Work from Home and Migration*

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Abstract

We study how full-time work from home (WFH) affects migration and economic activity across cities. Using ACS and novel survey data, we show WFH workers migrate 40–50 percent more than comparable commuters, commuters who switch to WFH migrate more, plausibly exogenous WFH expansions raise migration, and WFH workers migrate to lower-cost cities than commuters. The post-Covid expansion in WFH coincided with a large increase in migration; WFH accounts for half of this increase and much of the cross-city variation in migration changes. Recently, WFH has stabilized at twice its pre-Covid rate. We study the long-run implications of this shift in a dynamic spatial equilibrium model of remote work, costly migration, and job search. Expanded WFH raises migration by shifting workers into more mobile remote jobs, reallocating people and tax revenue out of expensive cities and narrowing rent differentials. Welfare gains are sizable but concentrated among remote-capable workers in commuting jobs just before the shock, especially those in large cities. A higher WFH share also shifts more of the burden of local shocks onto commuters.

JEL Codes: J61, J11, J22, R10, O15
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1 Introduction

For most workers, the choices of where to live and where to work are closely intertwined. Commuting costs and the practical need to live near one's employer constrain residential location choices and, in doing so, shape the spatial distribution of economic activity. Full-time work-from-home (WFH) weakens this link by allowing workers to hold a job in one labor market while living in another. This paper studies how access to WFH shapes migration and, in turn, the allocation of workers and economic activity across labor markets.

We make three contributions. First, we establish empirically that, at the worker level, access to (full-time) WFH increases inter-MSA migration and that WFH workers move to lower-cost cities than commuters. Second, we show that the well-documented increase in WFH since the Covid-19 pandemic accounts for an important share of the recent increase in aggregate migration and net migration flows across cities. Third, to study the long-run implications of the persistent post-Covid rise in WFH, we develop a dynamic spatial equilibrium model with remote work, costly migration, and job search. We use the model to quantify how the rise in WFH impacts population, wages, rents, and local tax revenues across cities, and to assess the welfare gains from WFH when workers must incur costly moves to realize many of its benefits.

We first document several facts linking WFH and migration. Using the American Community Survey (ACS), we show that WFH workers are $40-50\%$ more likely to move across MSAs than observably similar commuters. This relationship exists prior to the Covid-19 outbreak and persists after the outbreak, despite a tripling of the WFH rate from roughly 5% to 15% of workers.

Higher migration by WFH workers, even after controlling for observable characteristics, may reflect unobserved differences between workers rather than a causal effect of WFH itself. To address this concern, we leverage quasi-panel data from the Real-Time Population Survey (RPS), a nationwide online survey designed to track commuting behavior and labor market developments before and after the Covid-19 outbreak (Bick and Blandin, 2023).[1] In addition to current WFH status, the RPS includes retrospective questions on pre-pandemic work arrangements and recent migration.

The RPS allows us to examine whether gaining access to WFH increases migration at the worker level. We first establish that, among workers who commuted pre-pandemic, those

[1] Bick et al. (2023) use the RPS to document the evolution of WFH in the United States from the onset of the Covid-19 pandemic through June 2021. Bick et al. (2025a,b) show that the prevalence of WFH in the RPS closely aligns with the ACS and other U.S. datasets through 2023.

who switched from commuting to WFH had higher migration rates than those who continued commuting. This comparison is suggestive, but transitions into WFH may be correlated with other factors that also affect migration. We therefore instrument for WFH transitions using RPS questions on changes in employer remote-work policies since the Covid-19 outbreak. We find that plausibly exogenous increases in WFH access predict higher rates of WFH and migration, consistent with a causal effect of WFH on migration.

Our worker-level findings have important aggregate implications for migration and population changes across cities. The tripling of the WFH share, combined with the persistent migration gap between WFH workers and commuters, led to a sharp increase in migration after the Covid outbreak. A simple decomposition finds that the rise in WFH accounts for roughly half of the increase in inter-MSA migration between 2021 and 2024 relative to 2019. Moreover, MSAs with larger WFH expansions experienced larger increases in out-migration and decreases in net migration. In particular, WFH expanded more in large, expensive cities, while WFH movers disproportionately relocated to cities with lower rents and lower local tax rates.

These empirical results raise several questions. In the short run, how much of the observed changes in population, rents, and local tax revenues across cities can be attributed to the rise in WFH, rather than to other contemporaneous shocks? How does increased mobility reshape the distribution of these outcomes across cities over the long run? What are the welfare consequences for different groups of workers? Does WFH affect workers' responses to adverse local conditions by reducing the need to migrate?

To answer these questions, we develop a dynamic spatial equilibrium model with remote work, migration, and job search. Workers differ in their occupation: always-commuters can only work in local commuting jobs, while remote-capable workers can receive offers from either the local commuter market or a national remote market. A key feature of the model is that remote workers can relocate across cities without changing jobs, whereas commuters must change jobs when migrating. This difference in migration frictions allows the model to match the gap in migration rates between the two groups. Remote-capable workers also face frictions in finding remote jobs, which rationalizes the modest WFH share observed in the data. Search frictions create a trade-off. WFH makes migration more attractive, but workers cannot be certain of finding another remote job if their current match ends, potentially exposing them to lower local wages in their new location.

We calibrate the model to match key features of the pre-Covid economy, including migration rates, WFH rates, commuter wages, rents, and population across cities. The model also reproduces several untargeted moments. First, the model generates long-run migration elasticities similar to those estimated empirically by Hornbeck and Moretti (2024). Second, although WFH jobs originate in a national market, WFH wages are increasing in city size. Finally, as in the data, WFH workers are more likely to move to locations with lower rents, lower local wages, and lower local tax rates than observably similar commuters.

We use the calibrated model to simulate a Covid-induced expansion in WFH. The shock has two components, one transitory and one permanent. The first component is a one-time event that immediately shifts some remote-capable workers from commuting jobs to WFH jobs. The second component is a permanent increase in the probability of finding a WFH job. Together, these two components produce an immediate spike in the WFH share, driven primarily by within-job transitions, which then gradually declines to a new steady state above its pre-Covid level, consistent with the empirical path of WFH since the Covid outbreak (Bick et al., 2025b).

The model implies that the post-Covid expansion in WFH is reshaping economic activity across cities by creating a larger class of highly mobile WFH workers. As in the data, aggregate migration rises sharply after the shock as new WFH workers move to more desirable cities, then settles at a level above its pre-Covid baseline as the WFH share falls and WFH workers reallocate across cities. In the new steady state, roughly 40% of the initial increase in aggregate migration remains due to the permanently higher WFH share.

The expansion in WFH reallocates workers away from the largest cities with the highest wages and rents toward smaller, lower-cost cities. In the new steady state, the largest cities experience a net population loss of 0.8%, with most of the population gains flowing to the smallest cities. Average wages in small cities rise because WFH gives local workers access to higher-productivity jobs in the remote labor market. The population and wage changes reduce rents in the largest cities and raise rents in the smallest cities. Unlike population changes, which accumulate over time, some of the short-run changes in rental prices dissipate over time as the housing stock adjusts to accommodate changes in housing demand.

This reallocation also shapes local public finances. Tax revenues increase in smaller cities, both because population increases and because new WFH workers earn higher wages than commuters in these cities, increasing per capita revenues. Meanwhile, population losses reduce tax revenues in the largest cities. These fiscal effects raise the question of whether cities can profitably attract remote workers through migration subsidies, such as the Tulsa Remote program. When cities cannot target subsidies to marginal movers, the policy is not cost effective, but tighter targeting can substantially improve the net fiscal return.

While an expansion in WFH provides greater residential and job flexibility, the size of welfare gains is not obvious a priori. To realize gains from migration, workers must incur moving costs, trade off cheaper housing against potentially lower local amenities, and face the risk of losing their WFH jobs after relocating to a labor market with lower local wages. Moreover, in equilibrium, changes in rental prices dissipate some of the cost of living differences that made relocation desirable in the first place. In the model, the benefits of WFH dominate these limiting factors. Remote-capable workers experience average welfare gains of 1.95% in CEV terms, with the largest gains accruing to remote-capable workers who worked in commuter jobs in the largest cities just prior to the shock. These workers were most likely to experience an immediate transition to a WFH job, and had the most to gain from relocating to smaller, less expensive cities. Always-commuters in smaller cities experience small welfare declines due to rising rents, while always-commuters in the largest cities experience small welfare gains due to falling rents. WFH also shifts the incidence of local productivity shocks: remote-capable workers become less exposed, with lower migration responses and smaller welfare losses, but their lower out-migration keeps rents from falling as much, thereby increasing welfare losses and out-migration among always-commuters.

Related Literature This paper contributes to two strands of existing literature. First is a literature examining the implications of remote work in quantitative spatial equilibrium models. Existing analyses largely study static environments, within-city location choices, or part-time remote work (Brueckner et al., 2023; Davis et al., 2024, 2025; Delventhal et al., 2022; Delventhal and Parkhomenko, 2026; Monte et al., 2025; Richard, 2026). While some of these models allow workers to reallocate across metro areas or states, they generally abstract from the dynamic, costly migration decisions through which workers relocate over long distances.[2] They also abstract from search frictions over access to remote jobs, which generate a key tradeoff: WFH makes moving more attractive, but workers who relocate may not be able to find another remote job if their current match ends. These frictions may be less central for within-city moves or part-time remote work, but they are crucial in our setting. Without search frictions, our model could only rationalize low WFH rates by assigning a negative amenity value to WFH, which would contradict existing estimates of the amenity value of remote work (Barrero et al., 2023; Cullen et al., 2025; Mas and Pallais, 2017) and would have first-order effects on the welfare implications of WFH.

Relatedly, several existing papers provide indirect empirical evidence that is consistent with the predictions of these models. Althoff et al. (2022), Liu and Su (2021), and Ramani and Bloom (2021) show that housing demand shifted away from dense city-center locations

[2]Our model also contributes to a growing literature that develops dynamic quantitative spatial equilibrium models (Giannone et al., 2023; Greaney, 2026; Greaney et al., 2025; Hoffmann et al., 2025).

toward lower-density areas on the outskirts of cities. Brueckner et al. (2023) provide similar evidence at the county level. Mondragon and Wieland (2025) argue that the rise in remote work, and the resulting increase in demand for space, accounts for over one half of the increase in home prices between 2019 and 2023. Akan et al. (2025) use matched employer-employee payroll data to document a sharp post-pandemic increase in home-employer distances, driven largely by workers hired after March 2020, and show that continuing employees increasingly moved toward lower-tax states and lower-housing-cost areas. Agrawal and Chen (2025) document the same pattern in Census data.

Within this literature on the spatial implications of WFH, our paper provides the first direct individual-level evidence that access to WFH impacts migration: WFH workers migrate at higher rates than commuters, commuters who switch to WFH subsequently move at higher rates, employer expansions of WFH access predict migration, and relative to commuters WFH workers systematically migrate to locations with lower rents, wages, and local taxes. Brueckner (2026) confirms several of our empirical findings using an alternative instrument in ACS data, and 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 to 2021.

Second, our findings connect to the literature on the long-run decline in U.S. migration (Jia et al., 2023; Molloy et al., 2011), which prior work links to declining job-change rates (Molloy et al., 2017) and reduced geographic specificity of work (Kaplan and Schulhofer-Wohl, 2017). In this framework, WFH has ambiguous implications for migration because it weakens the connection between moving and changing jobs. On one hand, WFH may reduce job-related migration by making it less necessary to live near the workplace. On the other hand, WFH may increase migration by allowing workers to move for non-job-related reasons without giving up their current job. Our evidence suggests that the latter force dominates: WFH workers are more likely to migrate, commuters who switch to WFH migrate at higher rates, and employer expansions of WFH access predict migration.

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 U.S. households. We use the IPUMS cleaned version (Ruggles et al., 2024).

The ACS is well suited to our analysis for three reasons. First, the ACS has information on migration. By construction, the Census Bureau knows the current residence of all household members because the ACS is mailed to a specific address. It also asks for residential addresses 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.

We classify moves as either local or long-distance. The literature typically measures long-distance migration using either interstate or inter-MSA moves. Identifying interstate moves is straightforward because the current and past residential state for each individual are publicly available. We identify inter-MSA moves based on an individual's public-use-microdata area (PUMA), which is the smallest publicly available geographic unit.[3] Appendix B.5 shows that over 60% of interstate moves and over 70% of inter-MSA moves exceed 100 miles throughout our sample period. Because our model uses MSAs as the geographic unit of analysis, the main text focuses on inter-MSA migration. Appendix B.1 contains a parallel set of all our empirical analyses for interstate migration, revealing very similar results.

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 U.S. households yields a sample of over two million adults each year. This is particularly helpful when studying migration, which only a few percent of individuals do each year.

We highlight two points of context for interpreting ACS migration data. First, the Census Bureau reported that the 2020 ACS data collection was 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 formal analysis 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

[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.

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 we document similar patterns for interstate and inter-MSA migration. Consistent with this, Appendix Figure B.3 shows that the share of inter-MSA moves that were also interstate is roughly constant (between 61% and 63%) over our sample period, suggesting 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 address this limitation, we use the Real-Time Population Survey (RPS), a nationwide online 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. It is not a random sample of the U.S. population, even conditioning on the 94 percent of 18–64 year-olds in households with internet access (2019 ACS). 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 U.S. 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 the previous year.

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

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

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

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.

Despite these sampling targets, potential concerns about representativeness remain. 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 Deming and Stephan (1940) so that our weighted 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 not targeted in the sampling procedure, 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 provide the year and month of their move-in date. We use this information to assess whether the respondent had moved since the pandemic. For individuals who have moved, we ask their state and zip code of residence in February 2020.

Commuting status is derived from two survey questions on the individual's main job:

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

For the first question, respondents are presented with a slider that provides a choice of integers from 1 to 7, since this question is only asked of individuals who worked in the previous week; for the second question, the integers span 0 to 7. To align with the measure of WFH in the ACS, we classify an individual as working from home if they were fully remote; i.e., they worked at least one day in the previous week but did not commute on any day. We also ask respondents to think back to February of 2020, and present them with the same questions for the main job in that month.[7] Crucially, this allows us to identify workers who commuted pre-Covid and switched to WFH post-Covid. Bick et al. (2025b) compare RPS data with Google Mobility data (based on cell phone geolocation) and find similar trends in

[7]The retrospective questions do not ask about a specific week in February 2020. Instead, respondents were asked: *We would like you to think back to FEBRUARY 2020, just before the Covid-19 outbreak. 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 waves in our sample.

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 document similar WFH rates and migration rates (both overall and by WFH status) in the RPS and ACS throughout our sample period.

2.3 Sample Selection

We construct our ACS sample 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. We use similar criteria for the RPS, except that we cannot exclude group quarters because we do not observe them.

3 Work from Home and Migration

Figure 1a plots annual inter-MSA migration in the ACS separately for commuters (gray diamonds) and WFH workers (blue triangles). From 2015 to 2019, the migration rate averaged 2.67% among commuters on an annual basis, with minimal time trend. The migration rate among WFH workers was substantially higher, averaging 3.78% over the same period. These estimates imply that the MSA migration rate of WFH workers was 1.11 percentage points, or 1.11/2.67 = 42% higher than the migration rate of commuters over this time period. Figure 1b shows that the WFH-commuter gap in migration expanded after the Covid-19 outbreak in 2020. The average migration gap increased from 1.11 percentage points (or 42%) in 2015-2019 to 1.59 percentage points (or 57%) in 2021-2024.

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 migration beyond its correlates, we run the following linear probability regression:

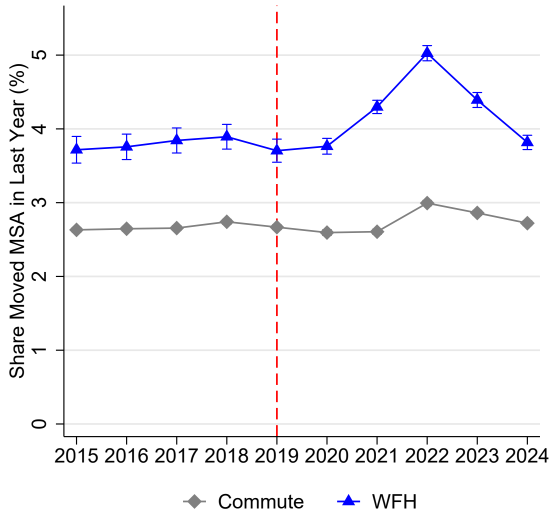
$$m_i = \beta_0 + \beta_W w_i + \gamma X_i + \epsilon_i \quad (1)$$

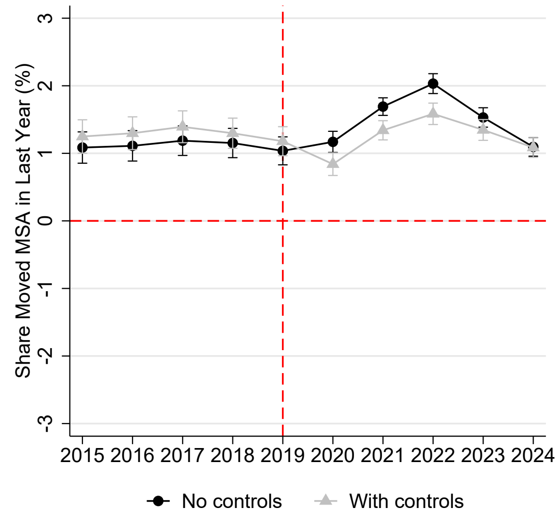
The left-hand side variable m_i is a dummy variable that is zero if the individual is living in the same MSA as one year ago and one if the individual is living in a different MSA. The variable X_i contains controls for sex, age, education, race, Hispanicity, marital status, the presence of children, log income, occupation, industry, and state of residence. The key

Figure 1: Work from Home and 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 commuters (gray diamonds), and WFH workers (blue triangles). Right Panel: the black circles 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 U.S. and lived in the U.S. in the previous year. Whiskers correspond to 95% confidence intervals based on heteroskedasticity-robust (Ecker-Huber-White) standard errors.

right-hand side variable is w_i, which is a dummy indicator for the individual's WFH status. Intuitively, the parameter β_W shows how much WFH increases the predicted probability of migration, holding the other controls in X constant. To examine whether the explanatory power of WFH status on migration has changed over time, we run the regression separately for each year from 2015 to 2024.

Figure 1b 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. In 2021-2023, the value of β_w increases both in the regression with controls and without controls. The increase is larger in the regression without controls, indicating that some of the increase in migration among WFH workers can be accounted for by other observables that are correlated with WFH after 2020. By 2024, the value of β_w had returned to roughly its pre-2020 level. We conclude that the WFH-commuter migration gap remained stable or widened slightly after 2019.

3.1 Impact of Switching to Work from Home on Long-Distance Migration

Higher migration rates among WFH workers may reflect unobservable differences in the types of workers who select into remote work, rather than an effect of WFH itself. We address this concern by asking whether workers become more likely to migrate after switching from commuting to WFH. While we cannot observe changes in WFH status in the ACS, the RPS does contain this information.

3.1.1 Work from Home Transitions and Long-Distance Migration

We restrict attention to respondents in the RPS who worked both in the reference week in 2022-2023 and in February 2020, just before the Covid-19 expansion in WFH. We partition this sample of workers 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:

$$m_i = \beta_{CC} cc_i + \beta_{WW} ww_i + \beta_{CW} cw_i + \beta_{WC} wc_i + \gamma X_i + \epsilon_i \tag{2}$$

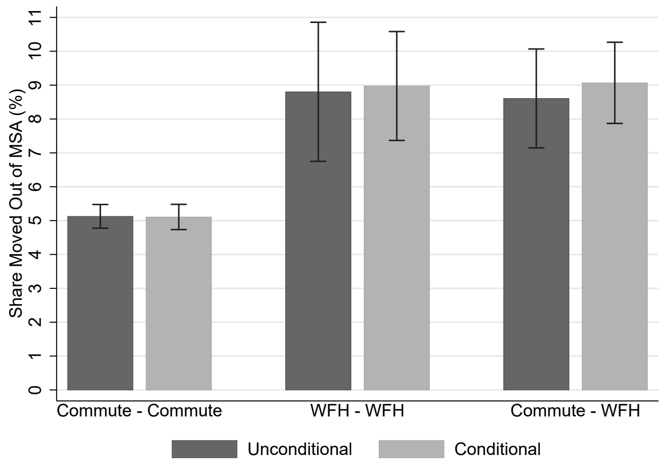
The left-hand side variable is a dummy that is one if the individual moved MSAs since February 2020 and is zero otherwise. The key right-hand side variables are dummy variables indicating which commuting group the worker is assigned to. We also include a set of controls for sex, age, education, race,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

Figure 2 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.

Among workers who commuted both before and after Covid, 5.1% migrated, compared with 8.8% for workers who WFH both before and after Covid and 8.6% of commuters who switched to WFH.[8] Including the additional controls in X has a minimal effect on these

[8] Migration rates in the RPS are higher than in the ACS (Figure 1) because the ACS measures moves within the past 12 months, while the RPS measures moves since February 2020. The two data sets display

Figure 2: Migration and Worker-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.

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.

3.1.2 A Work from Home Instrument: Changes in Employer Policies

We have shown that pre-pandemic commuters who switched to WFH following the Covid-19 outbreak migrated at higher rates than commuters who did not switch to WFH. One interpretation of this pattern is that access to WFH causally increases migration by reducing the cost of relocating far from the workplace. Consistent with this, Figure 1 showed that WFH workers already had high migration rates prior to 2020 and workers who switched to WFH since the pandemic migrated at similar rates to pre-pandemic WFH workers.

A competing interpretation is that (i) the pandemic 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 other words, the causation is reversed: the migration decision causes the individual to WFH. The crucial distinction is that in this interpretation the worker would

similar gaps in migration rates by current commuting status.

have moved even if they had not been able to WFH.

We address this concern using an instrument that predicts a switch to WFH but is plausibly uncorrelated with the desire to move: changes to employer WFH policies following the Covid-19 outbreak. The RPS contains two sets of questions about employer WFH policies. First, for all workers who commuted in February 2020, we ask:[9]

(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) find that most workers who switched from commuting to WFH after the Covid-19 outbreak report that their employers did not allow them to WFH prior to the pandemic, 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*

[9] The October 2022 and the February - October 2023 surveys used a slightly different phrasing. Appendix Section A.4 provides details and documents a consistent distribution of commuting reasons across surveys.

We note that (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 worker and their coworkers to be strongly correlated with idiosyncratic desires to move.

We analyze the relationship between WFH transitions, employer policies, and migration with two sets of regressions. Our dependent variable is a dummy, m_i, which has a value of one if worker i moved MSAs since February 2020. Our independent variable of interest is a dummy, cw_i, which has a value of one if worker 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 2022 or 2023.[10]

$$m_i = \beta_0 + \beta_{CW} cw_i + \gamma X_i + \epsilon_i \tag{3}$$

The variable X_i contains the same controls as the regression in Figure 2. 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. Intuitively, this estimate is similar to the WFH-commuter migration gap in Figure 2.

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.

The bottom panel of Table 1 reports first-stage results. Our instruments produce large Effective F statistics, regardless of whether controls or sample weights are included, implying they strongly predict switching to WFH. The top panel shows second-stage results alongside analogous OLS estimates. Switching to WFH positively predicts migration in both cases. Relative to OLS, the estimated 2SLS coefficient is larger, ranging from 0.0705 to 0.0927. The

[10]Among workers in 2022-2023 who were employed in February 2020, 74% had not changed employers since then.

Table 1: Switching to WFH and the Probability of Migration

	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					304.5	248.4	210.3	165.7
Critical Value					20.3	20.0	20.3	20.0
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.

coefficient is significant at the 1% level except in the specification with controls and sample weights, where it is significant at the 5% level. Brueckner (2026) finds similar results using a different approach in ACS data.

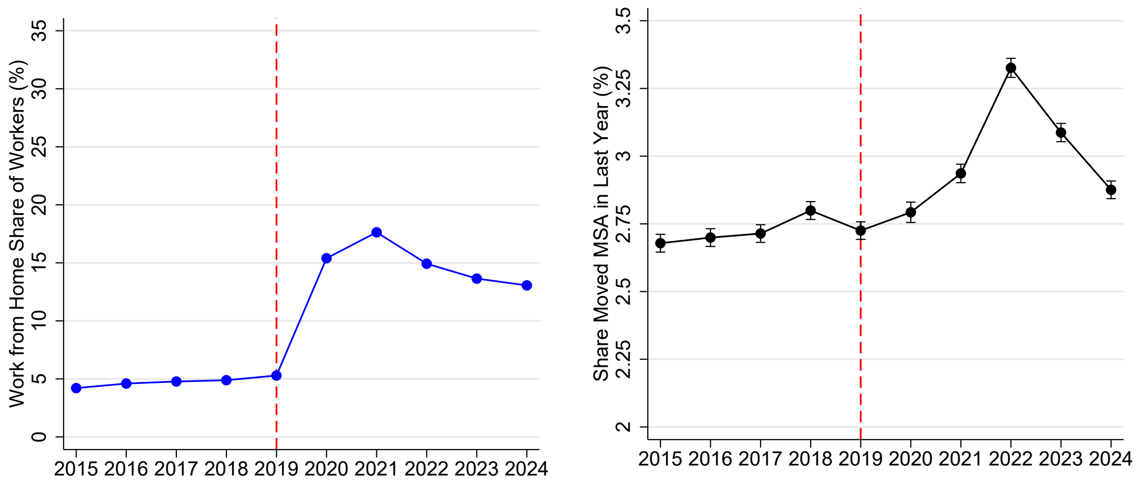
To summarize, we find that pre-pandemic commuters were more likely to switch to WFH if they had a WFH-capable job before the Covid-19 pandemic and if their employer's WFH policy changed since the pandemic began. These variables also predict long-distance migration since the pandemic. Since these variables 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 migrate.

4 Aggregate Trends in Work from Home and Migration

Our results so far suggest that an aggregate increase in WFH should have coincided with an increase in aggregate migration. Figure 3 verifies that this is indeed the case. Figure 3a shows the WFH share among workers in the ACS. From 2015 to 2019, the WFH share expanded gradually, from 4.2% in 2015 to 5.3% in 2019. Following the Covid-19 outbreak,

Figure 3: Work from Home and Worker Migration Before and After the Covid-19 Outbreak

(a) Share of Workers Who Work from Home (b) Inter-MSA Migration of Workers



Notes: American Community Survey (ACS). Panel 3a displays the share of workers (%) who WFH. Panel 3b displays annual MSA migration rates from 2015-2024. The sample is working-age adults (18-64) in civilian households who currently live in the U.S. and lived in the U.S. in the previous year. Whiskers correspond to 95% confidence intervals.

WFH more than tripled to 17.6% in 2021 and remained above 13% through 2024. (CPS data show stable full-time WFH rates into 2026; see Figure B.7.)[11]

Figure 3b displays annual migration rates for workers over the same time period. From 2015 to 2019, the migration rate was fairly stable between 2.68%-2.80%. Migration increased sharply in 2021 and 2022. It then declined in 2023 and 2024 but remained above 2019 levels. On average, from 2021-2024 migration was 12% above its 2019 rate.

These aggregate trends are evident in other datasets and robust to alternative measures and sample criteria. Appendix B.4 documents quantitatively similar patterns in interstate migration in the ACS and in the IRS data between 2019-2023. Foster et al. (2024) report a similar spike in interstate address changes in the United States Postal Service National Change of Address between 2019-2021. Appendix B.5 verifies that the rise in long-distance migration was not driven by short moves across state or MSA borders; in particular, the share of inter-MSA moves that exceed 100 miles increased slightly over this period. Appendix B.6 shows that these patterns were not driven by foreign-born workers. Finally, Appendix B.7 shows that migration trends are nearly identical whether or not last year's location is

[11]In addition to pandemic survey disruptions (see Section 2), the 2020 WFH rate reflects an unknown combination pre-pandemic survey responses (with low WFH) and post-pandemic responses (with high WFH).

imputed, although the non-imputed rates are somewhat lower than those in the full sample.

4.1 A Simple Accounting Exercise

How much of the increase in migration can be attributed to the rise in WFH? We can gauge the quantitative potential of this channel with a very simple decomposition exercise. Aggregate inter-MSA migration in year t, m_t, can be written as

$$m_t = \sum_{i=c,w} \theta_{i,t} m_{i,t} \tag{4}$$

where c, w denote commuters and WFH workers, respectively; $\theta_{i,t}$ denotes the population share of group i in year t; and $m_{i,t}$ 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 $\theta_{i,2019}$:

$$m_t^1 = \sum_{i=c,w} \theta_{i,2019} m_{i,t} \tag{5}$$

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 $m_{w,2019}$:

$$m_t^2 = \theta_{c,2019} m_{c,t} + \theta_{w,2019} m_{w,2019} \tag{6}$$

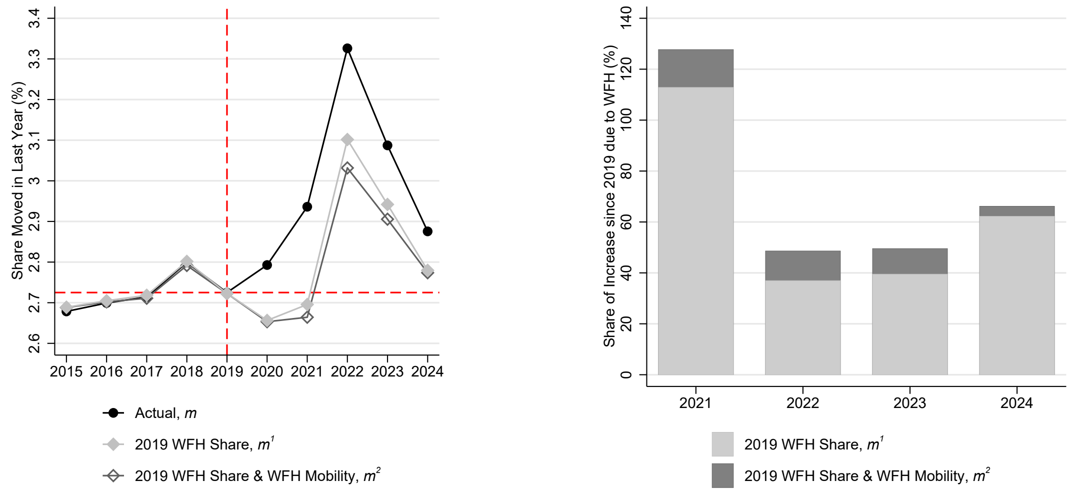
Intuitively, the difference between m_t and m_t^1 quantifies the effect of the increase in the WFH share after 2019, while the difference between m_t and m_t^2 also incorporates the contribution of the rise in migration among WFH workers after 2019.

Figure 4a plots aggregate migration, m_t, and the counterfactual series m_t^1 and m_t^2. The first takeaway is that the rise in WFH accounts for a sizable share of the increase in migration relative to 2019. On average between 2021 - 2024, actual migration was 12.2% higher than in 2019, while the counterfactual m_t^1 was only 5.7% higher. This implies that 53% of the increase in migration is statistically 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 migration, though this effect is more modest; see Figure 4b. On average from 2021 - 2024, the increase in the WFH share and WFH migration rates jointly account for 64% of the increase in migration (versus 53% for the WFH share alone).

Figure 4: Accounting Exercise: The Impact of Work from Home on Aggregate Migration

(a) Migration: Actual vs. Counterfactual (b) % of Migration Increase due to WFH



Notes: American Community Survey (ACS). Left 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 have remained at the 2019 share and the migration of WFH workers would have remained at the 2019 rate (see text for details). Right panel: bars represent the share (percent) of the increase in aggregate migration relative to 2019 accounted for by WFH in each counterfactual. The sample is employed working-age adults (18-64) in civilian households who currently live in the U.S. and lived in the U.S. in the previous year.

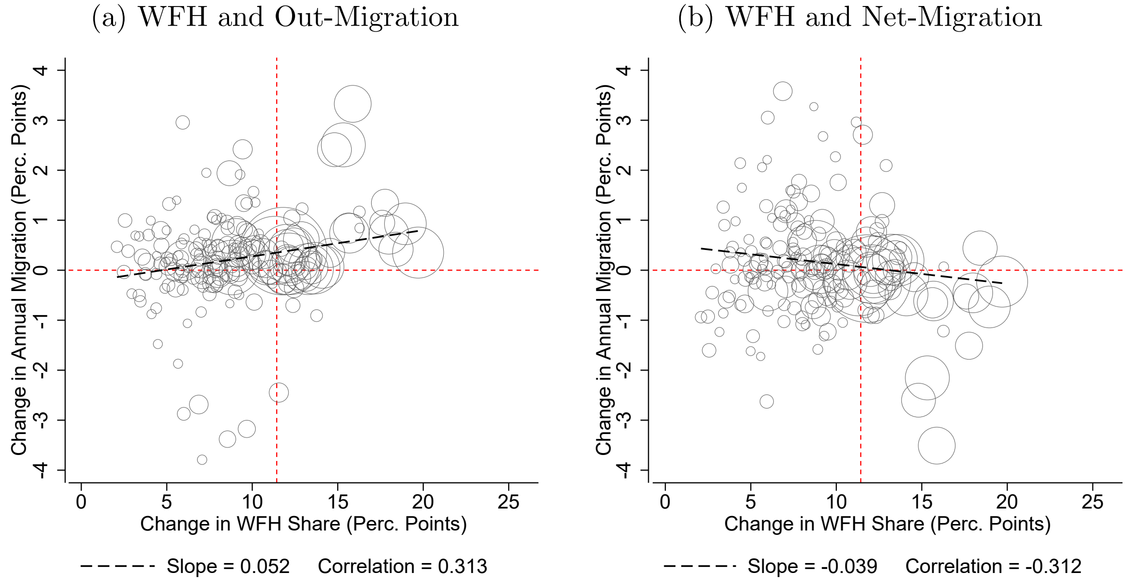
4.2 Geographic Variation in Work from Home

The increase in WFH was uneven across cities. For example, after 2019 the WFH share increased 21 percentage points in San Francisco-Oakland, CA, but only 3 percentage points in Bakersfield, CA. We now show that changes in local WFH rates predict changes in migration.

Figure 5a uses ACS data to plot the change in an MSA's out-migration rate (2021-2024 minus 2015-2019) against the change in its WFH share over the same time period. The WFH share for an MSA s in year t is the share of workers living in s in year $t-1$ who WFH in year t (including those who moved between $t-1$ and t). To construct the out-migration rate for an MSA s in year t, we start from the sample of workers who lived in s in $t-1$. The out-migration rate is the share of those workers who lived in a different MSA $r \neq s$ in year t. To account for pre-pandemic differences across MSA's, both variables are expressed as percentage point deviations from their average value from 2015-2019. We exclude MSAs with less than 200,000 residents in 2019 because estimates for these MSAs are very noisy.

Figure 5a reveals a correlation of 0.313, indicating that out-migration increased more in MSAs with larger increases in WFH. In a linear regression, the WFH coefficient is 0.052,

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



Notes: American Community Survey (ACS). Left Panel: Circles plot the post-pandemic change in an MSA's WFH share (2021-2024 vs. 2015-2019) against the post-pandemic change in its out-migration rate (2021-2024 vs. 2015-2019). Right Panel: Circles plot the post-pandemic change in WFH share against the post-pandemic change in net-migration rate. Circle areas are proportional to MSA population. We exclude MSAs with 2019 population below 200,000. Dashed black lines estimated with OLS.

which is significant at the 1% level, and implies that a 10-percentage point increase in a WFH share is associated with an increase in out-migration of 0.52 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 the change in an MSA's net migration rate against the change in its WFH rate. An MSA's net migration rate is the difference between its in-migration rate and out-migration rate. To construct the in-migration rate for an MSA s in year t, we start from the sample of individuals who lived in s in t. The in-migration 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 correlation of -0.312, indicating that net migration fell more in MSAs with larger increases in WFH. In a linear regression, the WFH coefficient is -0.039, implying that a 10-percentage point increase in an MSA's WFH share is associated with a decrease in net migration of 0.39 percentage points. The magnitude of this coefficient is similar to the estimated coefficient for the leave rate, implying that higher out-migration in high-WFH

MSAs was not fully offset by higher in-migration. Appendix Figure B.12 documents similar patterns if we instead use a measure of MSA WFH capacity (Dingel and Neiman, 2020).

4.3 Work from Home and Migration Destination

Figure 5b showed that cities with larger increases in WFH experienced larger out-migration that was not offset by higher rates of in-migration. One potential driver is that cities with larger increases in WFH tended to be large cities (larger circles), which on average have high wages but also high rents and local tax rates. Some workers may have responded to their new WFH access by migrating to lower-cost cities.

To investigate this channel, we ask whether WFH workers in the ACS systematically migrate to lower-cost cities compared to observably similar commuters. For each mover, we measure how three city characteristics differ between their destination and origin MSA: mean log rent, mean log wages, and mean state income tax rates. We run the regression

$$\Delta y_i = \beta_W w_i + \beta_t + \gamma X_i + \epsilon_i \tag{7}$$

where Δy_i is the destination-origin difference in city characteristics for worker i, β_t is a year fixed effect, and X_i is a set of worker controls. The key right-hand side variable is w_i, a WFH dummy. Our sample is workers in the 2015-2024 ACS who migrated in the past year.

The estimated coefficients β_W (Appendix Table B.2) indicate that, compared to commuters, WFH workers migrate to cities where mean wages are 1.8 percent lower, rent prices are roughly 3.5 percent lower, and state tax rates are 0.35 percentage points lower. (See also Agrawal and Chen (2025), who find that remote workers are more likely to relocate to lower-tax states.) We conclude that WFH workers tend to relocate to places with lower wages, lower rents, and lower state income taxes than commuters.

5 A Spatial Equilibrium Model of WFH and Migration

This section develops a dynamic spatial equilibrium model with remote work, costly migration, and job search. The model is designed to rationalize two central patterns in the data: remote workers are more likely to migrate and they systematically relocate to different cities than commuters. We use the model to study the spatial implications of WFH.

5.1 Model Environment

The model embeds a McCall (1970) search framework into a dynamic spatial equilibrium model with remote work and long-distance migration. Time is discrete and runs from $t = 1, \dots, \infty$. The economy is populated by a unit mass of infinitely lived workers, who live in one of G locations, indexed by $g \in \{1, \dots, G\}$. Workers consume a bundle of a tradable final good, x, and housing, h. The price of the final good is normalized to one in each period. The price of a unit of housing in location g and time t is $q_{g,t}$. Housing in each city is supplied by a developer who invests in housing and rents it to workers.

Workers can be employed or unemployed. An employed worker's job match is characterized by productivity z. They produce z units of the final good and receive a wage equal to their marginal product, $w = z$. With probability δ, an employed worker is hit by an exogenous separation shock and becomes unemployed. Unemployed workers receive unemployment benefits specific to their city, b_g and draw a wage offer. They decide whether to accept the offer or reject it and continue searching next period.

Each worker has a permanent occupation type, $o \in \{AC, RC\}$. A mass L^{AC} of workers are "always-commuters," representing workers in low work-from-home-capacity occupations such as manufacturing or retail. Unemployed always-commuters draw wage offers from a local distribution tied to their city of residence, $f_g(w)$.

The remaining mass L^{RC} of workers are "remote-capable," representing workers in high work-from-home-capacity occupations such as technology or finance. Remote-capable workers may receive either a remote or a commuter job offer. Search is random: with probability p_g^r, they draw a remote-job wage from the national remote distribution, $f^r(w)$, and with probability $1 - p_g^r$, they draw a commuter-job wage from the local distribution, $f_g(w)$.[12] We emphasize that occupation type and job type are distinct objects: always-commuters, AC, work exclusively in commuter jobs, c, while remote-capable workers, RC, may work in either a commuter job c or a remote job r.

Workers decide where to live each period. When relocating across cities, workers incur a migration cost, denominated in utility units, $\psi^u(g_t, g_{t+1})$. Additionally, to move commuters must quit their job and search for a new job in the destination city, incurring a period of unemployment.[13] In contrast, workers in remote jobs can move across cities without changing

[12] An alternative is directed search, in which remote-capable workers choose between remote and commuter markets and are indifferent in equilibrium. We instead use random search: in our calibration, workers prefer a draw from the remote distribution, but access is limited by employer policies and job availability, captured in the model by p_g^r.

[13] An alternative setup would allow workers to search for jobs in destination cities before migrating. Model-

jobs.

Search frictions are essential for two reasons. First, they prevent all remote-capable workers from immediately sorting into remote jobs, allowing for realistic remote-work shares and amenity values. Second, they create a natural wedge between the mobility of remote workers and commuters. To relocate, commuters must change jobs, whereas remote workers can keep their existing job. This also creates a tradeoff for remote workers. They can move to a lower-rent city while keeping a high-wage remote job, but if that match ends they may struggle to find a new remote job and must instead work in the local commuter market.

5.2 Worker's Problem

Timing. Figure 6 summarizes the model timing, focusing on remote-capable workers. Panel (a) describes unemployed workers. At the beginning of each period, unemployed workers receive unemployment benefits, which they use to consume the final good and housing. They then draw a job offer. With probability p_g^r, the offer is from the remote distribution, $f^r(w)$, which is independent of the local labor market; with probability $1 - p_g^r$, it is from the local commuter distribution, $f_g(w)$. Workers may either accept the offer and begin work in the next period or reject it and continue searching.

Accepted offers, whether remote or commuter, become active in the worker's current city the following period. Thus, accepting an offer in period t commits the worker to remain in that city until the end of period $t + 1$, while rejecting it preserves the option to move after drawing location-preference shocks. For newly accepted remote jobs, workers can relocate while retaining the job at the end of period $t + 1$, once the job is active.[14]

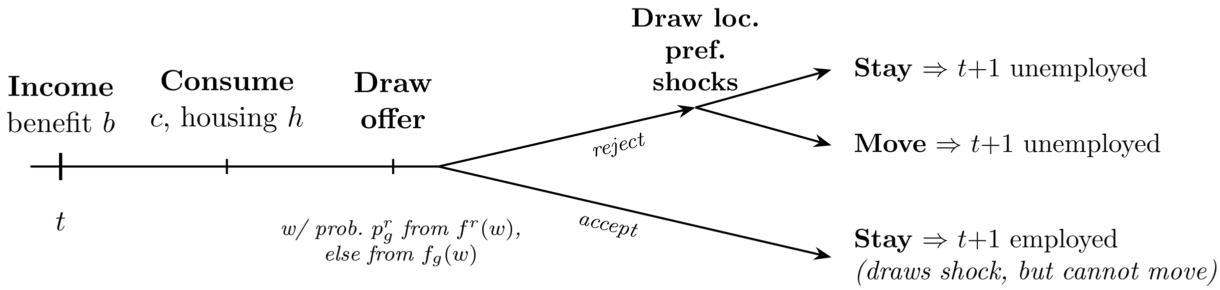
Panels (b) and (c) describe the timeline for remote-capable workers in remote jobs and commuting jobs. Both types first work and receive wages, which they use to consume the final good and housing. They are then hit by a separation shock with probability δ. With probability p^s, remote-capable commuters who are not separated learn that their job will become remote next period. As with newly accepted remote jobs, these workers cannot move until their remote job is active in $t + 1$. Finally, workers draw location-preference

ing this channel would require origin- and destination-specific reservation thresholds and assumptions about the relative cost of non-local search. The key mechanism would remain: as long as migration requires interrupting the current job match or spending time out of work, search frictions act as migration frictions for commuters. Because our model is quarterly, the quantitative impact of requiring a period of non-work is modest. Compared with a model in which workers move with offers in hand, the main difference is that movers face additional uncertainty about the offer they receive.

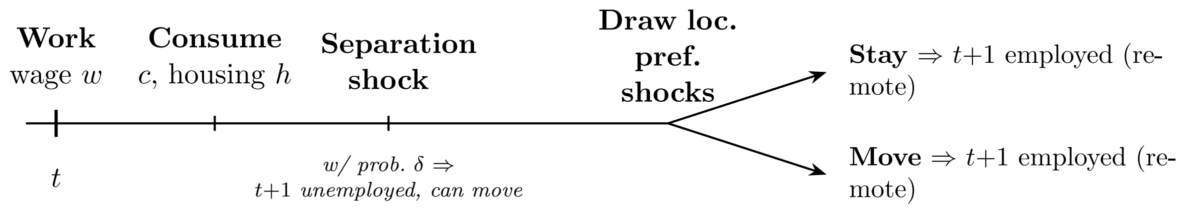
[14] Workers who accept a new job draw a location-preference shock for the current city, but because no location choice is made that period, the mean-zero shock does not affect expected values.

Figure 6: Time Line for Remote-Capable Types

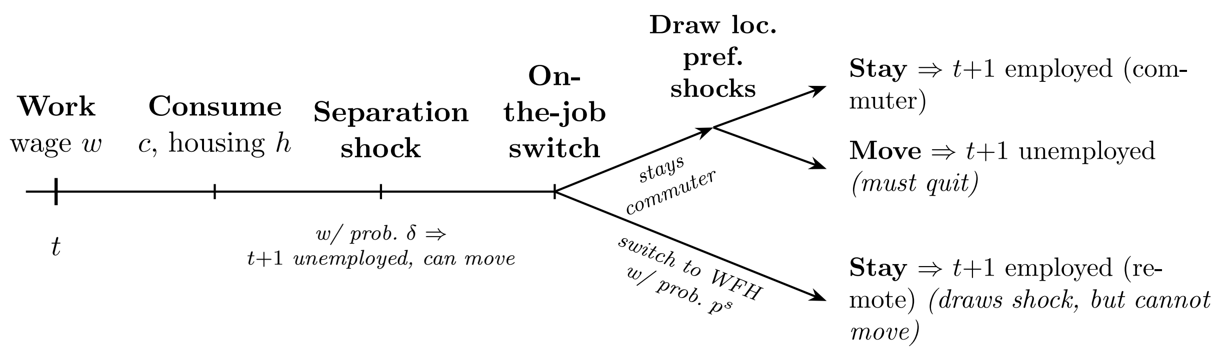
(a) Unemployed



(b) Remote worker



(c) Remote-capable commuter



Note: Every move incurs the utility cost $\psi^u(g, g')$.

shocks. Workers who entered the period in remote jobs may choose where to live next period, subject to the utility cost of moving, whereas commuters may move only by quitting into unemployment. Recently separated workers may also move at the end of the current period.

The timing works similarly for always-commuters. However, these workers never receive a remote offer in panel (a) and never experience an on-the-job switch to remote work in panel (c), and so never work in a remote job (panel b).

Always-Commuters. We begin with the value function for an always-commuter who is employed at wage w and lives in city g. The worker chooses consumption of the final good, x_t, and housing, h_t, at rental price $q_{g,t}$ to maximize within-period utility:

$$
\begin{aligned}
V_t^{AC}(g,w) &= \max_{x_t,h_t} \log\big(B_g x_t^{\eta} h_t^{1-\eta}\big) + \delta\beta\mathcal{U}_{t+1}^{AC}(g) + (1-\delta)\beta\mathcal{V}_{t+1}^{AC}(g,w) \\
\text{s.t.} \quad & w(1-\tau_g) = x_t + q_{g,t}h_t.
\end{aligned} \tag{8}
$$

Here, τ_g is the local income tax rate and B_g is the local amenity. $\mathcal{U}_{t+1}^{AC}(g)$ is the expected continuation value of unemployment for workers hit by a separation shock, and $\mathcal{V}_{t+1}^{AC}(g,w)$ is the expected value of remaining employed; we define these continuation values below.

The value of an always-commuter who is unemployed is

$$
\begin{aligned}
U_t^{AC}(g) &= \max_{x_t,h_t} \log\big(B_g x_t^{\eta} h_t^{1-\eta}\big) + \beta \int_w \max\big\{\mathcal{U}_{t+1}^{AC}(g), V_{t+1}^{AC}(g,w)\big\}\, f_g(w)\, dw \\
\text{s.t.} \quad & b_g(1-\tau_g) = x_t + q_{g,t}h_t.
\end{aligned} \tag{9}
$$

Here, b_g denotes the unemployment benefit in city g. The worker follows a reservation-wage strategy, accepting any job offer above a threshold $\underline{w}_g$, where $\underline{w}_g$ is the wage that makes the worker indifferent between accepting the offer and continuing to search. Job offers are drawn from the local commuter-job distribution $f_g(w)$.

At the end of the period, an unemployed worker may move across cities, incurring utility cost $\psi^u(g_t, g_{t+1})$. The worker draws location-specific idiosyncratic preference shocks ϵ_g that are i.i.d. Gumbel (Type-I extreme value) with mean zero. Shocks enter utility as $\theta\epsilon_g$, where θ governs the dispersion of location preferences. The expected continuation value is therefore

$$
\mathcal{U}_{t+1}^{AC}(g_t) = \mathbb{E}_{\epsilon}\left[\max_{g_{t+1}} \left\{U_{t+1}^{AC}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right\}\right]. \tag{10}
$$

Similarly, an always-commuter who is employed at wage w may quit into unemployment in order to move across cities. The worker's location-preference shocks are drawn from the same Gumbel distribution as for unemployed workers. The expected continuation value is

$$
\mathcal{V}_{t+1}^{AC}(g_t, w) = \mathbb{E}_{\epsilon}\left[\max_{g_{t+1}} \left\{ \begin{array}{ll} V_{t+1}^{AC}(g_t, w) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} = g_t, \\ U_{t+1}^{AC}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} \neq g_t. \end{array} \right\}\right] \tag{11}
$$

The first term is the value of remaining employed at the current wage and city. The second term is the value of quitting, moving cities, and entering the next period unemployed. If the worker quits, they begin the next period unemployed in the destination city, receive unemployment benefits, and draw a local job offer. Their problem is then given by Eq. (9).

Under the assumption that the preference shocks are Gumbel, the continuation values and transition probabilities have closed-form expressions, see Appendix C.1. The law of motion for the population of always-commuters follows from these migration probabilities, the endogenous quit decision, the exogenous separation rate, and the job finding rate.

Remote-Capable Workers. The value of being employed in a remote job at wage w while living in city g is

$$\begin{aligned} V_t^{RC,r}(g,w) &= \max_{x_t,h_t} \log\left(B_g B_g^r x_t^{\eta} h_t^{1-\eta}\right) + \delta\beta\mathcal{U}_{t+1}^{RC}(g) + (1-\delta)\beta\mathcal{V}_{t+1}^{RC,r}(g,w) \\ &\text{s.t.} \quad w(1-\tau_g) = x_t + q_{g,t}h_t. \end{aligned} \tag{12}$$

Remote workers enjoy both the amenity value of living in city g, given by B_g, and the amenity value of working remotely in that city, given by B_g^r. We allow the remote-work amenity B_g^r to vary across cities, reflecting differences in commuting costs or amenities that may be particularly valuable for remote workers.

Unlike commuters, remote workers can move across cities without destroying their job match. Their expected continuation value is

$$\mathcal{V}_{t+1}^{RC,r}(g_t,w) = \mathbb{E}_{\epsilon}\left[\max_{g_{t+1}}\left\{V_{t+1}^{RC,r}(g_{t+1},w) - \psi^u(g_t,g_{t+1}) + \theta\epsilon_{g_{t+1}}\right\}\right]. \tag{13}$$

We assume that both the shock scale θ and the migration cost $\psi^u(g_t,g_{t+1})$ are the same for remote workers as for commuters.

The value of a remote-capable worker who is employed in a commuter job is

$$\begin{aligned} V_t^{RC,c}(g,w) = \max_{x_t,h_t} &\log\left(B_g x_t^{\eta} h_t^{1-\eta}\right) + \delta\beta\mathcal{U}_{t+1}^{RC}(g) \\ &+ (1-\delta)\beta\left[(1-p^s)\mathcal{V}_{t+1}^{RC,c}(g,w) + p^s V_{t+1}^{RC,r}(g,w)\right] \\ \text{s.t.} \quad &w(1-\tau_g) = x_t + q_{g,t}h_t. \end{aligned} \tag{14}$$

There are three possible outcomes for a remote-capable worker employed in a commuter job. With probability δ, the worker loses the job and becomes unemployed, yielding continuation value $\mathcal{U}_{t+1}^{RC}(g)$. With probability $(1-p^s)(1-\delta)$, the worker remains in the commuter job and receives continuation value $\mathcal{V}_{t+1}^{RC,c}(g,w)$. Finally, with probability $p^s(1-\delta)$, the worker is allowed to switch into a remote job at the current wage and receives continuation value

$V^{RC,r}_{t+1}(g, w)$. We discuss the motivation for this on-the-job switching probability in Section 6.

An unemployed remote-capable worker in city g receives benefit b_g and has a value

$$
\begin{aligned}
U^{RC}_t(g) = & \max_{x_t, h_t} \log\big(B_g x_t^\eta h_t^{1-\eta}\big) \\
& + \beta p^r_g \int_w \max\Big\{\mathcal{U}^{RC}_{t+1}(g), V^{RC,r}_{t+1}(g, w)\Big\}\, f^r(w)\, dw \\
& + \beta(1 - p^r_g) \int_w \max\Big\{\mathcal{U}^{RC}_{t+1}(g), V^{RC,c}_{t+1}(g, w)\Big\}\, f_g(w)\, dw \\
\text{s.t.} \quad & b_g(1 - \tau_g) = x_t + q_{g,t} h_t.
\end{aligned} \tag{15}
$$

With probability p^r_g, the worker receives an offer from the national remote wage distribution, $f^r(w)$. With probability $1-p^r_g$, the worker receives an offer from the local commuter distribution, $f_g(w)$. Workers follow reservation-wage strategies, accepting offers above a threshold. These thresholds differ by job type because remote jobs confer both an amenity value and the option to relocate without unemployment. As a result, remote-capable workers have a different reservation wage for commuter jobs than always-commuters because of the option value of waiting for a remote offer.

Next, we define the continuation values for remote-capable workers who are employed in a commuter job, $\mathcal{V}^{RC,c}_{t+1}(g_t, w)$, and who remain unemployed, $\mathcal{U}^{RC}_{t+1}(g_t)$. A worker in a commuter job may either remain in the current city at the current wage or quit into unemployment in order to move to a different city. The expected continuation value is

$$
\mathcal{V}^{RC,c}_{t+1}(g_t, w) = \mathbb{E}_\epsilon\left[\max_{g_{t+1}} \left\{ \begin{array}{ll} V^{RC,c}_{t+1}(g_t, w) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} = g_t, \\ U^{RC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} \neq g_t. \end{array} \right\}\right]. \tag{16}
$$

The first term is the value of remaining employed at the current wage and city. The second term is the value of quitting, migrating, and entering the next period unemployed. The continuation value for a remote-capable worker who remains unemployed is

$$
\mathcal{U}^{RC}_{t+1}(g_t) = \mathbb{E}_\epsilon\left[\max_{g_{t+1}} \left\{U^{RC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right\}\right]. \tag{17}
$$

5.3 Closing the Model

Production. For tractability, we take the wage offer distributions as exogenous and do not explicitly model vacancy creation or wage bargaining.[15] Since wages equal marginal products, $w = z$, the equilibrium distribution of wages equals the distribution of worker output, and total output of the final good is the integral over the output of employed workers. [16]

Housing. Housing is supplied by a representative landlord in each city, who transforms the final good into housing. The landlord solves a dynamic housing-accumulation problem to maximize the discounted stream of profits from renting $H_{g,\tau}$ housing units at rental rate $q_{g,\tau}$ to workers:

$$\max_{\{I_{g,\tau}\}_{\tau=t}^{\infty}} \sum_{\tau=t}^{\infty} \beta^{\tau-t} \left(q_{g,\tau} H_{g,\tau} - I_{g,\tau}\right) \tag{18}$$

$$\text{s.t.} \quad H_{g,\tau} = (1-\delta^h) H_{g,\tau-1} + \bar{\zeta}_g I_{g,\tau}^{\zeta_g} \qquad \forall \tau. \tag{19}$$

Here, $I_{g,\tau}$ denotes housing investment in units of the final good and δ^h is the housing depreciation rate. In steady state, housing supply in city g at time t is given by

$$H_{g,t} = \frac{\bar{\zeta}_g}{\delta^h} \left(\frac{\zeta_g \bar{\zeta}_g q_{g,t}}{1-(1-\delta^h)\beta} \right)^{\frac{\zeta_g}{1-\zeta_g}}. \tag{20}$$

Define $\tilde{\zeta}_g \equiv \frac{\zeta_g}{1-\zeta_g}$ as the housing supply elasticity in city g, and $\bar{\zeta}_g$ as a housing supply shifter.

General Equilibrium. Given model parameters, a steady-state equilibrium consists of rents, $\{q_g\}$, and worker distributions for always commuters $\{L^{AC}(u,g), L^{AC}(w,g)\}$ and remote-capable workers $\{L^{RC}(u,g), L^{RC,c}(w,g), L^{RC,r}(w,g)\}$ such that households and landlords optimize, worker populations are consistent with worker choices, housing markets clear in each city, and the national final-goods market clears. See Appendix C.2 for a formal definition.

[15] Complementary work by Sedláček and Shi (2025) studies the productivity implications of remote work where firms choose the share of employees working remotely, but abstracts from spatial implications.

[16] We assume a fixed wage-offer distribution, which imposes perfectly elastic local labor demand and abstracts from endogenous agglomeration externalities through which WFH could affect local productivity (Davis et al., 2024; Delventhal and Parkhomenko, 2026; Monte et al., 2025). Modeling these forces would require taking a stand on how remote-work adoption maps into local productivity spillovers.

6 Model Calibration

This section outlines the calibration of the model. Section 6.1 describes the pre-Covid steady state, Section 6.2 presents three untargeted validations of that steady state, and Section 6.3 describes the calibration of the Covid WFH shock.

6.1 Calibration of Pre-Covid Steady State

We calibrate the model's initial steady state to match pre-Covid data on population, rents, migration rates, and WFH shares across cities (MSAs).

The complexity of solving and calibrating the model increases with the number of cities. To reduce the dimensionality of the problem, we group cities into 5 bins and assume cities within a bin are identical, implying that cities within a bin share the same equilibrium outcomes. This allows us to work with 260 cities and retain realistic migration flows while keeping the number of calibrated parameters and equilibrium objects tractable. We use data from the 2019 ACS and group cities by average wage. Each bin contains approximately 20% of the population. Higher wage cities tend to be larger, so the number of cities in each bin is decreasing with bin wage. For example, there are 11 cities in bin 5 (highest wage) versus 130 cities in bin 1 (lowest wage). See Appendix C.3 for additional details.

A model period corresponds to one quarter, so parameters—such as the discount factor β and the separation rate δ—are specified at a quarterly frequency. However, several calibration targets, such as migration rates, are measured annually, so we match those moments using their annual equivalents implied by the quarterly model.

Our calibration proceeds in two steps. First, we externally assign a set of parameters using standard values from the literature; see panel (a) of Table 2. We set the housing supply elasticity, $\tilde{\zeta}_g$, to the average estimate in Saiz (2010) for each bin. The share of workers who are remote-capable, L^{RC}, is set to match the fraction of jobs that can be performed remotely in Dingel and Neiman (2020). We assume that unemployment benefits are 40% of the average wage in each city, a commonly used value in the literature (e.g., Shimer, 2005) and consistent with estimates from Unemployment Insurance data (U.S. Department of Labor, 2024).

Finally, we set the exogenous separation rate, δ, using CPS data. Because the model is quarterly, we define a separation in the CPS as a transition from employment to an unemployment spell that lasts at least three months, implying that the separation probability is the share of workers who are employed in month t who are then unemployed in each of months $t+1$, $t+2$, and $t+3$. This yields an implied monthly separation rate of 0.009, which

Table 2: Model Calibration

(a) Externally Set Parameters

Param.	**Description**	**Source**	**Value**
β	Discount factor	—	0.99
δ	Separations rate	CPS	0.03
b_g	Unemployment benefit	40% average wage	[0.40, 0.43, 0.44, 0.46, 0.50]
$1-\eta$	Housing share	Davis and Ortalo-Magné, 2011	0.24
L^{rc}	Share remote-capable	Dingel and Neiman, 2020	0.370
δ_h	Housing depreciation	Piazzesi and Schneider, 2016	0.01
$\tilde{\zeta}_g$	Housing supply elasticity	Saiz, 2010	[2.35, 1.78, 2.24, 1.63, 1.35]
τ_g	Income tax rate	ACS & Taxsim	[0.03, 0.04, 0.05, 0.06, 0.07]

(b) Internally Calibrated

Param.	**Description**	**Value**	**Moment**	**Data**	**Model**
B_g	City amenity	[1.000, 1.004, 1.025, 1.037, 1.086]	Population	Figure 7	
B_g^r	WFH amenity	[1.012, 1.072, 1.120, 1.128, 1.180]	WFH share	Figure 7	
$\bar{\zeta}_g$	HS shifter	[0.009, 0.006, 0.009, 0.005, 0.004]	Rents	Figure 7	
ψ_g^u	Mig. cost (utility)	[15.44, 13.98, 13.85, 13.53, 12.31]	Out mig.	Figure 7	
μ_g	Mean log wage offer	[0.01, 0.06, 0.11, 0.11, 0.21]	Commuter wage	Figure 7	
μ^r	Mean log wage offer	0.10	WFH wage	1.135	1.127
σ	Std. of wage-offer distn.	0.044	U rate	0.045	0.041
θ	Dispersion of pref. shocks	2.798	$\frac{\text{mig. wfh}}{\text{mig. ato}}$	1.50	1.49
p_g^r	Prob. of WFH offer	[0.014, 0.014, 0.014, 0.013, 0.020]	Net-mig, wfh	Figure 7	
p^s	Prob. of WFH switch	0.004	$\frac{\text{mig. wfh-wfh}}{\text{mig. ato-wfh}}$	1.000	1.013

we convert into a quarterly rate: $\delta = 1 - (1 - 0.009)^3 = 0.027$.

We calibrate the remaining parameters internally to match key moments in the data. While all parameters are jointly calibrated, panel (b) of Table 2 reports the parameters and the primary moment used to identify each of them. In particular, we choose city amenities, B_g, the amenity value of remote work, B_g^r, and the housing supply shifter, $\bar{\zeta}_g$, to match population, the WFH share, and rents across cities, respectively. Figure 7 shows that the model matches these moments well.

The calibrated WFH amenity ranges from 1.01 in bin 1, corresponding to a 1% additional amenity of WFH, to 1.18 in bin 5, consistent with remote work being more valuable in larger cities where commuting costs are higher. The mean value is 1.10, which is broadly in line with estimates of willingness to pay for WFH (Barrero et al., 2023; Cullen et al., 2025; Mas and Pallais, 2017). Smaller amenity values in low-wage bins are consistent with lower commuting costs in those cities.

We parameterize migration costs between cities g and g' with the symmetric form,

$$\psi^u(g,g') = \psi^u(g',g) = \begin{cases} 0, & \text{if } g' = g, \\ \psi_g + \psi_{g'}, & \text{if } g' \neq g. \end{cases}$$

so that the cost of moving from g to g' is the same as the cost of moving from g' to g.[17] This reduces the number of free parameters to the five bin-specific terms $\{\psi_g\}$. We discipline these parameters using city-level out-migration rates. In a stationary equilibrium, out- and in-migration rates must coincide; in the data, they are very similar but not identical, so we target out-migration rates. Figure 7 shows that the model closely matches the out-migration targets and also illustrates the remaining differences in in-migration.

We assume that wage-offer distributions are log normal with location parameter μ_g for the commuter distribution in city g and μ^r for the national remote-offer distribution. We adjust wages in the data for composition before computing the averages across cities and job types. Figure 7 verifies that the model matches mean commuter wages by city. The parameter for the remote wage offer distribution is calibrated to match the mean WFH wage of 1.14 (i.e., 14% higher than mean commuter wage offers in city 1), which lies between mean commuter wages in cities 1 and 5. All wage-offer distributions have the same scale parameter, σ, which is calibrated to match the aggregate unemployment rate. Greater dispersion in wage offers raises the option value of remaining unemployed, increasing equilibrium unemployment.

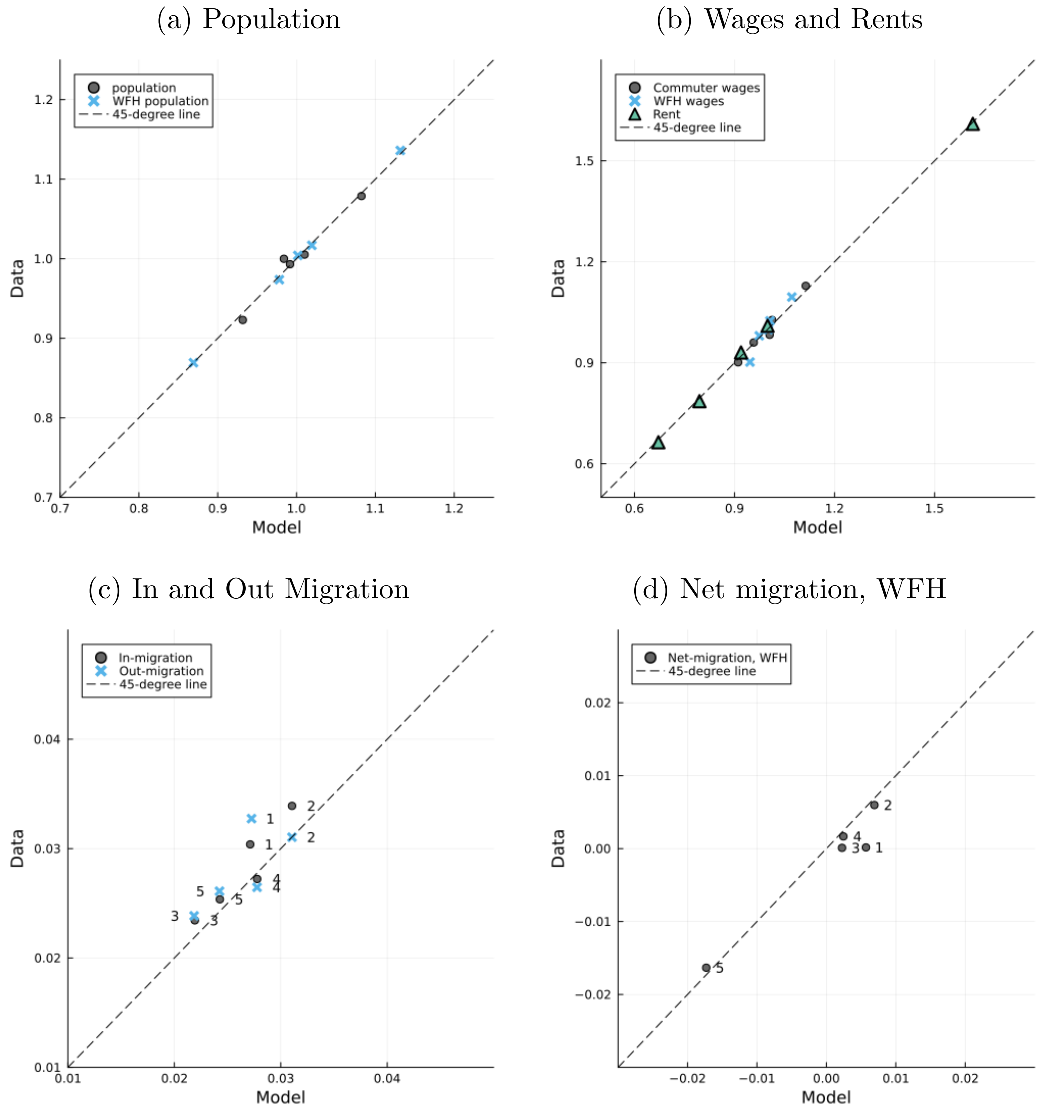
The dispersion of the location-specific idiosyncratic preference shocks, θ, is calibrated to match the migration rate of WFH workers relative to commuters. Remote workers are 50% more likely to move than commuters, after controlling for observables, reflecting that they can relocate without giving up their remote jobs and entering unemployment. Moreover, they have an incentive to move out of high-rent cities and carry their wage to lower-rent cities, where their real wage is higher. Intuitively, if the dispersion in the preference shocks is high, both commuters' and remote workers' migration decisions are driven primarily by idiosyncratic preferences rather than fundamentals, which compresses the difference in their migration rates. As the dispersion decreases, fundamentals become more important, and WFH workers migrate more.[18]

We calibrate p_g^r to match the net migration rate of WFH workers across cities, which is

[17] We do not separately model persistent idiosyncratic location preferences or home bias. Instead, the calibrated migration-cost can be interpreted as capturing direct moving costs as well as a household's attachment to their current location, which are not separately identified (Kennan and Walker, 2011).

[18] One concern is that WFH workers may face lower migration frictions because they tend to have higher incomes and education levels. However, insofar as their higher migration rates reflect observable characteristics such as occupation and wages, these differences are already controlled for in our empirical moments.

Figure 7: Model Calibration



Notes: Figure shows that the model replicates the data on the relative population, WFH population, wages, rents, in- and out-migration, and net-migration of WFH workers across cities. For population, wages, and rents, the values in city-1 are normalized to 1.

linked to the rate at which workers find remote jobs. In steady state, the mass of remote workers by city is constant, so remote inflows into a city must equal outflows. Inflows include remote workers migrating into the city and local remote-capable workers finding remote jobs. Outflows include remote workers migrating out of the city and job separations. Thus, conditional on the separation rate δ and the other parameters that govern migration flows, the remote job-finding rate helps determine the net migration rate of WFH workers. This allows the model to match the pattern in Panel (d) of Figure 7, which shows that

WFH workers exhibit negative net migration from the largest cities (bin 5) and positive net migration into bins 1–4.

We calibrate p^s to match the relative migration rates of workers who remain remote over the year (WFH–WFH moves) and workers who switch into WFH over the year (ATO–WFH moves). In the RPS, these rates are not statistically different (Figure 2), so we target this relative rate to be one. While both p^s and p^r_g affect the number of workers who transition into remote work, they generate different types of ATO–WFH workers. Holding p^r_g fixed, a higher p^s increases the share of ATO–WFH workers who switch into remote work on-the-job. These workers keep the wage from their commuter job while gaining the option to work remotely. This incentive is especially strong for former bin 5 commuters, who can carry their high wage to a lower-rent city. Thus p^s affects not only the size of the ATO–WFH group, but also, by changing its composition, its migration rate relative to incumbent WFH workers.[19]

6.2 Validation of Calibrated Model's Pre-Covid Steady State

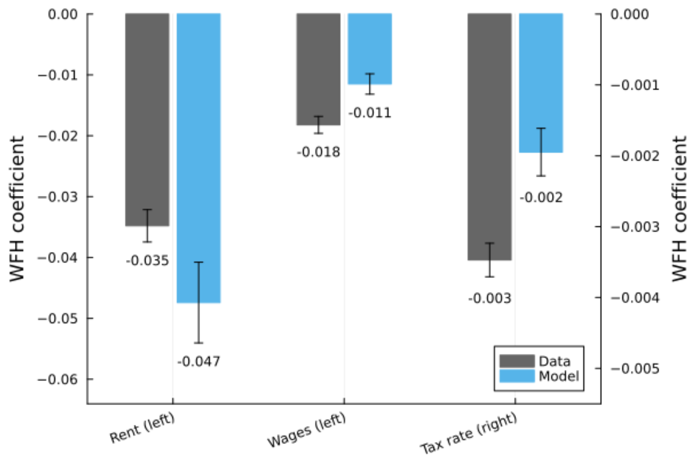
Here we discuss three untargeted validations of the model's pre-Covid steady state.

WFH wages across cities. The model matches the empirical pattern that remote wages are higher in cities with higher commuter wages. Although remote wages are drawn from a common national distribution, remote reservation wages increase with local commuter wages and commuters can switch into remote work while retaining their current wage. Figure 7 shows that average remote wages across cities closely match their empirical counterparts despite not being targeted. In the model, average WFH wages in bin 5 are 13% higher than in bin 1, compared with 21% in the data.

Migration elasticities. The model generates long-run migration elasticities in line with the estimates in Hornbeck and Moretti (2024). To compute model migration elasticities, we shock the mean of the log-wage-offer distribution one city at a time, lowering the mean by 0.1%. We then solve for the model's new long-run equilibrium. We define the local migration elasticity as the percent change in the city's population divided by the 0.1% productivity decline. The population-weighted average local migration elasticity in the model is 5.4, implying that a 1% decline in productivity lowers a city's long-run population by 5.4%. This is close to the estimate in Hornbeck and Moretti (2024), who find a long-run population

[19] We assume that p^s is constant across cities because our moment, the relative migration rate of switchers to WFH and WFH incumbents, is not available by city-bin.

Figure 8: Remote Workers Migrate to Lower-Rent, Lower-Wage, and Lower-Tax Cities



Notes: This figure reports destination-minus-origin differences in city characteristics for remote workers and commuters, comparing the model to the data. The corresponding empirical moments are reported in Table B.2.

elasticity with respect to TFP shocks of 4.03, with a standard error of 1.52.

Remote workers migrate to different cities. Conditional on migrating, remote workers move to systematically different places than similar commuters, relocating toward cities with lower rents, wages, and taxes (Table B.2). Figure 8 shows that the model replicates this pattern. The destination-minus-origin difference in local rents is 3.5 percentage points lower for WFH workers than for commuters in the data, versus 4.7 percentage points in the model; the wage gap is 1.8 versus 1.1 percentage points; and the tax-rate gap is 0.3 versus 0.2 percentage points.

6.3 Calibration of a Covid WFH Shock

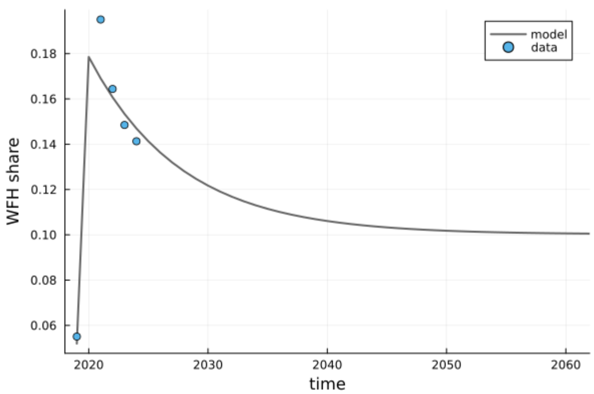
We use the calibrated model to study a Covid-inspired WFH shock. To replicate the Covid-era increase in remote work, we adjust three parameters. First, in the initial period of the transition, we temporarily increase p^s, the probability of switching from a commuter job into remote work, to match the observed rise in the WFH share across cities. In the initial and final steady states, this switching probability, p^s, is common across cities. During the Covid shock, the temporary increase in this probability varies across cities so that the model matches the larger rise in WFH rates in larger cities. In particular, 64% of remote-capable commuters in bin 5 transition to remote work in the initial period, versus 30% in bin 1. Second, we permanently raise p^s and p^r_g to match the expected long-run increase in the

Figure 9: WFH Shock

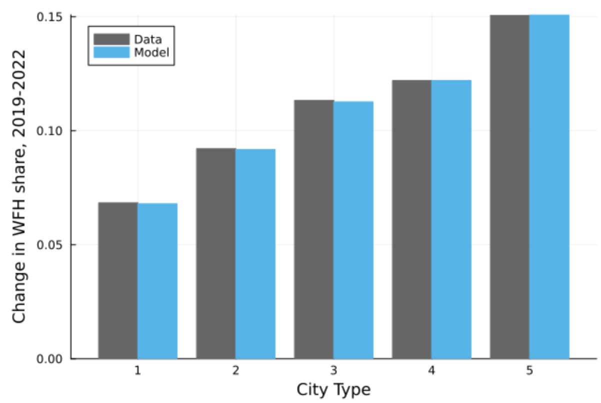
(a) Calibration of WFH Shock

Parameter	Description	Value	Moment	Data	Model
$p^s_{2020,g}$	Reallocation shock	[0.296, 0.364, 0.448, 0.466, 0.640]	Δ WFH sh., city	Panel (c)	
Δp^s	Prob. WFH switch	0.0003	Δ mig. gap	0.297	0.236
Δp^r_g	Prob. WFH offer	0.0895	Δ WFH sh., LR	10.000	10.022

(b) WFH Share



(c) Change in WFH share by city



WFH share (see Figure 1) and the relatively small change in the gap between the migration rates of remote workers and commuters (see Figure 1). Although the eventual steady-state WFH share is uncertain, we target 10%, consistent with the level at which WFH appears to have stabilized in the CPS and RPS (see Appendix Figure B.7 and Bick et al., 2025b).[20]

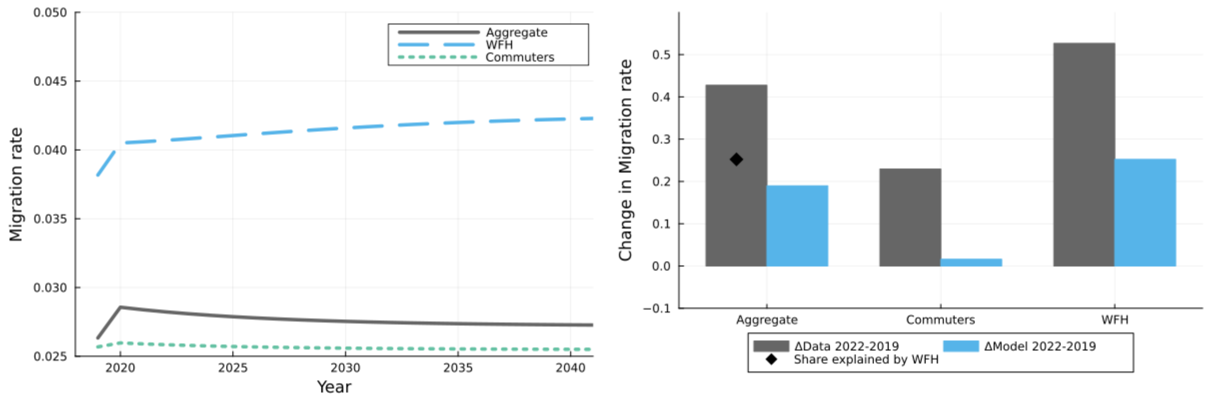
Panel (b) of Figure 9 plots the aggregate WFH share. The WFH share jumps to 18% on impact and then converges to its long-run target of 10%. The initial jump is targeted: the model matches the increase in the WFH share between 2019 and 2021, shown by the difference between the first and third data points. The subsequent speed of convergence is not targeted. It is determined endogenously by the model's separation rate and remote-job finding rates. Panel (c) compares the increase in the WFH share across cities in the model and data. In both the model and the data, the WFH share rises by 15 percentage points in bin 5 but by only 7 percentage points in bin 1.

Motivated by micro evidence in Bick et al. (2023), we model the WFH expansion as an

[20]As discussed in Section 6.1, p^s and p^r_g affect the migration rate of WFH workers by changing the composition of the WFH group between workers who transition to remote work on the job and those who transition through unemployment. In our calibration, the former have slightly higher migration rates. As a result, along the transition, matching the small change in the WFH–commuter migration-rate gap requires only a very small increase in p^s.

Figure 11: Response of Migration Rates to WFH-Shock

(a) Migration Before & After the WFH Shock (b) Change in Migration: Model vs. Data



Notes: Panel A shows the aggregate migration rate in the model after the WFH shock. Panel B shows the change in the migration rate for WFH workers and commuters (including the unemployed). The black diamond indicates the increase in aggregate migration explained by WFH according to the accounting exercise in Section 4.1.

increase in access to remote jobs, operating through higher p_g^r and p^s, while holding the remote and commuter wage-offer distributions fixed. The relative productivity of remote work does not change, in contrast to Davis et al. (2024) and Delventhal and Parkhomenko (2026). As we show below in Section 7.1, this is sufficient to match a large share of the cross-city pattern of wage growth without introducing changes to the relative productivity of remote work.

7 The Implications of the Covid WFH Shock

7.1 Migration and Worker Reallocation Across Cities

Here we briefly summarize how the WFH shock affects migration and population across cities. The shock raises annual migration rates, primarily by increasing the share of workers in high-mobility remote jobs. Over time, a larger share of highly-mobile remote workers reallocates population away from the largest, highest-rent cities toward smaller cities, dampening cross-city differentials in population and rental prices. While much of the increase in migration is transitory, reflecting adjustment along the path to the new steady state, the resulting changes in population accumulate over time and are persistent.

Annual Migration Rates. Figure 11a displays the evolution of aggregate annual migration rates after the WFH shock, as well as migration rates for WFH and commuter workers separately. In both the model and data, we define the WFH migration rate as the share of current WFH workers who migrated in the past year, which is what we observe in the ACS. We define the commuter migration rate analogously and include unemployed workers in this group to simplify the presentation.

Immediately after the shock, the aggregate migration rate in the model rises by 0.22 percentage points (or 8.5 percent). This is just under half of the observed increase in long-distance migration in the data. It is also close to the 0.27 percentage-point increase attributed to WFH in the accounting exercise in Section 4.1, shown by the black diamond in Figure 11b.

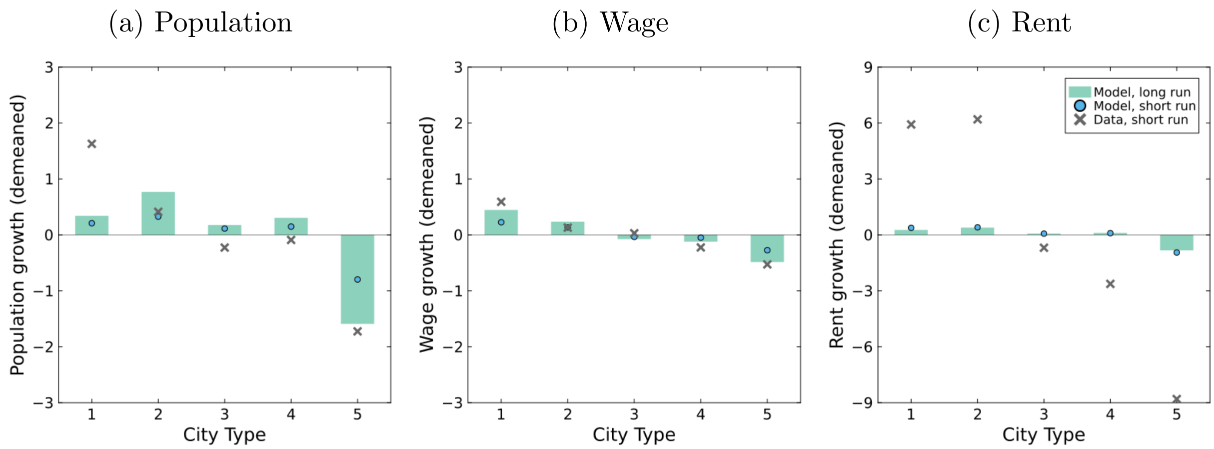
The increase reflects two channels: a compositional shift toward the more mobile remote group, and a rise in remote workers' migration rate. The majority of the aggregate increase is driven by composition: remote workers are more mobile than commuters, so tripling the remote worker share raises aggregate migration. The impact of the increase in the remote migration rate is quantitatively more modest because even after the shock the remote share of workers remains below 20 percent. In both the data and the model, about 80 percent of the WFH-induced increase in migration is composition-driven (Section 4.1).

The increase in migration is largest during the transition to the new steady state. As the WFH share declines from its pandemic peak toward its long-run level, aggregate migration also falls. In the long run, the migration rate settles 0.09 percentage points (or 3.5 percent) above its pre-shock steady state, roughly 40 percent of the initial spike in migration. WFH workers' migration rate also rises permanently, though this is not a primary driver of the aggregate changes. Before the WFH shock, some remote workers do not move to low-rent cities because, in the event of a job loss, they would have to search in a labor market with lower local wages. After the shock, this risk declines: the permanently higher probability of finding a new remote job makes WFH workers more willing to relocate.

Reallocation Across Cities. Figure 12 shows how population, rents, and wages change in response to the WFH shock. Empirical changes are de-meaned to focus on relative changes across cities because the model is not designed to match persistent trends that already prevailed before the Covid shock.

On net, the WFH shock reallocates workers away from the largest, highest-rent cities and toward smaller cities. In the new steady state, population in the largest cities (bin 5) falls by 1.6%, while population rises in the other bins. Population changes grow over time

Figure 12: Impact of the WFH Shock on Population and Rental Prices



Notes: Panel A reports population growth across cities, Panel B reports growth in average wages, and Panel c reports rent growth in the data and in the model. Rent, population, and wage growth are demeaned so that the cross-city average equals zero.

because workers continue to reallocate gradually during the transition.

Population changes are not perfectly monotonic in city size because migration decisions depend on a combination of local amenities, wages, rents, and migration costs. The smallest cities, in bins 1-2, experience the largest net increase in population. In these bins, the Remote-Capable population increases by 8% in the long-run. This inflow increases rents, which reduces the Always-Commuter population by 3%, dampening their net population increase. Bins 3 and 4 experience the same pattern, but with smaller magnitudes: their remote-capable population rises by 2%, while their always-commuter population falls by 1%.

The largest cities are the exception. Bin 5 experiences a 17% decline in its remote-capable population as remote-capable workers become less tied to high-rent locations. This outflow reduces rents, which attracts always-commuters into these cities. The resulting 9% increase in Always-Commuters in Bin 5 cities dampens their overall population decline.

Roughly half of the long-run change in population occurs within the first few years of the shock. The short-run population changes in the model are qualitatively similar to what we observe in ACS data. In both model and data, from 2019-2022, population declines in bin 5, is roughly unchanged in bins 3-4, and increases in bins 1-2. Quantitatively, the data exhibits a larger short-run population loss in bin 5 and a larger increase in bin 1 than predicted by the model. The model therefore captures a meaningful share of the observed reallocation, while leaving room for non-WFH forces absent from the model, such as Covid-related aversion to density, changes in local crime rates, or shifting political preferences.

Figure 12b shows the change in average wages across cities. Changes in mean wages are driven primarily by shifts in local WFH shares. Although WFH rises in all cities, its effect on average wages varies across locations because WFH workers earn less on average than commuters in large cities but more in small cities. This narrows the gap in average resident wages between large and small cities: in particular, access to the national remote market lets residents of smaller cities hold higher-paying jobs than were available locally.

Figure 12c shows that, as remote workers move toward smaller cities, rents rise in those locations and fall in the largest cities, consistent with the evidence in Brueckner et al. (2023). The increase in small-city rents is amplified because remote workers earn more on average than small-city commuters and therefore demand more housing per capita. Unlike changes in population, which accumulate over time, changes in rents are slightly larger in the short run. Housing gradually expands in growing cities and contracts in shrinking cities, easing pressure on rents over time.

In the short run, the model and data exhibit similar qualitative patterns of rent equalization across cities. However, the model substantially underpredicts the magnitude of these changes. One reason is that short-run population changes are smaller in the model, generating less pressure on rents. But another is that in the data the percent changes in rent are more than triple the corresponding population changes. Because the housing supply elasticities from Saiz (2010) all exceed one, all else equal, in the model a given percentage change in population produces a smaller change in rents over time. Reconciling the observed rent changes with population flows alone would therefore require much lower short-run housing supply elasticities (Oh et al., 2024). Alternatively, rent changes may reflect other shifts in housing demand across cities beyond those generated by the WFH shock, such as the increased demand for residential space emphasized by Mondragon and Wieland (2025) or the contemporaneous surge in immigration.

7.2 Welfare

How valuable is the ability to work in one labor market while living in another? On the one hand, WFH allows workers to earn relatively high wages while living in low-rent cities. This channel is potentially powerful: pre-shock rents in the largest cities are more than twice as high as in the smallest cities. On the other hand, these gains are limited by lower amenity values in smaller cities, moving costs, equilibrium rent responses, and the risk that a remote worker who loses her job may have to search in a weaker local labor market.

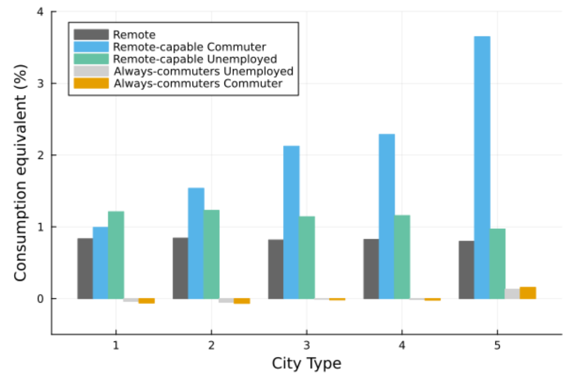
We evaluate welfare using a consumption-equivalent measure, defined as the percent

Figure 13: Consumption Equivalent Welfare Changes

(a) By worker type and employment status

	All	Remote-capable	Always-commuter
Panel A: By type			
Average	0.72%	1.96%	-0.00%
Panel B: By employment status			
Unemployed	–	1.14%	0.00%
Commuter	–	2.20%	-0.01%
Remote	–	0.82%	–

(b) By city, type, and employment status



Notes: Table shows average consumption equivalent overall, by worker type, and by employment status. Figure shows the same objects by city.

change in consumption and housing that would make a worker indifferent between remaining in the initial steady state and experiencing the transition.[21] Figure 13a reports the average consumption equivalent for all workers and broken down by worker type and employment status. On average, workers would need to be compensated 0.72% of initial steady-state consumption to remain indifferent between the initial steady state and the transition. Nearly all of these gains accrue to remote-capable workers, whose average consumption equivalent is 1.96%. Always-commuters are essentially unaffected on average.

The gains for remote-capable workers reflect several channels. First, remote work provides a direct amenity benefit. Second, it expands access to the national remote labor market. This is especially valuable in small cities, where remote wages exceed commuter wages. Third, remote work allows workers in large cities to relocate to lower-rent locations, raising real wages even when remote wages are lower than local commuter wages. Finally, WFH improves geographic matching: because remote workers can move without becoming unemployed, they can respond more easily to idiosyncratic location preferences

These gains are largest for remote-capable workers who held commuting jobs at the time of the shock. Many of these workers immediately transition into remote jobs, and the share doing so increases across city bins. As a result, Figure 13b reveals especially large gains for workers initially located in large cities, where the WFH shock is largest and the option to relocate to lower-rent cities is most valuable. Unemployed remote-capable workers also gain because the probability of receiving a remote offer increases permanently after the shock.

[21] With log utility, the consumption equivalent can be computed in closed form: $CE = (\exp((1-\beta)(V^{tr} - V^0)) - 1) \times 100$, where V^{tr} is the value along the transition and V^0 the value in the initial steady state.

Remote-capable workers already in remote jobs experience the smallest gains within this group: they do not benefit immediately from a change in job status, but gain in expectation because remote jobs are easier to find after separation.

Always-commuters experience small average effects, but the sign varies across cities. In small cities, where WFH raises rents, always-commuters experience modest welfare losses. In the large cities, where rents fall, they experience modest gains.

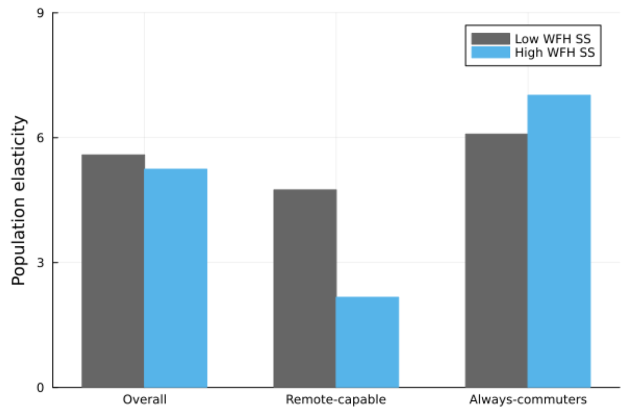
Putting our welfare results in context. Our welfare gains are smaller than those in several recent contributions, and the sources of the gains are different. The closest comparisons are Davis et al. (2025), which builds on Davis et al. (2024), along with Delventhal and Parkhomenko (2026) and Monte et al. (2025). Four features of our model account for these differences.

First, our model is dynamic and incorporates both search and migration frictions. Remote jobs cannot be obtained instantly and moves across cities are costly. These frictions reduce realized welfare gains relative to a frictionless and static comparison. This distinction is quantitatively important. The average static amenity value of WFH in our calibration is about 10 percent, consistent with estimates in the literature. But the consumption-equivalent gains are much smaller, because workers lack frictionless access to high-amenity remote jobs and must incur search and migration costs to realize many of the benefits. We quantify the impact of these frictions in Appendix C.5.

Second, motivated by evidence in Bick et al. (2023), we model the shock that expands WFH differently. In our model, the WFH expansion is an access shock: (p_g^r) and (p^s) increase, while the productivity and amenity value of remote jobs are held fixed. This contrasts with models in which the rise of WFH is generated by an improvement in the productivity or attractiveness of remote work, as in Davis et al. (2025) and Delventhal and Parkhomenko (2026). As a result, the gains we measure are primarily reallocative. They come from improved access to remote jobs, better worker-job matches, and sorting toward preferred locations, rather than from a large aggregate productivity gain. At the same time, the transition matters. The shock moves many commuters into remote jobs on impact, generating a windfall for affected workers that a purely steady-state comparison would miss, similar in spirit to the transition dynamics in Greaney et al. (2025).

Third, we focus on full-time remote work and long-distance migration. This means that we do not capture gains from hybrid work arrangements or within-city relocation, which are central mechanisms in Davis et al. (2025) and Delventhal and Parkhomenko (2026). Our

Figure 14: Migration Elasticity to a Local Productivity Shock



welfare results therefore isolate a different margin: the value of being able to work in one labor market while living in another, subject to costly migration and job-search frictions.

Finally, the welfare effects for workers who cannot work remotely differ because of how our model treats housing supply and agglomeration. We calibrate housing supply using the elasticities in Saiz (2010), all of which exceed one. This places our model between Davis et al. (2025), where inelastic housing supply implies that higher housing demand raises prices and generates losses for non-remote workers, and Delventhal and Parkhomenko (2026), where elastic supply and commercial-to-residential conversion can lower prices. In our calibration, rents fall in large cities and rise in smaller cities, leaving always-commuters on average roughly unaffected. We also abstract from agglomeration externalities, which are an important channel through which non-remote workers lose from WFH in Monte et al. (2025) and Delventhal and Parkhomenko (2026). Davis et al. (2025) also includes agglomeration forces, but the welfare losses for non-remote workers are driven primarily by inelastic housing supply. Absent both a large housing-price increase and an agglomeration loss, always-commuters experience little average welfare change in our model.

Taken together, our results provide a complementary perspective. Rather than quantifying the welfare gains from a remote-work productivity boom, we quantify how an expansion in access to remote jobs is realized through costly and gradual migration, and how those gains are distributed between remote-capable and always-commuter workers.

7.2.1 WFH and the Incidence of Local Shocks

An expansion in WFH also changes workers' exposure to local labor-market risk. Specifically, access to the national remote labor market weakens the link between local productivity and the value of remaining in a city for remote workers. This in turn changes the equilibrium response of rents to local productivity shocks, which has implications for commuters.

To quantify these effects, we analyze the effects of a negative local productivity shock in both the low- and high-WFH steady states. Specifically, we reduce one city's average commuter wage offers by 0.1%. We conduct 10 experiments, shocking a representative city from each of the five bins under both steady states.

Figure 14 shows the migration responses to the negative productivity shock before and after the WFH shock. The overall migration elasticity to a local productivity shock is only slightly lower in the high-WFH steady state. However, this masks substantial heterogeneity between worker types. As we move from the low-WFH to the high-WFH steady state, the migration elasticity to the negative productivity shock declines by 2.6 for remote-capable workers but increases by 0.9 for always-commuters. This divergence reflects the different response of rents across the two steady states. In the high-WFH steady state, remote-capable workers can potentially remain in the shocked city while earning national-market wages, so local rents fall by less in the high-WFH steady state. Always-commuters therefore face both lower local wages and relatively higher rents, increasing their incentive to leave.

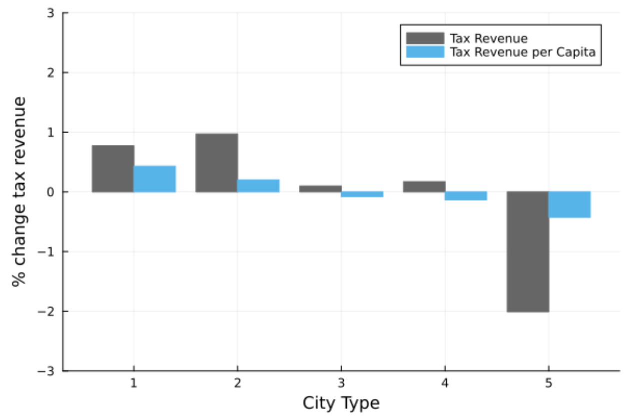
The welfare consequences of the local productivity shocks mirror the migration elasticities. In the high-WFH steady state, the consumption equivalent welfare loss from a local productivity decline is 11.3% smaller for remote-capable workers. However, the CE welfare loss for always-commuters increases by 6.3%.

We highlight two key takeaways from this exercise. Greater access to WFH shields many workers from the negative consequences of a decline in local productivity. However, these benefits do not extend to workers who are unable to work remotely. Instead, lower out-migration by remote-capable workers prevents rents from falling as much as they otherwise would. Always-commuters therefore face relatively higher rents after the WFH expansion, shifting a greater share of the negative shock onto them.

7.3 Fiscal Implications

The same forces that redistribute workers and welfare across cities also reshape local public finances. We first examine how the expansion in WFH affects local tax revenues. Because the model features a simple proportional income tax, these results are best interpreted as illustrating how WFH reshapes local tax bases rather than as a full accounting of municipal public finance. Then, inspired by policies such as the "Tulsa Remote Program", we ask whether migration subsidies to attract remote workers can be cost-effective.

Figure 15: Tax Revenue Responses



7.3.1 Local Tax Revenue

Figure 15 displays long-run changes in local tax revenues. The smallest cities, in bins 1 and 2, experience an increase in total tax revenue of 0.8 to 1.0 percent. This largely reflects the population reallocation documented above: the WFH shock shifts residents from the largest cities and toward smaller cities. Tax revenues in the smallest cities also increase because per capita tax revenues increase. In small cities WFH workers tend to earn more than commuters, so a greater WFH share raises wages and taxes per capita. The same forces apply in the opposite direction in the largest cities. These cities experience a decline in total tax revenue of roughly 2 percent, and a decline in per-capita tax revenue of 0.4 percent.

These results highlight that the fiscal effects of WFH depend not only on net population flows, but also on which workers move. Cities that lose remote workers may experience large declines in total revenue but only modest declines in revenue per capita, while cities that attract high-wage remote workers can experience gains in both total and per capita revenue.

7.3.2 Migration Subsidies for Remote Workers

The impact of WFH on local tax revenues raises a natural policy question: can cities profitably attract remote workers through relocation subsidies? This question is motivated by real-world programs such as the Tulsa Remote Program, which provides a one-time $10,000 payment to remote workers who relocate to Tulsa and stay for at least one year.

We study this policy in the model's high–WFH steady state. The policy takes the form of a one-time transfer to remote workers who relocate to the city. Although each recipient receives the transfer only once, the policy itself is permanent: the government commits to offering the subsidy to all eligible movers in perpetuity. We implement the policy one city at a time, abstracting from strategic interactions across cities (Agrawal and Brueckner, 2025). The subsidy equals 10 percent of the annual wage in zone 1, or about $4,000 in the model.

On average across cities, in the post-policy steady state, the policy generates $0.51 in additional quarterly tax revenue for each dollar of quarterly program expenditure. The key reason is that the government cannot target the subsidy exclusively to marginal movers. Many recipients are inframarginal: they would have relocated to the city even without the program. In the model, 97% of the program cost goes towards subsidizing the inframarginal movers rather than the marginal movers. Subsidizing these workers raises program costs without generating additional migration or tax revenue. Instead, if one could perfectly target the marginal movers, the program would raise $17 for every dollar spent. Figure C.13 shows how the results vary by city-bin.

8 Conclusion

This paper presents a wealth of evidence that (full-time) WFH has important spatial economic implications. When workers do not have to commute to a job, migration increases and population shifts toward lower-cost cities, affecting local rents, tax bases, and welfare. These effects are not confined to the immediate post-pandemic period: WFH has stabilized at roughly twice its pre-Covid rate, and our model suggests the reallocation of workers and fiscal resources across cities will continue gradually for years.

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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 displays the breakdown of the sample sizes across survey months.

Table A.1: 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 Deming and Stephan (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. For additional details, see Bick and Blandin (2023).

A.2 Definition of Demographic Groups and Industries

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

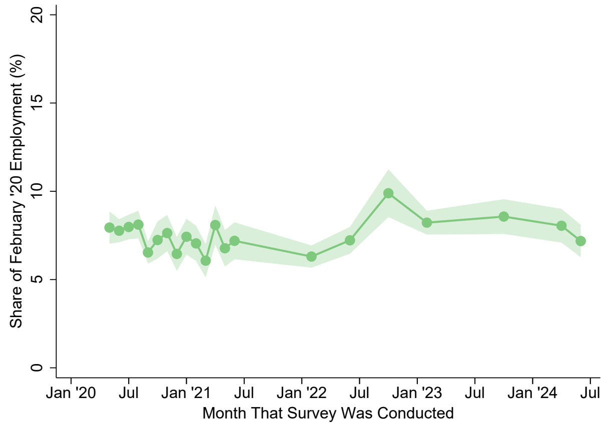
- Age
  - **Younger**: Ages 18-29
  - **Mid Age**: Ages 30-49
  - **Older**: Ages 50-64
- Race and Ethnicity
  - **Black**: Identify as Black and not Hispanic
  - **Hispanic**: Identify as Hispanic
  - **White**: Identify as White and not Hispanic
  - **NonBlackHispWhite** or **Non B/H/W**: All other 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.1: 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.1 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 June 2024. Reassuringly, we find that reported WFH outcomes in February 2020 are fairly stable across survey months.

A.4 February 2020 Commuting Requirement

Our instrument relies on two sets of questions. In this section, we discuss some details on the first question in Section 3.1.2, which we re-state here.

(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*

In October 2022, February 2023, and October 2023, we adjusted the phrasing and asked everyone.

(Q1a) "If you [your spouse/partner] ever commuted voluntarily in February 2020, please only report the days you were [your spouse/partner was] required to commute. How often were you [was your spouse/partner] usually required to commute to this job?

i. *4 or more days per week*

ii. *1 to 3 days per week*

iii. *Every other week*

iv. *A few times per month*

v. *A few times per year*

vi. *Hardly ever or not at all*

vii. *It varied a lot*

Answer option i. was only displayed for people who reported usually commuting 4 or more days per week, and answer option ii. for people who reported usually commuting 1 to 3 days per week. Anyone who chose answer options i. to iv. or vii. was then asked.

(Q1b) "'What was the main reason you [your spouse/partner] were required to commute on these days?"

a) *Some aspects of my [spouse/partner's] job required me [them] to commute on these days*

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*

To maintain consistency across waves, we construct the equivalent of *Q1* for the last three waves as follows and name this variable *Q1**:

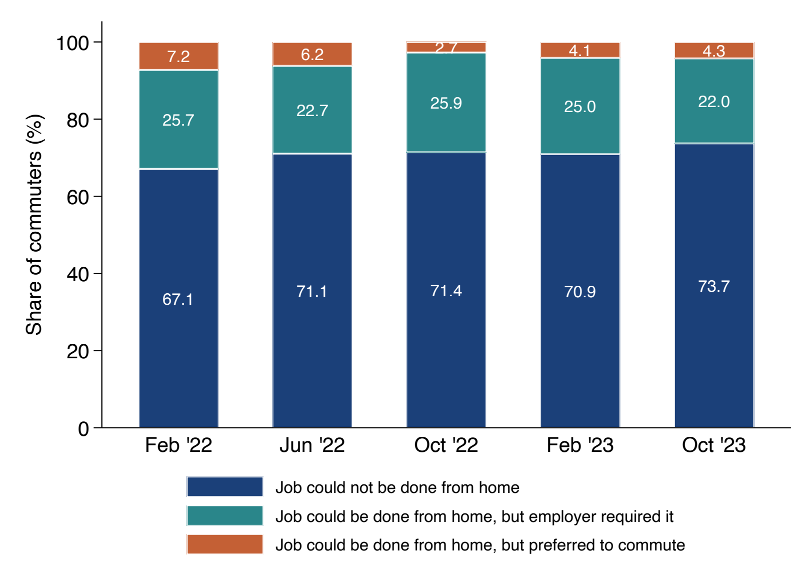
a) if answer to *Q1b* is a)

b) if answer to *Q1b* is b)

c) if respondent [spouse] usually commuted at least some days in February 2020 but answered to *Q1a* answer options v. or vi.

In addition, since workers who worked usually WFH full-time in February 2020 were not asked *Q1* in the February and June 2022 surveys, we set *Q1** to missing for workers who worked usually WFH full-time in the October 2022, February 2023, and October 2023 surveys. Figure A.2 shows that the distribution of reason for commuting in February 2020 is very similar across all waves, with the first two waves having a slightly higher share of respondents who preferred to commute in February 2020.

Figure A.2: February 2020 WFH Reasons for Commuting by Survey Month

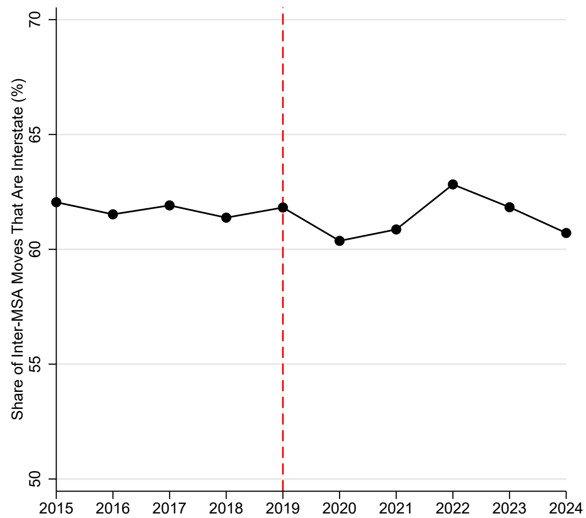


Notes: Real-Time Population Survey, ages 18-64, February 2020 observations, sample from column 1 in Table 1. The figure plots the reasons for commuting in February 2020.

B Additional Facts on WFH and Interstate Migration

B.1 Inter-MSA versus Interstate Migration in the ACS

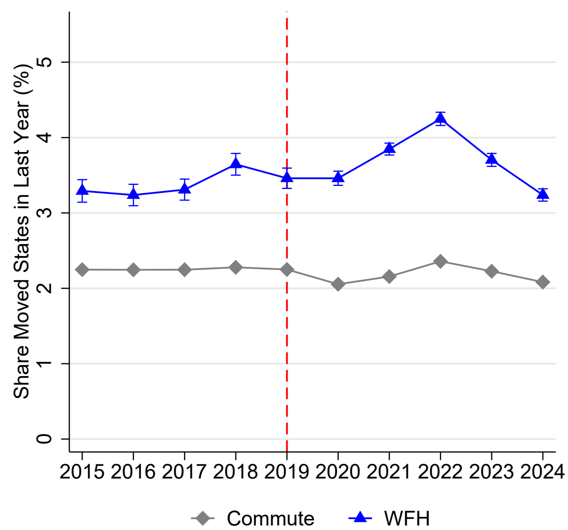
Figure B.3: Share of Inter-MSA Moves That Are Also Interstate



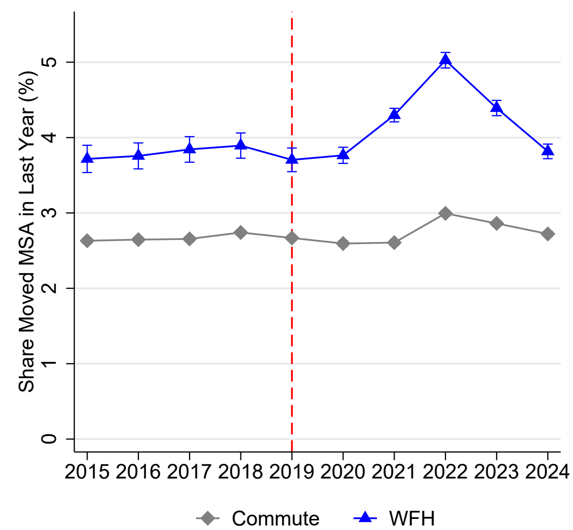
Notes: American Community Survey (ACS). The figure shows the percentage share of inter-MSA moves that are also inter-state. The sample is employed working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year.

Figure B.4: Work from Home and Long-Distance Migration

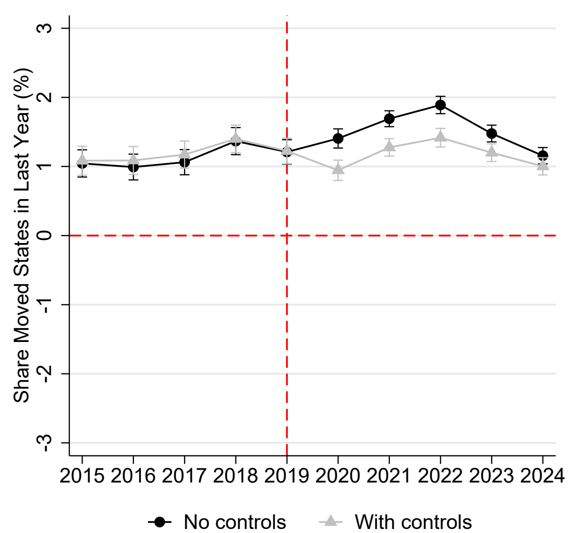
(a) Interstate Migration by Commute Status



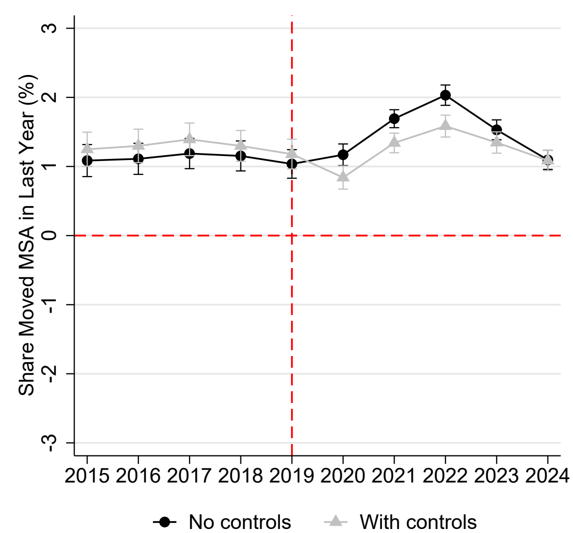
(b) Inter-MSA Migration by Commute Status



(c) Interstate Migration: WFH−Commuters



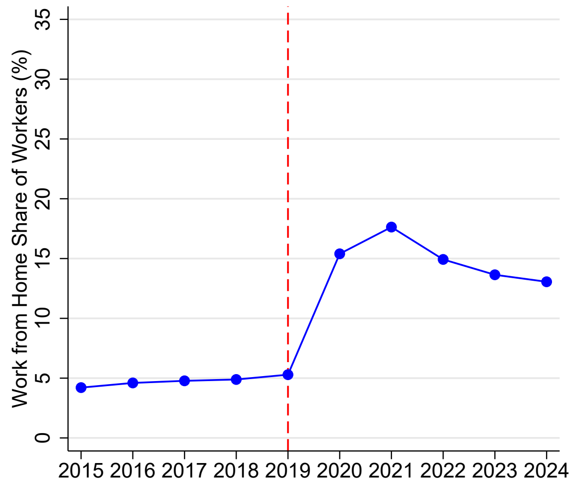
(d) Inter-MSA Migration: WFH−Commuters



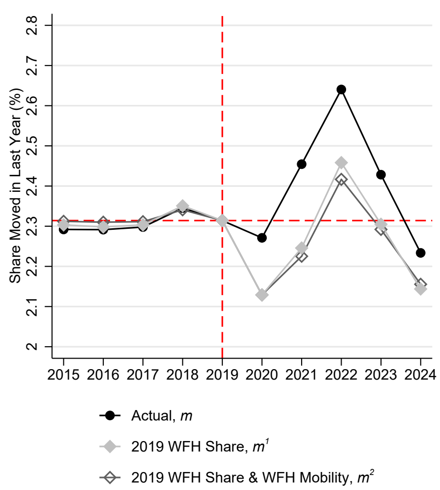
Notes: American Community Survey (ACS). Left Panels: annual interstate / inter-MSA migration rates for three population groups: commuters (gray diamonds), and WFH workers (blue triangles). Right Panels: the black squares are the difference between WFH and Commuters from the left panel; the gray triangles 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.5: Accounting Exercise: The Impact of Work from Home on Long-Distance Migration

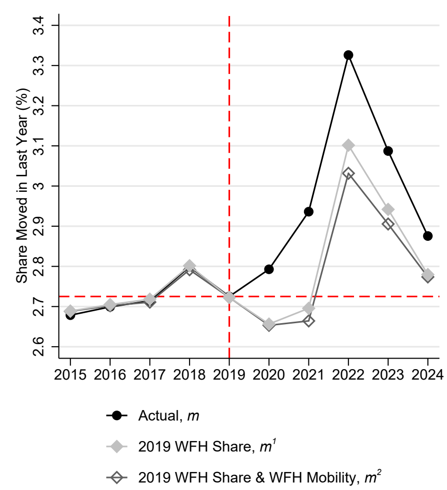
(a) Share of Workers Who Work from Home



(b) Impact on Interstate Migration



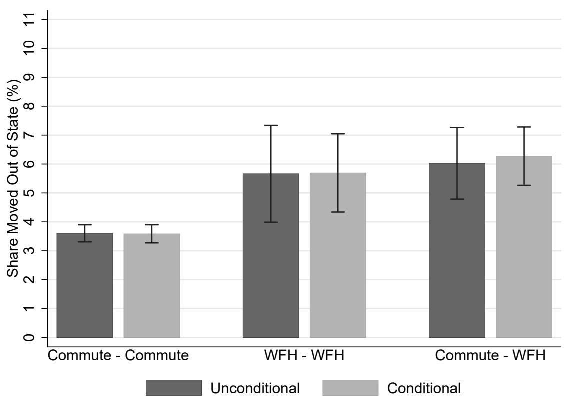
(c) Impact on Inter-MSA Migration



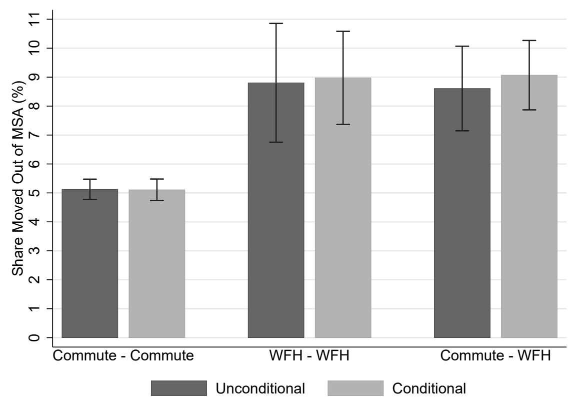
Notes: American Community Survey (ACS). Top Panel: the share of workers (%) who WFH. Bottom Panels: black circles are actual migration rates for workers in the ACS; gray diamonds are the counterfactual migration path if WFH would have remained at the 2019 share; hollow black diamonds are the counterfactual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

Figure B.6: 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.

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:

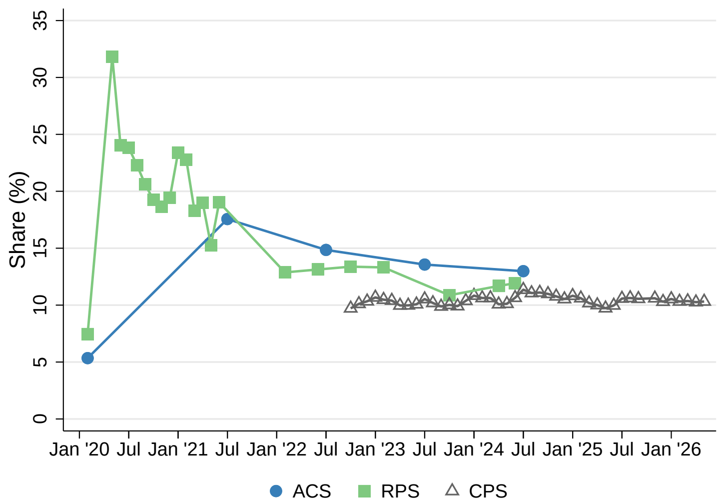
1. "At any time LAST WEEK, did (you/name) telework or work at home for pay?"
2. "LAST WEEK, (you/name) worked (# hours worked last week at all jobs) hours (total/at all jobs). How many of these hours did you telework or work at home for pay?"

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.7 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 2021-2024 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.

FIGURE B.7: 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 2019 ACS data points as the February 2020 observation to facilitate comparison with the RPS's February 2020 data. We plot 2021-2024 ACS data in the midpoint (July) 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.

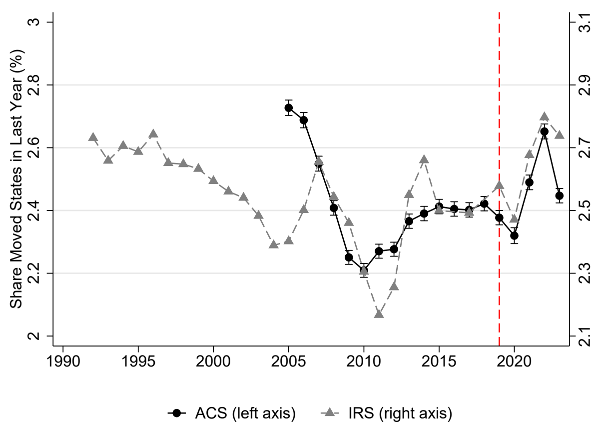
B.3 Comparing Migration in the ACS and RPS

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.8: 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.8 displays interstate migration in IRS and ACS data. ACS data (left axis) run from 2005 to 2022 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 2022. 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 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. (2025) build models in which an expansion in WFH induces some workers to make local moves: from high-rent city centers near workplaces to more distant suburbs with lower rents or better amenities. Brueckner et al. (2023) and Delventhal and Parkhomenko (2026) 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.

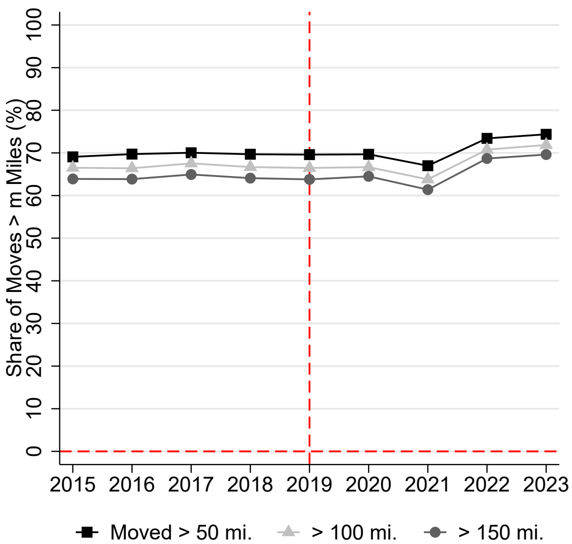
We can evaluate the fraction of interstate and inter-MSA moves in the ACS that are long-distance using county-level distance information. Specifically, for any individual who moves across state or MSA lines, we compute the distance between their origin county and destination county. Counties are not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

Figure B.9 plots the share of all interstate or inter-MSA 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.

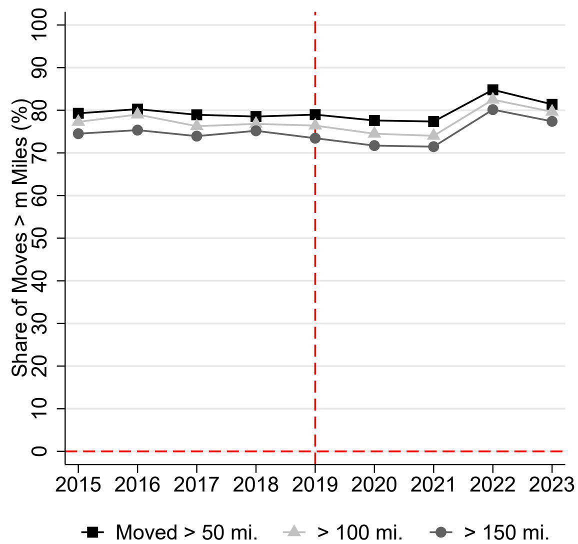
We emphasize three main takeaways. First, a large majority of inter-state and inter-MSA moves are long-distance. Second, these shares have remained fairly stable over time, and if anything have increased since the Covid pandemic. Third, the share of inter-state and inter-MSA moves that are long-distance are slightly higher for WFH workers. Collectively, we conclude that interstate and inter-MSA moves are a good proxy for long-distance moves across labor markets, especially for WFH workers.

Figure B.9: Share of Long-Distance Moves Among Interstate / Inter-MSA Migrants

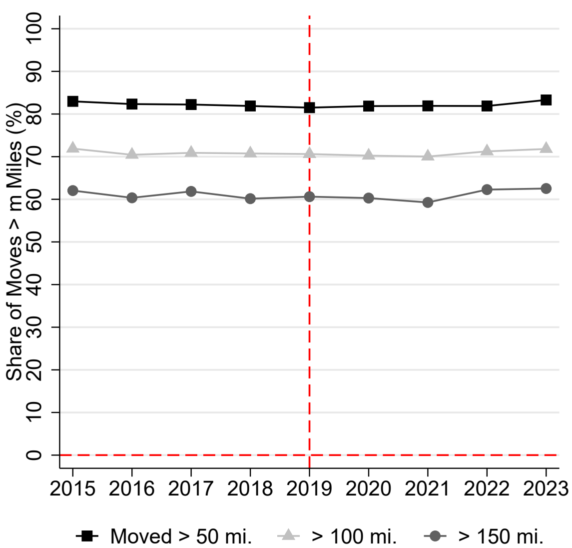
(a) Interstate Migration: Commuters



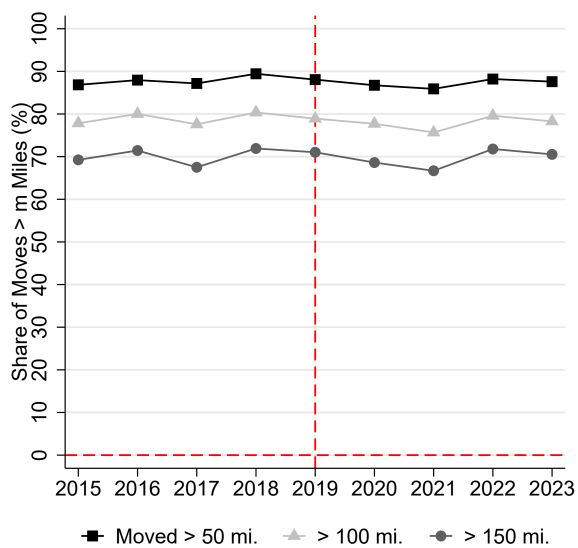
(b) Interstate Migration: Work from Home



(c) Inter-MSA Migration: Commuters



(d) Inter-MSA Migration: Work from Home



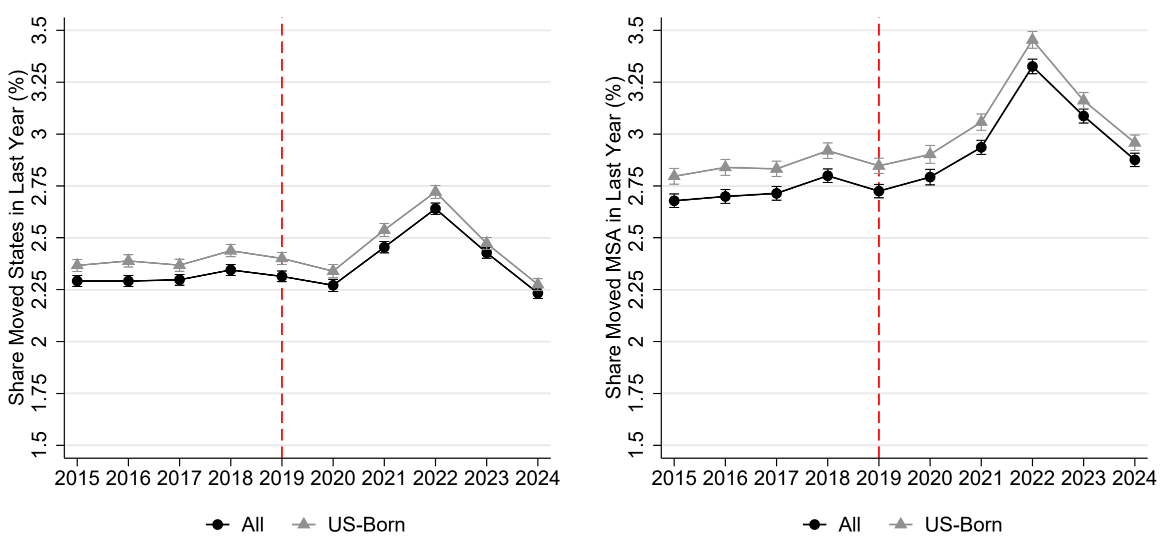
Notes: American Community Survey (ACS). The figure displays the share (%) of interstate or inter-MSA moves in a given year whose estimated distance exceeded 50, 100, or 150 miles. Moving distance is measured as the distance between two counties; see text for details. The sample is employed working-age (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 or MSA compared to one year ago.

B.6 Overall Trends versus Trends for US Natives

International immigration patterns were volatile since 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.10 compares the national interstate migration rates in the main text to interstate migration rates for US natives. We find essentially identical patterns in the two series, implying that foreign-born individuals are not directly driving the rise in interstate migration after 2020.

FIGURE B.10: Long-Distance Migration: All vs. Native-Born

(a) Interstate Migration (b) Inter-MSA Migration

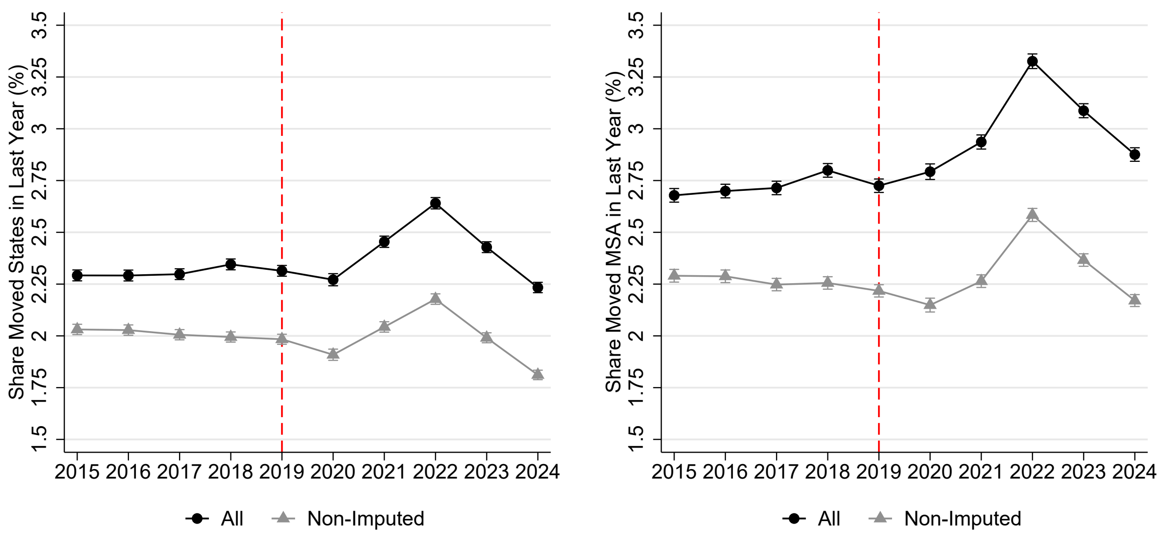


Notes: American Community Survey (ACS). The basic sample is employed working-age (18-64) adults in civilian households who currently live in the US and lived in the US in the previous year. The figure displays annual migration rates for two groups: all individuals in the basic sample, and only US-born individuals. Whiskers correspond to 95% confidence intervals.

B.7 Imputed Migration in the ACS

Figure B.11: Long-Distance Migration: All vs. Imputed Moves

(a) Interstate Migration (b) Inter-MSA Migration



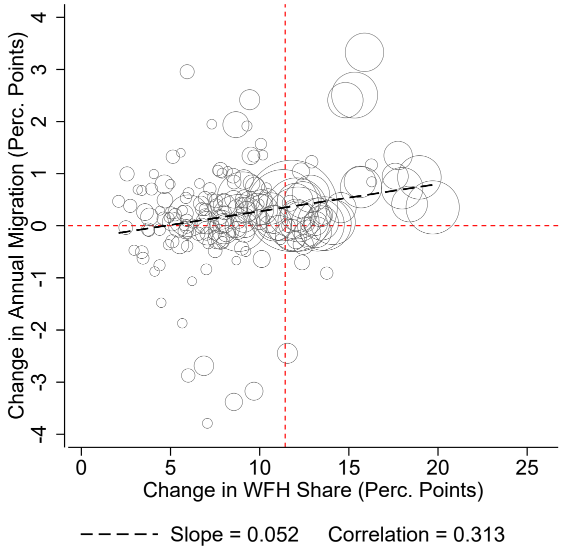
Notes: American Community Survey (ACS). The basic sample is working-age (18-64) adults in civilian households who currently live in the US and lived in the US in the previous year. The figure displays annual migration rates for two groups: all individuals in the basic sample, and only individuals whose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

B.8 Measuring Local WFH Capacity Using Dingel and Neiman (2020)

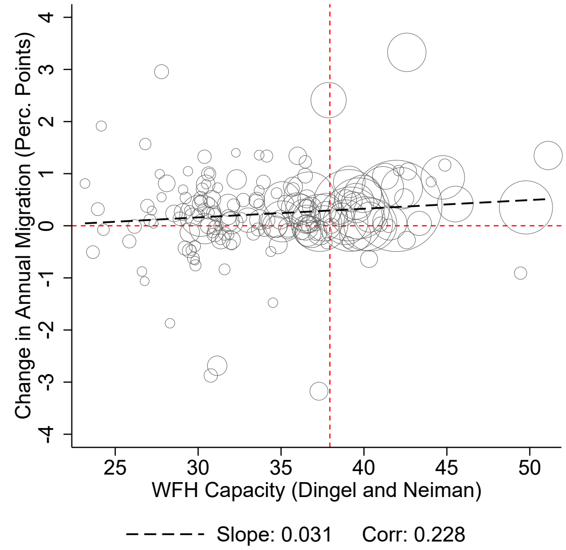
Section 4.2 showed that local variation in WFH changes was highly predictive of migration rates. This section shows that we find similar results if we instead use a measure of a MSA's WFH capacity based on Dingel and Neiman (2020). They construct a measure of WFH capacity based on the tasks involved in an occupation and whether these tasks could feasibly be done from home. Figure B.12 plots local out-migration and net-migration rates against actual WFH rates in 2021-2022 (left panels) and WFH Capacity (right panels).

FIGURE B.12: Work from Home and MSA Out-Migration

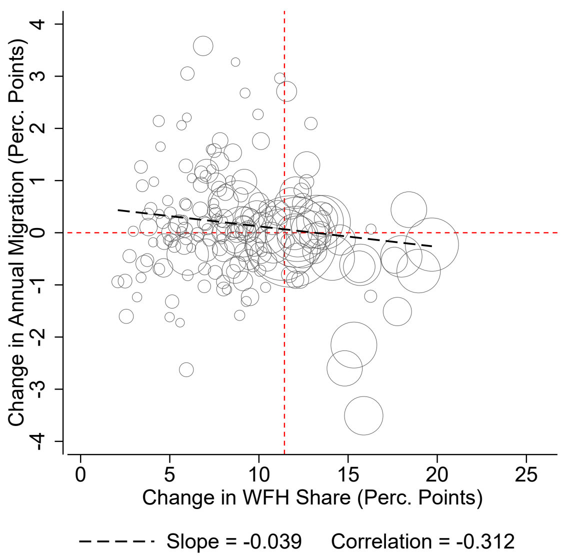
(a) WFH and MSA Out-Migration



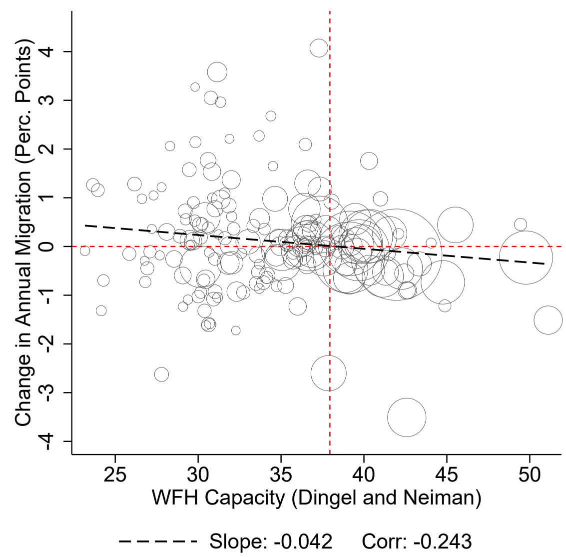
(b) WFH Capacity and MSA Out-Migration



(c) WFH and Net-MSA Migration



(d) WFH Capacity and Net-MSA Migration



Notes: American Community Survey (ACS). Top panels: Circles plot the post-pandemic increase in a MSA's WFH share (2021-2024 vs. 2015-2019), or its WFH Capacity, against the post-pandemic increase in its out-migration rate (2021-2024 vs. 2015-2019). Right Panel: Circles plot the post-pandemic increase in a MSA's WFH share, or its WFH Capacity, against the post-pandemic increase in its net-migration rate. WFH capacity is based on a state's occupation mix; see Dingel and Neiman (2020). Circle areas are proportional to MSA population. Dashed black lines are estimated using OLS. We exclude MSAs whose 2019 population is below 200,000.

Table B.2: Migration Destination Characteristics: Work from Home vs. Commuters

	Δ Mean Log Wage	Δ Mean Log Rent	Δ State Tax Rate
WFH Coefficient	-0.0182^{***}	-0.0348^{***}	-0.0035^{***}
	(0.0014)	(0.0027)	(0.0002)
N	212169	212149	212169

Notes: American Community Survey (ACS). The basic sample is employed working-age (18-64) adults in civilian households who currently live in the US and lived in the US in the previous year.

B.9 Work from Home and Migration Destination

C Model Appendix

C.1 Model Population Dynamics

Continuation Values. Workers draw location-specific preference shocks ϵ_g that are i.i.d. Gumbel (Type-I extreme value) with mean zero, where θ governs the dispersion of location preferences. Given this structure, the expected continuation values have closed-form expressions. For always-commuters who are unemployed, the continuation value is given by

$$\begin{aligned}\mathcal{U}^{AC}_{t+1}(g_t) &= \mathbb{E}_\epsilon\left[\max_{g_{t+1}}\left\{U^{AC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right\}\right] \\ &= \theta\ln\left(\sum_{g_{t+1}}\exp\left(\frac{U^{AC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1})}{\theta}\right)\right).\end{aligned}$$

For always-commuters employed with wage w, who have the option to quit to unemployment and move to a new city,

$$\begin{aligned}\mathcal{V}^{AC}_{t+1}(g_t, w) &= \mathbb{E}_\epsilon\left[\max_{g_{t+1}}\left\{\begin{array}{ll} V^{AC}_{t+1}(g_t, w) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} = g_t, \\ U^{AC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} \neq g_t, \end{array}\right\}\right] \\ &= \theta\ln\left(\sum_{g_{t+1}}\left[\mathbb{I}(g_{t+1} \neq g_t)\exp\left(\frac{U^{AC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1})}{\theta}\right) + \mathbb{I}(g_{t+1} = g_t)\exp\left(\frac{V^{AC}_{t+1}(g_t, w)}{\theta}\right)\right]\right).\end{aligned}$$

For remote-capable workers employed remotely with wage w,

$$\begin{aligned}\mathcal{V}^{RC,r}_{t+1}(g_t, w) &= \mathbb{E}_\epsilon\left[\max_{g_{t+1}}\left\{V^{RC,r}_{t+1}(g_{t+1}, w) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right\}\right] \\ &= \theta\ln\left(\sum_{g_{t+1}}\exp\left(\frac{V^{RC,r}_{t+1}(g_{t+1}, w) - \psi^u(g_t, g_{t+1})}{\theta}\right)\right).\end{aligned}$$

For remote-capable workers employed in a commuter job with wage w,

$$\begin{aligned}\mathcal{V}^{RC,c}_{t+1}(g_t, w) &= \mathbb{E}_\epsilon\left[\max_{g_{t+1}}\left\{\begin{array}{ll} V^{RC,c}_{t+1}(g_t, w) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} = g_t, \\ U^{RC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}, & \text{if } g_{t+1} \neq g_t, \end{array}\right\}\right] \\ &= \theta\ln\left(\sum_{g_{t+1}}\left[\mathbb{I}(g_{t+1} \neq g_t)\exp\left(\frac{U^{RC}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1})}{\theta}\right) + \mathbb{I}(g_{t+1} = g_t)\exp\left(\frac{V^{RC,c}_{t+1}(g_t, w)}{\theta}\right)\right]\right)\end{aligned}$$

For remote-capable workers who are unemployed,

$$\mathcal{U}_{t+1}^{RC}(g_t) = \mathbb{E}_\epsilon\left[\max_{g_{t+1}} \left\{U_{t+1}^{RC}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right\}\right] \tag{C.1}$$

$$= \theta \ln\left(\sum_{g_{t+1}} \exp\left(\frac{U_{t+1}^{RC}(g_{t+1}) - \psi^u(g_t, g_{t+1})}{\theta}\right)\right). \tag{C.2}$$

Transition Probabilities: Always-Commuters. Given the assumption that workers draw their preference shocks from a Gumbel distribution, the probability that an unemployed always-commuter moves to city g_{t+1} is

$$\pi_t^{AC,u}(g_t, g_{t+1}) = \frac{\exp\left(U_{t+1}^{AC}(g_{t+1}) - \psi^u(g_t, g_{t+1})\right)^{\frac{1}{\theta}}}{\sum_{g'_{t+1}} \exp\left(U_{t+1}^{AC}(g'_{t+1}) - \psi^u(g_t, g'_{t+1})\right)^{\frac{1}{\theta}}}.$$

Similarly, the probability that an always-commuter employed at wage w stays in the current job is

$$\pi_t^{AC,stay}(w, g_t) = \frac{\exp\left(V_{t+1}^{AC}(g_t, w)\right)^{\frac{1}{\theta}}}{\exp\left(\mathcal{V}_{t+1}^{AC}(g_t, w)\right)^{\frac{1}{\theta}}},$$

and the probability of quitting and moving to city $g_{t+1} \neq g_t$ is

$$\pi_t^{AC,quit}(w, g_t, g_{t+1}) = \frac{\exp\left(U_{t+1}^{AC}(g_{t+1}) - \psi^u(g_t, g_{t+1})\right)^{\frac{1}{\theta}}}{\exp\left(\mathcal{V}_{t+1}^{AC}(g_t, w)\right)^{\frac{1}{\theta}}}.$$

Law of Motion for Always-Commuters. The law of motion for the population of always-commuters follows from the transition probabilities, the probability that a worker receives an offer above their reservation wage, and the exogenous separation rate.

Let $L_t^{AC}(u, g)$ denote the mass of unemployed always-commuters in city g at time t, and let $L_t^{AC}(w, g)$ denote the mass of employed always-commuters in city g at wage w. Let $P_g^{AC,e}$ denote the probability that an unemployed always-commuter in city g receives a job offer above their reservation wage. Then the law of motion for unemployment is

$$L_{t+1}^{AC}(u, g) = \sum_{g'} \pi_t^{AC,u}(g', g)\left[L_t^{AC}(u, g')\left(1 - P_{g',t}^{AC,e}\right) + \delta \int_w L_t^{AC}(w, g')\, dw\right]$$
$$+ \sum_{g' \neq g} \int_w (1-\delta)\pi_t^{AC,quit}(w, g', g) L_t^{AC}(w, g')\, dw.$$

The first term captures unemployed workers who remain unemployed and move to city g, together with workers who are exogenously separated and then move to city g. The second term captures employed workers in other cities who quit, move to city g, and enter the next period unemployed there.

Given a wage grid indexed by w_s, the law of motion for employed always-commuters at wage w_s in city g is

$$L_{t+1}^{AC}(w_s, g) = (1-\delta)L_t^{AC}(w_s, g)\pi_t^{AC,stay}(w_s, g) + L_t^{AC}(u, g)\mathbf{1}\{w_s \geq \underline{w}_{g,t}^{AC}\}\left[F_g(w_{s+1}) - F_g(w_s)\right].$$

The first term is the mass of workers at wage w_s who neither separate nor quit. The second term is the mass of unemployed workers in city g who draw and accept a job offer in wage bin w_s.

Transition Probabilities for Remote-Capable Workers. Given the assumption that the preference shocks follow a Gumbel distribution, the probability that an unemployed remote-capable worker moves to city g_{t+1} is

$$\pi_t^{RC,u}(g_t, g_{t+1}) = \frac{\exp\left(U_{t+1}^{RC}(g_{t+1}) - \psi^u(g_t, g_{t+1})\right)^{\frac{1}{\theta}}}{\sum_{g'_{t+1}} \exp\left(U_{t+1}^{RC}(g'_{t+1}) - \psi^u(g_t, g'_{t+1})\right)^{\frac{1}{\theta}}}.$$

The probability that a remote worker moves to city g_{t+1} is

$$\pi_t^{RC,r}(w, g_t, g_{t+1}) = \frac{\exp\left(V_{t+1}^{RC,r}(g_{t+1}, w) - \psi^u(g_t, g_{t+1})\right)^{\frac{1}{\theta}}}{\sum_{g'_{t+1}} \exp\left(V_{t+1}^{RC,r}(g'_{t+1}, w) - \psi^u(g_t, g'_{t+1})\right)^{\frac{1}{\theta}}}.$$

The probability that a remote-capable worker keeps their commuter job and stays in the same city is

$$\pi_t^{RC,c,stay}(w, g_t) = \frac{\exp\left(V_{t+1}^{RC,c}(g_t, w)\right)^{\frac{1}{\theta}}}{\exp\left(\mathcal{V}_{t+1}^{RC,c}(g_t, w)\right)^{\frac{1}{\theta}}}.$$

The probability that a remote-capable worker quits to unemployment and moves to city $g_{t+1} \neq g_t$ is

$$\pi_t^{RC,c,quit}(w, g_t, g_{t+1}) = \frac{\exp\left(U_{t+1}^{RC}(g_{t+1}) - \psi^u(g_t, g_{t+1})\right)^{\frac{1}{\theta}}}{\exp\left(\mathcal{V}_{t+1}^{RC,c}(g_t, w)\right)^{\frac{1}{\theta}}}.$$

Law of Motion for Remote-Capable Workers. The law of motion for the population of remote-capable workers is similar to that of always-commuters, except that we separately track remote workers, remote-capable commuters, and the unemployed.

Given a wage grid indexed by w_s, the law of motion for remote-capable workers employed in remote jobs at wage w_s in city g is

$$\begin{aligned} L_{t+1}^{RC,r}(w_s, g) = &\sum_{g'} (1-\delta)\pi_t^{RC,r}(w_s, g', g) L_t^{RC,r}(w_s, g') \\ &+ p_{g,t}^r L_t^{RC}(u, g) \mathbf{1}\{w_s \geq \underline{w}_{g,t}^{RC,r}\} \left[F^r(w_{s+1}) - F^r(w_s)\right] \\ &+ (1-\delta) p_t^s L_t^{RC,c}(w_s, g). \end{aligned}$$

The first term is the mass of remote workers who do not separate and choose city g. The second term is the mass of unemployed remote-capable workers in city g who receive and accept a remote offer in wage bin w_s. The third term is the mass of remote-capable commuters who do not separate and switch into remote work on-the-job in city g.

Given a wage grid indexed by w_s, the law of motion for remote-capable workers employed in commuter jobs at wage w_s in city g is

$$\begin{aligned} L_{t+1}^{RC,c}(w_s, g) = &(1-\delta)(1-p_t^s)\pi_t^{RC,c,stay}(w_s, g) L_t^{RC,c}(w_s, g) \\ &+ (1-p_{g,t}^r) L_t^{RC}(u, g) \mathbf{1}\{w_s \geq \underline{w}_{g,t}^{RC,c}\} \left[F_g(w_{s+1}) - F_g(w_s)\right]. \end{aligned}$$

The first term is the mass of remote-capable commuters who do not separate, do not switch into remote work, and choose to keep their commuter job in city g. The second term is the mass of unemployed remote-capable workers in city g who receive and accept a local commuter offer in wage bin w_s.

Finally, let $P_{gt}^{RC,e}$ denote the probability that a remote capable worker receives an acceptable offer:

$$P_{g,t}^{RC,e} = p_{g,t}^r \left(1 - F^r(\underline{w}_{g,t}^{RC,r})\right) + (1-p_{g,t}^r)\left(1 - F_g(\underline{w}_{g,t}^{RC,c})\right).$$

Then, the law of motion for the population of remote-capable unemployed workers is

$$\begin{aligned} L_{t+1}^{RC}(u, g) = &\sum_{g'} \pi_t^{RC,u}(g', g) \left[L_t^{RC}(u, g')\left(1 - P_{g',t}^{RC,e}\right) + \delta \int_w L_t^{RC,r}(w, g')\, dw + \delta \int_w L_t^{RC,c}(w, g')\, dw\right] \\ &+ \sum_{g' \neq g} \int_w (1-\delta)(1-p_{g',t}^s)\pi_t^{RC,c,quit}(w, g', g) L_t^{RC,c}(w, g')\, dw. \end{aligned}$$

The first term is the mass of remote-capable unemployed workers, including newly separated remote and commuter workers, who move to city g and remain unemployed. The second term is the mass of commuter workers in other cities who quit, move to city g, and enter the next period unemployed there.

C.2 Definition of General Equilibrium

Given city amenities for commuters, $\{B_g\}_{g=1}^G$, city-specific remote-work amenities, $\{B_g^r\}_{g=1}^G$, local commuter wage-offer distributions, $\{f_g(w)\}_{g=1}^G$, the national remote wage-offer distribution, $f^r(w)$, the probability of receiving a remote offer, $\{p_g^r\}_{g=1}^G$, the probability of switching into remote work, p^s, the separation rate, δ, unemployment benefits, $\{b_g\}_{g=1}^G$, housing-supply parameters, $\{(\bar{\zeta}_g, \zeta_g)\}_{g=1}^G$, housing depreciation, δ^h, migration costs, $\{\psi^u(g,g')\}$, the housing expenditure share, $1-\eta$, the scale of location shocks, θ, and the masses of always-commuters and remote-capable workers, L^{AC} and L^{RC}, a steady-state equilibrium consists of rents, $\{q_g\}$, and worker distributions for always commuters $\{L^{AC}(u,g), L^{AC}(w,g)\}$ and for remote-capable workers $\{L^{RC}(u,g), L^{RC,c}(w,g), L^{RC,r}(w,g)\}$ such that:

1. Landlords optimize, and housing supply is given by Eq. (20);
2. Households optimize, choosing consumption and housing, reservation wages for commuter and remote job offers, and migration decisions;
3. Worker populations evolve according to the laws of motion in Appendix C.1;
4. Housing markets clear in each city and the national final-goods market clears.

C.3 Details on Binning Cities

This section describes how we reduce the dimensionality of the model while preserving the number of possible migration destinations. We group MSAs into $G = 5$ bins, indexed by $g \in \{1, \ldots, G\}$. Bins are constructed by sorting MSAs by average wage and assigning MSAs to bins so that each bin contains approximately 20 percent of the population.[1] Higher-wage bins contain larger MSAs on average, so the number of MSAs per bin declines with the average wage of the bin. Bin 1 contains 130 MSAs, while bin 5 contains 11 MSAs.

Table C.3 reports the main bin-level moments used in the calibration. Wages and rents are normalized by the average commuter wage in bin 1. The WFH share is increasing in Bins

[1] We do not split MSAs across bins, so the 20% share is not exact.

1 to 4 but then declines in Bin 5, likely due to the higher commuter wage there. Commuter wages, WFH wages, rents, and tax rates are all strongly increasing with city size. All prices are normalized so that the wage in Bin 1 is equal to 1. Housing supply is generally more elastic in the smaller bins. An exception is in Bin 3 which is more elastic than Bin 2.

Table C.3: City Moments

Moment	**Bin 1**	**Bin 2**	**Bin 3**	**Bin 4**	**Bin 5**
N MSAs	130	58	29	32	11
Population	0.201	0.200	0.216	0.185	0.199
WFH share	0.048	0.055	0.058	0.061	0.054
Commuter wage	1.000	1.065	1.091	1.140	1.252
WFH wage	1.022	1.110	1.130	1.160	1.240
Rent	0.150	0.177	0.210	0.228	0.363
Tax rate	0.028	0.036	0.052	0.060	0.067
HS elasticity	2.349	1.779	2.236	1.626	1.348

The model treats all MSAs within a bin as symmetric. Thus, all cities in bin g have the same equilibrium rent, value functions, reservation wages, housing supply parameters, and amenities. This greatly reduces the number of equilibrium objects. Instead of solving for rents, value functions, and reservation wages in each of the 260 MSAs, we solve for one set of objects for each of the five bins. At the same time, we retain the full number of migration destinations through a multiplicity adjustment in the location-choice problem.

The need for this adjustment comes from the log-sum structure of the location-choice problem. A worker's expected value of moving depends on the number of possible destination draws, because the expected maximum of the idiosyncratic location-preference shocks increases with the number of alternatives. If we simply replaced 260 MSAs with 5 representative locations, we would understate the option value of moving.

However, this introduces one complication. When I see a worker who stays in bin 1 between period t and $t+1$, I need to distinguish between whether they have stayed within the same city within bin 1, or whether they have moved to a different city within bin 1. If they have moved to a different city within bin 1, then they are subject to the migration cost and should also count as a mover in the migration rate. For the transition matrices, rather than keeping track of all the possible transitions between 260 cities, we keep track of the transitions between bins and add a state variable indicating whether the worker has moved within the bin, across bins, or stayed in the same city within the bin.

To implement this adjustment, we distinguish three types of location transitions. Let

$d \in \{1, 2, 3\}$, where

$$d = \begin{cases} 1, & \text{stay in the same MSA,} \\ 2, & \text{move to another MSA within the same bin,} \\ 3, & \text{move to an MSA in a different bin.} \end{cases}$$

For an origin bin g, destination bin g', and transition type d, define the number of distinct destination MSAs represented by the transition as

$$\omega_{dgg'} = \begin{cases} 1, & d = 1 \text{ and } g' = g, \\ N_g - 1, & d = 2 \text{ and } g' = g, \\ N_{g'}, & d = 3 \text{ and } g' \neq g, \\ 0, & \text{otherwise.} \end{cases}$$

The case $d = 1$ represents staying in the same MSA. The case $d = 2$ represents moving to one of the other $N_g - 1$ MSAs in the same bin. The case $d = 3$ represents moving to one of the $N_{g'}$ MSAs in a different bin. For moves that are not valid, ω is set to 0. For example, a worker cannot have $d = 2$ indicating a within-bin move and $g \neq g'$.

For example, consider a worker who lives in a bin-1 MSA. If the worker chooses $(d, g') = (1, 1)$, the worker remains in the same MSA and does not count as a mover. If the worker chooses $(d, g') = (2, 1)$, the worker moves to another MSA within bin 1. This move does not change the population of bin 1, but the worker pays the migration cost and counts as an inter-MSA mover. If the worker chooses $(d, g') = (3, 5)$, the worker moves to one of the N_5 MSAs in bin 5.

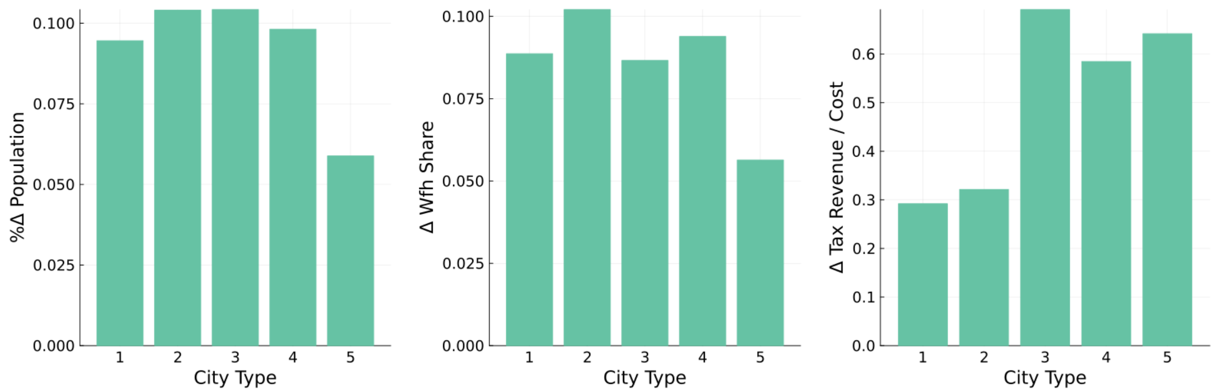
The multiplicity adjustment enters the continuation values through the log-sum terms. For example, the continuation value for an unemployed remote-capable worker in bin g is

$$\mathcal{U}_{t+1}^{RC}(g) = \theta \log \left[\sum_{d=1}^{3} \sum_{g'=1}^{G} \omega_{dgg'} \exp\left(\frac{U_{t+1}^{RC}(g') - \psi_{dgg'}^{u}}{\theta} \right) \right],$$

where $\psi_{dgg'}^{u}$ is the utility cost of a transition of type d from bin g to bin g', and $\psi_{1gg}^{u} = 0$. Since all value functions within the bin are the same, this is mathematically equivalent to summing over all possible destination cities as in Equation C.1. Recall that, by definition, $\omega_{dgg'} = 0$ for invalid moves.

FIGURE C.13: Impact of a Local Migration Subsidy for Remote Workers

(a) Population Growth, % (b) Change in WFH share, pps (c) ΔRevenue / Cost



Notes: The figure illustrates the effects of a city introducing a migration subsidy to attract remote workers. The policy is implemented unilaterally, with one city adopting the subsidy at a time. The reported effects correspond to the case in which a single city within a given bin adopts the policy. Panel A reports the change in the city's population. Panel B reports the percentage-point change in the city's work-from-home share. Panel C reports the change in tax revenue relative to the program's cost.

The same multiplicity adjustment appears in the transition probabilities. For example, the probability that an unemployed remote-capable worker moves from bin g to a destination of type (d, g') is

$$\pi_t^{RC,u}(d,g,g') = \frac{\omega_{dgg'} \exp\left(\frac{U_{t+1}^{RC}(g') - \psi^u_{dgg'}}{\theta}\right)}{\sum_{\tilde{d}=1}^{3} \sum_{\tilde{g}=1}^{G} \omega_{\tilde{d}g\tilde{g}} \exp\left(\frac{U_{t+1}^{RC}(\tilde{g}) - \psi^u_{\tilde{d}g\tilde{g}}}{\theta}\right)}.$$

This probability is the probability of choosing any MSA represented by the pair (d, g'). Conditional on drawing a within-bin move, the worker is assigned uniformly across the $N_g - 1$ other MSAs in the same bin. Conditional on drawing a move to another bin g', the worker is assigned uniformly across the $N_{g'}$ MSAs in that bin. This allows us to compute migration rates at the MSA level even though equilibrium prices and value functions are solved at the bin level.

C.4 Additional Model Results

Section 7.3.2 examines a place-based policy in which cities offer migration subsidies to attract remote workers. This section provides additional results on how the effects of the subsidy vary across city-size bins.

Figure C.13 reports the results. Panels (a) and (b) show that the subsidy generates only modest increases in population and the WFH share. Population increases by about 0.09–0.10 percent in bins 1–4, but only 0.06 percent in the largest city-size bin. The WFH share rises by 0.09 percentage points on average, with a smaller increase of 0.06 percentage points in the largest bin.

Panel (c) shows that the untargeted subsidy does not pay for itself through higher local tax revenue in any city-size bin. The fiscal return is lower in smaller cities: the program raises roughly \$0.3 in additional tax revenue for each dollar spent in the smallest bins, compared with about \$0.6 per dollar spent in the largest bins.

C.5 Quantifying the importance of dynamics.

Previous work has largely studied the welfare impact of WFH in static models. In this exercise, we ask how much the welfare results change when households must reallocate across cities and jobs, subject to migration and search frictions, before fully benefiting from the high-WFH steady-state environment.[2]

Specifically, we compare two consumption-equivalent welfare gains between the low- and high-WFH steady states. The first holds a worker's initial state fixed and asks how much it gains from the high-WFH steady-state environment starting from that state. In this case, the worker can still make optimal migration and job-search decisions going forward, but it begins the high-WFH economy with its pre-shock location, employment status, and wage. The second instead evaluates the worker at the state it is expected to reach after reallocation to the high-WFH steady state. This comparison isolates how much of the welfare gain comes from changes in workers' state variables, especially their location and employment status, rather than from the high-WFH environment holding those states fixed.[3]

On average, welfare gains are 39% higher when workers are evaluated at the state they are expected to reach in the high-WFH steady state rather than at their initial state. This difference reflects the welfare cost of beginning the high-WFH economy from the pre-shock allocation and needing to reallocate through costly migration and search decisions. This exercise highlights the importance of modeling the search and migration frictions. Within

[2]This exercise measures the welfare change between the low- and high-WFH dynamic steady states, not welfare along the transition path, which includes an additional temporary shock.

[3]Let ι summarize a household's state variables. The same-state welfare gain is $CE^{\text{same}}(\iota) = 100\left\{\exp\left[(1-\beta)\left(V^{\text{high-WFH}}(\iota) - V^{\text{low-WFH}}(\iota)\right)\right] - 1\right\}$. The reallocated-state welfare gain is $CE^{\text{realloc}}(\iota) = 100\left\{\exp\left[(1-\beta)\left(E\left[V^{\text{high-WFH}}(\iota') \mid \iota\right] - V^{\text{low-WFH}}(\iota)\right)\right] - 1\right\}$, where ι' is the household's state after reallocation to the high-WFH steady state. We average these household-level consumption equivalents using the initial steady-state distribution.

our dynamic framework, allowing workers to skip these reallocation costs would overstate the welfare gains from WFH by almost 40%.