Work from Home and Long-Distance Migration*

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Abstract

Long-distance migration by workers in the US declined substantially during the Great Recession and remained subdued through 2019. We document that worker migration rose sharply following the 2020 Covid-19 outbreak, 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, migration by WFH workers was consistently 40-50% 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 migration. An aggregate accounting exercise suggests that over half of the rise in long-distance migration since 2019 can be accounted for by the rise in the WFH share. We develop and calibrate a spatial equilibrium model with remote work and long-distance migration. A shock to the share of remote-capable workers replicates post-COVID trends in migration, population, and rents. The model implies that the rise in WFH had substantial effects on geographic reallocation, rental prices, and welfare.

JEL Codes: J61, J11, J22, R10, O15
Keywords: Interstate Migration, Work from Home, Remote Work, Labor Mobility

Contact: alexander.bick@stls.frb.org; adam.blandin@vanderbilt.edu; mertens.karel@gmail.com; hannah.rubinton@stls.frb.org. A previous version of this paper was titled "Work from Home and Interstate Migration." We thank seminar/conference participants at the Society for Economic Dynamics, Vanderbilt University, and the Federal Reserve Bank of St. Louis for helpful comments. Kevin Bloodworth II, Aidan Caplan, and Tristan Caplan provided excellent research assistance. We thank the Center for the Advanced Study in Economic Efficiency at ASU, the Office of the Vice President for Research and Innovation at VCU, the Federal Reserve Bank of Dallas, and the Federal Reserve Bank of St. Louis for generous financial support. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Banks of Dallas and St. Louis or the Federal Reserve System.

1 Introduction

Long-distance migration in the US fell sharply during the Great Recession and remained subdued for a decade. For example, 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 partially recovered 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 long-distance migration rose sharply in the years after the 2020 Covid-19 outbreak and shows that much of this increase can be attributed to the concurrent rise in remote work. We begin by establishing four key empirical facts linking remote work to migration. First, even before the pandemic, remote workers migrated at higher rates than commuters. Second, as remote work expanded, so did overall migration; an accounting exercise suggests that 50–60% of the increase in migration can be attributed to remote work. Third, using novel survey data on employer WFH policies, we demonstrate that the relationship is causal: workers who experienced a change in their employer's WFH policy were more likely to move across cities or states. Fourth, we show that pre-pandemic WFH capacity predicts cross-state and cross-MSA migration patterns. Motivated by these findings, we develop a spatial equilibrium model incorporating remote work and long-distance migration. We calibrate the model to match pre-COVID migration patterns and then triple the share of remote-capable workers to reflect post-pandemic changes. The model successfully replicates post-COVID trends in migration, population growth, and rents, allowing us to analyze the welfare gains of WFH, many of which arise from workers' increased ability to relocate based on preferences or cost of living.

This paper starts by documenting that long-distance migration rose sharply in the years after the 2020 Covid-19 outbreak. On average from 2021-2023, interstate migration in the ACS was 9% above its 2019 rate and inter-MSA migration was 14% above its 2019 rate. We document quantitatively similar patterns in change-of-address data by the IRS and the United States Postal Service, and show that rising migration was not driven by foreign-born individuals or by local moves that crossed state or MSA boundaries. Because the Covid-19 pandemic disrupted many aspects of life, it is not obvious *a priori* what drove the increase in 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 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 increase in long-distance migration since 2019 was primarily driven by one particular consequence of the pandemic: the rise in the share of workers who work from home (WFH) full time. 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, migration rates were consistently 40-50% higher among full-time WFH workers compared with commuters, even after controlling for a host of observable characteristics. This gap has persisted since then. 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 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 migration in 2022 relative to 2019. Moreover, changes in WFH are predictive of geographic 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 long-distance migration. Our data comes from the Real-Time Population Survey (RPS), an online nationwide survey designed to track commuting behavior and labor market developments before and after the Covid-19 outbreak (Bick and Blandin, 2023).[1] While ACS data show high long-distance 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 migration rates than commuters who did not switch to WFH.

Next, we address a potential concern that the pandemic increased the desire to migrate 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 make a long-distance move may request permission to remain with their employer but work remotely, 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 migration. Finally, consistent with the interpretation that WFH reduces

[1] Bick et al. (2023) use the RPS to document the evolution of WFH in the US from the onset of the Covid-19 pandemic through June 2021. Bick et al. (2024a,b) show that the prevalence of WFH in the RPS closely aligns with the ACS, and other US datasets, through 2023.

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 migrate, and (ii) among workers who migrate, WFH workers are less likely to change employers.

Next, we develop a spatial equilibrium model that incorporates remote work and long-distance migration to analyze the long-run implications of WFH and its welfare effects. In the model, a subset of workers is remote-capable, meaning they can either work in their local labor market or participate in a national remote market that is independent of their residential location. Remote workers face fewer migration frictions, allowing them to relocate more easily across cities. We calibrate the model to match the pre-COVID gap in inter-MSA migration rates between remote workers and commuters. We then triple the share of workers who are remote-capable, mirroring the increase in remote work post-COVID. The model's dynamic response to the WFH shock closely aligns with post-COVID trends in migration rates, population growth, and rents across cities. Finally, we use the model to assess the welfare impacts of remote work.

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, an increase in 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 4.3 that WFH workers are more likely to migrate 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. Althoff et al. (2022), Liu and Su (2021), and Ramani and Bloom (2021) provide evidence that housing demand shifted away from city-center locations with high population density toward lower-density areas on the outskirts of cities. Brueckner et al. (2023) provides similar evidence at the county level. 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, it could be the case that this correlation is driven by other pandemic-related factors correlated with WFH capacity, like crime or health. 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) find that remote work is often cited as a primary motive for long-distance moves in moving company data from 2020-2021.

To the extent that higher rates of WFH persist (which is still the case in the most recent Current Population Survey), our results have several important implications.[2] 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, an increase 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 across 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 uses quasi-panel data to examine individual-level changes in WFH and long-distance migration, leverages employer policies as a plausibly exogenous source of variation in WFH, and shows that migration and employer changes are less closely related for WFH workers than for commuters. Section 5 documents cross-state variation in WFH and migration and develops a spatial equilibrium model incorporating WFH and long-distance migration. Section 6 concludes.

[2]Since October 2022, the CPS permits to construct a WFH rate that is conceptually comparable to the ACA. In 2022 and 2023, the WFH rate in the CPS is somewhat lower than in the ACS, but has been stable over time, including the most recent data points in 2025, see Figure B.15.

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. We use the cleaned version made available on IPUMS (Ruggles et al., 2024).

Several features of the ACS are well-suited to our analysis. First, the ACS has information on migration. The Census Bureau knows the current residence of all household members because the ACS is mailed to a specific address. It also collects the residential address of all household members one year ago by asking each member: *"Where did this person live 1 year ago?"*. A "residential move" is assigned whenever these two addresses differ.

Our analysis requires classifying each move as either local or long-distance. We primarily use two concepts of long-distance: interstate moves and inter-MSA moves. (Appendix B.7 shows that a large majority of such moves exceed 100 miles, using county distance as a proxy for move distance.) The current and past residential state for each individual are publicly available, so identifying inter-state moves is straightforward. Our procedure for identifying inter-MSA moves is based on an individual's public-use-microdata area (PUMA), which is the smallest publicly available geographic unit.[3]

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.[4]

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 long-distance 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. This

[3]Most PUMAs lie entirely within a single MSA. However, PUMAs occasionally straddle MSA boundaries, in which case individuals cannot be assigned to a single MSA with certainty. We follow the IPUMS procedure and assign individuals to the MSA in which the majority of their PUMA population resides. If this procedure would misassign at least 15 percent of an MSA's population, IPUMS does not assign the individual an MSA (these cases are primarily for small MSAs). In the last decade the share of individuals whose MSA cannot be determined is between 15-16 percent and is stable over time.

[4]The 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.

allows us to assess potential time trends in pre-pandemic migration.

We highlight two points of context for interpreting the ACS migration data. First, the Census Bureau reported that the 2020 ACS data collection was significantly impacted by the Covid-19 pandemic, potentially leading to 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, our analysis largely ignores the 2020 estimates and instead focuses on the years before and after 2020.

Second, some PUMA boundaries were updated in 2022 based on the 2020 Census. This does not affect our measurement of whether a move occurred because the move variable is based on address changes. It also does not create any inconsistency in PUMAs for an individual move because in any given year the same PUMA boundaries are used for both the past and current residence. However, it is possible that changes to PUMA boundaries affect the share of moves that are labeled inter-MSA after 2022. Importantly, this change is not relevant for interstate moves, and throughout the paper we document similar patterns for interstate and inter-MSA migration. Consistent with this, Appendix Figure B.10 shows that the share of inter-MSA moves that were also interstate is roughly constant (between 61% and 63%) over our sample period. These results suggest that the inter-MSA migration trends we document are not substantially affected by changes in some PUMA boundaries.

2.2 The Real-Time Population Survey

While the ACS contains a wealth of valuable information, an important limitation is that it 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 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.[5] 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

[5]The survey takes about 15 minutes to complete, implying an hourly pay rate for respondents of roughly $8.40-$14.00.

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.[6] 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 previous 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

[6]Specifically, the surveys were conducted in the following months: 02/2022, 06/2022, 10/2022, 02/2023, 10/2023.

the second question, the integers span 0 to 7.[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.[8] Crucially, this allows us to identify workers who commuted pre-Covid and switched to WFH post-Covid. Bick et al. (2024b) compare RPS data with Google Mobility data (based on cell phone geolocation) and find similar trends in commuting volume during the Covid-19 pandemic. They also report comparable WFH rates between the RPS and several household surveys (ACS, American Time Use Survey, Current Population Survey, and Survey of Income and Program Participation). Appendices B.2 and B.3 documents similar WFH rates and migration rates (both overall and by WFH status) in both surveys 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 employed adults in civilian households. We exclude households in group quarters (e.g., boarding houses and military barracks) and households with an active duty member of the military. We then restrict attention to the employed 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

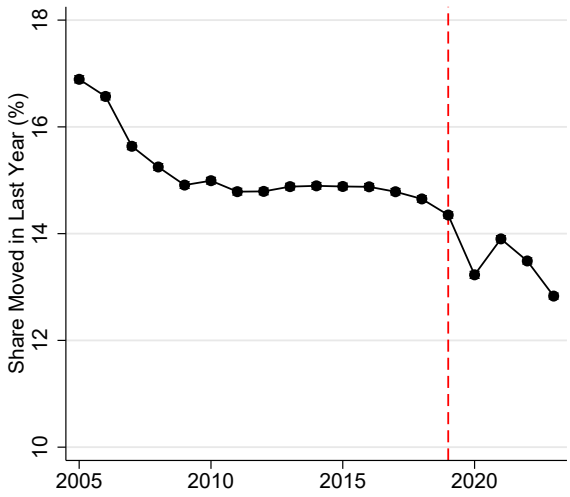
Figure 1a displays annual residential migration rates in the ACS from 2005 through 2022 among workers aged 18-64. This series includes all moves, both local and long-distance. Overall residential migration declined in the years around the Great Recession, from 16.89% in 2005 to 14.99% in 2010, then remained fairly stable throughout the next decade. 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. By 2023, overall

[7] The 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.

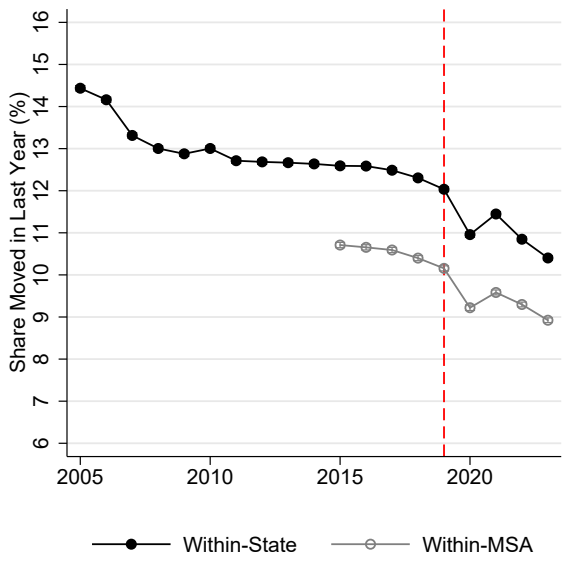
[8] The retrospective questions do not ask about a specific week in February 2020. Instead, they are phrased as in the following: *For this question, we would like you to think back to February of this/last year (2020). In February 2020, which of the following best describes your work experience?* Appendix A.3 shows that the results based on the retrospective questions remain broadly consistent across the months in our sample.

Figure 1: Annual Residential Migration of Workers Before and After the Covid-19 Outbreak

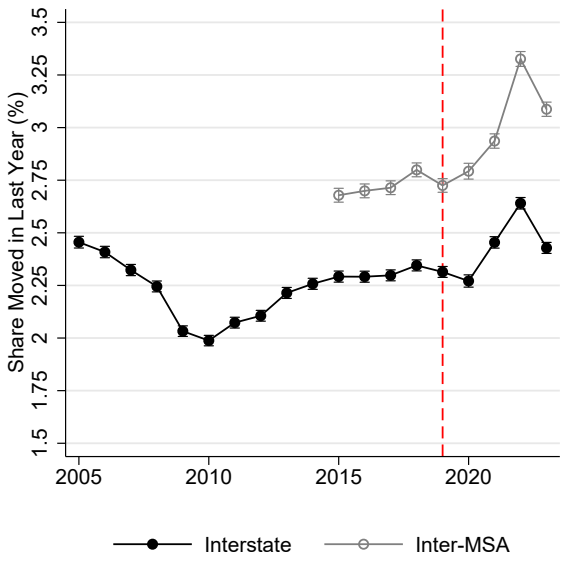
(a) Total Residential Migration of Workers



(b) Local Migration of Workers



(c) Long-Distance Migration of Workers



Notes: American Community Survey (ACS). Panels 1a-1c display annual migration rates from 2005-2023. 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.

residential migration had declined to 12.83%. Figure 1b reveals qualitatively similar trends in two measures of local migration, within-state and within-MSA, which account for a majority of overall migration. (We plot within-MSA migration only from 2015-on because prior to 2015 the Census made major changes to MSA definitions.)

Figure 1c displays two measures of long-distance migration: between-state and between-MSA. In the years around the Great Recession, interstate migration declined, from 2.46% in 2005 to 1.99% in 2010 (Kaplan and Schulhofer-Wohl, 2017; Molloy et al., 2011). During the recovery from the Great Recession, interstate migration partially recovered. From 2015 to 2019, the interstate migration rate was fairly stable in the range of 2.29%-2.34%, and inter-MSA migration was fairly stable between 2.68%-2.79%.

Following the Covid-19 outbreak, both measures of long-distance migration increased sharply. Relative to 2019, in 2022 interstate migration increased 14% and inter-MSA migration increased 22%. Long-distance migration declined from 2022 to 2023, but remained above 2019 levels. On average from 2021-2023, interstate migration was 9% above its 2019 rate and inter-MSA migration was 14% above its 2019 rate.

Appendix B.4 documents a quantitatively similar spike in interstate migration in IRS data between 2019-2022. Foster et al. (2024) report a quantitatively similar spike in interstate address changes in the NCOA between 2019-2021. Appendix B.7 verifies that the rise in long-distance migration was not driven by short moves across state or MSA borders; in particular, the share of long-distance moves that exceed 100 miles increased slightly over this period. Appendix B.6 shows that these patterns were not driven by foreign-born individuals.

Because our model uses MSAs as the geographic unit of analysis, going forward we focus on inter-MSA migration in the main text. Appendix B.1 contains a parallel set of all our empirical analyses for interstate migration, revealing very similar results.

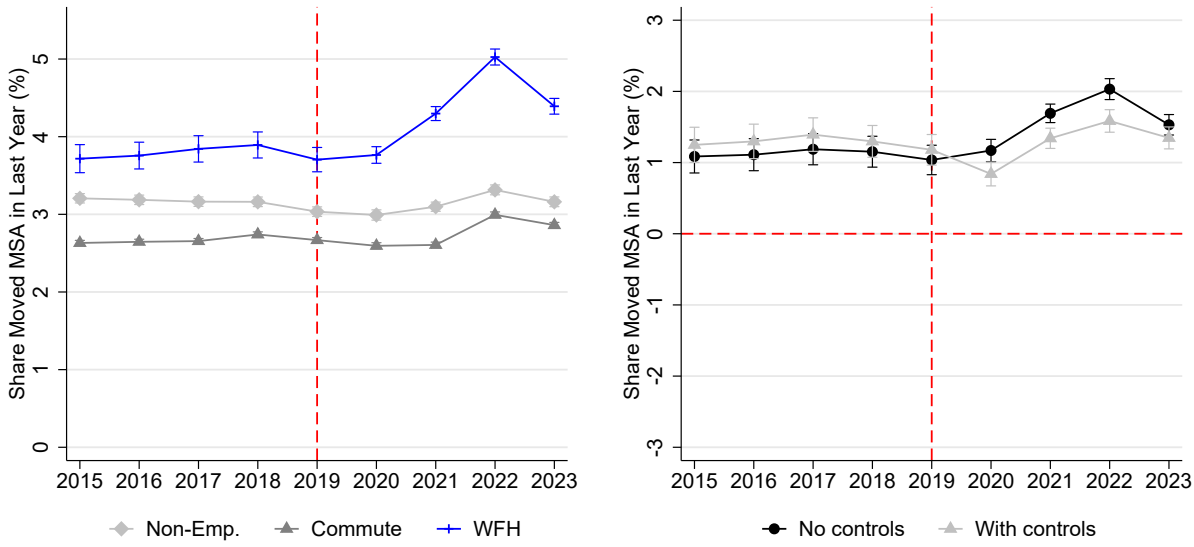
3.1 Work from Home and the Rise in Interstate Migration

An important consequence of the Covid-19 pandemic was a persistent increase in the share of workers who WFH (Barrero et al., 2023; Bick et al., 2023). For example, the WFH rate in the ACS increased from 5% in 2019 to 18% in 2021, and remained at 14% as of 2023.[9] Because WFH, especially full-time WFH, reduces the benefits of living near a workplace, it is natural to ask whether WFH workers are more likely to move long distances, and to what extent the sudden increase in the availability of WFH arrangements contributed to the increase in long-distance migration.

[9]In the RPS and in the Current Population Survey, which contain more recent data, the share of workers who WFH full time was stable from 2023 through early 2025.

Figure 2: Work from Home and Long-Distance Migration

(a) Inter-MSA Migration by Commute Status (b) Inter-MSA Migration: WFH−Commuters



Notes: American Community Survey (ACS). Left Panel: annual inter-MSA migration rates for three population groups: non-employed (light gray diamonds), commuters (dark gray triangles), and WFH workers (blue crosses). Right Panel: the black squares are the difference between WFH and Commuters from the left panel; the gray triangles are the coefficients on WFH from a linear probability regression of inter-MSA migration with several demographic controls using sample weights (see text for details). 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 based on heteroskedasticity-robust (Ecker-Huber-White) standard errors.

Figure 2a plots annual inter-MSA migration in the ACS separately for three different commuting groups: non-employed individuals, employed commuters, and employed WFH workers. Prior to 2020, WFH workers had substantially higher rates of inter-MSA migration. From 2015 to 2019, the inter-MSA migration rate averaged 2.67% among commuters and 3.15% among non-workers on an annual basis, with a minimal time trend. By contrast, among WFH workers, the inter-MSA migration rate was substantially higher, averaging 3.78% over the same period. These estimates imply that the MSA migration rate of WFH workers was 1.12 percentage points, or $1.12/2.67 = 42\%$ higher than the migration rate of commuters over this time period.

Figure 2a shows that the WFH-commuter gap in inter-MSA migration expanded after 2020. The average WFH-commuter migration gap increased from 1.12 percentage points (or 42%) in 2015-2019 to 1.75 percentage points (or 62%) in 2021-2023.

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 additional explanatory power for inter-MSA migration beyond its correlates, we run the following linear probability regression:

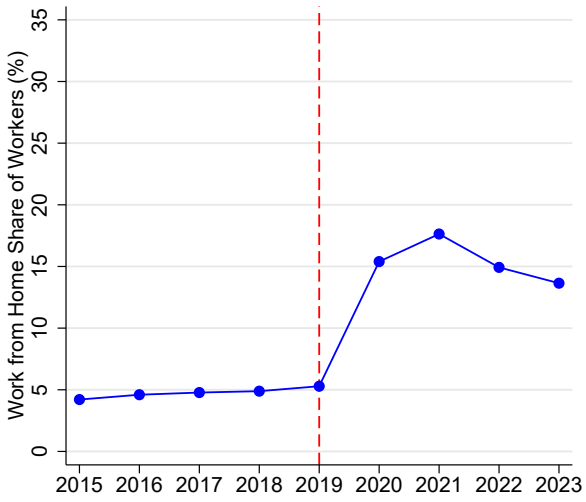
$$m_i = \beta_0 + \beta_w w_i + \gamma X_i + \epsilon_i \tag{1}$$

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 β_w will say how much WFH increases the predicted probability of an inter-MSA 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 inter-MSA migration has changed since the Covid-19 outbreak, we run the regression separately for each year from 2015 to 2023.

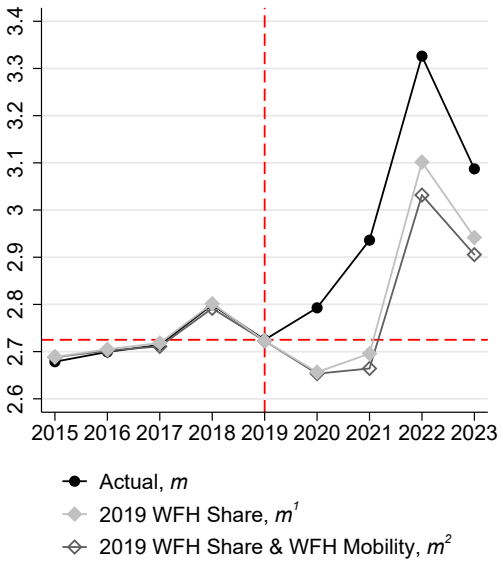
Figure 2b displays the estimated coefficient β_w for a version of the regression with and without the controls in X. Prior to 2020, the WFH effect with controls is very similar to the estimate without controls, indicating that the WFH-commuter gap in migration is not accounted for by other observables. After 2020, the value of β_w increases both in the regression with controls and without controls, but the effect is larger in the regression without controls. This indicates that much of the increase in inter-MSA migration among WFH workers can be accounted for by other observables that are correlated with WFH after 2020. The key point is that the WFH-commuter migration gap was stable or slightly increased after 2019, even after controlling for observables.

Figure 3: Accounting Exercise: The Impact of Work from Home on Long-Distance Migration

(a) Share of Workers Who Work from Home



(b) Impact on Inter-MSA Migration



Notes: American Community Survey (ACS). Left Panel: the share of workers (%) who WFH. Right Panel: black circles are actual migration rates for workers in the ACS; gray diamonds are the counterfactual migration path if WFH would have remained at the 2019 share; hollow black diamonds are 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 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.

The impact that WFH workers had on aggregate inter-MSA 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 4.2% in 2015 to 5.3% in 2019. Following the Covid-19 outbreak, WFH more than tripled to 17.6% in 2021 and remained above 13% through 2023.[10]

The results thus far show that WFH workers consistently have higher long-distance migration rates than commuters, and that the WFH share increased following the Covid-19 outbreak. These two facts suggest that the post-Covid rise in WFH may have contributed to the aggregate increase in long-distance migration. To gauge the quantitative potential of this channel, we conduct the following decomposition exercise. Aggregate inter-MSA migration in year t, m_t, can be written as

$$m_t = \sum_{i=c,w} \theta_{i,t} m_{i,t} \tag{2}$$

[10]The 2020 WFH rate should be interpreted with caution: in addition to survey disruptions related to the pandemic, it reflects an unknown combination of responses from pre-pandemic months with low WFH rates and post-pandemic months with very high WFH rates.

Here, 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 migration rate of group i in year t. We now define two counterfactual aggregate migration rates. Define m_t^1 to be the counterfactual aggregate migration in year t if the group shares had remained fixed at their 2019 level $\theta_{i,2019}$:

$$m_t^1 = \sum_{i=n,c,w} \theta_{i,2019} m_{i,t} \tag{3}$$

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

$$m_t^2 = \theta_{c,2019} m_{c,t} + \theta_{w,2019} m_{w,2019} \tag{4}$$

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

Figure 3b plots aggregate inter-MSA migration, m_t, as well as the counterfactual series m_t^1 and m_t^2. Figure 3b plots the same series for inter-MSA migration. The first takeaway is that the rise in WFH accounts for a sizable share of the increase in inter-MSA migration relative to 2019. On average between 2021 - 2023, actual inter-MSA migration was 14.0% higher than in 2019, while the counterfactual m_t^1 was only 7.6% higher. This implies that 46% of the increase in inter-MSA migration is accounted for by the rise in WFH.

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. On average between 2021 - 2023, the higher WFH share and higher WFH migration rates together account for 59% of the increase in inter-MSA migration (versus 46% explained by the WFH share alone).

3.2 Summary

To summarize, this section established three key facts:

1. Following the Covid-19 outbreak in 2020, long-distance migration rates increased relative to 2015-2019.

2. Throughout 2015-2023, WFH workers had substantially higher rates of long-distance migration, even after controlling for demographic variables.

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 long-distance migration as causal? Second, if WFH does increase long-instance migration, what are the aggregate and spatial implications of the post-Covid rise in WFH?

4 The Impact of Switching to WFH on Long-Distance Migration

4.1 Individual-Level Changes in WFH and Long-Distance Migration

Because the ACS is not a panel dataset, we cannot observe whether switching from commuting to WFH is associated with higher migration rates at the individual level. Fortunately, the RPS does contain this information.

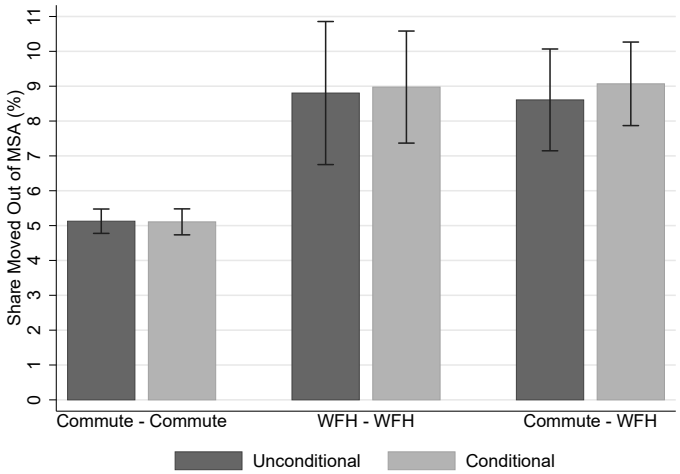
To see whether switching to WFH is associated with higher migration, we first restrict attention to respondents in the RPS who report working both in February 2020 — just before the Covid-19 outbreak — and in the survey week in 2022 or 2023. We partition this sample of individuals into four commuting 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:

$$m_i = \beta_{CC} cc_i + \beta_{WW} ww_i + \beta_{CW} cw_i + \beta_{WC} wc_i + \gamma X_i + \epsilon_i \tag{5}$$

The left-hand side variable is a dummy variable that is one if the individual moved MSAs 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 β_{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 on WFH groups are comparable to the regression without controls. The whiskers indicate 95% confidence intervals.

Figure 4: Long-Distance Migration and Individual-Level Changes in Work from Home



Source: Real-Time Population Survey (RPS). Bars reflect the share (%) of the population who moved MSAs 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.

Figure 4 shows an inter-MSA migration rate of 5.1% for workers who commuted both before and after Covid, compared with 8.8% for workers who WFH both before and after Covid and 8.6% of commuters who switched to WFH. Importantly, including the additional controls in X has a minimal effect on these estimates. We conclude that commuters who switched to WFH did indeed migrate at higher rates compared with observationally similar commuters who did not switch to WFH.

4.2 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 migrate, and (ii) workers who were about to migrate were more likely to request and receive permission to WFH after 2019. 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 and workers who switched to WFH since Covid-19 migrated at similar rates as pre-pandemic WFH workers. 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 are plausibly 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*

Importantly, (Q2) could be correlated with an individual worker's idiosyncratic desire to move: for example, if a worker who plans to move requests special permission to WFH. However, we would not expect a new WFH policy that affects the individual and their coworkers to be strongly correlated with idiosyncratic desires to move.

We analyze the relationship between WFH transitions, employer policies, and inter-MSA 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 MSAs since February 2020. Our independent variable of interest is a dummy variable, cw_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). The first set of regressions consists of linear probability models of inter-MSA migration on WFH estimated by OLS:

$$m_i = \beta_0 + \beta_{CW} cw_i + \gamma X_i + \epsilon_i \tag{6}$$

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 0.0334 to 0.0418, indicating that switching to WFH increases the predicted probability of moving MSAs by 3.3 to 4.2 percentage points.

Table 1: Switching to WFH and the Probability of A Long-Distance Move

	Probability of an Inter-MSA Move							
	OLS				2SLS			
WFH Switch	0.0372***	0.0418***	0.0334***	0.0359***	0.0910***	0.0927***	0.0721***	0.0705**
	(0.0091)	(0.0094)	(0.0106)	(0.0109)	(0.0243)	(0.0281)	(0.0274)	(0.0336)
Controls		✓		✓		✓		✓
Sample Weights			✓	✓			✓	✓
Effective F								
Critical Value								
N	10824	10639	10824	10639	10824	10639	10824	10639
	First-Stage Parameters							
WFH-Capable Job					0.0993***	0.0933***	0.1004***	0.0918***
					(0.0065)	(0.0065)	(0.0086)	(0.0084)
New Emp. Policy					0.1193***	0.1043***	0.1376***	0.1166***
					(0.0072)	(0.0071)	(0.0099)	(0.0097)

Source: Real-Time Population Survey, ages 18-64. $*/**/***$ denote significance at the 10, 5 and 1 percent levels, respectively. The sample is working age adults (18-64) employed in February 2020 and in the survey reference week who did not change employers since February 2020. See text for details.

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 are strong predictors of switching to WFH. In the second-stage regressions, switching to WFH continues to positively predict inter-MSA migration. Relative to our OLS estimates, the estimated coefficient is larger, ranging from 0.0705 to 0.0927. The coefficient is significant at the 1% level except for the specification with controls and sample weights, which is signficant at the 5% level.

To summarize, we find 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 long-distance 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.

4.3 Long-Distance Moves, Employer Changes, and Work from Home

A simple explanation for why WFH increases migration is that it reduces the benefit of living near a workplace. If this explanation is correct, then we should observe that WFH workers are (i) more likely to migrate conditional on not changing employers, and (ii) less likely to change employers conditional on migrating. We now test these predictions within the RPS. (The ACS does not observe employer changes.)

Our test is based on two regressions:

$$m_i = \beta^m_{WW} ww_i + \beta^m_{CW} cw_i + \gamma^m X_i + \epsilon_i \tag{7}$$

$$e_i = \beta^e_{WW} ww_i + \beta^e_{CW} cw_i + \gamma^e X_i + \epsilon_i \tag{8}$$

Table 2: Work from Home, Long-Distance Migration and Employer Changes

	Moved MSA c/o Same Employer		Changed Employer c/o Moved MSA	
WFH-WFH	0.046***	0.042***	−0.267***	−0.177***
	(0.007)	(0.007)	(0.059)	(0.062)
Commute-WFH	0.029***	0.030***	0.007	0.061
	(0.006)	(0.006)	(0.046)	(0.046)
Constant	0.031***	0.033***	0.561***	0.539***
	(0.002)	(0.002)	(0.018)	(0.019)
Individual Controls		✓		✓
R^2-adj	0.00	0.01	0.02	0.11
N	12888	12632	997	981

Source: Real-Time Population Survey, ages 18-64. $*/**/***$ denote significance at the 10, 5 and 1 percent levels, respectively. The first two columns report estimates from a linear probability model of inter-MSA migration since February 2020, among workers who remained with their same employer between February 2020 and the survey reference week. The second two columns report estimates from a linear probability model of employer changes between February 2020 and the survey reference week among workers who moved MSAs (bottom panel). The sample is working age adults (18-64) employed in February 2020 and in the survey reference week. See text for details.

The dependent variable of equation (7) is a dummy variable that is one if the individual moved MSAs between February 2020 and their interview in 2022-2023. We run regression (7) on the sample of RPS workers who did not change employers since February 2020. On the right-hand side, ww_i is a dummy variable that is one if i WFH both in February 2020 and in the reference week; cw_i is a dummy variable that is one if i commuted in February 2020 but WFH in the reference week. The coefficients β^m_{WW} and β^m_{CW} describe the extent to which WFH workers are more or less likely to migrate conditional on not changing employers. Equation (7) also includes 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.

The first two columns of Table 2 display the estimates from (7) with and without the controls in X. The estimates show that WFH positively predicts 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 4.6 percentage points more likely to move MSAs compared with commuters. When individual controls are included this gap decreases slightly to a 4.2 percentage point difference. The difference is significant at the 1% level and represents an increase of 148% 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.

Equation (8) investigates whether workers who move MSAs are less likely to change employers if they WFH. The dependent variable of equation (8) is a dummy variable that is one

if the individual changed employers since February 2020. We run regression (8) on the sample of individuals who moved MSAs since February 2020. The right-hand side of (8) is identical to that of (7).

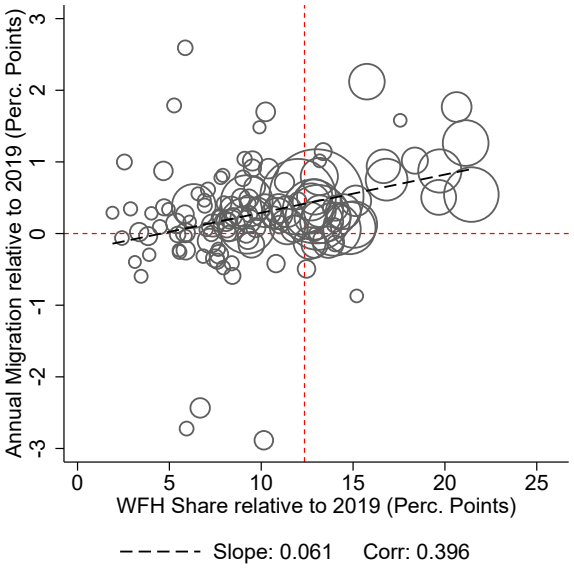
The second two columns of Table 2 show that workers who WFH both pre- and post-pandemic (WFH-WFH) were less likely to change employers conditional on moving MSAs. Among workers who moved MSAs since February 2020, WFH-WFH workers are 26.7 percentage points less likely to change employers compared with commuters. When individual controls are included this difference decreases to 17.7 percentage points. This difference is significant at the 1% level and represents a decrease of 33% 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 MSAs, 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. For example, conditional on not moving MSAs, 36% of workers who switched to WFH changed employers compared to 25% of commuters. For this reason, the coefficient on WFH-WFH is more relevant for our analysis.

4.4 Taking Stock

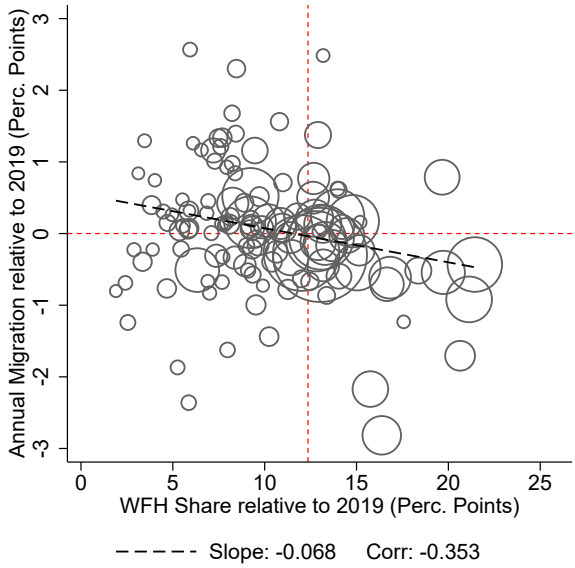
This section found that (i) access to WFH increases a worker's propensity to migrate long distances, (ii) WFH workers are more likely to migrate even conditional on not changing employers and (iii) WFH workers are less likely to change employers conditional on migrating. We view these results as consistent 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 long-distance migration; e.g., Amior (2024), Kaplan and Schulhofer-Wohl (2017), and Molloy et al. (2017). For workers who face geographically-heterogeneous work opportunities, their migration decisions will be more influenced by labor market factors than non-work amenities. Alternatively, for workers who face geographically-homogenous work opportunities, their migration decisions will be more influenced by non-work amenities. From this perspective, our results suggest that (full-time) WFH can be viewed as an extreme decrease in the geographic specificity of work opportunities, which we would expect to decrease the frequency of job-related migration but increase the frequency of amenity-related migration.

Figure 5: Geographic Variation in Work from Home and Long-Distance Migration

(a) WFH and Out-Migration



(b) WFH and Net-Migration



Notes: American Community Survey (ACS). Left Panel: Circles plot a MSA's average 2021-2023 WFH share against its average 2021-2023 out-migration rate relative to 2019. Right Panel: Circles plot a MSA's average 2021-2023 WFH share against its average 2021-2023 net-migration rate relative to 2019. Net-migration for MSA s in year t is the difference between the in-migration rate and out-migration rate. The WFH share of MSA s in year t is the share of individuals living in s in t who WFH in year t. Circle areas are proportional to MSA population. Dashed black lines are estimated using OLS. We exclude MSAs whose 2019 population is below 200,000.

5 A Spatial Equilibrium Model of WFH and Migration

An increase in the WFH share may lead to geographic reallocation of workers, for two reasons. First, if in their residential choices WFH workers put relatively less weight on local wages and more weight on non-wage factors such as local amenities or rental prices, then WFH workers may systematically locate in different places compared with commuters. Second, the increase in WFH was not evenly distributed across geographic locations. For example, 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 first establish empirically that geographic variation in WFH is highly correlated with local rates of out-migration and net-migration. We then analyze the implications of these findings in a spatial equilibrium model of WFH and migration.

5.1 Geographic Variation in Work from Home and Migration

Figure B.14c plots a MSA's average leave rate in 2021-2023 against its average WFH share in 2021-2023 using ACS data. The WFH share for a MSA 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 MSA 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 MSA $r \neq s$ in year t. Both of these variables are expressed as percentage point deviations from their 2019 value. The figure excludes MSAs with less than 200,000 residents as of 2019 because estimates from these MSAs are very noisy.

Figure B.14c reveals a positive correlation of 0.396, indicating that MSAs with larger increases in WFH tended to experience larger leave rates. In a linear regression, the point estimate is 0.061, implying that a 10-percentage point increase in a MSA's WFH share is associated with an increase in the leave rate of 0.61 percentage points.

An important follow-up question is whether greater out-migration in high-WFH MSAs led to net population losses, or whether these MSAs simultaneously experienced higher rates of in-migration. For example, an exodus of WFH workers could lower local rental prices or raise local wages, attracting migrants from other MSAs.

Figure 5b plots a MSA's net migration rate in 2021-2023 against its average WFH share in 2021-2023 (again, both variables are relative to the MSA's 2019 value). An MSA's net migration rate is the difference between its enter rate and leave rate. To construct the enter rate for a MSA s in year t, we start from the sample of individuals who lived in s in t. The enter rate for MSA s in year t is the share of individuals who lived in s in t who lived in a different MSA $r \neq s$ in $t-1$.

Figure 5b reveals a negative correlation of 0.353, indicating that MSAs with larger increases in WFH tended to experience lower net migration rates. In a linear regression, the point estimate is -0.068, implying that a 10-percentage point increase in a MSA's WFH share is associated with an increase in the leave rate of 0.68 percentage points. The magnitude of this coefficient is very similar to the estimated coefficient for the leave rate, implying that in high-WFH MSAs higher out-migration was not offset by higher in-migration.

5.2 Model Environment

This section develops a spatial equilibrium model in which an exogenous share of workers can WFH and live anywhere, while others must reside in the same location as their workplace. We calibrate the model to match pre-COVID data on migration rates for commuters and remote workers, as well as the aggregate share of remote workers. We then consider an exogenous shock

to the share of workers with a WFH choice, replicating the increase in WFH documented in Figure 3a. The model matches the post-COVID increase in migration, along with the observed changes in population and rents. We use the model to study the long-run consequences of a permanent increase in WFH on these variables and welfare.

The economy is populated by a unit mass of infinitely-lived workers, each assigned an exogenously given occupation, $o \in \{1, 2\}$. Workers in occupation 2 are "remote-capable", representing those in high work-from-home capacity occupations, such as technology or finance. Remote-capable workers choose their job type, $\tau \in \{n, r\}$ where n denotes commuting and r denotes remote work. In contrast, workers in occupation 1 are not remote-capable and are constrained to always be commuters ($\tau = n$).

Workers choose to live in one of G locations, denoted by $g \in \{1, ..., G\}$. Each worker provides one unit of labor and consumes a freely-traded final good and housing. Commuters must live and work in the same city, with their wage determined in their local labor market. In contrast, remote workers are employed in a national labor market and earn the same wage regardless of where they live.

Workers incur a migration cost denominated in units of utility, $u_{g_0,g}$, when relocating across cities. Additionally, they face a job-switching cost, denominated in terms of lost wages, which serves as a reduced-form way of introducing job search frictions. This cost applies when transitioning between remote work and commuting or when a commuter moves to a different city.

In each city, a representative firm employs the local commuters, while a national representative firm employs the remote workers. A developer in each city invests in housing and rents to workers.

5.3 Worker Problem

A worker's state variables consist of their job-type, $\tau = \{n, r\}$ and their city, g, in both the current and previous period. For ease of notation, let $x_t = \{\tau_t, g_t\}$ refer to their state variables in period t.

A worker of occupation $o \in \{1, 2\}$ who begins with state x_{t-1}, derives the following value from living in city g_t with commuting status τ_t:

$$V_t^o(x_{t-1}, x_t) = \max_{c,h} B(x_t) \left(\frac{c}{\beta}\right)^{\beta} \left(\frac{h}{1-\beta}\right)^{1-\beta} + \delta \mathcal{V}_{t+1}^o(x_t) \tag{9}$$

subject to the budget constraint

$$w_t(x_t)(1-\lambda_w(x_t)) - m^c(x_{t-1},x_t) = c_t + r_{g,t}h_t$$

where δ is the discount rate, $r_{g,t}$ is the rental price of housing in city g, $\lambda(x_t)$ is the income tax rate, $m^c(x_{t-1},x_t)$ is a migration cost that depends on the change in the workers state variables, $B(x_t)$ is the amenity associated with state x_t, and $\mathcal{V}^o_{t+1}(x_t)$ is the continuation value of the job type–location pair (τ_t, g_t), which will be determined below. The worker chooses their consumption of the final good, c, the price of which is normalized to 1, and the amount of housing to rent at price r_g to maximize their within-period utility.

Though the workers' problem is written the same, there are three key differences between occupation-1 and occupation-2 workers. These differences are in migration costs $m^c(x_{t-1},x_t)$, amenities $B(x_t)$, and wages $w(x_t)$. First, the migration cost is given by,

$$m^c(x_{t-1},x_t) = \begin{cases} \mu^r r_{g,t} + \underbrace{\mu^w(w_{t-1}(x_{t-1}) + w_t(x_t))}_{\text{lost wages}}, & \text{if } (\tau_{t-1}\neq\tau_t)|(\tau_t = n \;\&\; g_{t-1}\neq g_t) \\ \mu^r r_{g,t}, & \text{otherwise.} \end{cases}$$

All workers pay a fraction, μ^r of the annual rent upfront as a migration cost, making moves to high-rent cities more expensive. In addition, there is an extra migration cost for workers who switch jobs. These are either commuters who move across cities ($\tau_t = n \& g_{t-1}\neq g_t$) or workers who between commuting and remote work ($\tau_{t-1}\neq\tau_t$). This extra job switch cost is a fraction m^c of their current- and last-period wage, representing the wasted time it takes workers to find a new job. This implies that commuters who move across cities and workers switching between remote and commuting jobs must change employers and pay the job search cost. In contrast, remote workers can freely relocate across cities without needing to switch employers. This assumption is consistent with our findings in Section 4.3, which shows that those who were WFH pre-COVID and post-COVID are 21 percentage points less likely to switch employers conditional on moving than commuters or newly remote workers.

The second difference between occupation-1 and occupation-2 workers is in the amenity. The amenity the worker enjoys depends on their city of residence, home location, and commuting status. Specifically, we assume

$$B(x_t) = \begin{cases} \frac{B_g}{e^{\kappa m_g}}, & \text{if } \tau = n \\ B_g B^r, & \text{if } \tau = r \end{cases}$$

where B_g is the exogenous amenity of city g. The amenity value of living in city g is further scaled up (or down, depending on the calibration) if the worker is a remote ($\tau = r$), reflecting

that working remotely itself provides an intrinsic amenity value. The amenity for commuters is scaled down by the commuting cost of city g which depends on the city's average commuting time m_g and the κ is the elasticity of the disutility of commuting with respect to minutes commuting. The amenities are multiplicative rather than additive, implying that the relative impact of remote work and commuting costs on amenities scales proportionally with the city's baseline amenity.

Finally, the third difference between the worker types is in their wage, which depends on their city and job type, given by:

$$w(x_t) = \begin{cases} w^r, & \text{if } \tau_t = r \\ w_g, & \text{if } \tau_t = n. \end{cases}$$

Remote workers ($\tau_t = r$) receive a wage w^r set in the national market for remote workers, independent of their city of residence. In contrast, commuters ($\tau_t = n$) earn a wage w_g, which is determined by local labor market conditions.

Migration and WFH Decision. Workers choose their next-period city g_{t+1} and commuting status τ_{t+1} to maximize their value net of the migration cost

$$\mathcal{V}^o_{t+1}(x_t) = \mathbb{E}_\epsilon \left[\max_{x_{t+1}} \left[V^o_{t+1}(x_t, x_{t+1}) - \mu^g \mathcal{I}[g_t \neq g_{t+1}] + \theta \epsilon_x \right] \right]$$

where ϵ_x is a vector of idiosyncratic preference shocks that are Gumbel distributed with mean 0, $\epsilon_x \sim exp(-exp(-\epsilon_x - \bar{\gamma}))$ where $\bar{\gamma}$ is the Euler constant.[11] θ scales the variance of the idiosyncratic preference shocks. μ^g is the migration cost paid in units of utility. Workers pay this utility cost when moving across cities regardless of whether they are commuters or remote workers. $\mathcal{V}^o_{t+1}(x_t)$ gives the expected value of commuting–location pair (τ_t, g_t) before the worker draws their idiosyncratic preference shocks for the next period. Given the distributional assumption of the shocks, the expected value can be written

$$\mathcal{V}^o_{t+1}(x_t) = \theta ln \left(\sum_{x_{t+1}} \exp \left(\frac{1}{\theta} V^o_{t+1}(x_t, x_{t+1}) - \frac{1}{\theta} \mu^g \mathcal{I}[g_t \neq g_{t+1}] \right) \right), \tag{10}$$

and the probability of going from x_t to x_{t+1} is

$$\pi^o_t(x_t, x_{t+1}) = \frac{\exp\left(V^o_{t+1}(x_t, x_{t+1}) - \mu^g \mathcal{I}[g_t \neq g_{t+1}] \right)^{\frac{1}{\theta}}}{\sum_{x'_{t+1}} \exp\left(V^o_{t+1}(x_t, x'_{t+1}) - \mu^g \mathcal{I}[g_t \neq g'_{t+1}] \right)^{\frac{1}{\theta}}}. \tag{11}$$

[11] This structure means that workers draw an idiosyncratic preference for a location-commuting pair. They might like being a remote worker in NYC but dislike being a remote worker in St. Louis.

Again, those in occupation one, $o = 1$, are not remote-capable and are constrained to have $\tau = n$. The equations for their transition probabilities and expected value are the same, with their state variable x_t not dependent on τ.

Population. In time $t+1$, the population of state (τ, g) is the number of workers who move there from all other states

$$L^o_{t+1}(x_{t+1}) = \sum_{x_t} \pi^o_t(x_t, x_{t+1}) L^o_t(x_t), \tag{12}$$

where $L^o_t(x_t)$ is the population of occupation o in state (τ_t, g_t) at time t and π^o_t is the transition rate given by Equation (11).

The population of commuters and remote workers in each city in time t is given by

$$L_t(n, g) = L^1_t(n, g) + L^2_t(n, g) \quad \text{and} \quad L_t(r, g) = L^2_t(r, g). \tag{13}$$

Note that the population of commuters comprises both occupation-1 workers who are always commuters and occupation-2 workers who have chosen to commute in time t.

5.4 Closing the Model

Production. A representative firm in each location hires local commuters and produces with productivity A_g, and a national work-from-home firm produces with productivity A^r. They produce a non-differentiated final good that is freely traded. The price of the final good is normalized to 1. The production function for both firm types is linear in labor,

$$y_g = A_g L_t(n, g) \quad \text{and} \quad y^r = A^r L_t(r)$$

so that the wage of commuters in location g and remote workers is given by

$$w(n, g) = A_g \quad \text{and} \quad w(r, g) = A^r. \tag{14}$$

Housing. Housing is supplied by a representative landlord in each city who turns the final good into housing with the production function $\bar{\zeta}_g I_{gt}^{\zeta_g}$. The landlord solves a dynamic housing accumulation problem to maximize their discounted stream of profits from renting housing to commuters:

$$\max_{\{I_{g,s}\}_{s=t}^{\infty}} \sum_{s=t}^{\infty} \delta^s \left(r_{sg} H_{sg} - I_{sg} \right)$$

such that

$$H_{sg} = (1 - \delta^h)H_{s-1,g} + \bar{\zeta}_g I_{gs}^{\zeta_g} \ \ \forall s$$

where I_g is the investment in housing in units of the final good and δ^h is the depreciation rate for housing. In steady state, the housing supply is

$$H_{g,t} = \frac{\bar{\zeta}_g}{\delta^h} \left(\frac{\zeta_g \bar{\zeta}_g r_{g,t}}{1 - (1 - \delta^h)\delta} \right)^{\frac{\zeta_g}{1-\zeta_g}} \tag{15}$$

where $\eta_g \equiv \frac{\zeta_g}{1-\zeta_g}$ is the housing supply elasticity in city g and $\bar{\zeta}_g$ is a supply shifter.

General Equilibrium. Given amenities $\{B_g\}_{g \in G}$ and B^r, productivities, $\{A_g\}_{g \in G}$ and A^r, parameters of the housing supply equation, $\{\bar{\zeta}_g, \zeta_g\}_{g \in G}$, and δ^h, parameters of the migration cost, $\{\mu^r, \mu^w, \mu^g\}$, the housing share of consumption, $1 - \beta$, the scale of the variance of the preference shocks, θ, the mass of workers that are remote-capable, L^2; a steady-state equilibrium is a set of wages for commuters, $\{w_g\}_{g \in G}$, a wage for remote workers, w^r, rents, $\{r_g\}_{g \in G}$, and the population of remote workers and commuters in each city, $\{L(n, g), L(r, g)\}_{g \in G}$ such that:

1. Firms optimize, or the wage is given by Eq. (14)
2. Landlords optimize, and housing supply is given by Eq. (15)
3. Households optimize, choosing consumption and housing to maximize Eq. (9) and their city and commuting status according to Eq. (11)
4. Population follows the law of motion given by Eq. (12) and the population is unchanging and given by Eq. (13)
5. The housing and commuter labor markets clear in each city; the national remote-worker market clear; and the national final-goods market clears.

Discussion. Before discussing the calibration of the model and the shock to the share of remote-capable workers, we briefly discuss a key feature of the model. Remote-capable workers make a joint decision about their work type and location. These decisions are made taking into account the future value of being in that work type and location pair and the transition costs they would face if they wish to switch their work type or location in the future. A remote worker can choose to live in a low-income and low-rent city while earning the higher remote wage. However, they must also consider the likelihood that they will switch to being a commuter in the future and the possibility they will need to undertake a costly move should they wish to access the commuter wage in the high-income city. The job-switching cost and

the migration cost add persistence to the remote/commute choice such that a worker who is remote today will expect to be remote in the near future.

5.5 Model Calibration

We calibrate the initial steady state of the model to match data on population, rents, migration rates, and the aggregate WFH share pre-COVID. We use data from the 2019 ACS and bin cities into 5 groups based on their average wage.

Our calibration proceeds in two steps. First, we set a number of parameters externally using common values from the literature. Panel A of Table 3 summarizes these parameters and the source for their value. These include the discount factor, δ, the housing share of consumption, $1-\beta$, and the housing supply elasticity ζ_g, which we set to the average from Saiz (2010). We set θ, which scales the Gumbel shocks, to match the estimates of the migration elasticity from Caliendo et al. (2019). We set $\mu^r = \frac{1}{12}$ to be one-twelfth of the annual rent to represent a one month upfront security deposit. We start with 8% of the population able to work remotely, based on the share of remote-capable workers in the RPS pre-COVID.

Next, we internally calibrate the remaining parameters to match the data. While all the parameters are jointly calibrated, Panel B shows the parameters and the moments we use to calibrate them. Figure C.21 in Appendix C.1 shows that the model can perfectly match the data on the relative population, rents, and wages across cities. The national work-from-home wage is 1.18, which is just under the commuter wage in the largest city but above the commuter wage in the smaller cities. The amenity value of work from home is 1.245, suggesting that WFH provides substantial intrinsic value, scaling up the workers' utility by 25%.

Migration Rate for Remote Workers. In the model, the migration rate is higher for remote workers than for commuters for two reasons. The first reason is mechanical and due to the job switching cost. We assume that commuters must find a new job when they move across locations, while remote workers can move across locations while keeping the same job. Thus, the job switching cost adds to the migration cost paid by commuters.

The second reason for the gap in migration rates is due to differences in the value of living in each city. Remote-capable workers and commuters are facing a different set of options. Even for two workers who are currently commuters, a remote-capable worker has the option of switching to a remote job, which alters their expected pay-off from living in a given city. Given the different pay-offs, they might be more or less likely to move in response to a new draw of their idiosyncratic preference shock. Whether this second-factor increases or decreases the migration rate of remote workers relative to commuters depends on the model's calibration.

Table 3: Model Calibration

Panel A: Externally Set Parameters

Parameter	Description	Source	Value
δ	Discount factor	—	0.96
β	Housing share of consumption	Monte et al., 2018	0.60
η	Housing supply elasticity	Saiz, 2010	1.78
θ	Shape parameter of Gumbel	Caliendo et al., 2019	2.05
L_1	Share remote-capable	RPS data	0.080
δ_h	Housing depreciation	Piazzesi and Schneider, 2016	0.02
κ	Commuting time elasticity	Delventhal and Parkhomenko, 2023	0.009
μ^r	Migration cost in rent	1st month rent deposit	0.08
λ_w	Income tax rate	—	0.10

Panel B: Internally Calibrated

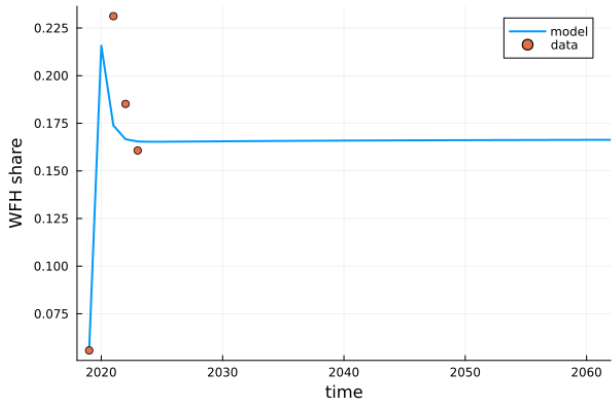
Parameter	Description	Value	Moment	Data	Model
B^r	WFH-amenity	1.249	WFH-share	0.056	0.056
m^w	Extra migration cost	0.146	Migration rate, commuters	0.027	0.027
μ	Utility cost moving	9.160	Migration rate, WFH	0.040	0.040
w^r	Remote wage	1.184	WFH wage	1.184	1.184
B_g	Amenities	–	Population	Figure C.21	
$\bar{\zeta}_g$	Housing shifter	–	Rents	Figure C.21	
A_g	Productivity commuters	–	Wages	Figure C.21	

In our current calibration, this effect widens the gap in migration rates. The intuition is that remote-capable workers are less drawn to a specific city than commuters, making them more responsive to idiosyncratic shocks when deciding where to live. In contrast, commuters derive a much higher pay-off from living in the big city due to its high local wages. They need a large idiosyncratic preference shock to convince them to leave the big city, resulting in lower migration rates among commuters.

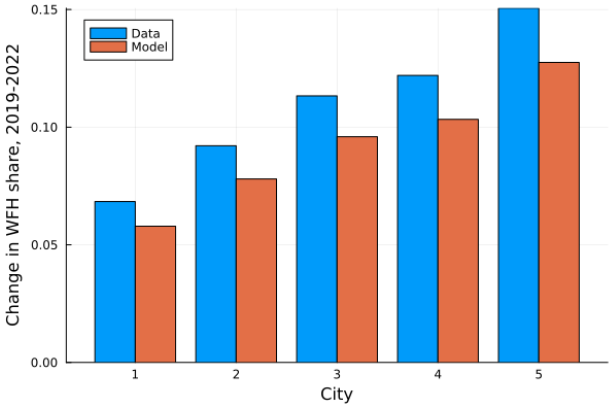
We evaluate how much of the gap in the rate of interstate migration comes from each of these two channels. To do this, we set the job-switching cost to zero and re-solve the model leaving all other calibrated parameters unchanged. The share of the gap that remains is 33.9%. Thus, we attribute 66.1% of the gap in the migration rate between remote workers and commuters to the job-switching cost, while 33.9% is attributed to the fact that they face different payoffs to living in each city.

Figure 6: WFH Shock

(a) WFH Share



(b) Change in WFH share by city



5.6 Shock to WFH-Share

We now use our calibrated model to consider a shock to the share of the population that is remote-capable. We exogenously switch a number of occupation 1 workers to occupation 2, tripling the number of remote-capable workers. Moreover, to mimic the pandemic, we automatically switch them into work-from-home jobs without them having to pay the job-switching cost (specifically, we set $\tau_{t-1} = \tau_t = r$). The incidence of the shock was not even across cities. We distribute the shock geographically to match the larger increase in the WFH share between 2019 and 2022 in big cities versus small cities.

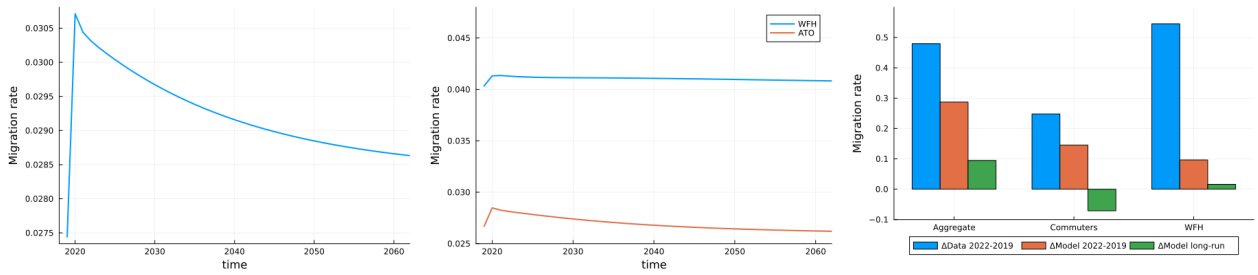
The share of the population that is WFH is plotted in Figure 6. The WFH share spikes to 21.57 right after the shock before settling to it's long-run rate of 16.66. Panel (b) shows the increase in the WFH share across cities in the model versus the data. We do not match (or target) the level of the increase in the WFH-share in 2021 and 2022. Tripling the share of remote-capable workers gives us a long-run wfh rate of about 16%. Note that we only count workers as WFH in these figures if they are choosing $\tau = r$. So while 16% of workers are remote in the long-run, 24% of workers are remote-capable.

Migration Rate. Next we look at how the migration rate responds to the WFH-shock. Panel (a) of Figure 7 shows the response of the aggregate migration rate. The aggregate migration rate increases from its pre-COVID rate of 2.74% to 3.07% immediately following the WFH shock, an increase of 0.33pps. The model predicts that much of this spike is temporary. In the long-run, the aggregate migration remains 0.09 higher than the pre-shock steady state.

Panel (b) shows the migration rate for remote workers and commuters separately. When calculating the migration rate by WFH-status in the data, we cannot see whether a worker

Figure 7: Response of Migration Rate to WFH-Shock

(a) Aggregate (b) By WFH Status (c) Model vs. Data



Notes: Panel A shows the aggregate migration rate in the model after the WFH shock. Panel B shows the migration rate for WFH workers, as defined by their current WFH status, and commuters.

migrating across cities is also switching their job type. We treat workers the same way in the model, classifying them only based on their current WFH status. Thus, as in the data, commuters include both always-commuters and remote-capable workers who are currently working in commuter jobs.

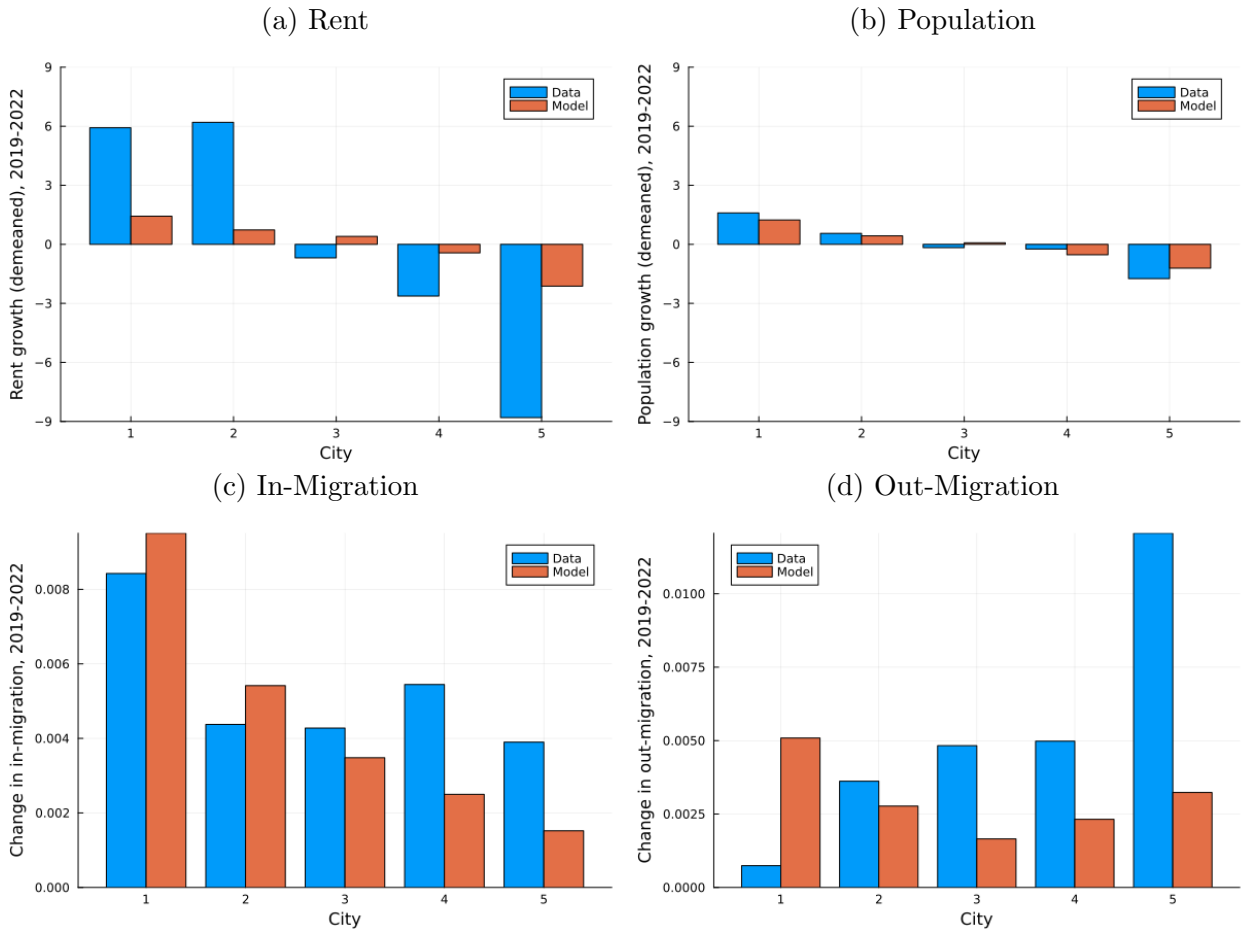
Panel (b) shows that the migration rate for remote workers and commuters is largely unchanged. The aggregate increase in migration is mostly driven by a composition effect: the share of remote workers has increased and remote workers have higher rates of migration. This is consistent with our accounting exercise in Section 3.1 which showed that approximately 50% of the increase in migration is driven by such composition effects, and only a small share of the increase can be attributed to within-type changes in migration.

Panel (c) shows how the short-run changes in the model compare to the data. In the data the aggregate migration rate increased by 0.5pps between 2019 and 2022. The WFH-shock in the model can account for about 0.33 or 66% of this increase.

Rents and Population. Figure 8 shows the growth in rents and population across cities between 2019 and 2022. In the data, rent growth is positive in all cities. Since we do not have aggregate population growth in our model, we demean the average growth rate in both the model and the data.

The model predicts the direction of both rent and population growth across cities very well. Rent and population growth are larger in the small cities than the big cities. This is because remote-capable workers can now earn the WFH wage while living in the small city with cheaper rents. The correlation coefficient between the data and the model is 0.95 for rent growth and 0.97 for population growth. Though the model matches the direction of the changes well, it under-predicts the magnitude of the changes in rent in the big city versus the small city. In the data their is a 15pp gap between rent growth in the small city (+6%) and rent growth in the big city (-9%). The model matches 3.5pps of this gap.

Figure 8: Response of Rent and Population to WFH Shock



Notes: Panel A shows the growth in rents and Panel B the growth rate in population across cities in the data in the model. Rent and population growth are demeaned so that the average across cities is zero.

Panels (c) and (d) split population growth into changes in in- and out-migration. While the model is successful in matching the changes in in-migration across cities, it is less successful in matching the changes in out-migration. Specifically, the model (counterfactually) predicts an increase in out-migration for city 1. This is driven by commuter households leaving in response to the increase in rents caused by the inflow of WFH workers.

Welfare. Next, we look at the welfare effects of the WFH shock. To evaluate the welfare effects for newly remote-capable workers, we must first address the change in the structure of their value function. With the ability to choose between two job types τ in each city, there is a mechanical increase in the value function—specifically, the expected value over preference shocks (as defined by Equation 10) increases with the number of available choices. To isolate and remove the impact of this mechanical increase, we calculate a counterfactual value function in the initial steady state for newly WFH-capable workers. This counterfactual provides them with two commuter-job options in each city, ensuring they have the same number of job choices

Table 4: Welfare Results

	Average	Always Commuters	Always Remote-Capable	Newly Remote-Capable
Baseline	3.34	0.04	−0.34	20.84

as WFH-capable workers, but assumes that they receive the wage and amenity associated with the commuter job for both types.

We consider the consumption equivalent measure of welfare, which quantifies the percentage of consumption and housing a worker would require as compensation in the initial steady state in order to be indifferent between remaining in the inital steady state and undergoing the transition. Table 4 presents the average consumption equivalent for all workers weighting everyone equally. Additionally, it breaks down the average consumption equivalents for three worker groups: those in type-1 commuter occupations before and after the WFH shock, those who were remote-capable before the pandemic, and those who transitioned from type-1 commuter roles to type-2 remote-capable roles during the WFH shock.

On average, workers would need to be compensated 3% of their initial steady-state consumption to remain indifferent between the initial steady state and the transition. This indicates significant welfare gains from the adoption of remote work. However, these gains are not evenly distributed, primarily benefiting those workers that are newly allowed to WFH.

The workers who are now remote-capable experience substantial welfare gains, with the ability to work remotely valued at 20.8% of their initial steady-state consumption and housing. Beyond the direct amenity value of WFH in our model, additional benefits stem from eliminating commuting costs and gaining access to remote work wages, particularly advantageous for workers in smaller cities with lower local market wages. Furthermore, remote workers have greater flexibility to relocate based on their idiosyncratic preferences. We further explore the sources of these welfare gains below.

The workers who were already remote-capable before the pandemic are hurt by the shock due to the higher rents in the cities where they were living. They would give up 0.34% of their consumption to avoid the transition. Similarly, commuters gain by 0.04% of their pre-shock consumption and housing as rents decline in the cities where they live.

Sources of Welfare Gains Workers who are switched to the remote capable occupation see welfare gains equivalent to a 20.8% increase in their pre-shock consumption and housing. We now discuss the main drivers of these welfare gains. Specifically, we re-calculate their consumption equivalent, turning off each of the wedges between type-1 and type-2 workers.

Table 5: Sources of Welfare Gains

	Baseline	WFH wages	WFH-Amenity	No Commuting Cost
Cons. Equiv.	20.8	19.7	7.1	3.8

The results are displayed in Table 5.

If workers had been able to earn the remote wage in the initial steady state, their consumption equivalent would fall from 20.8 to 19.7%. This indicates that only a small portion of the welfare gains (1pps) are attributed to the WFH wage. Although remote workers can earn a higher wage in smaller cities, most commuters reside in the large city where commuter wages are already higher, limiting the benefit of access to the WFH wage. Instead, the largest welfare gains stem from the direct amenity value of remote work, B^r, and the elimination of commuting costs. If initial steady-state commuters had received the WFH amenity or had not incurred commuting costs, their consumption equivalent would decrease to 7.1% and 3.8%, respectively.

A final welfare gain from remote work arises from the increased flexibility of remote workers to relocate in response to idiosyncratic preference shocks. This allows them to better match with cities and job types that align with their preferences, thereby increasing the expected value of their idiosyncratic preference shock. The expected value is given by:

$$\begin{aligned}\mathcal{M}(x_{t-1}, x_t) &= \mathbb{E}\left[\epsilon_{x_t} \mid (V(x_{t-1}, x_t') - \mu(x_{t-1}, x_t') + \theta\epsilon_{x_t'}) < (V(x_{t-1}, x_t) - \mu(x_{t-1}, x_t) + \theta\epsilon_{x_t}),\ \forall x'\right] \\ &= \theta \ln\left(\frac{1}{\pi_{t-1}(x_{t-1}, x_t)}\right).\end{aligned}$$

The match effect is inversely related to the probability of a worker transitioning from state x_{t-1} to x_t. Intuitively, when the probability of moving to a state is high, it implies that the value offered by that state, $V(x_{t-1}, x_t)$, is high. Consequently, workers require only a small draw of the idiosyncratic preference shock to justify the move. Conversely, if the value of moving to state x_t is low, it must require a high idiosyncratic preference to justify the move.

Table 6: Match Effect in Consumption Equivalents, Initial Steady-State

	Always Commuters	WFH-capable
Cons. Equiv.	0.7	3.0

Table 6 shows the average value of this match effect, converted into consumption equivalent units for occupation-1 and 2 workers. Workers that are WFH-capable, have a match effect valued at 3% of their consumption and housing, while for commuters, it is only 0.7%. This suggests that many commuters are living and working in the big city based on the local wage rather than an idiosyncratic preference for that city. Meanwhile, due to the added flexibility of

Table 7: Probability of Interstate Moves and Switches to WFH: Data vs. Model

	Data		Model	
	OLS	2SLS	OLS	2SLS
WFH Switch	0.036***	0.071**	0.019**	0.029***
	(0.011)	(0.034)	(0.009)	(0.011)

remote work, WFH-capable workers are more likely to live in a city for which they have a high idiosyncratic preference.

5.7 Regression Results

In this section, we replicate the regressions shown in Table 1 within the model. We begin by generating a simulated dataset of workers based on the model's pre-COVID steady state. Next, we simulate their paths through the transition period, during which 16% of workers experience a shock to their WFH capability.

We run a regression of the probability that workers move across cities between the initial steady state and 2 years after the shock (corresponding to 2022) on whether they switched to WFH. Not all workers who receive the shock enabling them to WFH will choose to do so. Some will continue commuting, either due to personal preferences or because certain cities offer higher wages for commuters. As in the data, we use the shock to their ability to WFH to instrument for the actual WFH switch.

The results are presented in Table 7. In the data, workers who switch to WFH are 3.6 percentage points more likely to move across MSAs versus 1.9 percentage points in the model. As in the data, when instrumenting for the WFH change using the change in their ability to WFH, the impact of WFH on migration is higher. A WFH switch increases interstate migration by 4.4 percentage points in the data versus 2.9 percentage points in the model.

In both the data and the model, the OLS results are biased downward relative to the IV estimates, suggesting that the causal effect of WFH treatment is larger than what simple correlations between WFH and migration imply. The model helps identify the source of this bias: selection effects. Workers newly treated by the WFH policy were, by definition, commuters before the pandemic, whereas those already working remotely had different pre-pandemic location choices. Because newly remote workers had previously been constrained in their location choice, their migration response to the WFH policy change is stronger, leading to a downward bias in the OLS.

6 Conclusion

This paper argues that the surge in long-distance migration in the US after 2019 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, changes in WFH are predictive of geographic variation in out-migration and net migration.

Motivated by these findings, we develop a spatial equilibrium model incorporating remote work and long-distance migration. We calibrate the model to match pre-COVID migration patterns and then triple the share of remote-capable workers to reflect post-pandemic changes. The model successfully replicates post-COVID trends in migration, population growth, and rents, allowing us to analyze the welfare gains of WFH, many of which arise from workers' increased ability to relocate based on preferences or cost of living.

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ONLINE APPENDIX

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.1.8 displays the breakdown of the sample sizes across survey months.

Table A.1.8: Sample Sizes by Survey Month in the RPS

Month	Number of Observations	Number Employed
02/2020	28586	22400
02/2022	7620	5446
06/2022	5941	4170
10/2022	2580	1749
02/2023	8407	6091
10/2023	4038	2991

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:

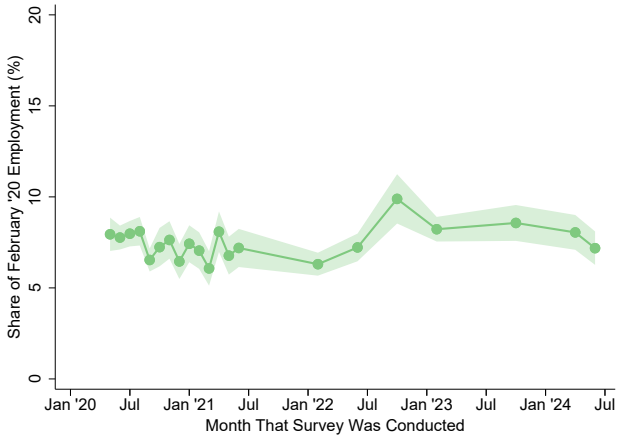
- Age
  - **Younger**: Ages 18-29
  - **Mid Age**: Ages 30-49
  - **Older**: Ages 50-64
- Race and Ethnicity
  - **Black**: Identify as Black and not Hispanic
  - **Hispanic**: Identify as Hispanic
  - **White**: Identify as White and not Hispanic
  - **NonBlackHispWhite** or **Non B/H/W**: All other 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)

FIGURE A.9: February 2020 WFH Rates by Survey Month



Notes: Real-Time Population Survey, ages 18-64, February 2020 observations. The figure plots the share of February 2020 workers who WFH full-time. The shaded region corresponds to 95% confidence intervals.

A.3 February 2020 WFH Rates Across Survey Months

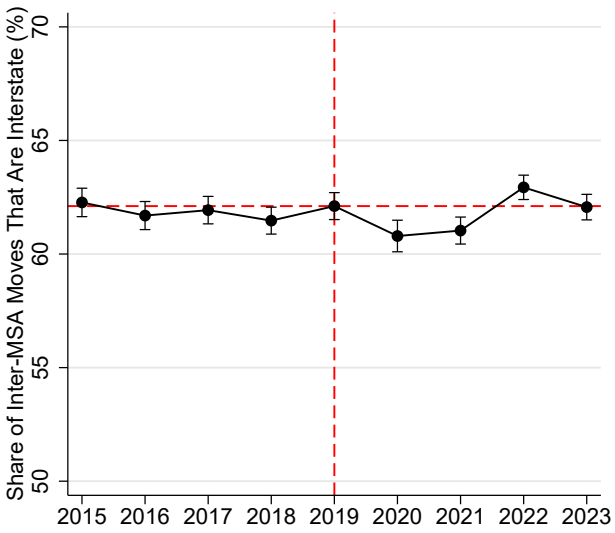
The RPS asks individuals about employment and WFH outcomes in February 2020, just prior to the COVID-19 pandemic. A potential concern is whether respondents are able to accurately answer such retrospective questions, particularly for later months in the survey. One indication of recall difficulties would 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.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 Inter-MSA versus Interstate Migration in the ACS

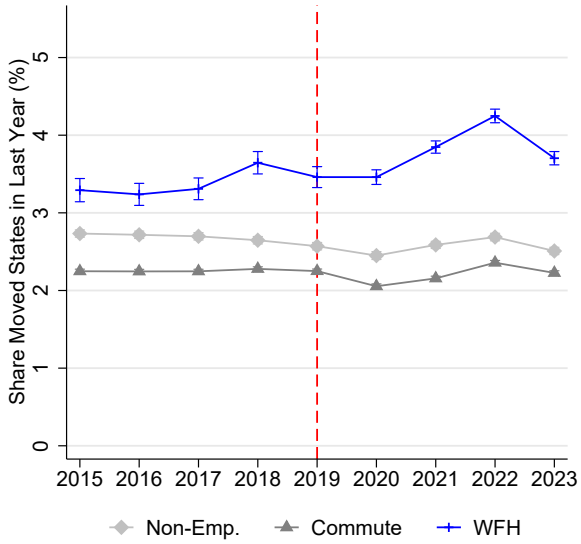
FIGURE B.10: Share of Inter-MSA Moves That Are Also Interstate



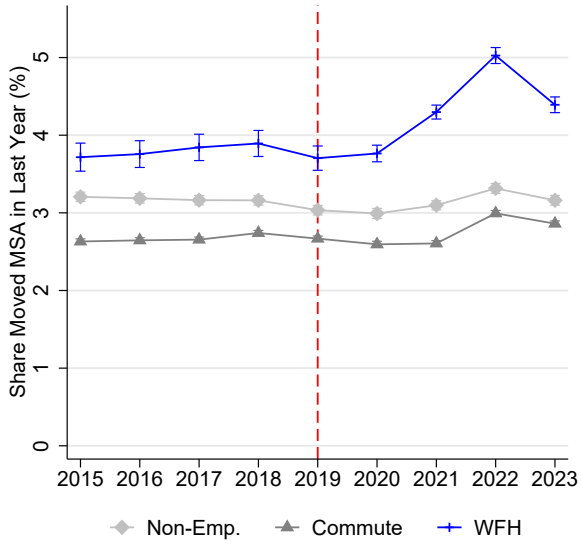
Notes: American Community Survey (ACS). The figure shows the percentage share of inter-MSA moves that are also inter-state. The sample is employed working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.

FIGURE B.11: Work from Home and Long-Distance Migration

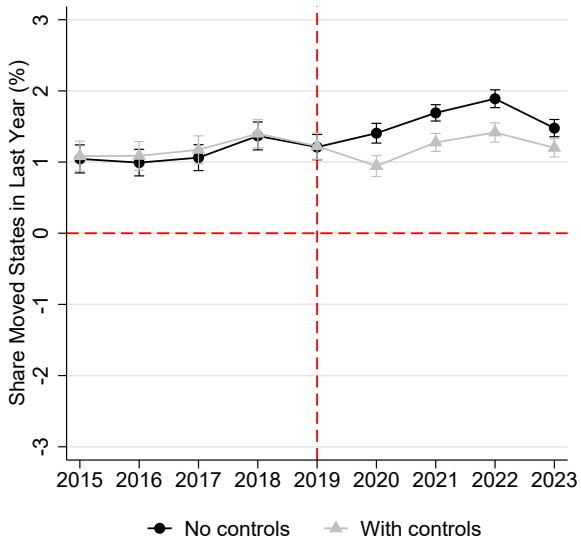
(a) Interstate Migration by Commute Status



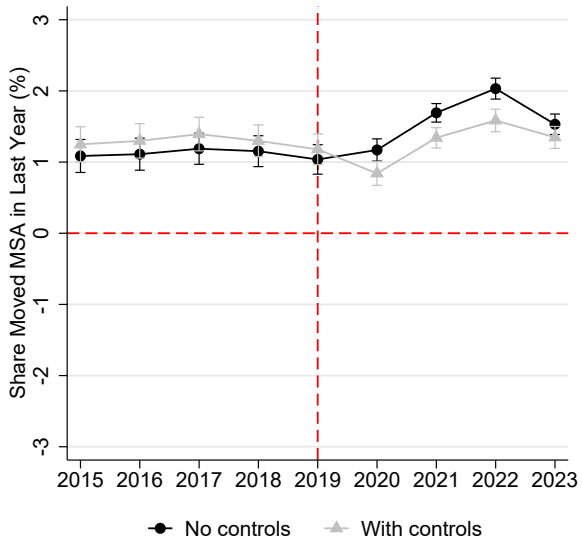
(b) Inter-MSA Migration by Commute Status



(c) Interstate Migration: WFH−Commuters



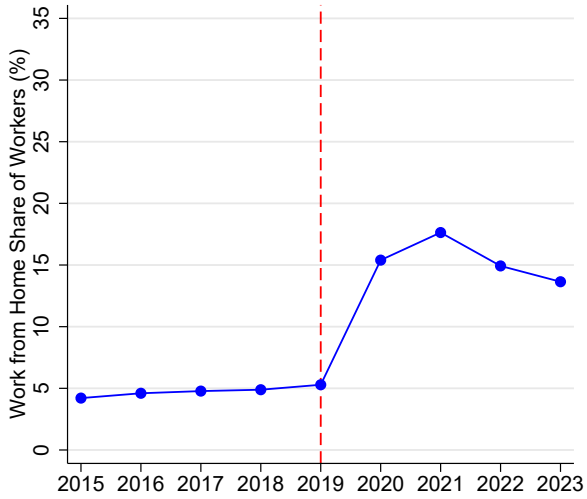
(d) Inter-MSA Migration: WFH−Commuters



Notes: American Community Survey (ACS). Left Panels: annual interstate / inter-MSA migration rates for three population groups: non-employed (light gray diamonds), commuters (dark gray triangles), and WFH workers (blue crosses). Right Panels: the black squares are the difference between WFH and Commuters from the left panel; the gray triangles are the coefficients on WFH from a linear probability regression of migration with several demographic controls using sample weights (see text for details). 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 based on heteroskedasticity-robust (Ecker-Huber-White) standard errors.

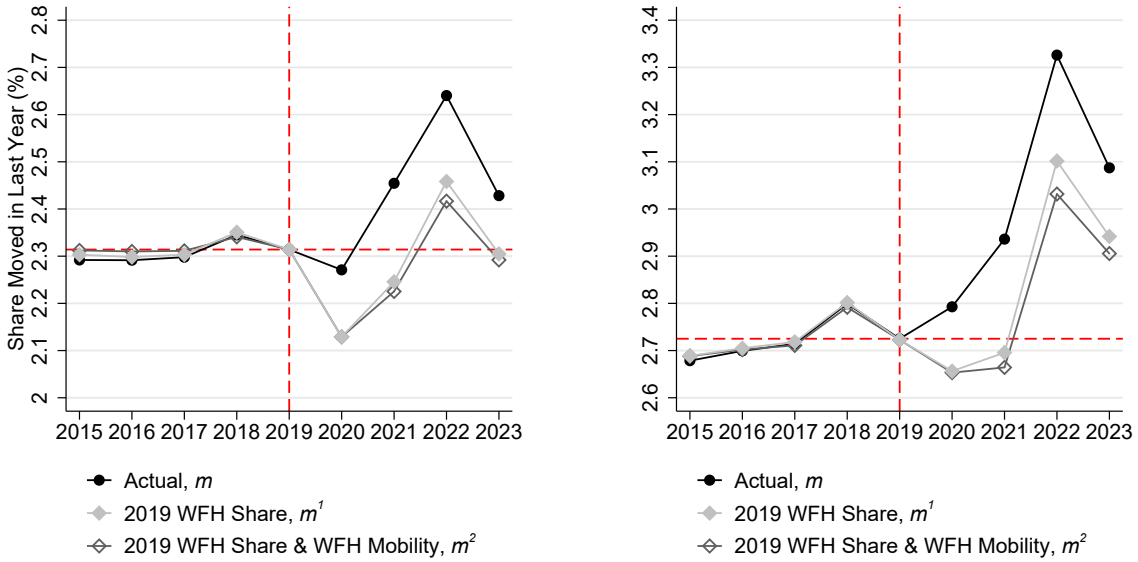
FIGURE B.12: Accounting Exercise: The Impact of Work from Home on Long-Distance Migration

(a) Share of Workers Who Work from Home



(b) Impact on Interstate Migration

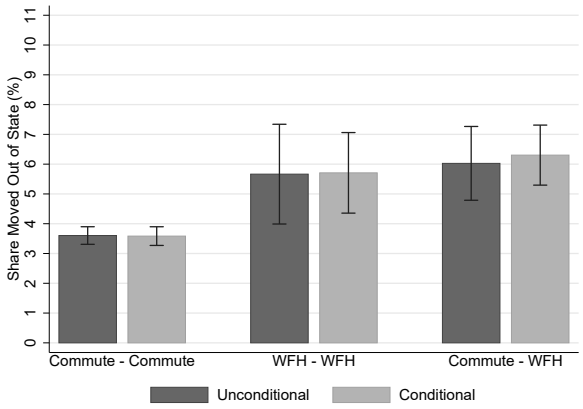
(c) Impact on Inter-MSA Migration



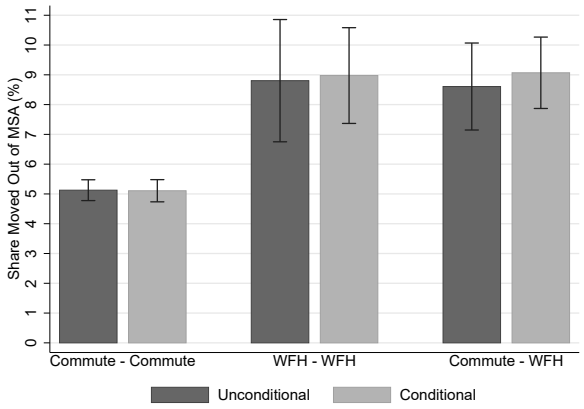
Notes: American Community Survey (ACS). Top Panel: the share of workers (%) who WFH. Bottom Panels: black circles are actual migration rates for workers in the ACS; gray diamonds are the counterfactual migration path if WFH would have remained at the 2019 share; hollow black diamonds are the counterfactual 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 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.

FIGURE B.13: Long-Distance Migration and Individual-Level Changes in Work from Home

(a) Interstate Migration



(b) Inter-MSA Migration



Source: Real-Time Population Survey (RPS). Bars reflect the share (%) of the population who migrated 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.

Table B.1.9: Switching to WFH and the Probability of A Long-Distance Move

	Probability of an Interstate Move							
	OLS				2SLS			
WFH Switch	0.0298***	0.0302***	0.0247***	0.0255***	0.0748***	0.0660***	0.0483**	0.0448*
	(0.0079)	(0.0080)	(0.0090)	(0.0092)	(0.0201)	(0.0229)	(0.0222)	(0.0260)
Controls		✓		✓		✓		✓
Sample Weights			✓	✓			✓	✓
Effective F								
Critical Value								
N	10824	10639	10824	10639	10824	10639	10824	10639
	First-Stage Parameters							
WFH-Capable Job					0.0993***	0.0933***	0.1004***	0.0918***
					(0.0065)	(0.0065)	(0.0086)	(0.0084)
New Emp. Policy					0.1193***	0.1043***	0.1376***	0.1166***
					(0.0072)	(0.0071)	(0.0099)	(0.0097)

Source: Real-Time Population Survey, ages 18-64. $*/**/***$ denote significance at the 10, 5 and 1 percent levels, respectively. The sample is working age adults (18-64) employed in February 2020 and in the survey reference week who did not change employers since February 2020. See text for details.

Table B.1.10: Work from Home, Long-Distance Migration and Employer Changes

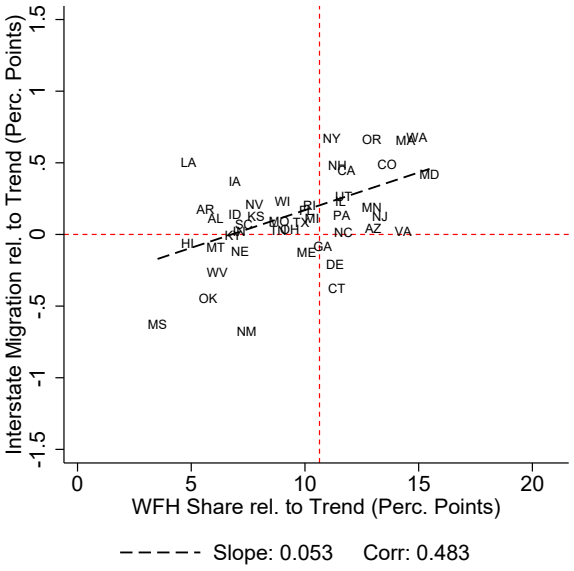
	Moved State c/o Same Employer		Changed Employer c/o Moved State	
WFH-WFH	0.024^{***}	0.022^{***}	-0.227^{***}	-0.201^{***}
	(0.006)	(0.006)	(0.073)	(0.078)
Commute-WFH	0.018^{***}	0.018^{***}	0.015	0.058
	(0.005)	(0.005)	(0.055)	(0.056)
Constant	0.021^{***}	0.022^{***}	0.581^{***}	0.583^{***}
	(0.001)	(0.001)	(0.021)	(0.023)
Individual Controls		✓		✓
R^2-adj	0.00	0.01	0.01	0.08
N	12888	12632	700	686

	Moved MSA c/o Same Employer		Changed Employer c/o Moved MSA	
WFH-WFH	0.046^{***}	0.042^{***}	-0.267^{***}	-0.177^{***}
	(0.007)	(0.007)	(0.059)	(0.062)
Commute-WFH	0.029^{***}	0.030^{***}	0.007	0.061
	(0.006)	(0.006)	(0.046)	(0.046)
Constant	0.031^{***}	0.033^{***}	0.561^{***}	0.539^{***}
	(0.002)	(0.002)	(0.018)	(0.019)
Individual Controls		✓		✓
R^2-adj	0.00	0.01	0.02	0.11
N	12888	12632	997	981

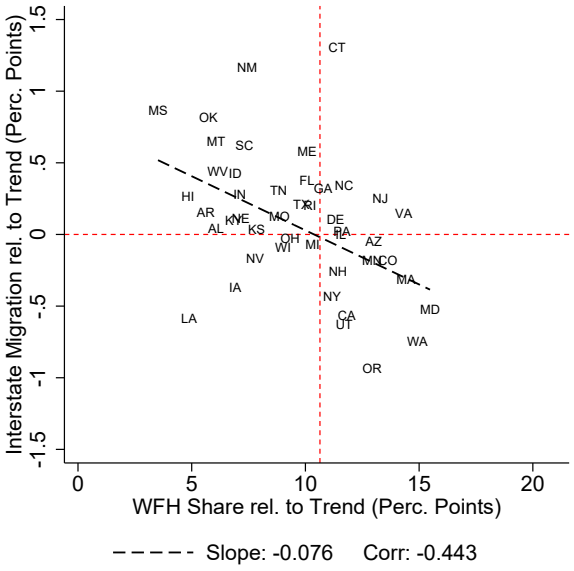
Source: Real-Time Population Survey, ages 18-64. $*/**/***$ denote significance at the 10, 5 and 1 percent levels, respectively. The first two columns report estimates from a linear probability model of migration since February 2020, among workers who remained with their same employer between February 2020 and the survey reference week. The second two columns report estimates from a linear probability model of employer changes between February 2020 and the survey reference week among workers who migrated (bottom panel). The sample is working age adults (18-64) employed in February 2020 and in the survey reference week. See text for details.

FIGURE B.14: Geographic Variation in Work from Home and Long-Distance Migration

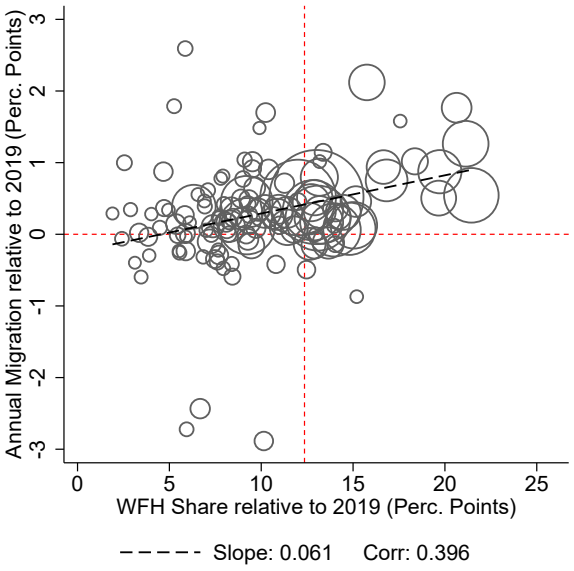
(a) State-Level Out-Migration



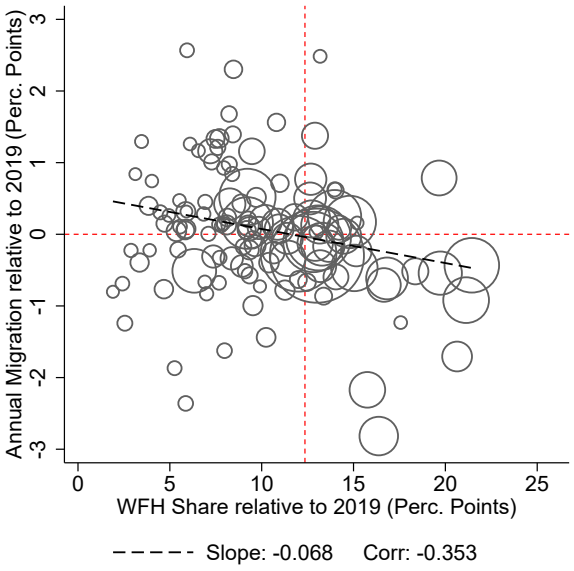
(b) State-Level Net-Migration



(c) MSA-Level Out-Migration



(d) MSA-Level Net-Migration



Notes: American Community Survey (ACS). Left Panels: Abbreviations/circles plot a state's/MSA's average 2021-2023 WFH share against its average 2021-2023 out-migration rate relative to 2019. Right Panels: Abbreviations/circles plot a state's/MSA's average 2021-2023 WFH share against its average 2021-2023 net-migration rate relative to 2019. Net-migration for location s in year t is the difference between the in-migration rate and out-migration rate. The WFH share of location s in year t is the share of individuals living in s in t who WFH in year t. Circle areas are proportional to MSA population. Dashed black lines are estimated using OLS. We exclude MSAs whose 2019 population is below 200,000 and states whose 2019 population is below 1,000,000.

B.2 Comparing Work from Home in the ACS, CPS, and RPS

We first explain how we measure WFH in the CPS. Since October 2022, the CPS asks respondents several questions related to WFH or telework, including:

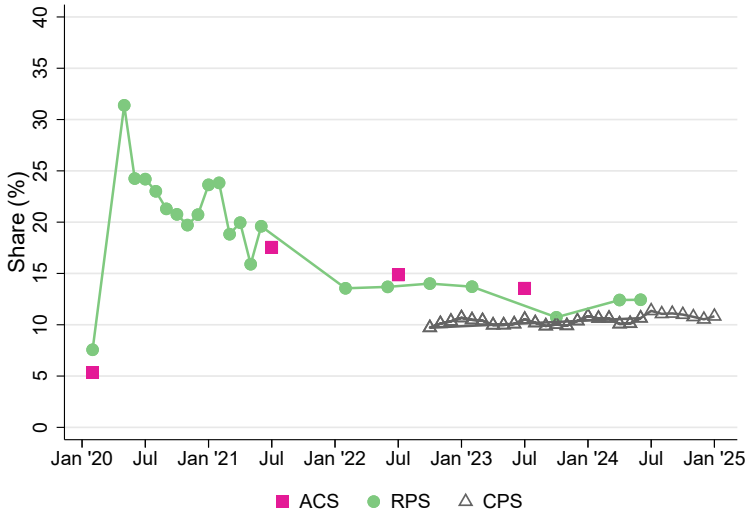
1. "At any time LAST WEEK, did (you/name) telework or work at home for pay?"
2. "LAST WEEK, (you/name) worked (# hours worked last week at all jobs) hours (total/at all jobs). How many of these hours did you telework or work at home for pay?"

To the first question respondents report either "yes" or "no": to the second question, respondents report an integer number of hours. Combined with information actual hours worked last week, we classify individuals as WFH full-time similar to the ACS and RPS, namely anyone for whom actual hours worked last week are identical to the hours teleworked / WFH for pay.

Figure B.15 displays the share of workers aged 18-64 who WFH full-time in several US datasets. The pink squares correspond to the ACS, the gray triangles to the CPS, and the green triangles correspond to the RPS. The ACS data is annual. We plot 2019 ACS data points as the February 2020 observation to facilitate comparison with the RPS's February 2020 data. We plot 2020-2023 ACS 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) and 7.7% in the RPS (02/2020). WFH increased sharply in both datasets in mid 2020 after the Covid-19 outbreak, and gradually declined after that. In the RPS the WFH rate in 2024 is about the same as in 2023, albeit being slightly higher than in October 2023. The WFH rate in the CPS is lower than in the ACS for both 2022 and 2023 but has habeen stable around 10% through time.

FIGURE B.15: Share of Workers Who Work from Home Full Time



Notes: American Community Survey (ACS), Current Population Survey (CPS) and Real-Time Population Survey (RPS), ages 18-64. ACS data is annual, CPS and RPS data is from selected months. We plot 2021-2023 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.

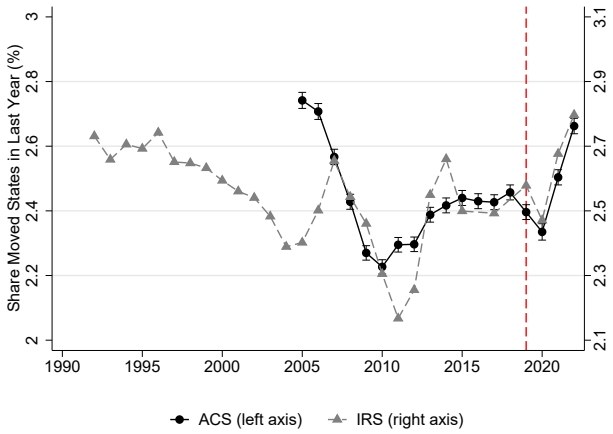
B.3 Comparing Migration in the ACS and RPS

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 yields a 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.

B.4 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 migration in the IRS and ACS data align closely in most years.

FIGURE B.16: Comparing Interstate Migration in ACS and IRS Data



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. This anomaly has also been highlighted by others, see e.g. DeWaard et al. (2022).

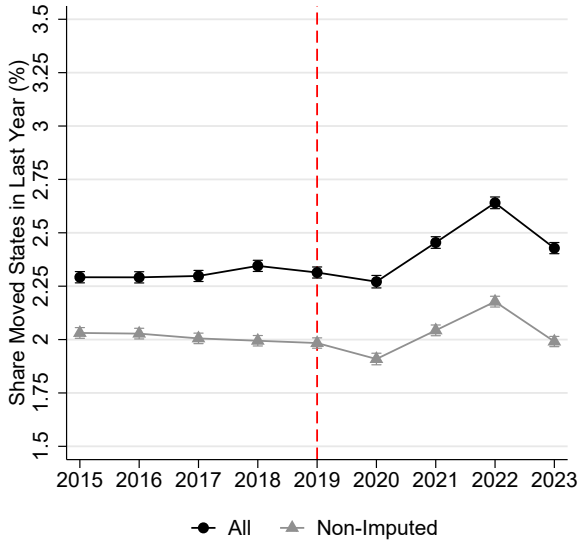
Figure B.16 displays interstate migration in IRS and ACS data. ACS data (left axis) run from 1992 to 2002 and use the same sample criteria for civilian working-age adults as in the main text. IRS data (right axis) span a longer time series, from 1992 to 2002. We allow for a slightly shifted axis for 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 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.

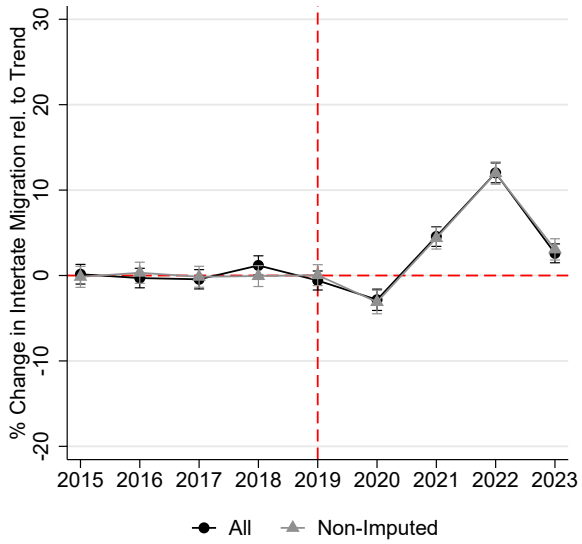
B.5 Imputed Migration in the ACS

FIGURE B.17: Long-Distance Migration: All vs. Imputed Moves

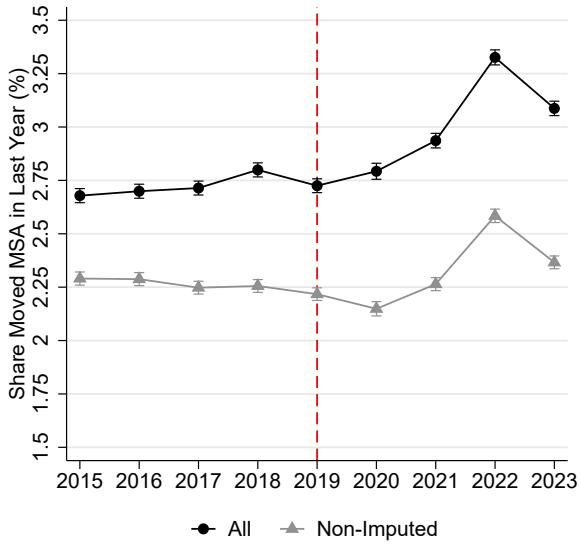
(a) Interstate Migration



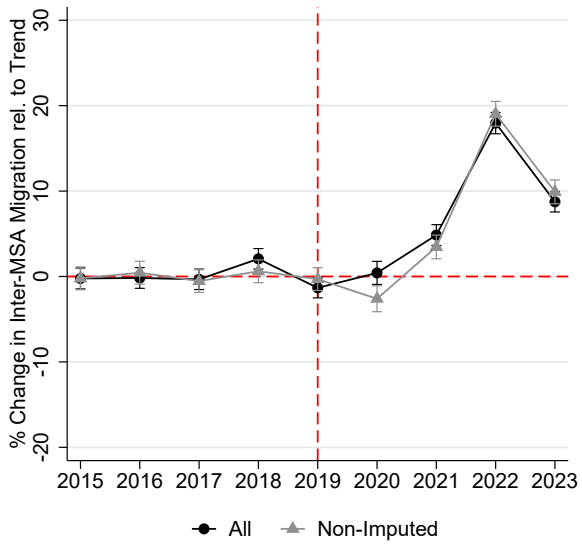
(b) Interstate Migration Relative to Trend



(c) Inter-MSA Migration



(d) Inter-MSA Migration Relative to Trend

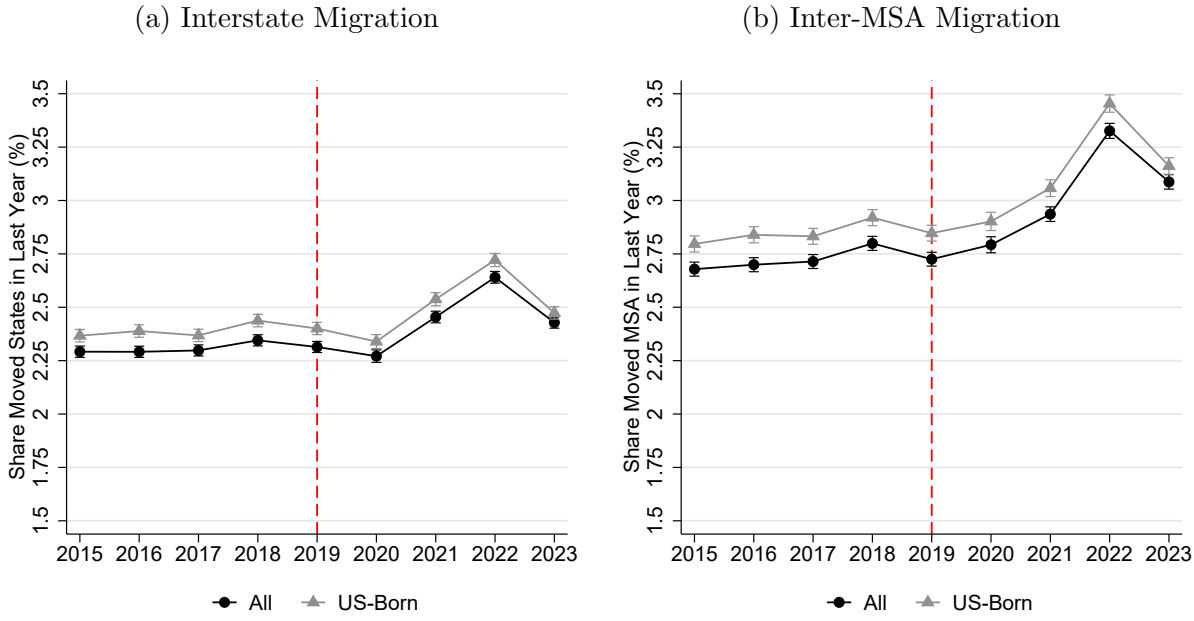


Notes: American Community Survey (ACS). The basic sample is working-age (18-64) adults in civilian households who currently live in the US and lived in the US in the previous year. The figure displays annual migration rates for two groups: all individuals in the basic sample, and only individuals whose migration indicator has not been imputed. Whiskers correspond to 95% confidence intervals.

B.6 Long-Distance Migration: 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.18 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 intersate migration after 2020.

FIGURE B.18: Long-Distance Migration: 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. Whiskers correspond to 95% confidence intervals.

B.7 Moving Distance

The emerging literature on residential migration 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 **??** 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.

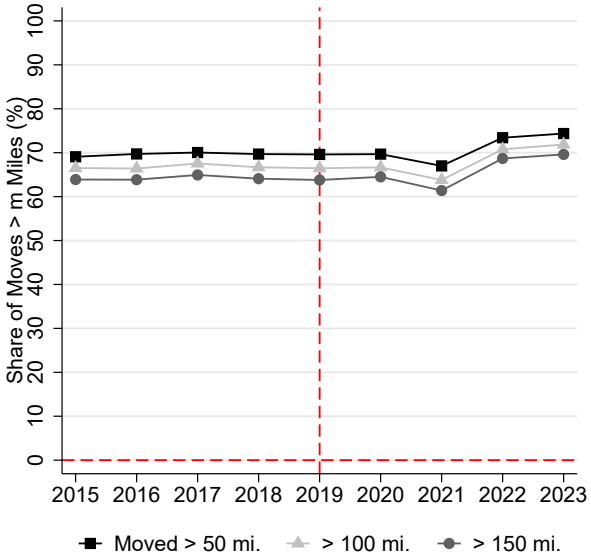
Figures **??** and **??** show that interstate moves by WFH workers tended to be longer distances than interstate moves by commuters. For example, in 2019, the share of interstate moves exceeding 50 miles was 70% for commuters versus 79% for WFH; the share exceeding 150 miles was 64% for commuters versus 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.

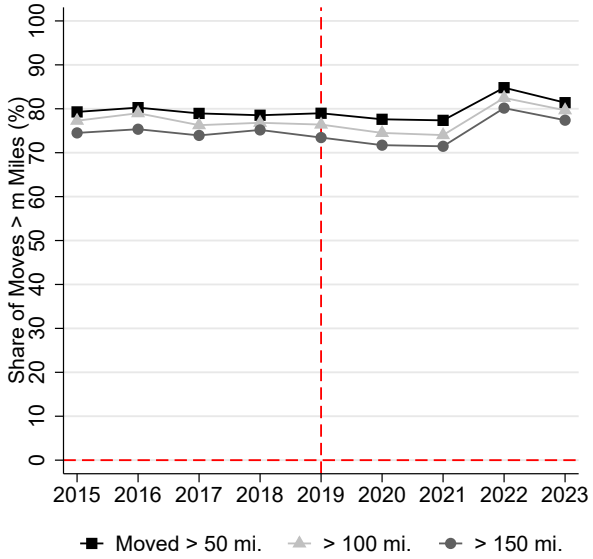
We conclude that only a minority of interstate moves were local and a majority of interstate moves were long-distance. This is especially true for WFH workers. For example, 73% of WFH interstate moves exceeded 150 miles in 2019 and 80% did so in 2022.

FIGURE B.19: Share of Long-Distance Moves Among Interstate / Inter-MSA Migrants

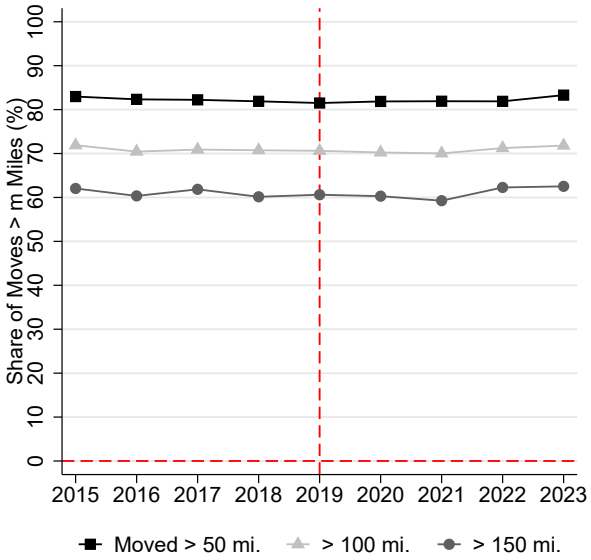
(a) Interstate Migration: Commuters



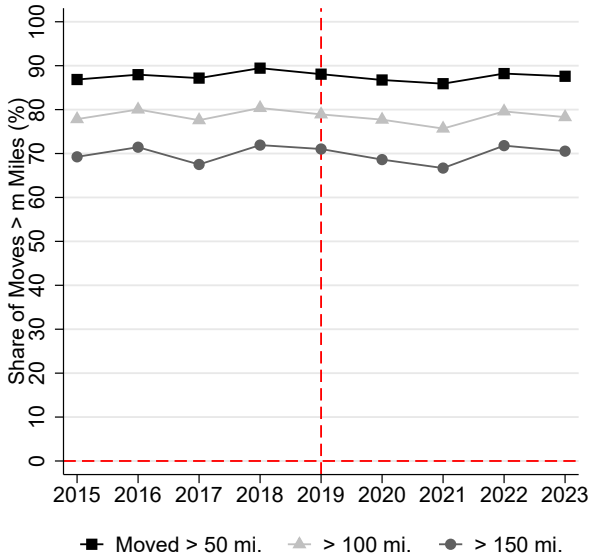
(b) Interstate Migration: Work from Home



(c) Inter-MSA Migration: Commuters



(d) Inter-MSA Migration: Work from Home



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 **??** is for all interstate movers. Panel **??** is for interstate movers who are employed and commute to work. Panel **??** 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.8 Measuring State WFH Capacity Using Dingel and Neiman (2020)

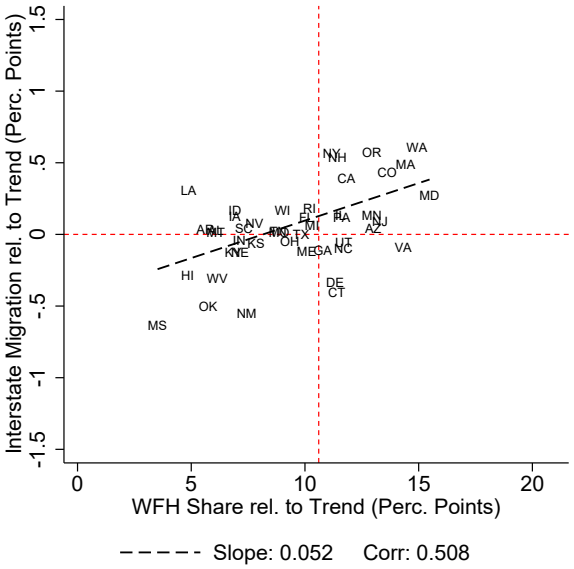
Section **??** showed that post-Covid WFH rates accounted for a sizable portion of the state-level variation in post-Covid interstate migration. That section also showed that a state's WFH capacity, based on a state's occupation mix and actual WFH rates in 2022 in each occupation, was predictive of its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

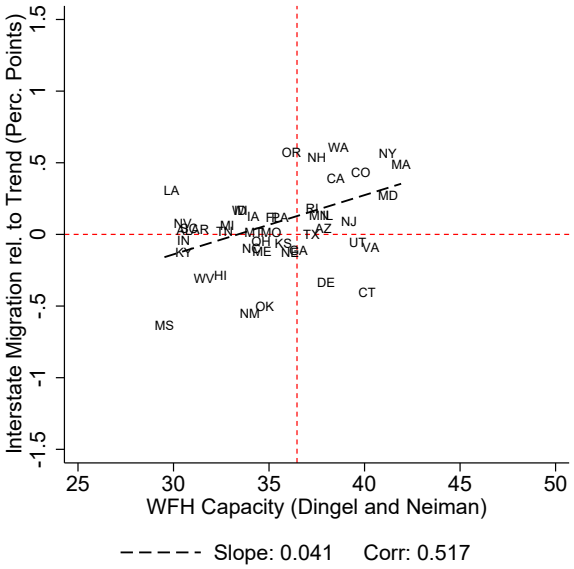
Figures B.20 and **??** plot state out-migration, in-migration, and net-migration rates against actual WFH rates in 2021-2022 (left panels) and DN WFH Capacity (right panels). Qualitatively, both WFH and WFH capacity predict interstate migration with the same sign. However, the correlation between migration and WFH capacity is lower than between migration and WFH, and the slope for WFH capacity tends to be flatter as well.

FIGURE B.20: State-Level Variation in Work from Home and Interstate Migration

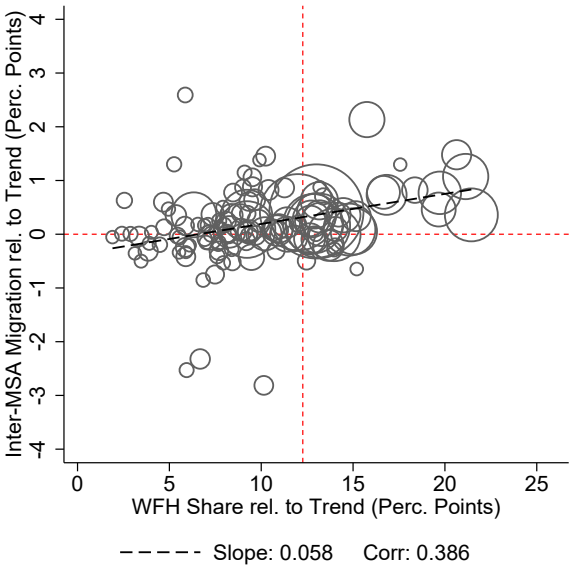
(a) WFH and Interstate Migration



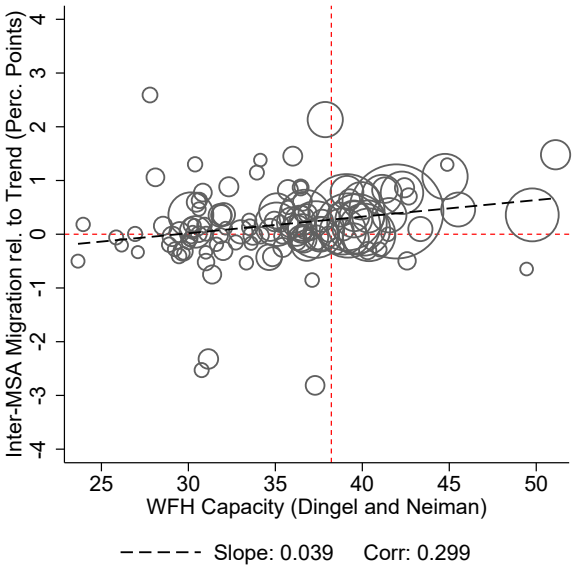
(b) WFH Capacity and Interstate Migration



(c) WFH and Inter-MSA Migration



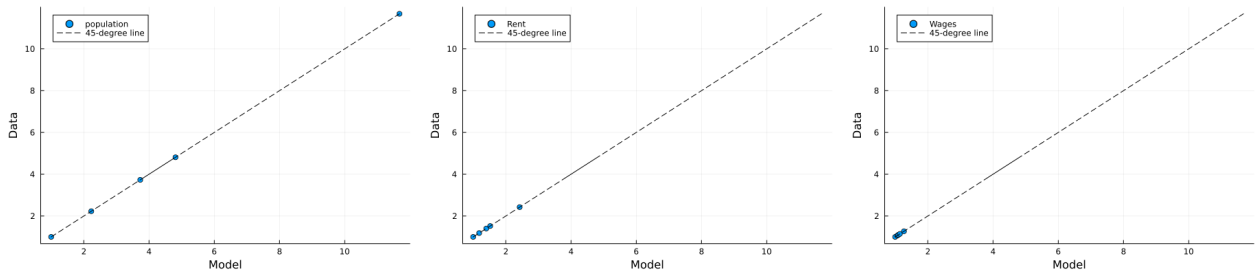
(d) WFH Capacity and Inter-MSA Migration



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 C.21: Model Calibration

(a) Population (b) Rent (c) Wages



Notes: Figure shows that the model can perfectly match the data on the relative wages, rents and population across cities. The values in city-1 are normalized to 1.

C Model Appendix

C.1 Model Calibration

Figure C.21 shows that the using the amenities, the productivity of the housing supply sector, and the productivity of the final goods producer in each city, the model can perfectly match the data on rents, wages, and population.