The Great Reshuffle: Residential Sorting During the COVID-19 Pandemic and Its Welfare Implications*

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Abstract

Using individual-level micro data of location histories, we document a sudden rise of net migration toward suburban neighborhoods and smaller cities in the US during the COVID-19 pandemic. We demonstrate that such a migration wave was driven disproportionately by the movement of the high-income population, and, thus, it has "undone" some of the spatial sorting observed over the decades before the pandemic. As a result of the migration, housing costs rose in the locations receiving the migration influx but declined in the areas experiencing the exodus. Demand for local services and, consequently, local service jobs moved in the same direction as the migration. Using a simple spatial model and an instrumental variable approach, we show that the pandemic-era migration tempered the robust gains in job access from the adoption of work from home (WFH). Moreover, the migration alleviated the housing cost burden faced by both high- and low-income people, but more for low-income people. On the net, the spatial sorting during the first two years of the pandemic reduced welfare inequality. However, the gains are small in magnitude relative to the worsening of inequality stemming from the differences in WFH availability by worker income.

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1 Introduction

Since 1980, skill-biased technological growth has fueled the rapid increases in wages in large cities in the US, particularly for high-skilled workers. Housing costs have also skyrocketed in these places, driving the low-skilled workers to smaller and cheaper areas (Giannone, 2018; Eckert et al., 2022). A similar phenomenon has also occurred within these large cities, with housing costs rising much faster in neighborhoods near city centers than in neighborhoods farther away, forcing low-skilled workers to reside in cheaper outlying locations (Couture and Handbury, 2020; Su, 2022).[1] Such spatial sorting between high- and low-skilled workers, and hence, the high- and low-income people, has contributed to the widening well-being inequality in the country (Diamond, 2016; Couture et al., 2021; Diamond and Gaubert, 2022; Su, 2022).

The outbreak of the COVID-19 pandemic in March 2020 disrupted this spatial sorting trend. In the wake of the pandemic, residential housing demand abruptly shifted from central city neighborhoods to less densely populated suburban neighborhoods and from large and high-density MSAs to smaller and lower-density MSAs. Recent research has shown that the sudden rise in work-from-home (WFH) options, which allowed many workers to decouple their residential locations from their job locations, is a driving force of this sudden shift in housing demand (Liu and Su, 2021; Gupta et al., 2022b; Meeker and Mota, 2021; Whitaker, 2021).

Since the option to work remotely is much more available to high-skilled professionals than to workers in service and retail, where face-to-face interactions with customers are often required, this shift in housing demand is likely dominated by high-income and high-skilled workers (Dingel and Neiman, 2020; Su, 2020; Bartik et al., 2020; Bick et al., 2021; Barrero et al., 2021; Brynjolfsson et al., 2020). If so, the sudden acceleration of the movement toward the suburbs and lower-density MSAs may have partially reversed the spatial sorting seen in the previous four decades. The spatial difference in the growth in housing costs and labor demand due to this "reversal" of spatial sorting could have also undone some of the rises in the well-being inequality accrued in the preceding decades.

In this paper, we use an anonymized individual-level micro dataset, the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (referred to as the FRBNY Consumer Credit Panel/Equifax or the CCP), to analyze changes in migration and spatial sorting patterns in US cities after the outbreak of the pandemic and to understand their welfare implications. The FRBNY Consumer Credit Panel/Equifax is a nationally repre-

[1] In the most recent years leading up to the pandemic, the high-income population was also starting to see net out-migration from high-cost cities and high-cost neighborhoods.

sentative anonymous random sample from Equifax credit files. It tracks all consumers with a US credit file residing in the same household from a random, anonymous sample of 5% of US consumers with a credit file. A key feature of the data is that it records the location at which a person receives his/her bills for credit card and loan payments. The location geocodes we use are based on precise address information.[2] To study spatial sorting between the high- and low-income population groups, we use observed characteristics in the CCP together with information from the Survey of Consumer Finances (SCF) to impute people's income, following Coibion et al. (2020). Based on the imputed income, we study the differential migration patterns exhibited by high- and low-income individuals during the COVID-19 pandemic and the impact of the migration on the well-being of high- and low-income populations, respectively.

We show that the pandemic did lead to significantly more net outflows of people from densely populated neighborhoods near city centers to suburban neighborhoods with lower population density. It also led to considerably larger flows toward smaller MSAs with low population density. Importantly, the rise in migration toward the suburbs and lower-density MSAs was disproportionately driven by *high-income* residents.

As residents, particularly the high-income residents, migrated to the suburbs and lower-density MSAs, housing costs rose disproportionately in the destination locations relative to the origin locations. In other words, we observe a spatial change in housing costs in line with the direction of migration. Migration during the pandemic increased the cost burden for residents living in the locations receiving the migration flows but reduced the cost burden for residents living in the locations that experienced the outflows. Additionally, we document that the demand for local goods and services moved spatially along with the net migration flows, which implies that the growth in local service jobs in locations receiving the migration was much more robust than the local service job growth in locations experiencing population outflow.

To assess the welfare consequences of these new migration patterns, we construct a simple spatial model where workers face their housing cost burden based on the neighborhoods in which they live. They also face spatially varying job access, modeled in the same way as the commuter market access featured in the transportation economics literature (Donaldson, 2018; Tsivanidis, 2022), where job access is determined by the abundance and the wage levels of the jobs surrounding the community that a worker lives in. A decrease in commuting costs to jobs (due to the adoption of remote work) or rapid growth in the number of jobs within a short commuting distance could raise a worker's job access and vice versa.

[2] Whenever a person moves and updates his/her address with the creditors, the creditors will update such information with the credit bureaus. For example, if a person changes the mailing address with the credit card issuer, which then reports it to the credit bureaus, the new address will appear on the person's credit report. We observe the geocodes of the addresses but do not observe or use the addresses directly.

Given the model, we study how migration during the pandemic affected housing costs and workers' job access through its effect on local wages and employment. To that end, we employ an instrumental variable (IV) approach to recover the causal effect of migration on local housing costs, local employment, and wages. We exploit the fact that large pre-pandemic employment clusters hosting teleworkable jobs saw a sharp rise in out-migration during the pandemic, and the pre-pandemic topography of teleworkable jobs is unlikely correlated with other factors that drove out residents. We use both the neighborhood-level number of teleworkable jobs and the MSA-level share of teleworkable jobs as IVs to estimate migration's effects on our local outcome variables. We compute the effect of migration on job access by calculating the counterfactual job access using the spatial change in employment and wages attributed to migration.

The model confirms that high-income workers benefited much more from their higher frequency of WFH work arrangements through increased job access, which vastly widened the welfare inequality between high- and low-income workers. Calibrating the model to the new regime of WFH arrangements, we show that migration during the pandemic lowered access to local service jobs in large cities and increased job access in small cities. Migration also lowered local service job access in city centers but raised job access in the exurbs. Since the low-income population is disproportionately represented in local service sectors, this spatial shift in local job access affected the low-income population more. Furthermore, since the low-income population is more likely to reside in urban neighborhoods, from which local service jobs were moving, the average low-income person saw their job access reduced by migration.

Professional service jobs, in which high-income workers are more likely to be employed, did not see as much spatial movement. However, migration lowered the high-income population's job access because the high-income population moved to exurbs and remote cities at a higher rate during the pandemic. The welfare calculation shows that the reduction of job access by migration has partially offset the large gains in job access afforded by the adoption of WFH, to a similar degree for high- and low-income people.

With the housing costs, we find that migration during the pandemic *alleviated* the housing costs facing both the high- and low-income populations, but more so for the low-income population. This result may seem counterintuitive at first sight, as we did witness unprecedented rental and home price growth during the pandemic (Mondragon and Wieland, 2022). It is, however, important to keep in mind that during the pandemic, the population generally moved from localities with low housing supply elasticities to localities with high housing supply elasticities. Since the pandemic caused an unprecedented increase in housing demand, local housing markets were likely on the upward-sloping portion of the housing supply curve. As a result, migration toward places with more elastic housing supply, on average, led to lower growth in housing costs. In other words, housing costs would have surged even more in high-density places had it not been for the migration toward low-density places.

We can think of such movement during the pandemic as a "de-congestion" process. This "de-congestion" benefited the low-income population particularly strongly because it pulled housing demand away from neighborhoods where the low-income population predominantly lives. Such disproportionate migration from low-income neighborhoods has been coined as "de-gentrification" by Ding and Hwang (2022). Indeed, we show that while it is undoubtedly the case that in star cities such as New York City, San Francisco, and Los Angeles, the average low-income person saw a lower cost of housing induced by an exodus from these MSAs as a whole, it is also the case that low-income population living in both large and small MSAs also saw housing cost exposure reduced by the suburbanization of demand, despite the fact that many of the small MSAs as a whole saw net *inflows* of demand.

In summary, migration during the pandemic has lowered job access for both high- and low-income populations, offsetting some of the massive gains in job market access provided by the strong adoption of WFH arrangements. But the change in job access due to migration was not a significant force that changed welfare *inequality*. On the other hand, migration did lower housing costs more for the low-income population. Thus, it did "undo" some of the welfare inequality through its differential effect on housing cost exposure. But the magnitude, while economically significant, is modest compared with the large increase in welfare inequality accrued over the past 30 years and the further welfare inequality created by the unequal adoption of WFH across income groups.

Our paper contributes to the growing body of research on the impact of COVID-19 on location demand. 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) also document that the demand for housing shifted toward smaller and cheaper MSAs during the pandemic. Ramani and Bloom (2021) use data from the US Postal Service and Zillow and find that, within large US cities, households, businesses, and real estate demand have moved from dense central business districts (CBDs) toward lower-density suburban zip codes. Haslag and Weagley (2021) document a similar pattern using micro-data from a moving company. Using the CCP, Whitaker (2021) also finds migration outflows from urban neighborhoods in 2020. Meeker and Mota (2021) reach the same conclusion after analyzing purchase mortgage applications. Besides the demand for residential locations, Rosenthal et al.

(2021) and Gupta et al. (2022a) demonstrate that, because of the prevalence of WFH, the value firms place on prime office locations and the price of office real estate declined significantly. Another closely related paper is Mondragon and Wieland (2022), which analyzes how WFH raised housing demand, holding migration *constant*. By contrast, we estimate *migration's* impact on housing costs.

On the theoretical front, Behrens et al. (2021), Davis et al. (2021), and Brueckner et al. (2023) develop models to explore the effect of WFH technology on labor market outcomes and city structure. Delventhal et al. (2021) develop a model that emphasizes on urban agglomeration and traffic externalities and evaluate the effect of the WFH shock. In particular, Delventhal and Parkhomenko (2021)'s model quantifies the spatial consequences of WFH shocks across the US due to the pandemic at a highly detailed geographic scale, echoing our paper. Our paper provides empirical tests for the model predictions on migration patterns, spatial changes in housing costs, and job access.

Our paper mirrors the pre-pandemic literature on how spatial sorting is an additional driver of welfare inequality on top of income inequality (Moretti, 2013; Diamond, 2016; Couture et al., 2021; Su, 2022). We provide extensive evidence of spatial sorting within and across MSAs during the pandemic and emphasize that such patterns sharply contrast with the well-documented pre-pandemic long-term trend. We show that the pandemic-era migration and sorting "reversed" the rise in inequality, albeit by a small magnitude.

The rest of the paper is structured as follows. Section 2 describes the data and carries out data validation. Section 3 documents the migration and spatial sorting patterns. Section 4 presents a simple spatial model. Section 5 analyzes welfare implications using the calibrated model. Section 6 concludes.

2 Data Source and Data Validation

2.1 Data Source

The main outcome variable regarding individual migration decisions comes from the FRBNY Consumer Credit Panel/Equifax data. Location characteristics at the census tract, zip code, county, and MSA levels are sourced 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 obtain home-price index and rental prices from CoreLogic Solutions (referred to as CoreLogic) and Zillow Research, the employment and wage data at the industry (NAICS) level from the Quarterly Census of Employment and Wages (QCEW), and the aggregate visiting patterns from geospatial data from Google

Mobility. We also use Burning Glass/Lightcast data to supplement wage information by industry and across locations.

2.1.1 Individual Locations and Migration Flows

We study the migration patterns using the FRBNY Consumer Credit Panel/Equifax data. The credit panel is a nationally representative 5 percent random anonymous sample of all individuals with a Social Security number and a credit report (aged 19 and over) drawn from Equifax credit report data. The data set is structured as a quarterly panel, beginning in 1999, with snapshots of consumers' credit profiles captured at the end of each quarter. It includes detailed information on the liability side of the individual, including various debt holdings and their respective payment status. The data set reports the location geocode information based on the address at which the individual receives bills. In the next subsection, we will validate this assumption using ACS data from the census.

For the main analysis, we restrict our attention to individuals between the ages of 25 and 65. We track these individuals from the first quarter (Q1) of 2018 to the second quarter (Q2) of 2022 and keep only those who are present in all quarters.

To construct the migration flows between census tracts, we first count, at each quarter and for each census tract, the number of individuals that left the census tract and the number of individuals that moved into the census tract. Then we divide the number of people that moved away by the initial number of people residing in the origin census tract to obtain the out-migration rate for the origin census tract, and we divide the number of people that moved in by the initial number of people residing in the destination census tract to obtain the in-migration rate for the destination census tract. The migration flows at the MSA and state levels are constructed using the same procedure.

2.1.2 Local Characteristics

We obtain local characteristics such as population density and income level from the 2013-2017 ACS summary tables through the NHGIS (Manson et al., 2020). The data come at the census tract, zip code, county, and MSA levels. For each census tract, we calculate the Euclidean distance to the closest downtown. We geocode all the downtowns using the output of Holian and Kahn (2015).

2.1.3 Telework Compatability

To compute the share of jobs that are telework compatible for each census tract, we rely on the spatial distribution of jobs by occupation and an assignment of telework compatibility for each occupation using a telework indicator developed by Dingel and Neiman (2020) and Su (2020).[3]

The procedure is as follows. We first estimate the share of jobs that are telework compatible at each zip code using data from the 2016 ZCBP. Because the ZCBP comes at the NAICS level, we use an industry-to-occupation crosswalk to impute the local job distribution for each occupation. Based on the spatial job distribution at the zip code and the telework indicator for each occupation, we then estimate the share of jobs within a 3-mile radius of each zip code that are telework compatible. The distance measure between zip codes comes from the zip code Tabulation Area (ZCTA) Distance Database available on the NBER website. Next, we assign to each census tract the closest zip code to construct the share of workers that are in telework-compatible occupations for each census tract.

Similarly, for each MSA, we first calculate the share of full-time workers aged between 25 and 65 in each occupation using the 2013-2017 ACS from the IPUMS (Ruggles et al., 2020). Then we combine the information with the telework indicator for each occupation and obtain the share of workers in telework-compatible occupations.

2.1.4 Local Employment Growth and Wages

We obtain county-level employment growth and wages from the QCEW. Specifically, we use the quarterly employment and wage data at the 2-digit NAICS level. Note that the wage data in the QCEW files are averaged over workers' earnings and, thus, suffer from biases caused by the time-varying composition of full-time and part-time workers and workers' hours input. These biases may not be trivial during labor market turbulence, especially during the pandemic. To ensure our welfare results are robust, we also use the Burning Glass/Lightcast job posting data to measure wage offerings by each industry in each county. The caveat with using wage information from job posting data is that the wages are advertised wages, which may exhibit much stronger temporal variation than wages of all workers, including workers who have not changed jobs.

[3]Dingel and Neiman (2020) and Su (2020) use O*NET occupation characteristics to evaluate each occupation's suitability for telework and assign a telework indicator to each occupation. We use the telework indicator developed by Dingel and Neiman (2020).

2.1.5 Local Housing Market

We obtain the growth of the home price index (HPI) by zip code and by county from the CoreLogic HPI data. The HPI provided by CoreLogic uses repeated sales transactions in the past to estimate the change in home prices within a geographic unit. We obtain rental price growth data from the Zillow Observed Rent Index (ZORI) released by Zillow Research, a repeat-rent index that is weighted to the rental housing stock to ensure representativeness across the entire market, not just those homes currently listed for rent. ZORI is a smoothed measure of the typical observed market rents in a given region. We obtain the pre-pandemic levels of rent and home value from the 2013-2017 ACS data.

For the remainder of the paper, we construct the housing cost using a unified approach of "rental" cost. We impute the implied owners' equivalent rent of each location by multiplying the reported home value by 0.0785 (Peiser and Smith, 1985; Diamond, 2016). We compute the growth of the rent cost of each location by weighting the Zillow rent growth and CoreLogic HPI growth by the share of renters and owners in each geographic location shown in the ACS data.

2.2 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.[4]

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?"[5] Figure 1 presents the population-weighted binned scatterplot of the in-migration rates from the two data sets. The two rates line up well, and the corre-

[4] 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.

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

lation coefficient is 0.75.[6]

3 Migration Patterns During COVID-19

3.1 Migration Out of Neighborhoods Near Urban Centers and Densely Populated MSAs

We begin our empirical analyses by documenting several prominent changes in migration patterns since the outbreak of the COVID-19 pandemic in March 2020. Using the micro data, we compute the net in-migration rate (net in-migration/destination tract's prior period population) over the 8-quarter period before and the 8-quarter period after the start of the pandemic (Q1 2018 – Q1 2020 vs. Q1 2020 – Q1 2022) by the neighborhoods' distance to city centers and report the results in Figure 2a. Before the pandemic started, neighborhoods near city centers already saw slightly more net outflow of people than the suburbs. After the pandemic outbreak, the net outflow increased significantly near city centers, while the suburbs saw an increased net inflow. Not surprisingly, people have also increased moves to neighborhoods with lower population density after the pandemic outbreak (Figure 2b), consistent with the existing evidence that we reviewed in the introduction.

In Figure 2c, we present the binned scatter plot of the net in-migration rate against the number of telework-compatible jobs within a 3-mile radius of each census tract. As seen there, neighborhoods with access to a large number of telework-compatible jobs saw a dramatic increase in population outflow after the pandemic. By contrast, neighborhoods with access to a small number of telework-compatible jobs saw a significant increase in population inflow. This observation reflects the availability of WFH options induced by the pandemic that allowed people to relocate far from the locations of their employers.

We next turn to net population flows across MSAs. In Figure 3, we plot the MSA-level net in-migration rate, pre- and post-pandemic, against the MSA population, the MSA population density, and the availability of telework-compatible jobs, respectively. Interestingly but not surprisingly, people have also been migrating toward smaller and less densely populated MSAs. Moreover, MSAs with a higher share of the population working in telework-compatible jobs also saw a larger population outflow, indicating that the option of WFH also induced migration out of the MSAs in which their employers are located.[7]

[6] 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.

[7] To give some examples of the direction people moved before and after the pandemic, we rank states based on the net in-migration during the 8 quarters before the pandemic and the 8 quarters after the pandemic started in Table A1. We see that states with

3.2 Migration Patterns: High-Income vs. Low-Income Populations

To analyze the differential migration patterns by income, we follow Coibion et al. (2020) and impute income for individuals in the FRBNY CCP/Equifax using information from the Survey of Consumer Finances (SCF). The SCF contains information on debt balances and income as well as demographic characteristics, many of which we also observe in the FRBNY CCP/Equifax data. We use the 2019 SCF to estimate how income relates to debt and demographic characteristics available in both the FRBNY CCP/Equifax and SCF data. We then use the estimates to impute income for each individual in the FRBNY CCP/Equifax data in the fourth quarter of 2019. Appendix A describes in detail the estimation and imputation procedure and the results.

As a validation exercise, we compare our imputed income with the observed income in the HMDA-McDash-CRISM Database. HMDA-McDash-CRISM is an anonymized match of the CCP data with the mortgage loan service data, the Black Knight McDash (referred to as McDash) data, and the confidential Home Mortgage Disclosure Act (HMDA) data.[8] Our imputed log income has a correlation coefficient with the observed log income of 0.51. In Figure A1, we provide the binned scatterplot of the two variables. We see that the two variables have a nearly linear relationship, with a slope close to 1. This indicates that our imputed income measure is a reasonably good indicator of an individual's actual income.

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

3.2.1 Differential Migration Patterns by Income Across Neighborhoods

Starting with neighborhoods, in Figure 4, we present the binned scatterplots of net in-migration rates across census tracts by income against the tract's distance to downtown, its population density, and the number of telework-compatible jobs within a 3-mile radius of the tract, respectively. We see that, since the outbreak of

lower-density cities, such as Florida and Texas, saw a spike in net in-migration after the outbreak of the pandemic, while states with high population density, such as California and New York, saw a considerable uptick in net out-migration. The same patterns can be seen in Table A2, where we show the top MSAs in terms of net in- and out-migration before and after the start of the pandemic. To provide a more detailed look at the changing direction of migration during the pandemic, we report the largest state-to-state and MSA-to-MSA direction of net migration in Tables A3 and A4. We see that flows from states with more densely populated cities to states with less densely populated cities, such as from New York to Florida and from California to Texas, accelerated during the pandemic. And flows from large and high-density metros to smaller and lower-density metros became more prevalent.

[8] CRISM is short for Equifax Credit Risk Insight Servicing McDash. The HMDA-McDash-CRISM match is conducted by the Federal Reserve System's Risk Assessment, Data Analysis, and Research (RADAR) Group using the following logic: 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.

the pandemic, both high-income and low-income individuals have been moving away from neighborhoods close to city centers, neighborhoods with high population density, and neighborhoods close to a large number of telework-compatible jobs into neighborhoods farther away from city centers, neighborhoods with lower population density, and neighborhoods remote from telework-compatible jobs. However, high-income people are much more likely to have made a move in these directions than low-income people.

To further investigate the heterogeneous migration patterns, we explore the panel nature of the CCP data and calculate the average changes in various location characteristics such as population, population density, and share of jobs that are telework-compatible between the neighborhoods an individual lives in during the current quarter and the neighborhoods he/she resided in during the previous quarter. The average changes are depicted in Figure 5 for the period Q1 of 2019 to Q2 of 2022. Before the pandemic, both high-income and low-income individuals were moving to the suburbs but at a very slow pace, and there was little difference between the two groups. After the pandemic started in Q2 of 2020, however, high-income individuals picked up the pace of suburbanization sharply, while their low-income counterparts only moderately increased their pace. We observe similar differences in migration patterns between the two groups in the changes in the density of the neighborhoods they live. The most striking difference in migration patterns between the two groups is by telework-compatible jobs, consistent with the evidence that WFH arrangements are much more available to high-income workers (Bartik et al., 2020; Bick et al., 2021). After the outbreak of the pandemic, these options have allowed them to move away from job centers more easily.

3.2.2 Differential Migration Patterns by Income across MSAs

We now turn to migration patterns by income across MSAs. Figure 6 shows the net in-migration rate by MSA against the MSA's population, population density, and share of telework-compatible jobs, respectively. Since the pandemic, both high-income and the low-income individuals have moved away from large MSAs, MSAs with dense populations, and MSAs with large shares of telework-compatible jobs into smaller MSAs, MSAs with less dense populations, and MSAs with smaller shares of telework-compatible jobs; compared with low income individuals, high income individuals are much more likely to have moved in such directions.

As in the case of census tracts, we track each person and calculate the quarter-specific mean differences in the characteristics of the MSAs in which they live in the current quarter relative to the characteristics of the MSAs in which they lived in the previous quarter. Figure 7 demonstrates that both high- and low-income individuals began to move to smaller cities, less densely populated cities, and cities with a smaller share of telework-compatible jobs immediately after the outbreak of the pandemic in Q2 2020; but the pattern is much stronger for the high-income individuals than for the low-income individuals. Unlike the cross-neighborhood migration, cross-MSA migration toward low-density areas has continued even after the pandemic peaked.

In Appendix B, we discuss migration patterns by income quintiles, and by income and mortgage status. Our results are more pronounced when we compare individuals at the top income quintile with individuals at the bottom income quintile but are not affected significantly by age or mortgage status.

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

As people move, they take their demand for housing and local goods and services. The migration pattern we have documented will then lead to spatial differences in housing cost and labor market outcomes such as wage and job growth between locations people are leaving and locations people are moving to.

3.3.1 Housing Costs

Figure 8a reports changes in log housing cost at the census tract level against the census tracts' distance to downtown. We do so for two periods separately, both starting from Q1 of 2020. The first period extends to Q1 of 2021, which represents the first year of the pandemic. The second period extends to Q1 of 2022, which represents the first two years of the pandemic. We see that growth in housing cost was much more robust in suburban neighborhoods than in central city neighborhoods during the first year and the first two years of the pandemic. Moreover, the growth was faster in the second year of the pandemic than it was in the first year, as indicated by the much higher level of the red line than the blue line in the figure. Importantly, the differential growth in housing cost across neighborhoods by distance to downtown did not moderate in the second year, as the slope of the binned scatter plot over the two-year horizon did not flatten compared to the one-year horizon.

In Figure 8b, we plot changes in log housing cost at the MSA level against MSAs' population density for the same two periods. Similar observations emerge. MSAs with lower population density experienced much faster growth in housing cost than MSAs with higher population density; all MSAs experienced faster growth in housing cost in the second year of the pandemic than in the first year (the overall level of growth in the first two years is much higher than the growth in the first year); and the differences in housing cost growth across MSAs with heterogeneous population density remain large over the two years of the pandemic.

3.3.2 Demand for Local Services

To study how demand for local goods and services varies across locations during the pandemic, we turn to the Google Mobility Index. Using anonymized data, Google has produced a regularly updated dataset that records peoples' visits to specific categories of locations (e.g., grocery stores, parks, and train stations) throughout the pandemic. Figure 9 plots changes in the mobility indexes to retail and recreation locations and the mobility indexes to grocery stores and pharmacies, respectively, across counties from the baseline date defined as the median value from the 5 weeks during Jan 3 – Feb 6, 2020 (denoted as Q1 2020) against county population density. Similar to the housing cost analysis, we analyze two periods: the first year of the pandemic, Q1 2020 to Q1 2021, and the first two years of the pandemic, Q1 2020 to Q1 2022.

The first notable feature of the plots is that growth in visits to these local service venues is much larger in counties with low population density than in counties with high population density for both sample periods. In the first year of the pandemic, not surprisingly, visits were below the levels before the pandemic for all counties because of the nationwide restrictions on interactive activities in the wake of the pandemic (Liu and Su, 2021). But the decline in visits was much milder in low-density counties than in high-density counties.

By the second year of the pandemic, activities began to recover. The relation between the growth in visits and the density of the county, however, was unchanged. Low-density counties had much faster growth in visits than high-density counties. Notably, in low-density counties, the number of visits to local service venues was much higher than its pre-pandemic level. By contrast, in the high-density counties, the number of visits remained below its pre-pandemic level.[9]

Changes in overall activities in an area are driven by changes in the per-person intensity of visits in the area and by changes in the number of local residents. Under the reasonable assumption that the per-person intensity of visits to restaurants, grocery stores, and recreation activities did not increase substantially in the low-density counties during the pandemic, the sharp increase in these activities in local service venues reflects the increase in local residents and the increase in demand for local goods and services. We investigate this hypothesis formally in section 3.3.5.

[9]Relihan et al. (2022) document similar spatial patterns of changing demand for brick-and-mortar retail establishments using credit card data from a major US banking institution.

3.3.3 Employment

Changes in demand for local goods and services directly impact the local labor market, especially the sectors pertaining to local services. In Figure 10, we chart changes in county-level log employment in the local service sector and in the professional service sector, separately, against county population density. The service sector consists of nontradable services such as restaurants, retail, and construction industries. The professional service sector consists of highly skilled sectors such as the financial and legal industries.[10]

There exists a strong spatial relationship between local employment losses/gains in the local service sector and county population density, in line with the spatial pattern of the growth in visits to local service venues. While all areas of the nation experienced reduced employment growth in services, counties with high population density experienced a much larger decline in employment in services than counties with low population density. This is consistent with the spatial difference in the change in demand for local goods and services.

By contrast, the professional service sector did not see much spatial shift in job growth during this time. This is likely because a much higher percentage of professional service workers can work remotely than regular service workers. Even though many high-income people move their residence to lower-density locations, their *job* locations (based on firms' locations) need not move with them. Additionally, their line of work is not sensitive to local demand as a substantial fraction of workers in professional services provide tradable services used by consumers beyond local markets (Eckert, 2019).

3.3.4 Wages

As labor demand shifts spatially, a wage gap could potentially emerge across space as well. To examine this possibility, we first turn to the average quarterly earnings reported in the QCEW data. Figures 11a and 11b plot log wage (earnings) growths between Q1 2020 and Q1 2021 and between Q1 2020 and Q1 2022 of local service jobs and professional service jobs against county population density, respectively. There do not appear to be any strong or consistent patterns. We next turn to the Burning Glass/Lightcast data for the posted hourly wages across locations. Figures 11c and 11d plot log posted wage growth between the pooled years of 2018 and 2019 and the pooled years of 2020 (starting in April), 2021, and 2022 (the first three months). Among the local service jobs, wage growth is slightly higher in low-density counties, while professional service jobs did not see strong patterns with respect to county-level density. These results are consistent with Liu and Su

[10] Local service industries/sectors include NAICS sectors 23 (construction), 42 (wholesale trade), 44-45 (retail trade), and 72 (accommodation and food services). Professional service industries/sectors include NAICS sectors 51 (information), 52 (finance and insurance), and 54 (professional, scientific, and technical services).

(2022), where they show that the urban wage premium between the high- and low-skilled jobs on average did not change much since the pandemic. It is only the occupations in which WFH adoption was very high that saw the urban wage premium decrease significantly. The job postings data, while a reasonable source for robustness checks, do not capture the overall wage levels over time because posted wage levels do not reflect the wage levels of workers who do not switch jobs. In our welfare analysis, we therefore use the county-level wage measurement in the QCEW data.

3.3.5 Role of Migration

The figures we have shown so far demonstrate strong correlations between changes in various local economic statistics and location characteristics such as distance to downtown, population, or population density. In this section, we conduct regression analyses to further illustrate that these spatial differences in housing cost growth, service demand, and job growth are closely related to the directions of migration over the pandemic.

Table 1 presents the results of regressing the growth of housing cost on the net log high- and low-income in-migration flows over two different time horizons: Q1 2020 to Q1 2021 and Q1 2020 to Q1 2022. Across the two periods, the growth of local housing costs is strongly associated with the net in-migration of both high- and low-income populations, particularly the net in-migration of the high-income population.

Table 2 reports the results of regressing the change in the Google Mobility indexes on the net log high- and low-income in-migration flows over the same two horizons. Both the retail index and the recreation and grocery index grew faster in localities with stronger net in-migration of high- and low-income people during both periods. Importantly, the growth in both indexes is more positively associated with the net in-migration of high-income individuals than with the net in-migration of low-income individuals.

Table 3 presents the results of regressing changes in log employment of the local service sector and the professional service sector, respectively. Counties with more net in-migration of high-income people had higher employment growth in both sectors, and, as expected, the effects were stronger for the local service sector job growth. Counties with more net inflows of low-income individuals also had faster job growth in the local service sector, but the relationship is more significant over the first year of the pandemic than over the first two years.[11]

Finally, we regress changes in log wage on migration and report the results in Table 4. The relationships

[11]Interestingly, counties with net inflows of low-income individuals also had higher professional employment growth in the professional service sector, but the relationship is barely significant and limited to the first year of the pandemic.

are largely statistically insignificant, consistent with the patterns illustrated in Figure 11.

4 A Spatial Model of Workers' Welfare

Having documented the migration patterns and the associated equilibrium responses in the local housing market and the local labor market during the pandemic, we present a simple spatial model that captures these migration patterns to analyze the welfare implications of these changes. In the welfare calculations, we allow location-specific features such as the cost of housing and local market access to jobs to affect the well-being of each population group based on where people live. This setup lets us quantitatively decompose how migration affects high- and low-income population groups differently.

4.1 Workers' Utility

Let t denote time; j city; l neighborhood; k individual type, which can be H or L; and m work mode, which can be fully remote work, hybrid, or fully onsite. Since each neighborhood l belongs to a specific city, we use $j(l)$ to denote a neighborhood l in city j. To the worker, each location is characterized by the amenity level $A^k_{j(l)t}$ and the rent price $R_{j(l)t}$. Conditional on living in residential location $j(l)$, the workers of group k and work mode m face a set of jobs $O^{k,m}_t$, each of which is indexed by job o and a location $j'(l')$, and characterized by the wage offered by the job o, $W_{oj'(l')t}$, and the cost of commuting time from where the worker of type k lives and where job o at time t is located, $d^{k,m}_{j(l)j'(l')t}$.[12]

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

$$U^{k,m}_{ij(l)oj'(l')t} = \frac{A^k_{j(l)t} W_{oj'(l')t}}{R^{1-\beta^k}_{j(l)t} \, d^{k,m}_{j(l)j'(l')t}} \exp(\kappa_{ij(l)t} + \epsilon_{iot}).$$

The term β^k is the preference weight on nonhousing consumption, and $\kappa_{ij(l)t}$ is the idiosyncratic preference draw for the residential neighborhood, which captures factors that affect people's choice of residential locations other than amenities, rent, and job opportunities. ϵ_{iot} is each worker's idiosyncratic preference draw for job o, capturing factors that affect people's choice of workplace other than wages and commuting cost. We

[12]The term can also be generalized as the cost of taking up the job. For onsite job or hybrid jobs, this term represents the expected cost of commuting. For fully remote workers, this term could be understood as the cost of working at home (equipment, extra home space, coordination, etc.).

assume ϵ_{iot} is distributed as a Type-I Extreme Value Distributed random variable scaled by $1/\theta$.[13]

Based on the property of the Type-I Extreme Value Distribution, the expected utility of worker i living in location $j(l)$ at time t (before the realization of his job preference draw) is as follows:

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

which is a function of local amenity, rent, and local residents' access to jobs. The term $\sum_{o \in O_t^{k,m}} \left(\frac{W_{oj'(l')t}}{d_{j(l)j'(l')t}^{k,m}} \right)^{\theta}$ is identical to the market access term featured in, among others, Donaldson (2018) and Tsivanidis (2022). If a local labor market is losing jobs, the local residents' utility will decline, and vice versa. The parameter θ governs the sensitivity of local residents' welfare to changing wages and access to jobs. We define $\Phi_{j(l)t}^{k,m} = \ln \left(\sum_{o \in O_t^{k,m}} \left(\frac{W_{oj'(l')t}}{d_{j(l)j'(l')t}^{k,m}} \right)^{\theta} \right)$ as the job access for workers of type k, mode m living in $j(l)$ at time t.

Commuting time from residential neighborhood $j(l)$ to work location $j'(l')$ can be written as:

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

The parameter $\rho_t^{k,m}$ is the frequency at which workers of type k and work mode m work from home at time t, $\phi^{k,m}$ is the utility cost of working at home in the equivalent unit of commuting time, and $\tilde{d}_{j(l)j'(l')t}$ is the actual travel time between $j(l)$ and $j'(l')$. $d_{j(l)j'(l')t}^{k,m}$ thus captures the expected commuting time to jobs from home. Note that for onsite workers, $\rho_t^{k,onsite} = 0$, and therefore, $d_{j(l)j'(l')t}^{k,m} = \tilde{d}_{j(l)j'(l')t}$. For fully remote workers, $d_{j(l)j'(l')t}^{k,m} = \phi^{k,remote}$, namely the "cost of commuting" equals the cost of working at home fully (equipment, extra home space, coordination, etc.).

4.2 Fully Remote, Hybrid, and Onsite

We assume that the fractions of fully remote, hybrid, and onsite workers, $\lambda_t^{k,m}$, are exogenously given in each period. Furthermore, we assume that fully remote workers only have access to fully remote jobs, and hybrid workers only have access to hybrid jobs, and onsite workers only have access to onsite jobs. In other words, the job choice set that workers of mode m have access to, $O_t^{k,m}$, is $\lambda_t^{k,m}$ times all jobs contained in overall

[13] The term $1/\theta$ is thus the standard deviation of the idiosyncratic preference draw. We can consider θ as the relative importance of the observable wages and commuting cost in driving people's choice of jobs.

job choice set O_t^k. Hence, the job access terms for these three types of workers can be written as follows:

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

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

$$\Phi_{j(l)t}^{k,onsite} = \ln\left(\sum_{o\in O_t^k} (1-\lambda_t^{k,remote}-\lambda_t^{k,hybrid})\left(\frac{W_{oj'(l')t}}{d_{j(l)j'(l')}}\right)^{\theta}\right).$$

The average job access for workers of type k living in $j(l)$ at time t is then:

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

The parameters are largely calibrated from prior estimates in the recent empirical literature. These include the preference scaling factor θ, housing expenditure share β_k, the prevalence of WFH arrangements before and after the pandemic $\lambda_t^{k,m}$, the frequency of WFH among hybrid workers before and after the pandemic $\rho_t^{k,hybrid}$, and the cost of remote work for fully remote workers and hybrid workers $\phi^{k,m}$. The parameter calibration for the model is shown in Table 8.

4.3 Migration's Effect on Labor Market Access

As defined above, workers living in each location face a location-specific set of jobs. In light of the empirical evidence presented earlier, we allow each location's job availability and wages to be influenced by migration. Specifically, we assume that the log wage and log number of jobs at location $j(l)$ are determined as follows:

$$w_{j(l)t}^{k} = \iota_{wt}^{k} + \xi_y^{wk} y_{j(l)t} + \zeta_{j(l)t}^{wk}, \;\; k = H, L, \tag{1}$$

$$\ln N_{j(l)t}^{k} = \iota_{nt}^{k} + \xi_y^{nk} y_{j(l)t} + \zeta_{j(l)t}^{nk}, \;\; k = H, L, \tag{2}$$

where $w_{j(l)t}^{k}$ is the log wage and $\ln N_{j(l)t}^{k}$ is the log number of the k type jobs located at $j(l)$ at time t. $y_{j(l)}$ denotes the log aggregate income in neighborhood $j(l)$. As people move out of location $j(l)$, aggregate income $y_{j(l)}$ will decrease accordingly. We define aggregate income as the number of high-income people in

$j(l)$ times the average income of high-income people plus the number of low-income people in $j(l)$ times the average income of low-income people. The above two equations thus illustrate how local wages and labor demand are determined by local demand for goods and services.

4.4 Migration's Effect on Housing Supply

Housing is supplied according to an inverse supply equation. Since people spend a fraction of their income on housing expenditure, we let the log aggregate income of residents in each location track the local housing demand. We assume that log rents respond to local housing demand in each location $j(l)$, which is proxied by the local log aggregate income $y_{j(l)t}$, as follows:

$$r_{j(l)t} = \alpha_{rt} + \psi_{j(l)} y_{j(l)t} + \eta_{j(l)t}. \tag{3}$$

The inverse elasticity of housing supply, $\psi_{j(l)}$, can vary with location. In our empirical analysis, we allow it to differ by the Wharton Residential Land Use Regulation Index (WRLURI) (Gyourko et al., 2019), the fraction of area within a 50-mile radius of an MSA downtown that is unavailable for development (Saiz, 2010), and the neighborhood's distance to downtown.

4.5 Welfare Impact of Pandemic-Era Spatial Sorting

With the utility setup and the observed location-specific changes in rent, wage, and employment, we can calculate welfare changes separately for high-income and low-income populations stemming from migration over the pandemic. We log-transform the utility and arrive at the mean expected utility for group k as follows:

$$E_{kt}(U^k_{ij(l)t}) = E_{kt} a^k_{j(t)t} + E_{kt} \Phi^k_{j(l)t} - \theta(1 - \beta^k) E_{kt} r_{j(l)t} + E_{kt} \kappa_{ij(l)t}, \tag{4}$$

where lower-case letters indicate the log of the upper-case letter variables. From the equation, we see that the average well-being of each group increases with the group's average exposure to amenities and the average job market access and decreases with the average exposure to local rents. How much rents reduce well-being depends on $1 - \beta^k$, the group-specific budget share of the housing expenditure and the size of θ, the scaling factor.

To compute the change in well-being inequality between group types, we take the first difference of the welfare equation:

$$\Delta E_{kt}(U^k_{ij(l)t}) = \Delta E_{kt} a^k_{j(t)t} + \Delta E_{kt}\Phi^k_{j(l)t} - \theta(1-\beta^k)\Delta E_{kt} r_{j(l)t} + \Delta E_{kt}\kappa_{ij(l)t}. \tag{5}$$

The welfare inequality depends on changes in the average exposure of each population group k to the following two observable objects: job access $\Phi^k_{j(l)t}$, which is a function of the spatial distribution of jobs, their associated wages $w^k_{oj(l)t}$, where $o \in O^k_t$, the cost of commuting matrix $d^{k,m}_{j(l)j'(l')t}$, and fractions of work modes $\lambda^{k,m}_t$; and local rents $r_{j(l)t}$. There are also two unobservable objects: amenities $a^k_{j(t)t}$ and idiosyncratic preference shifter $\kappa_{ij(l)t}$. We focus on how migration affects the two observable objects: job market access and rent.

Changes in O^k_t, $w^k_{oj(l)t}$, $d^{k,m}_{j(l)j'(l')t}$, and $\lambda^{k,m}_t$ jointly affect the job market access term $\Phi^k_{j(l)t}$ as follows:

1. The rise in the prevalence of WFH means that both the fraction of people working fully remote and hybrid increased and that the commuting matrix $d^{k,m}_{j(l)j'(l')t}$ for hybrid workers shortens due to the rise in $\rho^{k,m}_t$. The increase in fully remote and hybrid modes was especially pronounced for high-income workers, implying that workers, especially high-income workers, would have a significant improvement in market access to jobs.

2. The spatial changes in wages directly affect wages of workers working in a specific location. Workers living in $j(l)$ are affected more by wage changes of jobs closer by (i.e., jobs with a short commuting time from $j(l)$) than by wage changes of jobs far away.

3. The spatial movement of jobs affects workers' job market access. Spatial movement of jobs into the suburbs and small cities means that workers, especially low-income workers who still predominantly commute to their onsite workplace, living in suburban neighborhoods or neighborhoods in small cities may experience a rise in their job market access, while low-income workers in central-city neighborhoods in large cities may experience a decline in job market access.

For the rest of the paper, we analyze how migration affected $\Phi^k_{j(l)t}$ and $r_{j(l)t}$ and evaluate how migration and the endogenously changing $\Phi^k_{j(l)t}$ and $r_{j(l)t}$ jointly impact the welfare of high- and low-income populations.

5 Model Estimation and Welfare Analyses

5.1 Estimating Local Rent, Wage, and Employment Responses to Migration

To evaluate how migration impacted local rents and job market access faced by workers living in each location, we estimate first differences of rent, wage, and job numbers as functions of local aggregate income as follows:

$$\Delta r_{j(l)t} = \Delta\alpha_r + \psi_r^{j(l)} \Delta y_{j(l)t} + \Delta\eta_{j(l)t}, \tag{6}$$

$$\Delta w^k_{j(l)t} = \Delta\iota^k_{wt} + \xi^{wk}_y \Delta y_{j(l)t} + \Delta\zeta^{wk}_{j(l)t}, \ \ k = H, L, \tag{7}$$

$$\Delta \ln N^k_{j(l)t} = \Delta\iota^k_{nt} + \xi^{nk}_y \Delta y_{j(l)t} + \Delta\zeta^{nk}_{j(l)t}, \ \ k = H, L, \tag{8}$$

where $\psi_r^{j(l)}$, ξ^{wk}_y, and ξ^{nk}_y govern how net migration of local spending power affects local rent, wages offered by local employers, and the number of local jobs available at location $j(l)$, respectively. With these estimates, we first calculate how much the observed changes in rent, wages, and job distribution are driven by migration. Then, using the migration-driven changes in wages and job distribution, we compute the migration-driven change in commuter job market access $\Phi^k_{j(l)t}$ for $k \in \{H, L\}$.

5.1.1 IV Estimation

The standard ordinary least square (OLS) estimation of the effect of the shift in local income on local rent, wages, and employment is subject to endogeneity concerns. For example, an exogenous housing supply expansion shock in neighborhood $j(l)$ could have both reduced rents and led to an aggregate migration flow into $j(l)$, raising its aggregate income level. Not accounting for this endogeneity will lead to a downward bias in the estimate of $\psi_r^{j(l)}$. For the labor market, an exogenous productivity increase in location $j(l)$ will lead to a rise in wages and in labor demand, driving up in-migration and resulting in an increase in aggregate income. This, in turn, will lead to an upward bias in the estimates for ξ^{wk}_y and ξ^{nk}_y.

To correct for these biases and to isolate the causal effect of local aggregate income changes stemming from migration on local rents, wages, and employment, we employ an instrumental variable (IV) approach. In other words, we instrument for the changes in local aggregate income using variables uncorrelated with the unobserved housing supply shocks and local productivity shocks by exploiting the fact that the availability of telework enabled many workers to out-migrate from locations with previously convenient access to their job locations. Specifically, we first compute, for each MSA and for high- and low-income populations, respectively, the shares of the population who work in telework-compatible jobs based on pre-pandemic data. Then, for each county, we calculate the number of telework-compatible jobs within 3 miles of the neighborhoods where people live. Last, we interact the group-specific share of telework-compatible jobs at the MSA level with each county's average number of telework-compatible jobs located close (within 3 miles) to residents. We use the interactive IVs to provide exogenous variation that shifts the change in local aggregate income at the county level during the pandemic. The identification assumption here is that the spatial variation in the telework intensity of local employment can predict how much out-migration there is for each population group but is uncorrelated with the unobserved pandemic-era shifts in local housing supply or local productivity factors that shift local wages and employment demand in the absence of WFH shock.

Table 6 presents our estimation results on the effect of local aggregate income on rent for high- and low-skilled workers, respectively, using the changes over the 4 quarters between Q1 2020 and Q1 2021. Table 7 presents the estimates of the same equations over the 8 quarters between Q1 2020 and Q1 2022. We see that the effect of local aggregate income on rent remains robust at two different horizons. We also see that the impact of local aggregate income on rent is much larger in cities where land use is more regulated and where lands are more topographically constrained. At the neighborhood level, rent responses are larger in neighborhoods closer to downtown. The spatial difference in rent responses is largely consistent with the findings in Baum-Snow and Han (2021).[14] To summarize, in response to migration, housing costs responded much less in locations where the housing supply is more elastic.

Turning to the labor market, migration affects both local service employment and professional service employment, but the effect is much bigger on local service employment than on professional service employment. By contrast, migration didn't affect wages statistically significantly for either local service or professional service jobs. The strong effect for local service job employment and the lack of statistically significant effects on wages are consistent with the spatial patterns documented earlier in the paper.

With estimates of $\psi_r^{j(l)}$, ξ_y^{uk}, and ξ_n^{uk} ($k = L, H$), we can now calculate the rent, wages, and employment growth due to local net migration as follows:

$$\Delta \hat{r}_{j(l)t} = \hat{\psi}_r^{j(l)} \Delta y_{j(l)t}, \tag{9}$$

[14]We did not directly apply the housing supply estimates in Baum-Snow and Han (2021) because their estimates focus on a 5- or 10-year time horizon. Our approach captures the geographic variation in housing supply elasticities in a more reduced-form way.

$$\Delta \hat{w}^k_{j(l)t} = \hat{\xi}^{wk}_y \Delta y_{j(l)t}, \;\; k = H, L, \tag{10}$$

$$\widehat{\Delta \ln N^k}_{j(l)t} = \hat{\xi}^{nk}_y \Delta y_{j(l)t}, \;\; k = H, L. \tag{11}$$

5.2 Empirical Welfare Decomposition

We now examine the impact of migration and spatial sorting on the welfare of high- and low-income populations and the implications on welfare inequality. We focus on the two channels our paper has studied so far: the spatial changes in job access and housing cost.

5.2.1 The Effect of WFH on Job Access

As a first step, we introduce a WFH shock that affects job access to account for the fact that the WFH arrangements were widely adopted since the outbreak of the pandemic. Specifically, we compute the change in job access $\Delta\Phi^k_{j(l)t}$ by allowing $\lambda^{k,m}_t$ to adjust and $d^{k,m}_{j(l)j'(l')t}$ to change because of the adjustment of $\rho^{k,m}_t$, while holding the spatial distribution of jobs and wages at their respective Q1 2020 levels. In other words, we let the model adapt under the new WFH regime but hold the job distribution constant. We do this for high- and low-income workers, separately, over the two years between Q1 2020 and Q1 2022. The calibration of the model parameters are described in Table 8.

The blue bars in Figure 12 present the effect of WFH on job accesses for the two groups of workers, as measured in the log-wage-equivalent welfare unit. Figure 12a shows the effect in the national sample. Figures 12b-12e show the effect in the star cities (New York, Los Angeles, and San Francisco), the largest 25 cities except for the star cities, cities ranked between 26th and 100th, and cities ranked below 100th, respectively. The rise in WFH greatly improved job access for both high- and low-income workers. But because the increase in WFH prevalence is much higher among high-income workers than among low-income workers, the welfare improvement due to increased job access was much larger for high-income people than for low-income people, substantially widening welfare inequality. This result suggests that the different degrees of WFH availability were a major factor driving welfare inequality during the pandemic.

Furthermore, the improvement in job access due to the rise in WFH was considerably larger in small cities than in large cities. This result was largely due to the increase in the prevalence of fully remote work arrangements. For fully remote workers, the cost of working for jobs anywhere is constant and location invariant. Workers living in locations that were previously remote from major job centers would suddenly gain access to jobs as a result of the ability to work remotely, while workers living in locations already close to job centers gained substantially less in job access.[15] The larger gain in job access in small cities as a result of the rise in fully remote adoption is consistent with the migration wave from large cities to small cities.

Potential Bias for the Impact of WFH on Job Access We have so far assumed that there does not exist unobserved spatial heterogeneity in job types and spatial correlations between those types. This is obviously a simplifying assumption. For workers with jobs in Silicon Valley, as an example, it is likely that fully remote work does not enable them to access all jobs in their skill category. Instead, it is likely that jobs that become available to them because WFH are geographically correlated. Put it simply, the types of jobs becoming available to a worker who lives or works in Silicon Valley may be disproportionately in Silicon Valley anyway. If such unobserved heterogeneity in job types and match value to workers are spatially correlated, our exercise may overstate the benefit from WFH on job access. The bias may be particularly strong among high-income workers if we believe that high-skilled jobs exhibit stronger spatial specificity.[16]

5.2.2 The Effect of Migration on Job Access

Given the WFH adjustment built into the model, we next assess the effect of migration during the pandemic on job access. Namely, in addition to adjusting $\lambda_t^{k,m}$ and $\rho_t^{k,m}$, we also allow the number of jobs in each county and wage offered in each county to adjust based on the changes predicted by observed migration: $\hat{r}_{j(l)t}$, $\hat{w}^k_{j(l)t}$, and $\hat{N}^k_{j(l)t}$, and recalculate $\Delta\Phi^k_{j(l)t}$ using these predicted values.

The red bars in Figure 12 present the results. The comparison between the red bars and blue bars informs us on the effect of migration on job access. We see that both high-income workers and low-income workers in the national sample saw a negative overall effect of migration on job access.

Migration affects low-income workers' job access via two margins: First, movement from large cities to small cities shifted the demand for goods and services to small cities, and small cities tend to have more

[15] The increased prevalence of hybrid work and the increase in the frequency of WFH among hybrid workers also contributed to the increase in job access. However, for hybrid workers, access to jobs increased more in large cities, particularly in the suburbs of large cities, than in small cities. This is because hybrid workers still need to commute to work, although much less than onsite workers. The lowered but non-zero commuting cost will make jobs within a reasonable distance much more accessible, and thereby raise the job access for workers living in suburbs of large cities, which are reasonably close to job centers. However, for workers living in small cities away from major job centers, the cost of commuting to jobs thousands of miles away is still prohibitively high and thereby limits the extent of job access improvement.

[16] Another source of bias in the welfare result comes from the wage effect of WFH. In the cases of WFH raising or reducing the wages that workers receive or inducing lower wages because of its compensating differential, the wages received by workers who WFH may be different from workers who work onsite. If WFH lowers wages, then the option of WFH may not raise welfare as much as shown in our results because of the mitigating effect of WFH on wages. Unfortunately, the data we use do not allow us to distinguish wages by WFH arrangement.

low-income workers than larger cities. As a result, the cross-metro migration should bring jobs to the average low-income worker.

This positive effect, however, is entirely offset by the second margin, that is, the migration wave toward higher-income suburbs. Suburbanization during the pandemic brought local service jobs to the suburbs.[17] Since low-income people disproportionately live in city centers, the exodus of labor demand from neighborhoods where low-income people tend to live led to a large negative effect on job access. Even in small cities, migration still reduced job access for the average low-income resident. Put simply, within the MSAs where local service job growth outpaced the nation because of large net inflow of people, these local service jobs were created away from the urban locations where low-income workers disproportionately live. The reduction in high-income workers' job access comes entirely from their movement away from large cities and centrally located neighborhoods with more job access and the fact that not all of their jobs can be done entirely remotely.

5.2.3 The Effect of Migration on Housing Cost

Turning to the effect of migration on housing cost exposures, we analyze tract-level rent growth induced by migration computed in the previous section, along with observed migration by high- and low-income populations at the tract level.

The green bars in Figure 12a depict the effects of migration on the growth of log rent exposure by high- and low-income groups, measured in welfare equivalent log wage unit. We see that migration reduced the rent exposure by both high- and low-income groups. Notably, the mitigating effect is larger on the rent growth experienced by the low-income population than that experienced by the high-income population. These calculations indicate that pandemic-era migration has improved the welfare of both high- and low-income populations through its negative effect on rent growth and has mitigated the welfare inequality between the groups through the change in housing cost exposure.

It may seem counter-intuitive that migration during the pandemic can reduce overall rent exposure, especially with Mondragon and Wieland (2022)'s finding that the rapid adoption of WFH and the increased demand for space during the pandemic likely raised housing demand and housing costs.[18] The crucial difference between our result and theirs is that they analyze the effect of WFH on housing demand, *controlling*

[17]See Table 5 for the regression results, which show both high- and low-income populations were moving to higher-income neighborhoods within cities and to lower-income cities.

[18]The increased cost of working at home, including the cost of acquiring more space, is included in the calibration of $\phi^{k,m}$.

for the effect of migration, whereas we focus on the effect of *migration* on housing costs. The reason migration reduced the overall housing cost exposure is that both high- and low-income population groups were, on net, migrating toward neighborhoods and MSAs with a *higher* housing supply elasticity. As people move from low-supply-elasticity localities to high-supply-elasticity localities, the alleviation in housing cost in the origination localities due to the outgoing demand is larger than the increases in housing cost in destination localities due to the incoming demand. Since housing demand was surging nationally, most local housing markets were likely on the upward-sloping portion of the housing supply curves (Glaeser and Gyourko, 2005). Hence, on aggregate, the reduction in rents from out-migration is not fully offset by the increase in rents due to in-migration. This leads to a net negative effect of migration on rent exposure by both population groups.

The larger negative effect on rent exposure for the *low-income* population was driven by the fact that the cross-neighborhood migration during the pandemic disproportionately pulled housing demand away from neighborhoods predominantly inhabited by the low-income population. Consequently, the lowered rents in those neighborhoods disproportionately reduced rents faced by the average low-income person. In Table 5, columns 1 and 2, we regress net in-migration rates on the census tract-level initial income. We see that, controlling for the MSA fixed effects, both high- and low-income people migrated away from low-income neighborhoods and toward higher-income neighborhoods during the pandemic. This phenomenon is consistent with the so-called de-gentrification documented in Ding and Hwang (2022).

In columns 3 and 4, we regress net in-migration rates on the MSA-level initial income. In contrast with columns 1 and 2, we see that now the coefficients turn negative, indicating that people were largely moving from higher-income MSAs toward lower-income MSAs. Hence, while the cross-neighborhood movement had contributed to a stronger mitigating effect on rent exposure for the low-income population, the cross-MSA movement had increased rent exposure for the low-income population. Our calculation in Figure 12 suggests that the rent effects due to cross-neighborhood movement dominated the overall equilibrium rent effect of migration.

To provide additional corroborating evidence that cross-neighborhood movements drove down the low-income population's exposure to rent more, we next examine migration's effect on rent exposure separately for different classes of cities: star cities consisting of New York, Los Angeles, and San Francisco, where we see a very high surge of net out-migration; the cities with a population ranked at 25th or above minus the elite cities; cities with a population ranked between 26th and 100th; cities with a population ranked at 101st or lower. Figure 12c demonstrates that for the star cities where out-migration had led to a dramatic outward shift in housing demand, spatial sorting had caused a reduction in rent growth equivalent to a growth of 0.05 point of log wage for the low-income population, higher than the welfare effect of the reduction of rent experienced by the high-income population.

As we move down the ranks, as shown in Figures 12c, 12d, and 12e, we see that the mitigating effect of migration on rent exposure became smaller, but it never turned symmetrically positive for the low-income population, even in cities ranked below 100th. This result reflects the fact that most cities' urban cores, from which people were moving, were inhabited disproportionately by the low-income population.[19]

5.3 Summary of Migration's Effects on Welfare and Inequality

Two factors drove our welfare analyses: the sudden adoption of WFH arrangements during the pandemic and the pandemic-induced migration. We have shown that the sudden availability to WFH reduced commuting costs and increased access to jobs for both types of workers, and such an increase benefited the high-income population more than the low-income population, significantly widening the welfare inequality between them.

The welfare gain from the WFH-enabled increase in job access, however, was partially offset by migration. For low-income workers, migration reduced job access: Job opportunities moved away from central urban locations toward wealthy suburbs as people took the demand for local services with them as they moved. Since the low-income population primarily lives in neighborhoods people have been moving away from, that lowered their job access. For high-income workers, their reduced job access was largely led by their own migration toward locations with low overall job access (e.g., exurbs and small cities).

Migration further affected welfare by alleviating housing cost exposure for both population groups, but more so for the low-income population. On net, migration-induced uneven rent growth lowered welfare inequality. The reduction in overall housing cost exposure was driven by the fact that people were moving toward localities with more elastic housing supply, and migration lowered housing cost pressure through a "de-congestion" effect. Moreover, since people moved from low-income neighborhoods to high-income neighborhoods, the reduced housing market congestion benefited the low-income population disproportion-

[19] In the analyses, we have treated all individuals as renters in the original location and in the destination location. In Appendix C, we examine possible changes in housing arrangements for individuals; that is, whether movers moved in with families or purchased houses upon moving. The results suggest movers created housing demand by renting and purchasing houses. In our welfare calculation, we don't differentiate between homeowners versus nonhomeowners. Conceivably, movers who were homeowners before suffered from either selling at a lower price or having to pay for two residences. Additionally, homeowners in locations that experienced house price appreciation may have benefited from the appreciation. The benefits, however, accrue mostly to old homeowners looking to downsize. See, among others, Li and Yao (2007). Presumably, the same was true for renters who moved but couldn't break their old leases. However, the reality was far more complicated, given the many mortgage forbearance plans and stays on evictions implemented by the federal, state, and/or local governments. We thus abstract from this consideration.

ately.

Before we conclude, it is important to point out that even though migration appeared to have lowered welfare inequality by around 1.2 percentage points of equivalent income gap, the magnitude was much smaller than the massive spike in welfare inequality caused by the differential adoption of WFH arrangements (over 50 percentage points of equivalent income gap) or the welfare inequality accrued due to spatial sorting over the few decades before the pandemic.[20]

6 Conclusion

In this paper, using the FRBNY Consumer Credit Panel/Equifax anonymized micro data, we document detailed migration patterns across cities and neighborhoods in the US before and after the start of the COVID-19 pandemic. We find that, because of the sudden rise of the option to work from home, a large number of people moved out of dense neighborhoods near city centers into suburban neighborhoods with lower density. Also, many moved from large cities with high population densities to small cities with lower population densities. Importantly, this rise in migration toward the suburbs and smaller cities was disproportionately driven by high-income residents. We stress that these new spatial sorting patterns observed during the pandemic are partially "reversing" the spatial sorting seen over the past few decades.

In response to the migration and spatial sorting, housing costs rose in the destination locations but declined in the origin locations. Jobs grew in the local service sector at the destination locations but shrank or grew more slowly in the origin locations. Furthermore, the movement of local service jobs toward the suburbs and small cities reduced job access by low-income workers. The large movement by high-income workers toward low-density locations also lowered their job access. While the divergent growth in housing costs across space due to migration and spatial sorting reduced housing costs faced by both high- and low-income people, the reduction was larger for low-income people than for high-income people. On net, these forces resulted in a slight narrowing of welfare inequality during the first two years of the pandemic. It is important to point out that the increased prevalence of WFH raised the welfare of both high- and low-income populations through improved job access and caused a massive hike in welfare inequality. The narrowing of the welfare inequality

[20]For comparison, Diamond (2016) shows that cross-city spatial sorting during 1980-2000 added 30 percentage points of equivalent wage inequality between college and non-college workers. Su (2022) shows that cross-neighborhood spatial sorting driven by the changing value of time between 1990 and 2010 led to a rise in welfare inequality equivalent to 3.7 percentage points of earnings inequality between high- and low-skilled workers. Couture et al. (2022), similarly, conclude that spatial sorting within cities over 1990-2014 led to a widening of welfare gap between the top and bottom deciles equivalent to a 3.6 percentage point wage gap.

led by migration is modest by comparison.

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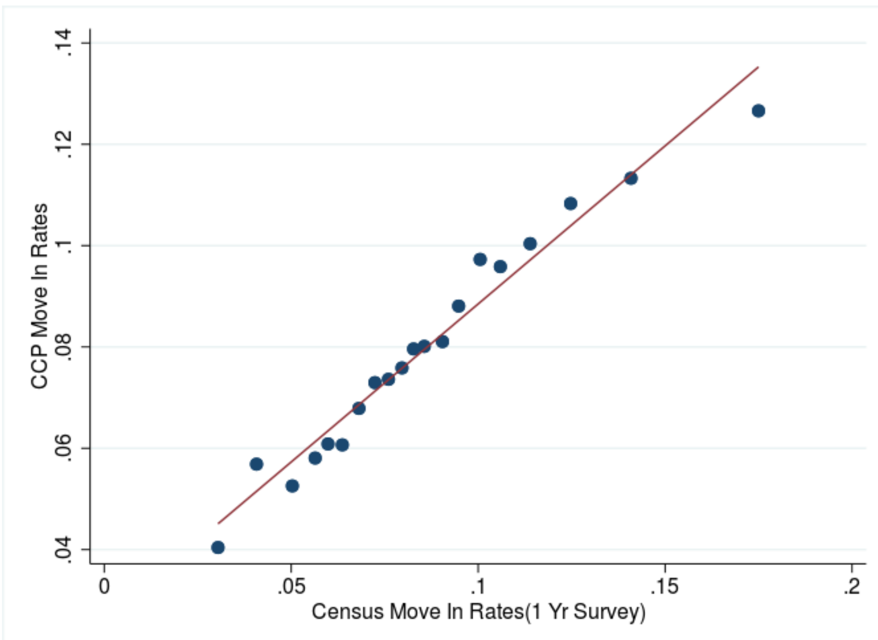
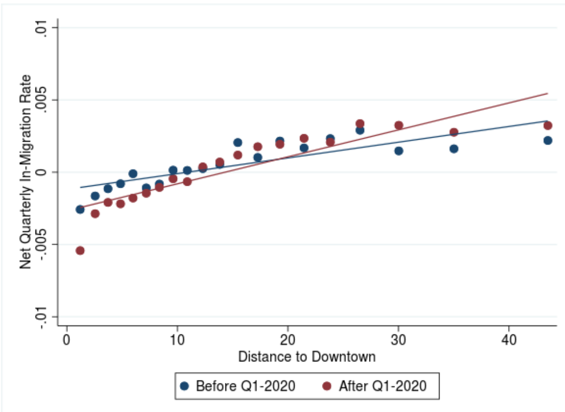
Figure 1: Data Validation: Move In Rates

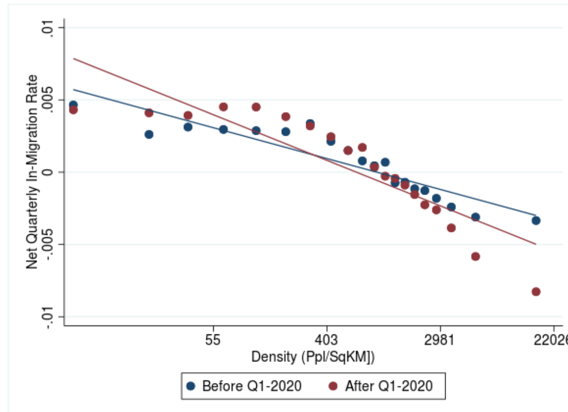


Note: This binned scatterplot compares county-level in-migration rates between March 2017 and December 2018 from the CCP data with county-level move in rates from the 2015-2019 ACS. Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey.

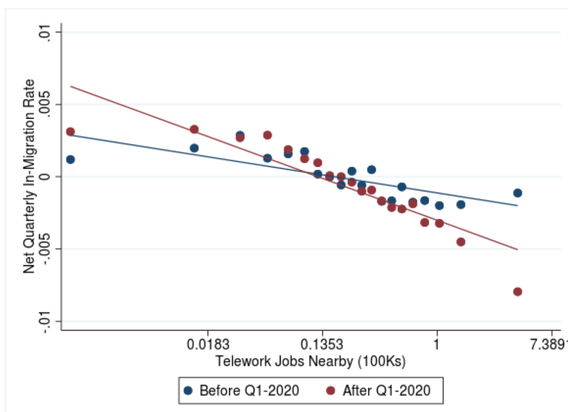
Figure 2: Binned Scatterplot: Net In-Migration Rate at Census Tract Level, Pre- and Post-Q1 2020



(a) Distance to Downtown



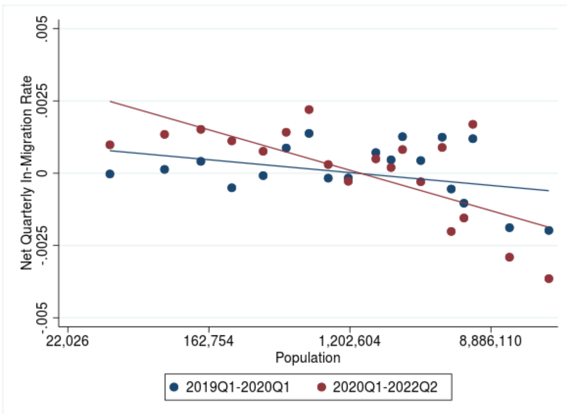
(b) Population Density



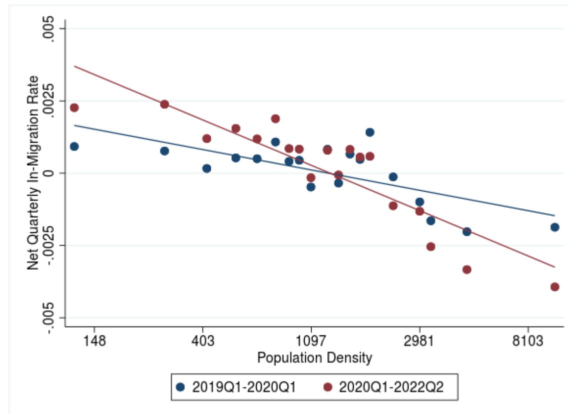
(c) Nearby Telework-Compatible Jobs

Note: In each of the subfigures, we show the binned scatterplot of the net in-migration rates at the census tract level during the 8-quarter period Q1 2018 - Q1 2020 and the period Q1 2020 - Q1 2022, respectively, against selected tract-level characteristics. The net in-migration rate in each census tract is defined as the net inflow of population divided by the population of the receiving census tract in the preceding time. We plot net in-migration rates against (a) distance to downtown, (b) population density, and (c) nearby telework-compatible jobs. To compute the nearby telework-compatible jobs, we first impute the number of jobs by industry from the 2016 zip code Business Patterns data at zip code level. We then use an industry-occupation crosswalk to impute the job distribution for each occupation across zip code. Then, for each census tract, we compute the number of jobs located within a 3-mile radius that can be categorized as telework-compatible (Dingel and Neiman, 2020; Su, 2020),). Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS, and Holian and Kahn (2015).

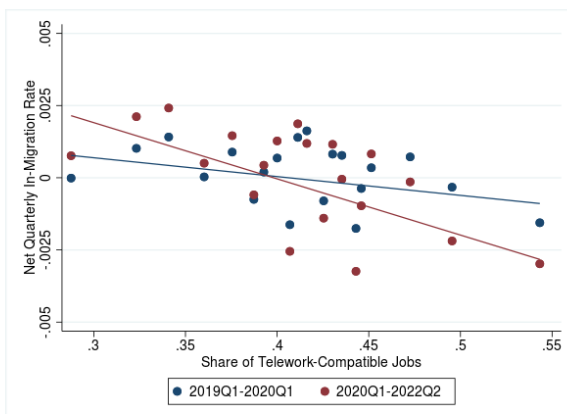
Figure 3: Binned Scatterplot: Net In-Migration Rates Across MSAs, Pre- and Post-Q1 2020



(a) MSA Population



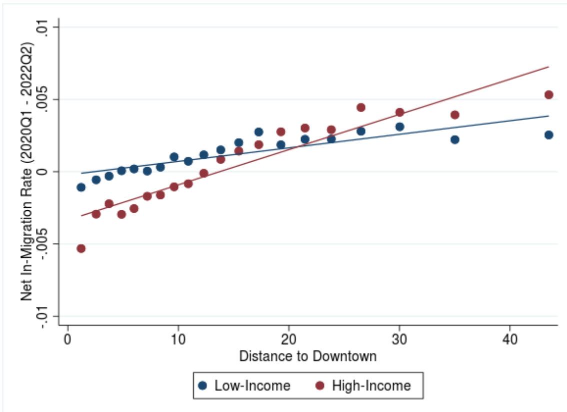
(b) Population Density



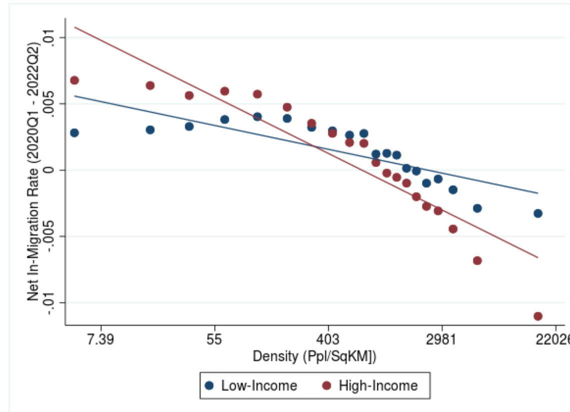
(c) Share of Telework-Compatible Jobs

Note: In each of the subfigures, we show the binned scatterplot of the net in-migration rates at the MSA level during the 8-quarter period Q1 2018 - Q1 2020 and the period Q1 2020 - Q1 2022, respectively, against selected MSA-level characteristics. The net inflow of population in each MSA is defined as the net inflow of population divided by the population of the receiving MSA in the preceding quarter. The net inflow is defined as the number of people who lived outside of the MSA in the preceding time but who lived inside of the MSA at the ending time period. We plot net in-migration rate against (a) the MSA's population, (b) the MSA's population density, and (c) the MSA's share of jobs that are telework-compatible. To compute the share of jobs that are telework-compatible at the MSA level, we use the 2013-2017 ACS and assign each occupation into two categories: telework-compatible or not. For each MSA, we calculate the share of jobs that are telework-compatible (Dingel and Neiman, 2020; Su, 2020). Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS.

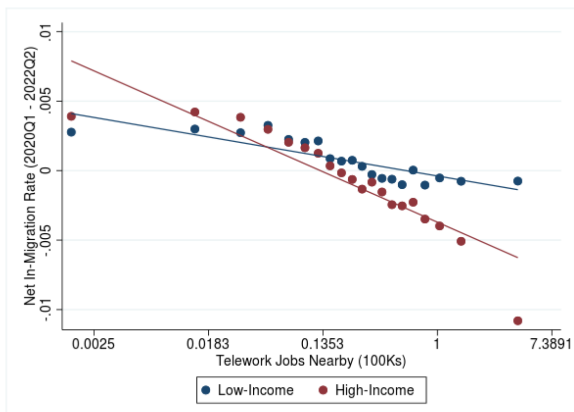
Figure 4: Binned Scatterplot: Q1 2020 - Q1 2022 Net In-Migration Rate by Census Tract, by Income



(a) Distance to Downtown



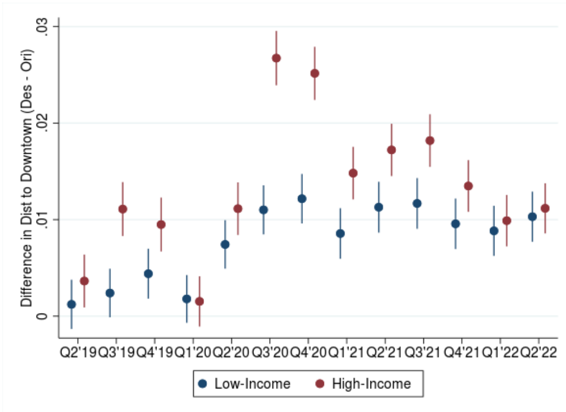
(b) Density



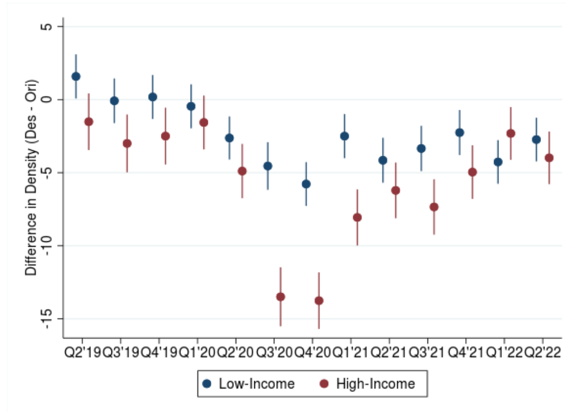
(c) Telework Jobs Nearby

Note: In each of the subfigures, we show the binned scatter plot of the net in-migration rates at the level of census tract for the subsample of people whose imputed income levels are in the upper half or the lower half of the sample (ranked in 2019 Q4), against selected tract-level characteristics. We refer to the individuals whose income falls in the upper half as high-income and others as low-income. We plot the inflow between Q1 2020 and Q1 2022. The net in-migration rate in each census tract is defined as the net inflow of population divided by the population of the receiving census tract in the preceding time. We plot net in-migration rate by income against (a) distance to downtown, (b) population density, and (c) nearby telework-compatible jobs. To compute the nearby telework-compatible jobs, we first impute the number of jobs by industry from the 2016 zip code Business Patterns data at zip code level. We then use an industry-occupation crosswalk to impute the job distribution for each occupation across zip code. Then, for each census tract, we compute the number of jobs located within a 3-mile radius that can be categorized as telework-compatible (Dingel and Neiman, 2020; Su, 2020). Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS.

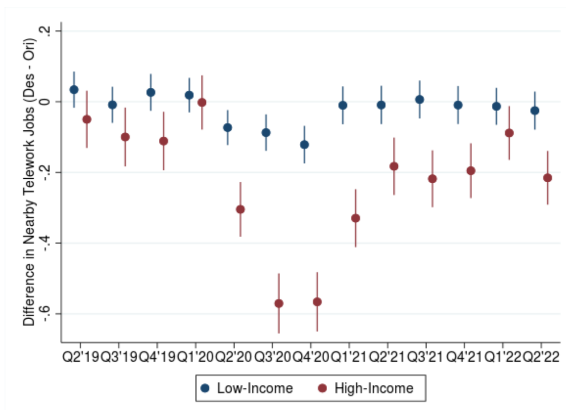
Figure 5: Direction of Tract-to-Tract Flows: High-Income vs. Low-Income Individuals



(a) Distance to Downtown



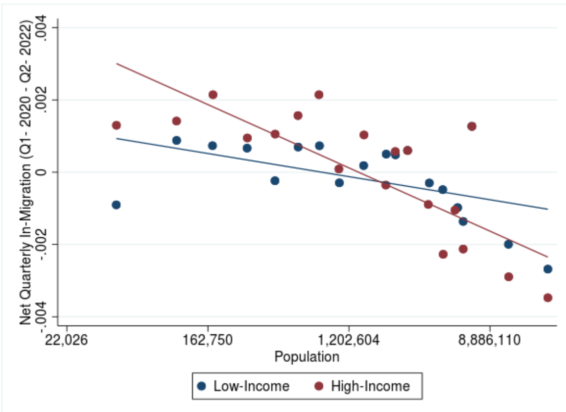
(b) Density



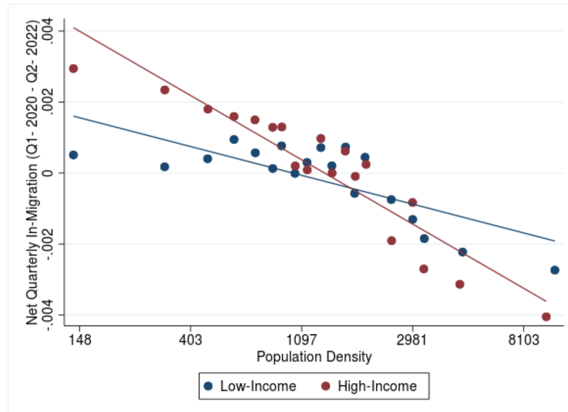
(c) Nearby Telework-Compatible Jobs

Note: The plotted numbers are the average changes in the (a) distance to downtown, (b) density, and (c) number of nearby telework-compatible jobs, between the destination neighborhoods and the origin neighborhoods. The sample contains all individuals, movers and non-movers. The value of each of the observed origin-destination differences for non-movers would be zero. We plot the results separately for individuals with imputed income falling in the upper half (high-income) and the lower half (low-income) of the sample (ranked in Q42019). The vertical lines represent the 95% confidence interval. Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS, and Holian and Kahn (2015).

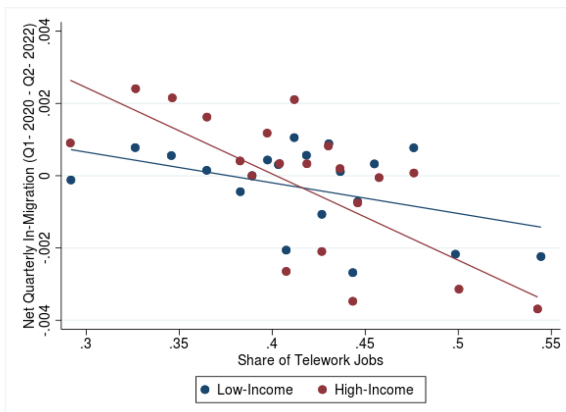
Figure 6: Binned Scatterplot: Q1 2020 - Q1 2022 Net In-Migration by MSA, by Income



(a) MSA Population



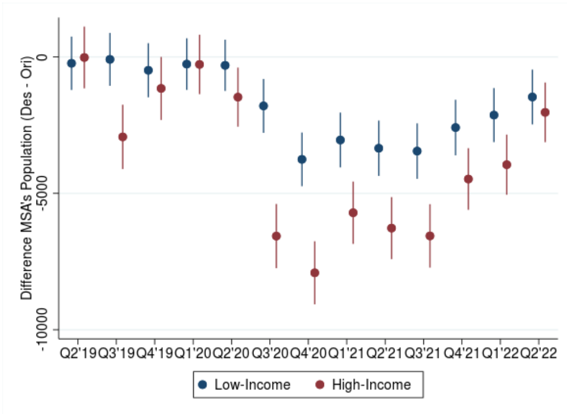
(b) MSA Density



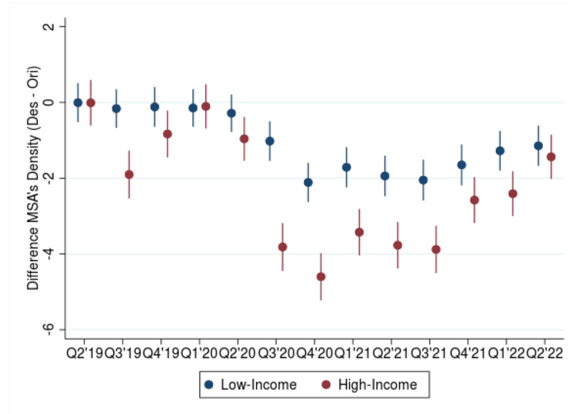
(c) Share of Telework Jobs

Note: In each of the subfigures, we present the binned scatter plot of the net in-migration rate at the MSA level for the subsample of people whose imputed income levels are in the upper half or the lower half of the sample (ranked in Q42019), against selected MSA-level characteristics. We refer to individuals whose income falls in the upper half as high-income, and others as low-income. We plot the inflow between Q1 2020 and Q1 2022. The net in-migration rate in each MSA is defined as the net inflow of population divided by the population of the receiving MSA in the preceding time period. We plot the net in-migration rate against (a) MSA's population, (b) MSA's population density, and (c) MSA's share of telework-compatible jobs. To compute the share of jobs that are telework-compatible at MSA level, we use the 2013-2017 ACS and assign each occupation into two categories: telework-compatible or not. For each MSA, we calculate the share of jobs that are telework-compatible (Dingel and Neiman, 2020; Su, 2020). Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS.

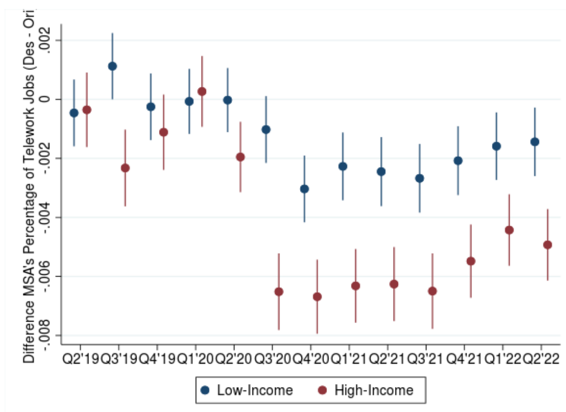
Figure 7: Direction of Metro-to-Metro Flow: High-Income vs. Low-Income Individuals



(a) MSA's Population



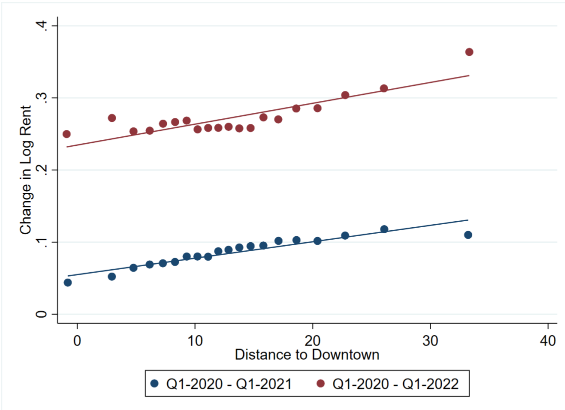
(b) MSA's Density



(c) MSA's Share of Telework Jobs

Note: The plotted numbers are the average changes in (a) the MSA's population, (b) the MSA's population density, and (c) the MSA's share of telework-compatible jobs, between the destination and origin MSAs. The sample contains all individuals, movers and non-movers. The value of each of the observed origin-destination differences for non-movers would be zero. We plot the results separately for individuals with imputed income falling in the upper half (high-income) and the lower half (low-income) of the sample (ranked in Q42019). The vertical lines represents the 95% confidence interval. Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS.

Figure 8: Spatial Variation in Rent Growth Across Census Tracts and Across MSAs

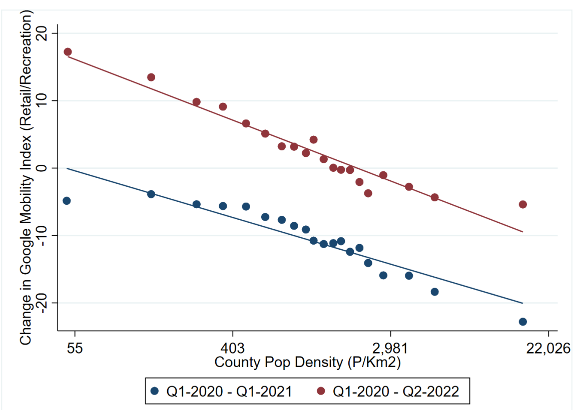


(a) Distance to Downtown

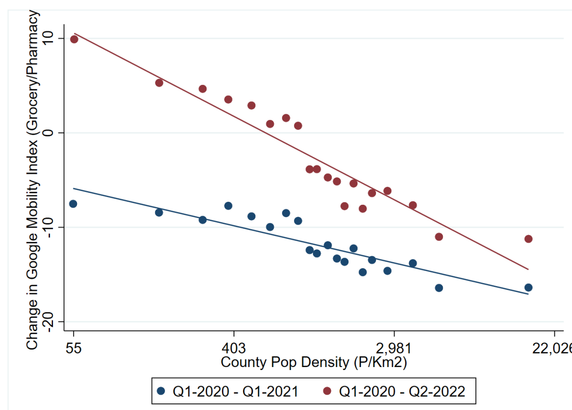
(b) MSA-Level Population Density

Notes: Subfigure (a) is the binned scatter plot that plots the change in census tract-level log rents by distance to downtown, controlling for the MSA fixed effect. We study the change in two periods: the period between Q12020 and Q12021 and the period between Q1 2020 and Q1 2022. We average the log change of the rent index reported in Zillow Research with the log change in HPI reported by CoreLogic weighted by each census tract's share of renters and owners, respectively. Subfigure (b) plots the change in MSA-level log rents against the MSA's population density. Data source: CoreLogic, American Community Survey/IPUMS NHGIS, Zillow.

Figure 9: Spatial Variation in Demand for Local Services Across Counties



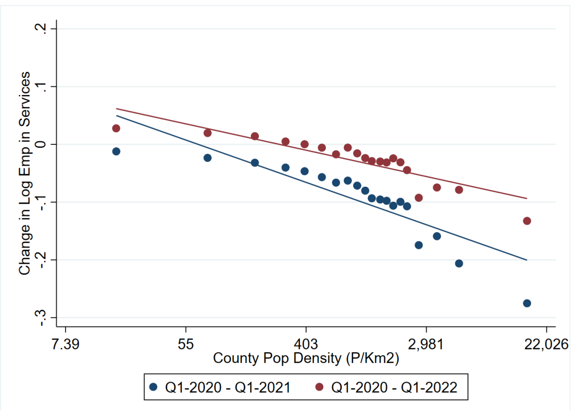
(a) Retail and Recreation



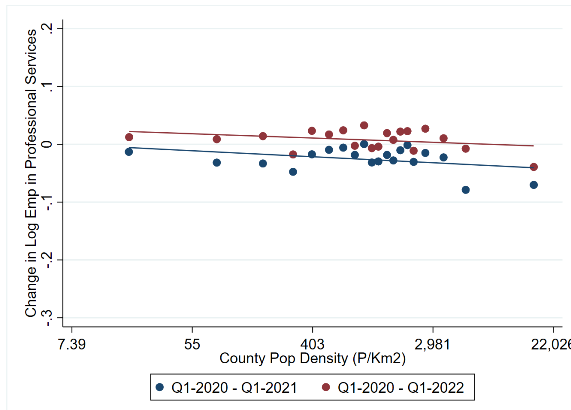
(b) Grocery and Pharmacy

Notes: We plot the percentage changes from the baseline in the Google Mobility index from Q12020 to Q12021 and from Q12020 to Q12022. The baseline date is the median value from the 5-week period Jan 3 – Feb 6, 2020. Subfigure (a) plots the changes in the retail and recreation index (places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters, as defined in the Google COVID-19 Community Mobility Reports). Subfigure (b) plots the changes in the grocery and pharmacy index (places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies, as defined in the Google COVID-19 Community Mobility Reports). Both indexes are calculated at the county level against the population density at the county level. Data Source: Google LLC "Google COVID-19 Community Mobility Reports," and American Community Survey/IPUMS NHGIS.

Figure 10: Spatial Variation in Job Growth Across Counties



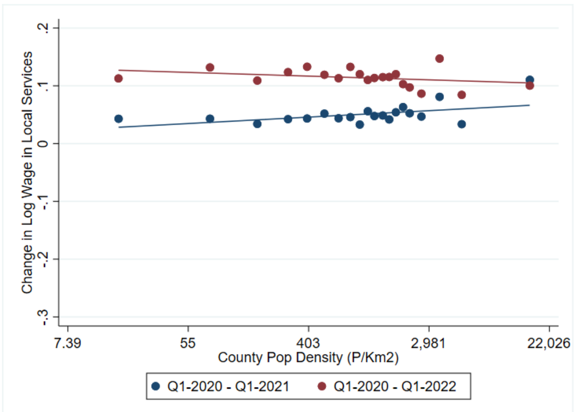
(a) Service Industries



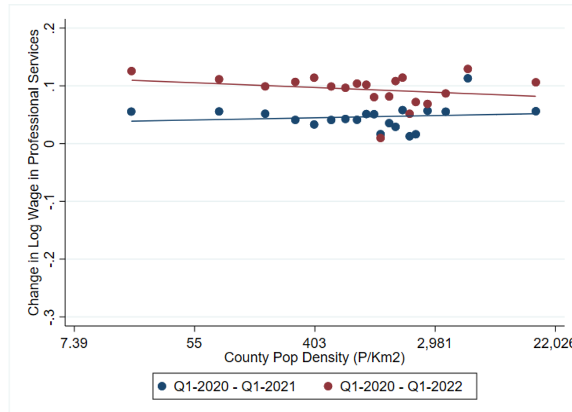
(b) Professional Services

Notes: Subfigure (a) plots changes in log employment in two periods, Q1 2020 to Q1 2021 and Q1 2020 to Q1 2022, respectively, in service industries (NAICS: 23, 42, 44-45, 72) against the county population density. Subfigure (b) plots changes in log employment in professional service industries (NAICS: 51, 52, 54). Data Source: Quarterly Census of Employment and Wages/Bureau of Labor Statistics, American Community Survey/IPUMS NHGIS.

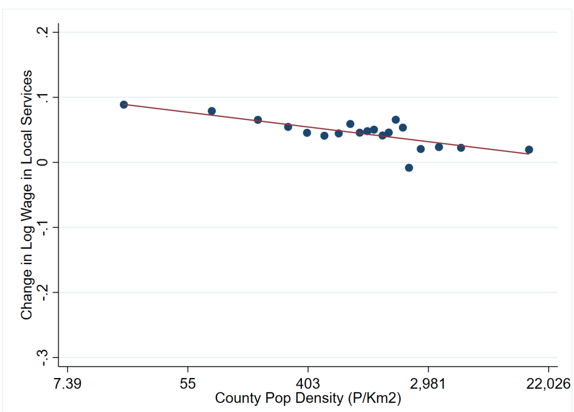
Figure 11: Spatial Variation in Changes in Wages Across Counties



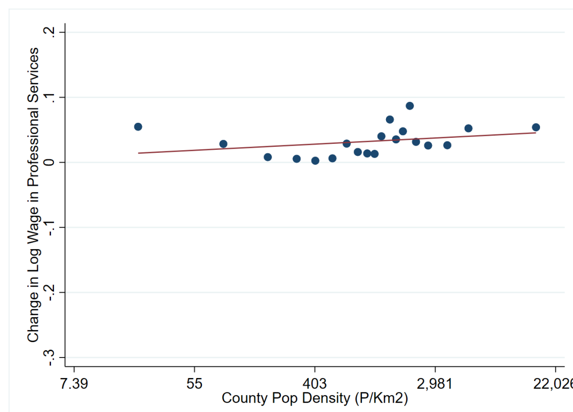
(a) Wages for Local Service Sector (QCEW)



(b) Wages for Professional Service Sector (QCEW)



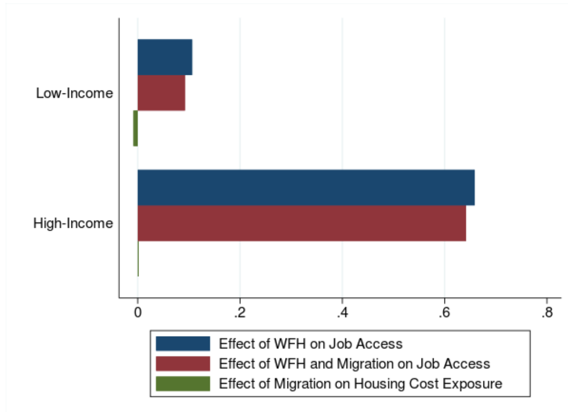
(c) Wages for Local Service Sector (Burning Glass/Lightcast)



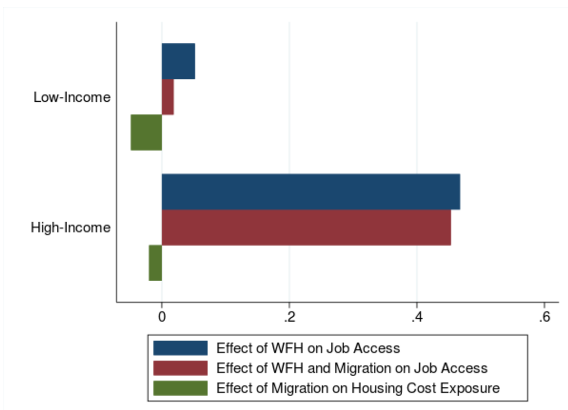
(d) Wages for Professional Service Sector (Burning Glass/Lightcast)

Notes: In subfigures (a) and (b), we use average earnings reported in the Quarterly Census of Employment and Wages (QCEW). QCEW earnings are reported at a quarterly frequency and at the NAICS level. We plot the change in log hourly wages over two periods (one from 2019 to 2020, and one from 2019 to 2021) for the local service sector and the professional service sector, respectively. In subfigures (c) and (d), we use the Burning Glass/Lightcast data to examine wages posted in job ads. In each county, we compute the mean log hourly wages of all ads posted in the county over the two-year period of 2019 and 2020 and the period of 2020 to 2021, excluding the first three months of 2020. We then plot the change in log hourly from the first two-year period to the second two-year period in (a) and (b). Data Source: Current Population Survey/IPUMS CPS, American Community Survey/IPUMS NHGIS, Burning Glass/Lightcast.

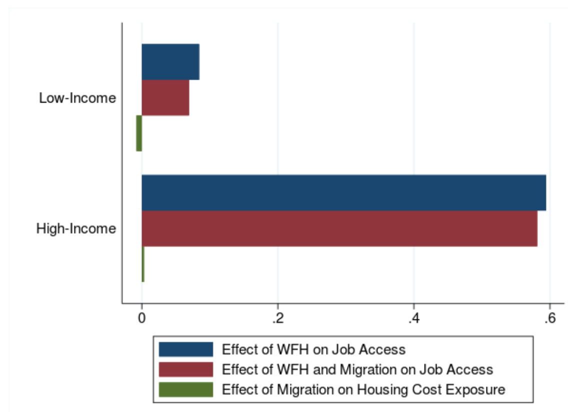
Figure 12: Welfare Impact of WFH and Migration on High- and Low-Income Populations



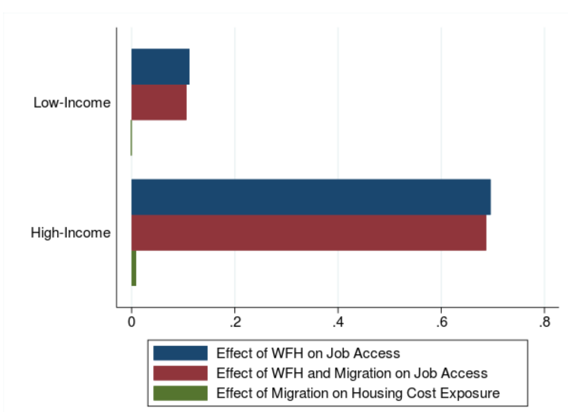
(a) National Average



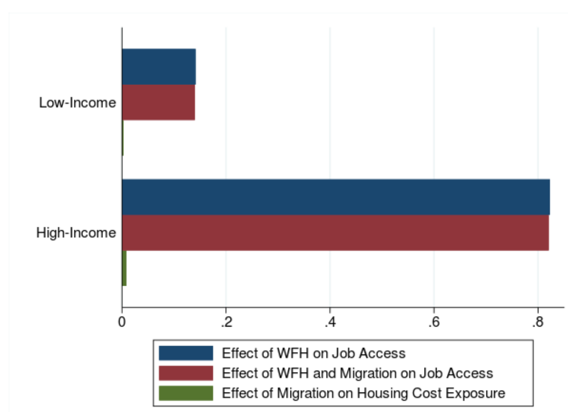
(b) Elite Cities: New York, Los Angeles, San Francisco



(c) Largest 25 Cities (Minus Elite Cities)



(d) Ranked 26 - 100



(e) Ranked 101+

Data Source: Current Population Survey/IPUMS CPS, American Community Survey/IPUMS NHGIS, FRBNY Consumer Credit Panel/Equifax.

Table 1: OLS Regression: Rent Growths on Net Migration

	Ln Rent Growth (2020Q1 - 2021Q1)	Ln Rent Growth (2020Q1 - 2022Q1)
Net Log In-Migration - High-Income	0.0128***	0.0342***
	(0.00073)	(0.00189)
Net Log In-Migration - Low-Income	0.00328***	0.0117***
	(0.00062)	(0.00212)
Constant	0.0968***	0.278***
	(0.000455)	(0.00103)
R2	0.0088	0.009
Observations	43,214	46,791

Note: We regress log rent growth on the net log in-migration at the census tract level. To obtain the log rent growth, we average the log change of the rent index reported in Zillow Research with the log change in HPI reported by CoreLogic weighted by each census tract's share of renters and owners, respectively. We do so for two periods, separately. The first period is between Q1 2020 and Q1 2021. The second period is between Q1 2020 and Q1 2022. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.
Data Source: Zillow, CoreLogic, American Community Survey/IPUMS NHGIS, FRBNY Consumer Credit Panel/Equifax.

Table 2: OLS Regression: Mobility Growths on Net Migration

	Retail Mobility (2020Q1 - 2021Q1)	Retail Mobility (2020Q1 - 2022Q1)	Grocery Mobility (2020Q1 - 2021Q1)	Grocery Mobility (2020Q1 - 2022Q1)
Net Log In-Migration	8.295***	7.386***	5.81***	8.74***
- High-Income	(0.994)	(0.659)	(0.684)	(0.877)
Net Log In-Migration	6.147***	3.383***	2.672***	2.633*
- Low-Income	(1.020)	(1.010)	(0.870)	(1.355)
Constant	10.257***	-4.549***	-11.558***	7.604***
	(0.233)	(0.175)	(0.180)	(0.233)
R2	0.2992	0.2977	0.16	0.2046
Observations	1,823	1,816	1,670	1,654

Note: We regress the Google Mobility index on the net log in-migration at the census tract level. We use the mobility indexes for retail and recreation (referred to as "Retail" in the table) and for grocery and pharmacy (referred to as "Grocery" in the table). We do so for two periods, separately. The first period is between Q1 2020 and Q1 2021. The second period is between Q1 2020 and Q1 2022. The Google Mobility Index tracks how much the visits and the time spent at each category of venues changed relative to the baseline days, which is the median value from the 5-week period Jan 3 – Feb 6, 2020, in percentage terms. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. Data Source: Google LLC "Google COVID-19 Community Mobility Reports," FRBNY Consumer Credit Panel/Equifax.

Table 3: OLS Regression: Employment Growths on Net Migration

	Service Emp (2020Q1 - 2021Q1)	Service Emp (2020Q1 - 2022Q1)	Professional Emp (2020Q1 - 2021Q1)	Professional Emp (2020Q1 - 2022Q1)
Net Log In-Migration	0.107***	0.0920***	0.0402***	0.0566***
- High-Income	(0.015)	(0.0112)	(0.0105)	(0.0127)
Net Log In-Migration	0.0551***	0.0217*	0.0242*	0.0357*
- Low-Income	(0.0120)	(0.013)	(0.0139)	(0.0193)
Constant	-0.0952***	-0.0276**	-0.0250***	-0.000968***
	(0.0037)	(0.00253)	(0.003)	(0.00364)
R2	0.2145	0.1860	0.0158	0.0256
Observations	2,788	2,873	2,788	2,873

Note: We regress the log employment growth of service industries (NAICS: 23, 42, 44-45, 72) and professional services industries (NAICS: 51, 52, 54) on the net log in-migration at the county level. We do so for two periods, separately. The first period is between Q1 2020 and Q1 2021. The second period is between Q1 2020 and Q1 2022. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. Data Source: Quarterly Census of Employment and Wages, FRBNY Consumer Credit Panel/Equifax.

Table 4: OLS Regression: Log Wage Growth on Net Migration

	Service (2020Q1 - 2021Q1)	Service (2020Q1 - 2022Q1)	Professional (2020Q1 - 2021Q1)	Professional (2020Q1 - 2022Q1)
Net Log In-Migration	-0.0127	-0.0286***	-0.00153	0.0279*
- High-Income	(0.0146)	(0.00928)	(0.0105)	(0.0145)
Net Log In-Migration	-0.00486	0.00112	-0.0247	-0.0312*
- Low-Income	(0.0142)	(0.0140)	(0.0168)	(0.018)
Constant	0.0496***	0.117***	0.0456***	0.0938***
	(0.00410)	(0.00309)	(0.00422)	(0.00478)
R2	0.004	0.0213	0.0049	0.0035
Observations	2,788	2,873	2,788	2,873

Note: We regress the change in log hourly wage for the local service sector and the professional service sector on the net log in-migration over the two time periods at the county level. The first period is from Q1 2020 to Q1 2021, and the second period is from Q1 2020 to Q1 2022. Data Source: Current Population Survey (ASEC), FRBNY Consumer Credit Panel/Equifax. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 5: Net Migration and Initial Income: Census Tract Level vs. Metro Level

	High-Income	Low-Income	High-Income	Low-Income
Ln Tract-Level Median Income	0.286***	0.149***		
	(0.0058)	(0.0060)		
Ln Metro-Level Income			-0.312***	-0.203***
			(0.0466)	(0.0343)
Constant	-3.169***	-1.645***	3.427***	2.237***
	(0.0649)	(0.0651)	(0.508)	(0.373)
FE	Metro	Metro	None	None
SE Clustering	Census Tract	Census Tract	Metro	Metro
R2	0.0998	0.0413	0.0135	0.0059
Observations	64,163	65,136	64,223	65,183

Note: We regress the net log in-migration at the census tract level on census tract-level log median income and metro-level log income, respectively. For the first two sets of regressions in which we regress on tract-level median income, we include the metro fixed effects. We construct net log in-migration separately for the high- and low-income. The time period used in these regressions is the 8-quarter period between Q12020 and Q12022. Data Source: American Community Survey (ACS), NHGIS, FRBNY Consumer Credit Panel/Equifax *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 6: IV Regression: Effects of Migration on Local Employment, Wages, and Rents (Q1 2020 - Q1 2021)

	Service Emp	Prof Emp	Service Wage	Prof Wage	Ln Rent	Ln Rent
Δ Local y	6.081***	0.708***	-1.667**	-1.04***	2.45***	1.638***
	(0.547)	(0.234)	(0.808)	(0.338)	(0.077)	(0.454)
Δ Local $y \times$ Saiz (2010) Land Unavail.						0.289
						(0.310)
Δ Local $y \times$ WRLURI Reg Index						0.722***
						(0.120)
Δ Local $y \times$ Dist. to Downtown						-0.0625***
						(0.0096)
Observations	862	862	862	862	44,100	43,868

Note: We regress log employment and wage growth for the local service sector and for the professional service sector at the county level on the change in log aggregate income interacted with county-level housing supply characteristics. The time period in this table is from Q1 2020 to Q1 2021, the first year of the pandemic. Both employment and wage data come from the Quarterly Census of Employment and Wages (QCEW). To compute the log aggregate income, we multiply the number of high-income residents by $\$65486.16$ (the mean imputed income for high-income individuals), and we compute the aggregate income of the low-income by multiplying the number of low-income residents by $\$26505.74$ (the mean imputed income for low-income individuals). The change in log aggregate income is determined by the in-migration of high- and low-income populations weighted by the income levels we assign. To identify the causal effect of log aggregate income on unemployment rates, we construct our instruments as follows. For each MSA, we calculate the shares of college-educated workers and noncollege-educated workers, respectively, who work in telework-compatible occupations. We then average each tract's number of nearby jobs (3-mile radius) that are telework-compatible up to the county level. We construct the IVs as those variables and their interactions. Data Source: American Community Survey (ACS), NHGIS, Quarterly Census of Employment and Wages, Saiz (2010), Gyourko, Hartley, and Krimmel (2019), FRBNY Consumer Credit Panel/Equifax *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 7: IV Regression: Effects of Migration on Local Employment, Wages, and Rents (Q1 2020 - Q1 2022)

	Service Emp	Prof Emp	Service Wage	Prof Wage	Ln Rent	Ln Rent
Δ Local y	1.913***	0.386**	0.250	-0.110	2.054***	1.461***
	(0.221)	(0.162)	(0.2)	(0.289)	(0.0578)	(0.374)
Δ Local $y \times$ Saiz (2010) Land Unavail.						0.545**
						(0.257)
Δ Local $y \times$ WRLURI Reg Index						0.231**
						(0.102)
Δ Local $y \times$ Dist. to Downtown						-0.0227***
						(0.00842)
Observations	864	864	864	864	44,141	43,909

Note: We regress log employment and wage growth for the local service sector and for the professional service sector at the county level on the change in log aggregate income interacted with county-level housing supply characteristics. The time period in this table is from Q1 2020 to Q1 2022, the first two years of the pandemic. Both employment and wage data come from the Quarterly Census of Employment and Wages (QCEW). To compute the log aggregate income, we multiply the number of high-income residents by $\$65486.16$ (the mean imputed income for high-income individuals), and we compute the aggregate income of low-income by multiplying the number of low-income residents by $\$26505.74$ (the mean imputed income for low-income individuals). The change in log aggregate income is determined by the in-migration of high- and low-income populations weighted by the income levels we assign. To identify the causal effect of log aggregate income on unemployment rates, we construct our instruments as follows. For each MSA, we calculate the shares of college-educated workers and noncollege-educated workers, respectively, who work in telework-compatible occupations. We then average each tract's number of nearby jobs (3-mile radius) that are telework-compatible up to the county level. We construct the IVs as those variables and their interactions. Data Source: American Community Survey (ACS), NHGIS, Quarterly Census of Employment and Wages, Saiz (2010), Gyourko, Hartley, and Krimmel (2019), FRBNY Consumer Credit Panel/Equifax *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 8: 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)
$\lambda^{k,remote}_{Q12020}$	0.028	0.014	Barrero et al. (2021)
$\lambda^{k,remote}_{Q12022}$	0.21	0.07	–
$\lambda^{k,hybrid}_{Q12020}$	0.134	0.0948	–
$\lambda^{k,hybrid}_{Q12022}$	0.368	0.212	–
			–
$\rho^{k,hybrid}_{Q12020}$	0.298	0.169	–
$\rho^{k,hybrid}_{Q12022}$	0.652	0.377	–
$\phi^{m,hybrid}$	0.2125	0.2125	Equivalent to 10 minutes commuting time
$\phi^{m,remote}$	0.2125	1.275	Equivalent to 10, 60 minutes commuting time

Notes: We calibrate the model by drawing on the estimates in related literature. 1. The θ scaling factor, which governs the marginal utility of log wage, is calibrated based on various trade and transportation economics literature listed in the table. The estimates of the comparable parameters are 3.3, 2.18, and 3. 2. The housing expenditure shares by high-income and low-income people (β^k) are calibrated based on the estimates by Diamond and Moretti (2021), who recover these housing shares using credit card transaction data. 3. Barrero et al. (2021) SWAA November 2022 survey shows that while 30% of the paid work days are done remotely, around 14% of workers are working fully remotely, and 29% of the workers work hybrid. We obtain $\lambda^{k,hybrid}_{Q12022}$ by assuming that high-income workers' total WFH days are 3 times those of low-income workers. Based on proportionality assumption, $\lambda^{k,hybrid}_{Q12022}$ for high-income workers should be $\sqrt{3}$ of low-income workers. We solve for $\lambda^{k}_{hybrid,Q12022}$ for high- and low-income workers by letting the average value equal 0.29. To obtain $\lambda^{k,remote}_{Q12022}$, we assume that the incomes of fully remote high-income workers are 3 times those of low-income workers. We solve for them by letting the average value equal to 0.14. We impute $\lambda^{k,hybrid}_{Q12020}$ and $\lambda^{k,remote}_{Q12020}$ by assuming the relative prevalence of fully remote and hybrid arrangement fixed in Q1 2020 and Q1 2022. Finally, we solve for $\rho^{k,hybrid}_{Q12020}$ and $\rho^{k,hybrid}_{Q12022}$ by letting the implied paid WFH days equal to 6% and 3% for high- and low-income workers in Q1 2020 and 45% and 15% for high- and low-income workers in Q1 2022.

Appendix A Imputation of Individual Income

In this appendix, we describe the procedure we used to impute income for individuals in the FRBNY 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 FRBNY CCP/Equifax and SCF data. We then use these estimates to impute income for individuals in the CCP data in 2019Q4. We restrict our sample to individuals between the ages of 25 and 65.

Table A5 presents the summary statics from the FRBNY CCP/Equifax and SCF sample for Q42019 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. Individuals in the FRBNY CCP/Equifax have in general smaller household size and less debt – mortgage debt in particular.

To impute income for individuals in the FRBNY CCP/Equifax 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.[21] $f(.)$ is a vector-valued function, that includes polynomials, interaction terms and dummy variables. The adjusted R-square for this regression is 0.58.[22] We present the regression results for the main variables in Table A6.

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

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

[21] 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 data sets. For example, in SCF, the bankruptcy variable captures all bankruptcy filings, while the FRBNY CCP/Equifax 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.

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

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.[23] Specifically, we keep all individuals that are present in the December 2019 HMDA-McDash-CRISM database and impute each individual's income using 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 A1, we provide a binned scatterplot of the two variables. As can be seen, the relationship is almost perfectly linear.

[23]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.

Appendix B Migration Patterns by Other Observable Characteristics

In the main text of the paper, we classified 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.

B.1 Top and Bottom Income Quintiles

As a first robustness check, we take only the population in the top or bottom income quintiles and investigate their respective migration patterns over the pandemic.

Figure A2 and Figure A3 present the results. The difference in migration flows between the top income quintile and bottom income quintile is much more pronounced than the difference between the upper and lower halves of the population. Moreover, the striking difference in migration patterns between the top and bottom income quintiles of the population was mainly driven by the fact that the bottom quintile hardly made the move toward the suburbs or lower-density MSAs during the pandemic.

B.2 Income and Age Groups

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 A7 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 be 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 confound 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 A7 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.

B.3 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 Q42019 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 A8 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 A8 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 C 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.

C.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 FRBNY CCP/Equifax 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 A9. 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.

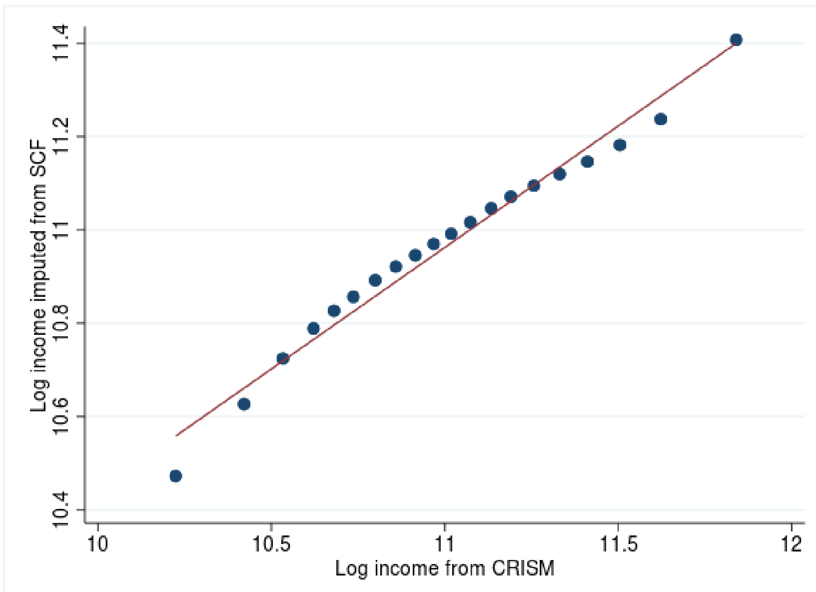
C.2 Homeownership

The FRBNY CCP/Equifax 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 A10, 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.

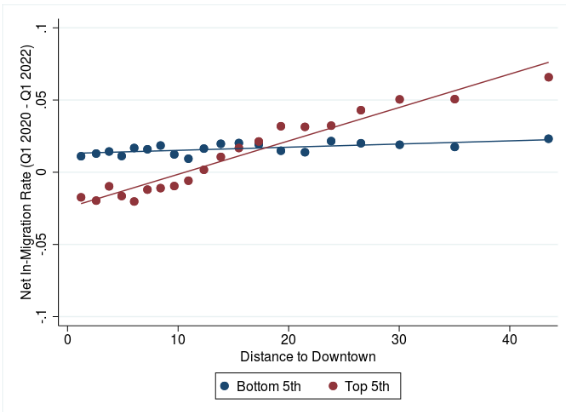
This exercise, therefore, demonstrates that movers created housing demand by purchasing houses in new locations, more so during the pandemic than they used to before the pandemic. Given that we are not able to capture those who did cash purchases, these numbers serve as a lower bound of the extent of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

Figure A1: Binned Scatterplot: SCF Imputed Income versus HMDA-McDash-CRISM Income

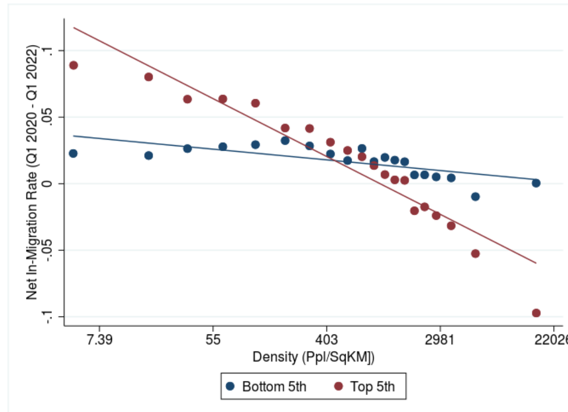


Note: We impute for all individuals present in the December 2019 HMDA-McDash-CRISM data using information from the 2019 SCF. See the main text of the paper for details. Data source: FRBNY Consumer Credit Panel/Equifax, Survey of Consumer Finances, HMDA-McDash-CRISM match, 3rd Generation.

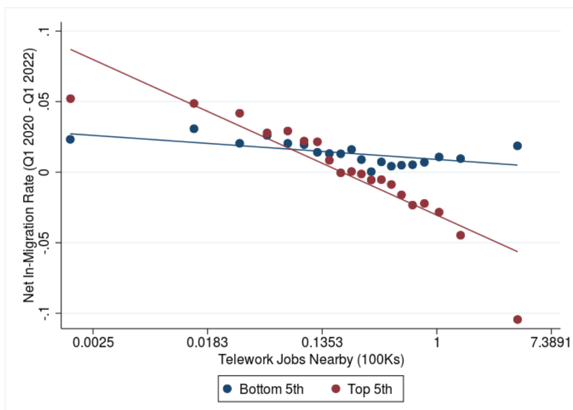
Figure A2: Binned Scatterplot: Post Q1 2020 Net In-Migration Rate by Census Tract, for Top and Bottom Income Quintiles



(a) Distance to Downtown



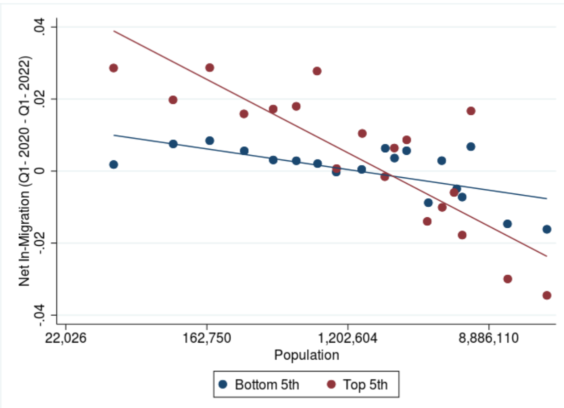
(b) Density



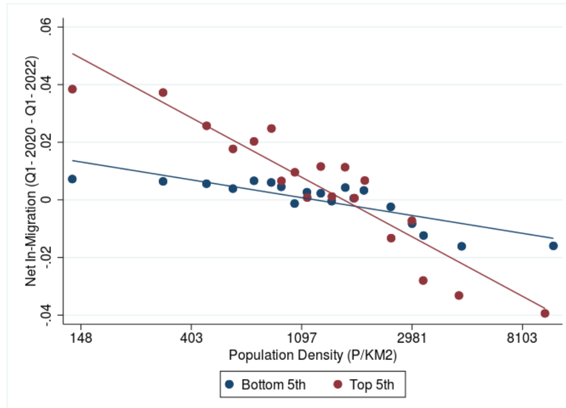
(c) Telework Jobs Nearby

Note: In each of the subfigures, we show the binned scatterplot of the net in-migration rate at the level of census tract for the subsample of people whose imputed income is in the top quintile and people whose imputed income is in the bottom quintile (ranked in Q42019), against selected tract-level characteristics. We plot the inflow between Q12020 and Q12022. The net in-migration rate in each census tract is defined as the net inflow of population divided by the population of the receiving census tract in the preceding quarter. We plot net in-migration rate by income quintile against (a) distance to downtown, (b) population density, and (c) nearby telework-compatible jobs. To compute the nearby telework-compatible jobs, we first impute the number of jobs by industry from the 2016 zip code Business Patterns data at zip code level. We then use an industry-occupation crosswalk to impute the job distribution for each occupation across zip code. Then, for each census tract, we compute the number of jobs located within a 3-mile radius that can be categorized as telework-compatible (Dingel and Neiman, 2020; Su, 2020). Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS.

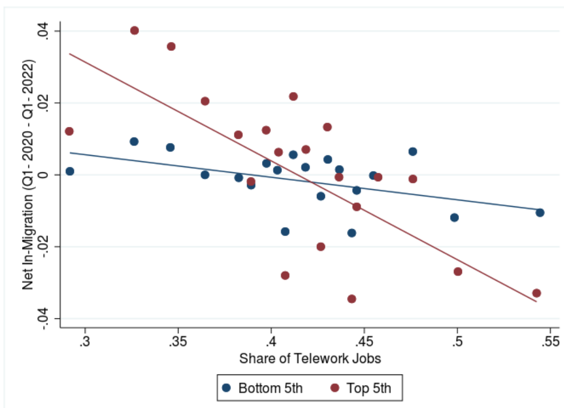
Figure A3: Binned Scatterplot: Post Q1 2020 Net In-Migration by MSA, for Top and Bottom Income Quintiles



(a) MSA Population



(b) MSA Density



(c) Share of Telework Jobs

Note: In each of the subfigures, we show the binned scatterplot of the net in-migration rate at the MSA level for the subsample of people whose imputed income is in the top quintile and people whose imputed income is in the bottom quintile (ranked in Q42019), against selected tract-level characteristics. We plot the inflow between Q1 2020 and Q1 2022. The net in-migration rate in each MSA is defined as the net inflow of population divided by the population of the receiving MSA in the preceding quarter. We plot net in-migration rate against (a) the MSA's population, (b) the MSA's population density, and (c) the MSA's share of telework-compatible jobs. To compute the share of jobs that are telework-compatible at the MSA level, we use the 2013-2017 ACS and assign each occupation into two categories: telework-compatible or not. For each MSA, we calculate the share of jobs that are telework-compatible (Dingel and Neiman, 2020; Su, 2020). Data source: FRBNY Consumer Credit Panel/Equifax, American Community Survey/IPUMS NHGIS.

Table A1: Migration Flows by State Before and After the Pandemic (1,000s)

	2020Q1 - 2022Q1 (Post)			2018Q1 - 2020Q1 (Pre)		
State	Inflow	Outflow	Net Inflow	Inflow	Outflow	Net Inflow
Florida	1264.8	816.1	448.7	1087.7	849.4	238.2
Texas	1063.9	756.2	307.7	981.8	809.2	172.7
North Carolina	559.7	414.6	145.1	545.1	444.3	100.7
Arizona	439.8	319.2	120.6	449.0	299.3	149.7
South Carolina	328.4	215.0	113.4	301.0	223.6	77.5
Tennessee	383.1	279.2	103.9	357.9	283.6	74.3
Georgia	521.1	442.8	78.4	511.7	469.1	42.6
Nevada	256.0	187.5	68.5	253.1	170.8	82.2
Idaho	141.9	78.0	63.9	125.8	78.3	47.5
Oklahoma	159.1	125.3	33.8	150.4	145.3	5.1
Alabama	189.1	158.9	30.2	183.6	173.7	9.9
Colorado	383.3	353.3	30.0	415.1	337.9	77.2
Montana	74.4	44.6	29.8	65.2	50.3	14.9
Maine	69.3	40.9	28.4	57.3	44.8	12.4
Utah	146.3	120.7	25.6	139.8	132.6	7.2
Arkansas	120.1	98.5	21.7	111.4	106.3	5.2
Delaware	72.1	51.4	20.7	63.5	53.0	10.5
Missouri	241.1	221.9	19.1	237.5	236.8	0.7
Oregon	221.3	202.4	18.9	242.1	185.9	56.2
New Hampshire	87.4	68.6	18.8	83.9	73.1	10.8
Washington	386.4	371.2	15.2	413.9	366.8	47.1
South Dakota	46.9	36.0	11.0	40.8	38.9	1.8
Vermont	36.7	27.3	9.4	32.0	33.3	-1.3
Kentucky	157.3	148.8	8.5	158.9	159.4	-0.6
Indiana	217.2	209.0	8.2	219.7	222.7	-3.0
Wisconsin	166.7	159.5	7.2	168.9	181.8	-12.9
Wyoming	39.9	34.9	5.0	37.7	40.5	-2.8
West Virginia	65.6	60.9	4.7	61.9	75.3	-13.4
New Mexico	99.9	96.1	3.9	99.4	99.8	-0.4
Rhode Island	53.8	53.0	0.8	52.3	54.0	-1.8
Nebraska	66.9	68.3	-1.3	69.8	77.1	-7.2
Mississippi	107.1	108.7	-1.7	102.7	115.9	-13.2
Connecticut	159.6	166.5	-6.9	138.3	179.6	-41.2
North Dakota	35.4	44.2	-8.9	45.4	50.5	-5.2
Iowa	95.6	104.6	-8.9	99.6	112.8	-13.2
Hawaii	82.5	92.8	-10.3	86.3	96.9	-10.6
Alaska	43.8	55.1	-11.2	47.0	59.5	-12.5
Kansas	122.6	136.6	-14.0	128.9	152.0	-23.1
Michigan	228.8	247.3	-18.5	228.7	266.9	-38.2
Ohio	282.6	309.6	-27.0	305.2	343.7	-38.5
Minnesota	149.7	177.1	-27.4	165.0	177.2	-12.2
Pennsylvania	381.8	412.2	-30.4	386.6	429.7	-43.1
District of Columbia	77.9	117.6	-39.7	103.1	105.0	-1.9
Virginia	431.4	474.7	-43.3	453.0	525.0	-72.0
New Jersey	358.5	404.4	-45.9	338.8	406.1	-67.4
Louisiana	122.8	169.4	-46.6	133.8	174.9	-41.1
Maryland	276.7	325.5	-48.8	295.5	331.8	-36.3
Massachusetts	216.6	306.9	-90.3	244.9	298.2	-53.2
Illinois	313.7	524.6	-210.9	353.5	521.2	-167.7
New York	519.1	1034.7	-515.6	631.8	875.0	-243.2
California	815.4	1409.0	-593.6	967.5	1234.8	-267.2

Note: Net inflow is inflow subtracted by outflow. The migration flows are first divided by 0.05 because the CCP samples 5% of the population with credit reports, and then by 0.628 as 62.8% of the population are between 25 and 65, assuming that the migration patterns of other age groups can be proxied by the patterns observed for this group. Data Source: FRBNY Consumer Credit Panel/Equifax.

Table A2: Migration Flows by Metro Before and After the Pandemic (1000s)

MSA	2020Q1 - 2022Q1 (Post)			2018Q1 - 2020Q1 (Pre)		
	Inflow	Outflow	Net Inflow	Inflow	Outflow	Net Inflow
	MSAs with Largest Net In-Migration Post-Q1 2020					
Dallas-Fort Worth-Arlington, TX	433.2	317.9	115.3	415.7	336.7	79.0
Tampa-St. Petersburg-Clearwater, FL	273.7	189.8	83.9	255.1	185.2	69.9
Phoenix-Mesa-Scottsdale, AZ	323.7	248.0	75.6	342.9	225.2	117.7
Austin-Round Rock, TX	216.6	151.8	64.8	213.9	142.3	71.6
North Port-Sarasota-Bradenton, FL	104.6	50.7	53.9	78.3	48.8	29.5
Houston-The Woodlands-Sugar Land, TX	310.5	259.9	50.5	293.3	284.1	9.2
Las Vegas-Henderson-Paradise, NV	195.1	146.1	49.0	193.7	131.7	62.0
Jacksonville, FL	148.2	100.7	47.5	131.7	101.1	30.5
San Antonio-New Braunfels, TX	171.9	124.9	47.0	168.9	135.7	33.2
Atlanta-Sandy Springs-Roswell, GA	358.0	312.8	45.2	357.1	319.7	37.4
Cape Coral-Fort Myers, FL	95.5	50.8	44.6	72.1	49.0	23.1
Lakeland-Winter Haven, FL	91.8	50.8	41.0	73.0	48.3	24.7
Charlotte-Concord-Gastonia, NC-SC	188.5	148.1	40.5	193.0	145.2	47.8
Riverside-San Bernardino-Ontario, CA	307.2	269.4	37.7	284.8	263.1	21.7
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	68.1	30.6	37.5	57.3	30.0	27.3
	MSAs with Largest Net Out-Migration Post-Q1 2020					
Urban Honolulu, HI	58.3	74.6	-16.3	65.0	77.5	-12.4
Baltimore-Columbia-Towson, MD	148.2	165.9	-17.6	156.0	173.1	-17.1
Detroit-Warren-Dearborn, MI	123.4	146.8	-23.4	132.3	155.9	-23.6
Minneapolis-St. Paul-Bloomington, MN-WI	115.2	142.8	-27.6	135.6	138.0	-2.4
Seattle-Tacoma-Bellevue, WA	236.2	273.0	-36.8	267.5	264.5	3.0
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	220.7	258.4	-37.7	232.8	252.7	-19.9
San Diego-Carlsbad, CA	202.6	249.5	-46.9	225.6	243.0	-17.4
Miami-Fort Lauderdale-West Palm Beach, FL	295.4	346.4	-51.0	265.8	336.8	-71.0
San Jose-Sunnyvale-Santa Clara, CA	125.1	199.2	-74.0	137.4	179.1	-41.7
Boston-Cambridge-Newton, MA-NH	201.0	286.1	-85.2	235.7	271.1	-35.4
Washington-Arlington-Alexandria, DC-VA-MD-WV	324.4	437.7	-113.3	372.5	433.5	-61.0
Chicago-Naperville-Elgin, IL-IN-WI	238.2	409.8	-171.6	280.1	394.0	-113.9
San Francisco-Oakland-Hayward, CA	237.2	415.7	-178.5	302.6	344.4	-41.8
Los Angeles-Long Beach-Anaheim, CA	444.5	740.4	-295.9	507.9	661.8	-153.9
New York-Newark-Jersey City, NY-NJ-PA	443.8	961.0	-517.2	550.6	803.7	-253.1

Note: In the table, for each MSA, we calculate the inflow to and outflow from each MSA and then take the difference to arrive at the net inflow to each MSA. We then rank the all the MSAs based on the net inflow post-Q1 2020. We report the MSAs with the largest positive net inflows and negative net inflows. Data Source: FRBNY Consumer Credit Panel/Equifax.

Table A3: Largest State-to-State Net Migration Flows Before and After the Pandemic (1000s)

Origin State	Destination State	Net In-Flows 2020Q1 - 2022Q1 (Post)	2018Q1 - 2020Q1 (Pre)
California	Texas	117.1	49.9
New York	Florida	109.2	62.4
New York	New Jersey	100.4	57.2
California	Arizona	74.6	56.8
California	Nevada	72.9	56.1
New Jersey	Florida	50.4	29.3
California	Oregon	40.4	38.9
California	Washington	38.6	26.9
Illinois	Florida	38.2	24.3
California	Idaho	38.0	24.7
New York	Connecticut	37.9	13.5
New York	Pennsylvania	36.9	17.3
California	Florida	33.2	6.3
New York	North Carolina	31.5	21.8
Pennsylvania	Florida	30.9	19.5
California	Tennessee	29.9	9.8
New York	Texas	28.4	9.5
California	Colorado	27.1	21.9
Illinois	Texas	25.7	14.5
Louisiana	Texas	22.8	20.6
Massachusetts	New Hampshire	22.6	16.6
Virginia	Florida	22.5	15.6
New York	Georgia	22.5	9.2
New York	California	21.9	10.6
California	Utah	21.8	13.3
Massachusetts	Florida	21.6	12.5
Maryland	Florida	20.9	10.2
Illinois	Indiana	20.5	14.0
District of Columbia	Maryland	19.7	8.0
California	North Carolina	19.0	5.8

Note: In the table, we rank the top state-to-state net migration flows based on the flow observed post-Q1 2020. Data Source: FRBNY Consumer Credit Panel/Equifax.

Table A4: Largest Metro-to-Metro Net Migration Flows Before and After the Pandemic (1000s)

Origin MSA	Destination MSA	Net In-Flows 2020Q1 - 2022Q1	2018Q1 - 2020Q1
Los Angeles-Long Beach-Anaheim, CA	Riverside-San Bernardino-Ontario, CA	97.3	67.9
New York-Newark-Jersey City, NY-NJ-PA	Miami-Fort Lauderdale-West Palm Beach, FL	44.8	17.7
New York-Newark-Jersey City, NY-NJ-PA	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	28.1	17.4
New York-Newark-Jersey City, NY-NJ-PA	Bridgeport-Stamford-Norwalk, CT	26.5	10.5
Los Angeles-Long Beach-Anaheim, CA	Las Vegas-Henderson-Paradise, NV	26.0	18.4
San Francisco-Oakland-Hayward, CA	Sacramento–Roseville–Arden-Arcade, CA	23.1	11.8
New York-Newark-Jersey City, NY-NJ-PA	Atlanta-Sandy Springs-Roswell, GA	21.3	8.4
New York-Newark-Jersey City, NY-NJ-PA	Orlando-Kissimmee-Sanford, FL	19.1	12.6
Miami-Fort Lauderdale-West Palm Beach, FL	Port St. Lucie, FL	18.4	13.5
Washington-Arlington-Alexandria, DC-VA-MD-WV	Baltimore-Columbia-Towson, MD	18.1	8.5
New York-Newark-Jersey City, NY-NJ-PA	Tampa-St. Petersburg-Clearwater, FL	17.8	11.8
Los Angeles-Long Beach-Anaheim, CA	Phoenix-Mesa-Scottsdale, AZ	17.8	14.0
New York-Newark-Jersey City, NY-NJ-PA	Los Angeles-Long Beach-Anaheim, CA	17.5	13.8
New York-Newark-Jersey City, NY-NJ-PA	Allentown-Bethlehem-Easton, PA-NJ	14.5	9.9
Orlando-Kissimmee-Sanford, FL	Lakeland-Winter Haven, FL	14.4	9.9
San Francisco-Oakland-Hayward, CA	Stockton-Lodi, CA	14.2	9.9
San Jose-Sunnyvale-Santa Clara, CA	San Francisco-Oakland-Hayward, CA	14.1	18.7
New York-Newark-Jersey City, NY-NJ-PA	Charlotte-Concord-Gastonia, NC-SC	14.1	11.3
San Francisco-Oakland-Hayward, CA	Los Angeles-Long Beach-Anaheim, CA	13.7	2.0
Miami-Fort Lauderdale-West Palm Beach, FL	Orlando-Kissimmee-Sanford, FL	13.5	11.4
Los Angeles-Long Beach-Anaheim, CA	Oxnard-Thousand Oaks-Ventura, CA	13.2	9.7
Los Angeles-Long Beach-Anaheim, CA	Dallas-Fort Worth-Arlington, TX	13.1	7.8
New York-Newark-Jersey City, NY-NJ-PA	Dallas-Fort Worth-Arlington, TX	12.4	5.3
Chicago-Naperville-Elgin, IL-IN-WI	Phoenix-Mesa-Scottsdale, AZ	11.7	9.3
Boston-Cambridge-Newton, MA-NH	Providence-Warwick, RI-MA	11.3	7.9
San Diego-Carlsbad, CA	Riverside-San Bernardino-Ontario, CA	11.1	5.7
Boston-Cambridge-Newton, MA-NH	Worcester, MA-CT	10.7	7.0
New York-Newark-Jersey City, NY-NJ-PA	Raleigh, NC	9.8	5.1
Los Angeles-Long Beach-Anaheim, CA	Bakersfield, CA	9.5	8.1
Miami-Fort Lauderdale-West Palm Beach, FL	Tampa-St. Petersburg-Clearwater, FL	9.3	7.7

Note: In the table, we rank the top MSA-to-MSA flows based on the flow observed post-Q1 2020. Data Source: FRBNY Consumer Credit Panel/Equifax.

Table A5: Summary Statistics of FRBNY CCP/Equifax and SCF (2019)

Category	Mean	S.d.	Median
Panel A: FRBNY CCP/Equifax Q42019			
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: FRBNY Consumer Credit Panel/Equifax, SCF.

Table A6: 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: SCF.

Table A7: Regression: Differential Migration Patterns by Income and Age

	Net In-Migration Rate	
	(1)	(2)
Distance to Downtown	2.99e-06	
	(0.000196)	
Bottom fifth & Older than 45	0.000786***	
× Distance to Downtown	(0.000217)	
Top fifth & Younger than 45	0.00423***	
× Distance to Downtown	(0.000255)	
Top fifth & Older than 45	0.00173***	
× Distance to Downtown	(0.000292)	
Metro-Level Ln Pop Density		-0.00648***
		(0.00113)
Bottom fifth & Older than 45		0.0000132
× Metro-Level Ln Pop Density		(0.00113)
Top fifth & Younger than 45		-0.0131***
× Metro-Level Ln Pop Density		(0.00136)
Top fifth & Older than 45		-0.0127***
× Metro-Level Ln Pop Density		(0.00270)
FE	Metro	None
R2	0.0275	0.2012
Observations	244,741	3,668

Note: We compute the net in-migration rates from Q12020 to Q12022 separately for individuals in the top fifth income and bottom fifth income quintiles (ranked in Q42019) 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. Each of the observations for the column (1) regression represents a census tract. We include metro-level fixed effects for the column (1) regression. Each of the observations for the column (2) regression represents a metro, which include micropolitan. Data Source: American Community Survey (ACS), NHGIS, FRBNY Consumer Credit Panel/Equifax. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A8: Regression: Differential Migration Patterns by Income and Mortgage Status

	Net In-Migration Rate	
	(1)	(2)
Distance to Downtown	0.000208	
	(0.000230)	
Bottom fifth & With Mortgage	-0.0000345	
× Distance to Downtown	(0.000366)	
Top fifth & No Mortgage	0.00139***	
× Distance to Downtown	(0.000314)	
Top fifth & With Mortgage	0.00271***	
× Distance to Downtown	(0.000276)	
Metro-Level Ln Pop Density		-0.00864***
		(0.00247)
Bottom fifth & With Mortgage		-0.000421
× Metro-Level Ln Pop Density		(0.00296)
Top fifth & No Mortgage		-0.0100***
× Metro-Level Ln Pop Density		(0.00270)
Top fifth & With Mortgage		-0.0104***
× Metro-Level Ln Pop Density		(0.00280)
FE	Metro	None
R2	0.0385	0.0655
Observations	129,658	3,519

Note: We compute the net in-migration rates from Q12020 to Q12022 separately for individuals in the top fifth income and bottom fifth income quintiles (ranked in Q42019) 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 standalone indicator variables for each of the non-omitted categories. Each of the observations for the column (1) regression represents a census tract. We include metro-level fixed effects for the column (1) regression. Each of the observations for the column (2) regression represents a metro, which include micropolitan. Data Source: American Community Survey (ACS), NHGIS, FRBNY Consumer Credit Panel/Equifax. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A9: Family Characteristics of Movers and Nonmovers

Category	2019Q1-2020Q1					2020Q2-2022Q2				
	Mean	S.d.	Median	P25	P75	Mean	S.d	Median	P25	P75
Panel A: Movers										
Household size	1.27	1.17	1	1	1	1.27	1.159	1	1	1
Changes in household size	0.0041	1.566	0	0	0	-0.003	1.581	0	0	0
Age of the individual	39	10.541	37	30	48	41	10.572	39	32	49
Age of the youngest	39	10.636	36	30	47	40	10.738	38	31	48
Panel B: Nonmovers										
Household size	1.23	1	1	1	1	1.23	1.003	1	1	1
Changes in household size	0.0004	0.174	0	0	0	-0.0002	0.163	0	0	0
Age of the individual	44	10.99	45	35	54	46	11.436	46	36	55
Age of the youngest	43	11.32	44	33	53	45	11.436	45	35	55

Note: This 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 1.6 million for for 2019Q1-2020Q1 and 2.6 million for 2020Q2-2022Q2. The number of observations in panel B is 35 million for 2019Q1-2020Q1 and 62 million for 2020Q2-2022Q2. Data Source: FRBNY Consumer Credit Panel/Equifax.

Table A10: First Mortgages of Movers and Nonmovers

Category	2019Q1-2020Q1			2020Q2-2022Q2		
	Mean	S.d.	Median	Mean	S.d	Median
Panel A: Movers						
Number of first mortgages	0.292	0.455	0	0.317	0.465	0
Changes in the number of first mortgages from the previous year	0.039	0.268	0	0.044	0.284	0
Panel B: Movers with Equifax Risk Score over 720						
Number of first mortgages	0.480	0.499	0	0.499	0.500	0
Changes in the number of first mortgages from the previous year	0.060	0.331	0	0.066	0.346	0
Panel C: Nonmovers						
Number of first mortgages	0.309	0.462	0	0.323	0.468	0
Changes in the number of first mortgages from the previous year	0.0007	0.199	0	0.0001	0.200	0
Panel D: Nonmovers with Equifax Risk Score over 720						
Number of first mortgages	0.423	0.494	0	0.426	0.494	0
Changes in the number of first mortgages from the previous year	0.0006	0.236	0	0.0001	0.230	0

Note: This 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 1.6 million for 2019Q1-2020Q1 and 2.6 million for 2020Q2-2022Q2. The number of observations in panel C is 35 million for 2019Q1-2020Q1 and 62 million for 2020Q2-2022Q2. Data Source: FRBNY Consumer Credit Panel/Equifax.