Work from Home and Long-Distance Migration*

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Abstract

Full-time work from home (WFH) breaks the link between where workers live and where they work, with important implications for migration and the spatial distribution of labor. We show that WFH increases long-distance migration: WFH workers are 40–50% more likely to move than commuters, and plausibly exogenous changes in firms' remote-work policies raise migration. Motivated by these facts, we develop and calibrate a quantitative spatial equilibrium model with migration, remote work, and job search. We use the model to quantify how the rise in WFH affects migration, cross-city changes in population, wages, and rents, and the welfare consequences of remote work.

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1 Introduction

For most workers, the choice of where to live and where to work is closely intertwined. Commuting costs and the practical need to be 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. A worker who never commutes faces far fewer geographic constraints on where they live. A large literature studies the implications of WFH for real estate, commuting patterns, and agglomeration forces.[1] This paper studies how WFH shapes long-distance migration and, in turn, the allocation of workers and economic activity across labor markets.

Ex ante, the effect of WFH on long-distance migration is ambiguous. On the one hand, WFH provides opportunities for workers to improve their welfare through migration: without changing jobs, they can move to lower-rent, higher-amenity areas or to places that better match their idiosyncratic preferences. On the other hand, WFH provides access to a national labor market, allowing workers to change jobs without moving and insulating them from local shocks. Understanding these opposing forces is crucial for assessing the dynamic welfare gains from full-time WFH.

To that end, this paper provides evidence that, on net, the first force dominates: access to WFH causally increases long-distance migration. We then build a quantitative spatial equilibrium model incorporating remote work, long-distance migration, and job search. We use the model to quantify how the rise in WFH affects migration, post-COVID changes in rents, population, and wages across cities, and to assess the welfare gains from WFH when workers must incur costly moves to realize many of its benefits.

We begin by documenting several facts linking WFH and long-distance migration. Using the American Community Survey (ACS), we show that even before COVID, remote workers were $40-50\%$ more likely to move across MSAs or states than observably similar commuters. This relationship persists after the onset of COVID, despite a tripling of the WFH rate from roughly 5% to 15% of workers. A key question is whether this relationship is causal. While ACS data show higher migration rates among WFH workers relative to observably similar commuters, this 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), an online nationwide survey designed to track commuting behavior and labor market developments before and after the COVID-19 outbreak (Bick and Blandin, 2023).[2] In

[1] See, for example, Davis et al. (2024a), Delventhal and Parkhomenko (2023), Haslag and Weagley (2021), Liu and Su (2021), Monte et al. (2023), Ramani and Bloom (2021), and Richard (2024).

[2] 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. (2024a,b) show that the prevalence of WFH in the

addition to current WFH status, the RPS includes retrospective questions on pre-pandemic work arrangements and recent migration.

Using RPS data, we provide evidence that WFH has a causal effect on long-distance migration. We first establish that pre-pandemic commuters who switched to WFH had much higher migration rates since the pandemic than commuters who did not switch to WFH. A remaining concern is that the pandemic may have increased the desire to migrate, with WFH simply facilitating moves that would have occurred anyway. To address this, we instrument for transitions into WFH using novel RPS questions on changes in employer WFH policies since the COVID-19 outbreak. We exploit variation in whether pre-pandemic commuting reflected job requirements, preferences, or employer policies, combined with reported changes in employer WFH policies. We find that plausibly exogenous shifts toward WFH increase both WFH adoption and migration, consistent with a causal effect of WFH on migration.

These individual-level findings have large aggregate implications for migration rates 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 rise in long-distance migration after 2019, with levels recovering to those not seen since before the Great Recession. A simple decomposition implies that the rise in WFH accounts for roughly half of the increase in inter-MSA migration between 2021 and 2023 relative to 2019. Moreover, the increase in WFH was uneven across cities, and MSAs where WFH grew more experienced larger increases in out-migration and more negative net migration.

While these empirical results establish that WFH increases migration, they leave open several key economic questions. How does increased mobility reshape the equilibrium distribution of population, wages, rents, and local tax revenue, both in the short and long run? What are the welfare consequences for different groups of workers? How does WFH affect workers' responses to local productivity shocks, and in particular, does it reduce the need to migrate in response to adverse local conditions?

To answer these questions, we develop a dynamic spatial equilibrium model with remote work, long-distance migration, and job search. Workers differ in their occupation: always-commuters are tied to their local labor market, while remote-capable workers can receive offers from either a 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 enter unemployment before finding a job in their new city. This difference in migration frictions allows the model to match the observed pre-COVID gap in migration rates between the two groups. Equally important is the role of search frictions in finding remote jobs. If workers could freely choose between remote work and commuting, all remote-capable workers

RPS closely aligns with the ACS and other U.S. datasets through 2023.

would immediately choose remote work, producing a counterfactually high WFH share. With search frictions, workers face a trade-off: moving is more attractive under WFH, but workers cannot be certain they will find another remote job if their current match ends. We calibrate the model to match key features of the pre-COVID economy, including migration rates, WFH rates, wages, rents, and population across cities, and we simulate a COVID-era WFH shock.

We use the model for four main exercises. First, we examine the extent to which the WFH shock can explain post-COVID changes in migration and cross-sectional changes in rents, population, and wages. The model accounts for 40% of the post-COVID population equalization between the highest- and lowest-wage cities and 44% of the equalization in average wages, and we discuss the associated fiscal impacts. Second, we examine the welfare gains of the WFH shock. Most of these accrue to remote-capable workers who, on average, gain 1.95% in consumption equivalent terms. These gains arise through a combination of the direct amenity value of remote work, access to higher wages from the national market even when living in low-wage cities, and the ability to relocate to lower-rent, high-amenity locations. Third, we study how WFH alters the economy's response to negative local productivity shocks. By giving workers access to the national remote labor market, WFH creates an alternative to either staying in a deteriorating local labor market or paying the cost of moving. We find that as the WFH rate rises, both the migration elasticities and the consumption-equivalent welfare costs of a negative local productivity shocks decline. Finally, we use the model to evaluate place-based migration subsidies, like the Tulsa Remote program, that offer one-time payments to attract remote workers.

Related Literature This paper contributes to two strands of existing literature. First is a rapidly growing literature examining the implications of remote work in quantitative spatial equilibrium models. Existing quantitative analyses largely study static environments, within-city location choices, or part-time remote work (Brueckner et al., 2023; Davis et al., 2024a,b; Delventhal et al., 2022; Monte et al., 2023; Richard, 2024). While these models can speak to the geographic reallocation induced by WFH, they generally abstract from the costly long-distance migration through which much of that reallocation takes place.[3] They also abstract from search frictions over access to remote jobs, and therefore from a central trade-off workers face: moving is attractive under WFH, but workers who relocate do not know whether they will be able to find another remote job if their current match ends. These search frictions are quantitatively important. In our calibrated model, if workers were able to freely choose remote work versus commuting, all would choose remote work, implying a WFH rate significantly higher than the data. Without search frictions, the model could only rationalize low WFH rates by assigning a negative amenity value to WFH, which would be counterfactual with existing estimates of the

[3]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).

amenity value of remote work (Barrero et al., 2023; Cullen et al., 2025; Mas and Pallais, 2017) and this 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 toward lower-density areas on the outskirts of cities. Brueckner et al. (2023) provides similar evidence at the county level. Mondragon and Wieland (2022) argue that the rise in remote work, and the resulting increase in demand for space, accounts for about half of the increase in home prices between 2019 and 2021. 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. Our paper is the first to provide empirical evidence that (i) individuals who WFH migrate at higher rates than commuters, (ii) commuters who switch to WFH have higher migration rates, and (iii) changes in employer WFH policies predict higher migration. Brueckner (2026) confirms our findings using an alternative instrument in ACS data.

Second, our findings connect to a large literature studying the decline in migration since the 1980s (see reviews by Molloy et al., 2011 and Jia et al., 2023). Molloy et al. (2017) argue that declining interstate migration is related to declining rates of job change. Kaplan and Schulhofer-Wohl (2017) argue that declining interstate migration can be partially explained by a decline in the geographic specificity of occupations. Ex ante, the relationship between WFH and migration is ambiguous in this framework. To the extent that WFH reduces the benefit of living near the workplace, it can be viewed as an extreme decline in the geographic specificity of work, which should reduce job-related migration. On the other hand, because workers can move while keeping their job intact, WFH also lowers migration frictions and allows workers to move more easily for non-job-related reasons, thereby increasing migration. We provide direct evidence on these mechanisms by showing that WFH workers are more likely to migrate across states than commuters, that commuters who switch to WFH experience higher migration rates, and that changes in employer WFH policies predict migration.

The remainder of the paper proceeds as follows. Section 2 describes the data and our measures of migration and WFH. Sections 3 and 4 document the relationship between WFH and long-distance migration at both the individual and aggregate levels. Sections 5 and 6 develop and calibrate the model. Section 7 uses the model to study post-pandemic reallocation across cities, the welfare effects of WFH, its fiscal implications, and its effects on adjustment to local productivity shocks. Section 8 concludes.

2 Data Sources and Measurement

2.1 The American Community Survey

Our primary data source is the American Community Survey (ACS), an annual survey of one percent of US households. We use the cleaned version made available on IPUMS (Ruggles et al., 2024).

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

Our analysis requires classifying each move as either local or long-distance. The existing literature has typically used two concepts of long-distance: interstate moves and inter-MSA moves. The current and past residential state for each individual are publicly available, so identifying inter-state moves is straightforward. Our procedure for identifying inter-MSA moves is based on an individual's public-use-microdata area (PUMA), which is the smallest publicly available geographic unit.[4] Appendix B.5 shows that a large majority of both interstate and 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.[5]

A third useful feature of the ACS is its large sample size. A one percent sample of US

[4]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.

[5]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.

households yields a sample size of over two million adults each year. This is particularly helpful when studying long-distance migration, which only a few percent of individuals do in a given year. A final useful feature of the ACS is that it has comparable data going back to 2005. This allows us to assess potential time trends in pre-pandemic migration.

We highlight two points of context for interpreting the ACS migration data. First, the Census Bureau reported that the 2020 ACS data collection was significantly impacted by the Covid-19 pandemic, potentially leading to non-response bias. The ACS released a set of "experimental weights" that attempt to correct for this bias. For transparency, all our time series display the 2020 ACS estimates using these experimental weights. However, our analysis largely ignores the 2020 estimates and instead focuses on the years before and after 2020.

Second, some PUMA boundaries were updated in 2022 based on the 2020 Census. This does not affect our measurement of whether a move occurred because the move variable is based on address changes. It also does not create any inconsistency in PUMAs for an individual move because in any given year the same PUMA boundaries are used for both the past and current residence. However, it is possible that changes to PUMA boundaries affect the share of moves that are labeled inter-MSA after 2022. Importantly, this change is not relevant for interstate moves, and we document similar patterns for interstate and inter-MSA migration. Consistent with this, Appendix Figure B.16 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 fill in this gap, we use the Real-Time Population Survey (RPS), an 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.[6] The Qualtrics

[6]The survey takes about 15 minutes to complete, implying an hourly pay rate for respondents of roughly

panel includes about 15 million members and is not a random sample of the US population, even if one would condition on the 94 percent of individuals aged 18-64 living in households with internet access according to the 2019 American Community Survey. However, researchers can direct Qualtrics to target survey invitations to desired demographic groups. In the case of the RPS, the sample was targeted to be nationally representative of the US along several broad demographic characteristics: gender, age, race and ethnicity, education, marital status, number of children in the household, Census region, and household income in 2019.

We use data from five waves of the RPS spanning February 2022 through October 2023 that contain comparable questions on migration.[7] These five survey waves contain an average sample size of 3,498 respondents each. Similar to the ACS, the RPS also asks respondents to answer the same questions on behalf of spouses or any unmarried partners in the same household. This additional information expands the average number of observations to 5,717 individuals per survey wave for a total sample size of 28,586.

Even with our sampling targets, there remain some potential concerns about the representativeness of the sample for the population of US adults aged 18 to 64. First, the targets are not met exactly; second, live-in spouses and partners are not incorporated into the sampling targets; third, budget constraints limit our sample size, preventing even greater granularity in the sampling targets. To alleviate these concerns, we construct sample weights using the iterative proportional fitting (raking) algorithm of 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, including the share of workers paid hourly, weekly hours worked, the usual weekly earnings distribution, sectoral and industry composition, and job tenure.

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

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

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

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

$8.40-$14.00.

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

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.[8] 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.[9] Crucially, this allows us to identify workers who commuted pre-Covid and switched to WFH post-Covid. Bick et al. (2024b) compare RPS data with Google Mobility data (based on cell phone geolocation) and find similar trends in commuting volume during the Covid-19 pandemic. They also report comparable WFH rates between the RPS and several household surveys (ACS, American Time Use Survey, Current Population Survey, and Survey of Income and Program Participation). Appendices B.2 and B.3 document similar WFH rates and migration rates (both overall and by WFH status) in both surveys throughout our sample period.

2.3 Sample Selection

We set our sample criteria in the ACS to be consistent with the prior literature's emphasis on employed adults in civilian households. We exclude households in group quarters (e.g., boarding houses and military barracks) and households with an active duty member of the military. We then restrict attention to the employed population 18 to 64. 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 Long-Distance Migration

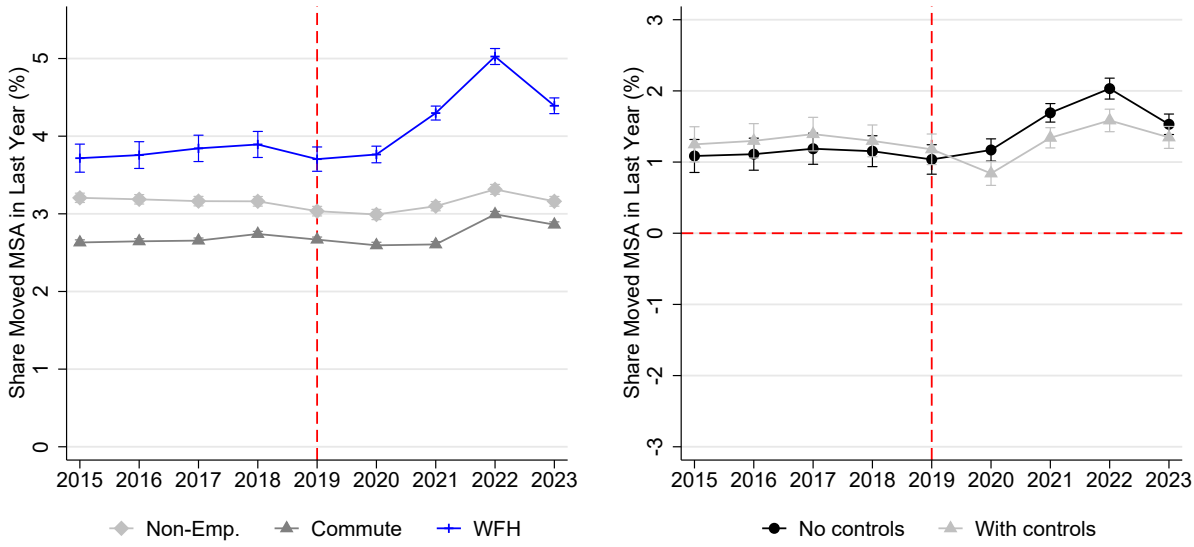
All else equal, commuters prefer to reduce the length of their commute by living near their workplace (Alonso, 1964; Mills, 1967; Muth, 1969). The ability to WFH full time reduces the benefit of living near a workplace because commuting is no longer required. Workers who WFH full-time may therefore be more willing to live far from their workplace and to migrate long-distances. Figure 1 confirms this intuition. Figure 1a plots annual inter-MSA migration in the ACS separately for commuters (dark gray triangles) and WFH workers (blue crosses).

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

[9] The retrospective questions do not ask about a specific week in February 2020. Instead, they are phrased as in the following: *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 months in our sample.

Figure 1: Work from Home and Long-Distance Migration

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



Notes: American Community Survey (ACS). Left Panel: annual inter-MSA migration rates for three population groups: non-employed (light gray diamonds), commuters (dark gray triangles), and WFH workers (blue crosses). Right Panel: the black squares are the difference between WFH and Commuters from the left panel; the gray triangles are the coefficients on WFH from a linear probability regression of inter-MSA migration with several demographic controls using sample weights (see text for details). The sample is working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals based on heteroskedasticity-robust (Ecker-Huber-White) standard errors.

For reference, we also include non-employed individuals (light gray diamonds). Prior to 2020, WFH workers had substantially higher rates of inter-MSA migration. From 2015 to 2019, the inter-MSA migration rate averaged 2.67% among commuters and 3.15% among non-workers on an annual basis, with a minimal time trend. By contrast, among WFH workers, the inter-MSA migration rate was substantially higher, averaging 3.78% over the same period. These estimates imply that the MSA migration rate of WFH workers was 1.12 percentage points, or $1.12/2.67 = 42\%$ higher than the migration rate of commuters over this time period.

Figure 1a shows that the WFH-commuter gap in inter-MSA migration expanded after the Covid-19 outbreak in 2020. The average WFH-commuter migration gap increased from 1.12 percentage points (or 42%) in 2015-2019 to 1.75 percentage points (or 62%) in 2021-2023.

The propensity to WFH is highly heterogeneous; for example, it is correlated with age, education, industry, and occupation (Barrero et al., 2023; Bick et al., 2023; Dingel and Neiman, 2020). To verify whether WFH status has additional explanatory power for inter-MSA migra-

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

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

The left-hand side variable m_i is a dummy variable that is zero if the individual is living in the same 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, and industry. The key right-hand side variable is w_i, which is a dummy indicator for the individual's WFH status. Intuitively, the parameter β_w will say how much WFH increases the predicted probability of an inter-MSA move, holding the other controls in X constant. We run this regression on workers in the ACS using individual sample weights. To examine whether the explanatory power of WFH status on inter-MSA migration has changed over time, we run the regression separately for each year from 2015 to 2023.

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. After 2020, the value of β_w increases both in the regression with controls and without controls, but the increase is larger in the regression without controls. This indicates that some of the increase in inter-MSA migration among WFH workers can be accounted for by other observables that are correlated with WFH after 2020. The key point is that the WFH-commuter migration gap was stable or slightly increased after 2019, even after controlling for observables.

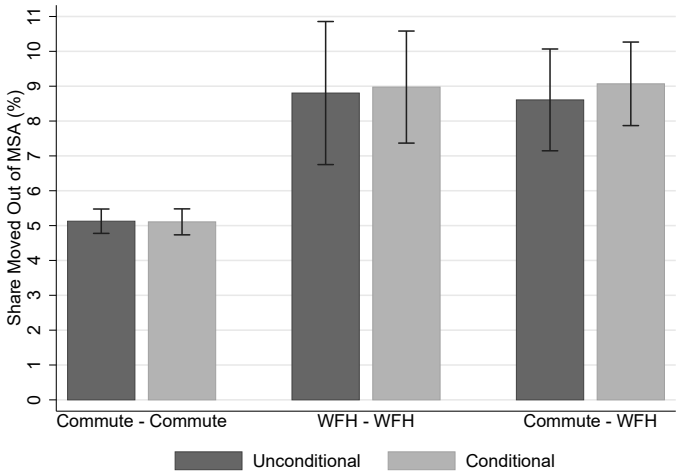
3.1 Impact of Switching to Work from Home on Long-Distance Migration

WFH workers may systematically differ from commuters along dimensions that are unobservable, raising the concern that the migration gap in Figure 1b reflects selection rather than the causal impact of WFH on migration. One way to address this concern is to ask whether an individual is 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

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

Figure 2: Long-Distance Migration and Individual-Level Changes in Work from Home



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

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

Figure 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.

Figure 2 shows an inter-MSA migration rate of 5.1% for workers who commuted both before and after Covid, compared with 8.8% for workers who WFH both before and after Covid and 8.6% of commuters who switched to WFH. [10] Importantly, including the additional controls in X has a minimal effect on these estimates. We conclude that commuters who switched to WFH did indeed migrate at higher rates compared with observationally similar commuters who did not switch to WFH.

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, 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 migration would have occurred even if the individual had not been able to WFH.

To address this concern, we can create an instrument that predicts a change in WFH status but is plausibly uncorrelated with the desire to move. A promising candidate is changes to employer WFH policies following the Covid-19 outbreak. Bick et al. (2023) show that most workers who switched from commuting to WFH after the COVID-19 outbreak were not permitted to WFH before the pandemic but then were permitted to do so after the outbreak.

The RPS contains two sets of questions about employer WFH policies that are well-suited to our purpose. First, for all workers who commuted in February 2020, we ask:

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

a) *My [spouse/partner's] job could not be done from home*

[10] Migration rates in the RPS are higher than in the ACS (Figure 1a) because the ACS measures moves within the past 12 months, while the RPS measures moves since February 2020. The gap in migration rates by current commuting status is very similar across both data sets.

b) *Some or all of my [spouse/partner's] job could have been done from home, but my [spouse/-partner's] employer required me [them] to commute*

c) *Some or all of my [spouse/partner's] job could have been done from home, but I [my spouse/partner's] preferred to commute*

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

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

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

a) *Yes, the policy is different*

b) *No, the policy is not different*

c) *My employer does not have a policy on telework or working from home*

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

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

a) *The new policy affects only me*

b) *The new policy affects me and some or all of my co-workers*

c) *The new policy affects some or all of my co-workers, but not me*

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

We analyze the relationship between WFH transitions, employer policies, and inter-MSA migration with two sets of regressions. Our dependent variable is a dummy variable, m_i, which takes on a value of one if the individual i moved MSAs since February 2020. Our independent variable of interest is a dummy variable, cw_i that takes on a value of one if the individual i switched to WFH since February 2020. Our sample is employees in the RPS who commuted in February 2020 and who were still working for their pre-pandemic employer in the survey

reference week in 2022 or 2023.[11] The first set of regressions consists of linear probability models of inter-MSA migration on WFH estimated by OLS:

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

The variable X_i contains controls for sex, age, education, race, Hispanicity, marital status, the presence of children, log income, industry, pre-pandemic state of residence, and the month that the survey was conducted. We run the above regression with and without controls, and with and without sample weights. Across these four specifications, the coefficient on switching to WFH is significant at the 1% level, and the coefficient ranges from 0.0334 to 0.0418, indicating that switching to WFH increases the predicted probability of moving MSAs by 3.3 to 4.2 percentage points.

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

In the first-stage regressions, our instruments produces large Effective F statistics, regardless of whether we include controls or use sample weights. This implies that the instruments are strong predictors of switching to WFH. In the second-stage regressions, switching to WFH continues to positively predict inter-MSA migration. Relative to our OLS estimates, the estimated coefficient is larger, ranging from 0.0705 to 0.0927. The coefficient is significant at the 1% level except for the specification with controls and sample weights, which is significant at the 5% level.

To summarize, we find that pre-pandemic commuters were more likely to switch to WFH if their jobs or employer required them to commute before the 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

[11] Q2 and Q3 were only asked of workers whose employer had not changed since February 2020. Among workers surveyed in 2022-2023 who were also employed in February 2020, 74% had not changed employers since February 2020.

causally increases an individual's propensity to migrate.

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

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

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

4 Aggregate Trends in Work from Home and Long-Distance Migration

Our results so far suggest that an aggregate increase in WFH should have coincided with an increase in aggregate long-distance migration rates. 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, WFH more than tripled to 17.6% in 2021 and remained above 13% through 2023.[12]

Figure 3b displays annual MSA migration rates over the same time period. From 2015 to 2019, the inter-MSA migration was fairly stable between 2.68%-2.79%. Following the Covid-19 outbreak, migration increased sharply in 2021 and 2022. It then declined in 2023 but remained substantially above 2019 levels. On average, from 2021-2023 inter-MSA migration was 14% above its 2019 rate.

These aggregate trends are evident in several datasets and robust to alternative measures and sample criteria. Appendix B.4 document quantitatively similar patterns in interstate migration in the ACS over the same time period and in the IRS data between 2019-2023. Foster et al. (2024) report a quantitatively similar spike in interstate address changes in the United States Postal Service National Change of Address (NCOA) 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 long-distance moves that exceed 100 miles increased slightly over this period. Appendix B.6 shows that these patterns were not driven by foreign-born individuals, whose population share increased in 2022-2024. Finally, Appendix B.7 shows that migration trends are nearly identical whether or not last year's location is imputed, although the non-imputed rates are somewhat lower than those in the full sample.

4.1 A Simple Accounting Exercise

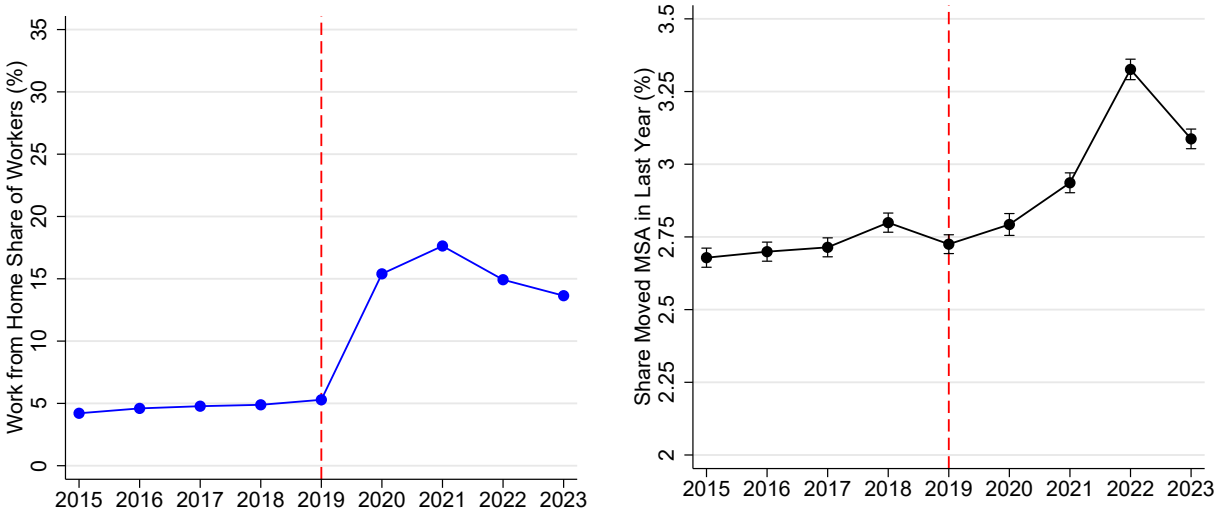
To what extent can the increase in WFH account for the aggregate increase in long-distance migration? To gauge the quantitative potential of this channel, we conduct a very simple decomposition exercise. Aggregate inter-MSA migration in year t, m_t, can be written as

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

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

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

(a) Share of Workers Who Work from Home (b) Long-Distance Migration of Workers



Notes: American Community Survey (ACS). Panel 3a displays the share of workers (%) who WFH. Panel 3b displays annual MS migration rates from 2015-2023. The sample is working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.

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

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

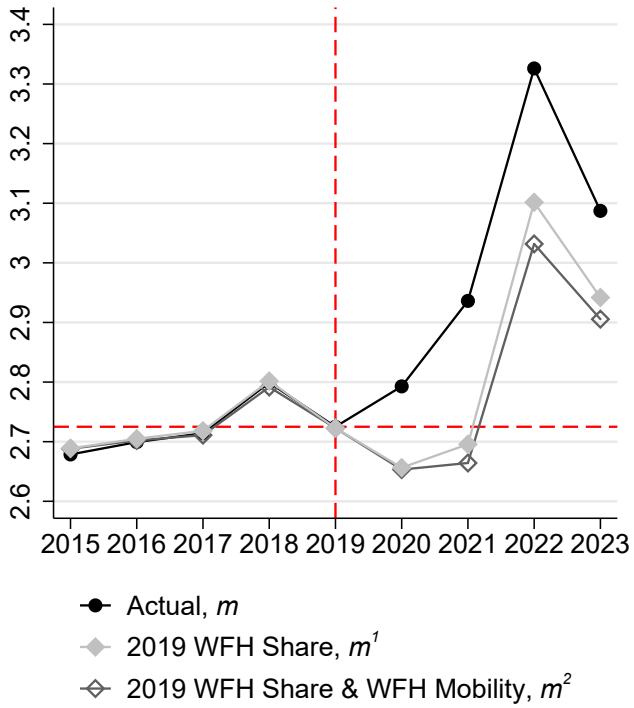
Next, define m_t^2 to be the counterfactual aggregate migration in year t if (i) the group shares had remained fixed at their 2019 level $\theta_{i,2019}$ as in m_t^1, and (ii) migration among WFH workers also remained fixed at its 2019 rate $m_{w,2019}$:

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

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

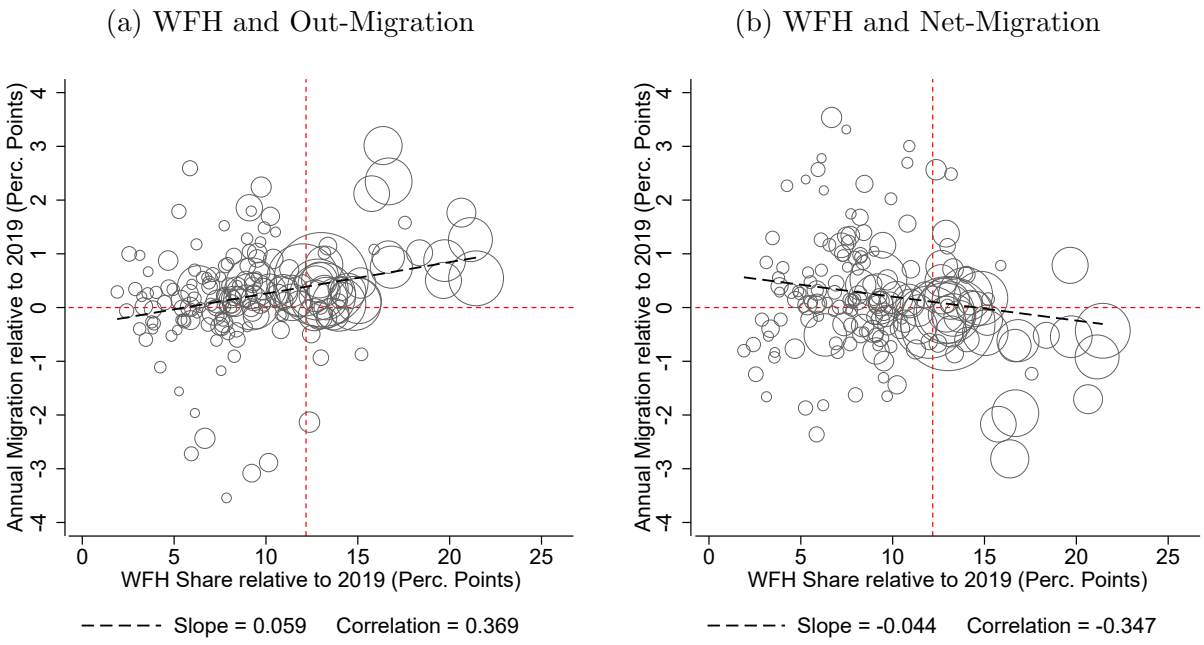
Figure 4 plots aggregate inter-MSA migration, m_t, as well as the counterfactual series m_t^1

Figure 4: Accounting Exercise: The Impact of Work from Home on Long-Distance Migration



Notes: American Community Survey (ACS). 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 5: Geographic Variation in Work from Home and Long-Distance Migration



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

and m_t^2. Figure 4 plots the same series for inter-MSA migration. The first takeaway is that the rise in WFH accounts for a sizable share of the increase in inter-MSA migration relative to 2019. On average between 2021 - 2023, actual inter-MSA migration was 14.0% higher than in 2019, while the counterfactual m_t^1 was only 7.6% higher. This implies that 46% of the increase in inter-MSA migration is accounted for by the rise in WFH.

The second takeaway is that the rise in migration among WFH workers also accounts for some of the rise in aggregate interstate migration, though quantitatively, this effect is more modest. On average between 2021 - 2023, the higher WFH share and higher WFH migration rates together account for 59% of the increase in inter-MSA migration (versus 46% explained by the WFH share alone).

4.2 Geographic Variation in Work from Home

The increase in WFH was not evenly distributed across MSAs. For example, the WFH share increased 17.7 percentage points in Boston-Cambridge-Newton, but only 5.4 percentage points

in Bakersfield, CA. We now show that variation in local WFH rates statistically accounts for an important share of variation in long-distance migration.

Figure 5a plots a MSA's average leave rate in 2021-2023 against its average WFH share in 2021-2023 using ACS data. The WFH share for a MSA s in year t is the share of workers living in s in year $t-1$ who WFH in year t. To construct the leave rate for a MSA s in year t, we start from the sample of individuals who lived in s in $t-1$. The leave rate is then the share of those individuals who lived in a different MSA $r \neq s$ in year t. Both of these variables are expressed as percentage point deviations from their 2019 value to account for pre-pandemic differences in migration. The figure excludes MSAs with less than 200,000 residents as of 2019 because estimates from these MSAs are very noisy.

Figure 5a reveals a positive correlation of 0.369, indicating that MSAs with larger increases in WFH tended to experience larger leave rates. In a linear regression, the point estimate is 0.059, implying that a 10-percentage point increase in a MSA's WFH share is associated with an increase in the leave rate of 0.59 percentage points.

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

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

Figure 5b reveals a negative correlation of 0.347, indicating that MSAs with larger increases in WFH tended to experience lower net migration rates. In a linear regression, the point estimate is -0.044, implying that a 10-percentage point increase in a MSA's WFH share is associated with an increase in the leave rate of 0.44 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 offset by higher in-migration.[13]

[13]Beginning in 2022, after the Covid-19 pandemic had ended, international migration began to mitigate some of the population loss in very large MSAs (Frey, 2025). However, domestic migration, which is our focus, has remained negative on net.

5 A Spatial Equilibrium Model of WFH and Migration

Motivated by the empirical results, this section develops a dynamic spatial equilibrium model that can rationalize the differences in migration rates between remote workers and commuters. In Section 6, we calibrate the initial steady state of the model to match key moments on WFH rates, population, wages, and rents across cities prior to the "COVID Shock". We the use the model to simulate a "COVID" shock that replicates the actual short- and plausible long-run increase in the WFH share. Section 7 shows that the model successfully predicts post-COVID trends in migration, population, wages, and rents, and we use the model to analyze the welfare gains from remote work. Finally, we use the model to examine how WFH shapes the welfare cost of a negative local productivity shock and to consider the impact of a recent placed-based policy in which cities provide a migration subsidy for remote workers.

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.

The economy is populated by a unit mass of infinitely-lived workers, each assigned an exogenously given occupation, $o \in \{ac, rc\}$. L^{ac} of the workers are "always-commuters", representing those in low work-from-home capacity occupations, such as manufacturing or retail. The remaining L^{rc} are assigned "remote-capable" occupations, representing those in high work-from-home capacity occupations, such as technology or finance. Workers live in one of G locations, denoted by $g \in \{1, ..., G\}$.

An endogenous share of the workers will be unemployed and searching for a new job. Each period they receive a wage offer. For "always-commuters", the wage offer comes from a local wage-offer distribution tied to the city g in which they live, $f_g(w)$. They can decide to accept the offer or to reject it and continue searching in the next period.

In contrast, "remote-capable" workers can receive an offer for either a remote or WFH job. Search is random; with probability p_g^r, they receive offers from the national remote wage distribution, $f^r(w)$, and with probability $1 - p_g^r$, they receive a commuting offer from the local distribution, $f_g(w)$. Remote and commuter job types are denoted by $\{r, n\}$, respectively.

Each worker provides one unit of labor and consumes a freely-traded final good and housing. For tractability, we abstract from the vacancy creation decision of firms. A worker earning wage w is operating a technology with productivity z that produces $y = zl$ units of the final good where $l = 1$. We assume perfect competition in the final good market and normalize its price to one. Hence, their wage equals their marginal product, $w = z$. With probability δ, employed

workers are hit with a separation shock and become unemployed.

Workers incur a migration cost denominated in units of utility, $\psi^u(g_t, g_{t+1})$, when relocating across cities. In order to move, commuters must quit their job and search for a new job in their destination city, incurring a period of unemployment. In contrast, remote workers can move across cities without searching for a new job. A developer in each city invests in housing that it rents to workers.

5.2 Worker's Problem

Timing. At the beginning of each period workers receive their wage or unemployment benefit that they use to consume the final good and housing. If they are unemployed the receive a wage offer that they can either accept to begin work in the next period or decide to continue searching. If they accept, they must remain in the same city and wait to move until the end of their first quarter of employment. Meanwhile, after consuming, employed workers receive their exogenous separation shock, losing their job with probability δ. Finally, before the next period begins (but after they have consumed, worked, and possibly lost their job), they draw their idiosyncratic location preferences and make their migration decision. Unemployed and remote workers will choose to move across cities, keeping their job status. Commuters will have to decide if they want to quit their job and move to another city, enduring a period of unemployment while they search for a new job in their destination city.[14]

Always-Commuters. We start by defining the value function for an "always-commuter", who is employed with wage w and living in city g. The worker chooses their consumption of the final good, c, and the amount of housing to rent at price r_g to maximize their within-period utility.

$$
\begin{aligned}
V_t^{ac}(g, w) = \max_{c_t, h_t} & \log\left(B_g c_t^{\eta} h_t^{1-\eta}\right) + \delta\beta\mathcal{U}_{t+1}^{ac}(g) + (1-\delta)\beta\mathcal{V}_{t+1}^{ac}(g, w) \\
\text{s.t.} \quad & w(1-\tau_g) = c_t + r_g h_t,
\end{aligned} \tag{7}
$$

where τ_g is the income tax rate and B_g is the amenity associated with city g. $\mathcal{U}_{t+1}^{ac}(g)$ is the expected continuation value for a worker who is hit with an unemployment shock with probability δ. $\mathcal{V}_{t+1}^{ac}(g, w)$ is the expected continuation value for a worker who is not terminated.

[14] Workers who have just accepted a job also draw a location preference shock, but we restrict their choice set to remaining in their current city. Because the shock has mean zero and there is no alternative location in the choice set, the draw does not affect their expected value.

The value of an "always-commuter" who is unemployed is given by:

$$U_t^{ac}(g_t) = \max_{c_t, h_t} \log\left(B_g c^{\eta} h^{1-\eta}\right) + \beta \int_w \max\{\mathcal{U}_{t+1}^{ac}(g), V_{t+1}^{ac}(g,w)\} f_g(w) dw \quad (8)$$
$$\text{s.t.} \quad b_g(1-\tau_g) = c_t + r_g h_t,$$

where b_g is the unemployment benefit in city g. The worker will follow a strategy of accepting any job offer over a threshold $\underline{w}_g$, associated with the wage of the job that would make them indifferent between accepting and continuing to search. The distribution of job offers in their local labor market is given by $f_g(w)$. At the end of the period, unemployed workers can choose to move across cities, subject to a utility cost given by $\psi^u(g_t, g_{t+1})$. They draw 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. Thus, their expected continuation value is given by:

$$\mathcal{U}_{t+1}^{ac}(g_t) = \mathbb{E}_{\epsilon}\left[\max_{g_{t+1}} \left(U_{t+1}^{ac}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right)\right]. \quad (9)$$

Given the assumption that the preference shocks follow a Gumbel distribution, the continuation value has a closed form solution, which we include in Appendix C.1.

Similarly, an "always-commuter" who is employed with wage w can choose to quit to unemployment in order to move across cities. Their preference shocks for this choice are drawn from the same Gumbel distribution as unemployed workers. Their expected continuation value is given by:

$$\mathcal{V}_{t+1}^{ac}(g_t, w) = \mathbb{E}_{\boldsymbol{\epsilon}}\left[\max_{g_{t+1}} \left\{ \underbrace{V_{t+1}^{ac}(g_t, w_i) + \theta\epsilon_{g_{t+1}}}_{\text{stay if } g_{t+1}=g_t}, \underbrace{U_{t+1}^{ac}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}}_{\text{move if } g_{t+1}\neq g_t} \right\}\right]$$

where the first term is the value of remaining employed at their current wage in their current city and the second term is the value of being an unemployed worker in a city that is different from the one in which they currently live. If the worker quits, they start the next period unemployed in the destination city, receive unemployment benefits, and draw a local job offer. Their problem is given by Eq. (8).

Given the assumption that the preference shocks follow a Gumbel distribution, the expected continuation values and transition probabilities have closed form solutions, which we include in Appendix C.1. The law of motion for the population of Type-1 workers will follow from their migration probabilities, quit rate, exogenous separations rate, and job finding rate. These are also included in Appendix C.1.

Remote-Capable Workers. Unlike "always-commuters", "remote-capable" workers can be employed either in a fully remote job or a commuter job. We will denote their value of being employed in a remote job as $V^r(g_t, w)$ and in a commuter job as $V^n(g_t, w)$. The value of being remote-capable unemployed worker is given by $U^{rc}(g_t)$.

The value of a remote-capable worker who is employed in a remote job with wage w and living in city g is given by:

$$\begin{aligned} V_t^r(g_t, w) = \max c_t, h_t \log(B_g B_g^r c_t^\eta h_t^{1-\eta}) + \delta\beta \mathcal{U}_{t+1}^{rc}(g_t) + (1-\delta)\beta \mathcal{V}_{t+1}^r(g_t, w) \\ \text{s.t.} \quad w(1-\tau_g) = c_t + r_g h_t. \end{aligned} \tag{10}$$

Remote workers enjoy an amenity value of living in a city, B_g, and an amenity value of being a remote worker, B_g^r. We allow the amenity value of being a remote worker to differ across cities, reflecting differences in commuting times and modes, and other amenities for remote workers, like the availability of co-working spaces. Unlike commuters, remote workers can move across cities while keeping their current wage. Their expected continuation value is given by:

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

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

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

$$\begin{aligned} V_t^n(g_t, w) = \max_{c_t, h_t} \log(B_g c_t^\eta h_t^{1-\eta}) + \delta\beta \mathcal{U}_{t+1}^{rc}(g_t) + (1-\delta)\beta \left[(1-p^s)\mathcal{V}_{t+1}^n(g_t, w) + p_s V_{t+1}^r(g_t, w) \right] \\ \text{s.t.} \quad w(1-\tau_g) = c_t + r_g h_t, \end{aligned}$$

There are three possible outcomes for a remote-capable worker who is employed in a commuter job: with probability δ, they lose their job and become unemployed. They have the option to move across cities so they get the expected continuation value $\mathcal{U}_{t+1}^{rc}(g_t)$. With probability $(1-p_s) \times (1-\delta)$, they keep their commuter job, and get the continuation value $\mathcal{V}_{t+1}^n(g_t, w)$. Finally, with probability $p_s \times (1-\delta)$, they are offered the option to switch to being remote with their current wage. They get the value $V_t^r(g_t, w)$. We discuss the reasons we build in the probability of on-the-job switching to remote work in Section 6.

The value of a remote-capable worker who is unemployed is given by:

$$\begin{aligned} U_t^{rc}(g_t) = \max_{c_t,h_t} \log(B_g c_t^{\eta} h_t^{1-\eta}) + \beta p_g^r \int_w \max\{\mathcal{U}_{t+1}^{rc}(g_t), V_{t+1}^r(g_t,w)\} f^r(w) dw ... \\ + \beta\left(1-p_g^r\right) \int_w \max\{\mathcal{U}_{t+1}^{rc}(g_t), V_{t+1}^n(g_t,w)\} f_g(w) dw \\ \text{s.t.} \quad b_g(1-\tau_g) = c_t + r_g h_t, \end{aligned}$$

where b_g is the unemployment benefit in city g. Search is random. With probability p_g^r, remote-capable workers receive an offer from a national remote wage distribution, $f^r(w)$. With probability $1-p_g^r$, they receive an offer from the local commuter distribution, given by $f_g(w)$. Workers follow a reservation wage strategy, accepting offers above a threshold. The threshold will differ by job type because remote jobs confer both an amenity value and the option to relocate without unemployment. In addition, remote-capable workers require a higher wage to accept a commuter job than always-commuters since they have the option to wait for a remote offer in the next period.

Finally, we define the continuation values for remote-capable workers who are employed in a commuter job, $\mathcal{V}_{t+1}^n(g_t,w)$, and remote-capable workers who are unemployed, $\mathcal{U}_{t+1}^{rc}(g_t)$. Workers in a commuter job can either remain in their current city at their current wage or quit to unemployment if they wish to move to a different city. They draw the same location-specific preference shocks ϵ_g as above, so their expected continuation value is given by:

$$\mathcal{V}_{t+1}^n(g_t,w) = \mathbb{E}_{\epsilon} \max_{g_{t+1}} \left\{ \underbrace{V_{t+1}^n(g_t,w) + \theta\epsilon_{g_{t+1}}}_{\text{stay if } g_{t+1}=g_t}, \underbrace{U_{t+1}^{rc}(g_{t+1}) - \psi^u(g_t,g_{t+1}) + \theta\epsilon_{g_{t+1}}}_{\text{move if } g_{t+1}\neq g_t} \right\}$$

where the first term gives the value of remaining employed at their current wage in their current city, and the second term gives the value of being an unemployed worker in a city that is different from the one in which they currently live. The expected continuation value for remote-capable workers who are unemployed looks the same as Equation (9), but with the value of being unemployed specific to remote-capable workers, $\mathcal{U}_{t+1}^{rc}(g_t)$.

Given the assumption that the preference shocks follow a Gumbel distribution, all of the expected continuation values and transition probabilities have closed-form solutions, which we include in Appendix C.1. The law of motion for the population of remote-capable workers follows from the transition probabilities, the probability that a worker receives a remote or commuter job offer above their threshold wage, and the exogenous job separations rate. These are also included in Appendix C.1.

5.3 Closing the Model

Production. For tractability we abstract from the firm problem. We assume that a worker with wage w is operating a technology that produces produces $y = zl$ units of the final good when employing one unit of labor. The price of the final good is normalized to 1. Under perfect competition, the worker will receive their marginal product $w_i = z_i$. The wage-offer distributions $f_g(\cdot)$ and $f^r(\cdot)$ are therefore equivalent to distributions of match productivities.

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

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

such that

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

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

$$H_{g,t} = \frac{\bar{\zeta}_g}{\delta^h} \left(\frac{\zeta_g \bar{\zeta}_g r_{g,t}}{1 - (1 - \delta^h)\beta} \right)^{\frac{\zeta_g}{1-\zeta_g}} \tag{11}$$

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

General Equilibrium. Given amenities $\{B_g\}_{g \in G}$ for commuters and $\{B_g^r\}_{g \in G}$ for remote workers, a wage-offer distribution for commuters $f_g(w)$ and remote workers $f^r(w)$, the probability of receiving a remote offer p_g^r, the probability of being allowed to switch to remote work p^s, the job separations rate δ, the unemployment benefit b_g, the parameters of the housing supply equation, $\{\bar{\zeta}_g, \zeta_g\}_{g \in G}$, and housing depreciation δ^h, migration costs, $\{\psi^u(g_t, g_{t+1})\}_{g_t, g_{t+1} \in G}$, the housing share of consumption, $1 - \eta$, the scale of the preference shocks, θ, the mass of workers that are always commuters, L^{ac}, the mass of workers that are remote-capable, L^{rc}, a steady-state equilibrium is a set of rents, $\{r_g\}_{g \in G}$, and the population of unemployed always-commuters workers, $L_t^{ac}(u, g_t)$, the population of always-commuters at wage w, $L_t^{ac}(w, g_t)$, the population of remote-capable unemployed workers, $L_t^{rc}(u, g_t)$, the population of remote-capable commuters at wage w, $L_t^n(w, g_t)$, and the population of remote-capable workers employed in a WFH job, $L_t^r(w, g_t)$ such that:

1. Landlords optimize, and housing supply is given by Eq. (11)

2. Households optimize, choosing consumption and housing to maximize their within period utility, the wage thresholds above which they accept a commuter or remote job offer, and their transition probabilities between locations.

3. Population follows the law of motion given in Appendix C.1.

4. The housing markets clear in each city and the national final-goods market clears.

6 Model Calibration

This section outlines how we calibrate the model. Section 6.1 covers the pre-COVID steady state, Section 6.2 provides two untargeted validations of the pre-COVID 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 the aggregate WFH share.

The complexity of solving and calibrating the model increases with the number of cities. To reduce the problem's dimensionality, we group cities into 5 bins and assume that all cities within each bin are identical. This allows us to work with 260 cities and compute meaningful inter-MSA migration rates while keeping the number of calibrated parameters and equilibrium objects tractable. Since all cities within a bin are the same, they will have the same equilibrium rents, wage thresholds, populations, housing stocks, and the value function for living in those cities are the same, greatly reducing the dimensionality of the model solution.

We use data from the 2019 ACS and group cities by average wage. We group the cities so that each bin has approximately 20% of the population. Because the cities in bin 5 are substantially bigger than the cities in bin 1, bin 5 has only 11 cities while bin 1 has 130 cities. Appendix C.2 provides more detail on the binning.

A model period corresponds to one quarter, so key parameters—such as the discount factor β and the separations rate δ—are specified at a quarterly frequency. However, several calibration targets (e.g., 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 assign a set of parameters using standard values from the literature. Table 2 reports these externally set parameters and their sources. These include the discount factor, β, the housing share of consumption, $1-\eta$, and the housing

supply elasticity ζ_g, which we set to the average estimate in Saiz (2010) for each bin. We set L^{rc}, the share of workers who are remote-capable, using the fraction of jobs that can be performed remotely in Dingel and Neiman (2020). We set the unemployment benefit to 40% of the average wage in each city, a commonly used value in the literature (e.g., (Shimer, 2005)) and consistent with estimates from the Department of Labor UI data (U.S. Department of Labor, Employment and Training Administration, 2024).

Finally, we calibrate the separation rate δ using CPS data. We define a separation as a transition to an unemployment spell lasting at least three months. Specifically, we compute the probability that an individual employed in month t is unemployed in months $t+1$, $t+2$, and $t+3$. This yields a monthly separation probability of 0.009. Because the model period is quarterly, we convert this monthly separation rate into a quarterly rate assuming independence across months:

$$\delta = 1 - (1 - 0.009)^3,$$

which is the probability of separating at least once within a quarter.

Next, we internally calibrate the remaining parameters to align with key moments in the data. While all parameters are jointly calibrated, Panel B shows the parameters and the primary moment used to calibrate 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, respectively, the population, the WFH share, and the rents across cities. Figure 6 shows that the model can match the data on these moments almost perfectly.

The calibrated WFH amenity ranges from 1.0 in bin 1 (no additional amenity) 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 workers' willingness to pay for WFH—typically on the order of 5 to 30 percent depending on whether WFH is full- or part-time and on the worker population studied (Barrero et al., 2023; Cullen et al., 2025; Mas and Pallais, 2017).

We parameterize the migration costs between cities g and g' as

$$\psi^u(g, g') = \psi^u(g', g) = \psi_g + \psi_{g'}$$

This specification imposes symmetry, i.e., the costs to move into and out of a city are identical, and 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 6 shows that the model matches the out-migration targets and also illustrates the remaining differences in in-migration. We note that the city-level out-

Table 2: Model Calibration

Panel A: Externally Set Parameters

Param.	Description	Source	Value
β	Discount factor	—	0.99
δ	Separations rate	CPS	0.03
w_g^u	Unemployment benefit	40% average wage	See below
η	Housing share of consumption	Davis and Ortalo-Magné, 2011	0.76
L_1	Share remote-capable	Dingel and Neiman, 2020	0.370
δ_h	Housing depreciation	Piazzesi and Schneider, 2016	0.01
$\tilde{\zeta}$	Housing supply elasticity	Saiz, 2010	See below
τ	Income tax rate	ACS & Taxsim	See below

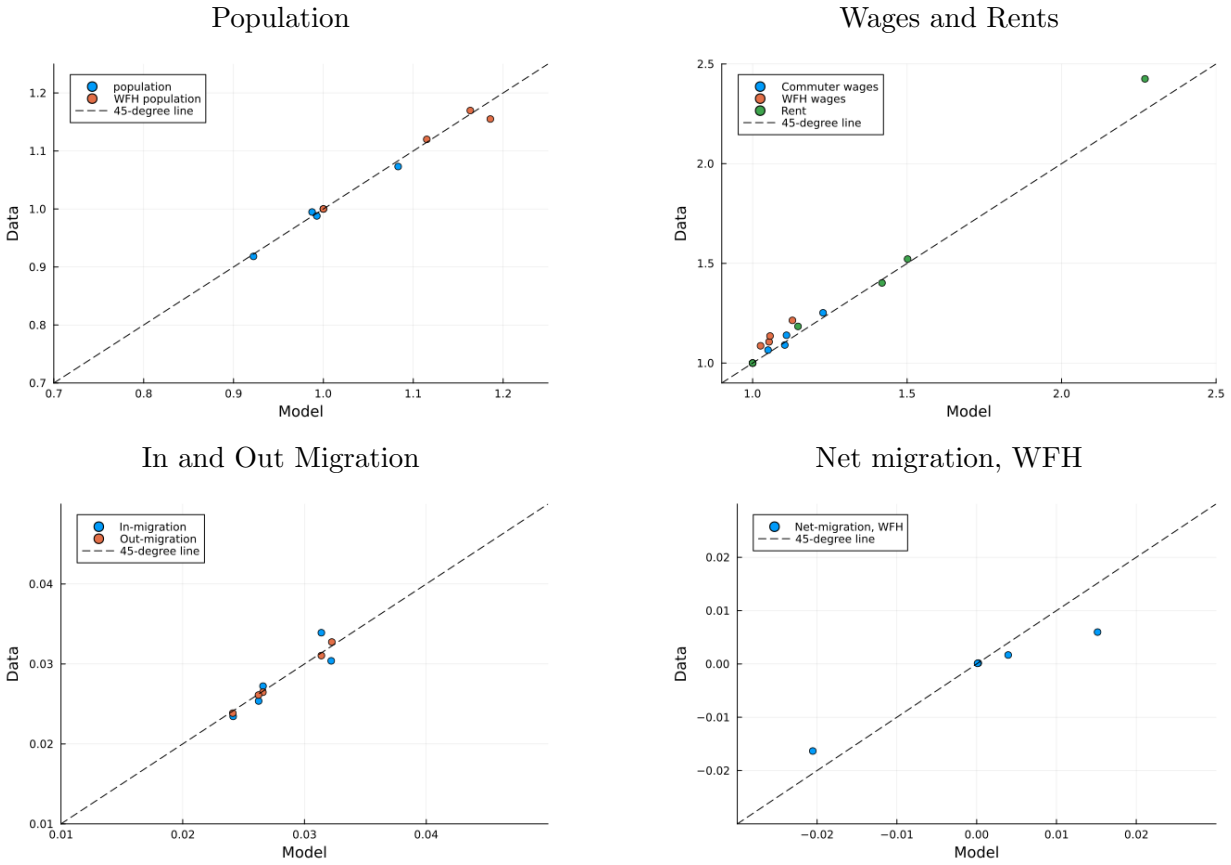
City-specific parameters		
b_g	Unemployment benefit	[0.40,0.43,0.44,0.46,0.50]
$\tilde{\zeta}_g$	Housing supply elasticity	[2.40,1.76,2.23,1.61,1.22]
τ_g	Income tax rate	[0.03,0.04,0.05,0.06,0.07]

Panel B: Internally Calibrated

Parameter	Description	Value	Moment	Data	Model
B_g	City amenity	See below	Population	▷ calib. fig.	
B_g^r	WFH amenity	See below	WFH-share	▷ calib. fig.	
$\bar{\zeta}_g$	HS shifter	See below	Rents	▷ calib. fig.	
ψ_c^u	Mig. cost, utility	See below	In & Out mig.	▷ calib. fig.	
μ_g	Location of log wage-offer distn	See below	Commuter wage	▷ calib. fig.	
μ^r	Location of log wage-offer distn	0.09	WFH wage	1.135	1.133
σ_g	Std. of wage-offer distn	0.050	U rate	0.045	0.044
θ	Scale parameter of Gumbel	2.833	$\frac{\text{mig rate wfh}}{\text{mig rate ato}}$	1.50	1.51
p_g^r	Prob. of WFH offer	See below	Net-mig, wfh	▷ calib. fig.	
p^s	Prob. of ATO to WFH switch	0.004	$\frac{\text{mig rate wfh-wfh}}{\text{mig rate ato-wfh}}$	1.000	1.001

City-specific parameters		
B_g	City amenity	[1.000,1.000,1.036,1.045,1.070]
B_g^r	WFH amenity	[1.000,1.094,1.115,1.135,1.180]
$\bar{\zeta}_g$	Housing supply shifter	[0.009,0.006,0.009,0.005,0.003]
ψ_c^u	Migration cost (utility)	[15.23,14.19,13.81,13.92,12.31]
μ_g	Location of log wage-offer distn.	[0.01,0.06,0.11,0.11,0.21]
p_g^r	Probability of WFH offer	[0.023,0.005,0.017,0.016,0.023]

Figure 6: 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.

migration rates will aggregate to the overall inter-MSA migration rate. Thus, there is no separate parameter that targets the overall migration rate.

The wage-offer distributions are assumed to be log normal with location μ_g for the commuter distribution in each city and μ^r for the national remote offer distribution. Figure 6 shows that the model can match the average commuter wage across cities. We assume that remote-capable workers who receive a remote offer draw wages from a national remote distribution. We calibrate the distribution's location parameter to match the average WFH wage of 1.13, which lies below the average commuter wage in the largest city but above commuter wages in smaller cities.

We assume that the scale of all the wage-offer distributions, σ, is the same across cities, and calibrate it to match the unemployment rate. Intuitively, if the dispersion in the wage offer distribution is high, workers have a higher option value of remaining unemployed and are less likely to accept a given job offer, raising the unemployment rate.

The probability that a remote-capable worker receives a remote offer, p_g^r, is calibrated to match the net-migration rate of remote workers across cities. In steady state, the WFH population in each city must be constant, so inflows of remote workers, including transitions into remote work from unemployment and commuter jobs, must equal outflows. Because workers can change their WFH status and location, remote workers can exhibit nonzero net migration across cities even though total net migration must be zero in each city for the overall population to be stationary. We note that this is the case for large cities: remote workers are more likely to leave large cities than move into them. Conditional on the other parameters, variation in p_g^r allows the model to reproduce this observed pattern in the data.

The scale parameter for the location-specific idiosyncratic preference shocks, θ, is calibrated to match the migration rate of WFH workers relative to commuters and unemployed workers. Remote workers are 1.5 times more likely to move than commuters, reflecting that they can relocate without giving up their remote jobs and entering unemployment. Moreover, they face a strong incentive to move out of the high-rent city and carry their wage to a low-rent city, where their real wage will be higher. Intuitively, if the variance of the preference shocks is high, both commuters' and remote workers' migration decisions are driven by idiosyncratic preferences rather than fundamentals, which equalizes their migration rates. As the variance decreases, fundamentals become more important, and WFH workers are more likely to move.

Finally, we calibrate p^s, the probability of an on-the-job transition from commuting to remote work. We build in the probability that a remote-capable commuter can switch to remote work with their current employer for three reasons. First, without this margin, the model would need to match the WFH share only through transitions via unemployment; with a high remote job-finding rate, that would encourage workers to quit into unemployment and

move in hopes of finding a remote job. Though this incentive still exists in the model, allowing on-the-job switching lets us use a lower remote job-finding rate so this is not the primary driver of migration. Second, it helps match cross-city wage differences for remote workers while preserving the assumption that remote offers are drawn from a national distribution. Third, it provides a natural mechanism for the "COVID" shock: we temporarily raise p^s to mimic the initial spike in WFH by allowing commuters to switch to remote with their current employer.

We calibrate p^s to match the relative migration rates of remote workers who move while keeping their remote job (WFH–WFH moves) versus those who move through unemployment and then find a new remote job. In the RPS, the migration rate among workers who remain WFH is not statistically different from the migration rate among workers who switch WFH status (Figure 2), so we target this relative rate to be one. A higher value of p^s increases the prevalence of WFH–WFH moves in the model relative to those who move while unemployed and later find a remote job.

6.2 Model Validation

Before considering discussing the calibration of the Covid shock, this section discusses two validations of the model's pre-Covid steady state.

WFH wages across cities. First, we show that the model can match cross-city differences in the average WFH wage, despite the fact that we assume the remote-wage offer distribution to be the same across cities. Although we do not directly target the cross-city variation in remote wages, the model generates it endogenously because reservation thresholds for remote offers differ by location, remote workers can relocate without changing jobs, and commuters can transition to remote work on the job. Figure 6 shows that, even without targeting it, the model reproduces the pattern of average remote wages across cities reasonably well. In the model, the average WFH wage in bin 5 is 13% higher than in bin 1, compared with 21% in the data.

Migration elasticities. Next, we show that the model generates long-run migration elasticities in line with the estimates in Hornbeck and Moretti, 2024. To compute comparable elasticities in the model, we shock the mean of the wage-offer distribution in one city at a time, lowering the average offered wage by 0.1%, and 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% decline in productivity.

The population-weighted average local migration elasticity in the model is 5.3, implying

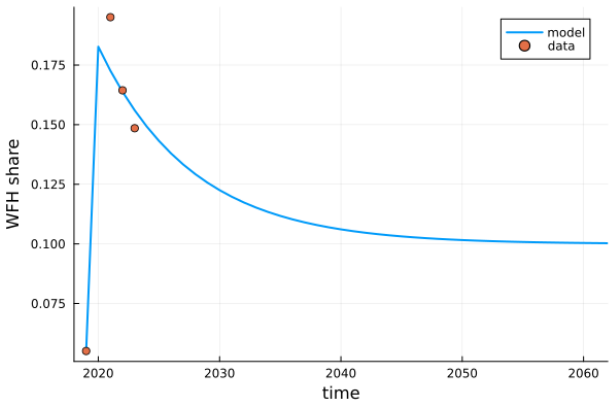
Figure 7: WFH Shock

Panel A: Calibration of WFH Shock

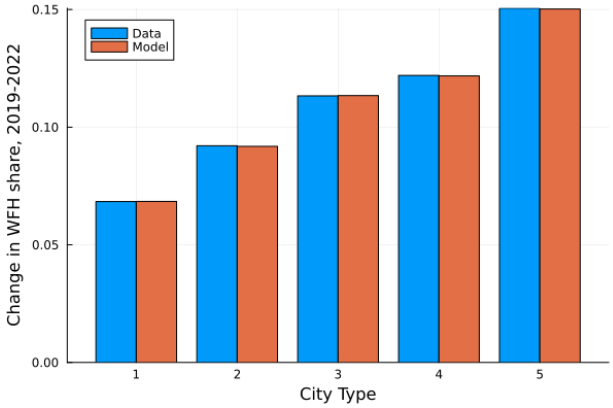
Parameter	Description	Value	Moment	Data	Model
p^s_{2020}	Reallocation shock	See below	Change WFH-share	See Panel (c)	
Δp^r_g	Prob. WFH offer	8.182	Δ gap in mig rate	0.297	0.225
Δp^s	Prob. ATO to WFH	0.028	Δ Long-run WFH sh.	10.000	9.994

City-specific WFH shock parameters		
$p^s_{2020}(g)$	Reallocation shock	[0.322,0.341,0.470,0.486,0.656]

(b) WFH Share



(c) Change in WFH share by city



that a 1% decline in productivity reduces a city's long-run population by 5.3%. This is close to the estimate in Hornbeck and Moretti, 2024, who find a long-run population elasticity with respect to TFP shocks of 4.03, with a standard error of 1.52. Section 7.3 shows how these migration elasticities vary with the WFH rate.

6.3 Calibration of a COVID WFH Shock

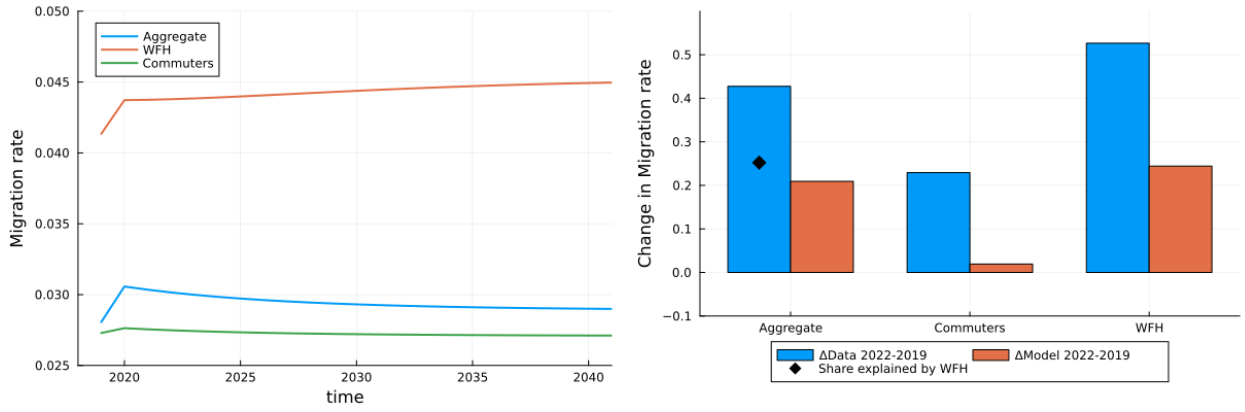
Motivated by the sharp increase in remote work during COVID, we now use our calibrated model to simulate a COVID-inspired WFH shock.

To replicate the COVID-era shock to remote work, we adjust three parameters. First, in the first period of the transition, we temporarily increase p^s, the probability of switching into remote work from a commuter job, to match the observed rise in the WFH share across cities. Because the increase in WFH was larger in big cities, 66% of remote-capable commuters in bin 5 transition to remote work, compared with 32% in bin 1. Second, we permanently raise p^s and p^r_g to match both the expected long-run increase in the WFH share and the relatively

Figure 9: Response of Migration Rate to WFH-Shock

(a) By WFH Status

(b) 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.

small change in the gap between the migration rates of remote workers and commuters (see Figure 1b). While 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 (Bick et al., 2024b).

Panel (b) of Figure 7 plots the aggregate share of the population working from home. The WFH share jumps to 18% immediately following the shock and then converges to its long-run target of 10%. Panel (c) compares the model-implied increase in the WFH share across cities with the data, which is matched by the temporary increase in p^s. 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.

7 The Implications of the WFH Shock

This section examines the implications of the WFH shock. We first assess the extent to which the model can account for the changes in aggregate migration rates and migration by WFH status documented in Sections 3 and 4. We then show that the model generates cross-city patterns in the growth of rents, population, and wages, and discuss the associated fiscal implications. Section 7.2 evaluates the welfare effects of WFH. Finally, Section 7.3 impacts the welfare consequences and the migration response to a negative local productivity shock and Section 7.4 uses the model to analyze the impact of recent placed-based policies in which local governments offer migration subsidies to remote workers, modeled after programs such as the Tulsa Remote Program.

7.1 Migration, Population, Wages, and Rents

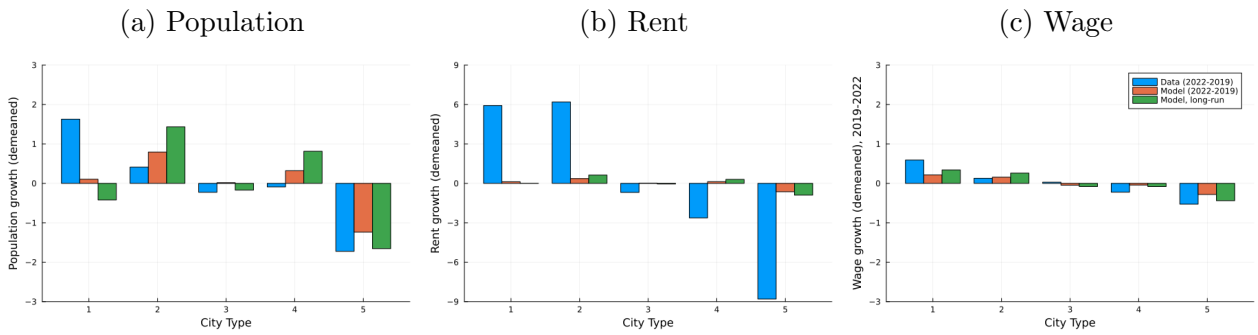
Migration Rate. First, examine the extent to which the WFH shock can account for post-COVID changes in migration. Panel (a) of Figure 9 reports the aggregate migration rate as well as migration rates separately for remote workers and commuters. In the ACS, we do not observe transitions in WFH status, so migration and job-type transitions cannot be jointly identified, i.e. we cannot determine whether a worker who moves also switches job type. We replicate this limitation in the model by classifying workers solely according to their current WFH status. The commuter group includes both always-commuters and remote-capable workers who are either employed in commuter jobs or unemployed. Although commuters cannot relocate while keeping a commuter job, they may move while unemployed and subsequently accept a commuter job in the destination city. Because migration is measured at an annual frequency in the data while the model operates at a quarterly frequency, such workers may be recorded as migrants who end the year employed in commuter jobs. Similarly, workers who move while unemployed and later accept a remote job are classified as remote movers. This mirrors the ACS classification, where pre-migration WFH status is unobserved.

Panel (b) reports the short-run change in migration and compares it to the data. Immediately after the shock, the aggregate migration rate rises from its pre-COVID level of 2.81% to 3.06%, an increase of 0.25 percentage points. This is close to the 0.27 percentage-point increase attributed to WFH in the accounting exercise in Section 4.1. Migration changes little for commuters. By contrast, the migration rate for remote workers increases by 0.21 percentage points—roughly half the increase observed for WFH workers in the data.

The rise in aggregate migration is driven primarily by composition rather than by higher within-type migration among remote workers. The WFH share increases, and remote workers have higher baseline migration rates. This mechanism mirrors the accounting exercise in Section 4.1, which shows that most of the WFH-induced increase in migration reflects compositional shifts rather than changes within groups: 78% of the increase attributed to WFH is composition-driven in the data, compared with 79% in the model. Consistent with this mechanism, as the WFH share declines from its pandemic peak toward its long-run steady state, the aggregate migration rate also falls. In the long run, the aggregate migration rate remains only 0.08 percentage points above its pre-shock steady state.

Population, Wages, and Rents. Figure 10 shows that the "COVID" shock can qualitatively reproduce the cross-city patterns in population, wages, and rents observed in the data. We focus on relative changes across cities, demeaning the growth rates since the model is not designed to match aggregate changes. The first two bars compare the growth between 2019–2022 in the data to the corresponding short-run model response; the third bar shows the long-run

Figure 10: Response of Population, Wages, and Rents to WFH Shock



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

effects.

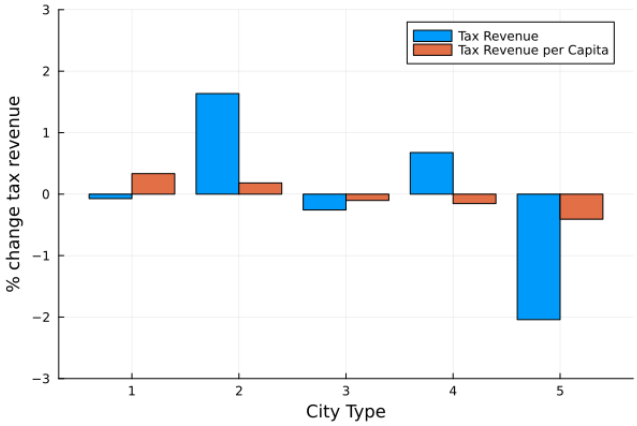
The model correctly predicts the direction of population changes: workers move out of the largest cities and into smaller ones. There is a 3.4pps gap between population growth in the smallest city (+1.6%) and population growth in the biggest city (-1.7%). In the model the gap is 1.3pps, or 40% of the data. Population responses are nonlinear with city size. While bin 5 experiences population declines, bins 1 through 4 all see short-run population increases of varying magnitudes. In the long-run the population of bin 1 falls, with more WFH going to bins 2 and 4, where there is a better mix of cheap rents but also better opportunities in the local labor market. These patterns reflect the equilibrium interaction of the initial rent calibration, the probability of obtaining a WFH job, the commuter wage-offer distribution, and the WFH amenity.

Wage adjustments follow a similar pattern, increasing in small cities and decreasing in big cities. The evolution of average wages is primarily driven by the increase in the WFH share. Although WFH is rising across all cities, its effect on average wages varies by location. In large cities (bin 5), WFH workers earn slightly less on average than commuters. While they are partially compensated by the WFH amenity, many relocate to smaller cities where their real wages are higher. In contrast, in smaller cities, WFH workers earn more than commuters, which raises average wages in bins 1 and 2.[15] The model explains 44% of the observed equalization in average wages between the biggest and smallest city. Because workers are paid their marginal products, these wage changes also reflect changes in productivity. As a result, the expansion of WFH has an equalizing effect on productivity differences between large and small cities.

Finally, rent adjustments mirror changes in population and average wages, although the

[15]Panel (b) of Table 2 shows that the location parameter of the wage distribution for remote workers is 0.09—higher than the corresponding parameter for commuters in bins 1 and 2, but lower than in bins 3–5.

Figure 11: Tax Revenue Responses



impact of increased housing demand in smaller cities is partially mitigated by their higher housing supply elasticities. As a result, the model under-predicts the equalization in rents. There is a 15pp gap between rent growth in the small city (+6%) and rent growth in the big city (-9%). The model matches 0.8pps, or 5%, of this gap.

Though the changes in the aggregate migration rate are largely transitory, the impact on rents, population, and wages is permanent. As workers continue to migrate, the impact of the COVID shock is slightly amplified in the long-run.

The Tax Implications of WFH. Next, we briefly consider the fiscal implications of the increase in the WFH share. Figure 11 reports the long-run change in total tax revenue and tax revenue per capita.

Two forces drive the changes in tax revenue across cities. First, population reallocation alters the tax base as cities gain or lose residents. Second, changes in average wages affect per capita tax revenue.

Large cities experience a decline of roughly 2% in total tax revenue, but the reduction in per capita revenue is much smaller. This indicates that they primarily lose remote workers, who earn less on average than commuters in those cities. In contrast, the growth in per capita tax revenue is higher than total tax revenue in bin 1, where incoming remote workers earn higher wages than local commuters, thereby increasing the per capita tax base.

7.2 Welfare Implications of WFH

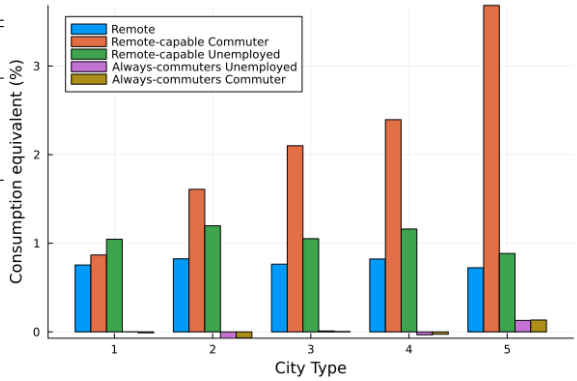
We next evaluate the welfare effects of the WFH shock using a consumption-equivalent measure of welfare. This measure captures the percent increase in consumption and housing that would

Figure 12: Consumption Equivalent Welfare Results

(a) Consumption equivalents by type and employment status

	All	Remote-capable	Always-commuters
Panel A:			
Average	0.73%	1.95%	0.01%
Panel B: By employment status			
Unemployed	–	1.06%	0.01%
Commuter	–	2.22%	0.01%
Remote	–	0.78%	–

(b) Average consumption equivalent 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.

make a worker indifferent between remaining in the initial steady state and experiencing the transition.[16]

Figure 12 reports the average consumption equivalent for all workers, weighting individuals equally, as well as separately for remote-capable and always-commuters, irrespective of employment status. Panel (b) further decomposes these averages by worker type and employment status.

On average, workers would need to be compensated 0.73% of their initial steady-state consumption to remain indifferent between the initial steady state and the transition. This indicates significant welfare gains from the adoption of remote work. However, these gains are not evenly distributed. All of the welfare benefits accrue to remote-capable workers whose average consumption equivalent is even higher at 1.95% of consumption,

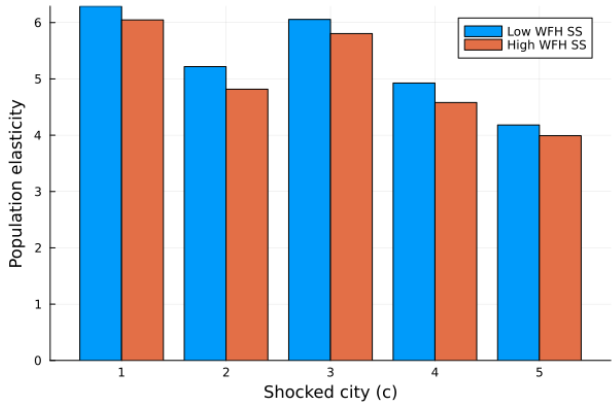
In contrast, always-commuters who are not eligible for remote work are slightly better off. Their consumption equivalent of 0.01% is driven by rents decreasing in the cities where they live. Examining their consumption equivalent by cities, shows that it is negative in the small cities where rents rise, but slightly positive in the biggest city where rents fall.

Looking at the welfare gains by employment status, the biggest gains accrue not to the workers who are already remote, but to the remote-capable commuters. As the shock hits, these workers are likely to be transitioned on-the-job to remote status, keeping their high commuter wage. The gains increase with city size, reaching over 3% in bin 5, where commuter

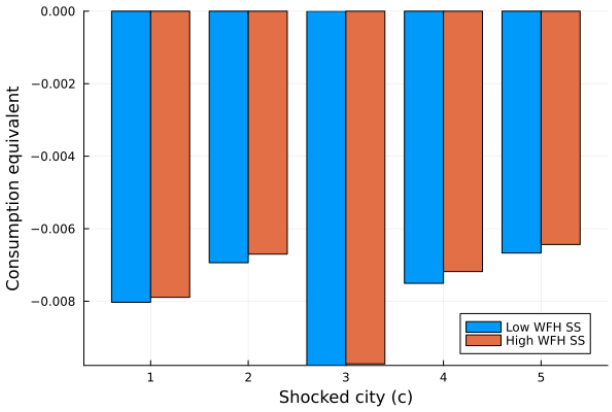
[16] With log utility, the consumption equivalents can be computed in closed form using the standard expression $CE = (\exp((1-\beta)(V^{tr} - V^0)) - 1) \times 100$, where V^{tr} denotes the worker's value function along the transition and V^0 the value in the initial steady state.

Figure 13: Impact of a Local Productivity Shock by WFH Share

(a) Migration Elasticities



(b) Consumption Equivalent Welfare



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.

wages are the highest. These high-wage commuters will now be high-wage remote workers who benefit from the WFH amenity and can also move to a low-rent city, thereby increasing their real wage. However, there are also substantial gains for remote-capable unemployed and those who are already remote, who benefit from the higher remote job finding rate going forward.

The welfare gains for remote-capable workers arise through several channels. In addition to the amenity value of remote work, workers in smaller cities benefit from access to the national remote labor market, where wages exceed those available in their local commuter market. In larger cities, although remote wages are lower than commuter wages in nominal terms, remote workers can relocate to lower-rent smaller cities, thereby increasing their real wages. A further source of welfare gains comes from improved *matching* across locations. Because remote workers can move between cities without experiencing unemployment, they are better able to respond to idiosyncratic location-preference shocks, leading to better sorting across cities.

7.3 The Response to a Negative Local-Productivity Shock

In this section, we examine how WFH alters the way the economy adjusts to a negative local productivity shock. In the past, migration was the only way for workers to insure against these local shocks. Their options were to endure the worse outcomes in their local market or undergo a costly move to another city. With the rise in WFH, remote-capable workers have a new option to work in the national remote market.

Within the low- and high-WFH steady states, we shock one city's μ_g, the location of the wage-offer distribution, by $-.001$, amounting to a -0.1% decline in the average wage offer for local commuters. Specifically, we run 5 separate experiments, shocking a representative city from each bin, one at a time. We run the same experiment in the low- and high-WFH steady states to examine how WFH shapes the impact of the local shocks.

Figure 13 shows the migration elasticities in response to the negative productivity shock in Panel (a) and the average consumption equivalent welfare impact of the shock for residents of the impacted city in Panel (b).

As the WFH rate increases, the migration elasticities fall. Workers no longer need to relocate to avoid the negative productivity shock. The consumption equivalent welfare cost is also smaller as the WFH rate rises.

7.4 A Migration Subsidy

Finally, we examine the effects of a city offering a migration subsidy to attract remote workers. This exercise is motivated by real-world programs such as the Tulsa Remote Program, which provides a $10,000 payment to remote workers who relocate to Tulsa.

We conduct the analysis in the model's high–work-from-home steady state and consider a one-time transfer paid to remote workers who relocate to the city. Although the transfer to each worker is a one-time payment, the policy itself is permanent. That is, we study the new steady state that arises when the government commits to offering this one-time subsidy to all eligible movers in perpetuity.

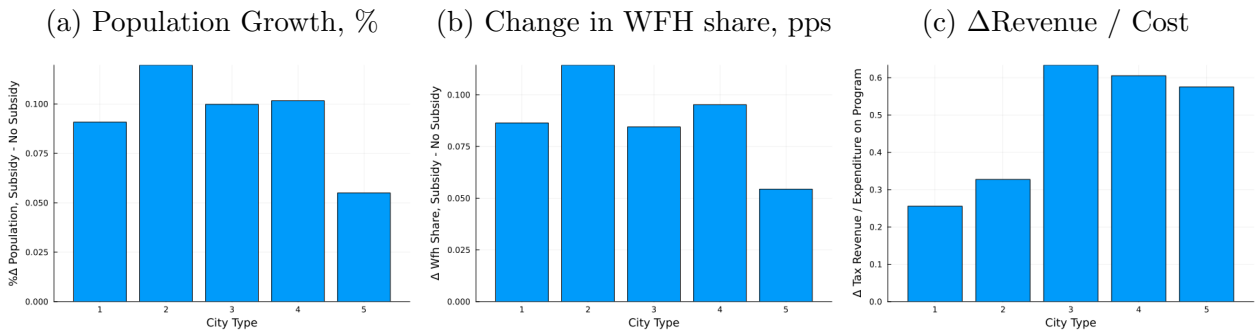
The policy is implemented one city at a time, ignoring the political economy of cities competing for remote workers. The subsidy is calibrated to 10 percent of the wage in zone 1, which corresponds to approximately $4,000 in the model.

Figure 14 reports the effects of the policy. Panels (a) and (b) show the impact on the city's population and WFH share. The subsidy generates a modest increase in population, with effects that decline with city size: population rises by 0.09% in the small city and by 0.05% in the large city. The WFH share increases by 0.1 percentage points on average.

However, panel (c) shows that the program is clearly not cost-effective. The figure plots the change in tax revenue relative to program expenditures. On average across cities, the policy generates 0.44 dollars in additional tax revenue for each dollar spent.

Two mechanisms drive this result. First, the government cannot target the subsidy exclusively to marginal movers. As a result, it gives transfers to remote workers who would have

Figure 14: Migration Subsidy



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.

relocated even without the program, raising the total cost. Second, remote workers are a relatively mobile group and more likely to move away in the future, limiting the durability of tax base gains.

8 Conclusion

This paper argues that the surge in long-distance migration in the US after 2019 was primarily driven by the rise in work from home (WFH) following the Covid-19 outbreak. ACS data reveals that interstate migration rates were consistently higher among full-time WFH workers compared to commuters prior to the pandemic, even after controlling for observable characteristics. The share of full-time WFH workers tripled after the pandemic, and the gap in interstate migration between WFH workers and commuters widened further. Quasi-panel data reveals that workers who switched to WFH since the pandemic migrated at higher rates. We find similar results using plausibly exogenous changes in employer WFH policies, suggesting that greater access to WFH after the Covid-19 outbreak causally increased interstate migration. A reduced-form aggregate accounting exercise suggests that the rise in WFH can account for more than half of the increase in national interstate migration in 2022 relative to its pre-Covid trend. Additionally, changes in WFH are predictive of geographic variation in out-migration and net migration.

Motivated by these findings, we develop a spatial equilibrium model incorporating remote work and long-distance migration. We calibrate the model to match pre-COVID migration patterns and then triple the share of remote-capable workers to reflect post-pandemic changes. The model successfully replicates post-COVID trends in migration, population growth, and

rents, allowing us to analyze the welfare gains of WFH, many of which arise from workers' increased ability to relocate based on preferences or cost of living.

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ONLINE APPENDIX

A RPS: Measurement and Definitions

A.1 Sample Construction and Weighting

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

Table A.1.3: 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.

A.2 Definition of Demographic Groups and Industries

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

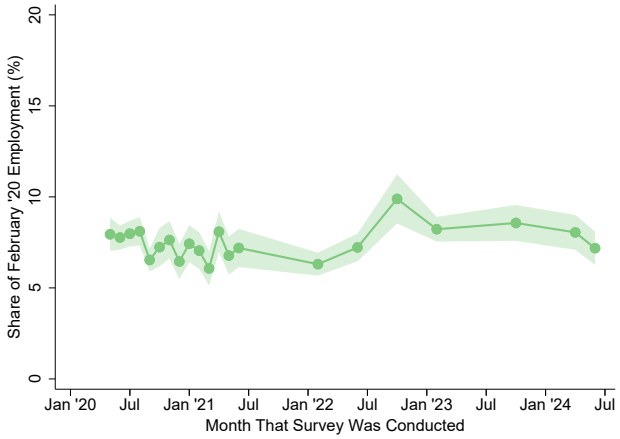
- Age
  - **Younger**: Ages 18-29
  - **Mid Age**: Ages 30-49
  - **Older**: Ages 50-64
- Race and Ethnicity
  - **Black**: Identify as Black and not Hispanic
  - **Hispanic**: Identify as Hispanic
  - **White**: Identify as White and not Hispanic
  - **NonBlackHispWhite** or **Non B/H/W**: All other 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.15: 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.15 displays rates of full-time WFH in February separately for various months that the survey was conducted. We include data from RPS waves collected between May 2020 and October 2023. Reassuringly, we find that reported WFH outcomes in February 2020 are fairly stable across survey months. For example, 7.9 percent of individuals surveyed in May 2020 reported to be WFH Only in February 2020, compared with 7.7 percent of individuals surveyed in 2022-2023 and 8.5 percent of individuals in the most recent survey in October 2023. These differences are not statistically significant at the 5 percent level.

FIGURE B.17: Work from Home and Long-Distance Migration

(a) Interstate Migration by Commute Status (b) Inter-MSA Migration by Commute Status

(c) Interstate Migration: WFH−Commuters (d) Inter-MSA Migration: WFH−Commuters

Notes: American Community Survey (ACS). Left Panels: annual interstate / inter-MSA migration rates for three population groups: non-employed (light gray diamonds), commuters (dark gray triangles), and WFH workers (blue crosses). Right Panels: the black squares are the difference between WFH and Commuters from the left panel; the gray triangles are the coefficients on WFH from a linear probability regression of migration with several demographic controls using sample weights (see text for details). The sample is working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals based on heteroskedasticity-robust (Ecker-Huber-White) standard errors.

FIGURE B.18: Accounting Exercise: The Impact of Work from Home on Long-Distance Migration

(a) Share of Workers Who Work from Home

(b) Impact on Interstate Migration (c) Impact on Inter-MSA Migration

Notes: American Community Survey (ACS). Top Panel: the share of workers (%) who WFH. Bottom Panels: black circles are actual migration rates for workers in the ACS; gray diamonds are the counterfactual migration path if WFH would have remained at the 2019 share; hollow black diamonds are the counterfactual migration path if WFH would remained at the 2019 share and if the migration of WFH workers would have remained at the 2019 rate (see text for details on these counterfactuals). The sample is employed working-age adults (18-64) in civilian households who currently live in the US and lived in the US in the previous year. Whiskers correspond to 95% confidence intervals.

B Additional Facts on WFH and Interstate Migration

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

FIGURE B.16: Share of Inter-MSA Moves That Are Also Interstate

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

FIGURE B.19: Long-Distance Migration and Individual-Level Changes in Work from Home

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

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

Table B.1.4: Switching to WFH and the Probability of A Long-Distance Move

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

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

FIGURE B.20: Geographic Variation in Work from Home and Long-Distance Migration

(a) State-Level Out-Migration

(b) State-Level Net-Migration

(c) MSA-Level Out-Migration

(d) MSA-Level Net-Migration

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

Table B.1.5: Work from Home, Long-Distance Migration and Employer Changes

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

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

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

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.21 displays the share of workers aged 18-64 who WFH full-time in several US datasets. The pink squares correspond to the ACS, the gray triangles to the CPS, and the green triangles correspond to the RPS. The ACS data is annual. We plot 2019 ACS data points as the February 2020 observation to facilitate comparison with the RPS's February 2020 data. We plot 2020-2023 ACS data in the midpoint (July) of the corresponding year.

We find similar rates of WFH across all three datasets, both in terms of levels and trends over time. The pre-pandemic full-time WFH rate was 5.4% in the ACS (2019) and 7.7% in the RPS (02/2020). WFH increased sharply in both datasets in mid 2020 after the Covid-19 outbreak, and gradually declined after that. In the RPS the WFH rate in 2024 is about the same as in 2023, albeit being slightly higher than in October 2023. The WFH rate in the CPS is lower than in the ACS for both 2022 and 2023 but has habeen stable around 10% through time.

FIGURE B.21: Share of Workers Who Work from Home Full Time

Notes: American Community Survey (ACS), Current Population Survey (CPS) and Real-Time Population Survey (RPS), ages 18-64. ACS data is annual, CPS and RPS data is from selected months. We plot 2021-2023 ACS data in the midpoint (June) of the corresponding year. We do not plot 2020 ACS data because it reflects an uncertain combination of pre-pandemic months with very low WFH rates and post-pandemic months with very high WFH rates.

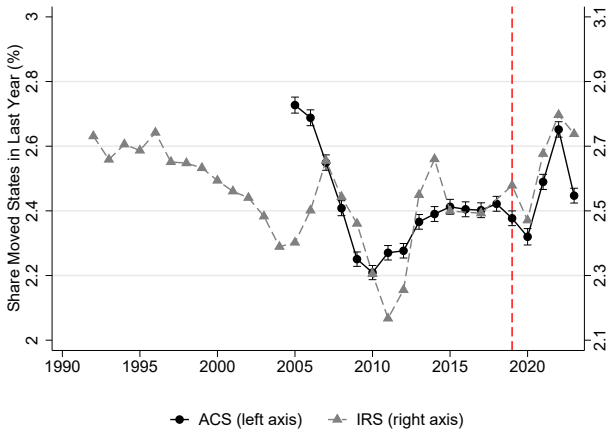
B.3 Comparing Migration in the ACS and RPS

In the ACS, interstate moves are identified using the respondent's residence one year prior. In the RPS, interstate moves are identified using the respondent's residence in February 2020, just before the Covid-19 outbreak. This difference means that we cannot cleanly validate interstate migration rates in the RPS (since February 2020) with interstate migration rates in the ACS (in the past year). However, in both datasets we can observe whether the respondent has moved within the last year (but not whether they have moved states in the last year). In 2022, 13.1% of respondents had moved in the last year in the ACS, compared with 11.7% in the RPS. Among commuters, the rates are 13.2% in the ACS and 9.9% in the RPS; among WFH workers, the rates are 15.2% in the ACS and 12.8% in the RPS. This yields a migration gap between commuters and WFH workers of 2.0% in the ACS and 2.9% in the RPS. We conclude that overall migration rates are slightly higher in the ACS than the RPS, while the WFH-commuter migration gap is slightly higher in the RPS.

B.4 Interstate Migration in the ACS and IRS

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

FIGURE B.22: 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.22 displays interstate migration in IRS and ACS data. ACS data (left axis) run from 1992 to 2002 and use the same sample criteria for civilian working-age adults as in the main text. IRS data (right axis) span a longer time series, from 1992 to 2002. We allow for a slightly shifted axis for each dataset because each has a different sample (the IRS data does not condition on civilian status and does not include non-filers). In a few years (2005, 2006, 2010, 2011, 2014) the two datasets display large discrepancies. However, both reveal quantitatively similar overall trends. In particular, both datasets show fairly stable migration rates from

2015-2019, a decline in migration in 2020, and a sharp increase in migration in 2021 and 2022.

B.5 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. (2024a); and Monte et al. (2023) construct models that predict an expansion in WFH will induce some WFH workers to make local moves from city centers near workplaces where rent is high to more distant suburbs where rent is lower or amenities are better. Brueckner et al. (2023) and Delventhal and Parkhomenko (2023) analyze models in which some full-time WFH workers move larger distances, such as across metro areas or states. Local moves may be more relevant if workers still need to occasionally commute to work or if workers already have strong local ties. Long-distance moves may be more relevant if workers rarely need to commute or if they have strong preferences for other distant locations. On average, interstate moves will tend to be longer distance than within-state moves, but this is not necessarily the case for all interstate moves. For example, some individuals may live near a state border and move only a few miles to another state. This may be more common in the Northeast, which has smaller states on average.

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

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

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

FIGURE B.23: Share of Long-Distance Moves Among Interstate / Inter-MSA Migrants

(a) Interstate Migration: Commuters

(b) Interstate Migration: Work from Home

(c) Inter-MSA Migration: Commuters

(d) Inter-MSA Migration: Work from Home

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

was 69% for commuters versus 80% for WFH.

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

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.24 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.24: Long-Distance Migration: All vs. Native-Born

(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 US-born individuals. Whiskers correspond to 95% confidence intervals.

B.7 Imputed Migration in the ACS

FIGURE B.25: Long-Distance Migration: All vs. Imputed Moves

(a) Interstate Migration

(b) Interstate Migration Relative to Trend

(c) Inter-MSA Migration

(d) Inter-MSA Migration Relative to Trend

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

FIGURE B.26: State-Level Variation in Work from Home and Interstate Migration

(a) WFH and Interstate Migration

(b) WFH Capacity and Interstate Migration

(c) WFH and Inter-MSA Migration

(d) WFH Capacity and Inter-MSA Migration

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

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

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

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

Figures B.26 and **??** plot state out-migration, in-migration, and net-migration rates against actual WFH rates in 2021-2022 (left panels) and DN WFH Capacity (right panels). Qualitatively, both WFH and WFH capacity predict interstate migration with the same sign. However, the correlation between migration and WFH capacity is lower than between migration and WFH, and the slope for WFH capacity tends to be flatter as well.

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 can be solved in closed form and written as: For always-commuters who are unemployed:

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

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

$$\begin{aligned}\mathcal{V}^{ac}_{t+1}(g_t, w) &= \mathbb{E}_{\boldsymbol{\epsilon}}\left[\max_{g_{t+1}}\left\{\underbrace{V^{ac}_{t+1}(g_t, w_i) + \theta\epsilon_{g_{t+1}}}_{\text{stay if } g_{t+1}=g_t},\ \underbrace{U^{ac}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}}_{\text{move if } g_{t+1}\neq g_t}\right\}\right] \\ &= \theta\ln\Bigg(\sum_{g_{t+1}}\Big[\mathbb{I}(g_{t+1}\neq g_t)\ \exp\left(\frac{1}{\theta}U^{ac}_{t+1}(g_t, g_{t+1}) - \frac{1}{\theta}\psi^u(g_t, g_{t+1})\right)... \\ &\qquad +\mathbb{I}(g_{t+1}= g_t)\ \exp\left(\frac{1}{\theta}V^{ac}_{t+1}(g_t, w_i)\right)\Big]\Bigg)\end{aligned}$$

For remote-capable workers employed remotely with wage w:

$$\begin{aligned}\mathcal{V}^{r}_{t+1}(g_t, w) &= \mathbb{E}_\epsilon\left[\max_{g_{t+1}}\left[V^{r}_{t+1}(g_t, g_{t+1}, w) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}\right]\right] \\ &= \theta\ln\left(\sum_{g'}\exp\left(\frac{1}{\theta}V^{r}_{t+1}(g_{t+1}, w) - \frac{1}{\theta}\psi^u(g_t, g_{t+1})\right)\right)\end{aligned}$$

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

$$\mathcal{V}^n_{t+1}(g_t, w) = \mathbb{E}_\epsilon \max_{g_{t+1}} \left\{ \underbrace{V^n_{t+1}(g_t, w) + \theta\epsilon_{g_{t+1}}}_{\text{stay if } g_{t+1}=g_t}, \underbrace{U^{rc}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) + \theta\epsilon_{g_{t+1}}}_{\text{move if } g_{t+1}\neq g_t} \right\}$$

$$= \theta \ln\left(\sum_{g_{t+1}} \left[\mathbb{I}(g_{t+1} \neq g_t) \exp\left(\frac{1}{\theta} U^{rc}_{t+1}(g_{t+1}) - \frac{1}{\theta}\psi^u(g_t, g_{t+1}) \right) ... \right.\right.$$

$$\left.\left. + \mathbb{I}(g_{t+1} = g_t) \exp\left(\frac{1}{\theta} V^n_{t+1}(g_t, w) \right) \right] \right)$$

For remote-capable workers who are unemployed:

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

$$= \theta \ln\left(\sum_{g_{t+1}} \exp\left(\frac{1}{\theta} U^{rc}_{t+1}(g_{t+1}) - \frac{1}{\theta}\psi^u(g_t, g_{t+1}) \right) \right)$$

Transition Probabilities Always-Commuters Given the assumption that the workers draw their preference shocks from a Gumbel distribution, the probability that a an unemployed always-commuter will move to a new city is given by:

$$\pi^{ac,u}(g_t, g_{t+1}) = \frac{\exp\left(U^{ac}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) \right)^{\frac{1}{\theta}}}{\sum_{g'_{t+1}} \exp\left(U^{ac}_{t+1}(g'_{t+1}) - \psi^u(g_t, g'_{t+1}) \right)^{\frac{1}{\theta}}}$$

Similarly, the probabilities that an always-commuter stays employed in their current job versus quit to unemployment and move to a new city are given by:

$$\pi^{ac,stay}(w, g_t) = \frac{\exp\left(V^{ac}_{t+1}(g_t, w) \right)^{\frac{1}{\theta}}}{exp(\mathcal{V}^{ac}_{t+1}(g_t, w))^{\frac{1}{\theta}}}; \quad \pi^{ac,quit}(w, g_t, g_{t+1}) = \frac{\exp\left(U^{ac}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1}) \right)^{\frac{1}{\theta}}}{exp(\mathcal{V}^{ac}_{t+1}(g_t, w))^{\frac{1}{\theta}}}$$

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 a job offer above their threshold wage, and the exogenous job separations rate.

Let $L^{ac}_t(u, g)$ be the population of unemployed workers in city g and time t and $L^{ac}_t(w, g)$ be the population of workers employed with wage w in city g, and let P^e_g be the probability of

getting an offer above the wage threshold in city g. Then

$$L^{ac}_{t+1}(u,g) = \sum_{g_t} \pi^{ac,u}(g_t, g_{t+1}=g)\left(L^{ac}_t(u,g_t)(1-P^e(g_t)) + \delta\int_w L^{ac}_t(w,g_t)dw\right)... \\ + \sum_{g_t\neq g}\int_w \pi^{ac,quit}(w_{it},g_t,g_{t+1}=g)(1-\delta)L^{ac}_t(w,g_t)dw$$

The first line sums over the unemployed workers who move to city g and the employed workers who were hit with a separation shock that move to city g. The summation in the second line sums over the employed workers in every other city who quit their job with wage w and move to city g.

Given a grid over the wage distribution indexed by w_s, the law of motion for the mass of employed workers at wage w_s is given by:

$$L^{ac}_{t+1}(w_s,g) = (1-\delta)L^{ac}_t(w_s,g)\pi^{stay}(w_{it},g_t) + L^{ac}_t(u,g)(F(w_{s+1})-F(w_s))$$

where the first term gives the mass employed at wage w_s who do not lose their job or quit. The second term includes the unemployed workers who find a job at wage w_s, where $F(w_s)$ gives the CDF of the wage offer distribution.

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 across cities is given by:

$$\pi^{rc,u}(g_t,g_{t+1}) = \frac{\exp\left(U^{rc}_{t+1}(g_{t+1}) - \psi^u(g_t,g_{t+1})\right)^{\frac{1}{\theta}}}{\sum_{g'_{t+1}}\exp\left(U^{rc}_{t+1}(g'_{t+1}) - \psi^u(g_t,g'_{t+1})\right)^{\frac{1}{\theta}}}$$

The probability that a remote worker moves across cities is given by:

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

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

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

The probability that they quit to unemployment in a new city is given by:

$$\pi^{n,quit}(w, g_t, g_{t+1}) = \frac{\exp\left(U^{rc}_{t+1}(g_{t+1}) - \psi^u(g_t, g_{t+1})\right)^{\frac{1}{\theta}}}{exp(\mathcal{V}^n_{t+1}(g_t, w))^{\frac{1}{\theta}}}$$

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, but now we separately keep track of remote workers and commuters. The law of motion for the population of remote workers employed at wage w in city g is given by:

$$L^r_{t+1}(w_s, g_{t+1}) = \sum_{g_t}(1-\delta)\pi^r(g_t, g_{t+1}, w_s)L^r_t(w_s, g_t) + p^r L^{rc}_t(u, g_t)(F(w_{s+1}) - F(w_s)) + (1-\delta)p^s L^n_t(w_s, g_t)$$

The first term is the mass of remote workers who keep their job and move to city g_{t+1} from any other city. The second term is the mass of remote-capable unemployed workers who find a job at wage w_s in city g_{t+1}. The third term is the mass of remote-capable workers in a commuter job who can switch to a remote job.

The law of motion for the population of remote-capable workers employed in commuter jobs is given by:

$$L^n_{t+1}(w_s, g_{t+1}) = (1-\delta)(1-p^s)\pi^{n,stay}(w_{it}, g_t)L^n_t(w_s, g_t) + (1-p^r)\, L^{rc}_t(u, g_t)(F(w_{s+1}) - F(w_s))$$

The first term is workers who keep their commuter job and stay in city g_{t+1}. The second term is unemployed workers who find a commuter job at wage w_s in city g_{t+1}. Finally, the law of motion for the population of remote-capable workers who are unemployed is given by:

$$\begin{aligned} L^{rc}_{t+1}(u, g_{t+1}) = &\sum_{g_t} \pi^{rc,u}(g_t, g_{t+1}) \left(L^{rc}_t(u, g_t)(1 - P^{rc,e}_g) + \delta \int_w L^r_t(w, g_t)dw + \delta \int_w L^n_t(w, g_t)dw \right) \dots \\ &+ \sum_{g_t} \int \pi^{n,quit}(w_{it}, g_t, g_{t+1}) L^n_t(w_s, g_t) \end{aligned}$$

where the first term gives the mass of remote-capable unemployed workers (including those who are newly separated) who move to city g. This term is multiplied by $(1 - P^{rc,e}_g)$ to account for the fact that some of these workers will have found a remote or commuter and exited unemployment before the end of the period. $P^{rc,e}_g = p^r_g(1 - F^r(\underline{w}^r_g)) + (1 - p^r_g)(1 - F_g(\underline{w}_g))$ is the probability of getting an offer above the wage threshold in city g. The second term gives those who quit their commuter job to unemployment and move to city g.

C.2 Details on Binning Cities