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Spatial Sorting and Inequality

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Abstract

The spatial segregation of college-educated and non-college-educated workers between commuting zones in the United States has steadily grown since 1980. We summarize prior work on sorting and location and document new descriptive patterns on how sorting and locations have changed over the past four decades. We find that there has been a shift in the sorting of college-educated workers from cities centered primarily around production in 1980 to cities centered around consumption by 2017. We develop a spatial equilibrium model to understand these patterns and highlight key places where further research is needed. Our framework helps understand the causes and consequences of changes in spatial sorting; their impact on inequality; and how they respond to, and feed into, the changing nature of cities.

1. INTRODUCTION

The dramatic increase in the wage gap between college-educated and lower-skill workers over the past four decades has been accompanied by a substantial increase in the geographic sorting of workers by skill. We review the literature that studies the causes of these changes in spatial sorting and their consequences for inequality and policy.

In terms of scope, our analysis is focused on studying sorting between cities in the United States, leaving aside related questions that the literature has been tackling, in particular the small but burgeoning literature that studies within-city sorting.[1] We focus on sorting by education level, specifically on the location choices of two worker groups: those with a 4-year college degree versus those without, following previous work such as that by Moretti (2013) and Diamond (2016).[2] We refer to these groups as high-skill and low-skill workers.

In Section 1, we document stylized facts related to changes in spatial skill sorting from 1980 to today. We show in particular that high-skill workers have shifted from sorting into cities centered primarily around production in 1980 to cities centered around consumption by 2017. Section 2 develops a spatial equilibrium model with heterogeneous agents to think through these descriptive patterns. It highlights (*a*) the important feedback loops that exist between changes in location choices of skill groups and (*b*) endogenous changes in location characteristics (such as wage, rents, and amenities). We use this template to organize our review of the existing literature, and we flag where more research is needed. Section 3 discusses the implications of spatial sorting for the measurement of inequality and for policy. Section 4 concludes.

2. MEASURING SPATIAL SORTING AND INEQUALITY

A wide variety of statistics quantify segregation and sorting of different groups across geographic areas. We focus on the exposure gap index to measure how high- and low-skill workers tend to live in areas with systematically different characteristics, such as average wages, housing costs, or indicators of quality of life. The exposure gap at time t for characteristic Y is defined as

$$\text{exposure}_t = \sum_J \frac{H_{jt} Y_{jt}}{\sum_k H_{kt}} - \sum_J \frac{L_{jt} Y_{jt}}{\sum_k L_{kt}},$$

where H_{jt} and L_{jt} are the number of high- and low-skill workers living in location j, respectively, and Y_{jt} is some characteristic of location j. Conceptually, these exposure gaps tell us, first, how different the average location experienced by high-skill workers is from the average location of low-skill workers. Intuitively, they therefore shed light on how sorting may contribute to inequality, in terms of income and quality of life—an analysis we complement in Section 2 with corresponding theoretically consistent measures of well-being inequality. Second, when Y_{jt} is the high-skill share of location j $\left(Y_{jt} = \frac{H_{jt}}{H_{jt}+L_{jt}}\right)$, the exposure gap constitutes a measure of segregation itself.

[1] This literature has a close connection in methodology and questions with our object of study. We refer the interested reader to papers analyzing trends in neighborhood change and gentrification in US cities (Guerrieri et al. 2013, Baum-Snow & Hartley 2020, Couture & Handbury 2020, Hoelzlein 2020, Almagro & Domínguez-Iino 2021, Couture et al. 2022, Su 2022), changes in transportation infrastructure (Tsivanidis 2019), public school choice (Bayer et al. 2007), and the impacts of these various forces on sorting.

[2] Some other studies have focused on sorting by income level and have shown that residential income segregation in the United States has been continuously rising since the 1980s (Reardon & Bischoff 2011, Reardon et al. 2018, Gaubert et al. 2021a). We prefer to focus on skill sorting because income is shaped, in part, by one's place of residence.

We follow Diamond (2016) and focus on full-time full-year-employed workers between the ages of 25 and 55 to study worker location sorting. We use the 1980 and 2000 5% samples of micro data from the Decennial Censuses (Ruggles et al. 2021). To track the most recent evolutions in location choices, we use the 2015–2019 5-year pooled American Community Survey (ACS) sample and label this as year 2017, the average year of the 5-year ACS data. We define a city on the basis of the 1990 commuting zones (CZs). The Census and ACS public-use data report households' place of residence at the public-use micro area (PUMA) level. We translate these to 1990 CZs on the basis of each PUMA's population overlap with each CZ.[3]

2.1. Spatial Skill Sorting: 1980–2017

We begin by documenting the level of and change in spatial skill sorting from 1980 to 2017. We measure the exposure gap of college-educated versus non-college-educated workers to the local high-skill share, a measure of spatial skill segregation, as explained above. Column 1 of panel *a* in **Table 1** shows that in 1980, the average college graduate lived in a CZ with a high-skill share 1.9 percentage points (pp) higher than the average non–college graduate. This gap increased to 3.1 pp by 2000 and to 3.9 pp by 2017 (columns 4 and 7 of panel *a* in **Table 1**). Therefore, high- and low-skill workers have been and are still moving away from each other. However, interestingly, the speed of divergence has slowed substantially over the two last decades. Of course, these measures may be mechanically driven by the nationwide growth in high-skill share. However, repeating the analysis holding fixed this nationwide share at its 1980 level (but allowing sorting patterns to change) paints a similar picture of deceleration in spatial segregation at the CZ level. Indeed, with a fixed aggregate share of high-skill workers, the exposure gap would have increased to 2.6 pp in 2000 and 2.9 pp in 2017. While segregation is clearly increasing, the economic magnitude of this index is a bit hard to interpret. To help interpret these magnitudes, we investigate how the average high-skill worker's CZ differs from the average low-skill worker's CZ along a variety of dimensions.

Spatial skill sorting has been increasing. We next document how this sorting and its change over time contribute to differences in earnings, housing costs, and quality of life experienced by college-educated and non-college-educated workers.

2.2. Geographic Differences in Earnings

We first investigate how spatial sorting has been shaping differences in earnings between skill groups.

2.2.1. Measuring exposure gaps in earnings.

A key reason why high- and low-skill workers may choose different CZs is local labor market conditions: CZs that pay high wages for high-skill labor need not be the same places that pay the best wages for lower-skill labor. To measure CZ wages, we run a regression by using the Census/ACS micro data on log earnings, where we control for a quartic in age, race dummies, and gender. CZ–skill group fixed effects proxy for local wages.[4] Exposure indexes based on these measures are reported in panel *b* of **Table 1**, which we now discuss.

In 1980, the average college-educated worker lived in a CZ that paid high-skill workers 2.6% more than what they would earn where the average non-college-educated worker lived.

[3]We use crosswalks provided by David & Dorn (2013).

[4]These wages are not adjusted for any differences in local prices or purchasing power.

Table 1 College-educated–non-college-educated gap in location characteristics: 1980–2017

Commuting zone characteristics	Exposure gap 1980 (*1*)	Place effect 1980–2000 (*2*)	Sorting effect 1980–2000 (*3*)	Exposure gap 2000 (*4*)	Place effect 2000–2017 (*5*)	Sorting effect 2000–2017 (*6*)	Exposure gap 2017 (*7*)
(*a*) Segregation							
Share college graduate	0.019			0.031			0.039
Share college graduate, no aggregate growth	0.019			0.026			0.029
(*b*) Wages and housing costs							
Log college-educated wage	0.026	0.013	0.008	0.048	0.008	−0.002	0.054
Log non-college-educated wage	0.026	0.007	0.006	0.039	−0.007	−0.002	0.030
Log wage gap	0.000	0.006	0.002	0.009	0.015	0.000	0.024
Log rent	0.045	0.021	0.010	0.077	0.008	−0.004	0.080
Log home value	0.073	0.019	0.014	0.106	0.020	−0.006	0.121
(*c*) Public amenities							
AQI, ninetieth percentile	1.805	−1.453	−0.356	−0.004	0.035	−0.968	−0.936
Flood risk	−0.016			−0.025			−0.027
Log property crimes per capita	0.073	−0.068	−0.006	−0.001	−0.007	−0.010	−0.019
Log violent crimes per capita	0.104	−0.061	0.008	0.051	−0.023	−0.013	0.015
Log median commute time	0.042	−0.003	0.011	0.051	0.005	−0.001	0.055
(*d*) Consumption amenities							
Log restaurants per capita	0.011	0.000	0.003	0.014	0.023	0.003	0.040
Log gyms per capita	0.047	0.001	0.018	0.066	0.037	0.004	0.107
Log salons per capita	0.015	0.035	0.021	0.071	0.050	0.008	0.129
Log clothing stores per capita	0.000	0.022	0.008	0.030	0.016	−0.006	0.040

Data on location choices, wages, rents, housing values, and commute times come from the 1980 and 2000 5% samples of the US Census. The 2017 data are from the 2015–2019 5-year pooled American Community Survey data. Air Quality Index (AQI) data are from the US Environmental Protection Agency. Flood risk data are from Flood Factor. Crime data from county-level Uniform Crime Reports are provided by the Federal Bureau of Investigation. Consumption amenity data are from County Business Patterns. Samples of college-educated and non-college-educated workers are restricted to 25–55-year-old full-time, full-year workers.

This accords with the intuition that high-skill workers choose to locate in CZs that pay them well. However, interestingly, these same locations preferred by high-skill workers also paid non-college-educated workers 2.6% more than locations preferred by low-skill workers, which is more surprising, as it shows that the low skill chose to live in CZs that offered them lower wages. Overall, the different location choices of high- and low-skill workers at the time did not seem to reflect the comparative advantages of CZs in high- versus low-skill labor.

As sorting intensified from 1980 to 2000, the earnings premium of high-skill locations increased, and a comparative advantage wage gap opened up. By 2000, high-skill workers lived in CZs that paid them 4.8% more than the CZs chosen by low-skill workers. The former CZs still also paid low-skill workers more, but only by 3.9%. The high-skill wage premium was therefore 0.9 pp higher in the average high-skill location. To tease out how much of these changes is driven by places changing over time versus migration patterns, we hold fixed the location choices of workers in 1980 but allow wages to evolve as observed in the data from 1980 to 2000. The corresponding exposure gap captures what we refer to as a place effect (column 2 of **Table 1**). The remainder to explain the total change in exposure (reported in column 4 of **Table 1**) is due to differences in net migrations between skill groups. We term this the sorting effect (reported in column 3 of **Table 1**). We find a more important role played by place effects relative to sorting effects: Place effects drive two-thirds of the growth in the college-educated wage exposure gap and half of the growth in the non-college-educated wage exposure gap.

From 2000 to 2017, the earnings premium of high-skill locations further increased to 5.4% for college-educated workers and 3.0% for non-college-educated workers such that the comparative advantage wage gap spiked to 2.4 pp. This increasingly wide skilled wage premium in high-skill CZs echoes the findings of Autor (2019). He finds that historically dense (and thus high-skill) cities paid high wages to middle- and high-skill labor in 1980 but that the urban wage premium to middle-skill work has eroded and is essentially nonexistent today, while, in contrast, the urban wage premium to high-skill work has continued to intensify. We find that this increase in the skilled wage premium in high-skill CZs is entirely due to place effects and is not driven by differential migration between college-educated and non-college-educated workers. Specifically, in locations historically chosen by high-skill workers, wages of college-educated workers increased by 0.8 pp, while wages of non-college-educated workers decreased by 0.7 pp. Migration actually contributed to slightly narrowing the exposure wage gaps (−0.02 pp). While small in magnitude, this pattern stands in stark contrast to the 1980–2000 period, when high-skill workers were migrating to places that paid them especially well. Overall, in the past 20 years, high-skill workers have been differentially migrating to places that pay a high wage, but to a lesser extent than in the earlier period, such that migration tied to labor market conditions appears to be waning. Investigating this change in migration patterns is a ripe place for future research.

2.2.2. Place effect or sorting on unobserved ability? A key question in measuring differences in local labor markets across space is whether the observed wage differences across space represent the true causal effect of place on earnings. Alternatively, there could be sorting of workers based on unobserved ability measures that confound measurement of earnings differentials across space: CZs that appear to pay high wages for a given skill group might actually just hire especially high-ability workers. Glaeser & Mare (2001) first investigated this question by using survey data from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics and analyzing wages of movers. Their findings suggest that places did impact earnings substantially but that these earnings effects accrued slowly over time. More recent work using administrative data has built on this study. Using French administrative panel earnings data, Combes et al. (2008) show that 40–50% of the observed differences in mean wages across space are due to worker sorting. They also find that place effects due to agglomeration are important. Using Spanish administrative data, De La Roca & Puga (2016) find that worker sorting on unobserved initial ability plays essentially no role in cross-city earnings differentials. Instead, they find important differences in human capital acquisition across cities, where large, high-wage cities enable workers to accumulate skills that they could take to other cities if they were to move. These differences in city-acquired human capital explain approximately half of the cross-sectional differences in mean earnings. Dauth et al. (2022) perform a similar analysis using German data but focus more on the importance of worker-firm match effects and how they vary by city size. These researchers find that worker characteristics (observed and unobserved) explain approximately 40% of the cross-sectional variance in wages across cities and that large cities allow workers and firms to match better. Most recently, Card et al. (2021) use US administrative data to study worker moves. A key advance of their work is to study the impact of place on earnings separately by workers' education level. They find that, for low-skill and high-skill workers, sorting on ability explains 33% and 53%, respectively, of the cross-sectional variation in CZ earnings. High-skill workers are much more sorted by ability into high-wage CZs. Indeed, the higher-skill wage premium found in large cities seems to be entirely due to workers sorting on unobserved ability.

A key question for future research would be to understand how sorting on unobserved ability has changed over time. Baum-Snow & Pavan (2013) show that the positive relationship between city size and wage inequality developed only after 1990. Card et al. (2021) use data from 2010 to 2018, while the initial work by Glaeser & Mare (2001) uses data mostly from before 1990. How much of the growth in the positive relationship between city size and wage inequality is due to worker sorting versus place effects? The exposure analysis in Section 2.2 suggests a slowdown in skill sorting on labor market earnings over the past two decades relative to the 1980–2000 period. At the same time, the literature focused on measuring unobserved worker skills shows a very high level of ability sorting within the college-educated group. Has sorting within skill group become the more dominant force relative to between-group sorting? Reconciling the literature focused on changes in sorting and wage premia across space with the literature focused on unobserved ability sorting in the cross section is a very open research topic.

2.3. Geographic Differences in Local Prices

High-skill workers are increasingly located more in high-paying CZs relative to low-skill workers, contributing to the increase in nationwide wage inequality. Moretti (2013) shows that, at the same time, these locations tend to have high housing costs, a force that mitigates the increase in nationwide real wage inequality. We therefore continue our empirical analysis by zooming in on changes in exposure gaps to housing affordability between college-educated and non-college-educated workers. To measure housing affordability, we use the Census/ACS micro data on log monthly gross rents (for renters) and log housing values (for owners) and regress them on a CZ-fixed effect, controlling for year built, number of units in the structures, and number of bedrooms. The estimated CZ-fixed effect is our measure of local housing costs.

Panel *b* of **Table 1** shows that in 1980, the average high-skill worker lived in a CZ that cost 4.5% more in rent and 7.3% more in home values than the average location of low-skill workers. Therefore, in 1980, sorting was already much more apparent in housing costs than in wages, consistent with the notion that housing costs place a disproportionate burden on lower-skill, lower-income workers. By 2000, these differences had increased: The average high-skill worker lived in a CZ that cost 7.7% more in rent and 10.6% more in housing value than the average CZ of low-skill workers. Similar to what we saw for wages, changes in place effects played a dominant role in this change (approximately 60–70%) relative to net migration. In the 2000–2017 period, the exposure gap for housing costs further increased (+0.3 pp in rents and +1.5 pp in housing values), but again here the rate of growth slowed substantially. Strikingly, more than 100% of the growth in the exposure gap to housing costs is due to place effects: Had workers remained in the 2000 locations, the rent and housing value exposure gaps would have increased even more, by 0.8 and 2.0 pp, respectively. Therefore, the changing location choices of the two skill groups between 2000 and 2017 have tended to narrow the housing affordability gap between groups. In contrast to the 1980–2000 period, during which college-educated workers were disproportionately migrating to expensive cities on net, college-educated workers are now disproportionately migrating to relatively more affordable CZs relative to non-college-educated workers. We are not aware of any work exploring this sharp change in migration patterns.

Housing costs, available in Census data, are only a component of household expenditure. More generally, Diamond & Moretti (2021) study how consumption and expenditure by skill vary across space, using detailed bank account and credit card data. They find that housing prices constitute a larger share of the consumption bundle of lower-income households and that local prices of other goods are higher in high-housing-price cities. The results of Card et al. (2021) suggest that high-wage CZs have such high housing prices that these prices more than offset higher nominal wages, leading to lower real earnings in high-housing-price CZs.

2.4. Geographic Differences in Local Amenities

A last important difference across geographic locations is the local amenities that they provide, which directly impact quality of life. Diamond (2016) highlights that local amenities influence location choices, especially for high-skill workers. We measure here changes in the exposure gap of college-educated and non-college-educated workers to a range of local amenities. We start with public amenities, which one has access to by simply being present (and paying taxes) in the city. Our first measure is the Air Quality Index (AQI), where a higher value of AQI indicates worse air. In 1980, exposure to the ninetieth percentile of a CZ's annual AQI was 1.8 points higher for the average high-skill worker relative to the average low-skill worker (panel *c* of **Table 1**). That is, the urban areas disproportionately chosen by college-educated workers had worse air. This negative amenity gap was fully eroded by 2000, when the AQI gap fell to −0.004. Approximately 80% of that improvement was due to place effects, while 25% was due to migration. By 2017, college graduates lived in CZs with better air relative to low-skill workers (with an exposure gap of −0.94), and more than 100% of this widening air quality gap was due to migration. The migration of high-skill workers to high-air-quality places has substantially increased and accelerated, in contrast to their sorting on wage and rent. Data measuring flood risk paint a similar picture.[5] In 1980, college-educated workers lived in CZs with a 1.6 pp lower probability of an annual flood. Due to migration, this changed to a 2.5 pp lower probability by 2000 (and to 2.7 pp by 2017). These results suggest that college-educated workers are increasingly sorted on environmental amenities. Another interesting local amenity is local crime rates.[6] In 1980, college-educated workers lived in CZs with 7.3% higher property crime rates per capita and 10.4% higher violent crime rates per capita. These statistics paint the picture of urban centers as production hubs that come with urban disamenities. In 1980, college-educated workers lived in larger cities with higher housing costs that paid them well. However, these production advantages did not come along with the amenity advantage that we associate with large cities today. Workers had to endure worse air and higher crime there. By 2017, exposure gaps to property crime had turned to a negative 1.9% (and a small positive 1.5% for violent crime). Taken together with our environmental quality results, these results suggest that we have seen a transformation away from production cities toward production and consumer cities offering both high wages and better amenities (along with higher housing costs). Commute times are an exception to these patterns. Indeed, we measure that college-educated workers lived in CZs with 4.2% longer median commutes in 1980, a gap that increased to 5.1% in 2000 and 5.5% in 2017. Since longer commutes are considered a disamenity, this is the only amenity we find that college-educated graduates are increasingly negatively sorted on.

To further analyze the shift of high-skill cities becoming hubs of consumption, we investigate sorting on consumption amenities, such as the variety of restaurants and other privately provided local services.[7] In 1980, college-educated workers lived in CZs that had on average 1.1% more restaurants than the average low-skill CZs. This gap increased slightly by 2000, to 1.4%. By 2017, the exposure gap for restaurants per capita had grown to 4.0%. We find very similar patterns in exposure gaps to the log number of gyms per capita (growing from 4.7% to 10.7% over 1980–2017) and log salons per capita (growing from 1.5% to 12.9% over 1980–2017). In all cases, the driver of these exposure gap changes is changes in place effects between 2000 and 2017, although

[5]Our flood risk data come from Flood Factor (**https://floodfactor.com/**) and do not vary over time. Thus, changes in the exposure index can be driven only by migration.

[6]Our crime data come for county-level reports of crime from the Federal Bureau of Investigation.

[7]Consumption amenity data come from County Business Patterns (**https://www.census.gov/programs-surveys/cbp.html**).

migration also contributes to these exposure gap changes. Log clothing store per capita also exhibits growth in exposure, but more so during the 1980–2000 period than during the 2000–2017 period. Overall, establishments selling local services, more so than goods, appear to be increasingly highly concentrated in today's high-skill consumer cities.

Taking stock, we find that across both consumption and public amenities, high-skill workers continue to migrate more to better-amenity CZs from 2000 to 2017 than do low-skill workers, unlike our findings on wages and housing costs. Amenities and quality of life could be becoming increasingly important as the nationwide high-skill wage premium continues to rise.

In the next section, we discuss how a model can help structure the possible causes and consequences of the changes in jointly determined wages, housing costs, amenities, and location choices over time, and we use this template to review the corresponding literature.

3. CHANGE IN SKILL SORTING: FRAMEWORK

3.1. Setup

To organize our thoughts on the causes and consequences of spatial sorting, we lay out a framework in which heterogeneous workers sort across locations within a country. As in the quantitative spatial equilibrium models reviewed by Redding & Rossi-Hansberg (2017), worker demand for locations is modeled as a discrete choice, and the characteristics of locations are endogenous. Unlike the bulk of this literature, which is based on homogeneous agents, we model heterogeneous groups of agents, who may value location characteristics differently. On the production side, rather than modeling imperfect trade between locations, we consider an economy that is more stylized spatially, with two types of goods: (*a*) a homogeneous manufactured good that is freely traded across space and (*b*) housing, a local nontraded good.

3.1.1. Preferences.

Consider a spatial equilibrium framework with two skill groups (unskilled and skilled) $\theta = U, S$, who choose where to live among locations $i \in [1, \dots, N]$. Aggregate skill supply for each group, L^θ, is exogenously given, and each worker supplies one unit of labor for wage w_i^θ in location i. The utility of worker ω, who is of type θ and lives in location i, is

$$u_i^\theta(\omega) = \max_{c,h} \log U^\theta(A_i, c, h) + \varepsilon_i^\theta(\omega) \qquad \text{such that } c + r_i h = w_i^\theta.$$

Here, $\log U^\theta(\cdot)$ is the representative utility of a worker of type θ; c is consumption of the freely traded good and is taken as the numeraire; h denotes housing, with price r_i in location i; and A_i is a vector of amenities in location i. Finally, $\varepsilon_i^\theta(\omega)$ is a worker-specific preference shock for living in location i. This shock is independent and identically distributed across workers within a group and across locations.

The literature has made different choices of utility functions $U^\theta(\cdot)$. The first type of choices pertains to the consumption of c and h. A strand of the literature follows quantitative spatial models and uses Cobb-Douglas preferences over traded and nontraded goods. Another strand chooses nonhomothetic preferences for $U^\theta(\cdot)$, with housing modeled as a necessity. We make a middle-of-the-road assumption in which, in each group θ, workers have Cobb-Douglas preferences over the traded and nontraded goods, but we allow the housing expenditure share α^θ to be group specific and typically higher for the unskilled. We refer to Gaubert & Robert-Nicoud (2022) for a full analysis with nonhomothetic preferences. The assumption we make could capture true preference heterogeneity between groups. It is also a reduced-form way of qualitatively capturing forces that are due to nonhomotheticity and therefore allows us to speak to the main forces that may drive sorting, including income effects, with a streamlined exposition.

Second, we assume that amenities are separable from consumption. This assumption is shared by essentially all papers reviewed here, although this choice is arguably made in part for convenience. We allow amenities in location i to be valued differently by the two groups, as captured by a group-specific amenity level A_i^θ.

Third, preference shocks are typically chosen to be extreme value (EV) distributed. Papers in the tradition of urban and labor economics or industrial organization tend to use logit shocks, with normalized variance $\frac{\pi^2}{6}$ shifted by a factor $\frac{1}{\kappa^\theta}$, which together with Cobb-Douglas utility lead to the following indirect utility of worker θ in location i:

$$v_i^\theta(\omega) = \log A_i^\theta + \log w_i^\theta - \alpha^\theta \log r_i + \frac{1}{\kappa^\theta}\varepsilon_i^\theta(\omega).$$

Equivalently, papers in the tradition of trade and economic geography typically choose Fréchet shocks for $\varepsilon_i^\theta(\omega)$ with scale parameter $\kappa^\theta > 1$ that enter utility in a multiplicatively separable way (rather than additively).[8] In this case, the indirect utility of worker θ in location i is

$$v_i^\theta(\omega) = \frac{A_i^\theta w_i^\theta}{r_i^{\alpha^\theta}}\varepsilon_i^\theta(\omega).$$

In either case, location choices in group θ can be summarized with λ_i^θ, the share of θ workers who choose location i:

$$\lambda_i^\theta = \frac{L_i^\theta}{L^\theta} = \frac{\left(\frac{A_i^\theta w_i^\theta}{r_i^{\alpha^\theta}}\right)^{\kappa^\theta}}{\sum_{j=1}^N \left(\frac{A_J^\theta w_J^\theta}{r_J^{\alpha^\theta}}\right)^{\kappa^\theta}}. \qquad 1.$$

The parameter κ^θ captures the elasticity of population shares with respect to amenity-adjusted real wages and is therefore a measure of mobility of group θ, which we allow to be group specific. Expected utility for a worker in group θ across locations is

$$W^\theta = \delta^\theta \left[\sum_{k=1}^N \left(\frac{A_k^\theta w_k^\theta}{r_k^{\alpha^\theta}}\right)^{\kappa^\theta}\right]^{\frac{1}{\kappa^\theta}}, \qquad 2.$$

with $\delta^\theta = \Gamma\left(\frac{\kappa^\theta - 1}{\kappa^\theta}\right)$, and $\Gamma(\cdot)$ is the gamma function in the Fréchet case. The same expression (up to the constant δ^θ) captures the log of expected utility in the additive logit case, expressed in log wage units.[9] The two models are therefore intimately related. We proceed with the Fréchet formulation and multiplicative notations below.

3.1.2. Supply of goods, amenities, and housing.

We now close the model and formalize the supply of traded goods, local amenities, and housing.

3.1.2.1. Traded goods.

We first write down the labor demand side of the economy. In location i, output is produced by perfectly competitive firms. They combine skilled and unskilled labor, who are imperfect substitutes in production:

$$Y_i = \left[\left(z_i^{\mathrm{U}}\right)^{\frac{1}{\rho}}\left(L_i^{\mathrm{U}}\right)^{\frac{\rho-1}{\rho}} + \left(z_i^{\mathrm{S}}\right)^{\frac{1}{\rho}}\left(L_i^{\mathrm{S}}\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}. \qquad 3.$$

[8]The Fréchet distribution is $G(\varepsilon) = e^{-\varepsilon^{-\kappa}}$.

[9]Specifically, $\frac{E(U^\theta)}{\mathrm{d}U^\theta/\mathrm{d}\log w} = \log W^\theta + C$, where C is a constant.

In the constant returns to scale, constant elasticity of substitution (CES) production function (Equation 3), $\rho \geq 1$ is the elasticity of substitution between skills, and z_i^θ are location- and skill-specific productivity shifters. These shifters can be in part exogenous, reflecting fundamental differences between locations, such as natural resources. They can also be in part endogenous, reflecting externalities. That productivity is subject to local spillovers reflects traditional agglomeration forces dating back at least to Marshall (1890). Specifically, we assume that, for $\theta = \{\mathrm{U}, \mathrm{S}\}$ and $\forall i$,

$$z_i^\theta = z^\theta \left(\bar{Z}_i, L_i^{\mathrm{U}}, L_i^{\mathrm{S}}\right), \tag{4}$$

where $\bar{Z}_i$ is the exogenous productivity component of city i. Local productivity spillovers are allowed here to depend not just on city size or density but also on its composition $\left(L_i^{\mathrm{U}}, L_i^{\mathrm{S}}\right)$.[10] In addition, these agglomeration effects may differ by skill, as captured by a group-specific spillover function $z^\theta(\cdot)$. Given Equation 3, relative labor demand in location i is

$$\log\left(\frac{L_i^{\mathrm{S}}}{L_i^{\mathrm{U}}}\right) = \log\left(\frac{z_i^{\mathrm{S}}}{z_i^{\mathrm{U}}}\right) - \rho \log\left(\frac{w_i^{\mathrm{S}}}{w_i^{\mathrm{U}}}\right). \tag{5}$$

Furthermore, competition across cities ensures that the unit cost of production in all cities is 1, the common price of the freely traded good:

$$\sum_\theta z_i^\theta \left(w_i^\theta\right)^{1-\rho} = 1 \quad \forall i.$$

3.1.2.2. Amenities.

Similar to productivity, amenities A_i^θ are assumed to be driven by both exogenous differences (e.g., climate or scenery) and endogenous differences between cities; that is,

$$A_i^\theta = A^\theta(\bar{A}_i, L_i^{\mathrm{U}}, L_i^{\mathrm{S}}), \tag{6}$$

where A_i is the exogenous amenity component of city i. Endogenous amenities capture elements of quality of life (e.g., local pollution, quality of schools, crime, presence of entertainment options, variety of restaurants) that change when the size or composition of cities changes. When the function $A^\theta(\cdot)$ differs across type θ, different groups have systematically different preferences or valuation of locational amenities.

3.1.2.3. Housing.

Finally, we assume that housing is supplied by atomistic absentee landowners and that the aggregate housing supply function in city i is

$$H_i = \bar{H}_i r_i^{\eta_i}. \tag{7}$$

The housing supply elasticity η_i is allowed to be city specific. It captures, in a reduced-form way, forces that help or hinder the expansion of the housing stock in a given city. As Saiz (2010) documents, housing supply tends to be shaped by both exogenous forces (e.g., geographical constraints to expansion, such as mountains or a waterway delimitating the city) and endogenous forces (such as local land-use or housing regulations). Consistent with the dominant approach in the literature, we nevertheless take η_i as a parameter in the model.

A spatial equilibrium of this economy is a set of location choices $\{\lambda_i^\theta\}_{i,\theta}$, prices $\{w_i^\theta, r_i\}_{i,\theta}$, and amenities and productivity shifters $\{z_i^\theta, A_i^\theta\}_{i,\theta}$ such that workers and firms optimize, traded good firms make no profits, and markets clear. Since amenities and productivity shifters $\{z_i^\theta, A_i^\theta\}_{i,\theta}$

[10]For instance, Moretti (2004) estimates human capital spillovers that driven by the local skill share, $\frac{L_i^{\mathrm{S}}}{L_i^{\mathrm{U}}}$.

typically depend on the equilibrium distribution of economic activity, these local spillovers act as feedback loops that may amplify or dampen concentration and sorting. A question that remains largely unanswered is: Under what conditions is the sorting equilibrium unique? This question is important since quantitative frameworks can be used to compute model-based counterfactuals and to predict the effect of a shock or a policy on the spatial equilibrium; this exercise is well defined when the equilibrium is unique. The quantitative spatial literature has established sufficient conditions for uniqueness for a range of models with homogeneous workers. Establishing such conditions in the presence of two groups is complicated by the fact that spillovers to one group depend on the other group's distribution. Against this backdrop, the question of equilibrium uniqueness has been typically treated numerically, rather than formally, in the sorting literature. An exception is Fajgelbaum & Gaubert (2020), who derive conditions for uniqueness of a market equilibrium corrected by efficient taxes, when spillovers take a Cobb-Douglas form between two skill groups. More research is needed on this technical but important issue.

3.2. Drivers of Sorting

We now discuss conditions under which spatial sorting arises in equilibrium. In using the term spatial sorting, we mean the fact that the skilled and unskilled groups make different location choices; i.e., there exist locations i and j such that, denoting $\Delta X \equiv X_i - X_j$ for any variable X,

$$\Delta \log\left(\frac{L^{\mathrm{S}}}{L^{\mathrm{U}}}\right) \neq 0.$$

Given location choices (Equation 1), and combining labor supply (Equation 8) and labor demand (Equation 5), relative spatial labor supply is given by

$$\Delta \log\left(\frac{L^{\mathrm{S}}}{L^{\mathrm{U}}}\right) = \underbrace{\frac{\tilde{\kappa}^{\mathrm{S}}}{\rho}\Delta \log\left(\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}\right)}_{\equiv\Delta_z} + \underbrace{\tilde{\kappa}^{\mathrm{S}}\Delta \log\left(\frac{A^{\mathrm{S}}}{A^{\mathrm{U}}}\right)}_{\equiv\Delta_A} + \underbrace{\tilde{\kappa}^{\mathrm{S}}\left(\alpha^{\mathrm{U}} - \alpha^{\mathrm{S}}\right)\Delta \log r}_{\equiv\Delta_\alpha} + \underbrace{\frac{\tilde{\kappa}^{\mathrm{S}}}{\kappa^{\mathrm{U}}}\left(1 - \frac{\kappa^{\mathrm{U}}}{\kappa^{\mathrm{S}}}\right)\Delta \log L^{\mathrm{U}}}_{\equiv\Delta_\kappa}, \quad 8.$$

where we denote $\tilde{\kappa}^{\mathrm{S}} = \frac{\kappa^{\mathrm{S}}\rho}{\kappa^{\mathrm{S}}+\rho}$. Conceptually, one can therefore distinguish four sources of sourcing in this framework: We say that sorting is shaped by comparative advantage in production when $\Delta \log\left(\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}\right) \neq 0$, by amenities when $\Delta \log\left(\frac{A^{\mathrm{S}}}{A^{\mathrm{U}}}\right) \neq 0$, by housing prices when $\alpha^{\mathrm{S}} \neq \alpha^{\mathrm{U}}$, and by heterogeneous mobility across groups when $\kappa^{\mathrm{U}} \neq \kappa^{\mathrm{S}}$. Significantly, all of these four forces are endogenous to the sorting equilibrium, as we discuss in detail below. In turn, changes in sorting occur when any of the four forces Δ_z, Δ_A, Δ_α, and Δ_κ, as defined in Equation 8, changes over time. We examine these sources of sorting in turn, although they are cumulative (and interrelated) in practice.

3.2.1. Comparative advantage in production.

When does comparative advantage in production directly drive sorting? This happens only when the first term in Equation 8 is nonzero. Therefore, a first takeaway is that, when productivity is (multiplicatively) separable between a location shifter Z_i (perhaps subject to agglomeration effects) and nationwide group productivity z^θ so that $z_i^\theta = Z_i z^\theta$, the productivity advantage of a location is skill neutral and hence does not drive sorting directly. Likewise, changes in the Hicks-neutral productivity of location i or a nationwide skill-biased technical change (i.e., changes in $\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}$) can drive changes in sorting only indirectly, through equilibrium rents or heterogeneous mobility across groups, a case we return to below.

We now assume, in contrast, that some skill group has comparative advantage in production in some location over another so that $\Delta \log\left(\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}\right) \neq 0$. This comparative advantage could stem from exogenous differences between places; e.g., skilled workers could have a comparative advantage in locations specialized in services. In addition, it could stem from different skill groups benefiting differentially from agglomeration effects; e.g., skilled workers could benefit more from knowledge spillovers in dense cities. The literature has proposed different parameterizations for these agglomeration effects. For instance, z_i^θ might depend on the local skill share, population, and/or population of each group separately. For simplicity, we assume that local productivity depends on population, which is the most classic way to parameterize agglomeration effects, but with a different intensity γ_P^θ for different skill groups; that is,

$$z_i^\theta = \bar{z}_i^\theta \left(L_i^{\mathrm{U}} + L_i^{\mathrm{S}}\right)^{\gamma_P^\theta}. \tag{9}$$

In this expression, $\bar{z}_i^\theta$ are exogenous location-group productivity shifters. Equilibrium sorting is then pinned down by

$$\Delta \log\left(\frac{L^{\mathrm{S}}}{L^{\mathrm{U}}}\right) = \frac{\tilde{\kappa}^{\mathrm{S}}}{\rho} \Delta \log\left(\frac{\bar{z}^{\mathrm{S}}}{\bar{z}^{\mathrm{U}}}\right) + \frac{\tilde{\kappa}^{\mathrm{S}}}{\rho}\left(\gamma_P^{\mathrm{S}} - \gamma_P^{\mathrm{U}}\right) \Delta \log L + \Delta_A + \Delta_\alpha + \Delta_\kappa.$$

Changes in sorting due to productivity correspond to the first two terms on the right-hand side of the above equation. First, such changes may occur because of changes in exogenous comparative advantage $\Delta \log\left(\frac{\bar{z}^{\mathrm{S}}}{\bar{z}^{\mathrm{U}}}\right)$. Here again, productivity shocks would have to be city and skill biased to generate changes in sorting. Second, changes in sorting may occur because of changes in relative city sizes $\Delta \log L$ or because of changes in relative agglomeration forces $\gamma_P^{\mathrm{S}} - \gamma_P^{\mathrm{U}}$.

3.2.2. Amenities.

The term amenities is typically used to encompass a wide range of services, local public goods, and environmental conditions that impact residents' quality of life (Glaeser et al. 2001). We parameterize utility derived from amenities as a Cobb-Douglas aggregator of a vector of amenities $\{A_{ki}\}_k$ in location i, with skill group–specific preference parameters γ_{kA}^θ. This allows both skill groups to have different preferences over each city's amenity bundle:

$$A_i^\theta = \prod_k \left(A_{ki}\right)^{\gamma_{kA}^\theta}. \tag{10}$$

We allow a component of each amenity in the amenity bundle to be endogenous. Following Diamond (2016), we model the endogenous component of amenity as responding to the skill ratio $\frac{L_i^{\mathrm{S}}}{L_i^{\mathrm{U}}}$ of the city; that is,

$$A_{ki} = \widetilde{A}_{ki}\left(\frac{L_i^{\mathrm{S}}}{L_i^{\mathrm{U}}}\right)^{\beta_k}, \tag{11}$$

where $\widetilde{A}_{ki}$ is the exogenous component of amenity k and β_k measures how elastic the supply of amenity k is to the skill ratio. This formulation captures, in a reduced-form way, the notion that higher-skill, hence higher-income, individuals may spur the growth of consumption amenities in cities in which they reside or that they foster reductions in crime and pollution because of, for instance, their influence on the political process. With these formulations, equilibrium sorting is

$$\Delta \log\left(\frac{L^{\mathrm{S}}}{L^{\mathrm{U}}}\right) = \frac{\tilde{\kappa}^{\mathrm{S}}}{1 - \tilde{\kappa}^{\mathrm{S}}\left(\tilde{\gamma}_A^{\mathrm{S}} - \tilde{\gamma}_A^{\mathrm{U}}\right)} \Delta \log\left(\frac{\widetilde{A}^{\mathrm{S}}}{\widetilde{A}^{\mathrm{U}}}\right) + \frac{1}{1 - \tilde{\kappa}^{\mathrm{S}}\left(\tilde{\gamma}_A^{\mathrm{S}} - \tilde{\gamma}_A^{\mathrm{U}}\right)}\left[\Delta_z + \Delta_\alpha + \Delta_\kappa\right],$$

where we denote $\tilde{\gamma}_A^\theta = \sum_k \left[\beta_k\left(\gamma_{kA}^\theta\right)\right]$ and $\frac{\widetilde{A}_i^{\mathrm{S}}}{\widetilde{A}_i^{\mathrm{U}}} = \prod_k \left(\widetilde{A}_{ki}\right)^{\gamma_{kA}^{\mathrm{S}} - \gamma_{kA}^{\mathrm{U}}}$. The takeaways are twofold. First, amenities are a source of sorting in themselves only to the extent that the first term is nonzero, i.e., that valuations of the exogenous component of amenities are heterogeneous across groups ($\tilde{\gamma}_A^{\mathrm{S}} \neq \tilde{\gamma}_A^{\mathrm{U}}$). Second, the endogenous provision of amenities ($\beta_k \neq 0$) together with their heterogeneous valuation across skills ($\gamma_{kA}^{\mathrm{S}} - \gamma_{kA}^{\mathrm{U}} \neq 0$) serve only as an amplifier (or dampener) of other sorting forces. Sorting driven by productivity, housing prices, or heterogeneous mobility, in the bracketed term, is amplified by the feedback loop played by amenity provision, as long as agglomeration forces are not too strong so that the model remains well behaved [$0 < \tilde{\kappa}^{\mathrm{S}}\left(\tilde{\gamma}_A^{\mathrm{S}} - \tilde{\gamma}_A^{\mathrm{U}}\right) < 1$]. Similarly, sorting based on exogenous differences in amenities across places (the first term on the right-hand side of the equation above) is magnified in the presence of such endogenous amenities. In theory, endogenous amenities could dampen sorting if low-skill workers had a stronger preference for the endogenous amenity composite than did high-skill workers (that is, if $\tilde{\gamma}_A^{\mathrm{S}} - \tilde{\gamma}_A^{\mathrm{U}} < 0$), although most empirical evidence shows that endogenous amenities enhance, rather than dampen, skill sorting.

3.2.3. Housing prices.

We turn to the role of housing prices in driving sorting. To make clear the specific mechanisms at play here, we shut down the other sources of sorting by making the following assumption:

Assumption 1. $\Delta \log\left(\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}\right) = 0$, $\Delta \log\left(\frac{A^{\mathrm{S}}}{A^{\mathrm{U}}}\right) = 0$, and $\kappa^{\mathrm{U}} = \kappa^{\mathrm{S}}$.

Under Assumption 1, some cities may still be more productive or have higher amenities than others, but in a way that is skill neutral: There exist citywide shifters Z_i and A_i and nationwide group-specific shifters z^θ, A^θ such that $z_i^\theta = Z_i z^\theta$ and $A_i^\theta = A_i A^\theta$ for all locations i.

We see from Equation 8 that the groups that have a higher expenditure share on housing, all else equal, are underrepresented in expensive cities, as they are disproportionately hurt by the high housing cost there. If housing is a necessity, then $\alpha^{\mathrm{U}} - \alpha^{\mathrm{S}} > 0$, and skilled workers are overrepresented in expensive cities.

Which cities are more expensive in equilibrium? Given the housing supply equation (Equation 7), equilibrium housing prices are the implicit solution to

$$\frac{Z_i^{\frac{1+\kappa}{\rho-1}} A_i^{\kappa}}{\bar{H}_i} = r_i^{\eta_i} \left[\sum_{\theta} \omega^\theta f_i(r_i)\, r_i^{\kappa\alpha^\theta \frac{1-\rho}{\kappa+\rho} - 1} \right]^{-1}, \qquad 12.$$

where $f_i(r_i)$ captures that, in equilibrium, wages depend on rents. This function can be shown to be equal to 1 when skills are perfect substitutes, and it is a decreasing function of r_i otherwise. Given Equation 12, rents r_i increase with $\frac{Z_i^{\frac{1+\kappa}{\rho-1}} A_i^{\kappa}}{\bar{H}_i}$: More productive cities and cities with higher amenities (per unit of land) are more expensive in equilibrium. We denote $\mathscr{R}_i(\cdot)$ as the corresponding solution to Equation 12. Turning to the implication of housing rents for skill sorting, we obtain

$$\Delta \log\left(\frac{L^{\mathrm{S}}}{L^{\mathrm{U}}}\right) = \left(\alpha^{\mathrm{U}} - \alpha^{\mathrm{S}}\right) \Delta \log \mathscr{R}\left(\frac{Z^{\frac{1+\kappa}{\rho-1}} A^{\kappa}}{\bar{H}}\right), \qquad 13.$$

and high-skill workers sort into more productive and/or more attractive (per unit of land) locations. A first takeaway is that, when housing expenditure shares differ across groups, Hicks-neutral city advantage is enough to drive sorting through its impact on housing prices. That is, even if the productivity advantage of cities is skill neutral and their amenities are valued identically by both skill groups, the two groups will still make systematically different location choices because housing prices have a different weight on their real wages. Sorting is then driven by a form of nonhomotheticity in consumption. If, in contrast, preferences are homothetic and identical across groups, housing impacts all households proportionally, and no spatial sorting emerges under Assumption 1. A second takeaway is that the role of housing in mediating spatial sorting forces is stronger, all else equal, in locations with more inelastic housing supply (lower η). Inelastic supply directly leads to steeper $\mathscr{R}(\cdot)$, hence to a steeper response of housing prices to productivity and amenities, and in turn to a steeper response of the skill ratio through Equation 13.

3.2.4. Heterogeneous migration elasticities. Finally, a last possible driver of sorting arises when $\kappa^{\mathrm{U}} \neq \kappa^{\mathrm{S}}$. Empirical studies tend to find that higher-skill workers are more mobile than lower-skill workers, so, to take an example, we consider the case in which $\kappa^{\mathrm{S}} > \kappa^{\mathrm{U}}$. Equation 8 shows that if high-skill workers are more mobile, their sorting into attractive cities is reinforced, all else equal, in the sense that places that attract low-skill workers (high-$\Delta \log L^{\mathrm{U}}$ places) attract high-skill workers disproportionately more. To characterize the equilibrium in more detail, we isolate this force of sorting and shut down others with the following assumption:

Assumption 2. $\Delta \log \left(\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}\right) = 0$, $\Delta \log \left(\frac{A^{\mathrm{S}}}{A^{\mathrm{U}}}\right) = 0$, and $\alpha^{\mathrm{U}} = \alpha^{\mathrm{S}}$.

In this case, it is easy to see that

$$\Delta \log \left(L^{\mathrm{S}}\right) = \left[\underbrace{1 + \frac{\rho}{\kappa^{\mathrm{S}} + \rho}\left(\frac{\kappa^{\mathrm{S}}}{\kappa^{\mathrm{U}}} - 1\right)}_{>0}\right] \Delta \log L^{\mathrm{U}}. \qquad 14.$$

Under Assumption 2, there is no skill-biased amenity or productivity advantage of places. Still, the high-skill population increases faster than the low-skill population in attractive cities because members of the former group are more sensitive to city characteristics. The mobile high-skill workers move more to reap higher indirect utility, while less-skilled workers respond less and are therefore more spread out in equilibrium. Overall, higher-skill workers are overrepresented in places that are attractive for both skill groups. Similar to the case in which sorting is driven by housing prices, a skill-neutral advantage of cities (such as a Hicks-neutral productivity advantage) leads to spatial sorting when groups are heterogeneous in their mobility rates.

3.2.5. Urban skill premium and sorting. The above discussion shows how four different forces may shape skill sorting in spatial equilibrium. We now turn to considering how they shape the distribution of the skill wage premium in the cross section of cities, in equilibrium. Solving out for the equilibrium skill premium and its variation over space leads to

$$\Delta \log \left(\frac{w^{\mathrm{S}}}{w^{\mathrm{U}}}\right) = \frac{1}{\kappa^{\mathrm{S}}}\Delta_z - \frac{1}{\rho}\Delta_A - \frac{1}{\rho}\Delta_\alpha - \frac{1}{\rho}\Delta_\kappa. \qquad 15.$$

Comparing this expression with the one that summarizes skill sorting (Equation 8),

$$\Delta \log \left(\frac{L^{\mathrm{S}}}{L^{\mathrm{U}}}\right) = \Delta_z + \Delta_A + \Delta_\alpha + \Delta_\kappa,$$

directly yields the following insights. When sorting is driven by skill-biased productivity effects, the skill premium and skill ratios go in the same direction, both driven up by $\Delta \log \left(\frac{z^{\mathrm{S}}}{z^{\mathrm{U}}}\right)$. Absent other sources of sorting, skill premia and skill ratios are unambiguously positively associated in equilibrium. In contrast, when skill sorting is driven by any of the other forces [skill-biased amenities, housing price effects ($\alpha^{\mathrm{U}} > \alpha^{\mathrm{S}}$), or heterogeneous migration rates ($\kappa^{\mathrm{S}} > \kappa^{\mathrm{U}}$)], the skill premium and skill ratios tend to go in the opposite direction in the cross section. Absent skill-biased productivity differences, skill premia and skill ratios are negatively associated in equilibrium. This is because wages act as a compensating differential in these cases. High-skill workers are disproportionately attracted to cities that are attractive for reasons other than skill-biased productivity. In these cities, low-skill workers are therefore in relatively high demand on the labor market, pushing up their relative wages. In equilibrium, the skill premium is lower when high-skill workers are overrepresented.

3.3. Drivers of Sorting: Evidence

Having laid out the main potential drivers behind changes in sorting and in the city-skill premium, we now review the literature investigating these channels.

3.3.1. Productivity and sorting. Changes in labor demand are typically put forward as the triggering force behind the increased skill sorting and increased city-skill premium of the recent decades. Diamond (2016) estimates a spatial equilibrium model, with labor demand factors, amenities, rents, and heterogeneous preferences potentially shaping sorting. She finds that changes in return to skills, especially in cities that were initially high skill, are an important mechanism behind the Great Divergence. Baum-Snow et al. (2018) analyze the increasing wage inequality across space, with the skill premium increasing the most in larger cities. They estimate that the primary driver behind the increasingly positive relationship between skill premium and city size is an increase over time in the skill bias of agglomeration economies, that is, an increase in $\gamma_P^S - \gamma_P^U$ in the language of our model (see Equation 9). Giannone (2019) emphasizes a break in trend in the spatial distribution of wages in the United States: Before 1980, wages were converging across US cities, but they have been diverging since. In her model, the key force behind convergence is that technology diffuses over space, while the major force behind divergence is local skill-biased agglomeration effects, which drive spatial sorting. A key challenge with identifying agglomeration effects, especially skill-specific agglomeration effects, is that changes in the supply of workers not only impact agglomeration but also lead to standard shifts along firms' labor demand curves. When one is studying productivity and agglomeration with data aggregated to the skill-group-by-city level, labor demand shifts and agglomeration effects are perfectly colinear. Indeed, many of the papers discussed above have this colinearity problem and solve it by assuming functional form differences between the two forces. However, with micro data on firms, these two effects can be nonparametrically decoupled and credibly estimated, similar to the strategy taken by Moretti (2004). He estimates plant-level production functions to quantify the slopes of the labor demand curves and then shows that the citywide skill mix still appears to impact firm pay, over and beyond what the production function estimates imply. The setup in Moretti (2004) could be embedded into a spatial equilibrium model, such as the one above, along with clean variation in a city's skill mixes to provide a new estimate of skill-specific agglomeration forces. Finally, Eckert (2019) takes a different perspective to explain the increasing sorting of high-skill workers in high-skill cities; this approach does not rely on skill-biased agglomeration effects. In his model, trade between locations is costly so that local wages are determined not just by local productivity but also by market access. As communication costs fall following the rise of the Internet, markets integrate, and locations with a comparative advantage in business services, which are both communication cost intensive and skill intensive, increase their specialization in this sector. This drives up local relative demand for high skills and the local skill premium, while the opposite arises in locations specialized in manufacturing.

Through what channel can agglomeration effects be skill biased? The model laid out above is silent on the microfoundations and channels through which high-skill workers may benefit disproportionately from agglomeration forces. Theoretically, a branch of the literature microfounds heterogeneous agglomeration effects from local interaction between economic agents, both individuals and firms. An early contribution is that by Berry & Glaeser (2005), who propose a theory for the increasing clustering of skills. In the model, the driving force is that entrepreneurs tend to innovate locally and in technologies that are biased in favor of their own skill. Growth in local skill then correlates with the initial local skill level. More generally, the spatial labor demand for skilled workers can be concentrated in specific cities because firms that are skill intensive are located there. That is, the spatial sorting of firms may explain the spatial sorting of skills. Duranton

& Puga (2000) develop a theory of the life cycle of firms in which young, innovative firms are located in dense cities, where they benefit from knowledge spillovers, and older, established firms locate in low-density, cheaper areas, where production costs are low. To the extent that innovation is a skill-intensive activity, skilled workers will likewise cluster in dense cities. In a paper by Gaubert (2018), high-productivity firms benefit disproportionately from agglomeration effects offered by dense cities following the empirical finding by Combes et al. (2012). Hence, such firms sort disproportionately there. This sorting drives nearly half of the productivity advantage of large cities. To the extent that high-productivity firms are more skill intensive, skilled workers will also cluster in dense cities. Hendricks (2011) proposes a model in which skilled workers are complementary in production to business services, and business services feature local increasing returns to scale, generating forces akin to skill-biased agglomeration effects. The model explains why high-skill clustering correlates with the concentration of business services in the data. Finally, a strand of the literature, reviewed in detail by Behrens & Robert-Nicoud (2015), proposes complete models of systems of cities with a continuum of worker types and includes microfoundations for sorting. Such microfoundations include complementarities in learning between skill and the quality of the learning environment (Davis & Dingel 2019); complementarity in production between different skill types (Eeckhout et al. 2014); and an interplay between agglomeration, skill sorting, and the selection of efficient firms (Behrens et al. 2014).

3.3.2. Amenities and sorting. We turn to amenities as a potential force behind recent changes in spatial sorting. First, exogenous amenities may drive sorting: A classic example is weather and climate. Albouy et al. (2016b) estimate willingness to pay to live in cool and hot climates and find that college-educated households are willing to pay more than lower-skill ones to avoid excessive heat, while the college educated are relatively more tolerant of cold temperatures. Both groups prefer a temperate climate of 65°. Second, the logic of a feedback loop between sorting and amenity provision has also been put forward as a potential explanation of sorting. In an early contribution on the topic, Shapiro (2006) shows that local skill concentration leads to higher local employment growth, while unskilled concentration does not. Using a model-based approach in which amenities are treated as a residual to explain the spatial equilibrium, he finds that part of this effect is driven by quality of life: Higher-skill regions give rise to richer amenities, making them more attractive. Diamond (2016) shows that endogenous amenities play an important role in amplifying the increasing skill sorting. Amenities are captured by an index that aggregates empirical measures of a variety of amenities such as school quality, environmental quality, and retail environment. She estimates that this index responds positively to local skill mix and that college graduates' location choices are more sensitive to the amenity index level than are location choices of high school graduates. Finally, she finds that endogenous amenity changes were very important in amplifying the sorting of skilled workers initiated by productivity changes over the 1980–2000 period. Handbury (2021) provides interesting evidence on the role of cities in fostering consumption amenities in a way that is systematically different for different income groups. Using the Nielsen retail price data, she finds that the variety of products offered in wealthy cities is higher than in poorer cities, especially for goods preferred by wealthy consumers. In addition, the higher prices of stores in wealthier cities are muted for goods consumed by those of high income. On net, high-income households enjoy 40% higher utility per dollar expenditure in wealthy cities relative to poor cities and to low-income households. These results are consistent with the theory that amenities respond to the composition of cities so that preference externalities arise.

3.3.3. Housing prices and sorting. Finally, we review the key role played by housing markets in shaping spatial sorting patterns.

3.3.3.1. Income elasticity of housing demand. Despite the fundamental role of heterogeneous housing demand in location sorting, there are a wide range of estimates of how the expenditure share on housing (captured by α^{θ} in our model) varies across the income distribution. The first challenge to identifying the relationship between housing expenditure share and income is that housing choices are sticky (Chetty & Szeidl 2016), while annual income fluctuates. In years when income is idiosyncratically high, households do not move and they consume more housing, lowering their expenditure share on housing. In contrast, in years when income is low, expenditure shares on housing go up since these households have precommitted to their housing consumption. Thus, the cross-sectional correlation between annual income and annual housing expenditure is biased toward underestimating the income elasticity of housing consumption. Using this cross-sectional regression of housing prices on annual income, Rosenthal (2014) reports an income elasticity of 0.41 for owner-occupiers and 0.12 for renters.

The second difficulty is that data sets that can better measure permanent income proxies (such as total expenditure) often do not contain the geographic details to measure variation in local housing prices. Thus, it is impossible to separate out income effects on housing expenditure from price effects. Albouy et al. (2016a) make progress here and develop a demand system to estimate the price and income elasticity of housing demand. To overcome the transitory income measurement issues, they estimate relationships between housing, income, and expenditures at the city level, instead of at the household level, hoping to smooth out the transitory household-level fluctuations. They use the 2000 Census to measure geographically detailed housing prices. They estimate an elasticity of 2/3, close to the one also found by Finlay & Williams (2020). They also estimate that the price elasticity of housing demand is 2/3. This is consistent with the empirical fact that housing expenditure shares are higher in high-housing-price cities. Aguiar & Bils (2015) use CEX data and estimate a higher expenditure elasticity of housing at 0.9. They directly deal with measuring permanent income by proxying it with total expenditure. However, they cannot account for the geographic variation in housing prices. Since high-income households are likely to live in high-housing-price cities and housing demand elasticities with respect to price are likely less than one, Aguiar & Bils likely overestimated the elasticity of housing demand with respect to income. Finally, Davis & Ortalo-Magné (2011) compare median expenditure shares across US cities and find that they are approximately constant, justifying the use of Cobb-Douglas preferences with constant expenditure shares on housing. One possibility to reconcile these findings is that housing expenditures do fall with income, but systematic sorting of higher incomes to expensive cities pushes in the other direction: High housing costs increase housing expenditure share when housing is price inelastic. To our knowledge, this argument has not been formally studied.

3.3.3.2. Impact of housing prices on sorting. The papers we review next are chiefly interested in understanding housing price changes. They point at spatial sorting as an amplification mechanism behind housing price changes. Of course, conversely, housing price changes also impact sorting in these papers. Gyourko et al. (2013) aim to shed light on the wide dispersion in housing price increases across US communities between 1950 and 2000. They show that aggregate shocks such as aggregate population growth are enough, qualitatively, to generate increased skill sorting and increased housing price dispersion across places over time, without invoking any change in preferences or shocks that are heterogeneous over space. This mechanism is stronger for attractive locations with inelastic housing supply. Relatedly, Van Nieuwerburgh & Weill (2010) propose a dynamic quantitative model to investigate the empirical fact that housing price dispersion across places has gone up much more than wage dispersion. In the model, higher-skill workers outbid lower-skill workers in high-productivity locations. An increase in productivity dispersion across places is taken as the primary shock in the economy. Rent dispersion then adjusts to reflect dispersion of the indifference condition of marginal households between two cities. A reason why rent dispersion increases more than productivity is that sorting increase, hence the indifference condition, is pinned down by more and more dispersed ability across cities. Finally, Ganong & Shoag (2017) document the end of income convergence across US states. A driving force in their paper is the increase over time of land-use regulations mandated in high-skill places. This trend decreases housing supply elasticity and prices out the lower incomes there. This mechanism contributes to slowing down convergence, as places are populated by increasingly different skills.

3.3.4. Heterogeneous migration elasticities and sorting. There is robust evidence that local labor demand shocks lead to higher levels of migration by high-skill workers than by lower-skill ones (Bound & Holzer 2000). The literature has mixed results on what is driving this phenomenon. Notowidigdo (2020) finds it to be driven by the offsetting effect of means-tested government transfers mitigating the labor demand shock on low-skill workers. He finds that both skill groups actually have the same migration elasticity. Diamond (2016) finds this migration difference to be driven by low-skill workers' especially strong preference to live in their state of birth. She finds that, after controlling for preferences to live in one's state of birth, low-skill workers actually have higher migration elasticities than do high-skill workers. Piyapromdee (2020) finds that taking into account gender and immigrant status is important and finds that only nonimmigrant low-skill men are less mobile than nonimmigrant high-skill men. Immigrants are more mobile, and women, regardless of skill, are less mobile. More work is needed here to draw robust conclusions.

4. IMPLICATIONS

4.1. Measurement of Inequality

The past decades have seen an increase in nominal wage inequality nationwide, and this increase is becoming an important issue in the current policy debate. In parallel, spatial sorting has increased, and high-skill workers are increasingly sorted in high-productivity, high-amenity, and expensive cities. How has well-being inequality changed as a result? Do changes in spatial sorting reinforce, or mitigate, the welfare effects of nominal wage inequality? We explore here how the framework above and its quantification can shed light on these issues. Consistent with the focus on Section 1, we are concerned here with the welfare implications of changes in across-city sorting over the 1980–2017 period in the United States.

4.1.1. Model-based measure of welfare inequality. The model of Section 3 lends itself naturally to welfare analysis. Let W_t^θ denote the representative well-being of group θ in year t, defined in Equation 2. In the analysis below, we denote $\hat{x} = \frac{x_{t_2}}{x_{t_1}}$ as the proportional change in variable x between two equilibria t_2 and t_1. In particular, let $\hat{W}^\theta \equiv \frac{W^\theta_{2017}}{W^\theta_{1980}}$ denote changes in well-being for group θ over our period of analysis. First, given the structure of the model, changes in well-being for group θ are simply $\hat{W}^\theta = \left[\sum_{k=1}^N \left(\hat{V}_i^\theta\right)^{\kappa^\theta} \lambda^\theta_{i,1980}\right]^{\frac{1}{\kappa^\theta}}$ so that

$$\frac{\hat{W}^{\mathrm{S}}}{\hat{W}^{\mathrm{U}}} = \frac{\left[\sum_{k=1}^N \left(\hat{V}_i^{\mathrm{S}}\right)^{\kappa^{\mathrm{S}}} \lambda^{\mathrm{S}}_{i,1980}\right]^{\frac{1}{\kappa^{\mathrm{S}}}}}{\left[\sum_{k=1}^N \left(\hat{V}_i^{\mathrm{U}}\right)^{\kappa^{\mathrm{U}}} \lambda^{\mathrm{U}}_{i,1980}\right]^{\frac{1}{\kappa^{\mathrm{U}}}}}. \qquad 16.$$

That is, changes in well-being over time, within a group, are a weighted power mean of the change in the utility index in each city $\hat{V}_i^\theta = \frac{\hat{A}_i^\theta \hat{w}_i^\theta}{\hat{r}_i^{\alpha^\theta}}$, weighted by the initial distribution of population $\lambda_{i,1980}^\theta$ in each location. Therefore, knowledge of initial population distribution by group, migration elasticities κ^θ, and proportional changes in amenities, nominal wages, and housing costs for each group in each city allows us in principle to compute changes in well-being inequality over time, $\hat{W}^{\mathrm{S}}/\hat{W}^{\mathrm{U}}$.

If measuring changes in prices of labor and housing is in principle readily doable given typical data, measuring changes in amenities is more challenging. Following Rosen (1979) and Roback (1982), one strand of the literature typically backs out amenities as residuals that help explain the distribution of economic activity over space. Unfortunately, this method allows us to measure local amenities only up to a multiplicative shifter, which is necessary to make welfare statements. One way to make progress is to isolate the contribution of changes in endogenous amenities to welfare inequality, using a specific parameterization for it that can be estimated. We follow Diamond (2016) in assuming that amenity supply depends on the skill ratio and is valued by the two skill groups as in Equation 10. We use her estimates for the various parameters of the model.[11]

4.1.2. Decomposition by driver of sorting.

To understand how changes in spatial forces have shaped well-being inequality between 1980 and 2017, we decompose changes in well-being inequality into those driven by changes in nominal wages in isolation, then we add rents, and finally we add endogenous amenities.

First, one can compute what would have been the change in well-being inequality if only nominal wages had changed, but not rents or amenities. In this case, one can apply Formula 16 to changes in nominal wages ($\hat{V}_i^\theta = \hat{w}_i^\theta$) so that

$$\left(\frac{\hat{W}^{\mathrm{S}}}{\hat{W}^{\mathrm{U}}}\right)_{\text{nominal wage}} = \frac{\left[\sum_{k=1}^{N} \left(\hat{w}_i^{\mathrm{S}}\right)^{\kappa^{\mathrm{S}}} \lambda_{i,1980}^{\mathrm{S}}\right]^{\frac{1}{\kappa^{\mathrm{S}}}}}{\left[\sum_{k=1}^{N} \left(\hat{w}_i^{\mathrm{U}}\right)^{\kappa^{\mathrm{U}}} \lambda_{i,1980}^{\mathrm{U}}\right]^{\frac{1}{\kappa^{\mathrm{U}}}}}.$$

This nominal wage inequality increased by 16.7 pp between 1980 and 2000 and by 10.7 pp between 2000 and 2017. Second, adding the effects of change in rents (hence using now $\hat{V}_i^\theta = \frac{\hat{w}_i^\theta}{\hat{r}_i^{\alpha}}$) leads to a lower change in well-being inequality than the one suggested by nominal wages only: This real wage inequality increased by 15.2 and 9.6 pp between 1980 and 2000 and between 2000 and 2017, respectively. Over both of these time periods, rent increases mitigated approximately 10% of wage inequality increases. This is because, over the period, high-skill workers lived in increasingly expensive locations (Moretti 2013), as we find in Section 2. Finally, adding the effects of changes in endogenous amenities triggered by changes in sorting [hence using $\hat{V}_i^\theta = \left(\frac{\hat{L}_i^{\mathrm{S}}}{\hat{L}_i^{\mathrm{U}}}\right)^{\sum_k \beta_k \left(\gamma_{kA}^\theta\right)} \frac{\hat{w}_i^\theta}{\hat{r}_i^{\alpha^\theta}}$] leads to a higher change in well-being inequality, of 17.0 and 12.1 pp between 1980 and 2000 and between 2000 and 2017, respectively.[12] Consistent with our findings using the exposure index in Section 2, high-skill workers sorted in the high-amenity locations more from 2000–2017 than

[11]We simplify Diamond's model by not allowing for preference heterogeneity based on race or immigrant status or for preferences for living in one's state or Census division of birth. We use parameter estimates from column 3 of panel *a* in table 5 for nonblack, nonimmigrant workers from Diamond (2016). Endogenous amenity supply parameters come from column 3 of panel *d* in table 5 of Diamond (2016).

[12]Following Diamond (2016), we include only the welfare value of the changing endogenous amenities driven by changes in the sorting of high- and low-skill workers across CZs, not allowing the aggregate supply of college graduates nationwide to contribute to amenity increases in all CZs. See Diamond (2016) for more discussion of this issue.

they did during the 1980–2000 period. Taking amenities into account increases overall changes in inequality, particularly so in the later period.

4.2. Change in Skill Sorting: Policy Implications

Changes in skill sorting impact inequality between groups as well as the social diversity of cities. Both are major issues of interest for policy makers. We review here the main takeaways for policy implied by the literature on these topics.

4.2.1. Efficient sorting and efficient redistribution. In an economy as described in Section 3, the laissez-faire equilibrium is generically inefficient because of the presence of local externalities: The productivity and well-being of each resident depend directly on the location choices of others, in a way that residents do not take into account when choosing where to live. The extent of spatial sorting, in particular, will be generically inefficient. A natural question is then: Does the laissez-faire equilibrium feature too much or too little spatial segregation? What policies can lead to more efficient sorting? These questions are only a fraction of those considered in the vast literature concerned with place-based policies. We refer the reader to Neumark & Simpson (2015) for a broader discussion of spatial policies. Related questions have also been studied in the literature concerned with within-city sorting and neighborhood effects (Benabou 1993, 1996a,b). This literature, reviewed in detail by Durlauf (2004), typically finds that spatial sorting tends to compound disparities in human capital building and ends up being inefficient.

Fajgelbaum & Gaubert (2020) show how sorting can be inefficient using a model that nests the one presented in Section 3. They establish formulas for the optimal transfers between cities and groups that lead to an efficient allocation. The size of optimal subsidies to a given group-city is driven by (*a*) the strength of the within-group spillovers that a group generates and (*b*) the strength of the spillover that a group generates on the other group, compounded by how much group θ (which generates the spillover) is underrepresented relative to group θ' (which benefits from the spillover) in a city.[13] In their quantification based on the US economy, they find that a counterfactual efficient allocation features, in some cities, a higher concentration of the high-skill group and, in others, more mixing of the high-skill group with the low-skill group than in the observed allocation. For the largest cities, the first effect dominates. For the majority of cities, especially those at the bottom of the distribution, the second effect dominates. The efficient equilibrium features overall more mixing of skills than does the observed one. These findings are driven by the fact that high-skill workers have large within-group externalities, commanding more concentration of high skill together, but at the same time a large cross-group positive externality on less-skilled workers, commanding more mixing. Rossi-Hansberg et al. (2019) enrich the model with heterogeneous sectors that have heterogeneous local production externalities, which they estimate, but they do not model externalities in amenities. In their setup, aggregate productivity is enhanced by more concentration of high-skill workers in cognitive hubs.

Gaubert et al. (2021b) focus on a different rationale for place-based policies: Rather than studying the efficiency motives for place-based transfers, triggered by the prevalence of local externalities, they study the extent to which indexing the redistributive system on place of residence, rather than on income only, enhances equity. To focus on this point, their spatial equilibrium model features agents that are heterogeneous in skill, income, and location choice but abstracts from local

[13] Formally, within-group spillovers are defined as $\frac{\partial \log z_i^\theta}{\partial \log L_i^\theta}$, where z_i^θ is as defined in Equation 4 for production, and $\frac{\partial \log A_i^\theta}{\partial \log L_i^\theta}$, where A_i^θ is as defined in Equation 6 for amenities, while across-group spillovers are $\frac{\partial \log z_i^\theta}{\partial \log L_i^{\theta'}}$ and $\frac{\partial \log A_i^\theta}{\partial \log L_i^{\theta'}}$ for $\theta \neq \theta'$.

externalities. The government is averse to inequality. These researchers find that, when poorer households are spatially concentrated, transfers indexed on location yield equity gains that can outweigh the distortion in location choice they generate. Using their model calibrated to the United States, they find optimal place-based transfers that are of the same order of magnitude as prominent American place-based policies. Colas & Hutchinson (2021) study the distortive effects of the nationwide income tax in the United States, in a spatial equilibrium with heterogeneously skilled workers. The model does not feature externalities, so the no-tax equilibrium is efficient. The findings extend those of Albouy (2009), who argues that a progressive income tax leads to an additional deadweight loss when spatial equilibrium is taken into account, since it allocates workers away from high-productivity cities. Here, Colas & Hutchinson (2021) argue that, in addition, the income tax helps alleviate inequality more when spatial equilibrium is taken into account, because of differences in mobility and land ownership across groups.

4.2.2. Housing policy and sorting. Government intervention in the housing market is a key tool that can influence where different types of households locate. Changing the allocation of households to locations impacts not only the lives of those living in subsidized housing but the entire market through general equilibrium effects, as highlighted by the model above, such that analyzing the impact of such policies is complex.

Local governments of high-housing-cost areas, such as New York and San Francisco, worry that their cities are increasingly unaffordable to middle- and low-income households, and such governments put in place policies to prevent further displacement. Rent control is a popular local government policy to curb displacement, since it forbids rent increases among tenants already living in the city. Economists have long complained about the market inefficiencies of rent control, despite cities often wanting to expand or enact it. Diamond et al. (2019) show how both sides can be correct. They find that rent control expansions in San Francisco did help prevent displacement of renters who already lived in San Francisco at the time of rent control expansion. However, the benefits to these initial tenants were eroded away as landlords removed their properties from the rental market or redeveloped them to make them ineligible for rent control. This decrease in rental supply led to higher rents citywide, fully undoing the initial benefits accrued to tenants. This finding highlights the importance of studying general equilibrium effects along with the direct effects of policy interventions.

An alternative to regulating rent increases is to subsidize the development of properties that must be rented to low-income households at below-market rates. When built in high-quality neighborhoods, this subsidized housing can help bring low-income households to neighborhoods offering better opportunities. Chetty et al. (2014) and Chetty et al. (2016) show that moving families with young kids to better neighborhoods led to these kids' future earnings as adults to be substantially higher: Childhood location seems to be a key contributor to adult earnings. Fogli & Guerrieri (2019) embed this mechanism into a dynamic model to study the intergenerational effects of sorting on inequality and quantify how the increased residential segregation since 1980 has amplified wage inequality of the next generation.[14]

[14]Taking a different perspective, Bilal & Rossi-Hansberg (2021) highlight the fact that low-quality cities are affordable cities. They enable liquidity-constrained households to effectively borrow, in the form of low housing prices, in exchange for worse long-term outcomes, such as kids' future earnings. This trade-off of short-term savings at the expense of long-term gains acts as a credit market for those unable to access traditional credit. Access to this credit market can improve the well-being of low-income households, even if their long-run outcomes worsen.

These policies have natural limits, however, as it is unrealistic to move all low-income kids to high-opportunity areas. In addition, the housing constructed to house low-income families can have externalities on the receiving neighborhoods themselves. Diamond & McQuade (2019) study the place-based effects of new low-income housing construction and how it varies by neighborhood type. They find that building low-income housing in low-income neighborhoods acts as a catalyst to revitalization, since such housing corresponds to some of the nicest local housing stock. Low-income neighborhoods experience declines in crime, more in-migration of higher-income households, and a general increase in demand. In contrast, low-income construction in higher-income areas depresses prices. This highlights the stark trade-off of helping tenants of low-income housing (by building in a high-opportunity area) with helping the broader low-income population residing in private market housing in a low-income area. To develop optimal housing policies that influence sorting going forward—such as inclusionary zoning, the Low-Income Housing Tax Credit (LIHTC) housing vouchers, land-use regulation, or market-based new construction—accounting for both direct effects and indirect general equilibrium effects is crucial.

5. CONCLUSION

Spatial sorting between CZs has been increasing since 1980, although the rate of segregation has slowed in recent years. Spatial sorting of college-educated workers was initially strongly directed at high-wage locations but is now increasingly directed at high-amenity locations. We develop a framework to help think through the causes and consequences of spatial sorting changes. Importantly, the model embeds feedback loops through which economic shocks or policy changes impact equilibrium sorting, including their effect on locations' wages, rents, and amenities that may affect migration decisions of high- and low-skill workers differently. These general equilibrium forces are important to take into account when one is assessing the overall impact of a shock or policy. We expect the literature studying spatial sorting to continue to explode as more papers find ways to combine quasi-experimental research designs with general equilibrium analysis to better understand the causes and consequences of spatial sorting on inequality. Such developments could fruitfully contribute to the policy debate.

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