FEDERAL RESERVE BANK
PHILADELPHIA

Working Papers
RESEARCH DEPARTMENT

The Great Reshuffle
Remote Work and Residential Sorting

Wenli Li
Federal Reserve Bank of Philadelphia

Yichen Su
Southern Methodist University

WP 25-36

PUBLISHED
November 2025

FRB CFI
PHILADELPHIA

ISSN: 1962-5361

DOI: https://doi.org/10.21799/frbp.wp.2025.36

The Great Reshuffle: Remote Work and Residential Sorting*

Wenli Li† and Yichen Su‡

This Draft: October 2025
First Draft: December 2021

Abstract

This paper studies the significance of migration in evaluating the welfare impacts of remote work. By analyzing individual location history data, we first document an increase in net migration towards suburbs and smaller cities in the US since 2020. We demonstrate that the migration wave has been disproportionately fueled by high-income individuals, who were more likely to move due to remote work. Consequently, regions with substantial in-migration observed the greatest rise in housing expenses. This also led to changes in local demand for services and associated employment. Employing a stylized welfare accounting framework, we show that migration mitigated the increase in housing cost burdens for both high- and low-income groups, with the advantages being greater for low-income individuals. Conversely, dispersed job growth, as a result of migration away from major urban centers, curtailed the increase in job accessibility, especially for high-income groups. Factoring in the spatial impacts of migration on housing costs and job accessibility, the welfare inequality surge related to remote work is considerably tempered.

Keywords: Spatial Sorting; Migration; Housing Cost; Employment; Inequality; Remote Work; WFH
JEL Classification: R2; R3; D6

*The views expressed in this paper are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. We thank John Landon-Lane, Morris Davis, Eunjee Kwon, the editor, the two anonymous reviewers, and seminar participants at the AREUEA seminar series, Rutgers University, Federal Housing Finance Agency, American Enterprise Institute, the 2022 Econometric Society North America Summer Meeting, Southern Economic Association Meeting, the 2022 Society of Economic Dynamics Summer Meeting, and the 2023 American Economic Association Meeting for their comments.

†Federal Reserve Bank of Philadelphia: wenli.li@phil.frb.org.
‡Southern Methodist University: yichensu@outlook.com.

1 Introduction

The COVID-19 pandemic spurred a significant transition to remote work (Bartik et al., 2020; Barrero et al., 2021; Brynjolfsson et al., 2020; Bick et al., 2023), providing greater flexibility, eliminating geographical restrictions on job prospects, and potentially boosting the total factor productivity (TFP) (Choudhury et al., 2021; Bloom et al., 2024; Akan et al., 2025; Bloom et al., 2025). The growth in remote work, on the other hand, also raised the demand for residential home office space, driving up housing costs (Mondragon and Wieland, 2022; Davis et al., 2023, 2024). As remote work is more accessible to high-skilled workers, its boons disproportionately benefit them (Dingel and Neiman, 2020; Su, 2020), while the accompanying rise in housing costs is shared by low-skilled, low-income individuals. As such, the existing literature suggests that the expansion in remote work may have exacerbated welfare inequality (Davis et al., 2024).

This paper highlights another aspect crucial to the welfare consideration: the shift to remote work influences individuals based not only on their skill level but also on their *places of residence*. Specifically, the sudden rise in remote work enabled many workers, especially high-skilled workers, to relocate from dense urban centers to suburbs and smaller cities with better amenities and larger, more affordable homes (Liu and Su, 2021; Gupta et al., 2022b; Meeker and Mota, 2021; Whitaker, 2021; Akan et al., 2025). Some jobs also followed the outflow of workers. This spatial shift in housing demand caused a reduction in congestion within the urban centers of major metropolitan regions, thereby mitigating the increase in housing cost burdens for residents of densely populated areas. On the other hand, the spreading out of employment opportunities curtailed the increase in job accessibility associated with remote work. Because high- and low-income individuals are unevenly distributed spatially, these shifts in housing costs and job availability impacted them differently. Our analysis shows, collectively, these changes moderated the rise in welfare inequality.

We begin our analysis by documenting the detailed geographic patterns of migration before and after the onset of the COVID-19 pandemic, disaggregated by income level. To do so, we leverage a micro-level anonymized dataset, the Federal Reserve Bank of New York's Consumer Credit Panel/Equifax (CCP), to examine recent shifts in migration trends, spatial sorting, and their implications for welfare. The CCP is a nationally representative 5% anonymized sample of individuals drawn from Equifax. We identify residential locations using precise geo-information tied to the addresses where individuals receive their bills.[1] To estimate

[1]When individuals change their address and update it with creditors (e.g., a credit card issuer), this information is transmitted to credit bureaus and appears on their credit report. We use geocoded information to determine location but do not access actual addresses.

income, we impute earnings by combining observed characteristics in the CCP with data from the Survey of Consumer Finances, following the methodology in Coibion et al. (2020).

Our findings show that, since 2020, there has been a clear increase in net out-migration from densely populated urban cores to suburban areas, as well as substantial population shifts toward smaller, less densely populated MSAs. Notably, this migration surge has been disproportionately driven by *high-income* individuals. As of 2024, this trend toward lower-density areas has neither reversed nor subsided. These migration patterns have contributed to sharper increases in housing costs at destination locations relative to origin areas. However, because suburbs and smaller MSAs generally exhibit higher housing supply elasticities than dense urban centers, the shift in population toward these more supply-responsive areas has helped mitigate the upward pressure on housing costs caused by increased demand for housing space, particularly demand induced by the rise in remote work. Importantly, since the outflow was led by high-income individuals departing from urban cores, and because low-income populations are disproportionately concentrated in those urban areas, the migration-induced reallocation of housing demand has moderated the increase in housing costs faced by low-income residents.

In addition to housing, the demand for local goods and services also followed migrating residents. As a result, locations experiencing an influx of migrants saw stronger employment growth compared to those with net out-migration. This migration-driven reallocation of employment contributed to spatial dispersion of jobs, which in turn increased the average distance between residents and employment centers, thereby, curtailing the rise in job access on average. However, because the migration surge was concentrated in smaller MSAs, where low-income individuals are disproportionately located, it is plausible that the job access for low-income workers in these areas actually grew further as a result of the migration flows.

To assess the welfare effects of these new migration patterns on high- and low-income individuals, we introduce a stylized welfare accounting framework in which residents in different locations face distinct housing costs and job accessibility, both of which adjust in response to migration. Our framework incorporates changes in local housing costs driven by population inflows and accounts for heterogeneity in housing supply elasticities across census tracts. In particular, tracts experiencing higher net in-migration face larger increases in housing costs, especially in areas where housing supply is relatively inelastic.

Additionally, individuals face a range of employment opportunities that vary by location. We quantify the utility derived from job access using the concept of commuter market access from the transportation economics literature (Donaldson, 2018; Tsivanidis, 2022). Specifically, job access is determined by the availability of jobs and associated wages, discounted by the commuting cost from the individual's residential location. An increase in the number of jobs or in wages within a short commuting distance raises individuals' utility.

We use the calibrated welfare accounting framework to map observed and counterfactual housing costs and local job accessibility into welfare measures for residents. To quantify the causal impact of migration, operating through endogenous changes in housing costs and job access, we employ an instrumental variable (IV) approach. Our identification strategy leverages the fact that large pre-pandemic employment clusters with high availability of teleworkable jobs experienced sharp out-migration during the pandemic, particularly in MSAs where remote work was more feasible. This approach relies on the assumption that the pre-pandemic distribution of teleworkable jobs is uncorrelated with other unobserved factors that may have influenced out-migration or the outcome variables. We use two sources of variation to construct our IV: (1) the neighborhood-level number of teleworkable jobs, and (2) the MSA-level share of teleworkable jobs.

Our welfare calculations indicate that remote-work-induced migration *alleviated* average housing costs for both high- and low-income populations, with a more pronounced benefit for low-income individuals. While the pandemic period witnessed an unprecedented surge in both rental and home prices, largely driven by increased demand for home office space (Mondragon and Wieland, 2022), this occurred alongside substantial net migration flows from areas with *low* housing supply elasticities to those with *high* elasticities. As a result, the rising tendency for residents to relocate to regions with more flexible housing supply helped ease housing cost pressures. Put differently, absent the migration toward lower-density, more supply-responsive locations, the housing cost burden on the average resident would have been significantly greater. This pandemic-era shift can thus be interpreted as a process of "decongestion" in the housing market.[2]

Moreover, migration away from high-density areas disproportionately benefited the low-income population, as it redirected housing demand away from dense urban neighborhoods where low-income residents are more heavily concentrated.[3] In particular, we show that while elite cities such as New York City, San Francisco, and Los Angeles experienced significant outflows that reduced overall housing costs, the benefits were not limited to those leaving these MSAs. Low-income individuals residing in both large and small MSAs also experienced a reduction in housing cost burdens due to the broader suburbanization of housing demand. This migration-driven "decongestion" of neighborhoods heavily populated by low-income individuals resulted in greater welfare gains for the average low-income person relative to their high-income counterparts, thereby

[2]This finding is consistent with the results in Howard et al. (2023).

[3]This pattern of disproportionate out-migration from low-income neighborhoods has also been described as "de-gentrification" by Ding and Hwang (2022).

contributing to a narrowing of welfare inequality.

Beyond alleviating housing cost pressures, migration also affected residents' welfare by reshaping access to employment opportunities. We find that remote-work-driven migration toward lower-density areas generally mitigated access to local service jobs, particularly in large metropolitan areas. However, migration's negative effect on job access was significantly milder in smaller MSAs, and in some cases, these areas even experienced increases in job access due to in-migration. Since low-income individuals are disproportionately concentrated in smaller and less dense MSAs, this shift in job availability particularly benefited them.

At the same time, local service job access was curtailed in urban centers but increased in suburban areas by within-city migration. Because low-income residents are more likely to live in urban cores, this within-city shift could worsen their job access. However, the offsetting effect is limited, as intra-city job relocations have a smaller impact on access and welfare than inter-city shifts, as workers can typically commute more easily within cities than between them.

Professional service jobs, in which high-income workers are disproportionately employed, exhibited relatively limited spatial reallocation in response to migration. To the extent that these jobs did shift geographically, the movement was primarily inter-city and away from the MSAs where high-income workers are most concentrated. As a result, migration dampened the job access gains that would have otherwise been realized from remote work adoption, particularly for high-income individuals. Overall, our analysis indicates that this mechanism further moderated the rise in welfare inequality across income groups.

In terms of our paper's contribution to the literature, we highlight that spatial sorting, indirectly driven by the adoption of remote work, constitutes an additional channel through which welfare inequality evolves, beyond the direct effects of remote work itself. This mechanism mirrors the pre-pandemic literature on spatial sorting (Moretti, 2013; Diamond, 2016; Couture et al., 2024; Su, 2022). A recent paper by Davis et al. (2024) explores and demonstrates the unequal welfare effects of remote work on workers of different ability to adopt remote work. Their results stem from the fact that the remote work option is disproportionately available for high-skilled workers, raising high-skilled workers' welfare, but the rising housing cost due to the increased need for home office space by remote workers disproportionately eats away low-skilled workers' welfare gains and may, in fact, absolutely harm workers who cannot work remotely. Our paper contributes to this discussion by showing that, when accounting for the effects of remote-work-induced *migration* on housing costs and job accessibility, the welfare losses for low-skilled workers may have been smaller, and the overall rise in welfare inequality may have been more moderate.

Our paper also contributes to the body of research on how remote work has influenced the demand for different locations. Liu and Su (2021) and Gupta et al. (2022b) document that the rent-bid curve flattened during the pandemic within MSAs, indicating that the demand for housing in city centers declined relative to that in the suburbs. Liu and Su (2021) further document that the demand for housing shifted toward smaller MSAs during the pandemic. Ramani and Bloom (2021), using data from the U.S. Postal Service and Zillow, find that households, businesses, and real estate demand relocated from dense central business districts (CBDs) to lower-density suburban ZIP codes in large U.S. cities. Haslag and Weagley (2024) report consistent findings using microdata from a national moving company. Migration outflows from urban neighborhoods during 2020 are also documented by Whitaker (2021), using data from CCP, and by Meeker and Mota (2021), based on mortgage application records. Beyond residential demand, Rosenthal et al. (2021) and Gupta et al. (2022a) find that the shift to widespread work-from-home (WFH) significantly reduced the value firms place on premium office locations and led to declining prices for office real estate.

A closely related study by Mondragon and Wieland (2022) analyzes how WFH increased housing demand while holding migration patterns constant. In contrast to Mondragon and Wieland (2022), our paper focuses on estimating the impact of remote-work-induced *migration* on housing costs and its welfare implications. Another closely related study is Howard et al. (2023), who emphasize the long-term housing cost effects of migration from areas with low housing supply elasticities to those with higher elasticities. Our analysis complements and extends these studies by highlighting the distributional consequences of such migration, as the resulting changes in housing cost burdens differ markedly across income groups.

On the theoretical front, several studies develop models to examine the effects of remote work on labor market outcomes and urban structure. Behrens et al. (2021), Davis et al. (2023), and Brueckner et al. (2023) develop models to explore the effect of remote work technology on labor market outcomes and city structure. Delventhal et al. (2021) develop a model that emphasizes urban agglomeration and traffic externalities and evaluate the effect of the remote work shock. In particular, Delventhal and Parkhomenko (2021)'s model quantifies the spatial consequences of remote work shocks across the US due to the pandemic at a highly detailed geographic scale, echoing our paper.

The remainder of the paper is organized as follows. Section 2 describes the data and presents validation exercises. Section 3 documents patterns of migration and spatial sorting. Section 4 introduces a simple welfare accounting framework. Section 5 analyzes the welfare implications of migration. Section 6 concludes.

2 Data Source and Data Validation

2.1 Data Source

The main outcome variable for individual migration decisions is derived from the CCP data. Location characteristics at the census tract, ZIP code, county, and MSA levels are obtained from the 2013–2017 American Community Survey (ACS), the National Historical Geographic Information System (NHGIS), and the ZIP Code Business Patterns (ZCBP) (Manson et al., 2020).

We use home price indices and rent data from CoreLogic and Zillow Research. Industry-level employment and wage data (by NAICS classification) are sourced from the Quarterly Census of Employment and Wages (QCEW), and aggregate visiting patterns are drawn from geospatial mobility data provided by SafeGraph and Advan.

2.1.1 Individual Locations and Migration Flows

We analyze migration patterns using the CCP data. This credit panel is a nationally representative 5% random, anonymized sample of all individuals aged 19 and older who have a Social Security number and a credit report, based on Equifax data. The dataset is a quarterly panel that begins in 1999, capturing snapshots of individuals' credit profiles at the end of each quarter. It provides detailed information on liabilities, including various types of debt and their respective payment statuses. Location geocode is based on the address where individuals receive their credit-related bills. We assume that this billing address corresponds to the individual's place of residence.[4] We restrict our analysis to individuals between the ages of 25 and 65. We track these individuals from the fourth quarter of 2019 through the third quarter of 2024, retaining only those who are observed in every quarter during this period.[5]

To construct migration flows between census tracts, we begin by counting, for each quarter and each census tract, the number of individuals who moved out and the number who moved in. We then calculate the out-migration rate for each origin tract by dividing the number of people who moved out by the initial number of residents in that tract. Similarly, we compute the in-migration rate for each destination tract by dividing the number of people who moved in by the initial number of residents in that tract. We construct migration flows at the MSA level using the same approach.

[4] In Appendix A, we assess the validity of this assumption by comparing it to residential location data from the ACS.

[5] The CCP's migration to a cloud-based system in Q3'2024 altered the construction of consumer identifiers (CIDs) and address reporting processes, rendering post-migration data not directly comparable to earlier periods. We end our sample in Q3'2024.

2.1.2 Individual Income Levels

To analyze differential migration patterns by income, we follow Coibion et al. (2020) and impute income for individuals in the CCP data using information from the Survey of Consumer Finances (SCF). The SCF provides data on debt balances, income, and demographic characteristics, many of which are also available in the CCP dataset. Using the 2019 SCF, we estimate the relationship between income and the set of debt and demographic variables common to both datasets. We then apply these estimates to impute income for each individual in CCP as of the fourth quarter of 2019. Appendix B provides a detailed description of the estimation and imputation procedures, along with the results.

As a validation exercise, we compare our imputed income measure with observed income from the HMDA-McDash-CRISM database. HMDA-McDash-CRISM is an anonymized linkage of the CCP data with the ICE, McDash (referred to as McDash) mortgage servicing data and the confidential Home Mortgage Disclosure Act (HMDA) data.[6] The correlation between imputed and observed log income is 0.51. In Figure A2, we present a binned scatterplot comparing the two measures. The relationship appears nearly linear, with a slope close to one, suggesting that our imputed income is a reasonably accurate proxy for individuals' actual income.

Throughout the remainder of the paper, we classify individuals with incomes above the national median as high-income, and those with incomes at or below the median as low-income.

2.1.3 Local Characteristics

Local population density and income are obtained from the 2013–2017 ACS summary tables via the National Historical Geographic Information System (NHGIS) (Manson et al., 2020). These data are available at the census tract, ZIP code, county, and MSA levels. For each census tract, we calculate the Euclidean distance to the nearest downtown, with downtown locations geocoded using the dataset from Holian and Kahn (2015).

[6]CRISM stands for Equifax's Credit Risk Insight Servicing data and McDash data. The HMDA-McDash-CRISM match is conducted by the Federal Reserve System's Risk Assessment, Data Analysis, and Research (RADAR) Group using the following criteria: 1. The origination date and action date must be within five days of each other unless the loan was reported in McDash as originated on the first day of the month, in which case the loans may be matched if the origination date and action date fall within the same calendar month. 2. Origination amounts must be within $500 for years prior to 2018, and within $10 for years 2018 and 2019. 3. Property ZIP codes must match. 4. Lien types (e.g., first-lien mortgage) must match if fields are populated. 5. Loan purpose types (e.g., purchase mortgage) must match if fields are populated. 6. Loan types (e.g., conventional mortgage) must match if fields are populated. 7. Occupancy types (e.g., owner-occupied) must match if fields are populated.

2.1.4 Geography of Telework Compatibility

To compute the share of telework-compatible jobs in each census tract, we use the spatial distribution of employment by occupation and assign telework compatibility based on a telework indicator developed by Dingel and Neiman (2020).[7]

The procedure is as follows. We first estimate the share of telework-compatible jobs at the ZIP code level using employment data from the 2016 ZIP Code Business Patterns (ZCBP). Since the ZCBP provides data at the NAICS industry level, we employ an industry-to-occupation crosswalk to impute the occupational distribution of jobs within each ZIP code. Using the imputed occupational mix and the telework indicator for each occupation, we then estimate the number and the share of telework-compatible jobs within a 3-mile radius of each ZIP code. Distance between ZIP codes is measured using the ZIP Code Tabulation Area (ZCTA) Distance Database from the NBER. Finally, we assign each census tract to its nearest ZIP code and use this mapping to compute the number and share of telework-compatible jobs for each census tract.

Similarly, for each MSA, we first calculate the number of full-time workers aged 25 to 65 in each occupation using data from the 2013–2017 ACS, accessed via IPUMS (Ruggles et al., 2020). We then combine these occupational distributions with the telework indicator for each occupation to compute the share of workers employed in telework-compatible occupations at the MSA level.

2.1.5 Remote Work and Hybrid Adoption by Income

For welfare analysis, we assess the extent to which high- and low-income individuals adopted remote and hybrid work over time. To do so, we draw on the Survey of Working Arrangements and Attitudes (SWAA), developed by Barrero et al. (2021). Conducted monthly, the SWAA surveys between 2,500 and 10,000 respondents aged 20 to 64, providing valuable insights into the evolution of remote work since the onset of the COVID-19 pandemic. We use the SWAA data to estimate the shares of U.S. employees working fully remotely, in hybrid arrangements, or entirely onsite during Q1'2022 and Q1'2024. In addition, we use the survey to calculate the average share of remote workdays among hybrid workers in these periods.

Due to the lack of comprehensive data on the pre-pandemic prevalence of fully remote and hybrid work, we combine information from the American Time Use Survey (ATUS) and the ACS to impute their respective shares just prior to the pandemic. From the 2019 ACS, we identify the proportion of workers who reported

[7] Dingel and Neiman (2020) and Su (2020) assess the suitability of each occupation for telework using characteristics from the O*NET database and assign a binary telework indicator to each occupation. In our analysis, we use the telework classification developed by Dingel and Neiman (2020).

primarily working from home. Using the ATUS, we estimate the share of total work hours conducted remotely. Assuming that the fraction of remote work hours among hybrid workers in 2019 was similar to that in 2024, we infer the pre-pandemic shares of fully remote and hybrid workers. Appendix C details the underlying assumptions and imputation methodology.

2.1.6 Local Employment Growth and Wages

We obtain county-level employment and wage data at the 2-digit NAICS level from the Quarterly Census of Employment and Wages (QCEW).[8]

2.1.7 Local Housing Market

Home price indices (HPI) at the ZIP code and county levels are obtained from CoreLogic, which constructs the index using repeat sales transactions. Rental prices are sourced from the Zillow Observed Rent Index (ZORI), a repeat-rent index developed by Zillow Research and weighted to reflect the rental housing stock, ensuring market-wide representativeness. To calculate rent cost growth for each location, we take a weighted average of Zillow rent growth and CoreLogic HPI growth, using the share of renters and owners in each geographic area as reported in the ACS.

3 Migration Patterns and Local Responses: Empirical Facts

3.1 Migration Across Neighborhoods

Our empirical analysis begins by examining changes in migration patterns since the onset of the COVID-19 pandemic in Q1'2020. Using the panel structure of the CCP data, we compare characteristics of the census tracts where individuals reside in the *current* quarter to those of the tracts where they resided in the *previous* quarter. Specifically, we analyze changes in tract-level attributes such as the logarithmic distance to the nearest city center, population density (measured as individuals per square kilometer), and the number of telework-compatible jobs within a 3-mile radius. The sample includes both movers and non-movers; for non-movers, changes in local characteristics are mechanically zero.

[8] Wage data in the QCEW are reported as averages across all workers' earnings and may be biased due to time-varying composition effects, such as shifts between full-time and part-time employment or changes in hours worked. These biases can be particularly pronounced during periods of labor market disruption, such as the COVID-19 pandemic.

Figure 1 presents the average quarter-to-quarter changes in tract-level characteristics for all individuals from Q2'2018 to Q2'2024, shown in blue lines. As depicted in subfigure 1a, the pre-pandemic trend showed a gradual increase in average distance to city centers, reflecting a slow shift toward suburban areas. However, beginning in Q2'2020, this trend accelerated sharply, indicating a significant increase in suburban migration following the onset of the pandemic. Subfigure 1b shows a concurrent decline in neighborhood population density, consistent with a growing preference for lower-density living environments starting in Q2'2020. Finally, subfigure 1c reveals a sharp decline in proximity to telework-compatible job centers, suggesting that individuals increasingly relocated away from neighborhoods near such employment hubs. This pattern is consistent with existing literature indicating that the reduced need for commuting to dense workplace clusters contributed to the post-pandemic outflow from high-density urban cores.

Although the pandemic served as a catalyst for the surge in suburbanization, its end did *not* reverse this trend. As shown across all three subfigures, the location characteristics, greater distance from city centers, lower neighborhood population density, and reduced proximity to telework-compatible job centers, have not reverted to their pre-pandemic levels. The migration toward suburban areas, lower-density environments, and away from dense office clusters continued well beyond the conclusion of the pandemic.

3.1.1 Differential Migration Patterns by Income Across Neighborhoods

In addition to analyzing average changes in location characteristics for the full sample, we also examine these changes by income group. For simplicity, we divide individuals into two categories: those with imputed incomes above the national median (high-income) and those below the median (low-income). In Figure 1, average changes for high-income individuals are depicted by red lines, while those for low-income individuals are shown in green. The results indicate that the increase in suburbanization and the shift toward lower-density areas have been primarily driven by high-income individuals. Nonetheless, low-income individuals have also shown a growing tendency to relocate to suburban and lower-density neighborhoods.

The most notable divergence in migration patterns between the two income groups is the changes in proximity to telework-compatible jobs. Prior to the pandemic, both high- and low-income individuals exhibited minimal changes in the number of nearby telework-compatible jobs. However, following the onset of the pandemic, high-income individuals experienced a substantial decline in proximity to such jobs, indicating a pronounced shift away from employment hubs that offer telework-compatible positions. In contrast, low-income individuals saw only modest changes in this dimension. This pattern is consistent with the fact that remote work opportunities are significantly more accessible to high-income workers (Bartik et al., 2020; Bick et al., 2023). As a result, in the post-pandemic period, high-income individuals have been better positioned to relocate away from job centers.

3.2 Migration across MSAs

Next, we turn to migration trends across MSAs. Mirroring our neighborhood-level analysis, we track individual movements across MSAs by comparing the MSA in which a person resides in the current quarter to that of the previous quarter, and compute average changes in MSA-level characteristics. The key attributes of interest at the MSA level include total population, population density, and the MSA's share of jobs that are telework-compatible.

Figure 2 displays the quarter-by-quarter average changes in these MSA-level characteristics, with blue lines representing the averages for all individuals. The plots show that, beginning in Q2'2020, individuals increasingly relocated to smaller, less dense MSAs with lower shares of telework-compatible jobs. These cross-MSA migration patterns are consistent with earlier research highlighting a shift in housing demand from larger MSAs toward smaller ones, a trend catalyzed by the expansion of remote work, which decouples employment from residential location for a larger fraction of workers.

Importantly, similar to the neighborhood-level patterns, the end of the pandemic did *not* reverse this trend. As of 2024, average changes in all three MSA-level characteristics remain elevated relative to pre-pandemic levels. This persistence suggests that the population shift initiated in 2020 is not a short-lived, pandemic-induced temporary shock.[9] Instead, the ongoing movement toward smaller MSAs appears to reflect a more permanent spatial reallocation of the population.

3.2.1 Differential Migration Patterns by Income across MSAs

Analyzing MSA-level migration patterns by income category reveals that the trends are substantially more pronounced among high-income individuals than among their low-income counterparts. By early 2024, migration among low-income individuals toward smaller, lower-density MSAs with fewer telework-compatible jobs had largely returned to pre-pandemic levels. In contrast, the migration of high-income individuals to these areas has been both stronger and more persistent, showing no signs of reversal. Appendix D provides

[9] If the population shift were reversing, we would expect the blue lines in each subfigure of Figure 2 not only to return to pre-pandemic levels, but also to change signs. This is not observed.

a more detailed analysis of these patterns, including breakdowns by income quintile and by combinations of income and mortgage status. The divergence in migration behavior between individuals in the highest and lowest income quintiles is even more striking. Notably, age and mortgage status do not appear to significantly affect the observed trends.

3.3 Local Responses: Housing Costs, Demand for Local Services, Employment, and Wages

When individuals relocate, they carry with them their demand for housing as well as for local goods and services. As a result, the migration trends documented above can lead to regional variation in housing costs and labor market outcomes, including potentially divergent growth in employment opportunities between areas experiencing out-migration and those experiencing in-migration.

3.3.1 Housing Costs

Figure 3a presents the changes in logarithmic housing costs at the census tract level as a function of distance to the nearest downtown, for two distinct time periods beginning in Q1'2020.[10] The first period extends through Q1'2022, capturing the initial two years of the pandemic, while the second extends through Q1'2024, reflecting a longer-run horizon. Although housing costs increased broadly over both horizons, the rise was clearly more pronounced in suburban areas than in urban cores. This spatial pattern aligns closely with the documented shift in housing demand toward suburban neighborhoods.

Similarly, Figure 3b illustrates the relationship between changes in log housing costs and population density at the MSA level over the same two periods. The patterns mirror those observed at the neighborhood level: housing costs rose broadly, with larger increases over the longer time horizon. Importantly, MSAs with lower population density experienced significantly greater housing cost appreciation than their higher-density counterparts. This disparity widened over time, as evidenced by a steeper slope in the latter period's trend line, highlighting the increasingly uneven spatial distribution of housing cost growth.

3.3.2 Demand for Local Goods and Services

In addition to housing demand, migration can also induce spatial shifts in the demand for local amenities, including goods and services provided by the nontradable sector. To analyze how the change in demand for

[10]To compute tract-level housing cost growth, we use home price index (HPI) growth from CoreLogic and rent growth from Zillow's ZORI over the same period. We then calculate a weighted average of the two, using the tract-level population shares of homeowners and renters from the ACS.

such amenities varies geographically, we use anonymized mobility data from SafeGraph and Advan, which provide monthly counts of visits to specific categories of establishments with detailed geographic identifiers, covering periods both before and after the onset of the pandemic. For each county, we construct a quarterly measure of total visits to amenity-related establishments.[11]

Figure 4 plots the percent change in visits to amenity establishments at the county level over two periods, Q1'2020 to Q1'2022, and Q1'2020 to Q1'2024, against county population density. The plots reveal a clear pattern: growth in visits to local service establishments has been significantly greater in counties with low population density than those with high density, across both referenced periods. In fact, in low-density counties, the number of visits to local service venues rose well above pre-pandemic levels. In contrast, high-density counties experienced a decline in foot traffic during the first two years following 2020, and visit counts remained below pre-pandemic levels by 2022.[12] Much like the spatial variation in housing cost growth, the spatial redistribution of demand for local services closely mirrors the direction of net migration since 2020.

An exception arises in the highest-density counties, where foot traffic rebounded substantially over the longer horizon (i.e., Q1'2020 - Q1'2024). This rebound appears to be driven by the renewed appeal of large amenity clusters as leisure destinations in the post-pandemic period, as explored in depth by Qian and Su (2025). Nonetheless, at the county level, changes in demand for local services remain broadly aligned with migration flows.

3.3.3 Employment

Because demand for local goods and services directly influences labor demand, shifts in this demand can potentially affect local employment opportunities and wages, particularly in sectors tied to nontradable services. In Figure 5, we plot changes in county-level log employment for two distinct sectors, the local service sector and the professional service sector, against county population density over the two reference periods. The local service sector includes nontradable industries such as restaurants, retail, and construction, while the professional service sector comprises high-skilled industries such as finance and legal services.[13]

[11]Amenity establishments are defined as those classified under the following NAICS codes: 722 (Restaurants); 445, 446 (Grocery); 440–459 excluding 445 and 446 (Non-Grocery Retail); 713 (Gyms); 812 (Personal Care Services); 512 (Movie Theaters); and 712 (Recreation and Entertainment).

[12]Duguid et al. (2024) document similar spatial patterns in brick-and-mortar retail demand using credit card data from a major U.S. financial institution.

[13]Local service sectors include NAICS codes 23 (Construction), 42 (Wholesale Trade), 44–45 (Retail Trade), and 72 (Accommodation and Food Services). Professional service sectors include NAICS codes 51 (Information), 52 (Finance and Insurance), and 54 (Professional, Scientific, and Technical Services).

Consistent with the spatial redistribution of the change in demand for local services, we observe a strong negative relationship between population density and employment growth in the local service sector. While most areas experienced slowed or negative growth in local service employment during the first two years after 2020, counties with very low population density saw positive job growth in this sector. In contrast, high-density counties experienced notable employment losses. Extending the horizon to four years, we find that local service employment rebounded significantly overall; however, the densest counties still had not returned to their Q1'2020 employment levels.

In contrast, the professional service sector exhibited little spatial variation in job growth during the first two years after 2020. This muted geographic response is likely due to the fact that a high share of professional service jobs can be performed remotely, as well as the tradable nature of many of these services, which are less dependent on local consumer demand (Eckert, 2019). Consequently, while many high-income individuals relocated to lower-density areas in terms of their residential locations, their jobs, tied to firm locations, did not necessarily move with them. Over a four-year horizon, however, job growth in the professional service sector began to show modest dispersion toward lower-density counties.[14]

3.3.4 Wages

As labor demand shifts across space, wages may also grow differentially by location. To examine this possibility, we analyze average quarterly earnings from the QCEW data. Figure 6 plots the growth in log wages between Q1'2020 and Q1'2022, and between Q1'2020 and Q1'2024, for local service and professional service jobs, respectively, against county population density.

In the first two years following 2020, we observe no strong or consistent spatial patterns in wage growth for either sector. However, over the four-year horizon, wage growth in lower-density counties begins to outpace that in higher-density counties. The patterns over both horizons are consistent with findings from Liu and Su (2024), who document a decline in the urban wage premium, particularly among high-skilled workers, over the four years following the onset of the pandemic. Importantly, Liu and Su (2024) show that this shift in the urban wage premium first appeared in advertised wages posted in job listings, while official payroll wage data such as those from the QCEW initially showed little change. Over a longer horizon, however, these spatial wage differentials began to emerge in the payroll data as well, aligning with the patterns we document

[14] Liu and Su (2024) attribute this trend to a declining productivity premium associated with large cities in the era of remote work, which has contributed to the redistribution of payroll employment toward smaller, less dense MSAs.

here.

3.4 Potential Welfare Impacts

Differential changes in local housing costs and employment opportunities, shaped by the direction of migration flows, can have markedly different impacts on the welfare of residents across localities. Because high- and low-income groups tend to reside in different areas, these spatially varying changes can lead to substantial effects on aggregate welfare.

3.4.1 Housing Costs

For residents in central and urban neighborhoods of large MSAs, out-migration eased their housing cost burden. In contrast, residents in suburban areas and smaller MSAs faced a faster rise in housing costs due to in-migration. However, because suburbs and smaller MSAs generally have more elastic housing supply than the central areas of large MSAs, this migration, from low-elasticity to high-elasticity areas, should result in a net decline in average housing cost exposure at the aggregate level, as shown in Howard et al. (2023).

Because low-income individuals are disproportionately more likely to live in high-density urban centers, areas from which migration has been pulling housing demand away while high-income individuals are more likely to reside in suburbs, which have been the primary destinations for migration, migration is likely to have a larger effect in alleviating the housing cost burden for the average low-income individual than the average high-income individual. To corroborate this insight, Figure A3a in the appendix presents a binned scatterplot showing the relationship between net in-migration from Q1'2020 to Q1'2024 and the tract-level share of high-income residents. The relationship is strongly positive: the very high-income tracts experienced positive net migration, while the very low-income tracts experienced negative net migration.

Importantly, this migration pattern is driven more by migratory movement toward high-income neighborhoods within MSAs than by movement across MSAs. In Figure A3b, we present the same binned scatterplot, but with MSA fixed effects included. This version isolates the within-MSA relationship between the MSA-level in-migration and income shares. The relationship becomes even steeper, indicating that although migration toward lower-income MSAs somewhat attenuates the pattern, it does not eliminate the overall trend of migration favoring high-income neighborhoods.

3.4.2 Employment Access

In addition to easing housing costs, out-migration from central and urban neighborhoods of large MSAs reduced demand for local goods and services, thereby decreasing the availability of nearby local service jobs. In contrast, suburbs and smaller MSAs experienced a disproportionate rise in local service employment due to in-migration. This spatial reallocation of local service jobs may reduce the welfare of residents who lost access to nearby employment opportunities, while improving the welfare of those who gained better access.

First, the aggregate welfare effect of migration-induced changes in employment access is likely negative. The recent wave of suburbanization and movement to smaller MSAs represents a broader shift away from major population centers, resulting in more spatially dispersed job growth. This dispersion likely reduces the average individual's access to employment opportunities, tempering the improvement in employment access enabled by the rise of remote work.

Moreover, due to the differing residential geographies of income groups, the impact of migration on job access is not uniform. In particular, the way spatially uneven employment growth affects welfare across income groups may differ markedly from how migration affects housing costs. Suburbanization tends to shift the housing cost burden away from low-income neighborhoods and toward high-income ones. However, within-MSA shifts in employment may not significantly reduce job access for low-income individuals, given the potential for commuting and the availability of remote or hybrid work arrangements. In contrast, the movement of employment opportunities from large to small MSAs could meaningfully affect access for workers unable to work remotely.

Figure A3c in the Appendix shows a binned scatterplot of MSA-level net in-migration rates against the MSA-level share of high-income residents. Unlike the positive tract-level relationships shown in Figures A3a and A3b, the MSA-level relationship is negative, indicating that migration has been largely directed toward lower-income MSAs. Thus, while migration may have curtailed overall job access, this effect may be significantly mitigated for low-income workers.

These summary statistics suggest that the surge in net migration driven by the rise of remote work since Q1'2020 has led to substantial changes in local housing costs and job access. These shifts not only likely influence aggregate welfare but may also have markedly different effects across income groups.

4 Welfare Accounting of Remote Work Adoption and Migration

Motivated by these patterns documented in the previous section, we introduce a welfare accounting framework to analyze the impact of migration on high- and low-income population groups. This framework enables us to translate detailed empirical changes in housing costs and employment access into explicit measures of resident welfare.

4.1 Workers' Utility

Let t denote time; j neighborhood; k individual income group type, which can be H (high) or L (low); and m work mode, which can be fully remote work, hybrid, or fully onsite. Each location is characterized by the type-specific amenity level A_{jt}^k and the housing rent price R_{jt}. Conditional on living in residential location j, the workers of group k and work mode m face a set of jobs $O_t^{k,m}$, each of which is indexed by job o and a location j', and characterized by the wage offered by the job o, $W_{oj't}$, and the cost of commuting time from j where the worker of type k lives to j' where job o at time t is located, $d_{jj't}^{k,m}$.[15]

A worker i of type k and work mode m who lives in neighborhood j and works at workplace o in neighborhood j' at time t derives utility as follows:

$$U_{ijoj't}^{k,m} = \frac{A_{jt}^k W_{oj't}}{R_{jt}^{1-\beta^k} d_{jj't}^{k,m}} \exp(\kappa_{ijt} + \epsilon_{iot}).$$

The term β^k is the preference weight on nonhousing consumption and corresponds to the housing expenditure share implied by a Cobb-Douglas utility function over housing and non-housing goods for population type k. The term κ_{ijt} represents an idiosyncratic preference shock for person i at residential neighborhood j at time t, capturing unobserved factors beyond amenities, rents, and job opportunities. The term ϵ_{iot} is an idiosyncratic preference draw for job o by person i, reflecting individual-specific factors influencing workplace choice beyond wages and commuting costs. We assume ϵ_{iot} follows a Type-I Extreme Value Distributed random variable scaled by $1/\theta$.[16]

Based on the property of the Type-I Extreme Value Distribution, the expected utility of worker i of type k, living in location j at time t, before the realization of his job preference draw ϵ_{iot}, is given by:

[15] The term can also be broadly interpreted as the cost of taking up a job. For onsite or hybrid jobs, it represents the expected cost of commuting. For fully remote workers, it can be understood as the cost of working from home, including expenses such as equipment, additional home space, and coordination efforts.

[16] The term $1/\theta$ is the standard deviation of the idiosyncratic preference draw. We can consider θ as governing the relative importance of the observable factors (i.e., wages $W_{oj't}$ and commuting cost $d_{jj't}^{k,m}$) in determining individual's choice of jobs.

$$U_{ijt}^{k,m} = \frac{A_{jt}^{k}}{R_{jt}^{1-\beta^k}} \sum_{o \in O_t^{k,m}} \left(\frac{W_{oj't}}{d_{jj't}^{k,m}} \right)^{\theta} \exp(\kappa_{ijt}),$$

which is a function of local amenities, housing rent cost, and residents' access to jobs. A rise in housing rents R_{jt} reduces residents' welfare, with the negative effect being greater for those with larger housing expenditure share β^k.

The summation term, $\sum_{o \in O_t^{k,m}} \left(\frac{W_{oj't}}{d_{jj't}^{k,m}} \right)^{\theta}$, captures job accessibility and is equivalent to the market access term featured in, among others, Donaldson (2018) and Tsivanidis (2022). A decline in local employment opportunities, particularly in high-wage jobs, leads to a reduction in resident utility, while an increase improves it. The parameter θ governs the sensitivity of welfare to changes in wages and commuting costs.

We define the job access measure for workers of type k and mode m living in j at time t as:

$$\Phi_{jt}^{k,m} = \ln \left(\sum_{o \in O_t^{k,m}} \left(\frac{W_{oj't}}{d_{jj't}^{k,m}} \right)^{\theta} \right).$$

To capture the effect of work mode on both utility and job access, we allow the effective commuting cost $d_{jj't}^{k,m}$ to depend on physical travel time and the degree of remote work:

$$d_{jj't}^{k,m} = \ln \left((1 - \rho_t^{k,m}) \exp(\tilde{d}_{jj'}) + \rho_t^{k,m} \exp(\phi^{k,m}) \right),$$

where $\rho_t^{k,m}$ denotes the frequency at which workers of type k and work mode m work from home at time t; $\phi^{k,m}$ represents the utility cost of working from home, expressed in commuting-time-equivalent units; and $\tilde{d}_{jj't}$ is the physical travel time between locations j and j'. This formulation captures the effective cost of commuting across different work modes. For onsite workers, $\rho_t^{k,onsite} = 0$, and therefore, $d_{jj't}^{k,m} = \tilde{d}_{jj'}$. For fully remote workers, $d_{jj't}^{k,m} = \phi^{k,remote}$, representing the full cost of working from home (e.g., equipment, home office space, coordination costs).

4.2 Fully Remote, Hybrid, and Onsite

We assume that the fractions of fully remote, hybrid, and onsite workers, denoted by $\lambda_t^{k,m}$, are exogenously given and later estimated using data. Furthermore, workers of each work mode m have access only to jobs offered in the same mode. In other words, the job choice set available to workers of mode m, denoted by

$O_t^{k,m}$, consists of a share $\lambda_t^{k,m}$ of the overall job choice set O_t^k. Accordingly, the job access terms for the three work modes are defined as follows:

$$\Phi_{jt}^{k,remote} = \ln\left(\sum_{o\in O_t^k} \lambda_t^{k,remote}\left(\frac{W_{oj't}}{\phi^{k,remote}}\right)^{\theta}\right)$$

$$\Phi_{jt}^{k,hybrid} = \ln\left(\sum_{o\in O_t^k} \lambda_t^{k,hybrid}\left(\frac{W_{oj't}}{d_{jj't}^{k,hybrid}}\right)^{\theta}\right)$$

$$\Phi_{jt}^{k,onsite} = \ln\left(\sum_{o\in O_t^k} (1-\lambda_t^{k,remote}-\lambda_t^{k,hybrid})\left(\frac{W_{oj't}}{\tilde{d}_{jj'}}\right)^{\theta}\right).$$

The average level of job access for workers of type k residing in j at time t is thus given by a weighted average of the job access measures across the three work modes:

$$\Phi_{jt}^{k} = \lambda_t^{k,remote}\Phi_{jt}^{k,remote} + \lambda_t^{k,hybrid}\Phi_{jt}^{k,hybrid} + \left(1-\lambda_t^{k,remote}-\lambda_t^{k,hybrid}\right)\Phi_{jt}^{k,onsite}.$$

First of all, the level of job access Φ_{jt}^k is directly influenced by the prevalence of remote and hybrid work, captured by $\lambda_t^{k,remote}$ and $\lambda_t^{k,hybrid}$. Because remote and hybrid workers face significantly lower effective commuting costs than onsite workers, they enjoy higher levels of job access. This suggests that the widespread adoption of remote and hybrid work is likely to lead to a broad-based increase in job access across locations. Moreover, since high-income workers are more likely to adopt remote work, they are expected to experience larger gains in job access relative to low-income workers. Second, geographic shifts in local employment also contribute to the change in job access. For onsite workers, and to a lesser extent, hybrid workers, an increase in nearby employment opportunities can substantially boost job access, given their greater reliance on physical proximity to jobs. Finally, increases in wages, particularly for jobs located close to residential neighborhoods, also mechanically improve job access.

Taken together, this measure of job access comprehensively reflects the welfare individuals derive from the labor market through a combination of work mode flexibility, spatial proximity of jobs, and wage levels.

4.3 Migration's Effect on Labor Market Access

In light of the empirical evidence presented earlier, we allow each location's employment opportunities to be influenced by migration. Specifically, we assume that the log number of jobs at location j available to worker type k is given by:

$$\ln N_{jt}^{k} = \iota_t^k + \xi_y^k y_{jt} + \zeta_{jt}^k, \;\; k = H, L, \tag{1}$$

where $\ln N_{jt}^{k}$ denotes the log number of the k type jobs offered by employers at j at time t. The specification includes a time fixed effect ι_t^k, a component $\xi_y^k y_{jt}$ that captures the effect of local aggregate income on labor demand, and idiosyncratic term ζ_{jt}^k, that accounts for location- and time-specific deviations in employment opportunities not explained by local aggregate income.

If residents spend a portion of their income in or near the neighborhoods where they reside, their spending becomes a source of local labor demand, thereby influencing local employment. We let y_{jt} denote the log of aggregate income in neighborhood j at time t. We define aggregate income as the sum of income earned by high- and low-income residents: specifically, the number of high-income individuals in j multiplied by their average income, plus the number of low-income individuals multiplied by their average income. As people move out of neighborhood j, aggregate income y_{jt} decreases accordingly, and vice versa. The coefficient ξ_y^k captures the responsiveness of local employment for type k workers to changes in local aggregate income.

4.4 Migration's Effect on Housing Supply

To capture the effect of migration on housing rents, and, by extension, on welfare, we assume housing supply follows an inverse supply function, where log rents in each location j respond to local housing demand. We proxy demand using local log aggregate income y_{jt} yielding the following specification:

$$r_{jt} = \alpha_{rt} + \psi_j y_{jt} + \eta_{jt}. \tag{2}$$

We allow the inverse elasticity of housing supply, ψ_j, to vary across locations. In our empirical analysis, it differs by neighborhood, using the housing supply elasticity estimates in Baum-Snow and Han (2024).

The log rent r_{jt} can thus be decomposed into three components: first, α_{rt} captures national time effects influencing housing costs. Second, $\psi_j y_{jt}$ reflects local housing demand, which responds to changes in local aggregate income, potentially influenced by migration. Third, η_{jt} captures idiosyncratic local factors affecting housing rent prices, including demand for home-office space, as emphasized in recent studies such as Mondragon and Wieland (2022) and Davis et al. (2024).

4.5 Welfare Impact of Pandemic-Era Spatial Sorting

To assess the impact of employment access and housing costs on individuals' utility, we apply a log transformation to the utility function, which allows utility to be expressed as a linear combination of four components: local amenities, job access, housing costs, and an idiosyncratic term. As a result, the mean expected utility for group k can be written as:

$$E_{kt}(U_{ijt}^k) = E_{kt}a_{jt}^k + E_{kt}\Phi_{jt}^k - (1-\beta^k)E_{kt}r_{jt} + E_{kt}\kappa_{ijt}, \tag{3}$$

where lowercase variables denote the logarithms of their uppercase counterparts. This formulation implies that a group's average well-being increases with its average exposure to local amenities and job accessibility, but decreases with exposure to higher local housing rent prices. The extent to which rent prices reduce utility depends on $1-\beta^k$, which represents the share of income that group k allocates to housing.

To compute welfare changes for each type k, we take the first difference of the expected utility, which yields:

$$\Delta E_{kt}(U_{ijt}^k) = \Delta E_{kt}a_{jt}^k + \Delta E_{kt}\Phi_{jt}^k - (1-\beta^k)\Delta E_{kt}r_{jt} + \Delta E_{kt}\kappa_{ijt}. \tag{4}$$

Welfare changes are driven by shifts in group k's average exposure to four components: two observable, job access (Φ_{jt}^k) and local housing rents (r_{jt}), and two unobservables, local amenities (a_{jt}^k) and the idiosyncratic preference shock (κ_{ijt}). In our analysis, we focus on the observable channels, specifically how migration influences welfare through its effects on job access and housing costs.

In the next section, we empirically estimate the impact of remote-work-induced migration on Φ_{jt}^k and r_{jt}, calibrate the remaining parameters, and evaluate how the resulting endogenous changes in job access and housing costs affect the welfare of high- and low-income groups.

5 Parameter Estimation and Welfare Analyses

To empirically evaluate how migration affects welfare through job access and housing costs, we first need to identify the key parameters that govern these channels. This involves two steps. First, we estimate how migration influences local housing costs and employment levels. Second, we calibrate the parameters that determine how changes in these local conditions, in turn, affect residents' welfare. Specifically, we estimate the parameters ψ_r^j and ξ_y^k, which capture the effects of migration on housing costs and employment, using an instrumental variable approach. We then calibrate the remaining parameters using a combination of existing literature and multiple data sources, including the American Time Use Survey (ATUS), the American Community Survey (ACS), and the Survey of Working Arrangements and Attitudes (SWAA).

5.1 Estimating Local Housing Cost and Employment Responses to Migration: ψ_r^j and ξ_y^k

To assess how migration affected local housing costs and job market access for residents in each location, we estimate first-difference regressions of housing costs Δr_{jt} and employment levels $\Delta \ln N_{jt}^k$ on changes in local aggregate income:

$$\Delta r_{jt} = \Delta \alpha_r + \psi_r^j \Delta y_{jt} + \Delta \eta_{jt}, \tag{5}$$

$$\Delta \ln N_{jt}^k = \Delta \iota_t^k + \xi_y^k \Delta y_{jt} + \Delta \zeta_{jt}^k, \;\; k = H, L, \tag{6}$$

where Δy_{jt} represents the change in local aggregate income. The parameters ψ_r^j and ξ_y^k capture how changes in local spending power, driven by migration, affect housing costs and employment opportunities in location j, respectively.

5.1.1 Instrumental Variable Approach

Standard ordinary least squares (OLS) estimation of the effect of changes in local income on housing costs and employment is subject to endogeneity concerns. For instance, an exogenous expansion in housing supply in neighborhood j could simultaneously lower housing costs and attract in-migration, thereby increasing aggregate income. If this reverse causality is not accounted for, it will bias the estimate of ψ_r^j downward. Similarly, in the labor market context, an exogenous productivity shock in location j can increase labor demand, which in turn attracts more workers and raises local income. Failing to control for this simultaneity would lead to an upward bias in the estimate of ξ_y^k.

To address potential biases and isolate the causal effect of migration-induced changes in local aggregate income on housing costs and employment, we employ an instrumental variable (IV) strategy. Our instrument provides variation in local aggregate income that is plausibly exogenous to unobserved housing supply shocks and local productivity shocks. The IV approach exploits the fact that the rise of remote work enabled many workers to relocate away from locations that previously offered convenient access to their workplaces. Because the feasibility of remote work varies substantially across industries, industries with higher telework compatibility are more likely to offer remote work options. Given substantial geographic variation in industry composition and concentration, locations with a higher share and geographic concentration of jobs in telework-compatible industries were more likely to experience out-migration during the shift to remote work, while less teleworkable locations were less affected. The identifying assumption behind our IV strategy is that local availability of telework-compatible jobs is correlated with changes in migration patterns, but uncorrelated with other unobserved determinants of local housing costs and employment demand, such as contemporaneous housing supply or productivity shocks.

To fully capture spatial variation in the availability of telework-compatible jobs, we use information from multiple geographic levels. First, to measure variation in the prevalence of remote work adoption across metropolitan areas, we calculate for each MSA the share of college-educated and non-college-educated workers employed in telework-compatible occupations, denoted as $s^{MSA}_{tele,col,j}$ and $s^{MSA}_{tele,noncol,j}$, respectively.

Next, to capture neighborhood-level variation in the availability and spatial concentration of teleworkable jobs, we compute at the census tract level the number of nearby telework-compatible jobs within a 3-mile radius, denoted by $N^{tract}_{telework,j}$. We then impute the tract-level share of telework-compatible jobs by taking a weighted average of the MSA-level telework shares by education group, using tract-level educational composition. That is, we approximate the tract-level telework share as:

$$Telework\_share^{tract}_j = col\_share^{tract}_j \cdot s^{MSA}_{tele,col,j} + noncol\_share^{tract}_j \cdot s^{MSA}_{tele,noncol,j},$$

where $col\_share^{tract}_j$ and $noncol\_share^{tract}_j$ are shares of college- and noncollege-educated residents in tract j.

Finally, to capture both the expected increase in the fraction and the absolute number of remote jobs at the neighborhood level, we construct our instrument as the product of the imputed tract-level telework share and the number of nearby telework-compatible jobs:

$$IV^{tract}_j = Telework\_share^{tract}_j \cdot N^{tract}_{telework,j}.$$

This measure combines the predicted intensity of remote work and the local availability of teleworkable employment opportunities.

Note that the telework availability IV is constructed at the tract level, making it suitable for instrumenting changes in log aggregate income, driven by migration, measured at the tract level. This specification is appropriate for estimating equation 5. However, since local employment is measured only at the county level, we do not observe variation in employment across tracts within a county. As a result, we need to aggregate the telework availability IV to the county level for estimating equation 6. To do so, we follow a nearly identical procedure. First, we construct the telework share variable at the county level by applying the same weighted formula using county-level educational shares and MSA-level telework shares: $Telework\_share_j^{county}$. Second, we aggregate the number of nearby telework-compatible jobs from the tract level to the county level using tract-level population weights. This yields a county-level average number of nearby telework-compatible jobs $N_{telework,j}^{county}$. We then construct the county-level IV as the product of the county-level telework share and the county-level average of nearby telework-compatible jobs: $IV_j^{county} = Telework\_share_j^{county} \cdot N_{telework,j}^{county}$.

5.1.2 Potential Caveats of the IV Approach

The use of the IV approach is not without its caveats. The validity of the IV approach rests on the assumption that the spatial variation in the remote work availability is uncorrelated with the unobserved shocks in housing supply or productivity.

One concern we wish to highlight is that locations with a strong surge of remote work adoption may have experienced a decrease in productivity due to the loss of agglomeration economies. This pattern has been documented by Liu and Su (2024), particularly in the professional service sector, a sector that is especially relevant for high-income workers. Their study finds that the erosion of the local productivity premium in these areas contributed to a decline in payroll employment. This loss of productivity may be spatially correlated with the availability of telework-compatible jobs, which poses a potential concern for our empirical strategy. Specifically, such correlation could lead to upward bias in the estimates of ξ_y^k in equation 6.

Another source of concern is that areas experiencing a large increase in the availability of remote work may have faced a decline in demand for local services not only due to out-migration, but also due to a reduction in visits, particularly from commuters, a point emphasized in Qian and Su (2025). If locations that lost residents also tended to lose far-away visitors, then the observed decline in employment could reflect both residential and non-residential demand loss. In such cases, we may overestimate the parameter ξ_y^k in equation 6, as the reduction in employment might be incorrectly attributed solely to the loss of resident income, when in fact it also reflects a drop in demand from non-resident visitors. That said, evidence from Qian and Su (2025) indicates that while non-resident visit patterns are initially correlated with the local intensity of telework-compatible jobs, this relationship weakens over time. In particular, high-density, amenity-rich areas begin to attract more in-bound visitors. As shown in Figure 4, the highest-density counties ultimately experienced a substantial recovery in foot traffic to amenity establishments.

When we turn to the welfare analysis later in the paper, we will revisit the above issues and discuss how these potential biases might affect the interpretation of our welfare estimates.

5.1.3 Estimation Results

Migration's Effect on Local Employment Table 1 presents our estimates of the effect of local aggregate income, driven by the net migration of high- and low-income residents, on local employment in the local service and professional service sectors. In the OLS regressions, we find that migration-induced changes in local aggregate income are positively correlated with employment growth in both sectors over both 2-year and 4-year horizons. When we instrument for migration, the IV estimates indicate that positive net in-migration causally increases employment in both local services and professional services. However, the magnitude of the effect is substantially larger for local service employment: over a 4-year horizon, the elasticity of local service employment with respect to aggregate income is approximately 1.03, while the corresponding elasticity for professional services is 0.26.

Interestingly, the estimated elasticity for local service employment over the 2-year horizon is roughly twice as large as the 4-year estimate. We interpret this as potentially reflecting an upward bias in the short-run estimates, driven by the confounding effects of a sharp decline in non-resident visitors during the height of the pandemic, a period when resident migration and visitor loss were likely correlated. Nevertheless, the 4-year coefficient remains both economically meaningful and statistically significant, indicating a lasting causal relationship beyond the acute pandemic period.

Migration's Effect on Local Housing Costs Table 2 presents our estimates of the effect of local aggregate income on housing costs over two reference periods: Q1'2020 to Q1'2022 and Q1'2020 to Q1'2024. We find that the effect of migration-driven changes in local aggregate income on housing costs is consistently positive across both horizons, though weaker over the longer period. Specifically, a 1 percent increase in log aggregate income leads to a 2.5 percentage point increase in local housing costs over a 2-year horizon and a 1.83 percentage point increase over a 4-year horizon. The smaller long-run effect is intuitive, as housing supply may take time to adjust, thereby, dampening price pressures over time.

The impact is also more pronounced in neighborhoods with lower estimated housing supply elasticity. In other words, net in-migration leads to bigger increases in housing costs where supply is less responsive. Interestingly, this heterogeneity is more pronounced over the 2-year horizon than over the 4-year horizon. While the notion that supply elasticity reflects longer-run responsiveness would suggest greater heterogeneity in housing cost effect by local supply elasticity over time, we conjecture that a 4-year horizon remains relatively short in this context, particularly given the severe construction constraints, such as labor shortages and material supply disruptions, during this period. It is also possible that sustained migration to high-elasticity areas pushed those neighborhoods onto the steeper portion of their supply curves. We revisit the welfare implications of this finding in the next section.

Finally, even in neighborhoods with neutral net migration, those with low supply elasticity experienced disproportionately high housing cost growth. This likely reflects a broader rise in housing demand during the period, which translated into stronger price pressures in less elastic markets.

5.1.4 Calibration of Other Parameters: θ, β^k, $\lambda_t^{k,m}$, $\rho_t^{k,hybrid}$, $\tilde{d}_{jj'}$, and ϕ

For the remaining parameters needed in the welfare analysis, we calibrate a subset using estimates from recent empirical studies. These include the preference scaling factor θ and the housing expenditure shares β^k. We set $\theta = 3$, which aligns closely with estimates from several empirical papers that use similarly specified labor market access functions.[17] We calibrate the housing expenditure shares β^k for $k \in H, L$ based on the estimates in Diamond and Moretti (2021), who find that $\beta^H = 0.269$ for high-income individuals and $\beta^L = 0.462$ for low-income individuals.

We estimate the parameters governing the prevalence of remote and hybrid work arrangements before and after the pandemic, $\lambda_t^{k,m}$, as well as the fraction of workdays spent at home among hybrid workers, $\rho_t^{k,hybrid}$ (separately for high- and low-income workers), using a combination of data sources: the American Community Survey (ACS), the American Time Use Survey (ATUS), and the Survey of Working Arrangements and Attitudes (SWAA) conducted by Barrero et al. (2021). For $\lambda_t^{k,m}$ and $\rho_t^{k,hybrid}$ in Q1'2022 and Q1'2024, the SWAA microdata alone are sufficient for precise estimation. However, since the SWAA does not cover the pre-pandemic period, we estimate the parameters for Q1'2020 by combining information from the ACS

[17] In Monte et al. (2018), the shape parameter governing the sensitivity of job choice to wages and commuting costs is estimated to be 3.3 in a county-level analysis across the U.S. Severen (2023) estimates this parameter to be 2.18 within Los Angeles. Tsivanidis (2022) estimates it to be 2.07 for low-skilled workers and 2.25 for high-skilled workers.

and ATUS, along with a set of assumptions to impute their values. The detailed imputation procedures are provided in Appendix section C.

For the commuting parameters, we calibrate the cost of physical commuting, $\tilde{d}_{jj'}$, and the cost of remote work, $\phi^{k,m}$, for fully remote and hybrid workers when working from home. The backbone for $\tilde{d}_{jj'}$ is the county-to-county Euclidean distance matrix provided by the National Bureau of Economic Research (NBER). Since this matrix reflects straight-line distances, we adjust it using a detour index of 1.417, the average ratio of actual travel distance to straight-line distance, based on estimates from Boscoe et al. (2012). To convert distance into time, we assume an average commuting speed of 28 miles per hour, as reported in the 2019 American Community Survey by the U.S. Census Bureau (Burd et al., 2021). Lastly, we calibrate the cost of working at home, $\phi^{k,m}$, to be 0.167, which corresponds to 10 minutes of commuting.

The full set of calibrated parameters is summarized in Table 3.

5.2 Empirical Welfare Decomposition

With all parameters now estimated and calibrated, we proceed to evaluate the impact of migration on the welfare of high- and low-income populations. Our analysis focuses on the two primary channels examined in this paper: spatial changes in job access and housing costs.

5.2.1 The Effect of Changing Job Access Without Migration

As a first step, we assess the effect of changes in job access *without* accounting for the impact of migration. We begin with this exercise for two purposes. First, it allows us to replicate the baseline welfare effects of remote work adoption and changing wages, as documented in the existing literature. Second, it provides a benchmark against which we can compare the results once migration is allowed to influence local employment outcomes.

Specifically, we compute the change in job access, denoted by $\Delta\Phi^{k}_{no\_mig,jt}$, by adjusting the remote work adoption parameters $\lambda^{k,m}_{t}$, the commuting cost parameters $d^{k,m}_{jj't}$, and the observed wage levels from their values in Q1'2020 to those in Q1'2022 and Q1'2024.[18] In this exercise, we hold local employment levels fixed at their Q1'2020 values.[19] We perform this computation separately for high- and low-income workers

[18]The mean commuting cost $d^{k,hybrid}_{jj't}$ for hybrid workers evolves over time due to adjustments in the parameter $\rho^{k,m}_{t}$.

[19]Note that the job access term also depends on wage growth across employment opportunities. We directly account for the impact of observed wage growth on workers' welfare in our benchmark result, rather than modeling wages as an endogenous channel through which migration affects welfare.

across the two reference periods: Q1'2020 to Q1'2022 and Q1'2020 to Q1'2024.

In Table 4, the values under Φ_{no_mig} present the change in job access expressed in log wage-equivalent units, resulting from changes in remote work adoption, captured through adjustments in $\lambda_t^{k,m}$ and $d_{jj't}^{k,hybrid}$, as well as local wage growth. Results based on the national sample indicate that both high-income and low-income groups experience substantial gains in job access due to the increased adoption of remote work. However, these gains diminish over the longer horizon (i.e., 2020–2024 compared with 2020–2022), reflecting the decline in the prevalence of fully remote work following the end of the pandemic.

Moreover, the welfare improvement from enhanced job access is disproportionately larger for high-income individuals, primarily because remote work adoption is significantly more prevalent among this group. As a result, the unequal gains in job access contribute to widening welfare inequality, consistent with the findings of Davis et al. (2024).[20]

It is also notable that the improvement in job access from the benchmark result was considerably larger in small cities than in large cities. This pattern arises naturally from the increased prevalence of fully remote work arrangements. For fully remote workers, job access becomes location-invariant. As the share of workers able to work remotely rises, individuals living in small cities, who were previously geographically distant from major job centers, experience substantial gains in access to employment opportunities. In contrast, workers residing in large cities, who were already located near a dense concentration of jobs, experience comparatively smaller improvements in job access.[21]

5.2.2 The Effect of Changing Job Access with Migration

The benchmark welfare effect of changing job access does not account for the fact that the surge in net migration during this period led to a substantial spatial reallocation of employment opportunities. In the next exercise, we allow local employment levels, N_{jt}^k, to respond endogenously to remote-work-induced changes in local aggregate income, Δy_{jt}, as specified in equation 6. In this specification, job access is influenced not

[20]Our welfare framework captures the effect of increased remote work prevalence solely through changes in job access. This is just one of several channels through which remote work may influence welfare. Other important factors, such as greater time flexibility and improved on-the-job amenities, may also affect overall welfare and inequality. These additional benefits are not accounted for in our current analysis.

[21]The rise in hybrid work and the increase in the frequency of working from home among hybrid workers also contributed to the overall improvement in job access. However, in the case of hybrid workers, job access increased more in large cities, particularly in their suburbs, than in small cities. This is because hybrid workers still need to commute, albeit less frequently than onsite workers. The reduced, but non-zero, commuting cost improves accessibility to jobs within a reasonable distance. As a result, workers living in the suburbs of large metropolitan areas, relatively close to major job centers, experience notable gains in job access. In contrast, for workers in small cities located far from urban employment centers, the cost of commuting to jobs hundreds or thousands of miles away remains prohibitively high, thereby limiting the improvement in job access for this group.

only by changes in remote work parameters, $\lambda_t^{k,m}$ and $d_{jj't}^{k,hybrid}$, and observed wages, w_{ojt}, but also by the migration-driven shifts in local labor demand. Here, we analyze the effect of *remote-work-induced* migration, rather than observed migration per se. Specifically, we use the change in log aggregate income predicted by the IV, based on first-stage regression estimates, to generate employment outcomes via equations 6.

Procedurally, we begin with the initial employment levels, $N_{j,Q1'2020}^k$, and use the predicted changes in log employment, $\widehat{\Delta \ln N_{jt}^k}$, obtained from equation 6, to compute the employment levels for high- and low-income workers in Q1'2022 and Q1'2024. We then construct the job access measures using these predicted employment levels at each specified time point, rather than holding employment fixed at the Q1'2020 levels as we did in the first exercise. In Table 4, the values under Φ_{mig} present the changes in job access, expressed in log wage-equivalent units, resulting from the combined effects of remote work adoption, captured through changes in $\lambda_t^{k,m}$ and $d_{jj't}^{k,hybrid}$, local wage growth, *and* migration induced by the expansion of remote work.

To see the effect of migration on job access, we need to compare the *difference* between the changes in job access with and without migration, given by $\Phi_{mig} - \Phi_{no\_mig}$. Overall, the welfare effect of migration on job access has been negative, with the magnitude of this negative effect increasing over the longer horizon (i.e., from 2020 to 2024) compared with the shorter horizon (2020 to 2022).

Migration affects workers' job access through two key margins. First, migratory movements from large cities to smaller cities shift the demand for goods and services toward those smaller locations. This redistribution leads to a more dispersed spatial distribution of employment, which mechanically tends to *reduce* average job access by increasing the average distance between workers and jobs. This effect applies to both high- and low-income populations. However, because low-income workers are more likely to reside in smaller cities, and because migration into these areas brings employment with it, the relocation of jobs partially offsets the decline in job access for low-income workers. In other words, cross-city migration tends to move employment closer to the typical low-income worker, thereby *mitigating* the reduction in their job access.

The second margin operates through migratory movements from dense urban cores toward suburban areas. This suburbanization shifts some of the demand for local goods and services to the suburbs, leading to a more dispersed spatial distribution of employment within metropolitan areas. As a result, job access declines for both high- and low-income workers due to the spatial shift of employment, since employment is drawn away from traditional population centers. Unlike cross-city migration, where low-income individuals often benefit because they tend to reside in small cities which tend to receive inflows of population and jobs, within-city migration has the opposite distributional implication. Low-income workers disproportionately reside in central urban neighborhoods rather than in suburbs. Consequently, the shift of labor demand from city centers to suburban areas moves employment *away* from the average low-income worker, potentially exacerbating their loss in job access. However, this within-city effect is relatively limited in magnitude. Because job access is weighted by commuting costs, and commuting within a metro area is generally less costly than commuting across cities, the employment shift toward suburbs has only a modest effect on overall job accessibility. In contrast, the cross-city migration of employment toward smaller cities has a much more substantial impact.

Overall, these spatial employment shifts over the 4-year period serve to dampen the overall welfare gains from improved job access due to remote work adoption. The negative effect of migration on job access is especially pronounced for high-income workers.

In Section 5.1.2, we discuss two key concerns regarding the identification assumptions underlying our estimation of the causal effects of migration on local employment in both the local service and professional service sectors. If these concerns hold, they could introduce an upward bias in our estimates, as remote work may have influenced local employment through channels other than migration.

If the true effects of migration on local employment are smaller than our estimates suggest, then the resulting impacts on job access, and, by extension, the moderating effect of migration on welfare inequality, may be overstated. However, it is important to emphasize that any such upward bias would stem from alternative mechanisms also triggered by remote work adoption. These include, for example, the spatial reallocation of professional service employment due to weakened agglomeration economies in large cities, or the decline in local service employment resulting from reduced demand by non-resident visitors. Thus, while our estimates may reflect the combined effects of migration and other remote-work-related forces, the overall interpretation remains consistent: remote work has contributed to significant spatial impacts on employment with income-specific welfare implications.

5.2.3 The Effect of Changing Housing Costs without Migration

To assess the welfare effect of housing cost changes, we begin by calculating the impact of housing cost growth in a scenario where remote-work-induced migration does *not* occur. Specifically, we compute the welfare effect of $\Delta\eta_{jt}$ as defined in equation 5. This counterfactual housing cost growth, $\Delta\eta_{jt}$, captures all relevant factors influencing housing demand, such as the increased demand for home space due to remote work, *excluding* the effects of migration. To account for differences in housing expenditure shares across income groups, we weight the change in housing cost by β^k, the housing expenditure share for workers of type $k \in H, L$. The resulting welfare effect, expressed in log wage-equivalent units, is given by: $-\beta^k \Delta\eta_{jt}$.

In Table 4, the values under $-\beta\Delta\eta$ report the welfare effects of housing cost changes attributable to non-migration factors. As expected, and consistent with the findings in Davis et al. (2024), the increase in housing costs over both horizons (2020–2022 and 2020–2024) led to a significant reduction in welfare for both high- and low-income groups, with the effect being substantially larger for the low-income population.

Welfare Levels and Inequality This result indicates that, without accounting for the spatial effects of migration, the rise in housing costs since 2020 reduced the welfare of low-income individuals by 0.05 log wage-equivalent units more than that of high-income individuals. When we combine this with the gains from improved job access, also excluding migration's impact, low-income workers experienced a net welfare gain of 0.06 log wage-equivalent units, while high-income workers gained 0.20 units. Taken together, this implies that welfare inequality increased by 0.14 log wage-equivalent units over the period, *before* considering the distributional effects of migration.[22]

5.2.4 The Effect of Changing Housing Costs with Migration

Next, we incorporate the effects of migration into our housing cost calculations. Specifically, we account for both the observed changes in housing costs and the portion of those changes attributable to remote-work-induced migration. The total welfare effect from housing costs is expressed as $-\beta^k \Delta r_{jt}$, where the migration-driven component is given by $-\beta^k \hat{\psi}^j_r \Delta y_{jt}$. Again, we use the change in log aggregate income predicted by the IV's interactions with housing supply elasticity, based on first-stage regression estimates.

In Table 4, the values under $-\beta\Delta r$ report the welfare impact of the observed changes in housing costs, while the values under $-\beta\psi\Delta y$ isolate the welfare effect of the portion of housing cost changes predicted by remote-work-induced migration. All effects are expressed in log wage-equivalent units.[23] The results show that the increase in housing cost burden is mitigated once the effect of migration is taken into account. This mitigation arises because, on net, both high- and low-income populations have migrated toward neighborhoods and cities with a *higher* housing supply elasticity, as discussed in Section 3.4. When people move

[22] Davis et al. (2024) show that for low-skilled workers who do not have access to remote work, the welfare impact of remote work adoption is, in fact, negative in the absolute level, as these individuals are exposed to rising housing costs without receiving the compensating benefits of remote work. In our case, although low-income workers are significantly less likely to hold remote work jobs, our estimates based on the SWAA data indicate that low-income workers did experience a moderate increase in access to remote and hybrid work arrangements. As a result, while the benefits are limited, low-income workers still gain from remote work adoption, leading to an overall positive, albeit small, welfare effect for this group.

[23] Recall from equation 5 that $\Delta r = \Delta\eta + \psi\Delta y$.

from low-supply-elasticity areas to high-supply-elasticity areas, the resulting decline in housing demand in the origin locations leads to a more pronounced reduction in housing prices than the corresponding increase in housing costs in the destination locations caused by incoming demand.

Given the nationwide rise in housing demand, most local housing markets are likely situated on the upward-sloping portion of their supply curves (Glaeser and Gyourko, 2005). As a result, the moderation of housing cost growth due to out-migration from low-elasticity areas more than offsets the increase in housing cost growth caused by in-migration to more elastic areas. This asymmetric response produces a net negative effect of migration on the overall housing cost burden, thereby reducing the housing-related welfare loss for both high- and low-income groups.

In addition, the mitigating effect of migration on housing cost burdens is considerably larger for the low-income population than for the high-income population. This stronger negative effect for low-income individuals is primarily driven by the fact that cross-neighborhood migration disproportionately redirected housing demand away from high-density urban neighborhoods, which are disproportionately occupied by low-income residents. As a result, the reduction in housing costs was more pronounced for the average low-income worker.

While it is also true that the wave of net migration increased housing costs in smaller cities, where many low-income individuals reside, the incoming demand tended to be concentrated in higher-income neighborhoods within those cities. Consequently, on net, neighborhoods with a greater presence of high-income residents were more likely to experience net in-migration, whereas neighborhoods with a higher concentration of low-income residents were more likely to experience net out-migration. This pattern of migration and its distributional implications are illustrated in Figure A3a in the Appendix and discussed in greater detail in Section 3.4.

To provide additional corroborating evidence that cross-neighborhood migration disproportionately reduced the housing cost burden for the low-income population, we examine the effect of migration on housing costs separately across different classes of cities. Specifically, we distinguish between: (1) elite cities, consisting of the New York, Los Angeles, and San Francisco MSAs, which experienced a substantial surge in net out-migration; (2) large cities, defined as metropolitan areas ranked in the top 25 by population but excluding the elite cities; (3) medium-sized cities, ranked between 26th and 100th; and (4) small cities, ranked 101st or below in population size.

As shown in Table 4, in the elite cities, where out-migration led to a substantial outward shift in housing demand, migration reduced the housing cost burden for the low-income population by an amount equivalent to an increase of 0.058 log wage points. This reduction was larger than the corresponding welfare gain from declines in housing costs experienced by the high-income population in those same cities, which is 0.023 log wage points. As we move down the city size distribution, the mitigating effect of migration on housing cost burdens becomes smaller. However, it never reverses sign for the low-income population: even in cities ranked below 100th in population, migration does not lead to an increase in their housing cost burden. This persistent pattern reflects the fact that, in most cities, the urban core, from which residents were disproportionately relocating, tended to be occupied by low-income individuals.[24]

Welfare Levels and Inequality Taken together, once we account for the spatial effects of migration on job access and housing costs, the overall welfare gain for low-income individuals increases from 0.063 to 0.071 log wage-equivalent units, while the welfare gain for high-income individuals decreases from 0.204 to 0.185. This implies a moderation in the rise in welfare inequality, from 0.140 to 0.114 log wage-equivalent units.

The welfare implications of migration are particularly striking at the city level. In elite cities, low-income residents experienced an absolute welfare loss of -0.012 log wage-equivalent units over the four-year period when migration is not considered. However, once migration is taken into account, their welfare increases by 0.021 log wage-equivalent units. Although the mitigating effect of migration is smaller in smaller cities, it remains meaningful and robust.

6 Conclusion

In this paper, we examine how the adoption of remote work following the onset of the COVID-19 pandemic reshaped migration patterns, and how this remote-work-induced migration indirectly affected housing costs and job access for high- and low-income individuals. While remote work adoption increases welfare inequality across income groups, we show that once the indirect effects of migration are considered, the rise in welfare inequality is significantly moderated.

[24]In this analysis, we treat all individuals as renters in both their origin and destination locations. In Appendix E, we examine possible changes in housing arrangements following migration, for example, whether movers joined family households or purchased homes. The results suggest that most movers contributed to housing demand by either renting or purchasing units. Our welfare calculations do not distinguish between homeowners and renters. It is possible that former homeowners who sold during downturns or carried overlapping housing expenses suffered losses, while those who owned property in appreciating markets may have benefited, particularly older homeowners looking to downsize. See, among others, Li and Yao (2007). Renters who moved without being able to terminate existing leases may have also incurred losses. That said, the pandemic period was marked by widespread mortgage forbearance programs and eviction moratoria at various levels of government, which complicates any systematic treatment of these outcomes. For tractability, we abstract from these considerations in our analysis.

Using detailed microdata on individuals' residential location histories from the CCP, we document that the pandemic triggered significant migration flows, particularly among high-income individuals, away from dense urban centers toward suburbs and smaller metropolitan areas. Our analysis indicates that this migration was largely driven by the rising adoption of remote work. The migration redirected housing demand toward areas with more elastic housing supply, alleviating what would have otherwise been more severe upward housing cost pressures. Migration also contributed to a spatial redistribution of employment opportunities away from traditional population centers, tempering the average job access.

Importantly, the welfare implications of these shifts were not uniform across income groups. Because low-income individuals are disproportionately concentrated in dense urban neighborhoods, the migration-induced shifts of housing demand away from those areas helped ease the housing cost burden borne by low-income individuals. Additionally, since low-income individuals are overrepresented in small MSAs, areas that experienced relatively strong employment growth due to in-migration, the adverse impact of tempered job access was less pronounced for them. In contrast, high-income individuals were more likely to relocate to areas with limited employment density, resulting in slightly diminished job access.

The key insight of this paper is that accounting for group-specific migration responses is essential for understanding the complete welfare implications of remote work. By capturing the spatial effects of migration on both housing markets and labor market access, our analysis provides a more nuanced view of how remote work affects welfare levels and inequality across income groups.

References

AKAN, M., J. M. BARRERO, N. BLOOM, T. BOWEN, S. BUCKMAN, S. DAVIS, AND H. KIM (2025): "The New Geography of Labor Markets," *NBER Working Paper 33582*.

BARRERO, J. M., N. BLOOM, AND S. DAVIS (2021): "Why Working from Home Will Stick," *NBER Working Paper 28731*.

BARTIK, A., Z. CULLEN, E. GLAESER, M. LUCA, AND C. STANTON (2020): "What Jobs Are Being Done at Home During the COVID-19 Crisis? Evidence from Firm-Level Surveys," *Harvard Business School Working Paper*, 20, 138.

BAUM-SNOW, N. AND L. HAN (2024): "The Microgeography of Housing Supply," *Journal of Political Economy*, 132(6), 1897–1946.

BEHRENS, K., S. KICHKO, AND J.-F. THISSE (2021): "Working from Home: Too Much of a Good Thing?" *Manuscript*.

BICK, A., A. BLANDIN, AND K. MERTENS (2023): "Work from Home Before and After the COVID-19 Outbreak," *American Economic Journal: Macroeconomics*, 15(4), 1–39.

BLOOM, N., P. BUNN, P. MIZEN, P. SMIETANKA, AND G. THWAITES (2025): "The Impact of COVID-19 on Productivity," *Review of Economics and Statistics*, 107, 28–41.

BLOOM, N., R. HAN, AND J. LIANG (2024): "Hybrid Working from Home Improves Retention Without Damaging Performance," *Nature*, 630, 920–925.

BOSCOE, F., K. HENRY, AND M. ZDEB (2012): "A Nationwide Comparison of Driving Distance Versus Straight-Line Distance to Hospitals," *The Journal of Professional Geography*, 64(2), PMC3835347.

BRUECKNER, J., M. KAHN, AND G. LIN (2023): "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?" *American Economic Journal: Applied Economics*, 15(2), 285–319.

BRYNJOLFSSON, E., A. O. JOHN HORTON, D. ROCK, G. SHARMA, AND H.-Y. TUYE (2020): "COVID-19 and Remote Work: An Early Look at US Data," *NBER Working Paper 27344*.

BURD, C., M. BURROWS, AND B. MCKENZIE (2021): "Travel Time to Work in the United States: 2019," American Community Survey Reports, https://www.census.gov/content/dam/Census/library/publications/2021/acs/acs-47.pdf.

CHOUDHURY, P., C. FOROUGHI, AND B. LARSON (2021): "Work-from-Anywhere: The Productivity Effects of Geographic Flexibility," *Strategic Management Journal*, 42, 655–683.

COIBION, O., Y. GORODNICHENKO, M. KUDLYAK, AND J. MONDRAGON (2020): "Greater Inequality and Household Borrowing: New Evidence from Household Data," *Journal of European Economic Association*, 18(6), 2922–2971.

COUTURE, V., C. GAUBERT, J. HANDBURY, AND E. HURST (2024): "Income Growth and the Distributional Effects of Urban Spatial Sorting," *Review of Economic Studies*, 91(2), 858–898.

DAVIS, M., A. GHENT, AND J. GREGORY (2023): "The Work-from-Home Technology Boon and Its Consequences," *Review of Economic Studies*, 91(6), 3362–3401.

——— (2024): "Winners and Losers from the Work-from-Home Technology Boon," *Working paper*.

DELVENTHAL, M., E. KWON, AND A. PARKHOMENKO (2021): "How Do Cities Change When We Work from Home?" *Journal of Urban Economics: Insight*, 127.

DELVENTHAL, M. AND A. PARKHOMENKO (2021): "Spatial Implications of Telecommuting," *Working Paper*.

DEWAARD, J., J. E. JOHNSON, AND S. D. WHITAKER (2019): "Internal Migration in the United States: A Comprehensive Comparative Assessment of the Utility of the Consumer Credit Panel," *Demographic Research*, 41, 953–1006.

DIAMOND, R. (2016): "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 106(3), 479–524.

DIAMOND, R. AND E. MORETTI (2021): "Where Is Standard of Living the Highest? Local Prices and the Geography of Consumption," *Working Paper*.

DING, L. AND J. HWANG (2022): "Has COVID Reversed Gentrification in Major U.S. Cities? An Empirical Examination of Residential Mobility of Gentrifying Neighborhoods During the COVID-19 Crisis," *Manuscript*.

DINGEL, J. I. AND B. NEIMAN (2020): "How Many Jobs Can Be Done at Home?" *Journal of Public Economics*, 189, 1–8.

DONALDSON, D. (2018): "Railroads of the Raj: Estimating the Impact of Transportation Infrastructure," *American Economic Review*, 108(4-5), 899–934.

DUGUID, J., B. KIM, L. RELIHAN, AND C. WHEAT (2024): "The Impact of Work-from-Home on Brick-and-Mortar Retail Establishments: Evidence from Card Transactions," *Working Paper*.

ECKERT, F. (2019): "Growing Apart: Tradable Services and the Fragmentation of the U.S. Economy," *Working Paper*.

GLAESER, E. AND J. GYOURKO (2005): "Urban Decline and Durable Housing," *Journal of Political Economy*, 112(2), 345–375.

GUPTA, A., V. MITTAL, AND S. V. NIEUWERBURGH (2022a): "Work from Home and the Office Real Estate Apocalypse," *NBER Working Paper 30526*.

GUPTA, A., V. MITTAL, J. PEETERS, AND S. V. NIEUWERBURGH (2022b): "Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate," *Journal of Financial Economics*, 146, 594–636.

HASLAG, P. AND D. WEAGLEY (2024): "From L.A. to Boise: How Migration Has Changed During the COVID-19 Pandemic," *Journal of Financial and Quantitative Analysis*, 59(5), 2068–2098.

HOLIAN, M. J. AND M. E. KAHN (2015): "Household Carbon Emissions from Driving and Center City Quality of Life," *Ecological Economics*, 116, 362–368.

HOWARD, G., J. LIEBERSOHN, AND A. OZIMEK (2023): "The Short- and Long-Run Effects of Remote Work on U.S. Housing Markets," *Journal of Financial Economics*, 150(1), 166–184.

LI, W. AND R. YAO (2007): "The Life-Cycle Effects of House Price Changes," *Journal of Money, Credit, and Banking*, 39(6), 1375–1408.

LIU, S. AND Y. SU (2021): "The Impact of the COVID-19 Pandemic on the Demand for Density: Evidence from the U.S. Housing Market," *Economic Letters*, 207, 110010.

——— (2024): "The Effect of Working from Home on the Agglomeration Economies of Cities: Evidence from Advertised Wages," *Working Paper*.

MANSON, S., J. SCHROEDER, D. V. RIPER, AND S. RUGGLES (2020): "IPUMS National Historical Geographic Information System: Version 14.0 [Database]," Minneapolis, MN: IPUMS. 2019. http://doi.org/10.18128/D050.V14.0.

MEEKER, R. AND N. MOTA (2021): "COVID-19's Impact on Housing Demand in High-Density Areas – Evidence from Purchase Mortgage Applications," *Fannie Mae White Paper*.

MONDRAGON, J. AND J. WIELAND (2022): "Housing Demand and Remote Work," *NBER Working Paper No. w30041*.

MONTE, F., S. REDDING, AND E. ROSSI-HANSBERG (2018): "Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification," *American Economic Review*, 108(12), 3855–3890.

MORETTI, E. (2013): "Real Wage Inequality," *American Economic Journal: Applied Economics*, 5(1), 65–103.

QIAN, F. AND Y. SU (2025): "Remote Work and Consumer Cities," *Working Paper*.

RAMANI, A. AND N. BLOOM (2021): "The Donut Effect of COVID-19 on Cities," *NBER Working Paper 28876*.

ROSENTHAL, S., W. STRANGE, AND J. URREGO (2021): "Are City Centers Losing Their Appeal? Commercial Real Estate, Urban Spatial Structure, and COVID-19," *Journal of Urban Economics: Insight*, 127, 103381.

RUGGLES, S., S. FLOOD, R. GOEKEN, J. GROVER, E. MEYER, J. PACAS, AND M. SOBEK (2020): "IPUMS USA: Version 10.0 [dataset]," *Minneapolis, MN: IPUMS*.

SEVEREN, C. (2023): "Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification," *Review of Economics and Statistics*, 105, 1073–1091.

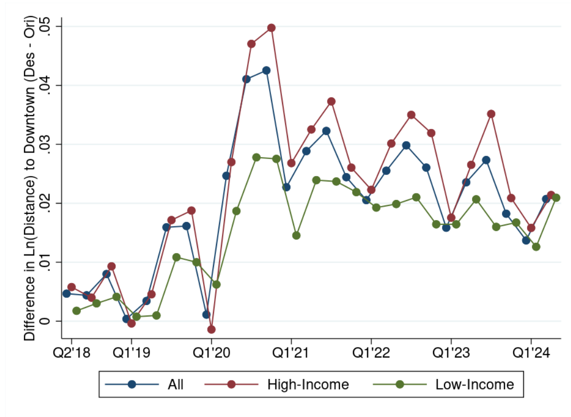
SU, Y. (2020): "Working from Home During the Pandemic: It's Not for Everyone," https://www.dallasfed.org/research/economics/2020/0407.

——— (2022): "The Rising Value of Time and the Origin of Urban Gentrification," *American Economic Journal: Economic Policy*, 14(1), 402–439.

TSIVANIDIS, N. (2022): "Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio," *Working Paper*.

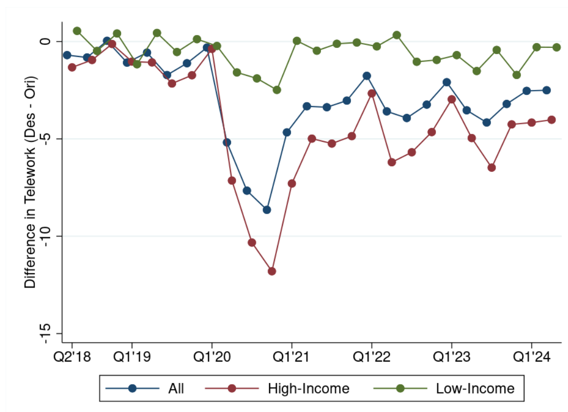
WHITAKER, S. D. (2021): "Did the COVID-19 Pandemic Cause an Urban Exodus?" Cleveland Federal Reserve Bank District Data Brief, https://www.clevelandfed.org/newsroom-and-events/publications/cfed-district-data-briefs/cfddb-20210205-did-the-covid-19-pandemic-cause-an-urban-exodus.aspx.

Figure 1: Direction of Tract-to-Tract Flows: High-Income vs. Low-Income Individuals



(a) Distance to Downtown

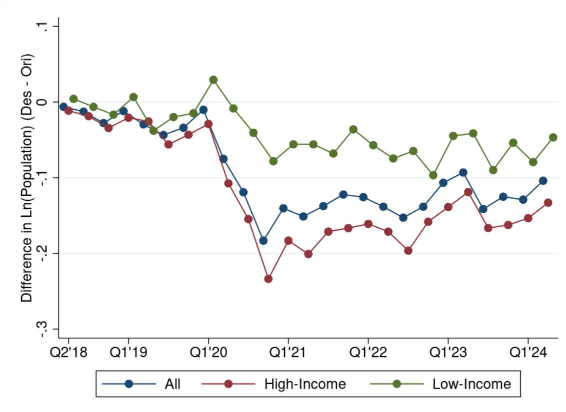
(b) Population Density



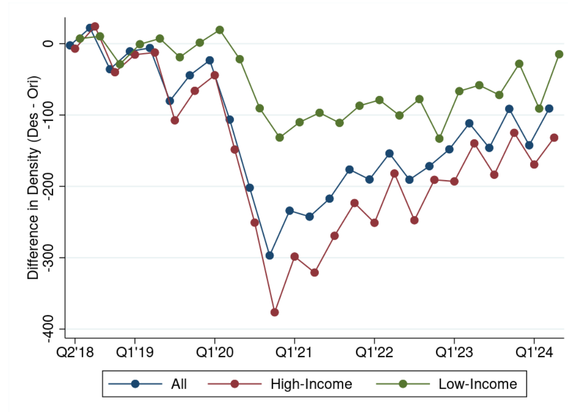
(c) Nearby Telework-Compatible Jobs

Note: The plotted values represent average changes between destination and origin neighborhoods in three dimensions: (a) log distance to downtown, (b) population density (people per square kilometer), and (c) the number of nearby telework-compatible jobs within a 3-mile radius. The sample includes both movers and non-movers. For non-movers, origin and destination are the same, so their observed neighborhood differences are zero by construction. We present the results separately for all individuals, as well as for subgroups based on imputed income as of Q4 2019: the upper half (high-income) and the lower half (low-income) of the distribution. Data source: CCP, American Community Survey/IPUMS NHGIS, and Holian and Kahn (2015).

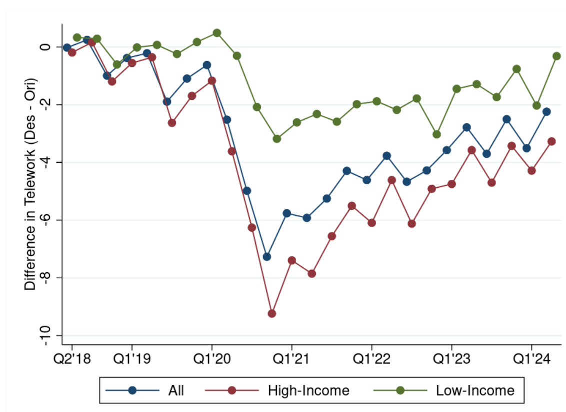
Figure 2: Direction of Metro-to-Metro Flow: High-Income vs. Low-Income Individuals



(a) MSA's Population



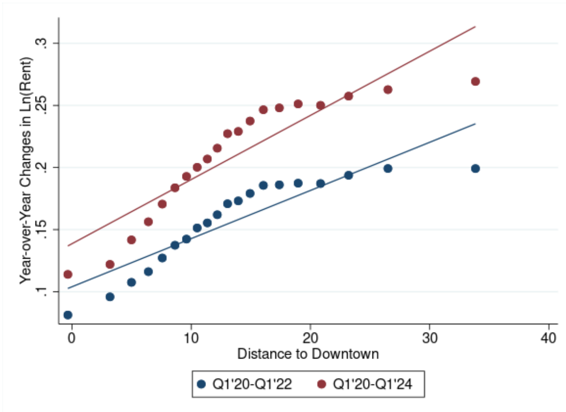
(b) MSA's Population Density



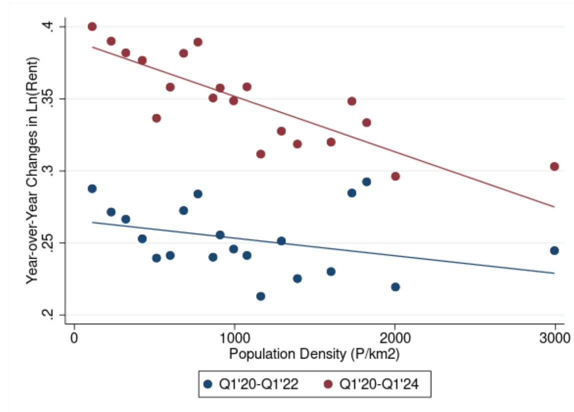
(c) MSA's Share of Telework Jobs

Note: The plotted values represent average changes between destination and origin MSAs along three dimensions: (a) total population, (b) population density (people per square kilometer), and (c) the share of telework-compatible jobs. The sample includes both movers and non-movers. For non-movers, the origin and destination MSAs are the same, so their observed differences are zero by construction. We report the results separately for all individuals, as well as for subgroups defined by imputed income as of Q4 2019: those in the upper half (high-income) and lower half (low-income) of the income distribution. Data source: CCP, American Community Survey/IPUMS NHGIS.

Figure 3: Spatial Variation in Changes in Housing Costs Across Census Tracts and Across MSAs



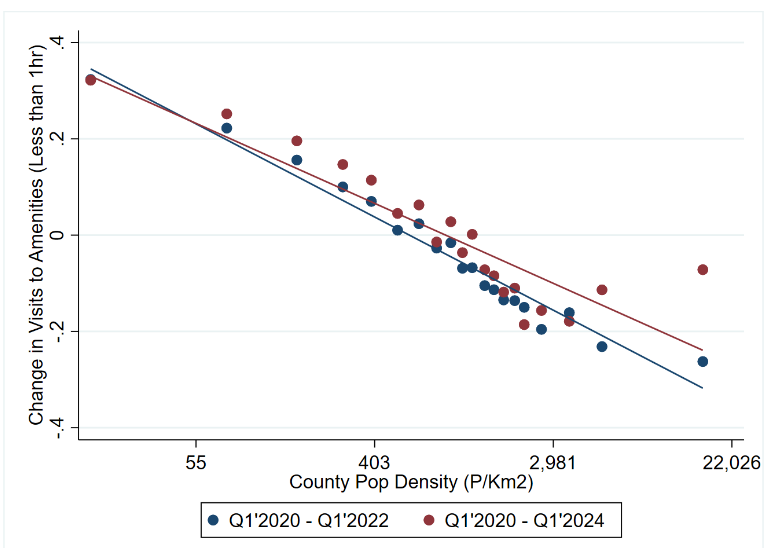
(a) Distance to Downtown



(b) MSA-Level Population Density

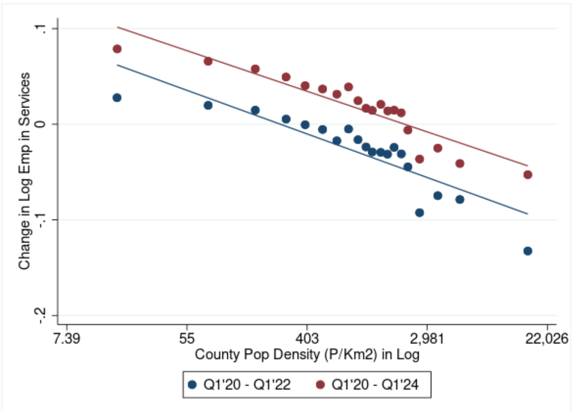
Notes: Subfigure (a) presents a binned scatter plot of changes in census tract-level log housing cost by distance to the downtown area, controlling for MSA fixed effects. We examine changes in housing cost over two periods: from Q1'2020 to Q1'2022, and from Q1'2020 to Q1'2024. The tract-level housing cost change is computed as a weighted average of the log change in Zillow's rent index and the log change in CoreLogic's home price index (HPI), using the tract's renter and owner shares as weights, respectively. Subfigure (b) plots changes in MSA-level log housing cost, constructed using the same approach as in (a), against MSA population density. Because housing markets exhibit strong seasonal patterns, we fix both the start and end of each measurement period to the same calendar quarter. Data source: CoreLogic, American Community Survey/IPUMS NHGIS, Zillow. The bridge between Zillow regionid and metrofips is provided by https://github.com/nmandaara/data-sets/blob/main/CountyCrossWalk_Zillow.csv.

Figure 4: Spatial Variation in Demand for Local Amenities

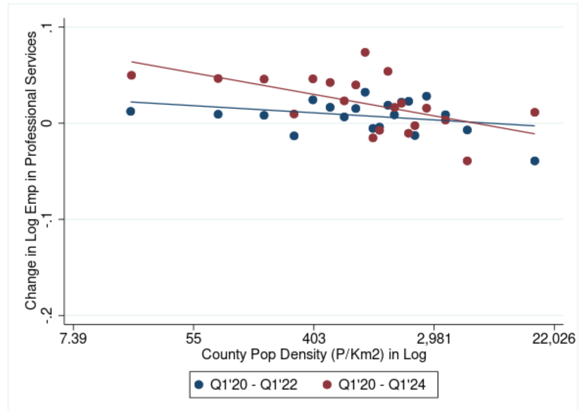


Notes: We plot percentage changes in county-level visits to establishments categorized as consumption amenities between Q1'2020 and Q1'2022, and between Q1'2020 and Q1'2024, against county-level population density. Consumption amenities are defined using the following NAICS codes: 722 (Restaurants); 445, 446 (Grocery); 440–459 excluding 445 and 446 (Non-Grocery Retail); 713 (Gyms); 812 (Personal Care); 512 (Movie Theaters); and 712 (Recreation and Entertainment). We restrict the analysis to visits lasting less than one hour. To mitigate distortions from abrupt jumps in the data caused by evolving definitions of location shape features over time, we apply the imputation procedure described in Qian and Su (2025). Data Source: SafeGraph and Advan.

Figure 5: Spatial Variation in Job Growth Across Counties



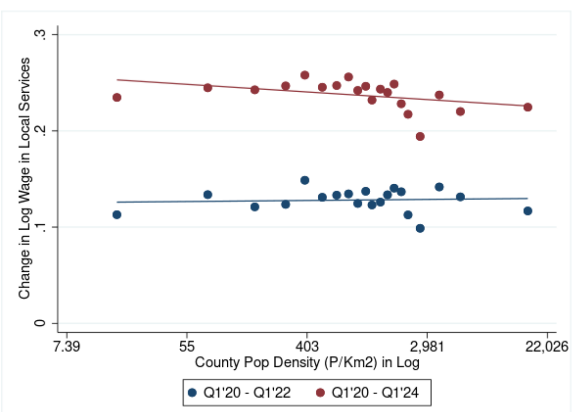
(a) Local Service Industries



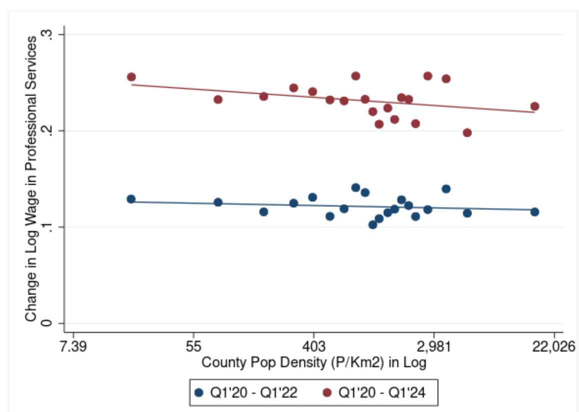
(b) Professional Services

Notes: Subfigure (a) plots changes in log employment in local service industries, defined by NAICS codes 23, 42, 44–45, and 72, against county population density. We examine changes over two periods: Q1'2020 to Q1'2022, and Q1'2020 to Q1'2024. Subfigure (b) presents analogous plots for professional service industries, defined by NAICS codes 51, 52, and 54. Because employment and wages exhibit strong seasonal patterns, we fix both the start and end of each measurement period to the same calendar quarter. Data Source: Quarterly Census of Employment and Wages/Bureau of Labor Statistics, American Community Survey/IPUMS NHGIS.

Figure 6: Spatial Variation in Changes in Wages Across Counties



(a) Wages for Local Service Sector (QCEW)



(b) Wages for Professional Service Sector (QCEW)

Notes: Subfigures (a) and (b) plot changes in log hourly wages using average earnings data from the Quarterly Census of Employment and Wages (QCEW), which reports quarterly earnings at the NAICS industry level. We examine changes over two periods, Q1'2020 to Q1'2022, and Q1'2020 to Q1'2024, for two sectors: the local service sector (NAICS 23, 42, 44–45, 72) in subfigure (a), and the professional service sector (NAICS 51, 52, 54) in subfigure (b). Because both employment and wages follow strong seasonal patterns, we fix the start and end of each period to the same calendar quarter. Data Source: Current Population Survey/IPUMS CPS, American Community Survey/IPUMS NHGIS.

Table 1: Regression Analyses: Effects of Migration on Local Employment

Panel A: First Stage for IV Regressions

	Q1'2020-Q1'2022	Q1'2020-Q1'2024
	ΔLocal y	ΔLocal y
Local telework availability IV	-0.0015***	-0.0034**
	(0.0005)	(0.0016)
Constant	yes	yes
Obs.	869	869
Cragg-Donald Wald F statistic	278.68	179.99
R^2	0.4279	04279

Panel B: Δ Employment

	Q1'2020-Q1'2022				Q1'2020-Q1'2024			
	Service OLS	Prof OLS	Service IV	Prof IV	Service OLS	Prof OLS	Service IV	Prof IV
ΔLocal y	1.4483***	0.9675***	2.3394***	0.3536***	0.9650***	1.0293***	1.0333***	0.2595**
	(0.1066)	(0.1949)	(0.3479)	(0.1147)	(0.0713)	(0.1610)	(0.2608)	(0.1176)
Constant	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	869	869	869	869	869	869	869	869

Note: We regress county-level log employment growth in both the local service and professional service sectors on changes in log aggregate income. Employment data are sourced from the Quarterly Census of Employment and Wages (QCEW). To construct log aggregate income, we assign \$65,486.16 as the mean imputed income for high-income individuals and \$26,505.74 for low-income individuals. We then multiply these values by the respective counts of high- and low-income residents in each county. Changes in log aggregate income are thus driven by the net migration of these population groups, weighted by their assigned income levels. To identify the causal effect of aggregate income on employment, we employ an instrumental variables (IV) strategy. For each MSA, we calculate the share of college-educated and non-college-educated workers employed in telework-compatible occupations: $s\_tele\_col_j^{MSA}$ and $s\_tele\_noncol_j^{MSA}$. At the tract level, we compute the number of nearby (within a 3-mile radius) telework-compatible jobs and aggregate this to the county level using tract-level population weights: $N\_telework_j^{county}$. We construct our instrument at the county level as the product of the MSA-level telework shares and the county-level telework-compatible job availability: $\left(col\_share_j^{county} \cdot s\_tele\_col_j^{MSA} + noncol\_share_j^{county} \cdot s\_tele\_noncol_j^{MSA}\right) \cdot N\_telework_j^{county}$, where $col\_share_j^{county}$ and $noncol\_share_j^{county}$ are the county-level college and noncollege population shares. Data Source: American Community Survey (ACS), NHGIS, Quarterly Census of Employment and Wages, CCP. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. Robust standard errors are reported in parentheses.

Table 2: Regression Analyses : Effects of Migration on Local Housing Costs

	Δ Ln Housing Cost: Q1'2020-Q1'2022				Δ Ln Housing Cost: Q1'2020-Q1'2024			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
ΔLocal y	0.2256***	0.2240***	2.4979***	3.6695***	0.2015***	0.2093***	1.8266***	2.7897***
	(0.0302)	(0.0354)	(0.1261)	(0.2205)	(0.0301)	(0.0348)	(0.0917)	(0.2840)
Elasticity		0.0298***		-0.0924***		0.0450***		-0.0847***
		(0.0096)		(0.0143)		(0.0121)		(0.0161)
ΔLocal y $\times$ Elasticity		-0.0924		-2.7873***		0.0450***		-0.1078
		(0.0614)		(0.7994)		(0.0121)		(0.6505)
Constant	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	41,594	40,287	41,594	40,287	41,572	40,266	41,572	40,266

Note: We regress log housing cost growth on the change in log aggregate income interacted with county-level housing supply characteristics. Rent and house price indexes are sourced from Zillow Research and CoreLogic, respectively. To compute the log aggregate income, To construct log aggregate income, we assign \$65,486.16 as the mean imputed income for high-income individuals and \$26,505.74 for low-income individuals. We then multiply these values by the respective numbers of high- and low-income residents in each tract. The change in log aggregate income is thus driven by the in-migration of these groups, weighted by their assigned income levels. To identify the causal effect of log aggregate income on housing costs, we construct our instruments as follows. For each MSA, we calculate the share of college-educated and non-college-educated workers employed in telework-compatible occupations: $s\_tele\_col_j^{MSA}$ and $s\_tele\_noncol_j^{MSA}$. At the tract level, we compute the number of nearby (within a 3-mile radius) telework-compatible jobs: $N\_telework_j^{tract}$. We construct our instrument at the tract level as the product of the MSA-level telework shares and the tract-level telework-compatible job availability: $\left(col\_share_j^{tract} \cdot s\_tele\_col_j^{MSA} + noncol\_share_j^{tract} \cdot s\_tele\_noncol_j^{MSA}\right) \cdot N\_telework_j^{tract}$, where $col\_share_j^{tract}$ and $noncol\_share_j^{tract}$ are the tract-level college and noncollege population shares. We report the first stage results in the appendix Table A7. Data Source: American Community Survey (ACS), NHGIS, Baum-Snow and Han (2024), CCP. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. Robust standard errors are reported in parentheses.

Table 3: Parameter Calibration for Welfare Analysis

	High-Income	Low-Income	Sources
θ	3	3	Monte et al. (2018); Severen (2023) Tsivanidis (2022)
β^k	0.269	0.462	Diamond and Moretti (2021)
$\lambda^{k,remote}_{Q12020}$	0.0634	0.0383	SWAA data (Barrero et al., 2021) Appendix section C for estimation
$\lambda^{k,remote}_{Q12022}$	0.203	0.142	–
$\lambda^{k,remote}_{Q12024}$	0.149	0.109	–
$\lambda^{k,hybrid}_{Q12020}$	0.110	0.0429	–
$\lambda^{k,hybrid}_{Q12022}$	0.324	0.181	–
$\lambda^{k,hybrid}_{Q12024}$	0.349	0.195	–
$\rho^{k,hybrid}_{Q12020}$	0.423	0.401	–
$\rho^{k,hybrid}_{Q12022}$	0.459	0.429	–
$\rho^{k,hybrid}_{Q12024}$	0.423	0.401	–
$\phi^{m,hybrid}$	0.167	0.167	Equivalent to 10 minutes commuting time
$\phi^{m,remote}$	0.167	0.167	-

Notes: See Section 5.1.4 for discussions of calibration.

Table 4: Welfare Effects on All Individuals and by Income Group

		Q1'2020-Q1'2022					
		Job Access			Housing Cost		
		Φ_{no_mig}	Φ_{mig}	Dif	$-\beta\Delta\eta$	$-\beta\Delta r$	$-\beta\psi\Delta y$
National	Low-inc	0.245	0.240	-0.004	-0.089	-0.073	0.015
	High-inc	0.423	0.421	-0.003	-0.041	-0.040	0.001
Elite cities	Low-inc	0.148	0.126	-0.023	-0.082	-0.037	0.045
	High-inc	0.297	0.291	-0.006	-0.040	-0.023	0.017
Large non-elite cities	Low-inc	0.207	0.202	-0.005	-0.091	-0.077	0.014
	High-inc	0.384	0.381	-0.003	-0.040	-0.042	-0.002
Medium-sized cities	Low-inc	0.253	0.251	-0.002	-0.089	-0.079	0.010
	High-inc	0.460	0.458	-0.002	-0.041	-0.045	-0.004
Small cities	Low-inc	0.314	0.314	0.000	-0.086	-0.078	0.008
	High-inc	0.547	0.545	-0.002	-0.042	-0.044	-0.002
		Q1'2020-Q1'2024					
		Job Access			Housing Cost		
		Φ_{no_mig}	Φ_{mig}	Dif	$-\beta\Delta\eta$	$-\beta\Delta r$	$-\beta\psi\Delta y$
National	Low-inc	0.159	0.147	-0.012	-0.096	-0.076	0.020
	High-inc	0.245	0.224	-0.021	-0.041	-0.039	0.002
Elite cities	Low-inc	0.077	0.052	-0.026	-0.089	-0.031	0.058
	High-inc	0.156	0.133	-0.024	-0.040	-0.018	0.023
Large non-elite cities	Low-inc	0.139	0.126	-0.014	-0.098	-0.078	0.020
	High-inc	0.235	0.215	-0.020	-0.041	-0.041	0.000
Medium-sized cities	Low-inc	0.165	0.154	-0.011	-0.097	-0.083	0.013
	High-inc	0.271	0.251	-0.020	-0.041	-0.045	-0.004
Small cities	Low-inc	0.220	0.212	-0.008	-0.097	-0.087	0.009
	High-inc	0.341	0.321	-0.020	-0.046	-0.048	-0.002

Note: The table reports the welfare effects of changes in job access and housing costs for high- and low-income individuals across the national sample, elite cities, large non-elite cities, medium-sized cities, and small cities, over two periods: Q1'2020–Q1'2022 and Q1'2020–Q1'2024. All values are expressed in log wage-equivalent units. For job access, we report three measures: Φ_{no_mig} captures the welfare effect due to remote work adoption and wage changes, specifically changes in λ, ρ, and w, while holding employment in each location fixed at its Q1'2020 level. Φ_{mig} incorporates the effects in Φ_{no_mig} along with changes in local employment driven by remote-work-induced migration. "Dif" denotes the difference, computed as $\Phi_{mig} - \Phi_{no_mig}$, isolating the effect of migration on job access. For housing costs, we also report three measures: $-\beta\Delta\eta$ represents the welfare impact of housing cost changes in the absence of remote-work-induced migration. $-\beta\Delta r$ captures the total welfare impact of observed changes in real housing costs. $-\beta\psi\Delta y$ isolates the welfare effect of migration-induced changes in housing costs. Data Source: American Community Survey (ACS), NHGIS, Baum-Snow and Han (2024), CCP.

Appendix A Validating Mobility Rates

The key assumption in our analysis is that a person's mailing address at which he/she receives bills from his/her lenders is also where he/she resides. To evaluate the accuracy of the assumption, we compare mobility rates constructed from the CCP to that from the American Community Survey (ACS) for the years 2015 to 2019. The ACS is a demographics survey program conducted by the US Census Bureau. It regularly gathers information previously contained only in the long form of the decennial census, including, among other things, information on migration.[25]

We compare the cross-county in-migration rates between the two data sets, since the most granular geographical level at which ACS reports migration statistics is county. In particular, we compare the county-level gross in-migration rates between Q1 of 2017 and Q4 of 2018 in the CCP data with those from the 2015-2019 ACS surveys. Our time choice in CCP is made so that the CCP statistics are comparable with the ACS survey question, which asks "Where did this person live 1 year ago?"[26] Figure A1 presents the population-weighted binned scatterplot of the in-migration rates from the two data sets. The two rates line up well, and the correlation coefficient is 0.75.[27]

Appendix B Imputation of Individual Income

In this appendix, we describe the procedure we used to impute income for individuals in the CCP/Equifax using information from the Survey of Consumer Finances (SCF), following Coibion et al. (2020). Particularly, we use the 2019 SCF to estimate how income relates to debt and demographic characteristics available in both the CCP and SCF data. We then use these estimates to impute income for individuals in the CCP data in Q4'2019. We restrict our sample to individuals between the ages of 25 and 65.

Table A1 presents the summary statics from the CCP and SCF sample for Q4'2019 and for 2019, respectively. Households in the two data sets are similar in many respects, including age, holdings of auto loans, credit card balance, and holdings of home equity line of credit (HELOCs). There are a few exceptions.

[25]The ACS data are used by many public-sector, private-sector, and not-for-profit stakeholders to allocate funding, track shifting demographics, plan for emergencies, and learn about local communities. Sent to approximately 295,000 addresses monthly (or 3.5 million per year), it is the largest household survey that the Census Bureau administers.

[26]https://www2.census.gov/programs-surveys/acs/methodology/questionnaires/2018/quest18.pdf.

[27]For more comprehensive (and particularly time series) data validation of the CCP, see DeWaard et al. (2019), who compares cross-sectional and longitudinal estimates of migration from the CCP to similar estimates derived from the American Community Survey, the Current Population Survey, Internal Revenue Service data, the National Longitudinal Survey of Youth, the Panel Study of Income Dynamics, and the Survey of Income and Program Participation. They establish the comparative utility of the CCP relative to other data sources on U.S. internal migration.

Individuals in the CCP have in general smaller household size and less debt – mortgage debt in particular.

To impute income for individuals in the CCP sample, we first run the following regressions using the SCF sample,

$$\log(Y_{i,SCF}) = \beta f(X_{i,SCF}) + \epsilon_{i,SCF}, \tag{A.1}$$

where Y_i is the income of household i, and X_i is the vector of the household characteristics, including log of mortgage balance, credit card balance, credit card limit, auto loan, HELOCs, student debt, an indicator for positive credit card limit, the credit card utilization rate conditional on positive credit card limit, the age of the head, and household size.[28] $f(.)$ is a vector-valued function, that includes polynomials, interaction terms and dummy variables. The adjusted R-square for this regression is 0.58.[29] We present the regression results for the main variables in Table A2.

Using the estimated β, we construct the expected imputed log income for each household in the CCP sample:

$$E(\log(Y_i)) = \hat{\beta} f(X_{i,CCP}), \tag{A.2}$$

and the expected imputed income in levels is

$$E(Y_i) = \exp(E[\log(Y_i)] + 0.5\sigma^2_{\hat{\epsilon}_{i,SCF}}), \tag{A.3}$$

where $\epsilon_{i,SCF} = 0.449$ is the variance of $\epsilon_{i,SCF}$ estimated in equation A.1.

As a next step, we validate our income imputation using HMDA-McDash-CRISM matched data. The HMDA-McDash-CRISM dataset contains credit bureau data on individual consumers' credit histories, matched to the mortgage-level McDash servicing data.[30] Specifically, we keep all individuals that are present in the December 2019 HMDA-McDash-CRISM database and impute each individual's income using the methodology described above. Our imputed log income has a correlation coefficient with the observed log income of 0.51. The Spearman rank correlation coefficient is also a high 0.50. In Figure A2, we provide a binned

[28] We don't use the indicator for bankruptcy nor the indicator of 60 days or more past due on any loan in the imputation, as the two variables have different definitions in the two datasets. For example, in SCF, the bankruptcy variable captures all bankruptcy filings, while the CCP bankruptcy indicator only reflects bankruptcy filings flagged by the credit bureau, i.e., the active ones. Including these two variables in the imputation, however, does not change our results much at all.

[29] We follow exactly the specification in equation (1) in Coibion et al. (2020) except for variables that involve delinquency rates or bankruptcy filing rates.

[30] Through a proprietary and confidential matching process, Equifax uses anonymous fields such as original and current mortgage balance, origination date, ZIP code, and payment history to match each loan in the McDash dataset to a particular consumer's tradeline.

scatterplot of the two variables. As can be seen, the relationship is almost perfectly linear.

Appendix C Imputation of Work-Mode Parameters

A set of key parameters governing work modes is needed for calibration: $\lambda_t^{k,remote}$, $\lambda_t^{k,hybrid}$, $\rho_t^{k,hybrid}$, where k denotes the income group and t denotes the quarter of reference. For the two quarters during and after the pandemic Q1'2022 and 2024, we calculate these parameters directly from the SWAA survey based on the work by Barrero et al. (2021).

However, to calculate these parameters for Q1'2020, there are no data sources that provide sufficiently rich information that distinguishes fully remote and hybrid work modes, nor remote work hours vs. onsite work hours among hybrid workers. To that end, we combine two sources of data - the American Time Use Survey (ATUS) and the American Community Survey (ACS) to impute $\lambda_{Q12020}^{k,hybrid}$ based on the assumptions on $\lambda_{Q12020}^{k,remote}$ and $\rho_{Q12020}^{k,hybrid}$ discussed in the next paragraph.

From the ATUS data, among workers aged between 25 and 65, we calculate the fraction of overall working hours that occurred at home in 2019 by workers in the high- and low-income groups, respectively. From the ACS data, among workers aged between 25 and 65, we calculate the fraction of workers who reported mainly working from home in the previous week in 2019. Under the assumption that workers who reported that they *mainly* worked from home over a specific week are fully remote workers and the assumption that $\lambda_{Q12020}^{k,hybrid} = \lambda_{Q12024}^{k,hybrid}$, we write down the following equation and impute $\lambda_{Q12020}^{k,hybrid}$:

$$frac\_hour\_remote_{Q12020}^{k} = \lambda_{Q12020}^{k,remote} + \lambda_{Q12020}^{k,hybrid}\rho_{Q12020}^{k,hybrid}.$$

We can re-arrange and re-write the fraction of hybrid workers as follows:

$$\lambda_{Q12020}^{k,hybrid} = \frac{frac\_hour\_remote_{Q12020}^{k} - \lambda_{Q12020}^{k,remote}}{\rho_{Q12020}^{k,hybrid}}.$$

Since each of the variables can be either estimated or assumed by assumption, we can compute the $\lambda_{Q12020}^{k,hybrid}$ by imputation. All calibrated parameters are reported in Table 3.

Appendix D Migration Patterns by Other Observable Characteristics

In the main text of the paper, we classify individuals as high- or low-income according to their imputed income. Specifically, an individual was considered high-income if his imputed income was above the national median and low-income if otherwise. In this section, we use a number of alternative group definitions to conduct robustness analyses of the heterogeneous migration patterns by income documented in the main paper.

D.1 Income and Age Groups

One alternative way to divide the sample is to cut the sample into income quintiles, based on imputed income, instead of dividing it by half. In the first robustness check, we take only the population in the top or bottom income quintiles and investigate their respective migration patterns over the pandemic.

In addition, based on the life-cycle income profile of typical individuals, one may surmise that income could be highly correlated with age. Therefore, by cutting the sample based on income, we might be capturing much of the different migration patterns driven by age differences rather than by income differences per se. For example, older individuals may be less likely to move than younger individuals and may possibly prefer a low-density environment more than young individuals, regardless of income.

We now assess whether age differentials across income group predominantly drove our migration results. Specifically, we examine the top and the bottom income quintiles. Within each of the top and bottom quintiles, we further divide the sample into individuals younger than 45 and individuals who are at least 45. In other words, we divide the population into four groups: bottom income quintile & younger than 45, bottom income quintile & 45 or older, top income quintile & younger than 45, and top income quintile & 45 or older.

Next, we construct the net in-migration rate in each census tract by each of the four population groups. We then regress the net in-migration rate on distance to downtown, interacted with the indicator variables for each of the non-omitted groups (3 of them). The omitted group is the bottom quintile & younger than 45.

Table A3 column (1) shows the regression results. The coefficients of the interactive terms indicate how much more the migration out of downtown is among the other three groups relative to the low-income young (< 45) individuals. We see that within the bottom fifth income quintile, older individuals are more likely to move outside neighborhoods close to downtown. But younger individuals in the top fifth income quintile are a lot more likely to move away from downtown than older individuals in the bottom fifth income quintile.

Compared to the younger individuals in the top fifth, older individuals in the top fifth are less likely to move away from downtown. But even so, the magnitude of out-migration of older individuals in the top fifth income quintile is still far higher than older individuals in the bottom fifth income quintile. These results thus demonstrate that income is the main predictor of the magnitude of out-migration from city centers.

Next, we analyze whether the difference in migration across age groups confounds the patterns of cross-metro migration. We conduct the exact same exercise as above but at the MSA level. Instead of distance to downtown, we look at how much net in-migration rates depend on the log population density by income and age at the metro level, and how such relation differs across the four aforementioned groups.

In Table A3 column (2), we show that for the omitted group (younger individuals in the bottom fifth income quintile), the net in-migration rate is lower in metros with higher population density. Older individuals in the bottom fifth income quintile exhibit weaker tendency to move toward lower-density metros. In contrast, both younger and older individuals in the top fifth income quintile similarly exhibit much stronger tendency to move toward lower-density metros than both younger and older individuals of the bottom income quintile.

D.2 Income and Mortgage Status

Another alternative explanation for the differential migration rates between the income groups is that high-income individuals are more likely to be homeowners and have mortgage debt. Homeowners and mortgage holders may be less likely to move than renters because of the higher cost associated with moving. To investigate how mortgage holding affects the differences in migration patterns across income groups, we again look at the top and bottom income quintiles. Within each quintile, we further divide the sample into individuals who held mortgage in Q4'2019 and individuals who did not hold any mortgage at the same time. In this exercise, we end up with four population groups: bottom income quintile & with no mortgage, bottom income quintile & with a mortgage, top income quintile & with no mortgage, and top income quintile & with a mortgage.

As before, we construct the net in-migration rate in each census tract and metro by each of the four aforementioned population groups and conduct a similar regression analysis. Table A4 column (1) shows the census tract regression results. We see that within the bottom fifth income quintile, both individuals with no mortgage and with a mortgage exhibit very little tendency to move away from downtown. In contrast, among the top income quintile, individuals both with a mortgage and without a mortgage would be moving away from downtown with statistical significance, with individuals who have mortgages exhibiting stronger movement away from downtown. Table A4 column (2) shows that for the omitted group (the bottom fifth income quintile with no mortgage), the net in-migration rate is lower in metros with higher population density. Within the bottom quintile, individuals with a mortgage do not exhibit a stronger tendency to move to lower-density metros. In contrast, individuals in the top income quintile exhibit a similarly stronger tendency to move toward lower-density metros, regardless of their mortgage holdings.

These results suggest that the different migration patterns across income groups were not driven by either the differential migration patterns by age or by mortgage status.

Appendix E Moving and Housing

In this appendix, we examine possible changes in housing arrangement for individuals, movers in particular. Movers here are defined as those who changed census tracts between two quarters. Unfortunately, our data do not provide information that allows us to answer the questions directly. Instead, we make inference with what we have on hand.

E.1 Moving in with Families

We first address concerns regarding individual migration that involves moving in with parents, relatives or friends. These kind of moves wouldn't generate as much additional housing demand as other moves where individuals will need to rent or purchase a place to stay. Note that we restrict our sample to individuals between the ages of 25 and 65. As a result, most college students are not in our sample.

The CCP provides household id that allows us to group individuals into households. Using this information, we construct for each individual in our sample at each quarter, a household size, i.e., number of individuals at the same address. We restrict the maximum family size to 10. We also calculate the age of the oldest as well as the youngest within the household and present the summary statistics for movers as well as nonmovers before and after the break out of the Covid-19 pandemic in Table A5. We do not see any noticeable differences in these demographics before or after the pandemic for movers or nonmovers. And we observe similar differences between movers and nonmovers before and after the outbreak of the pandemic, i.e., the nonmovers tend to be older by about 5 years.

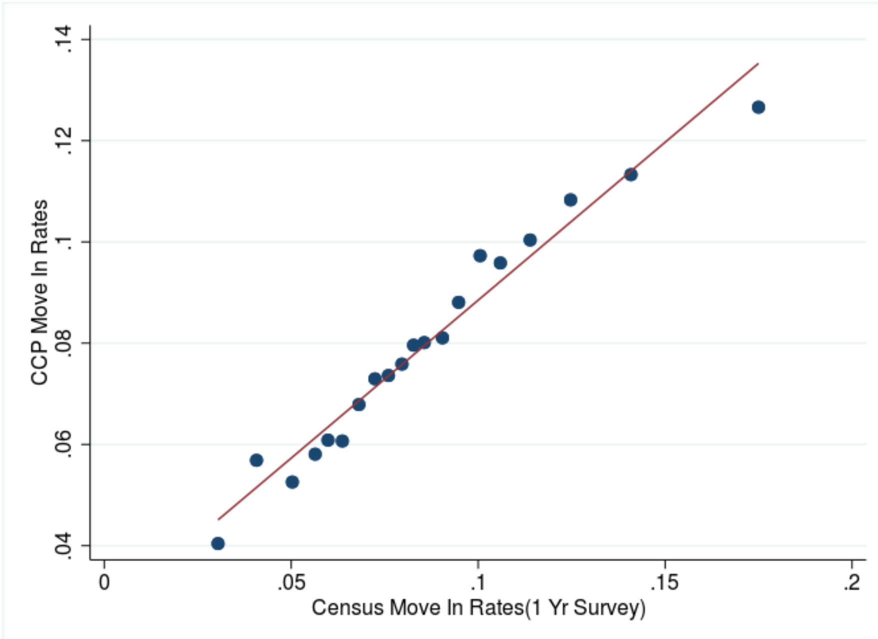
E.2 Homeownership

The CCP reports the number of first-lien mortgages that an individual has at each quarter, which corresponds to the number of residential properties the person has. In Table A6, we summarize the number of first mortgages as well as changes in the number of first mortgages between quarters for the period before the pandemic and for the period after the pandemic. We differentiate between movers and nonmovers, and within each group, we further differentiate between those with Equifax Risk Scores over 720 and those with Equifax Risk Scores 720 and below.

As is evident in the table, movers on average increased the number of first mortgages they held after the move while there is essentially no change in the number of first mortgages held by nonmovers between two quarters. More importantly, movers are 77 percent more likely during the pandemic to increase the number of first mortgages they hold after the move than they did before the pandemic. Additionally, as expected, individuals with high Equifax Risk Scores hold on average more first mortgages. Interestingly, however, the percentage increase in the number of first mortgages held by individuals with lower Equifax Risk Scores is slightly higher than the percentage increase in the number of first-lien mortgages held by individuals with high Equifax Risk Scores after the pandemic than before the pandemic.

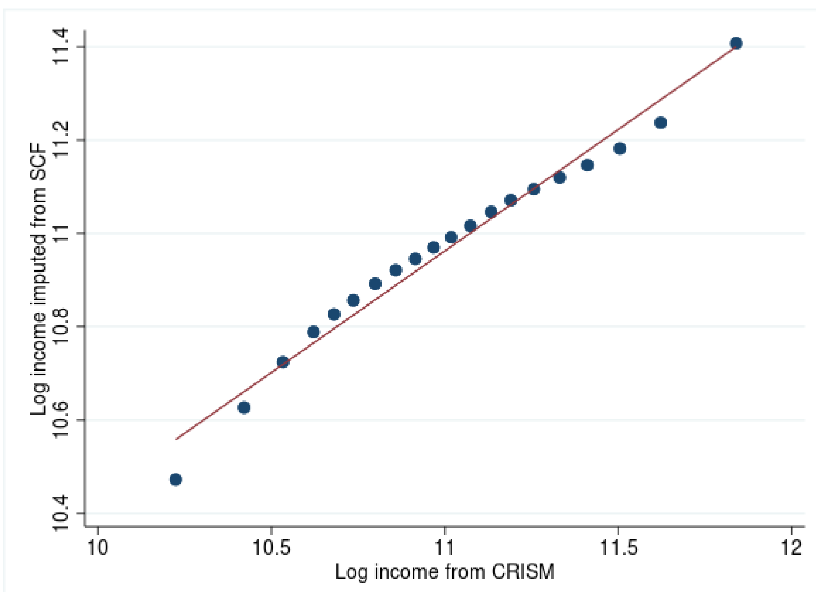
This exercise, therefore, demonstrates that movers created housing demand by purchasing houses in new locations, more so during the pandemic than they used to before the pandemic. Given that we are not able to capture those who did cash purchases, these numbers serve as a lower bound of the extent of increase in housing demand associated with movers after the pandemic.

Figure A1: Data Validation: Move In Rates



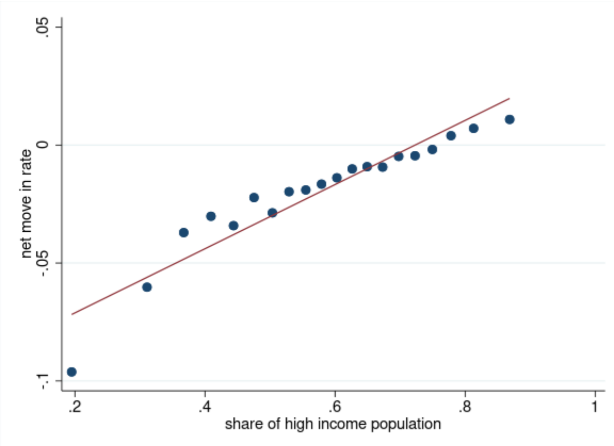
Note: This binned scatterplot compares county-level in-migration rates between March 2017 and December 2018 from the CCP data with county-level move in rates from the 2015-2019 ACS. Data source: CCP, American Community Survey.

Figure A2: Binned Scatterplot: SCF Imputed Income versus HMDA-McDash-CRISM Income

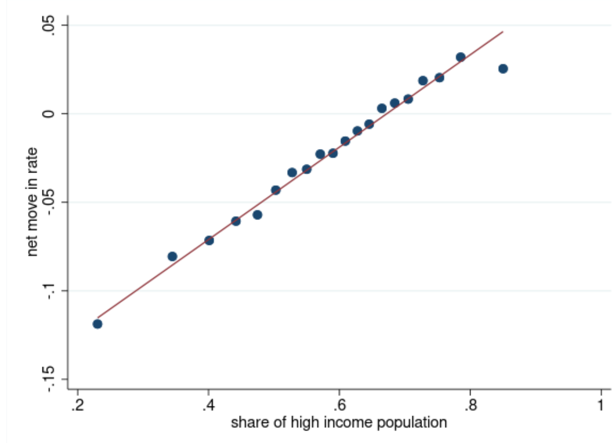


Note: We impute for all individuals present in the December 2019 HMDA-McDash-CRISM data using information from the 2019 SCF. See the main text of the paper for details. Data source: CCP, Survey of Consumer Finances, HMDA-McDash-CRISM match, 3rd Generation.

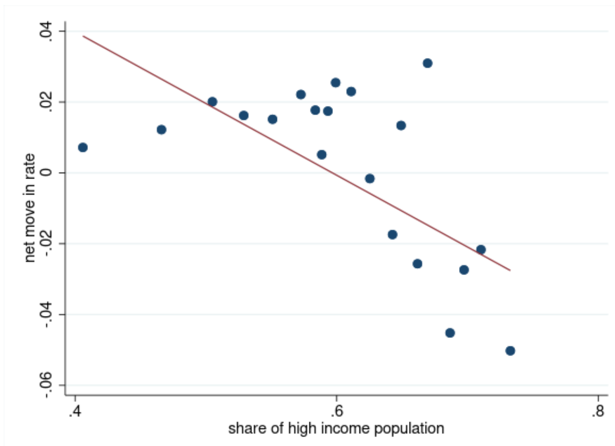
Figure A3: Relationship Between Migration and Local Income Profile



(a) Net Migration and Tract-Level Fraction of High-Income Residents



(b) Tract-Level with MSA FEs



(c) Net Migration and MSA-Level Fraction of High-Income Residents

Note: These figures present binned scatterplots that depict the relationships between the net migration rate over the period over Q1'2020 to Q1'2024 and the initial share of the locations' shares of high-income population. In subfigure A3a, we plot the tract-level net migration rate against the tract-level share of high-income population. In subfigure A3b, we plot the tract-level net migration rate against the tract-level share of high-income population, but with MSA fixed effects included. In subfigure A3c, we plot the MSA-level net migration rate against the MSA-level share of high-income population. Data Source: American Community Survey (ACS), and CCP.

Table A1: Summary Statistics of CCP and SCF (2019)

Category	Mean	S.d.	Median
Panel A: CCP Q4'2019			
Age of household head	45	12	45
Household size	1.08	0.81	1
Housing debt	50,134	124,193	0
Mortgage	48,457	120,706	0
HELOC	1,677	16,619	0
Auto loans	6,650	23,795	0
Credit card limit	18,946	32,386	7,520
Credit card balance	4,842	13,972	1,084
Student loan	4,157	15,708	0
Total debt	67,484	137,998	17,697
Credit card utilization rate	0.38	0.36	0.24
Panel B: SCF 2019			
Age of household head	46	12	46
Household size	2.7	1.5	2
Housing debt	77,038	120,570	0
Mortgage	75,370	118,248	0
HELOC	1,669	15,542	0
Auto loans	6,846	12,219	0
Credit card limit	20,471	44,047	7,500
Credit card balance	5,326	13,233	0
Student loan	9,123	23,746	0
Total debt	98,333	141,260	38,200
Credit card utilization rate	0.28	0.35	0.10

Note: This sample is restricted to households with heads between 25 and 65. The statistics are calculated using sampling weights for the SCF data. Housing debt is the total of mortgage and home equity line of credit (HELOC). The credit card utilization rate is calculated as credit card balance divided by credit card limit. The number of observations in panel A is 8.4 million. The number of observations in panel B is 20,685. Data Source: CCP, Survey of Consumer Finances.

Table A2: Income Regression (SCF 2019)

Category	Estimate	S.d.
Age: [30, 34]	0.355***	0.093
Age: [35, 39]	0.259***	0.100
Age: [40, 44]	0.208***	0.098
Age: [45, 49]	0.156***	0.096
Age: [50, 54]	0.243***	0.095
Age: [55, 59]	-0.141	0.092
Age: [60, 64]	-0.024	0.089
Household size	0.053*	0.032
Log_mortgage	1.750***	0.074
Log_HELOC	0.026	0.025
Log_auto loan	0.342***	0.049
Log_credit card balance	0.001	0.018
Have positive credit card limit	1.350***	0.244
Log_student loan	0.008	0.007

Note: We restrict the sample to households whose heads are between 25 and 65. The total number of observations is 20,685. We omit reporting the interaction variables. The adjusted R-square is 0.58. Data Source: Survey of Consumer Finances.

Table A3: Regression: Differential Migration Patterns by Income and Age

	Net In-Migration Rate	
	(1)	(2)
Distance to Downtown	0.0025***	
	(0.00022)	
Bottom fifth & Older than 45 × Distance to Downtown	-0.00049	
	(0.00027)	
Top fifth & Younger than 45 × Distance to Downtown	0.00471***	
	(0.00027)	
Top fifth & Older than 45 × Distance to Downtown	0.00139***	
	(0.00027)	
Metro-Level Ln Pop Density		0.0027***
		0.0003)
		(0.0035)
Bottom fifth & Older than 45 × Metro-Level Ln Pop Density		-0.0033***
		(0.0005)
Top fifth & Younger than 45 × Metro-Level Ln Pop Density		-0.0014***
		(0.0005)
Top fifth & Older than 45 × Metro-Level Ln Pop Density		-0.0037***
		(0.0005)
FE	Metro	State
Adjusted R2	0.027	0.023
Observations	221,507	3,652

Note: We compute the net in-migration rates from Q1'2020 to Q1'2024 separately for individuals in the top fifth income and bottom fifth income quintiles (ranked in Q4'2019) and by age (younger than 45 or not). Therefore, there are four categories of individuals for whom we construct net in-migration rates: bottom fifth & younger than 45, bottom fifth & older than 45, top fifth & younger than 45, and bottom fifth & older than 45. The category of bottom fifth & younger than 45 is the omitted category in the regression. In the regression, in addition to the coefficients we show, we also include the stand-alone indicator variables for each of the non-omitted categories. The regressions are weighted by local population. Each of the observations for the column (1) regression represents a census tract. Each of the observations for the column (2) regression represents a metro, which include micropolitan. Data Source: American Community Survey (ACS), NHGIS, CCP. *** $p <$ 0.01, ** $p <$ 0.05, *$p <$ 0.1.

Table A4: Regression: Differential Migration Patterns by Income and Mortgage Status

	Net In-Migration Rate	
	(1)	(2)
Distance to Downtown	0.00130***	
	(0.0001)	
Bottom fifth & With Mortgage × Distance to Downtown	0.00196***	
	(0.00002)	
Top fifth & No Mortgage × Distance to Downtown	0.00107***	
	(0.000135)	
Top fifth & With Mortgage × Distance to Downtown	0.00377***	
	(0.00014)	
Metro-Level Ln Pop Density		0.0017
		(0.0011)
Bottom fifth & With Mortgage × Metro-Level Ln Pop Density		-0.0305***
		(0.0014)
Top fifth & No Mortgage × Metro-Level Ln Pop Density		9.67e-06
		(0.0015)
Top fifth & With Mortgage × Metro-Level Ln Pop Density		-0.0028*
		(0.0015)
FE	Metro	State
Adjusted R2	0.0322	0.230
Observations	201,315	3,624

Note: We compute the net in-migration rates from Q1'2020 to Q1'2024 separately for individuals in the top fifth income and bottom fifth income quintiles (ranked in Q4'2019) and by mortgage status (whether holding mortgage debt). Therefore, there are four categories of individuals for whom we construct net in-migration rates: bottom fifth & no mortgage, bottom fifth & with mortgage, top fifth & no mortgage, and bottom fifth & with mortgage. The category of bottom fifth & no mortgage is the omitted category in the regression. In the regression, in addition to the coefficients we show, we also include the stand-alone indicator variables for each of the non-omitted categories. The regressions are weighted by local population. Each of the observations for the column (1) regression represents a census tract. Each of the observations for the column (2) regression represents a metro, which include micropolitan. Data Source: American Community Survey (ACS), NHGIS, CCP. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A5: Family Characteristics of Movers and Nonmovers

Category	Q2'2019-Q1'2020			Q2'2020-Q4'2021			Q1'2022-Q3'2024		
	Mean	S.d.	Median	Mean	S.d	Median	Mean	S.d	Median
Panel A: Movers									
Household size	1.100	0.513	1	1.160	0.712	1	1.161	0.733	1
Δ household size	-0.037	0.808	0	0.051	0.865	0	0.023	0.950	0
Individual age	40	9.701	38	41	9.689	40	43	9.991	41
Age of youngest	40	9.307	38	41	9.933	39	42	9.990	41
Panel B: Nonmovers									
Household size	1.070	0.357	1	1.080	0.404	1	1.097	0.487	1
Δ household size	-0.0007	0.121	0	0.0006	0.125	0	0.0011	0.136	0
Individual age	44	9.891	44	45	9.891	45	47	10.265	46
Age of youngest	43	10.058	44	44	10.333	45	46	10.167	46

Note: The sample is restricted to individuals with heads between 25 and 65. No restriction is placed on the age of those with the same household identification numbers. Movers are those who changed census tract between the two quarters. We set an upper bound for household size at 10. The number of observations in panel A is 1.14 million for Q2'2019-Q1'2020, 1.87 million for Q2'2020-Q4'2021, and 2.66 million for Q1'2022-Q3'2024. The number of observations in panel B is 29.57 million for Q2'2019-Q1'2020, 41.15 million for Q2'2020-Q4'2021 and 67.67 million for Q1'2022-Q3'2024. Data Source: CCP.

Table A6: First Mortgages of Movers and Nonmovers

Category	Q2'2019-Q1'2020			Q2'2020-Q4'2021			Q1'2022-Q3'2024		
	Mean	S.d.	Median	Mean	S.d	Median	Mean	S.d	Median
Panel A: Movers									
# of first mort.	0.350	0.598	0	0.367	0.606	0	0.361	0.614	0
Changes in #	0.032	0.325	0	0.033	0.357	0	0.026	0.305	0
Panel B: Movers with Equifax Risk Score over 720									
# of first mort.	0.598	0.717	0	0.602	0.712	0	0.580	0.724	0
Changes in #	0.050	0.416	0	0.049	0.453	0	0.041	0.381	0
Panel C: Nonmovers									
# of first mort.	0.399	0.591	0	0.406	0.590	0	0.413	0.597	0
Changes in #	0.0013	0.169	0	-0.0006	0.192	0	0.0010	0.159	0
Panel D: Nonmovers with Equifax Risk Score over 720									
# of first mort.	0.614	0.662	0	0.601	0.654	0	0.565	0.647	0
Changes in #	0.0018	0.198	0	-0.0006	0.233	0	0.0018	0.181	0

Note: The sample is restricted to individuals with heads between 25 and 65. We set number of first mortgages to zero for those without mortgages. Movers are those who changed census tract between the two quarters. The number of observations in panel A is 1.14 million for Q2'2019-Q1'2020, 1.87 million for Q2'2020-Q4'2021, and 2.66 million for Q1'2022-Q3'2024. The number of observations in panel B is 0.46 million for Q2'2019-Q1'2020, 0.83 million for Q2'2020-Q4'2021, and 1.25 million for Q1'2022-Q3'2024. The number of observations in panel C is 29.57 million for Q2'2019-Q1'2020, 41.15 million for Q2'2020-Q4'2021 and 67.67 million for Q1'2022-Q3'2024. The number of observations in panel D is 14.02 million for Q2'2019-Q1'2020, 21.07 million for Q2'2020-Q4'2021 and 63 million for Q1'2022-Q3'2024. Data Source: CCP.

Table A7: Regression Analyses : First Stages for the Local Housing Cost IV Regressions

Panel A. First Stage for Local Aggregate Income

	Q1'2020-Q1'2022	Q1'2020-Q1'2024
	ΔLocal y	ΔLocal y
Local telework availability IV	-0.00082***	-0.00012**
	(0.0004)	(0.00006)
Local housing supply elasticity	0.0528***	0.0875***
	(0.0031)	(0.0048)
Local telework availability IV $\times$ elasticity	-0.00079***	-0.00013***
	(0.0002)	(0.00003)
Constant	yes	yes
Obs.	40,287	40,266

Panel B. First Stage for Local Aggregate Income Interacted with Supply Elasticity

	Q1'2020-Q1'2022	Q1'2020-Q1'2024
	ΔLocal y $\times$ Elasticity	ΔLocal y $\times$ Elasticity
Local telework availability IV	0.00009***	0.00002***
	(0.00003)	(3.87e-06)
Local housing supply elasticity	0.02588***	0.0392***
	(0.0023)	(0.0038)
Local telework availability IV $\times$ elasticity	-0.00155***	-0.00025***
	(0.0004)	(0.00007)
Constant	yes	yes
Obs.	40,287	40,266
Rragg-Donald Wald F Statistics	257.37	325.26

Note: This table reports the first stage results in Table 2. Data Source: American Community Survey (ACS), NHGIS, Baum-Snow and Han (2024), CCP *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.