 13.1% of respondents had moved in the last year in the ACS, compared with 11.7% in the RPS. Among commuters, the rates are 13.2% in the ACS and 9.9% in the RPS; among WFH workers, the rates are 15.2% in the ACS and 12.8% in the RPS. This implies an overall migration gap between commuters and WFH workers of 2.0% in the ACS and 2.9% in the RPS. We conclude that overall migration rates are slightly higher in the ACS than the RPS, while the WFH-commuter migration gap is slightly higher in the RPS.

To see whether switching to WFH is associated with higher interstate migration, we first restrict attention to respondents in the RPS who report working both in February 2020 – just before the Covid-19 outbreak – and in the survey week in 2022 or 2023. We partition this sample of individuals into four commuting groups: those who commuted in both periods (“Commute-Commute”), those who WFH in both periods (“WFH-WFH”), those who switched to WFH (“Commute-WFH”), and those who switched to commuting (“WFH-Commute”). We then run the following linear probability regression:

\[ m_i = \beta_{CC} c_{ci} + \beta_{WW} w_{wi} + \beta_{CW} c_{wi} + \beta_{WC} w_{ci} + \gamma X_i + \epsilon_i \]

(5)

The left-hand side variable is a dummy variable that is one if the individual has moved states
Figure 4: Interstate Migration and Individual-Level Changes in Work from Home

Source: Real-Time Population Survey (RPS). Bars reflect the share (%) of the population who moved states since February 2020 in the RPS for three groups of workers: commuters pre- and post-pandemic (“Commute-Commute”), WFH pre- and post-pandemic (“WFH-WFH”), and pre-pandemic commuters who switched to WFH since the pandemic (“Commute-WFH”). Dark bars reflect means. Light bars reflect coefficients from a linear probability model with several demographic controls using sample weights (see text for details). The sample is working age adults (18-64) employed in February 2020 and in the survey reference week. Whiskers correspond to 95% confidence intervals based on heteroskedasticity-robust (Ecker-Huber-White) standard errors.

since February 2020 and is zero otherwise. The key right-hand side variables are dummy variables indicating which commuting group the individual is assigned to. We also include a set of controls for sex, age, education, race, Hispanicity, marital status, the presence of children, income, pre-pandemic and post-pandemic industry, and the month that the survey was conducted.

Figure 4 displays the estimated coefficients on commuting groups $\beta_{CC}$, $\beta_{WW}$, $\beta_{CW}$ (we omit the coefficient $\beta_{WC}$ from the figure because the estimates are imprecise due to a very small number of individuals who stopped WFH since 2020). The dark gray bars are estimates when the controls in $X$ are excluded, and the light gray bars are estimates with the controls included. For the regression with controls included we de-mean the variables in $X$ so that the coefficients are comparable to the regression without controls. The whiskers indicate 95% confidence intervals. We find that 6.30% of workers who switched to WFH post-Covid moved states since February 2020. By comparison, 3.58% of workers who commuted both pre- and post-Covid moved states over the same time period. Importantly, including the additional controls in $X$ has a minimal effect on these estimates.

Figure 4 also shows that workers who switched to WFH post-Covid moved states at higher rates (6.30%) than workers who WFH both pre- and post-Covid (5.71%). A higher migration rate for workers who recently switched to WFH is intuitive: workers who already WFH may have settled in their desired location. Based on a Wald Test, the estimates are not significantly
different, so this result should be treated with some caution. Regardless, the main takeaway from this figure is that workers who switch to WFH migrate between states at much higher rates than commuters.

3.3 Summary

To summarize, this section established three key facts:

1. In 2021 and 2022, aggregate interstate migration increased relative to its 2015-2019 trend.
2. WFH workers had substantially higher rates of interstate migration throughout 2015-2022, even after controlling for demographic variables and pre-pandemic WFH status.
3. The share of WFH workers increased sharply since the pandemic.

Our simple counterfactual analysis demonstrates that facts 2 and 3 together can account for at least half of fact 1. The remainder of the paper will address two open questions which naturally follow from this result. First, should we interpret the relationship between WFH and interstate migration as causal? Second, if WFH does causally impact interstate migration, does geographic variation in WFH help explain geographic variation in migration?

4 Employer Work from Home Policies and Migration

The previous section established that pre-pandemic commuters who switched to WFH since February 2020 moved states at higher rates than commuters who did not switch to WFH. One interpretation of this pattern is that access to WFH causally increased interstate migration by reducing the cost of migrating to a location far from the workplace. A competing interpretation is that (i) Covid-19 changed the amenity value of many locations due to factors like health concerns or crime, leading many people to move, and (ii) workers who were about to move states were more likely to request and receive permission to WFH. In this interpretation, the causation is reversed: individuals who were determined to move were more likely to switch to WFH, but they would have moved even if WFH would not have been possible.

One piece of evidence against the latter interpretation, which is based on Covid-19-related changes to local amenities, is that WFH workers already had high migration rates prior to 2020. A second piece of evidence against this interpretation is that we did not observe increases in within-state moves during this time period. To further mitigate concerns that high migration by WFH workers is actually driven by Covid-19-related changes in local amenities, we can instrument for switching to WFH using variables that we believe to be uncorrelated with the
desire to move. A promising candidate is employer policies regarding WFH. The RPS contains two sets of questions about employer WFH policies that are well-suited to our purpose. First, for all workers who commuted in February 2020, we ask:

(Q1) “Which of the following best explains why you [your spouse/partner] commuted to work in February 2020?”

a) My [spouse/partner’s] job could not be done from home
b) Some or all of my [spouse/partner’s] job could have been done from home, but my [spouse/partner’s] employer required me [them] to commute
c) Some or all of my [spouse/partner’s] job could have been done from home, but I [my spouse/partner’s] preferred to commute

Bick et al. (2023) show that most workers who switched to WFH since February 2020 reported that their main reason for commuting in February 2020 was (b) their employers did not allow them to WFH, which suggests that this question is a relevant predictor for switching to WFH.

Second, for all workers who are still working for their February 2020 employer, we ask:

(Q2) “Is your employer’s CURRENT policy on telework or working from home different compared to before the Covid-19 pandemic?”

a) Yes, the policy is different
b) No, the policy is not different
c) My employer does not have a policy on telework or working from home

For individuals who choose answer option (a), we then ask a follow-up question:

(Q3) “Who does this new policy on telework or working from home affect?”

a) The new policy affects only me
b) The new policy affects me and some or all of my co-workers
c) The new policy affects some or all of my co-workers, but not me

Relative to the first question on why individuals commuted in February 2020, the latter two questions provide information on whether the employer’s new WFH policy affected just the
respondent or multiple workers. In particular, we would not expect a new WFH policy that affects many coworkers to be strongly correlated with a given individual’s idiosyncratic desire to move.

We analyze the relationship between WFH transitions, employer policies, and interstate migration with two sets of regressions. Our dependent variable is a dummy variable, \( m_i \), which takes on a value of one if the individual \( i \) moved states since February 2020. Our independent variable of interest is a dummy variable, \( c_{w_i} \), that takes on a value of one if the individual \( i \) switched to WFH since February 2020. Our sample is employees in the RPS who commuted in February 2020 and who were still working for their pre-pandemic employer in the survey reference week in 2022 or 2023 (the questions about new employer policies were only asked of workers who were still working for their pre-pandemic employer).\(^9\) The first set of regressions consists of linear probability models of interstate migration on WFH estimated by OLS:

\[
m_i = \beta_0 + \beta_{CW} c_{w_i} + \gamma X_i + \epsilon_i
\]  

The variable \( X_i \) contains controls for sex, age, education, race, Hispanicity, marital status, the presence of children, log income, industry, pre-pandemic state of residence, and the month that the survey was conducted. We run the above regression with and without controls, and with and without sample weights. Across these four specifications, the coefficient on switching to WFH is significant at the 1% level, and the coefficient ranges from 0.024 to 0.029, indicating that switching to WFH increases the predicted probability of moving states by 2.4 to 2.9 percentage points.

We then instrument for switching to WFH using a set of variables based on the questions about employer policies described above. For question Q1, we construct a dummy variable that equals one if either answer (b) or (c) were selected. This variable indicates that the worker commuted in February 2020 because their employer required it or because they preferred to, which indicates that the job could potentially be done remotely. Next, we construct a dummy variable that equals one if (a) is selected for Q2 and (b) is selected for Q3. This variable will indicate that the individual’s employer changed its WFH policy since the Covid-19 outbreak and that this change affected both the respondent and other co-workers at that employer. We use these two variables—“WFH-Capable Job” and “New Employer Policy”—together to instrument for a switch to WFH using two-stage least squares.

In the first-stage regressions, our instruments produces large Effective F statistics, regardless of whether we include controls or use sample weights. This implies that the instruments

\(^9\)The interstate migration rate since February 2020 for individuals still working for their pre-pandemic employer is 4.2%, compared with 8.9% for individuals who have changed employers since February 2020.
Table 1: Probability of Interstate Moves and Switches to WFH

<table>
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<th></th>
<th>OLS</th>
<th></th>
<th></th>
<th></th>
<th>2SLS</th>
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<td></td>
<td><strong>0.029</strong>*</td>
<td><strong>0.029</strong>*</td>
<td><strong>0.024</strong>*</td>
<td><strong>0.025</strong>*</td>
<td><strong>0.070</strong>*</td>
<td><strong>0.063</strong>*</td>
<td><strong>0.046</strong>*</td>
<td><strong>0.044</strong>*</td>
<td></td>
</tr>
<tr>
<td></td>
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<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.019)</td>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>WFH Switch</td>
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<td></td>
<td></td>
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<td>√</td>
<td>√</td>
<td></td>
<td>√</td>
<td>√</td>
<td>√</td>
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<td></td>
</tr>
<tr>
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<td></td>
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<tr>
<td>Effective F</td>
<td>320.50</td>
<td>264.96</td>
<td>222.21</td>
<td>176.42</td>
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<td>11305</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

First-stage parameters

|                      |          |          |          |          |          |          |          |
| WFH-Capable Job      | **0.100*** | **0.094*** | **0.102*** | **0.094*** |          |          |          |
|                      | (0.005)    | (0.005)  | (0.005)  | (0.005)  |          |          |          |
| New Employer Policy  | **0.117*** | **0.103*** | **0.135*** | **0.116*** |          |          |          |
|                      | (0.005)    | (0.005)  | (0.005)  | (0.005)  |          |          |          |

Notes: Heteroskedasticity-robust (Ecker-Huber-White) standard errors in parentheses. ∗/∗∗/∗∗∗ denote significance at the 10, 5, and 1 percent levels, respectively. Individual controls are described in the main text. ‘Sample weights’ indicates whether the observations were weighted in the regressions. ‘Effective F’ is the test statistic for weak instruments described in Montiel Olea and Pfueger (2013). The critical values are for the null that the upper bound of the 2SLS bias is at least 10 percent of the worst-case benchmark at the 5 percent significance level, and are computed as in Lewis and Mertens (2022).
are strong predictors of switching to WFH. In the second-stage regressions, switching to WFH continues to positively predict interstate migration. Relative to our OLS estimates, the estimated coefficient is larger and varies more across specifications, ranging from 0.044 to 0.070. The coefficient is significant at the 1% level when we do not use sample weights, at the 5% level when we use sample weights with no controls, and at the 10% level when we use sample weights with controls.

To summarize, this section finds that pre-pandemic commuters were more likely to switch to WFH if their jobs or employer required them to commute before the pandemic and if their employer’s WFH policy has changed since the pandemic began. These variables also predict interstate migration since the pandemic. Since these variables are unlikely to be correlated with an individual’s idiosyncratic desire to move, we interpret this as evidence that access to WFH causally increases an individual’s propensity to move out of state.

5 Interstate Moves, Employer Changes, and Work from Home

A simple explanation for why WFH increases interstate migration is that it reduces the benefit of living near a workplace. This explanation suggests that WFH workers should be more likely to move states conditional on remaining in the same job. In the other direction, this explanation suggests that WFH workers should be less likely to change employers conditional on moving states. That is, if WFH reduces the benefit of living near a job, then WFH workers should be more likely to move states conditional on not changing jobs and should be less likely to change jobs conditional on moving states.

We now investigate these predictions within the RPS. (The ACS does not observe employment changes.) While the RPS does not measure job changes within an employer, it does record whether workers have changed employers since February 2020. We run two regressions:

\[
\begin{align*}
    m_i &= \beta_{mWW}^i w_{WW}^i + \beta_{mCW}^i c_{CW}^i + \gamma^m X_i + \epsilon_i \\
    e_i &= \beta_{eWW}^i w_{WW}^i + \beta_{eCW}^i c_{CW}^i + \gamma^e X_i + \epsilon_i
\end{align*}
\]

The left-hand side variable of equation (7) is a dummy variable that is one if the individual has moved states since February 2020 and is zero otherwise. We run regression (7) on the sample of individuals who have not changed employers since February 2020. \( w_{WW}^i \) is a dummy variable that is one if \( i \) WFH both in February 2020 and in the reference week; \( c_{CW}^i \) is a dummy variable that is one if \( i \) commuted in February 2020 but WFH in the reference week. The coefficients \( \beta_{mWW}^i \) and \( \beta_{mCW}^i \) describe the extent to which WFH workers are more or less likely to change states conditional on not changing employers. The left-hand side variable of equation (8) is a
Table 2: Work from Home, Interstate Migration and Employer Changes

<table>
<thead>
<tr>
<th></th>
<th>Moved States c/o Same Employer</th>
<th>Changed Employer c/o Moved States</th>
</tr>
</thead>
<tbody>
<tr>
<td>WFH-WFH</td>
<td>0.0245*** (0.0059)</td>
<td>0.0220*** (0.0060)</td>
</tr>
<tr>
<td></td>
<td>-0.2269*** (0.0732)</td>
<td>-0.2092*** (0.0779)</td>
</tr>
<tr>
<td>Commute-WFH</td>
<td>0.0183*** (0.0051)</td>
<td>0.0147 (0.0052)</td>
</tr>
<tr>
<td></td>
<td>-0.0147 (0.0549)</td>
<td>0.0475 (0.0561)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.0207*** (0.0014)</td>
<td>0.5808*** (0.0015)</td>
</tr>
<tr>
<td></td>
<td>0.5815*** (0.0209)</td>
<td>0.5826 (0.0226)</td>
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<tr>
<td>Individual Controls</td>
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<td>✓</td>
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<tr>
<td>R²-adjust</td>
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<td>0.010</td>
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<tr>
<td>N</td>
<td>12,888</td>
<td>12,632</td>
</tr>
</tbody>
</table>

Source: Real-Time Population Survey, ages 18-64. ∗/∗∗/∗∗∗ denote significance at the 10, 5 and 1 percent levels, respectively. Estimates from a linear probability model of interstate migration since February 2020. The sample is working age adults (18-64) employed in February 2020 and in the survey reference week. See text for details.

dummy variable that is one if the individual has changed employers since February 2020 and is zero otherwise. We run regression (8) on the sample of individuals who have moved states since February 2020. The coefficients $\beta_{eW}$ and $\beta_{eC}$ describe the extent to which WFH workers are more or less likely to change employers conditional on moving states. Both equations also include a set of controls $X$ for sex, age, education, race, Hispanicity, marital status, the presence of children, log income, pre-pandemic industry, and the month that the survey was conducted.

Table 2 displays the results. The first two columns show that WFH predicts interstate migration among workers who have not changed employers. Among workers still with their pre-pandemic employer, workers who WFH both pre- and post-pandemic (WFH-WFH) are 2.45 percentage points more likely to move states compared with commuters. When individual controls are included this gap decreases slightly to a 2.20 percentage point difference, all else equal. The difference is significant at the 1% level and represents an increase of 103% relative to the constant. The estimated coefficients on workers who commuted pre-pandemic but switched to WFH (Commute-WFH) have the same sign and are not significantly different, but the point estimates are slightly smaller in magnitude.

The second two columns show that workers who WFH both pre- and post-pandemic (WFH-WFH) were less likely to change employers conditional on moving states. Among workers who have moved states since February 2020, WFH-WFH workers are 22.69 percentage points less likely to change employers compared with commuters. When individual controls are included this difference decreases slightly to 20.92 percentage points, all else equal. The difference is
significant at the 1% level and represents a decrease of 36% relative to the constant. By contrast, the estimated coefficients on workers who commuted pre-pandemic but switched to WFH (Commute-WFH) are close to zero and not statistically significant. This implies that conditional on moving states, workers who switched to WFH were about as likely to change employers as commuters. One reason for this is that many switches to WFH since February 2020 were facilitated by an employer change; that is, workers who switched to WFH have higher rates of employer changes both conditional on moving states and conditional on not moving states.\textsuperscript{10} For this reason, the coefficient on WFH-WFH is more relevant for our analysis.

We view these results as consistent with the hypothesis that WFH reduces the benefit of living near a workplace. These results are relevant for the existing literature on the connection between the geography of work opportunities and interstate migration. Molloy et al. (2017) argue that the long-run decline in interstate migration was related to declining rates of job changes. Relatively, Kaplan and Schulhofer-Wohl (2017) write down a model in which decreasing dispersion in the geographic specificity of occupations since the 1980s leads to a reduction in job-related interstate moves. Absent any other changes, this would lead to an increase in the number of non-work amenity-related moves. To reconcile their model with declining interstate migration over this period, they posit that the precision of information about location-specific non-work amenities increased over this period, which reduced the need for “experimental” moves to test whether a new location was desirable. From this perspective, to the extent that WFH reduces the benefit of living near a workplace, WFH can be viewed as an extreme decrease in the geographic specificity of occupations. However, because it is unlikely that the precision of location-specific information changed much over the brief time period since 2020, the rise in WFH can be expected to increase the number of amenity-related moves.

6 Geographic Variation in Work from Home and Migration

On average, the WFH share of workers increased by 9.4 percentage points from 2019 to 2022. This increase varied substantially across states. On the low end, the increase in the WFH share was below 5 percentage points in Wyoming, Mississippi, South Dakota, Louisiana, Hawaii, and Arkansas. On the high end, the increase was above 15 percentage points in Washington, Massachusetts, and Maryland. In this section, we explore whether such state-level variation in WFH accounts for variation in interstate migration.

\textsuperscript{10}Conditional on not moving states, 37% of workers who switched to WFH changed employers compared to 26% of commuters. Conditional on moving states, 59% of workers who switched to WFH changed employers compared to 68% of commuters.
State-Level Variation in WFH and Out-Migration

Figure 5 displays a scatterplot of a state’s average WFH share in 2021-2022 against its average leave rate in 2021-2022 using ACS data. The WFH share for a state $s$ in year $t$ is the share of workers living in $s$ in year $t - 1$ who WFH in year $t$. To construct the leave rate for a state $s$ in year $t$, we start from the sample of individuals who lived in $s$ in $t - 1$. The leave rate is then the share of those individuals who lived in a different state $r \neq s$ in year $t$. Both of these variables are expressed as percentage point deviations from their 2015-2019 trend, which is estimated as described in Section 3 except now separately for each state. The figure excludes states with less than one million residents as of 2019 because estimates from these states are very noisy.\(^{11}\)

Figure 5 reveals a positive correlation of 0.431, indicating that states with larger increases in WFH tended to experience larger leave rates. In a linear regression, the point estimate is 0.051, implying that a one-standard-deviation (3.38 percentage point) increase in a state’s WFH share is associated with an increase in the leave rate of 0.17 percentage points.

The above relationship should not necessarily be interpreted as causal because state-level increases in WFH may have been caused by other developments that affect migration. For example, individuals in states with higher mortality during the pandemic may have tried to avoid getting sick either by working from home or by migrating out of the state. One way to address this concern is to substitute our measure of actual post-pandemic WFH with a pre-pandemic measure of WFH capacity.\(^{12}\) We construct such a measure of WFH capacity as follows:

\[
wfhc_{s,t} = \sum_{o} wfh_{o} \cdot sh_{s,o}
\]

where $wfh_{o}$ is the national average WFH share among occupation $o$ in 2021-2022 and $sh_{s,o}$ is the employment share of occupation $o$ in state $s$ in 2019. $wfhc_{s,t}$, therefore, measures the share of workers in state $s$ who would be expected to WFH in 2022 based on the state’s

---

\(^{11}\)For example, the ACS is a one percent sample of the population, so we can expect roughly 10,000 respondents from a state with 1 million residents, of which about 8,000 are at least age 18. A typical interstate migration rate is on the order of 2%, implying that we can expect a standard error for interstate migration of roughly $(0.03 \cdot (1 - 0.03)/8,000)^{1/2} = 0.16$ percentage points. This implies a 95% confidence interval that spans $2 \cdot 1.96 \cdot 0.16 = 0.61$ percentage points, which is quite noisy given a baseline estimate of 2%.

\(^{12}\)Another widely-used measure of WFH capacity is proposed by Dingel and Neiman (2020), which assigns each occupation a zero or a one depending on whether it could possibly be done remotely. The predictiveness of this measure for actual WFH behavior declined somewhat between 2020 and 2022. An intuitive example is teaching occupations, which have very high WFH capacity according to the Dingel and Neiman (2020) measure. Teaching occupations had high rates of WFH in 2020 when many schools conducted remote instruction but had lower rates of actual WFH in 2022 once most schools had returned to in-person instruction. More broadly, Appendix B.7 shows that a state’s WFH capacity according to Dingel and Neiman (2020) is predictive of its interstate migration, but the correlation is somewhat lower than when we use actual WFH to infer WFH capacity.
Figure 5: State-Level Variation in Work from Home and Out-Migration

Notes: American Community Survey (ACS). Initials plot a state’s average 2021-2022 WFH share relative to the trend against its average 2021-2022 interstate migration rate relative to the trend. Out-migration for state $s$ in year $t$ is the share of individuals living in state $s$ in year $t - 1$ who lived in a different state in $t$. The WFH share of state $s$ in year $t$ is the share of individuals living in $s$ in $t - 1$ who WFH in year $t$, regardless of where they lived in year $t$. The dashed black line is estimated using OLS. We exclude five states and Washington DC that have less than one million residents.
Figure 6: State-Level Variation in Work from Home Capacity and Out-Migration

(a) 2019 WFH Capacity and Post-2020 WFH  
(b) WFH Capacity and Post-2020 Out-Migration

Notes: American Community Survey (ACS). Left Panel: Initials plot a state’s 2019 WFH Capacity against its average 2021-2022 WFH share. The WFH share of state $s$ in year $t$ is the share of individuals living in state $s$ in year $t-1$ who WFH in year $t$, regardless of where they lived in year $t$. WFH capacity is based on a state’s occupation mix; see text for details. Right Panel: Initials plot a state’s 2019 WFH Capacity against its average 2021-2022 out-migration rate relative to trend. Out-migration for state $s$ in year $t$ is the share of individuals living in state $s$ in year $t-1$ who lived in a different state in $t$. The dashed black line is estimated using OLS. We exclude five states and Washington DC that have less than one million residents.

Figure 6a shows that WFH capacity in 2019 is highly predictive of WFH in 2021 and 2022 (the correlation is 0.930). This suggests that WFH capacity was an important determinant of actual WFH rates in a state. Figure 6b plots 2019 WFH capacity against the leave rate in 2021-2022, relative to trend. Compared to Figure 5 the correlation declines slightly, from 0.431 to 0.361. In a linear regression, the point estimate is 0.137. This implies that a one-standard-deviation (1.04 percentage point) increase in a state’s WFH share predicts an increase in the leave rate of 0.14 percentage points, compared to 0.17 point increase from Figure 5.

6.2 State-Level Variation in WFH and Net Migration

The previous section established that states with larger WFH increases experienced higher rates of out-migration. An important follow-up question is whether these higher rates of out-migration led to net population losses. Alternatively, states with larger WFH increases may have simultaneously experienced higher rates of in-migration; for example, an exodus of WFH
workers could lower real estate prices in a particular state, which might attract more migrants from other states.

Figure 7a displays the relationship between WFH and in-migration, with a correlation of $-0.396$. Figure 7b shows a weaker relationship between 2019 WFH capacity and in-migration: the magnitude of the correlation declines to $-0.290$, which is not statistically significant at the 5% level. The slope in this figure is also somewhat flatter than in Figure B.4.13: a one-standard-deviation increase in a state’s WFH capacity is associated with a decrease in the enter rate of 0.10 percentage points, compared with an increase in the leave rate of 0.14 percentage points.

The above results indicate that high-WFH states in 2021-2022 experienced higher rates of out-migration but weakly lower rates of in-migration, suggesting that high-WFH state experienced relatively negative net migration over this period. Figure 8 confirms this. Figure 8a displays a correlation of $-0.517$ between the change in WFH relative to the trend and the change in net interstate migration relative to the trend. The slope of the relationship is $-0.090$, implying that a one-standard-deviation increase in the WFH share is associated with a decrease
**Figure 8: State-Level Variation in Work from Home and Net Migration**

(a) WFH and Net Migration

![Graph showing state-level variation in work from home and net migration.](image)

Slope: -0.090  Corr: -0.517

(b) Pre-Covid WFH Capacity and Net Migration

![Graph showing state-level variation in work from home capacity and net migration.](image)

Slope: -0.227  Corr: -0.404

**Notes:** American Community Survey (ACS). Left Panel: Initials plot a state’s average 2021-2022 WFH share against its average 2021-2022 net migration rate relative to trend. Net-migration for state $s$ in year $t$ is the difference between the in-migration rate and out-migration rate; see Figures 5 and 7a. The WFH share of state $s$ in year $t$ is the share of individuals living in $s$ in $t$ who WFH in year $t$. Right Panel: Initials plot a state’s 2019 WFH Capacity against its average 2021-2022 net migration rate relative to trend. WFH capacity is based on a state’s occupation mix; see text for details. The dashed black line is estimated using OLS. We exclude five states and Washington DC that have less than one million residents.
in net-migration of 0.30 percentage points. If we instead use 2019 WFH capacity rather than actual WFH, the correlation weakens slightly to $-0.404$, and a one-standard-deviation increase in a state’s WFH share predicts a decrease in the net-migration rate of 0.24 percentage points.

We conclude that states with larger post-Covid increases in WFH experienced substantially higher rates of out-migration and substantially more negative rates of net migration. We find qualitatively similar results when we instead use state WFH capacity to predict migration, though quantitatively the magnitudes are slightly smaller.

7 Conclusion

This paper argues that the surge in US interstate migration in 2021-2022 was primarily driven by the rise in work from home (WFH) following the Covid-19 outbreak. ACS data reveals that interstate migration rates were consistently higher among full-time WFH workers compared to commuters prior to the pandemic, even after controlling for observable characteristics. The share of full-time WFH workers tripled after the pandemic, and the gap in interstate migration between WFH workers and commuters widened further. Quasi-panel data reveals that workers who switched to WFH since the pandemic migrated at higher rates. We find similar results using plausibly exogenous changes in employer WFH policies, suggesting that greater access to WFH after the Covid-19 outbreak causally increased interstate migration. A reduced-form aggregate accounting exercise suggests that the rise in WFH can account for more than half of the increase in national interstate migration in 2022 relative to its pre-Covid trend. Additionally, both actual WFH and pre-pandemic WFH capacity based on state occupation shares are predictive of cross-state variation in out-migration and net migration.

Our findings have important implications for understanding the changing nature of work and its impact on geographic mobility. They suggest that interstate migration will remain elevated above pre-pandemic rates to the extent that WFH also remains elevated. Higher rates of interstate migration have potentially important consequences for state government budgets, state housing prices, and state economic output. These consequences will depend on which WFH workers leave which locations and which locations they relocate to, an interesting topic for future research. Our results also suggest that WFH could reduce misallocation of economic activity across space by avoiding local housing supply constraints in highly productive cities. This, in turn, could lead to higher aggregate output and reduced income inequality between cities and states. Future research should explore the long-term effects of WFH on migration patterns, labor markets, and regional economic disparities, as well as the potential policy implications of these changes.
References


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ONLINE APPENDIX

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A RPS: Measurement and Definitions

A.1 Sample Construction and Weighting

The main text of this paper uses data from five RPS survey waves collected between February 2022 and October 2023. Collectively, these five waves include 29,812 individuals. We have two observations per individual: one corresponding to February 2020, and one corresponding to the survey month. From this, we delete (i) observations without the necessary demographic information to create sample weights, (ii) observations with missing employment data, and (iii) observations who are employed but who have missing WFH data. We then drop any individual who had one of their observations (either February or the current month) deleted in either of the steps above. These selection criteria mean that 4.1 percent of individuals in the original sample are dropped, yielding a final sample of 28,586 individuals. Table A.1.3 displays the breakdown of the sample sizes across survey months.

Table A.1.3: Sample Sizes by Survey Month in the RPS

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of Observations</th>
<th>Number Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>02/2020</td>
<td>28586</td>
<td>22400</td>
</tr>
<tr>
<td>02/2022</td>
<td>7620</td>
<td>5446</td>
</tr>
<tr>
<td>06/2022</td>
<td>5941</td>
<td>4170</td>
</tr>
<tr>
<td>10/2022</td>
<td>2580</td>
<td>1749</td>
</tr>
<tr>
<td>02/2023</td>
<td>8407</td>
<td>6091</td>
</tr>
<tr>
<td>10/2023</td>
<td>4038</td>
<td>2991</td>
</tr>
</tbody>
</table>

Notes: Real-Time Population Survey, ages 18-64. Sample sizes are unweighted.

As described in the body of the paper, we asked Qualtrics to administer the survey to a sample of respondents who match the US population along a few broad demographic characteristics: sex, five age bins (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, other), education (high school or less, some college or associate degree, bachelor degree or more), married or not, number of children in the household (0, 1, 2, 3 or more), three annual household income bins (<$50k, $50k-100k, >$100k) and four census geographic regions. Once the sample has been collected, we use an iterative proportional fitting (raking) algorithm by Stephan et al. (1940) to construct sampling weights to ensure the RPS matches an even richer set of demographic sample proportions. In addition, our sampling weights also target the Current Population Survey (CPS) employment rate in February 2020 and in the current month separately by demographic group.
A.2 Definition of Demographic Groups and Industries

Several tables control for demographic characteristics and industry. Demographic groups are defined as follows:

- **Age**
  - **Younger**: Ages 18-29
  - **Mid Age**: Ages 30-49
  - **Older**: Ages 50-64

- **Race and Ethnicity**
  - **Black**: Identify as Black and not Hispanic
  - **Hispanic**: Identify as Hispanic
  - **White**: Identify as White and not Hispanic
  - **NonBlackHispWhite or Non B/H/W**: All other racial and ethnic groups

- **Education**
  - **Low Educ**: High School degree or less
  - **Mid Educ**: Some college or associates degree, but no Bachelor’s degree
  - **High Educ**: Bachelor’s degree or more

Industries correspond to the 18 major industries in the NAICS, except that we combine Agriculture (NAICS=11) and Mining (NAICS=21) due to small sample sizes. The resulting 17 industries are defined as follows:

- **AgriMin**: NAICS = 11-21. Agriculture, Forestry, Fishing and Hunting and Mining, Quarrying, and Oil and Gas Extraction
- **Util**: NAICS = 22. Utilities
- **Const**: NAICS = 23. Construction
- **Manu**: NAICS = 31-33. Manufacturing
- **WTrade**: NAICS = 42. Wholesale Trade
- **RTrade**: NAICS = 44-45. Retail Trade
- **Transp**: NAICS = 48-49. Transportation and Warehousing
• **Info**: NAICS = 51. Information

• **Fina**: NAICS = 52. Finance and Insurance

• **RealEst**: NAICS = 53. Real Estate and Rental and Leasing

• **PBServ**: NAICS = 54-56. Professional, Scientific, and Technical Services and Management of Companies and Enterprises and Administrative and Support and Waste Management and Remediation Services

• **Educ**: NAICS = 61. Educational Services

• **Health**: NAICS = 62. Health Care and Social Assistance

• **ArtEntRec**: NAICS = 71. Arts, Entertainment, and Recreation

• **AccomFood**: NAICS = 72. Accommodation and Food Services

• **Other**: NAICS = 81. Other Services (except Public Administration)

• **Public**: NAICS = 99. Federal, State, and Local Government, excluding state and local schools and hospitals and the US Postal Service (OES Designation)
A.3 February 2020 WFH Rates Across Survey Months

The RPS asks individuals about employment and WFH outcomes in February 2020, just prior to the COVID-19 pandemic. A potential concern is whether respondents are able to accurately answer such retrospective questions, particularly for later months in the survey. One indication of recall difficulties would be if February statistics varied widely or systematically across the months that the survey was conducted.

To examine whether this is the case, Figure A.3.9 displays rates of full-time WFH in February separately for various months that the survey was conducted. We include data from RPS waves collected between May 2020 and October 2023. Reassuringly, we find that reported WFH outcomes in February 2020 are fairly stable across survey months. For example, 7.9 percent of individuals surveyed in May 2020 reported to be WFH Only in February 2020, compared with 7.7 percent of individuals surveyed in 2022-2023 and 8.5 percent of individuals in the most recent survey in October 2023. These differences are not statistically significant at the 5 percent level.
B Additional Facts on WFH and Interstate Migration

B.1 Work from Home Rates in the RPS and ACS

Fig B.1.10 displays the share of workers aged 18-64 who WFH full-time in several US datasets. The black squares correspond to the ACS, the blue diamonds correspond to the Survey of Income and Program Participation (SIPP), and the red circles correspond to the RPS. The ACS data is annual and we aggregate SIPP data to be annual as well. We plot 2019 ACS and SIPP data points as the February 2020 observation to facilitate comparison with the RPS’s February 2020 data. We plot 2020-2022 ACS and SIPP data in the midpoint (July) of the corresponding year.

We find similar rates of WFH across all three datasets, both in terms of levels and trends over time. The pre-pandemic full-time WFH rate was 5.4% in the ACS (2019), 7.7% in the RPS (02/2020), and 10.8% in the SIPP (2019). WFH increased sharply in all three datasets in mid 2020 after the Covid-19 outbreak, and gradually declined after that. In 2022, the WFH rate was 15.1% in the ACS and 13.7% in the RPS. (The SIPP is currently only available until 2021.)

B.2 Interstate Migration in the ACS and IRS

Another data source that can provide long-run estimates of migration rates is published migration statistics from the Internal Revenue Service (IRS). Each year the IRS publishes tabulations of interstate migration based on address changes for tax filers. A key benefit of this data source is that it is available for more years than the ACS data and is less subject to sampling concerns and measurement issues that are specific to household surveys. Two limitations of this data are that it does not reflect individuals who do not earn enough income to file taxes and it refers to mailing addresses rather than home addresses. Despite these limitations, we find that interstate mobility in the IRS and ACS data align closely in most years.

Figure B.2.11 displays interstate migration in IRS and ACS data. ACS data (left axis) run from 1992 to 2002 and use the same sample criteria for civilian working-age adults as in the main text. IRS data (right axis) span a longer time series, from 1992 to 2002. We allow for a slightly shifted axis for each dataset because each has a different sample (the IRS data does not condition on civilian status and does not include non-filers). In a few years (2005, 2006, 2010, 2011, 2014) the datasets the two datasets display large discrepancies. However, both reveal quantitatively similar overall trends. In particular, both datasets show fairly stable migration rates from 2015-2019, a decline in migration in 2020, and a sharp increase in migration in 2021 and 2022.
**Figure B.1.10: Share of Workers Who Work from Home Full Time**

![Graph showing the share of workers who work from home full time from January 2020 to January 2023.](image)

*Notes:* American Community Survey (ACS) and Real-Time Population Survey (RPS), ages 18-64. ACS data is annual, RPS data is from selected months. We plot 2021-2022 ACS data in the midpoint (June) of the corresponding year. We do not plot 2020 ACS data because it reflects an uncertain combination of pre-pandemic months with very low WFH rates and post-pandemic months with very high WFH rates.

**Figure B.2.11: Comparing Interstate Migration in IRS and ACS Data**

![Graph comparing interstate migration rates between IRS and ACS data from 1990 to 2020.](image)

*Notes:* American Community Survey (ACS), Internal Revenue Services (IRS). The IRS reports moves based on an address change for the tax return for years $t - 2$ and $t - 1$, which are submitted in years $t - 1$ and $t$, respectively. We, therefore, assign the moving rate based on those two returns to year $t$. Up until the 2018/2019 tax year, the IRS migration data are based on the number of exemptions per tax return. Afterwards, the IRS migration data are based on the number of individuals per tax return. We use those numbers to calculate the share who moved states in the last year and exclude individuals who moved abroad. We drop tax years 2014/2015 and 2016/2017 because the moving rates are implausibly low (1.8%) and high (3.4%), respectively.
Figure B.3.12: Interstate Mobility: All vs. Native-Born

Notes: American Community Survey (ACS). The basic sample is working-age (18-64) adults in civilian households who currently live in the US and lived in the US in the previous year. The figure displays annual migration rates for two groups: all individuals in the basic sample, and only US-born individuals. The migration rates are percent deviations relative to each series’ own pre-pandemic linear trend, which is estimated using OLS in years 2015-2019. Whiskers correspond to 95% confidence intervals.

B.3 Interstate Mobility: Overall Trends versus Trends for US Natives

International immigration patterns were somewhat volatile in the years around the Covid-19 pandemic. In the first year or two of the pandemic international immigration rates were very low. In subsequent years, health concerns subsided, the economy recovered, and immigration (including undocumented immigration) increased. A natural question is whether these shifts in international immigration may have somehow also contributed to migration across states. Figure B.3.12 compares the national interstate migration rates in the main text to interstate migration rates for US natives. We find essentially identical patterns in the two series, implying that foreign-born individuals are not directly driving the rise in interstate migration after 2020.

B.4 Interstate Mobility and Moving Distance

The emerging literature on residential mobility and WFH considers two categories of residential moves: local moves and long-distance moves. For example, Delventhal et al. (2022); Davis et al. (2024); and Monte et al. (2023) construct models that predict an expansion in WFH will induce some WFH workers to make local moves from city centers near workplaces where rent is high to more distant suburbs where rent is lower or amenities are better. Brueckner et al. (2023)
and Delventhal and Parkhomenko (2023) analyze models in which some full-time WFH workers move larger distances, such as across metro areas or states. Local moves may be more relevant if workers still need to occasionally commute to work or if workers already have strong local ties. Long-distance moves may be more relevant if workers rarely need to commute or if they have strong preferences for other distant locations. On average, interstate moves will tend to be longer distance than within-state moves, but this is not necessarily the case for all interstate moves. For example, some individuals may live near a state border and move only a few miles to another state. This may be more common in the Northeast, which has smaller states on average.

We can evaluate the fraction of interstate moves in the ACS that are long-distance using county-level distance information. Specifically, for any individual who moves across state lines, we compute the distance between their origin county and destination county. Counties are not directly observed in public ACS microdata. However, many counties are either coterminous with a single Public Use Microdata Area (PUMA) or completely contain a PUMA. In these cases we can use an individual’s PUMA, which is observed, to assign the individual a county. County-level distances are great-circle distances calculated using the Haversine formula based on internal points in the geographic area.

Figure B.4.13a plots the share of all interstate moves in the ACS that exceeded 50, 100, or 150 miles as measured by county distance. We view 50 miles as a lower bar for a long-distance threshold, in the sense that a 50-mile commute is quite long but still feasible. We view 150 miles as an upper bar for a long-distance threshold, as a 150-mile commute seems infeasible on a frequent basis. From 2015 to 2021, these shares were stable: in each year, roughly 75% of interstate moves were at least 50 miles, and over 60% were at least 150 miles. In 2022, moving distances among interstate migrants increased, so that 76% of interstate moves were at least 50 miles and 71% were at least 150 miles.

Figures B.4.13b and B.4.13c show that interstate moves by WFH workers tended to be longer distances than interstate moves by commuters. For example, in 2019, the share of interstate moves exceeding 50 miles was 70% for commuters versus 79% for WFH; the share exceeding 150 miles was 64% for commuters versus 73% for WFH. In 2022 moving distances among interstate migrants increased, especially for WFH movers. For example, the share exceeding 150 miles was 69% for commuters versus 80% for WFH.

We conclude that only a minority of interstate moves were local and a majority of interstate moves were long-distance. This is especially true for WFH workers. For example, 73% of WFH interstate moves exceeded 150 miles in 2019 and 80% did so in 2022.
Figure B.4.13: Share of Long-Distance Moves Among Interstate Migrants

(a) All Individuals

Notes: American Community Survey (ACS). The figure displays the share (%) of interstate moves in a given year whose estimated distance exceeded 50, 100, or 150 miles. Panel B.4.13a is for all interstate movers. Panel B.4.13b is for interstate movers who are employed and commute to work. Panel B.4.13c is for interstate movers who are employed and WFH. Moving distance is measured as the distance between two counties; see text for details. The sample is working-age (18-64) adults in civilian households who currently live in the US, who lived in the US in the previous year, and who live in a different state compared to one year ago.
B.5 The Impact of WFH on the Interstate Migration of Workers

Section 3.1 conducts an accounting exercise to gauge the potential quantitative effect of WFH on interstate migration for all individuals. In this section we lay out an analogous decomposition but restricted to workers. Aggregate interstate migration in year $t$, $m_t$, can be written as

$$m_t = \sum_{i=c,w} \theta_{i,t} m_{i,t}$$  \hspace{1cm} (B.5.10)

Here, $n, c, w$ denote commuters and WFH workers, respectively; $\theta_{i,t}$ denotes the population share of group $i$ in year $t$; $m_{i,t}$ denotes the interstate migration rate of group $i$ in year $t$. We now define two counterfactual aggregate interstate migration rates. Define $\tilde{m}_1^t$ to be the counterfactual aggregate migration in year $t$ if the group shares had remained at their 2019 level $\tilde{\theta}_{i,t}$:

$$\tilde{m}_1^t = \sum_{i=c,w} \tilde{\theta}_{i,t} m_{i,t}$$  \hspace{1cm} (B.5.11)

Next, define $\tilde{m}_2^t$ to be the counterfactual aggregate migration in year $t$ if (i) the group shares had remained at their 2019 level $\tilde{\theta}_{i,t}$ as in $\tilde{m}_1^t$, and (ii) in addition interstate migration among WFH workers had also remained at its 2019 rate $\tilde{\theta}_{w,t}$:

$$\tilde{m}_2^t = \tilde{\theta}_{c,t} m_{c,t} + \tilde{\theta}_{w,t} \tilde{m}_{w,t}$$  \hspace{1cm} (B.5.12)

Figure B.5.14b plots interstate migration by workers, $m_t$, as well as the counterfactual series $\tilde{m}_1^t$ and $\tilde{m}_2^t$. The rise in WFH accounts for a sizable share of the increase in interstate migration by workers since 2019. In 2021, $m_t$ is 8.9 percentage points higher than $\tilde{m}_1^t$. In 2022, $m_t$ is 7.8 percentage points higher than $\tilde{m}_1^t$, accounting for 56.8% of the increase. In 2022, $m_t$ is 9.6 percentage points higher than $\tilde{m}_2^t$, accounting for 69.8% of the increase.

B.6 Impact of WFH on Interstate Migration: Linear Trend Counterfactual

Section 3.1 conducts an accounting exercise to gauge the potential quantitative effect of WFH on interstate migration for all individuals. The reference point for that exercise was 2019. In this section, we conduct an analogous exercise except that we use as a reference point a linear trend estimated from pre-pandemic data. Specifically, we estimated a linear time trend in migration rates and group shares using the five years before the pandemic 2015-2019. We then define de-trended variables to be percent deviations from this linear trend.

The accounting exercise proceeds almost identically to Section 3.1 except that we now refer
Figure B.5.14: The Impact of Work from Home on Interstate Migration of Workers

(a) Share of Workers Who Work from Home

(b) Impact of WFH on Migration by Workers

Notes: American Community Survey (ACS). Left Panel: the share of workers (%) who WFH. Right Panel: the black circle is actual interstate migration by workers; the gray diamond is the counterfactual migration path if WFH would have remained at the 2019 share; the hollow black diamond is the counterfactual migration path assuming that WFH remains at the 2019 share and the migration of WFH workers remains at the 2019 rate (see text for details on these counterfactuals). The sample is employed working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.
to de-trended variables. De-trended aggregate interstate migration in year \( t \), \( m_t \), can be written as

\[
m_t = \sum_{i=n,c,w} \theta_{i,t} m_{i,t}
\]

Here, \( n, c, w \) denote the non-employed, commuters, and WFH workers, respectively; \( \theta_{i,t} \) denotes the population share of group \( i \) in year \( t \); \( m_{i,t} \) denotes the de-trended interstate migration rate of group \( i \) in year \( t \). We now define two counterfactual aggregate interstate migration rates. Define \( \tilde{m}_1 \) to be the counterfactual aggregate migration in year \( t \) if the group shares had evolved according to their 2015-2019 trend \( \tilde{\theta}_{i,t} \):

\[
\tilde{m}_1 = \sum_{i=n,c,w} \tilde{\theta}_{i,t} m_{i,t}
\]

Next, define \( \tilde{m}_2 \) to be the counterfactual aggregate migration in year \( t \) if (i) the group shares had evolved according to their 2015-2019 trend \( \tilde{\theta}_{i,t} \) as in \( \tilde{m}_1 \), and (ii) in addition interstate migration among WFH workers had also evolved according to its 2015-2019 trend \( \tilde{\theta}_{w,t} \):

\[
\tilde{m}_2 = \tilde{\theta}_{n,t} m_{n,t} + \tilde{\theta}_{c,t} m_{c,t} + \tilde{\theta}_{w,t} \tilde{m}_{w,t}
\]

Figure 3b plots detrended aggregate interstate migration, \( m_t \), as well as the counterfactual series \( \tilde{m}_1 \) and \( \tilde{m}_2 \). In 2021, \( m_t \) is 6.7 percentage points higher than \( \tilde{m}_1 \). In 2022, \( m_t \) is 5.9 percentage points higher than \( \tilde{m}_1 \), accounting for 54% of the increase in migration relative to trend. The second takeaway is that the rise in migration among WFH workers also accounts for some of the rise in aggregate interstate migration, though quantitatively, this effect is more modest. For example, in 2022 the higher WFH share and higher migration among WFH workers together account for 61% of the increase in interstate migration relative to trend, compared with 54% explained by the share alone.
Figure B.6.15: The Impact of Work from Home on Interstate Migration Relative to Trend

(a) Share of Workers Who Work from Home

(b) Impact of WFH on Migration rel. to Trend

Notes: American Community Survey (ACS). Left Panel: the share of workers (%) who WFH. Right Panel: the black circle is actual interstate migration relative to the 2015-2019 trend; the gray diamond is the counterfactual migration path if the WFH share would have evolved according to the trend; the hollow black diamond is the counterfactual migration path if the WFH share would have evolved according to the trend and if the migration rate of WFH workers would have remained at its pre-pandemic trend (see text for details on these counterfactuals). The sample is working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.
B.7 Measuring State WFH Capacity Using Dingel and Neiman (2020)

Section 6 showed that post-Covid WFH rates accounted for a sizable portion of the state-level variation in post-Covid interstate migration. That section also showed that a state’s WFH capacity, based on a state’s occupation mix and actual WFH rates in 2022 in each occupation, was predictive of its post-Covid interstate migration.

This section considers an alternative measure of Work from Home Capacity based on Dingel and Neiman (2020) (DN). Intuitively, the measure of WFH capacity in Section 6 was based on actual WFH in an occupation in 2022. By contrast, DN construct a measure of WFH capacity based on the tasks involved in an occupation and whether these tasks could feasibly be done from home. These measures will differ for a particular occupation if that occupation could feasibly be done from home but actual WFH rates in that occupation are low. This might occur if working from home is possible but less productive or less desirable in a particular occupation. For example, Educational Occupations (SOC 25-0000) score highly on the DN measure. However, in 2022 these occupations had a low national WFH rate of only 8.1%, compared to 15.0% among all occupations.

Figures B.7.16 and B.7.17 plot state out-migration, in-migration, and net-migration rates against actual WFH rates in 2021-2022 (left panels) and DN WFH Capacity (right panels). Qualitatively, both WFH and WFH capacity predict interstate migration with the same sign. However, the correlation between migration and WFH capacity is lower than between migration and WFH, and the slope for WFH capacity tends to be flatter as well.
Figure B.7.16: State-Level Variation in Work from Home and Interstate Migration - I

(a) WFH and Out-Migration

(b) WFH Capacity and Out-Migration

(c) WFH and In-Migration

(d) WFH Capacity and In-Migration

Notes: American Community Survey (ACS). Left Panels: Initials plot a state’s average 2021-2022 WFH share against its average 2021-2022 out-/in-migration rate relative to trend. The WFH share of state s in year t is the share of individuals living in s in t who WFH in year t. Right Panel: Initials plot a state’s 2019 WFH Capacity against its average 2021-2022 out-/in-migration rate relative to trend. WFH capacity is based on a state’s occupation mix; see text for details. The dashed black line is estimated using OLS. We exclude five states and Washington DC that have less than one million residents.
FIGURE B.7.17: State-Level Variation in Work from Home and Interstate Migration - II

(a) WFH and Net-Migration

(b) WFH Capacity and Net-Migration

Notes: American Community Survey (ACS). Left Panel: Initials plot a state’s average 2021-2022 WFH share against its average 2021-2022 net migration rate relative to trend. The WFH share of state $s$ in year $t$ is the share of individuals living in $s$ in $t$ who WFH in year $t$. Right Panel: Initials plot a state’s 2019 WFH Capacity against its average 2021-2022 net migration rate relative to trend. WFH capacity is based on a state’s occupation mix; see text for details. The dashed black line is estimated using OLS. We exclude five states and Washington DC that have less than one million residents.