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ABSTRACT

This chapter examines the role of spatial sorting in shaping economic inequality in the United States. We first document the evolution of firm and worker sorting by skill level between 1980 and 2017. We highlight a shift since 2000, where both high-education workers and firms increasingly sort away from high-wage, high-rent areas. Throughout the entire time period, high-education workers continue to sort to high amenity areas. We then develop a spatial equilibrium model that incorporates idiosyncratic worker and firm sorting and discuss estimation techniques to identify model parameters. We review recent empirical advancements in spatial sorting, including firm and worker location choices and their interactions with housing policy. We conclude by outlining the model's limitations and proposing directions for future research.

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1 Introduction

The causes and consequences of worker and firm location choices have been the focus of a large and growing literature over the past decade. The earliest urban economics work on spatial sorting grew out of local public finance, where sorting across government jurisdictions enabled different types of residents to access different levels of government services (Tiebout, 1956).[1] More recent work, however, has become more multi-disciplinary, with papers using methods and applying insights from macroeconomics, international trade, labor economics, public finance, industrial organization, and economic history. Increased academic interest in sorting mirrors real-world growth in spatial inequality, where economic disparities across cities have widened and spatial segregation of workers and firms by skill level has risen (Moretti, 2004, 2013; Diamond, 2016; Lindenlaub et al., 2024; Bilal, 2023)

Prior to 1980, differences in economic conditions across space were predictive of regional convergence (Barro and Sala-i Martin, 1991). This force pushed cities with very different economic conditions towards the average (Blanchard et al., 1992). Beginning in 1980, however, "the Great Divergence" saw a reversal of this trend, as convergence in economic conditions across cities in the US began to slow and workers increasingly sorted based on skill level (Moretti, 2004, 2013; Ganong and Shoag, 2017). While regional inequality is not problematic *per se*, it may become so if (1) there is limited mobility between high- and low-income areas and/or (2) places are persistently high- or low-income (Austin et al., 2018). Austin et al. (2018), who review the literature on regional inequality and place-based policies, suggest that both of these phenomena have become increasingly prevalent in the US.

This increase in regional inequality has important policy implications. Crafting policy that effectively addresses regional inequality requires an in-depth understanding of the factors that motivate the sorting of firms and workers. Moreover, this regional inequality may give rise to significant welfare inequality across space if high housing prices in wealthy places do not fully offset the benefits of higher wages and access to amenities for college-educated workers, as in Diamond (2016).

Over the past half century, spatial inequality has been driven by substantial changes in local labor markets, housing markets, and local amenity provision

[1] See Ross and Yinger (1999) for an early chapter in the *Handbook of Urban and Regional Economics* focused on the intersection of spatial sorting and local public finance.

throughout the United States. We begin by documenting a number of descriptive facts about both worker and firm sorting by skill in Section 2. While spatial sorting occurs across many demographic characteristics, including age, race, immigrant status, and state of birth, we build on a substantial literature related to skill-based worker sorting in this chapter (e.g., Diamond and Gaubert, 2022). We replicate the findings of the prior literature on worker sorting and show that spatial sorting of workers by skill was growing in the 1980s and 1990s. Relative to lower-skill workers, we find that high-skill workers were increasingly migrating to high-wage, high-rent, high-amenity cities. Additionally, we examine whether and how the spatial sorting of firms relates to the skill of the workers that they hire, a topic that has not been extensively analyzed over this time period. Indeed, we find in the 1980s and 1990s, high-skill establishments were increasingly located in high-wage, high-rent (though not necessarily high-amenity) cities relative to lower-skill establishments. However, we document opposite sorting patterns between firms and workers with respect to local taxes: high-education workers consistently sort toward high corporate tax areas and away from high sales tax areas, while high-skill establishments sort away from high corporate taxes and towards high sales taxes.

As we continue this descriptive analysis into the 2000s and 2010s, we find high-education workers are now migrating away from high-wage, high-rent cities, relative to low-education workers. However, high-education workers continue to migrate to high-amenity cities relative to their counterparts. Similar to workers, skill-intensive establishments are also sorting away from high-wage, high-rent areas since 2000—but we do not find any consistent patterns of firm sorting with respect to amenities. Finally, despite these marked changes from the earlier time period, we see consistent patterns in sorting on tax rates, with high-skilled workers and firms continuing to exhibit opposite sorting preferences between corporate taxes and sales taxes.

To understand the causes and consequences of these changing sorting patterns, in Section 3 we develop a structural model of worker and firm sorting that combines insights about worker location decisions from Diamond (2016) with insights about firm location decisions from Suárez Serrato and Zidar (2016). This model allows for both idiosyncratic and skill-level-based worker and firm sorting. The model also includes micro-founded housing supply curves, which enables researchers to study the impacts of policies like zoning and minimum lot sizes on sorting.

Importantly, and unlike the canonical Rosen-Roback model, this version allows for utility differences across space, which enables researchers to use it to study spatial inequality. We provide details in Section 4 on how to estimate such a model and how to use it to disentangle the effects of contemporaneous changes in wages, rents, amenities, and taxes. We also briefly discuss how to extend the model by incorporating dynamics, multi-unit firms, and richer preference heterogeneity.

In Section 5, we review the current literature on worker and firm sorting and their implications for inequality. We discuss the work on the rise of worker sorting as well as the increasing wage inequality between high and low-skilled workers. We note endogenous amenities as well as disparities in moving costs between college-educated and non-college-educated workers as two forces driving increased spatial sorting. We also devote particular attention to the role of housing policy in constraining housing supply, increasing housing prices, and thus limiting worker mobility in response to wages. Finally, the role of firm mobility, spillovers and competition for firms, and labor market frictions in perpetuating inequality across regions. Throughout, we contrast earlier, more stylized sorting models with newer ones that incorporate frictions, heterogeneity, and dynamics that enable the study of inequality across space and worker type.

Our modeling approach is not without limitations. Critically, estimation of the model relies on a revealed preferences framework: if we see workers or firms systematically locating in one location over another, our model implies that the chosen location offers more utility to workers and more profits to firms than the alternative location. However, this revealed preference assumption may fall short if individuals have unobserved constraints on their choice sets or lack the information or liquidity to move to an alternative location. In this case, the model may fail to deliver accurate estimates of the parameters of the utility or profit function, which can lead to inaccurate conclusions about how government policies would impact workers and firms. We discuss the evidence suggesting that constraints shape location decisions as well as the implications of this for analysis relying on the revealed preference assumption in Section 5.4.

Finally, in Section 6, we highlight a number of topics we feel are fruitful places for future research. We hope to see more work relaxing and investigating the validity of the revealed preference assumption in location choice models.

The limited research on firm sorting primarily focuses on sorting by total factor productivity. Understanding how firms sort across other firm characteristics (such as the skill mix of the workers they employ, which we study in this chapter) may shed light on the causes of regional inequality. Additionally, we expect to see growth in the housing policy and housing regulation literature that digs into the heterogeneous effects of different types of housing policies on both workers and firms. Because of the observable increase in inequality between regions and across worker skill levels, we expect the spatial sorting and inequality literature to continue to rapidly grow in the near future.

2 Descriptive Facts on Worker and Firm Sorting

Different locations expose firms and workers to different amenities, prices, policies, and kinds of people. In this section, we document patterns of establishment and worker sorting, as well as analyze how these patterns have changed over time.[2] Generally, we will focus on sorting by skill, where we define "high-education" workers as those with a college degree and "skill-intensive" or "high-skill" establishments as those that are in industries that employ an above-median share of college graduates. In the case that each establishment employs exactly one worker and all establishments employ the same skill mix of workers, worker and establishment sorting patterns would be identical. However, establishments often employ more than one worker and can choose a mix of worker skill types to employ. Thus, establishment and worker sorting may diverge from one another as employment counts and skill compositions change and analyzing them separately can shed light on why this may occur.

To understand how high-education vs. low-education workers and how skill-intensive vs. less skill-intensive establishments sorted across commuting zones (CZs) from 1980–2017, we calculate the differential exposure—or "exposure gap"—to CZs' characteristics between high- and low-skill establishments and workers. These include prices (wages and rent), amenities and disamenities (air quality, crime, commute times, and consumption amenities), and taxes (corporate, sales, and income tax rates). This allows us to understand whether high-education

[2]We use "establishment" to refer to an individual location or franchise of a business. A multi-unit firm may have multiple establishments. We discuss the literature on the establishment location decisions of multi-unit firms in Section 5.3.3.

workers and establishments sort together or whether they sort toward different features of places. In focusing on skill level, we build on an extensive literature on the changing importance of skill in American labor markets and its implications for sorting (Moretti, 2004, 2013; Autor and Dorn, 2013; Autor, 2019; Diamond and Gaubert, 2022).

During this time period, there have been substantial changes and shocks to industries in the US. Some of the divergence in worker and firm sorting we see could be due to these industry-specific trends. For example, Eckert et al. (2024) document that wages for both college and non-college workers in Business Services in dense urban areas have increased substantially compared to those in lower population density areas between 1980 and 2015. They attribute this to a decline in the price of information technology. Moreover, manufacturing is increasingly moving out of urban areas (Autor, 2019). The decline in manufacturing in particular has had a disproportionately stark impact on employment opportunities for non-college-educated men and may be influencing their sorting patterns (Charles et al., 2019). Import competition from China and automation may also be forces shaping the well-being of particular industries and thus the sorting of firms and workers (Autor et al., 2013; Acemoglu and Restrepo, 2020). Our empirical results should be interpreted as inclusive of these changes.

2.1 Exposure Gap

Following Diamond and Gaubert (2022), we examine sorting through an "exposure gap" that measures differential exposure to location-based characteristics. The exposure gap is defined as:

$$\text{Exposure Gap}_t^Y = 100 \times \left(\sum_J \frac{H_{jt} Y_{jt}}{\sum_k H_{kt}} - \sum_J \frac{L_{jt} Y_{jt}}{\sum_k L_{kt}} \right), \tag{1}$$

where Y_{jt} is the characteristic of interest and H_{jt} and L_{jt} respectively represent the numbers of high- and low-education workers (or establishments) in CZ j at time t. The denominators $\sum_k H_{kt}$ and $\sum_k L_{kt}$ represent the national total number of high- and low-education workers, respectively. This measure thus captures the average difference in Y consumed by H relative to L. While we use the exposure gap to compare high- vs. low-education workers and skill-intensive vs. less skill-intensive establishments in this chapter, in principle, this measure could be used to compare differential exposure to location characteristics for any kind of firm (e.g., industry) or worker characteristic (e.g., race, immigration status).

To illustrate this concept, consider the air quality index (AQI)—a measure of pollution where a higher AQI value denotes poorer air quality—in two cities A and B. Suppose 50% of low-education workers and 80% of high-education workers live in City A and that 50% of low-education workers and 20% of high-education workers live in City B. If City A has an AQI of 50 and City B has an AQI of 100, then the average low-education worker is exposed to an AQI of 75, while the average high-education worker is exposed to an AQI of 60. In this case, the exposure gap for AQI is $60 - 75 = -15$. Thus, high-education workers are exposed to less pollution than low-education workers on average. The exposure gap measure we calculate simply extends this analysis to all commuting zones in the US.

2.2 Data

2.2.1 Worker and Establishment Data

We focus on workers and establishments in the continental United States and leverage multiple public datasets from the US Census Bureau. Worker location and education data come from the 1980 and 2000 Decennial Censuses and the 2015–2019 American Community Survey (ACS) (Ruggles et al., 2022). We focus on full-time workers aged 25–55 years old and classify individuals as "college-educated" if they have four or more years of college (1980) or a bachelor's degree (2000 and 2015–2019).

Establishment location and industry data are taken from the 1986, 2000, and 2016 County Business Patterns (CBP) (US Census Bureau, 2024b).[3] Using Quarterly Workforce Indicator (QWI) data, we classify establishments as "skill-intensive" if their NAICS3 industry employed an above-median (22.2%) share of college graduates in Q3 of 2011 (US Census Bureau, 2022). Previous literature on establishment sorting has focused on sorting by productivity (Gaubert, 2018; Hong, 2024; Mann, 2024; Oh, 2024). While we cannot observe establishment-level productivity in the

[3] Per the methodology outlined in Section 4.4 of Eckert et al. (2021) for the SIC years of the CBP, we compute "remainders" for establishments assigned to SIC codes at a coarser, but not finer level of detail. We then crosswalk the 1986 CBP to 2012 NAICS at the finest level of industry detail available before collapsing up to NAICS3.

aggregated data we have access to, the skill composition of the workforce establishments employ dovetails nicely with our focus on worker skill level. To address changes in industry and geography classifications, we harmonize all industry codes to 2012 NAICS codes using concordances provided by Eckert et al. (2021) and Fort and Klimek (2018) and crosswalk all counties and Public Use Microdata Areas to 1990 commuting zones using crosswalks provided by Autor and Dorn (2013) and Autor (2019). These commuting zones, which may be comprised of multiple US counties, are the relevant location units for the purpose of our analysis.

2.2.2 Local Amenity, Wage, Price, and Tax Data

We also gather data on CZ wages, rents, amenities, and taxes in the years 1980, 2000, and 2017. Data on rent, commute times, wages for college and non-college workers, and county-level populations come from the US Decennial Census and ACS (Ruggles et al., 2022; Manson et al., 2022). We compute rents by calculating commuting zone fixed effects after controlling for the number of units in the building, the year built, and the number of bedrooms. Wages for college and non-college workers are similarly CZ-skill group fixed effects controlling for race, gender, and a quartic in age.

Data on county-level 90^{th} percentile AQI, which captures the severity of "bad" pollution days, come from the US Environment Protection Agency (US Environmental Protection Agency, 2024). Because the availability of AQI data at the county level changes over time, we only calculate the exposure gap for the set of counties for which there is consistent data over time for 1980, 2000, and 2017. We take a similar approach to the crime data, which we take from the Federal Bureau of Investigation's Uniform Crime Reports (Federal Bureau of Investigation, 2019).[4] We combine violent and property crime rates using principal component analysis to generate an index for each commuting zone.

Finally, data on consumption amenities—restaurants, gyms, salons, and clothing stores per 1000 residents—comes from the CBP (US Census Bureau, 2024b). We similarly create a consumption amenity index by using principal component analysis on the number of each of these categories of consumption amenity per thousand residents. For data on taxes, we rely on sales and corporate tax rates collected by

[4] 2017 data were not available in the Uniform Crime Reports, so we use 2016 data.

Suárez Serrato and Zidar (2016).[5] Based on data from the US Decennial Census and ACS, we calculate the income tax rate faced by the median college-educated worker in each state using the TAXSIM tool from the National Bureau of Economic Research (Feenberg and Coutts, 1993; Feenberg, 2022). Because commuting zones sometimes cross state lines, the tax rate faced in a given CZ is the average of tax rates in the states it includes, weighted by the number of establishments in each state in 1986.

2.3 Segregation of Establishments and Workers

We first examine broad segregation patterns between high- and low-skill establishments and workers. To assess this, we define Y_{jt} as the share of high-skill establishments or workers in a commuting zone (i.e., $Y_{jt} = \frac{H_{jt}}{H_{jt}+L_{jt}}$). We use this measure to calculate exposure gaps for both high-education workers and skill-intensive establishments in 1980, 2000, and 2017, which we report in Table 1. In this context, a large exposure gap can be interpreted as high collocation between workers and/or establishments of the same skill type.

We find that college graduates are increasingly collocated with other college graduates: by 2017, the exposure gap by worker skill level is roughly twice as large as in 1980. Though smaller in magnitude, skill-intensive establishments have similarly become more exposed to other skill-intensive establishments, with a gap that increased between 1980 and 2000 before stabilizing. Skill-intensive establishments became more collocated with college-educated workers between 1980 and 2000 but became slightly less so by 2017. This may be part of the trend reversal documented in Diamond and Gaubert (2022), where workers sorted toward amenities but away from high prices and wages in 2000–2017.

[5] 2017 data for state sales and corporate tax rates are not available, so we use 2012 data.

Table 1: Segregation of Establishments and Workers

Worker Sorting	(1) Mean 1980	(2) Exposure Gap 1980	(3) Exposure Gap 2000	(4) Exposure Gap 2017
Share college workers	17.9	1.9	3.2	3.9
Share high-skill establishments	44.3	.8	1.2	.9
Establishment Sorting				
Share college workers	17.9	.5	1	.8
Share high-skill establishments	44.3	.5	.8	.8

Note: This table shows that college workers are more collocated with each other compared to non-college workers and that high-skill establishments are similarly more collocated with other high-skill establishments. The exposure gap measure is calculated following Equation 1.
Source: Establishment count data by county come from the 1986, 2000, 2016 County Business Patterns; worker location and education data come from the 1980 and 2000 Censuses and the 2015–2019 ACS; NAICS and SIC code crosswalks from Eckert et al. (2021) and Fort and Klimek (2018); and data on employee education by NAICS3 industry from the 2011 QWI.

2.4 Industry Sorting

In this section, we examine the extent to which establishments in the same industry collocate in the same CZ and how these patterns change over time. Establishments may be incentivized to locate near one another if they (1) demand similar kinds of labor or benefit from access to specialized labor pools, (2) experience productivity benefits from knowledge spillovers, and/or (3) consume goods from or sell goods to other nearby establishments (Ellison and Glaeser, 1997).While we can only study collocation within industries, factors such shared labor pools or knowledge spillovers may still motivate establishments in the same industry to locate near each other.

To evaluate how sorting patterns over time differ across industries, we modify the exposure gap calculation by defining the commuting zone characteristic Y_{jt} as the share of establishments in a given industry within a CZ. In other words, we calculate $Y_{jt} = \frac{Own_{jt}}{Own_{jt}+Other_{jt}}$, where Own_{jt} represents the number of establishments in a NAICS3 industry in CZ j at time t and $Other_{jt}$ represents the number of establishments in all other industries in CZ j at time t, such that the exposure gap is defined as follows:

$$\text{Exposure Gap}_t^Y = 100 \times \left(\sum_J \frac{Own_{jt} Y_{jt}}{\sum_k Own_{kt}} - \sum_J \frac{Other_{jt} Y_{jt}}{\sum_k Other_{kt}} \right). \tag{2}$$

We interpret this "exposure gap" as the level of sorting (or agglomeration) for each NAICS3 industry relative to all others.[6]

We also consider three aggregated industry categories—manufacturing, tech, and professional and technical services—by taking a weighted average of the exposure gaps of the composite NAICS codes that comprise each category.[7] Finally, we create a weighted average for all NAICS3 industries, which we refer to as a "national average." The weights for all four of these measures are constructed based on the share of 1986 employment in each industry using data from Eckert et al. (2021)'s concorded and imputed CBP employment panel.

We find that overall, industry sorting increased modestly between 1986 and 2016. However, this masks substantial heterogeneity by industry. As shown in Figure 1, there is a high degree of variation across NAICS3 industries. For sectors of particular interest, we see diverging trends in sorting: whereas sorting in manufacturing has declined since 1986, sorting in both tech and professional and technical services has increased dramatically. Importantly, however, our manufacturing results may be partially due to a broader decline in manufacturing over this time period.

[6]Due to industry concordance issues, we calculate this measure for NAICS 42 (Wholesale Trade) instead of separately for its composite industries: NAICS 423, 424, and 425.

[7]The manufacturing category includes all establishments in NAICS 31–33. The technical and professional services category includes all establishments in NAICS 54. The tech category is comprised of 4-digit NAICS codes included in the Census Business Dynamics Survey's "High-Tech" industries, defined as industries with a "STEM employment share at least five times the national average STEM employment share across all industries" for at least 6 of the years between 2007 and 2017 (US Census Bureau, 2024a). These include the following NAICS codes, which do not change between 2012 and 2017: 3341 (Computer and Peripheral Equipment Manufacturing), 3342 (Communications Equipment Manufacturing), 3344 (Semiconductor and Other Electronic Component Manufacturing), 3345 (Navigational, Measuring, Electromedical, and Control Instruments Manufacturing), 3364 (Aerospace Product and Parts Manufacturing), 5112 (Software Publishers), 5182 (Data Processing, Hosting, and Related Services), 5191 (Other Information Services), 5413 (Architectural, Engineering, and Related Services), 5415 (Computer Systems Design and Related Services), 5417 (Scientific Research and Development Services).

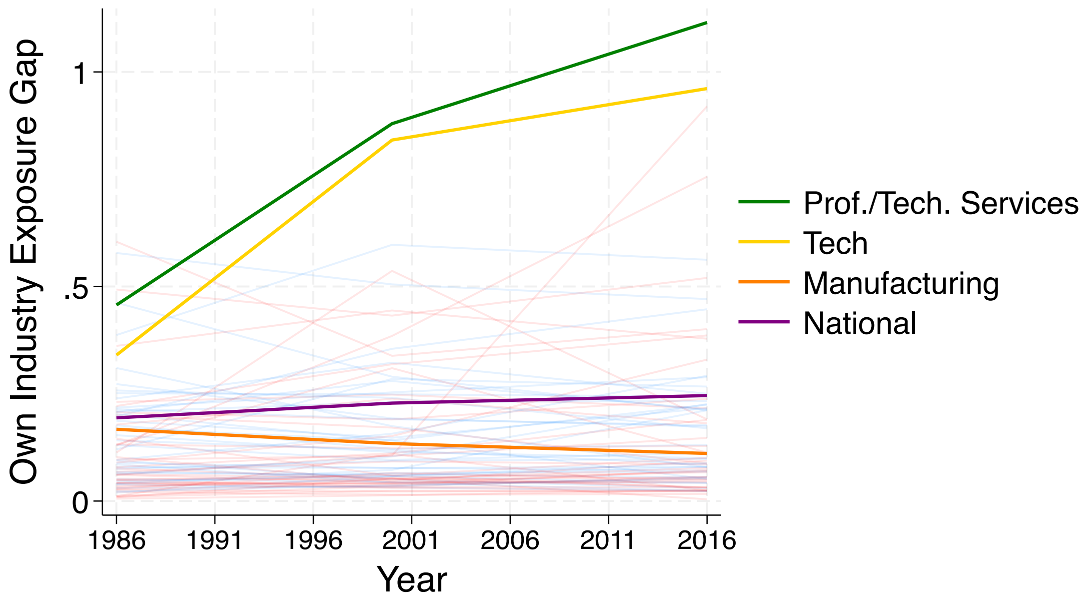

Figure 1: Industry Sorting over Time

Note: This figure shows a version of the exposure gap that measures the exposure of establishments to other establishments in their own industry, calculated using Equation 2. The transparent lines denote the exposure gaps NAICS3 industries. High-skill industries (industries with greater than median employment of college graduates) are red, while low-skill industries are blue.

Source: Establishment data comes from the 1986, 2000, 2016 County Business Patterns; harmonized and imputed County Business Patterns employment data and NAICS and SIC crosswalks come from Eckert et al. (2021) and Fort and Klimek (2018); and education by NAICS3 industry comes from the 2011 QWI.

Industry sorting reflects both where workers and firms decide to locate: it is determined in equilibrium and will be in the background of the model we develop in Section 3.

2.5 Exposure Gap to Local Wages, Rents, Amenities, and Taxes

To understand the types of places high- vs. low-skill workers and establishments are sorting to, we calculate each group's differential exposure to various commuting zone characteristics. As described above, we consider three broad characteristic categories: prices (wages and rent), amenities (AQI, crime, commute times, and consumption amenities), and taxes (corporate, sales, and income tax rates).

Changes in the exposure gap to these characteristics could be driven by two factors. First, skill-intensive establishments and college-educated workers may not move, but the places where they are located may change disproportionately relative to those favored by less skill-intensive establishments and non-college-educated workers. Alternatively, skill-intensive establishments and college-educated workers may move to places with different characteristics from those where less-educated workers and less-skill-intensive establishments move. As in Diamond and Gaubert (2022), we refer to the first of these as the "place effect" and the second as the "sorting effect."

To isolate the place effect, we calculate the difference in the exposure gap between periods t and $t+1$, holding worker location fixed in period t but allowing the CZ characteristic to change. We then calculate the sorting effect holding fixed the CZ characteristics at time t, but allowing the worker/establishment location to change. Table 2 shows the exposure gap for workers and establishments for each characteristic of interest by skill level (high vs. low). In addition to the exposure gap value, place effect value, and sorting effect value, we also report the mean across commuting zones in 1980 and the number of commuting zones used to calculate the exposure gap.[8]

Between 1980 and 2017, high-skill workers have become increasingly more exposed to higher rents, higher wages, and longer commutes relative to low-skill workers. By contrast, the exposure of high-skill establishments to high wages, high rents, and long commutes relative to low-skill establishments has stagnated since 2000, while exposure to non-college wages has declined outright. Both high-skill establishments and workers have also become less differentially exposed to disamenities like crime and pollution and more exposed to consumption amenities relative to their low-skill counterparts.

To better understand what drives these differences in the evolution of the exposure gap for establishments and workers, we decompose exposure gap changes into a place effect and a sorting effect. During 1980–2000, both high-skill workers and establishments sorted toward places with higher wages and rents. However, by 2000–2017, this pattern changed drastically, with both high-skill workers and establishments sorting *away* from high-wage and high-rent places. The magnitude of the sorting effect for establishments is larger than for workers.

[8]The number of commuting zones is smaller for the crime and AQI characteristics, as discussed in Section 2.2.

Table 2: Exposure Gap to Commuting Zone Characteristics by Skill for Establishments and Workers

A. Log Wages and Rents	(1) Mean 1980	(2) Exposure Gap 1980	(3) Place Effect	(4) Sorting Effect	(5) Exposure Gap 2000	(6) Place Effect	(7) Sorting Effect	(8) Exposure Gap 2017	CZs
Log college wage									
Establishment	10.8	1.2	.4	.5	2.2	.1	-.5	1.9	722
Worker	10.8	2.6	1.3	.8	4.8	.8	-.2	5.4	722
Log non-college wage									
Establishment	10.5	1.2	.1	.3	1.6	-.4	-.3	.9	722
Worker	10.5	2.6	.7	.6	3.9	-.7	-.2	3	722
Log rent									
Establishment	-.3	1.7	.7	.8	3.2	.5	-.7	3	722
Worker	-.3	4.5	2.2	1	7.7	.8	-.4	8.1	722
B. Amenities and Disamenities									
AQI / 100, P90									
Establishment	108.7	2.2	-1.2	.1	1	.1	.7	1.8	231
Worker	108.7	1.5	-1.9	-.8	-1.2	.4	-1.1	-1.9	231
Crime index									
Establishment	.3	14.7	-8	2.9	9.6	-5.2	.9	5.2	717
Worker	.3	26.7	-18.7	-.1	7.9	-7.3	-2.5	-1.8	717
Median commute									
Establishment	14.9	53.4	-6.9	12.2	58.6	9.1	-10.2	57.5	722
Worker	14.9	91.2	.5	23.9	115.6	18.8	-2.5	131.9	722
Consumption amenities									
Establishment	-.1	.3	1.4	.9	2.6	8.3	-5.1	5.7	722
Worker	-.1	3.9	8.1	4.7	16.7	17	1	34.7	722
C. Taxes									
Corporate tax									
Establishment	5.5	5.4	-3.5	-.4	1.5	-.2	-4.2	-2.9	722
Worker	5.5	16.6	-8.3	8.9	17.2	3.1	5.8	26.1	722
Sales tax									
Establishment	3.5	1.5	.1	.9	2.6	.6	1.2	4.4	722
Worker	3.5	4.8	-4.9	-1.4	-1.6	2.4	-2.4	-1.7	722
Median income tax									
Establishment	4.4	10.6	-5.6	-4.1	.8	2.4	.1	3.3	722
Worker	4.4	21.6	-6.3	3.6	18.9	4.1	2.1	25.1	722

Note: This table shows exposure gaps for college vs. non-college-educated workers alongside high- vs. low-skill establishments for local wages, rents, amenities, and taxes. The exposure gap measure is calculated following Equation 1.
Source: Establishment counts from the 1986, 2000, 2016 County Business Patterns establishment data; NAICS and SIC code crosswalks from Eckert et al. (2021) and Fort and Klimek (2018); employee education by NAICS3 industry from the 2011 QWI; wage, rent, and commute data from the 1980 and 2000 Censuses and 2015–2019 ACS; AQI data from the US EPA; population data from IPUMS NGHIS; crime data from the FBI Uniform Crime Reports; consumption amenities data from the County Business Patterns; income tax data from TAXSIM, and 1980, 2000, and 2012 sales and corporate tax rates from Suárez Serrato and Zidar (2016).

Indeed, we see larger magnitudes for workers sorting away from places with pollution, higher crime, and longer commutes from 2000 to 2017. Workers are still sorting toward consumption amenities, but the magnitude is smaller than in 1980–2000. The large increase in the exposure gap between 2000 and 2017 instead primarily reflects the place effect. This may be consistent with Diamond (2016), which suggests that amenities endogenously improve when high-skill workers move to a place in response to local demand. By contrast, we see no clear pattern of sorting with respect to amenities or disamenities for firms.

While there have been changes in sorting with respect to wages, rents, and amenities over time, the sorting patterns with respect to taxes have been consistent. While college-educated workers sort toward commuting zones with higher corporate taxes and lower sales taxes, skill-intensive establishments increasingly sort away from these commuting zones. Although both firms and workers benefit from public goods, each would benefit if the other contributed more to their funding. Thus, firms sort away from locations with higher taxes on their activities, and workers sort toward places with high corporate taxes and low sales taxes, where they bear less of the burden of funding these public goods.

These results ultimately describe patterns that arise in equilibrium. In the next section, we describe a model in which workers and firms sort across locations in response to changes in amenities, prices, and local taxes.

3 Spatial Equilibrium Model with Idiosyncratic Worker and Firm Sorting By Skill

Foundational spatial equilibrium models developed by Rosen (1979) and Roback (1982) can guide the way we think about location choices and spatial equilibrium. We start by presenting this relatively simple "Rosen-Roback model" and discuss its merits and limitations. However, in equilibrium, there is no inequality in utility across space in the Rosen-Roback model. It is thus impossible to use it to study spatial inequality. By incorporating spatial frictions and heterogeneity, we develop a model building on Rosen-Roback that allows researchers to study the impact of local policies on spatial inequality. We thus extend the model to allow for a number of forces missing in the Rosen-Roback framework by developing a new spatial equilibrium model of firm and worker sorting that incorporates insights from Diamond (2016) and Suárez Serrato and Zidar (2016).

3.1 Rosen-Roback Model

In the Rosen-Roback model, there exist J cities, each with fixed quantity of land $\bar{G}_j$ and an exogenously-endowed amenity level A_j. Higher values of A_j indicate workers like the amenity more. A_j varies across cities but is equal within a given city. Land can be rented at rate r_j. C is a composite consumption commodity, with prices fixed by a world market, normalized to one. All workers are identical and earn W_j labor income when living in city j. They consume the composite commodity, C, and land, G, to maximize utility:

$$\max_{C,G} U(C,G;A_j) \quad s.t. \quad W_j = C + R_j G$$

This implies there is an indirect utility function $V(W_j,R_j,A_j)$, which takes local wages, land rents, and amenities as inputs and outputs the utility a worker would receive if they were to live in city j. There are no moving costs, and workers will move to the city that offers the highest total utility. Because all workers are identical and perfectly mobile, any city with a positive population must offer the same total utility as all other cities, or workers would migrate. Thus, $V(W_j,R_j,A_j) = V(W_{j'},R_{j'},A_{j'}) = \bar{U}$, for all cities j,j' with positive population.

Firms are all identical with constant returns to scale production. Each firm produces the composite commodity C using production function $C = f(N;G^f,B_j)$, where N is the number of workers in the city, G^f is the amount of land rented by the firm, and B_j is the total factor productivity in city j. The total land rented between workers and firms must equal the total land supplied in the city: $\bar{G}_j = G + G^f$.

Firms minimize costs, subject to their production function, and sell C on the world market at a fixed price, normalized to 1. Unit costs at each location must equal the market price of 1 in each city in equilibrium, otherwise there would be entry and/or exit across cities.

While this simplistic framework is a great model for understanding the key forces driving local wage and land rents, the model lacks a number of features that would allow it to quantitatively match a number of empirical facts in the data. For example, this model implies that all workers have the same utility across space, which gives very limited scope for thinking about spatial inequality or within-group welfare inequality. Another issue is this model assumes that the elasticity of worker migration with respect to a change in the utility value of a given city is infinite. This leads to the extreme prediction that amenity differences across cities are exactly offset by wages and rents. Indeed, this implies that one can estimate the amenity value of each city simply by calculating the local "real wage" of a city.[9]

However, one upside of this simple framework is that one can derive comparative statics to study how amenity and productivity differences across space impact wages and land rents, as in Roback (1982). This allows for comparative static predictions without making explicit functional form assumptions about the shapes of the utility and production functions. This desire to make minimal assumptions about the exact functional forms of model primitives has led to an exciting and growing literature focused on the first-order welfare effects of policy interventions. This approach has been particularly popular in public finance, building on Chetty (2009). Leaning on the envelope theorem, this approach has shown that estimating a small number of reduced-form elasticities is sometimes all that is needed to estimate the first-order welfare effects of a policy intervention. However, as we show in the next section, the interconnectedness of cities in spatial equilibrium implies that this approach often does not lead to expressions that capture the effects of policy changes on worker welfare.

3.2 First-Order Welfare Effects

Evaluating first-order welfare effects of policy changes enables researchers to calculate welfare without making functional form assumptions on all the model primitives nor any explicit modeling assumptions about why some individuals choose to live in different locations. However, we show that we quickly encounter issues with this approach that undermine its usefulness due to the interconnectedness of cities in spatial equilibrium.

Consider now the possibility that workers have heterogeneous preferences. Denote the expected utility of workers of type k across all locations, V_k. When workers are all homogeneous, as in the case of the Rosen-Roback model, V_k is the

[9]Albouy (2008) extends the standard Rosen-Roback framework to incorporate taxes and non-labor income. This paper argues that the simplistic Rosen-Roback framework fits the data well once these forces are included.

utility value of every type k worker. If workers have heterogeneous tastes within type k, V_k represents the average utility of type k workers. Denote v_{jk} as the average indirect utility value of city j to type k workers. Let $v_{jk} = U_k(W_{kj}, R_j, A_j)$, where $U_k(W_{kj}, R_j, A_j)$ maps city j's wages, rents, and amenities to utility. The function U_k represents how city j's location characteristics are valued by type k workers, on average. Consider workers of type k's valuation of a specific non-market amenity a_j (e.g., pollution, school quality, or economic opportunity for children), where a_j is a scalar component of the vector of amenities A_j. The change in utility for individuals of type k when a_j increases, holding fixed all other amenities and prices, is then given by:

$$\frac{\partial V_k}{\partial a_j} = \frac{\partial V_k}{\partial v_{jk}} \frac{\partial v_{jk}}{\partial a_j} = N_{jk} \frac{\partial U_k(W_{kj}, R_j, A_j)}{\partial a_j}, \tag{3}$$

where $\frac{\partial U_k(W_{kj}, R_j, A_j)}{\partial a_j}$ represents the additional utility individuals of type k get from a small increase in a_j in location j and $\frac{\partial V_k}{\partial v_{jk}} = N_{jk}$ due to the envelope theorem (see, e.g., Busso et al., 2013).

However, it is likely unreasonable to assume that local prices and wages do not respond to most types of amenity improvements. Even marginal amenity improvements will create small migration responses. While these migration responses are not directly relevant to first-order welfare, they impact local prices and wages in locations , which in turn have first-order welfare effects. Thus, the first-order welfare effect of a local amenity improvement, inclusive of local price and wage effects, is:

$$\begin{aligned} \frac{dV_k}{da_j} &= \sum_l \left(\frac{\partial V_k}{\partial v_{lk}} \frac{dv_{lk}}{da_j} \right) \\ &= N_{jk} \left(\frac{\partial U_k(W_{kj}, R_j, A_j)}{\partial a_j} + \frac{\partial U_k(W_{kj}, R_j, A_j)}{\partial R_j} \frac{dR_j}{da_j} + \frac{\partial U_k(W_{kj}, R_j, A_j)}{\partial W_{kj}} \frac{dW_{kj}}{da_j} \right) \\ &\quad + \sum_{l \notin j} N_{lk} \left(\frac{\partial U_k(W_{kl}, R_l, A_l)}{\partial R_l} \frac{dR_l}{da_j} + \frac{\partial U_k(W_{kl}, R_l, A_l)}{\partial W_{kl}} \frac{dW_{kl}}{da_j} \right) \end{aligned} \tag{4}$$

In other words, to estimate first-order welfare effects, the researcher must know how the amenity change a_j impacts the rents R_l and wages W_{kl} in all locations l—and these rent and wage impacts across all locations depend on the migration response caused by the marginal change in a_j. This issue makes even first-order welfare effects challenging to measure without fully specifying the functional form of the entire model.

In the case of the Rosen-Roback model, we assume that all workers are identical and can freely migrate. This implies that the change in the indirect utility of city j due to an improvement in a_j, $\frac{dv_{jk}}{da_j} = \left(\frac{\partial U_k(W_{kj},R_j,A_j)}{\partial a_j} + \frac{\partial U_k(W_{kj},R_j,A_j)}{\partial R_j}\frac{dR_j}{da_j} + \frac{\partial U_k(W_{kj},R_j,A_j)}{\partial W_{kj}}\frac{dW_{kj}}{da_j}\right)$, is exactly equal to the change in indirect utility of all other cities:

$$\begin{aligned}\forall\, l: \quad & \left(\frac{\partial U_k(W_{kj},R_j,A_j)}{\partial a_j} + \frac{\partial U_k(W_{kj},R_j,A_j)}{\partial R_j}\frac{dR_j}{da_j} + \frac{\partial U_k(W_{kj},R_j,A_j)}{\partial W_{kj}}\frac{dW_{kj}}{da_j}\right) \\ = \quad & \left(\frac{\partial U_k(W_{kl},R_l,A_l)}{\partial R_l}\frac{dR_l}{da_l} + \frac{\partial U_k(W_{kl},R_l,A_l)}{\partial W_{kl}}\frac{dW_{kl}}{da_l}\right).\end{aligned}$$

While this assumption would dramatically simplify Equation 4, it relies on an extremely strong, empirically-unsupported assumption of perfect mobility of workers across space. This defeats the purpose of the first-order welfare approach , which is to avoid relying on modeling assumptions. The obvious additional downside of focusing on first-order effects is that for non-marginal changes in v_{jk}, there might be important higher-order effects that would be missed.

One possible additional solution to still estimate first-order welfare effects without specifying the entire structural model is to assume the increase in a_j has no price or wage effect in locations other than j , i.e., if $j \neq l$, $\frac{dR_l}{da_j} = 0$, $\frac{dW_{kl}}{da_j} = 0$. This is a tempting assumption since these effects can be small for any given location $j \neq l$. Moreover, it is a challenging assumption to empirically reject because picking up such small effects requires very small standard errors. However, these small price and wage effects can add up to large aggregate welfare effects. For example, assume (1) that the initial population distribution prior to the amenity increase had 2% of the total population living in j and 98% living outside of j, and (2) that the amenity improvement in location j led to a 5% local price increase in j and a 0.05% price decrease in all other locations. The magnitude of the price effect is 100 times larger in j than in all other locations. However, assuming utility is measured in log price units, the total first-order welfare effect of the price changes alone would be: $-0.02 * 0.05 + 0.98 * 0.0005 = -0.001 + 0.00049 = -0.00051$, where 49% of the welfare lost by higher prices in j is offset by lower prices everywhere else. Because the indirect effects of local shocks to other cities impact so many people, they can potentially dominate the direct local effects in aggregate calculations.

We should note that one case where it might be reasonable to ignore the welfare effects of a given local shock to other cities is when thinking about how local policymakers maximize welfare. A local government official may only care about the welfare of the city's inhabitants. In this case, they would ignore the welfare effects on other locations.

To make progress in all other cases, we now extend the Rosen-Roback model to allow for more flexibility in how workers and firms make choices, capture the richness of worker and firm location decisions as well as housing production, and permit researchers to quantify the full set of welfare effects. As with the Rosen-Roback model, we model the connection between the housing and labor markets through worker and firm location decisions. A key feature of that model, that housing and labor markets are connected and clear simultaneously, remains the same in our extension. However, we also incorporate frictions and heterogeneity, thus allowing for differential welfare across space and types. Moreover, by choosing appropriate functional forms, the estimating equations are linear or close to linear. This avoids the need for complicated, nonlinear estimation methods and allows researchers to use standard causal inference techniques to estimate many of the model primitives. For many of the key equations, we can use two-stage least squares to identify key parameters.

3.3 Spatial Equilibrium Model

To calculate the total welfare effect for a change in amenity a_j, inclusive of the price and wage adjustments in equilibrium, we need to know how individuals would migrate across locations in response to the change in a_j and how local prices and wages would adjust in turn to this migration. Drawing from Diamond (2016) and Suárez Serrato and Zidar (2016), we now fully specify the model.[10]

[10] Both Diamond (2016) and Suárez Serrato and Zidar (2016) draw on the discrete model of school district choice developed in Bayer et al. (2007), which itself builds on the industrial organization discrete choice framework outlined by Berry et al. (1995) by applying it to location choice.

3.4 Labor Supply

3.4.1 Step 1: Worker Utility Conditional on Location

Consider two types of workers, high-education workers H and low-education workers L.[11,12] They consume local housing good M at price R_{jt} and national good C at price P_t.[13] Each location is endowed with a set of amenities a_{jt}, which includes any factor other than price (e.g., wages or rent) that makes a place desirable to live in. This could include classic amenities like air or school quality along with market-based amenities like the variety of shops and restaurants. Workers of type $k \in \{H, L\}$ value these amenities according to the function f_k, which depends on their group-specific tastes. Thus, worker i of type k's value of amenities is:

$$A_{ijt} = f_k(a_{jt})\sigma_k \varepsilon_{ijt},$$

which depends on worker i's type as well as the worker's idiosyncratic taste ϵ_{ijt}, with standard deviation σ_k. This idiosyncratic taste parameter is drawn from the same Type One Extreme Value distribution across all commuting zones and allows us to rationalize why workers make different choices at the individual level in the data.[14] if some workers value certain amenities more highly than other workers of the same type). See Berry et al. (1995) and Berry et al. (2004) for examples of models that incorporate this consideration. However, doing so means that the estimating equations are no longer linear. See Section 4.4 for additional discussion. Choosing this functional form for the distribution of idiosyncratic tastes will lead to

[11]Fajgelbaum and Gaubert (2025), the chapter by Fajgelbaum and Gaubert in this same volume discusses the efficiency properties of models of sorting.

[12]This model could be extended to n kinds of workers based on fixed characteristics (e.g., race, immigration status). However, this framework is not easily extended to capture changing worker characteristics over time. There are other models better suited to modeling, for example, life-cycle sorting decisions. See Kennan and Walker (2011) for the canonical dynamic model of worker location decisions. This model has been elaborated and expanded on in other papers, including Bayer et al. (2016) and Bilal and Rossi-Hansberg (2021). Bishop and Murphy (2019) provides a computationally simpler method to incorporate dynamic effects.

[13]Implicitly, we assume all workers are renters. This assumption enables us to capture key intuitions with a relatively parsimonious model. However, it is possible to extend the model by adding homeownership and its accompanying dynamics. While this makes the problem computationally complex, Greaney (2023) has made significant progress in this area. It is also possible to add in trade costs such that the price of the local good captures not only housing, but also local prices; see, e.g., Fajgelbaum et al. (2019).

[14]It is possible to extend this by allowing for individual-level-within-type sorting (e.g.,

estimating equations that are easy to work with empirically, which we will discuss below.

For each location j, worker i maximizes their Cobb-Douglas utility over housing, M, and a nationally priced composite good, C, with respect to prices and taxes:[15]

$$\max_{M,C} \ln(M^{\gamma_k} C^{1-\gamma_k} A_{ijt}) \quad s.t. \quad (1+\tau_{jt}^{sales})(P_t C + R_{jt} M) = (1-\tau_{kjt}^{inc}) W_{kjt}.$$

3.4.2 Step 2: Worker Location Choice

To determine where to locate, the worker i compares indirect utility across locations j, taking into account take-home wages, amenities, taxes, and housing prices:

$$V_{ijt} = m_t + \ln(\tilde{W}_{kjt}) - \gamma_k \ln(R_{jt}) + \ln(f_k(a_{jt})) + \sigma_k \varepsilon_{ijt},$$

where the variable $\tilde{W}_{kjt}$ represents wages after sales tax, τ_{jt}^{sales}, and income tax, τ_{kjt}^{inc}:

$$\tilde{W}_{kjt} = W_{kjt} \times \frac{1-\tau_{kjt}^{inc}}{1+\tau_{jt}^{sales}}.$$

This formulation includes m_t, a location-invariant constant that represents the impact of aggregate tradable prices on worker utility. It also includes σ_k, which allows the dispersion of the idiosyncratic shock to vary across groups. Because this idiosyncratic draw comes from a Type One Extreme Value distribution, it is possible to integrate out the distribution of these idiosyncratic draws. Thus, a worker i chooses location j based on their indirect utility with probability:

$$Pr(j|k) = \frac{\exp\left\{\frac{m_t}{\sigma_k} + \frac{1}{\sigma_k}\ln(\tilde{W}_{kjt}) - \frac{\gamma_k}{\sigma_k}\ln(R_{jt}) + \frac{1}{\sigma_k}\ln(f_k(a_{jt}))\right\}}{\sum_{l\in J}\exp\left\{\frac{m_t}{\sigma_k} + \frac{1}{\sigma_k}\ln(\tilde{W}_{klt}) - \frac{\gamma_k}{\sigma_k}\ln(R_{lt}) + \frac{1}{\sigma_k}\ln(f_k(a_{lt}))\right\}}. \tag{5}$$

If $\sigma_k = 0$, then there is agreement within skill groups on the best locations. This replicates the result from the classical Rosen-Roback model. Alternatively, if σ_k is large, each individual's idiosyncratic utility from different locations is quite

[15] As formulated, workers make a decision about whether to supply labor across cities. It is possible to extend the model to incorporate both intensive and extensive margin labor supply decisions; see, e.g., Fajgelbaum et al. (2019); Su (2022). As before, this leads to equations that are no longer linear.

different from one another. In this case, some individuals would choose the location predominately based on their highest idiosyncratic draw, making the characteristics of the place nearly irrelevant. The result of this is that groups are able to have different elasticities of migration in response to local shocks. If the dispersion is very narrow, there will be large amounts of migration in response to a local shock. If the dispersion is wide, there will be very little.

The exponent of the indirect utility function for location j is in the numerator and the sum of the exponent of the indirect utility function for all other locations is in the denominator. This allows for general equilibrium feedback effects: if there is a change in any city's amenities or prices, it will affect the location probabilities of all other cities. If City A gets better, people from all the other cities now are more likely to move there. Conceptually, this suggests that there is no "true" control group: if City A receives a shock and City B does not, City B is still affected by the treatment because workers are less likely to locate there. This violates the Stable Unit Treatment Value Assumption (SUTVA), the standard assumption that the control group receives no treatment.

However, because of the functional form, it is possible to difference this out by comparing the log probability of choosing between two cities, j and j_0 :

$$\begin{aligned} &\ln(Pr(j|k)) - \ln(Pr(j_0|k)) = \\ &\quad \frac{1}{\sigma_k}(\ln(\tilde{W}_{kjt}) - ln(\tilde{W}_{kj_0t})) - \frac{\gamma_k}{\sigma_k}(\ln(R_{jt}) - \ln(R_{j_0t})) + \frac{1}{\sigma_k}(\ln(f_k(a_{jt})) - \ln(f_k(a_{j_0t}))). \end{aligned} \tag{6}$$

By taking the log of the probability of locating in a city relative to a base city j_0, the denominators cancel and we are left with an equation without this SUTVA violation. Using this method, it is possible to get back to a standard treatment effect estimator—though, of course, this does depend on the conditional logit model functional form chosen. While the conditional logit model places restrictions on the ways people can substitute across places, it simplifies the estimation and provides a clearer mapping to reduced-form causal estimation.

3.5 Labor Supply and Housing Demand

Worker location decisions determine labor supply and housing demand in that location. The share of workers locating in each area (and thus the amount of labor supplied there) is described by Equation 5. Housing demand depends not only on the number of workers living in the city, but also on how much housing each worker wants to consume. The total housing demand in location j can be written as:

$$M_{jt} = \sum_{k} \underbrace{\frac{\tilde{W}_{kjt}\gamma_k}{R_{jt}}}_{\substack{\text{Housing} \\ \text{demanded per worker}}} \times \underbrace{Pr(j|k) \times N_k}_{\substack{\text{Number of } k \text{ workers} \\ \text{in location } j}} . \tag{7}$$

The first term captures the intensive margin of housing demand based on prices and wages, while the second term captures the extensive margin based on worker location choices.

3.6 Housing Supply

3.6.1 The Production of Housing

Homogeneous developers produce housing with land G_{jt}, capital K_{jt}, and housing total factor productivity (TFP) B^H_{jt} under a Cobb-Douglas production function.[16] Local housing TFP captures the productivity of housing developers in a particular area, such that:

$$M_{jt} = B^H_{jt} K^{\alpha_j}_{jt} G^{1-\alpha_j}_{jt}.$$

Furthermore, each commuting zone is endowed with a fixed quantity $\bar{G}_j$ of land and a location-specific Cobb-Douglas parameter α_j. Commuting zones may have different quantities of land and different α_j. Both B^H_{jt} and α_j could differ based on variation in zoning or minimum lot size requirements. For example, the parameter α_j maps on nicely to policies like minimum lot size requirements, which forces developers to use more land relative to capital to produce housing. The parameter B^H_{jt} could represent construction costs or mandated building codes, which may vary across space.

[16] In the literature, researchers take different approaches to modeling housing supply. Some take the simple log-linear approach (e.g., Diamond, 2016; Suárez Serrato and Zidar, 2016) while others think more deeply about developer business decisions (e.g., Murphy, 2018; Diamond et al., 2025). We take a middle ground between these two extremes with our approach.

3.6.2 Housing Supply

Assume that the asset, land, and capital markets clear and are in a steady-state equilibrium without uncertainty. Developers rent capital at rate r_{jt} and the interest rate ι clears the asset market. Developers sell housing to absentee landlords who rent to workers. These assumptions are required to keep the model static and to ignore the complications that arise from the fact that housing is a durable asset; see Glaeser and Gyourko (2005) for housing supply implications of durable housing.

Under these assumptions, housing supply is determined by the housing TFP B^H_{jt}, the price of housing R_{jt}, the capital rental rate r_{jt}, the interest rate ι, the quantity of land in the commuting zone $\bar{G}_j$, and the Cobb-Douglas parameter α_j :

$$\ln(M_{jt}) = \frac{1}{1-\alpha_j}\ln\left(B^H_{jt}\right) + \frac{\alpha_j}{1-\alpha_j}\ln(R_{jt}) - \frac{\alpha_j}{1-\alpha_j}\ln(r_{jt}) + \frac{\alpha_j}{1-\alpha_j}\ln\left(\frac{\alpha_j}{\iota}\right) + \ln(\bar{G}_j). \quad (8)$$

Notice that the elasticity of housing supply with respect to the local rental rate depends only on α_j, the Cobb-Douglas parameter. If α_j is smaller, i.e., the commuting zone forces developers to use more land to produce housing, that will impact the elasticity. Additionally, rezoning additional land from agriculture to housing would additively increase the housing supply.[17]

The rental rate of housing is jointly determined by the housing supply equation, Equation 8, and the housing demand equation we derived previously, Equation 7.

3.7 Firm Sorting and Labor Demand

For the firm side of our model, we derive an equation for labor demand that incorporates substitution between types of workers, scale effects at the firm level, extensive margin responses from firm reallocation, and heterogeneity in firms' location-specific productivity. We develop the firm side of our model in three steps. First, firms minimize costs at each location j. Then, firms choose sale prices that maximize profits at each location j. Finally, firms choose locate in location j with the highest after-tax profit. Notice that the firm location decision problem parallels that of workers.

[17] Note that there is no concept of within-city neighborhoods in this model, and thus no concept of the difference in desirability between the peripheries and the city center.

3.7.1 Step 1: Cost Minimization

Firms minimize costs subject to high- and low-skill wages (w_{Hjt}, w_{Ljt}) and capital rents (r_{jt}) for a given level of production. Individual firms have Cobb Douglas-CES production functions with capital (k_{mjt}), low-education labor (l_{mjt}), and high-education labor (h_{mjt}) as inputs. Firms have a Cobb-Douglas parameter β for output elasticities between capital and labor; the substitutability between skill types is governed by ρ. City productivity is described by B_{jt} and the relative productivity of high- vs. low-eduction labor in city, j, is determined by α_j^q. Firm m produces variety q_{mjt} based on the production function:

$$q_{mjt} = \underbrace{k_{mjt}^{1-\beta}}_{\text{Capital}} \underbrace{\left[(l_{mjt}\alpha_j^q)^\rho + (h_{mjt}(1-\alpha_j^q))^\rho\right]^{\frac{\beta}{\rho}}}_{\text{CES Labor Aggregate}} \underbrace{B_{jt}\exp\{\sigma_F \xi_{mjt}\}}_{\text{Productivity}}.$$

As with the worker problem, we allow firms to have location-specific productivity ξ_{mjt} with dispersion σ_F, in addition to the fixed productivity of locations B_{jt}.[18] If all firms essentially agree on which locations are the most productive, σ_F will be small. If the dispersion is larger, this will result in the spreading out of firms for reasons that are not directly related to local fundamentals.

3.7.2 Step 2: Profit Maximization

We assume that each establishment produces an intermediate input q_{mj} that is assembled by a competitive, final goods producer using the aggregator:

$$C = \left(\int q_{mj}^{\frac{\varepsilon^{PD}+1}{\varepsilon^{PD}}} \right)^{\frac{\varepsilon^{PD}}{\varepsilon^{PD}+1}}.$$

This final good C is then consumed by households. Imperfect substitution between varieties implies that firms face a demand elasticity ε^{PD} for their output.[19]

[18] While it is possible that firms vary in their idiosyncratic skill-biased TFP, we cannot capture this force beyond city-wide skill-biased TFP. Allowing for a more idiosyncratic measure would break a lot of the closed-form and linear estimating equations we derive.

[19] While a universal elasticity of product demand is likely not supported empirically, it is a convention often used in trade and spatial models that simplifies the derivation of product demand substantially. By allowing product demand to be the same across products permits more transparent modeling of sorting, though it is possible including this richness would be useful for some research

Firms consider the after-tax profits from each location, which depend on their cost-minimizing choice of inputs and taxes on profits τ_j^{biz}. The firm's profit, π_{ijt}, if it were to locate in location j can be then written as:

$$\pi_{ijt} = \frac{\ln(1-\tau_{jt}^{biz})}{-(\varepsilon^{PD}+1)} - \underbrace{\beta \ln \bar{w}_{jt}}_{\text{CES wage index}} - (1-\beta)\ln r_{jt} + \ln B_{jt} + \sigma_F \xi_{ijt},$$

where:

$$\bar{w}_{jt} = \left[\left(\frac{w_{jt}^L}{\alpha_{jt}^q} \right)^{\frac{\rho}{\rho-1}} + \left(\frac{w_{jt}^H}{1-\alpha_{jt}^q} \right)^{\frac{\rho}{\rho-1}} \right]^{\left(\frac{\rho-1}{\rho}\right)}.$$

In maximizing profits, firms trade-off lower taxes, higher input costs, and higher average and firm-specific productivities. The firm-specific productivity term and its dispersion allow for different firms to find some places more productive than others. The CES wage index faced by firms, $\bar{w}_{jt}$, incorporates the wages of the high- and low-education workers, the rate of substitution between different types of workers, and the relative productivity of these worker types. Worker sorting impacts the composition of workers in a location, which in turn impacts the wages firms must pay.

3.7.3 Step 3: Firm Location Decision

Firms choose a location j to maximize their after-tax profits. Because the firm- and location-specific idiosyncratic productivities ξ_{ij} are drawn from a Type One Extreme Value distribution, integrating yields that the probability a firm chooses a location is given by:

$$E_{jt} = \frac{\exp\left\{ \frac{\ln(1-\tau_{jt}^{biz})}{-\sigma_F(\varepsilon^{PD}+1)} - \frac{\beta}{\sigma_F}\ln \bar{w}_{jt} - \frac{(1-\beta)}{\sigma_F}\ln r_{jt} + \frac{1}{\sigma_F}\ln B_{jt} \right\}}{\sum_{j\in J} \exp\left\{ \frac{\ln(1-\tau_{jt}^{biz})}{-\sigma_F(\varepsilon^{PD}+1)} - \frac{\beta}{\sigma_F}\ln \bar{w}_{jt} - \frac{(1-\beta)}{\sigma_F}\ln r_{jt} + \frac{1}{\sigma_F}\ln B_{jt} \right\}}.$$

When the total number of firms is normalized to equal 1, then the count of establishments in location j, E_{jt}, is equivalent to the share of establishments that locate in

questions.

location j. In other words, the probability a firm locates in location j is given by the exponent of the indirect profit function in location j relative to the exponentiated indirect profit functions across all the other locations. This functional form mirrors that of the worker location decision, with profits instead of utility.

As was the case with workers, this functional form implies a SUTVA violation when analyzing how one city is treated by a local shock and other cities are used as a control group due to general equilibrium feedback effects. This can be addressed by taking the difference in $\ln E_{jt}$ between locations j and j_0, thus eliminating the denominator:

$$\begin{aligned}\ln(E_{jt}) - \ln(E_{j_0t}) = \frac{\ln(1-\tau_{jt}^{biz})}{-\sigma_F(\varepsilon^{PD}+1)} - \frac{\ln(1-\tau_{j_0t}^{biz})}{-\sigma_F(\varepsilon^{PD}+1)} - \frac{\beta}{\sigma_F}(\ln \bar{w}_{jt} - \ln \bar{w}_{j_0t}) \\ - \frac{(1-\beta)}{\sigma_F}(\ln r_{jt} - \ln r_{j_0t}) + \frac{1}{\sigma_F}(\ln B_{jt} - \ln B_{j_0t}).\end{aligned}$$

3.8 Local Market Labor Demand

Firm location decisions then determine the total labor demand for each worker type k in each location j by aggregating across all firms in that location. Total demand for labor of a skill type k is determined by the substitution across different kinds of inputs, the scale effect, the number of firms in the area, and the productivity of the location.

$$\begin{aligned} L_{jt} &= \frac{\beta}{\alpha_j \bar{w}_{jt}} \left(\frac{w_{Ljt}}{\alpha_j \bar{w}_{jt}}\right)^{\frac{1}{\rho-1}} \left(r_{jt}^{1-\beta}\bar{w}_{jt}^{\beta}\right)^{\varepsilon^{PD}+1} E_{jt}^{1+(\varepsilon^{PD}+1)\sigma^F} B_{jt}^{-(\varepsilon^{PD}+1)}\kappa_{2t} \\ H_{jt} &= \underbrace{\frac{\beta}{(1-\alpha_j)\bar{w}_{jt}}}_{\text{K-L Sub.}} \underbrace{\left(\frac{w_{Hjt}}{(1-\alpha_j)\bar{w}_{jt}}\right)^{\frac{1}{\rho-1}}}_{\text{Within-Labor Sub.}} \underbrace{\left(r_{jt}^{1-\beta}\bar{w}_{jt}^{\beta}\right)^{\varepsilon^{PD}+1}}_{\text{Scale}} \underbrace{E_{jt}^{1+(\varepsilon^{PD}+1)\sigma^F}}_{\text{Firm Entry + Selection}} \underbrace{B_{jt}^{-(\varepsilon^{PD}+1)}\kappa_{2t}}_{\text{Local Prod.}} \end{aligned}$$

Conveniently, these labor demand equations depend only on location-specific characteristics. We will elaborate further on the ways this makes bridging the gap between the model and the causal estimates more straightforward in Section 4.

In conclusion, the model's treatment of firm sorting does two things. First, it relates firm location and labor demand for each type of worker to local prices, taxes, and productivity. Second, it clarifies the role of substitution, scale, and selection effects in determining labor demand.

4 Estimating Model with Idiosyncratic Worker and Firm Sorting By Skill

The model developed in Section 3 incorporates general equilibrium effects and permits welfare analysis while allowing for direct connections between model primitives and reduced-form causal inference estimation techniques. In this section, we will clarify the identification challenges in each of these equations. The model allows us to be specific about the endogenous variables in each equation (e.g., unobserved amenity in worker location, or unobserved productivity for firms) and provides insight into the source of valid (excludable) instruments. In this section, we will discuss identification challenges and valid instruments for each of the equations.

4.1 Estimation of Worker Decisions

4.1.1 Estimation of Labor Supply

Recall Equation 6, the baseline difference equation, which describes the difference in the probability of locating in j vs. j_0, where j_0 is an arbitrarily chosen baseline city to compare all other cities against:

$$\begin{aligned}&\ln(Pr(j|kt))-\ln(Pr(j_0|kt)\\ &=\frac{1}{\sigma_k}(\ln(\tilde{W}_{kjt})-ln(\tilde{W}_{kj_0t}))-\frac{\gamma_k}{\sigma_k}(\ln(R_{jt})-\ln(R_{j_0t}))+\frac{1}{\sigma_k}(\ln(f_k(a_{jt}))-\ln(f_k(a_{j_0t}))).\end{aligned}$$

This expression relates the relative probability of migrating to differences in wages and rents across locations. Here, $\frac{1}{\sigma_k}$ is the migration elasticity with respect to the wage. If workers have very dispersed idiosyncratic tastes, then a small change in wage will lead to small changes in migration. This is because workers generally like where they currently are for idiosyncratic rather than wage-related reasons, and so a small change in wage would be unlikely to reorder their rankings of cities. The migration elasticity with respect to local rents, $\frac{\gamma_k}{\sigma_k}$, depends on the dispersion of idiosyncratic tastes as well as the amount of after-tax income spent on housing, γ_k. If workers spend very little of their income on housing, γ_k will be small, and their location choices will not be very influenced by housing rents.

In theory, this equation could be estimated cross-sectionally, using variation across cities. However, it is often difficult to find powerful instruments that satisfy the exclusion restriction in the raw cross-section: the instruments would need to be randomly assigned across space in a persistent way over time. If we take the difference over time, relative to a base year, it is generally easier to find a credible instrument. Doing so, we have that:

$$\Delta ln(Pr(j|kt)) = \frac{1}{\sigma_k}(\Delta \ln(\tilde{W}_{kjt})) - \frac{\gamma_k}{\sigma_k}\Delta(\ln(R_{jt})) + \frac{1}{\sigma_k}\Delta(\ln(f_k(a_{jt}))) + \phi_t.$$

which looks similar to a difference-in-differences equation.[20]

We initially made no distinction between amenities that we could observe using the available data and unobserved amenities. Unless a regression of changes in log populations on wages, rents, and (observed) amenities fits with an R^2 of 1, implying we can perfectly predict location choices across space based on observables, we will need a structural residual to account for the difference between the model's prediction and the observed changes in population over time. This residual, which we interpret as the utility from the set of unobserved amenities, allows us to rationalize, for example, why we might observe people moving to a given city, even if wages, rents, or the observed amenities cannot rationalize such a pattern. Let X_{jt} be observed amenities and ξ_{kjt} be the utility from unobserved amenities. Incorporating this, we have that:

$$\Delta ln(Pr(j|kt)) = \frac{1}{\sigma_k}\Delta \ln(\tilde{W}_{kjt}) - \frac{\gamma_k}{\sigma_k}\Delta \ln(R_{jt}) + \frac{\beta_k}{\sigma_k}\Delta X_{jt} + \phi_t + \frac{1}{\sigma_k}\Delta \xi_{jkt}. \tag{9}$$

Estimating Equation 9 by OLS would likely lead to biased results. This is driven by the fact that when locations get unobservably nicer ($\Delta\xi_{jkt} > 0$), rents increase as value is capitalized into land.[21] This creates an endogeneity problem when places that are getting unobservably more desirable to live in are also likely to have housing price increases. Simply regressing population changes on housing prices would likely yield a positive coefficient. Naively, this would suggest that workers enjoy high housing prices. Indeed, the empirical exposure gap calculations in Table 2 suggest that workers were sorting toward high-rent places in the 1980s and 1990s. One way to rationalize this is that there is some amenity change compensating

[20]The location characteristics of city j_0 have been rolled into the ϕ_t.

[21]Moreover, if the amenity is productive (unproductive) for the firm, wages will increase (decrease).

workers for those high housing prices. Thus, to identify the parameters of interest, we need an instrument that is uncorrelated with unobserved amenities but can vary wages, rents, and potentially observed amenities.

For these equations, we want to identify three parameters: the local good expenditure share (γ_k), the migration elasticity with respect to after-tax wages ($\frac{1}{\sigma_k}$), and the migration elasticity with respect to amenity X ($\frac{\beta_k}{\sigma_k}$). One way to address this is by calibrating the housing expenditure share using data on the typical expenditure share on housing for the given group.[22] However, if we have the statistical power to estimate all of these elasticities directly using this equation and our migration data, calibration is a less desirable approach.

Even calibrating γ_k, there are still two endogenous variables: wages (net of housing costs) and amenities. A common assumption is that amenity changes are exogenous, which would leave only wages net of housing costs as the remaining endogenous variable.[23] Even if wages net of housing costs is the only endogenous variable, we need an instrument that shifts wages and that is uncorrelated with unobserved amenity changes. One option is to use Bartik-style shift-share instruments driven by labor demand shocks across industries to shift wages. This approach typically takes nationwide employment or wage changes in each industry over a 10-year time period and interacts those with baseline period employment shares of each industry in a given city j. Typically, we exclude the contribution of city j to the nationwide wage/employment change measures when calculating the instrument for city j, as notated by $\Delta W_{H,ind,t}^{-j}$ and $\Delta W_{L,ind,t}^{-j}$. Specifically, the instruments for high and low-education wages can be written as:

$$
\begin{aligned}
\Delta Z_{jt}^{H} &= \Delta W_{H,ind,t}^{-j} \frac{H_{ind,j,t_0}}{\sum_{ind} H_{ind,j,t_0}}, \\
\Delta Z_{jt}^{L} &= \Delta W_{L,ind,t}^{-j} \frac{L_{ind,j,t_0}}{\sum_{ind} L_{ind,j,t_0}}.
\end{aligned}
$$

Interacting these instruments with observable characteristics that impact local

[22]See Diamond and Moretti (2024) for how to calibrate the expenditure share on housing. The correct expenditure share on house prices must account for the fact that many other non-housing goods are more expensive in cities with high housing prices.

[23]Diamond (2016) finds that, particularly when studying high-education migration choices, the endogenous response of amenities to the composition of workers in a location is an important feature of the data and needs to be included as an endogenous variable.

housing supply elasticities, such as measure of land availability close to city centers (Saiz, 2010) or measure of land-use regulation (Gyourko et al., 2021) could create additional variation in housing supply elasticities. This would allow for heterogeneous incidence of a given magnitude of local labor demand shock on local housing prices vs. wages. See Diamond (2016) for further implementation details of this approach.

4.2 Estimation of the Housing Supply Equation

For the housing supply equation, we take the first difference over time in a given location j :[24]

$$\Delta \ln(M_{jt}) = \frac{1}{1-\alpha_j}\Delta \ln\left(B_{jt}^H\right) + \frac{\alpha_j}{1-\alpha_j}\Delta \ln(R_{jt}) - \frac{\alpha_j}{1-\alpha_j}\Delta \ln(r_{jt}) + \Delta \ln(\bar{G}_j).$$

Here, the omitted variable bias arises from housing productivity shocks $B_{jt}^H > 0$ that increases housing M_{jt} and reduces rental prices R_{jt}, thus biasing the housing supply elasticity, $\frac{\alpha_j}{1-\alpha_j}$, downward. We need an instrument that impacts house prices, but not housing productivity to identify the housing supply elasticity correctly. A standard candidate instrument is the industry shift-share instruments we presented above, which also can be used for the labor supply equation. This is not a perfect instrument in this case: if the construction sector also receives a labor shock and construction is an input into the housing sector, this could affect housing TFP. However, it is widely used despite these downsides and observable controls for construction wages and other construction input costs could be added. Another possible candidate is a change to the income or corporate tax rates. Taxes on all sectors but the housing developer sector should not directly affect developers and thus could be used to create variation in housing demand.

[24]As previously stated, almost any instrument is more believable in changes or shocks rather than in the raw cross-section. However, if there is an instrumental variable (IV) that credibly moves around house prices in different places in the cross-section and is uncorrelated with unobserved local housing TFP levels, that would be a valid IV.

4.3 Estimation of Firm Decisions

4.3.1 Estimation of Wage Index

The firm faces a choice about how much high- vs. low-education labor to hire. In order to estimate firm location and labor demand, we need to first measure the CES wage index $\bar{w}_{jt}$. If we take the ratio of high- to low-skill labor demand, the terms related to firm location decisions cancel and we find that relative demand of high- and low-skill labor just depends on their relative wages and their relative productivities. Thus, relative labor demand is given by:

$$\ln\left(\frac{L_{jt}}{H_{jt}}\right) = \frac{1}{\rho - 1}\ln\left(\frac{w_{Ljt}}{w_{Hjt}}\right) + \frac{\rho}{\rho - 1}\ln\left(\frac{1-\alpha_{jt}^{q}}{\alpha_{jt}^{q}}\right).$$

Using this relative labor demand equation, we can estimate skill substitutability within the firm, ρ, and the relative productivity of low-education labor, α_j^q. To do so, we need an instrument to shift the relative labor supply or relative wages through the labor supply of high and low-education workers. One such instrument could be relative changes in income tax rates between high- and low-education workers. With ρ estimated and α_{jt}^q inverted from the residual of the relative labor demand equation, we can directly compute the CES wage aggregate between high- and low-skill wages $\bar{w}_{jt}$.

4.3.2 Estimation of Firm Location

The establishment share equation is log-linear in $(1-\tau_{jt}^{biz}), \bar{w}_{jt}, r_{jt}$:

$$\Delta \ln E_{jt} = \frac{1}{-\sigma_F(\varepsilon^{PD}+1)}\Delta\ln(1-\tau_{jt}^{biz}) - \frac{\beta}{\sigma_F}\Delta\ln\bar{w}_{jt} - \frac{(1-\beta)}{\sigma_F}\Delta\ln r_{jt} + \frac{1}{\sigma_F}\Delta\ln B_{jt}.$$

Wage changes are likely positively correlated with unobserved productivity shocks B_{jt}. Because of this, we want instruments that are uncorrelated with productivity ΔB_{jt}, but shift wages, business taxes, and ideally capital rental rates to identify $\sigma_F, \varepsilon^{PD}$, and β. This could be shifts to local capital supply, change in local house prices, or a change in local income, business, or sales taxes. However, it is generally difficult to come up with instruments that powerfully shift labor supply. This makes it hard to separately estimate the elasticity of product demand ε^{PD} and

σ^F. While not ideal, researchers can make progress by calibrating ε^{PD} to values estimated by the prior literature.

4.3.3 Estimation of Labor Demand

The total labor demand equations for high- and low-education workers are log-linear in w_{Ljt}, w_{Hjt}, and r_{jt} :

$$
\begin{aligned}
\Delta \ln L_{jt} &= \frac{1}{\rho-1}\Delta \ln w_{Ljt} - \left(\frac{\rho}{\rho-1} + \beta(\varepsilon^{PD}+1)\right)\Delta \ln \bar{w}_{jt} + (1-\beta)(\varepsilon^{PD}+1)\Delta \ln r_{jt} \\
&\quad + \left(1 + (\varepsilon^{PD}+1)\sigma^F\right)\Delta \ln E_{jt} - (\varepsilon^{PD}+1)\sigma^F \Delta \ln B_{jt}, \\
\Delta \ln H_{jt} &= \frac{1}{\rho-1}\Delta \ln w_{Hjt} - \left(\frac{\rho}{\rho-1} + \beta(\varepsilon^{PD}+1)\right)\Delta \ln \bar{w}_{jt} + (1-\beta)(\varepsilon^{PD}+1)\Delta \ln r_{jt} \\
&\quad + \left(1 + (\varepsilon^{PD}+1)\sigma^F\right)\Delta \ln E_{jt} - (\varepsilon^{PD}+1)\sigma^F \Delta \ln B_{jt}.
\end{aligned}
$$

Because these equations and the firm location decision equation share many parameters in common, there are cross-equation restrictions which results in over-identification. Thus, it is not necessary to come up with separate instrumental variables for each elasticity in the model. We observe the count of establishments, the amount of high- and low-skill labor demanded, and how much each firm is hiring. Instruments for parameters in this equation should be uncorrelated with productivity ΔB_{jt}, as above. Candidates could include variation in local price and taxes, e.g., local income, business or sales taxes, or shifts to local capital supply. Ideally, one would estimate all the labor demand equations simultaneously using GMM to impose the model-implied cross-equation restrictions and maximize power.

It is often hard to find strong instruments that shift labor supply. In the absence of labor supply shocks, Suárez Serrato and Zidar (2023) use additional data moments to identify demand parameters. In particular, changes in the intensive margin of labor demand of incumbent firms and the average productivity of firms in a given area can identify the parameters σ_F and ε^{PD}.

4.4 Limitations and Extensions

This model allows workers to sort across locations according to their type, as well as their individual-specific idiosyncratic taste. Firms are allowed to sort across space due to their idiosyncratic TFP. However, a clear shortcoming of this model is that it does not allow for firms to sort across space based on the firm-specific relative productivity of high- and low-education labor. Indeed, the descriptive facts in Section 2 looking at firm sorting cannot be directly incorporated into this framework. Finding a modeling framework that allows for this type of firm sorting and utilizes simple, transparent estimating equations is a useful point of future work.

In theory, we could extend the model to account for within-group taste heterogeneity for specific location characteristics. Within college workers, there could be some people who care about pollution and others who care more about school quality. This would involve putting a random coefficient or distribution of coefficients on individual location characteristics. Workers would draw a preference parameter of how much they value school quality from some distribution in addition to drawing an idiosyncratic taste from the Type One Extreme Value distribution. However, this would mean that it is no longer possible to use linear regressions or two-stage least squares to capture the extent of this preference heterogeneity. Instead, it would be necessary to use simulated method of moments and potentially control functions, which makes the driving forces influencing the parameter estimates less transparent.

In our development of this model, there are no within-group earnings differences within a location: all college workers in a given city are paid the same wage. Incorporating within-group earnings differences into the model while maintaining transparency and linearity is not straightforward. However, the literature on two-way fixed effect models of wage determination suggests that this is a first-order feature of labor markets (Abowd et al., 1999). Moreover, this model lacks a distinction between places of work and places of residence: within a city, there is no heterogeneity in location. See Bayer et al. (2007), Su (2022), and Couture et al. (2024) for models that incorporate neighborhood choice.

Researchers could extend the housing supply microfoundation in several ways to improve the realism of the model. It is also possible to extend the model to microfound the housing sector through a commuting equilibrium, as in Alonso (1964); Mills (1967); Muth (1969). Additionally, it could be useful to include a labor input on the housing production side, such as the construction sector. Finally, we omit the homeownership decision from the current model because choices of when to buy and sell homes introduce dynamics into the model.

Firms face no trade costs when selling their homogeneous goods, they do not make local capital investments, and they all face the same elasticity of product demand. Relaxing these restrictions is a relatively straightforward extension of the model, but would require additional data to identify these added parameters, and would complicate estimation.. Finally, we also do not include dynamics to maintain the parsimony of the model.

This model also does not allow for multi-unit firms or inter-spatial linkages within firms. The location decisions for multi-unit firms may be more complex, taking into account how interrelated locations are and how firm supply chains function, both within and across firms linked in the production process. In Section 5, we discuss some papers that engage with the challenges of establishment location decisions within a firm network more deeply.

5 Empirical Advances in Spatial Sorting

In this section, we review recent research on household sorting (Section 5.1), housing supply and housing policy (Section 5.2), and firm sorting (Section 5.3) through the lens of these different components of spatial sorting models.

Spatial equilibrium models tightly link welfare to location choices by relying on an assumption of revealed preference. In Section 5.4, we discuss recent research on spatial sorting that showcases instances where this revealed preference assumption may not hold due to information frictions and unobserved restrictions on choice sets.

5.1 Household Sorting

5.1.1 Well-Being and Inequality

Sorting on Worker Skill: The 1980s and 1990s saw an increase in segregation between college-educated and non-college-educated workers across metropolitan statistical areas (MSAs), with college-educated workers increasingly sorting into high-wage, high-rent MSAs (Moretti, 2004, 2013; Diamond, 2016).[25] Moretti (2004)

[25]MSAs are composed of multiple counties and are intended to approximate urban areas. In contrast to commuting zones, not all counties in the US are part of an MSA.

finds that the average share of MSA residents who have a college degree has been increasing since the 1990s, as has the dispersion of this share across MSAs. The average share of college graduates in an MSA increased from 17% in 1980 to 23% in 2000—and importantly, the largest increases were concentrated in cities with a high initial share of college graduates (Moretti, 2004). These coinciding facts imply that college graduates are more sorted by 2000 than they were in the previous two decades, which is in line with our findings in Section 2.

Consistent with these findings, Diamond (2016) shows that this increased skill sorting from 1980 to 2000 was driven by skill-biased technological change.[26] However, the initial skill sorting driven by local labor demand changes was then amplified by endogenous amenity improvements within increasingly high-skill cities. These improved amenities, such as cleaner air, better schools, and lower crime rates, were valued the most by high-education workers, which made them more willing to pay the higher housing costs that came along with the amenities. This exacerbated the skill sorting initially driven by skill-biased technological change. Indeed, as we show in Table 2, sorting patterns in the 2000s and 2010s may be consistent with the amenity feedback loop described in Diamond (2016): we no longer see high-education workers moving to expensive places, but the migration toward high-amenity places continues. Sorting during the 2000–2020 period has been less studied, and understanding the mechanisms behind this reversal of the previous trend is a fruitful area for future research.

Some evidence suggests that increased segregation was also accompanied by a rise in wage inequality and an increase in the college wage premium, particularly in larger cities (Baum-Snow and Pavan, 2013). Davis and Dingel (2019) use agglomeration to rationalize the growth of the college wage premium in large cities. They develop a model in which bigger cities provide more opportunities for idea exchange and thus improve the productivity of producers of tradable goods, increasing the wages for the higher-ability workers they employ. Autor (2019) instead attributes this growth to increased globalization and automation, which have in turn led to a decline in the availability of middle-class, non-college jobs in dense cities. In dense cities, non-college workers now perform less-skilled work than before and their wage premium is smaller as a result. Other explanations

[26]Giannone (2022) finds that in addition to skill-biased technological change, knowledge spillovers can also explain increased spatial skill segregation since 1980.

for the growth of the urban college wage premium include increasing labor demand for skilled vs. unskilled labor in cities (Baum-Snow et al., 2018) and lower communication costs (Eckert, 2019).

Other research is more skeptical that the college wage premium has increased to a meaningful extent. Moretti (2013) suggests that while the college wage premium did increase, the concurrent increase in the number of college-educated workers locating in large cities with high housing costs indicates that the college wage premium was not increasing by as much in real terms. However, Diamond (2016) finds that once amenities are included in the welfare calculation, the growth in inequality between college and non-college workers due to a combination of changes in wages, housing costs, and amenities from 1980 to 2000 is even larger than the growth in the college wage premium alone. Both of these papers, along with almost all of the spatial equilibrium literature, do not consider whether the unobserved skill differences of workers within an education level play a large role in the observed urban college wage premium. Recent work by Card et al. (2025) finds that unobserved ability differences of college graduates in larger cities explains two-thirds of the wage gap between college and non-college workers. Whether the college wage premium is larger in larger cities thus remains a debate in this literature.

Sorting and Racial Segregation: Geographic racial segregation in the US is a long-standing phenomenon observed both at the neighborhood level and between MSAs. While racial segregation remains a prominent feature of geographic sorting today, Cutler et al. (1999) show that it has been declining since 1970. Historical Black-White segregation and differences in access to neighborhood amenities and opportunity have had lasting effects on Black-White inequality today (Althoff and Reichardt, 2024; Akbar et al., 2025). In particular, Derenoncourt (2022) shows that the Black Great Migration out of the US South from 1940 to 1980 led to White flight in cities receiving many Black in-migrants. White flight, along with local policy changes in cities receiving many Black migrants, reduced the benefits to Black people seeking to move to higher-opportunity locations. Racial segregation may also impact intergenerational mobility. Andrews et al. (2017) find that higher commuting-zone levels of segregation in the late 1880s are associated with reduced intergenerational mobility for children born in the early 1980s, even after controlling for contemporary segregation, which suggests that historical factors may have causal impacts independent of their role in shaping the current spatial landscape.

There is a much larger literature on this topic that goes beyond the scope of this chapter. Other papers examine the role of factors such as White flight (Shertzer and Walsh, 2019), preferences (Aliprantis et al., 2024), and highway construction (Bagagli, 2023; Mahajan, 2024; Weiwu, 2024) in generating and reinforcing racial segregation. See also the recent literature review by Logan and Parman (2025) or Abramitzky et al. (2025), the chapter in this volume by Abramitzky, Boustan, and Storeygard for a more complete treatment of this topic.

5.1.2 Amenities

Section 2 finds that amenities are an increasingly important factor in location choices, particularly for college-educated workers. Researchers initially considered amenities to be an exogenous characteristic of a place and thus often did not model why they would change over time (Roback, 1982). As college-educated workers increasingly sorted into high-wage, high-rent MSAs during the 1980s and 1990s, amenities improved in these same places. Diamond (2016) suggests that the rise in amenities in these locations is an endogenous response to the influx of college-educated workers: if more college-educated workers arrive, it incentivizes local businesses and governments to respond by improving the amenities in that location, which makes the place more desirable to live in. Because college-educated workers are usually willing to pay more for amenities than non-college-educated workers (Diamond, 2016), this cycle continues.

Recent work has shown how consumption amenities respond to demand within and across cities. Firms have been shown to cater their product offerings to the income-specific tastes of an area, which leads to a greater variety of higher-quality products in high-income areas. Handbury (2021) provides direct evidence of income-specific tastes for local consumption amenities, which may help explain why workers of similar income and skill levels collocate. She finds that, in wealthier areas, firms have a larger variety of product offerings with slightly higher prices. She shows that high-income households value this extra access to product variety, offsetting much of the higher prices of individual products. In contrast, lower-income households mostly care about product price and less about variety. This makes wealthy cities desirable to high-income consumers, but less desirable to low-income consumers.

Consumption amenities may also endogenously respond to local demand within cities. Almagro and Domínguez-Iino (2024) investigate the phenomenon that amenities endogenously respond to local demand using microdata from Amsterdam and leveraging variation in tourist distributions as demand shifters. Using this to construct a dynamic spatial equilibrium model of residential sorting where households have heterogeneous preferences and amenities respond endogenously to the households that locate in a particular neighborhood, they find significant heterogeneity both in residents' preferences over amenities and in supply responses across amenity types. This allows for "horizontal differentiation" across neighborhoods, where neighborhoods cater to the preferences of their residents and develop different amenities as a result.

The endogenous response of amenities to neighborhood composition has implications for gentrification. Couture et al. (2024) show that growth in income inequality *per se* can influence residential sorting. As the rich get richer, they demand more amenities, leading them to move downtown and for downtowns to increase their supply of amenities. This leads to rents in downtowns increasing and pricing out lower-income individuals who are not willing to pay as much for these high amenities in downtowns. There is an active literature debating the causes and consequences of gentrification (Ding et al., 2016; Couture and Handbury, 2020; Brummet and Reed, 2021; Couture and Handbury, 2023; Guerrieri et al., 2013). Analogously, other work finds that low-income, less-skilled, or minority households may disproportionately sort in low-amenity areas (Bakkensen and Ma, 2020; Heblich et al., 2021).

In our analysis in Section 2, despite a reversal in sorting based on wages and rents, sorting based on amenities continued in the 2000s and 2010s. This suggests that amenities continue to be a significant factor in household location decisions for high-education workers. Moreover, the consumption amenities index exposure gap increases are driven both by the place effect and the sorting effect, which could be consistent with places responding endogenously to local demand.

"Opportunity" as an Amenity: Neighborhood opportunity, defined as a neighborhood's impact on resident children's future adult income, is a neighborhood amenity that has received a lot of attention in the literature. Chetty et al. (2014)

document substantial geographic variation in opportunity across commuting zones: they find that the probability that a child born into the bottom fifth of the parental income distribution reaches the top fifth of that distribution varies from 4% in some cities and nearly 13% in others. Chetty et al. (2018) also show substantial variation in opportunity at the Census tract level, within MSAs.

In this context, "opportunity" can be considered an amenity due to the place-based nature of its effects. However, this amenity is not easy for households to observe. Indeed, no one knows for sure which locations provide the most opportunity today because children's adult earnings will not be observed until they have grown up. Moreover, when using location choice to reveal households' preferences for amenities, many high-opportunity areas do not appear to be in very high demand (Chetty and Hendren, 2018a,b). Recent work by Bergman et al. (2024) finds that information barriers in the housing search process are a key reason why families do not move to high-opportunity places.

Aloni and Avivi (2024) note that high-opportunity places may differ by family background. They provide evidence that, in Israel, the places that produce good outcomes for low-income native-born children differ from those that do so for low-income immigrant children. Moreover, places that are high-opportunity for children may not offer the most productive labor markets for adults. Sprung-Keyser and Porter (2024) show that MSAs that offer high opportunity for kids tend to offer lower wages for working adults, forcing families to face a trade off between higher earnings for their kids in the future with higher earnings for the family now.

5.1.3 Moving Costs and Birthplace Preferences

Empirically, cross-state migration is relatively infrequent. According to the 2023 American Community Survey, 2.3% of US individuals moved between states during the year (US Census Bureau, 2023). The observed infrequency of moves in the data is generally understood to be due to both moving costs and preference to live in one's birthplace, though distinguishing between the two can be empirically difficult. Moves may be limited by factors including spatial frictions (Schmutz and Sidibé, 2019), the value of local social networks (Huttunen et al., 2018; Koşar et al., 2022), information frictions (Wilson, 2021, 2022), and high financial or psychological costs of moving. Birthplace preferences may make moves away from one's home county or state particularly costly. The fact that college and non-college-educated workers may have different moving costs implies that non-college workers are differentially exposed to increases in housing prices, decreases in wages, and are relatively less able to relocate in order to take advantage of improved amenities elsewhere.

Kennan and Walker (2011) use a dynamic structural model to estimate the impact of moving costs on migration decisions, focusing on a sample of White male high school graduates. Using revealed preference, they find that individuals would be willing to pay $312,000 to avoid a cross-state move, which seems excessively high. However, these figures reflect both direct monetary costs and the disutility associated with relocation to a random location in the US.

Howard and Shao (2023) propose an alternative model where migration patterns are shaped not only by financial costs but also by persistent preferences for specific locations. Their model captures the fact that individuals' preferences for certain areas are long-lasting and correlated with nearby locations, which results in low migration rates even in the absence of substantial financial barriers. This persistent, unobserved heterogeneity is often not part of dynamic models, including Kennan and Walker (2011). Howard and Shao (2023) show that preference heterogeneity of this variety is a more plausible explanation than very high moving costs for the low moving rates observed in the data.

Current research has found substantial heterogeneity in moving costs, birth state preferences, and the likelihood of migration by worker skill type. Diamond (2016) suggests that, while both college-educated and non-college-educated workers prefer to live in their state of birth, birthplace preferences are stronger for non-college-educated workers. Other research concentrates on the causes of differential migration probabilities by worker characteristics including skill type. Bound and Holzer (2000) find that college-educated workers are more likely to migrate in response to shifts in labor demand compared to less-educated workers. They also find suggestive evidence that Black workers are less responsive to labor demand shifts than White workers, even when controlling for education levels. Similarly, Notowidigdo (2020) finds that declines in housing prices and government transfers serve to partially offset the effects of local demand shocks for low-education workers. Using a spatial equilibrium model, he concludes that because low-education workers receive less of the incidence, these workers are less likely to move in response to a local demand shock than high-education workers.

5.2 Housing Supply and Housing Policy

Inelastic housing supply contributes to increased skill sorting and spatial inequality. Ganong and Shoag (2017) show that since expenditure shares on housing decline with income, increased house prices will increase income and skill segregation across states. In particular, they find that land-use regulations have increased since 1970 and that the places experiencing a larger increase in land-use regulation had larger increases in house prices and reductions in in-migration from low-education workers. Diamond and Moretti (2024) examine how geographic variations in consumption and cost of living across the United States affect workers of different income levels and skill types. In line with Ganong and Shoag (2017), they find that workers with a high school degree or less experience less consumption and lower standards of living in cities with high housing prices. In contrast, college graduates are able to mitigate the effects of higher house prices because they spend a smaller share of their budget on housing and they earn higher wages in cities with high housing prices.

Furthermore, historical land-use regulations at the neighborhood level have been used to exclude racial minorities and perpetuate racial segregation. Song (2021) and Sahn (2024) show that bans on building more affordable housing limits the in-migration of lower income and racial minorities, exacerbating segregation in the process.

There is substantial spatial variation in housing supply elasticities (Saiz, 2010; Gorback and Keys, 2020; Baum-Snow and Han, 2024). Differences in housing supply elasticity across space might result in aggregate inefficiency if productive cities produce little housing, resulting in workers choosing lower-productivity jobs in other cities with lower housing costs. Hsieh and Moretti (2019) and Herkenhoff et al. (2018) study this misallocation using spatial equilibrium models and find that differences in productivity across places due to restrictive housing rules have slowed GDP growth and led to substantial spatial allocative inefficiency. While renters tend to be hurt by increased land-use restrictions due to an increase in housing rents, homeowners may benefit. Parkhomenko (2023) builds a model to describe endogenous land-use decisions that raise land prices and reduce congestion, generally benefiting homeowners but hurting renters. He finds that differential land-use policies across cities result in misallocation, but could be counteracted by federal policies that either compensate homeowners for removing (or limiting their gains from) restrictive land-use policies. However, because his model includes both homeowners and renters, the aggregate gains from relaxing land-use restrictions are much smaller than those in Hsieh and Moretti (2019).

Housing policy can affect housing supply, thus driving misallocation and sorting: see, for example, the literature on rent control (Diamond et al., 2019; Geddes and Holz, 2022; Mense et al., 2023; Cerqueiro et al., 2024), zoning (Lens and Monkkonen, 2016; Kulka, 2019; Trounstine, 2020; Acosta, 2021; Anagol et al., 2021; Kulka et al., 2024; Sahn, 2024), minimum lot sizes (Song, 2021), and floor-to-area ratios (Tan et al., 2020; Büchler and Lutz, 2021). Using a dynamic model calibrated to New York City, Favilukis et al. (2023) study the effect of multiple different housing policies on a wide variety of outcomes, including misallocation, welfare, and equity. Another strand of research examines the effects of institutional investors on housing quantity, housing prices, and renter welfare (Mills et al., 2019; Favilukis and Van Nieuwerburgh, 2021; Austin, 2022; Coven, 2023; Gurun et al., 2023). See Gyourko and Molloy (2015), Glaeser and Gyourko (2018), Baum-Snow (2023), and Kholodilin (2024) for a review of the literature on the impact of housing policy on housing supply.

5.3 Firm Sorting

5.3.1 Firm Mobility and Inequality

Firms decide where to locate in order to maximize profits, which contributes to spatial inequality when policies are not harmonized across space. Unlike earlier models, which focus on worker sorting and assume firms have perfect mobility and no profits (e.g., Glaeser and Gottlieb, 2009; Busso et al., 2013), newer models also allow firms to have heterogeneous productivity across space. This enables firm owners to benefit from local policies—a significant refinement that allows for a more nuanced understanding of how place-based policies affect different types of firms.

Recent work has improved our understanding of the extent to which firm location is sensitive to local shocks. Giroud and Rauh (2019) study the effects of state business taxation on the employment and capital of multi-state firms. They estimate that increases in state corporate tax rates lead to significant reductions in workers per existing establishment and in the number of establishments. Importantly, they show that about half of this decline is reallocated to other states.

Suárez Serrato and Zidar (2016) develop a spatial equilibrium model in which firm mobility influences the degree to which firms benefit from local shocks. As discussed in Section 3, firms have heterogeneous productivities across space, and firms are more mobile when these location-specific productivities are less dispersed across space. Using this framework, they evaluate the incidence of state corporate tax cuts and find that a substantial portion of state corporate tax cuts benefits firm owners directly, with the remainder split between land owners and workers. This distribution challenges the notion that local corporate tax cuts primarily benefit workers or are perfectly capitalized into land values.[27]

As we discuss above, a benefit of models such as the one presented in Section 3 is the ability to study the effects of local policies on other locations. Fajgelbaum et al. (2019) study the effects of harmonizing tax rates across locations, accounting for both the effects of local taxes and their effects on public goods produced by the government. They find that harmonizing tax rates—by removing distortions across locations—can raise welfare, particularly when the provision of public goods responds to changes in taxes.

5.3.2 Spillovers and Competition for Firms

A force that is absent from the model in Section 3 is the effect of firms' location decisions on the productivity of nearby firms. Greenstone et al. (2010) finds that incumbent manufacturing firms experience TFP growth when a large manufacturing plant enters their county. This externality is not taken into account by the entering firm when choosing an entry location.

Such spillover effects raise the possibility that the allocation of productive firms to less urban areas may be inefficient. Gaubert (2018) finds that, because of agglomeration effects, high-productivity firms disproportionately benefit from and sort to dense cities. This implies that subsidizing firms to locate in smaller cities may have negative impacts on aggregate productivity and welfare.

A budding field of research studies the effects of relocation subsidies offered by

[27] Malgouyres et al. (2023) correct incidence expressions in Suárez Serrato and Zidar (2016) by incorporating changes in the composition of firms. Suárez Serrato and Zidar (2023) use these corrected expressions, update their structural estimate of the incidence of corporate tax cuts, and show that state corporate tax cuts still yield significant benefits to firm owners.

local governments to attract businesses, as well as the extent to which these subsidies are efficient policy tools. These subsidies could correct for the uninternalized externality associated with the entry of productive establishments (e.g., Greenstone et al., 2010; Slattery and Zidar, 2020) or they could result in the misallocation of productive establishments (e.g., Gaubert, 2018). New models allow for firm heterogeneity in profits across states and heterogeneity in state valuations of firms, but can reach different conclusions about the impact of these subsidies on welfare. Using data on firm-specific property tax breaks in New York state, Mast (2020) finds that competition between jurisdictions increases tax breaks and that firms are responsive in their location decisions to tax incentives. However, in equilibrium, the vast majority of firms locate where they would have absent subsidies because the most profitable locations also value firms more, which suggests that subsidies primarily benefit firms. Kim (2023) develops a model in which local politicians derive political benefits from attracting firms through subsidies. He finds that benefits to politicians are a key driver of competition for firms. Slattery (2024) argues that subsidies may increase welfare when firms are valued heterogeneously by states. While her estimates show that allowing states to compete for firms leads to modest welfare gains, she also shows that most of the gains are competed away by states, such that firms are primary beneficiaries.

Positive spillovers on local productivity, growth, and worker welfare are often cited as justification for subsidy competition. However, empirical support for these spillovers is mixed. Slattery and Zidar (2020) find evidence that firm-specific incentives do not increase local growth. While they estimate positive effects on local employment in the industry of the awarded firm, they do not find strong effects on overall local employment. On the other hand, some work suggests that certain workers and firms may benefit when a large plant opens close by. Qian and Tan (2021) find that when a high-skill firm enters an area, high-skill incumbents—particularly homeowners—benefit as wages and housing prices increase. In contrast, low-skill renters are more likely to move to neighborhoods with lower income per capita, less upward mobility, and lower home values following the entry of a high-skill firm, or to leave the city entirely.

5.3.3 Spatial Sorting of Multi-Unit Firms

Though focusing on the spatial sorting of establishments provides a clear understanding of the location decisions of single-unit firms, a significant portion of employment—60% in the 2017 Economic Census per Jiang (2024)—is concentrated in firms with multiple establishments.

Modeling the location decisions of multi-unit firms is challenging due to the combinatorial nature of choosing multiple locations from a large pool of possibilities. Recent work by Arkolakis et al. (2023) and Oberfield et al. (2024) has made progress in this area by developing approaches that make it feasible to solve this problem under certain assumptions. These methods have been used to study the effects of information and communication technology adoption by multi-unit firms (Jiang, 2024) and the effects of environmental regulation (Curtis et al., 2025).

Kleinman (2024) establishes a link between firms' spatial expansion and increasing spatial income inequality. He argues that, as service firms expand across space, they can increase the productivity of their branches by hiring high-education workers at a national headquarters whose output is non-rival across locations. This leads to regional specialization: headquarters locations will experience increased demand for high-skilled workers, while branch locations specialize in lower-skilled tasks. These forces generate differential demands for skill across the firm network, such that firms' spatial expansion contributes to increasing spatial inequality.

5.3.4 Monopsony and Labor Market Frictions

Due to the local nature of labor markets, firms may make decisions about where to locate in order to access specific pools of labor. In markets where firms have monopsony power, the entry of a new firm can also impact the incumbent firms by increasing competition for workers. See Lindenlaub et al. (2024) and van der List (2024) for recent work in this area.

While firms choose their location in part based on the local labor market, conditions in labor markets can also be affected by the kinds of firms that choose to locate there. For example, Bilal (2023) finds that differences in job-loss rates are the primary source of spatial differences in unemployment, accounting for 73% of spatial unemployment variation in the US. Moreover, he notes that two-thirds of these spatial job-loss differences are due to employer-specific heterogeneity, while the remaining one-third is due to worker-specific heterogeneity. Thus, firm location decisions have implications for the local labor market conditions of workers and may impact inequality across regions through local labor markets.

5.4 When Revealed Preference Fails

The model we develop in this chapter is built on the core assumption of revealed preferences, where the preferences of workers and firms are inferred through their observed choices. However, this assumption may not hold in cases where unobserved constraints limit the choice set. If people are unable to move to a given location due to a lack of information, financial constraints, or discrimination, the model may interpret these constraints as a preference against that location. Growing evidence suggests that unobserved constraints may have first-order impacts on location choice, underscoring the need for additional work exploring their importance in shaping sorting patterns (e.g., Bayer et al., 2008, 2014; Schmutte, 2015; Hellerstein et al., 2019; Ouazad and Rancière, 2019; Christensen and Timmins, 2022; Maestas et al., 2023; Bergman et al., 2024; Bézy et al., 2024; Weiwu, 2024).

Decisions about where to locate may not just reflect the value an individual places on their wages in a particular location. Bottan and Perez-Truglia (2022) suggest that individuals also value how well off they are relative to their neighbors. The income of neighbors can be thought of as imposing a positive (increased public goods, better dating prospects) or negative externality (lower social status), depending on one's perspective. Since a given worker's wage is correlated with his peers' wages in the same location, estimating one's preference for a wage in a city may be confounded by the worker's preference over his peers' wages.

Financial and knowledge barriers may prevent individuals from moving to locations with better amenities, even if they value them. For example, Bézy et al. (2024) study a French government program to insure landlords against tenant nonpayment risk in order to encourage landlords to rent to riskier tenants, increasing the choice set of apartments risky tenants can rent. They find that the program facilitated moves to higher amenity neighborhoods among risky renters. This suggests that these renters value these neighborhoods, but were unable to convince landlords to rent to them, absent the nonpayment insurance. Standard revealed preference estimates using data on renters without access to the nonpayment insurance would conclude these renters do not value the high amenity neighborhoods since these renters rarely move to these areas. Bergman et al. (2024) find that, in a US context, receiving information about "high-opportunity" Census tracts in addition to housing search assistance resulted in durable "moves to opportunity." This suggests that the observed locations of households at least in part reflect these financial and informational frictions.

This issue also appears when valuing clean air. Currie et al. (2015) show a lack of housing price differentials between homes with different levels of exposure to toxic air pollutants, despite these pollution differences having meaningful health effects. If households don't fully know about or understand the value of a local amenity, revealed preference estimates of willingness to pay for that amenity many not be the social planner's preferred metric to value such an amenity. Barriers like moving costs may also complicate revealed preference analysis (Bayer et al., 2009).

Racial discrimination is another friction that can impede access to high-quality neighborhoods. Christensen and Timmins (2022) find that real estate and rental agents recommend minority households houses in worse neighborhoods with more pollution, worse schools, fewer college-educated residents, and higher poverty rates. In other words, minority households are "steered" toward homes in neighborhoods with worse amenities than White households. Christensen and Timmins (2023) also use a field experiment to study if and how response rates for online rental listings differ by the racial background of the rental applicant. They find that response rates are 8.3% lower for minority applicants and that minority applicants face more response rate discrimination for properties in neighborhoods with better amenities.

Historically, racist institutional barriers to entry have shaped the location decisions of minorities. Weiwu (2024) highlights the importance of institutional barriers and racism in shaping location decisions. In her analysis of the roll-out of the US Interstate Highway System, she identifies redlining as a major reason Black residents were unable to move to neighborhoods that would allow them to avoid the costs and take advantage of the benefits of the new highway system. The chapter in this volume by Abramitzky, Boustan, and Storeygard includes further discussion of the literature on redlining.

6 Directions for Future Research

In this chapter, as in Diamond and Gaubert (2022), we observe that high-education workers have sorted away from higher wages and rents and toward better amenities in the past 20 years. Future research on household sorting could investigate this phenomenon more completely. It could also build on the recent work being done by Bergman et al. (2024), Bézy et al. (2024), and Weiwu (2024) on the way that preferences and constraints jointly shape location decisions.

Following the COVID-19 pandemic, there was a thread of research on the impact of remote work on commercial real estate markets (e.g., Gupta et al., 2022; Rosenthal et al., 2022), worker location decisions (e.g., Delventhal et al., 2022; Brueckner et al., 2023; Monte et al., 2023; Davis et al., 2024; Richard, 2024), and demand for amenities (e.g., Althoff et al., 2022). However, there is less work on how the rise of remote work has affected firm location decisions. The paper closest to studying this topic is Delventhal et al. (2022), which jointly models worker and establishment sorting in the presence of remote work. Exploring this further could be a fruitful direction for future research.

A new and robust empirical fact is that unobserved skill sorting beyond observable education levels plays an important role in observable wage disparities across space and the urban college wage premium (Combes et al., 2008, 2012; Behrens et al., 2014; Roca and Puga, 2016; Card et al., 2025). A nascent literature in macroeconomics has started to build models with unobserved worker skills and firm productivities with simultaneous sorting (e.g., Hoelzlein, 2023; Hong, 2024; Mann, 2024; Oh, 2024). As in Hong (2024), an interesting avenue for developing this agenda is to build empirically-tractable models of worker and firm sorting that can directly incorporate reduced-form evidence in the style of Abowd et al. (1999) into structural models.

The literature on housing supply and housing policy is growing exponentially, and we expect this to continue. It will be important to unpack the multidimensional nature of land-use and zoning policies, as these different zoning policies may have heterogeneous effects across housing types and may be valued differently by different demographic groups. While the Wharton Land Use Regulation Index collected survey data to capture the multidimensionality of these measures, it is often aggregated into a single-dimensional index, obscuring much of the nuance inherent in the data (Saiz, 2010; Diamond, 2016).

Moreover, it is important to separate the amenity benefits of land-use policy vs. the exclusion effects as well as different impacts across groups to better understand what optimal zoning might look like. While the negative effects of zoning policies are well-documented (Ganong and Shoag, 2017; Herkenhoff et al., 2018; Hsieh and Moretti, 2019; Song, 2021), future research may contribute to a more nuanced approach to land-use and zoning policies by investigating potential positive aspects of zoning and land-use regulations when well-applied.

7 Conclusion

The study of spatial sorting and inequality has seen a renaissance, driven both by increasing segregation and the availability of new data and methods to study it. While older theories provide a foundation, they lack the frictions and heterogeneity necessary to take these models directly to the data. Newer models incorporate these elements, allowing for more realistic analyses of how workers and firms move across different locations, and how this impacts inequality.

In this chapter, we first document facts on firm and worker sorting on wages, housing costs, amenities and taxes. We find that, while high-skill workers and establishments initially sorted to high-price, high-amenity places in 1980–2000, high-skill workers and establishments began to sort away from high-price places in 2000–2017.

We then develop a model combining Diamond (2016) and Suárez Serrato and Zidar (2016) that allows researchers to study the impact of spatial sorting on inequality. We extend Suárez Serrato and Zidar (2016) to include two types of labor, high- and low-skill, in the firm's production function and extend Diamond (2016) by including firms with pricing markups. We also incorporate microfounded housing supply. Finally, we discuss modeling tradeoffs and the costs and benefits of these decisions, particularly in terms of the estimation procedure.

We use our model as an organizing framework to survey recent advances in the empirical literature. Recent research offers insights about three key ways in which spatial sorting contributes to spatial inequality. First, it suggests that high-skill workers have increasingly concentrated in high-wage, high-amenity cities, reinforcing spatial inequality. Second, it has furthered our understanding of the ways in which restrictions on housing supply can lead to increased spatial inequality. Finally, models of heterogeneous firm sorting have allowed researchers to examine how firm location decisions contribute to spatial sorting and inequality. We conclude our literature review by discussing cases where the revealed preference assumption breaks down due to financial or informational constraints or because of discrimination, underscoring the need for further research on spatial frictions and inequality.

We see the topics of spatial sorting, housing policy, firm sorting, and inequality as a place where we expect to see an immense amount of research activity in the coming years. As access to microdata on household and firm location choice continues to grow, along with growing spatial inequality, we hope to see many advances combining theory and empirics to guide policymakers and better understand the spatial dimensions of the economy.

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