The Welfare Effect of Spatial Mismatch: Evidence From the New York Metropolitan Area*

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Abstract

This paper quantifies the welfare consequences of non-college residence-workplace mismatch within the New York Metropolitan area. I find evidence that since 2000s, there is significant residential and job relocation within the city coupled with the rise in nominal wage inequality. While non-college jobs (non-tradable services) are more concentrated in the urban core, non-college residential share has been declining there. To facilitate welfare analysis, I develop a rich quantitative general equilibrium urban model that features (i) heterogeneous skills making endogenous choices of residence and workplace, (ii) multiple sectors hiring labor with different skill intensity. Using the estimated model, I find that moving from the early 2000 economy to the current one, the rise in welfare inequality exacerbates the rise in income inequality by 1%. Spatial mismatch between jobs and residence reduces the non-college welfare relative to the college group. Policy of relaxing floor area ratio in central locations helps to reduce welfare inequality.

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1 Introduction

If the hole-in-the-donut epitomized the urban crisis of the 1960s and 1970s, the New Urban Crisis is marked by the disappearing middle, the fading of the once large middle class and of its once stable neighborhoods......In many ways, more problematic dimension of the New Urban Crisis is the growing inequality, segregation, and sorting......

— Richard Florida, The New Urban Crisis

In the last three decades, U.S earning inequality has risen dramatically. Largest wage growth is concentrated among skilled labor and in large urban areas. Over the same period, the share of production occupations in those regions has been falling sharply, driving unskilled workers into non-tradable services; nevertheless, those non-tradable services are increasingly valued by the skilled workers (Moretti (2012), Giannone (2017), David and Dorn (2013), Couture and Handbury (2020)). On the surface, it seems that these facts constitute a perfect match as the expansion of non-tradable service jobs absorbs displaced unskilled workers. However, the remaining question is at the micro level, how are those growing service jobs distributed **within** the city. Most crucially, whether unskilled workers are sorted to reside close to expanding job opportunities. If locations with decent job potential are not desirable for residence, well-being will be compromised.

In this paper, I examine the welfare consequences of residential and job sorting triggered by the income growth and the change of location fundamentals[1] within the largest U.S. Core-Based Statistical Area (CBSA), the New York Metropolitan area since early 2000s. The paper seeks to answer the following questions: (i) is there any within-city skill-specific residential and job relocation behind the macro trends mentioned above; (ii) whether the welfare inequality between college and non-college workers, implied by the relocation, *exacerbates* the nominal wage inequality, and if it does, what is the trade-off that causes the exacerbation; (iii) is there any policy that helps to relax the trade-off? At the heart of the paper is the notion of *residence-workplace mismatch* faced by the non-college[2]. Namely, when a non-college worker decides the optimal residence-workplace pair, a good job location is not a good residential location, and separation of those two is by all means costly.

To answer those questions, I start by establishing some ongoing trends in the New York Metropolitan area since early 2000s. Along with divergent income growth, there exists massive sectoral reallocation of non-college labor over time. Non-college workers have been shunted out of manufacturing jobs and into non-tradable services. In addition, this aggregate reallocation

[1]This includes sectoral production productivity, skill-specific residential amenity, housing availability etc.

[2]The concept of "spatial mismatch" was first advanced in Kain (1968), where he argued that persistent unemployment in black communities around the city center is due to the suburbanization of jobs. However, racial discrimination and housing segregation prevent black workers from relocating closer to jobs.

coincides with significant within-city residential and job relocation. While non-tradable service jobs are more and more concentrated in the city center, only college residents are sorted into the city center. Non-college workers, however, have started to reside in more distant locations. Micro-data on commute patterns further confirms that the gap of commute time to work between college and non-college workers are shrinking throughout the years. These trends together highlight that in the era of "Great Divergence", non-college workers are exposed to spatial mismatch of ideal residence and ideal workplace. Although the city center offers good job opportunities, it is a unpleasant dwelling place.

To fully understand the economic forces at work and evaluate their welfare consequences, I develop a quantitative general equilibrium urban model to match the observed trends. The key ingredients are workers of heterogeneous skills making endogenous choices of residential and working locations based on income, cost-of-living, commute cost and residential amenities, and firms hiring labor in multiple sectors with different skill requirement. I introduce *non-homotheticity* into worker's preference: first, total income of workers directly influences the relative expenditure across manufacturing goods, services and housing; second, there exists minimum expenditure on housing. The non-homothetic preference is important to capture the divergent residential sorting pattern following the change of income. Due to the minimum housing expenditure, as a first-order effect, college workers are sorted into high housing cost locations (typically in the city center) after their positive income growth. Then larger concentration of non-tradable services in the city center further amplifies the sorting. This is because college workers value more the consumption of services and become increasingly so given their income growth and city center offers lower prices of non-tradable services. On the other hand, negative income growth pushes non-college workers out of the city center, and higher housing rents further exacerbate the problem. Firms in the model belong to three broad sectors: manufacturing, tradable and non-tradable service. Non-tradable service firms produce differentiated varieties whose demand lies entirely within the city; in the other two sectors, goods and services can be costly traded beyond the city boundaries. Such an industry structure implies that if non-college workers have comparative advantage in providing non-tradable services, a large portion of their wages is endogenously determined locally within the city. In locations with higher demand of non-tradable services, non-college wage is higher. The model's commute flows are shaped by residence and workplace choices. If these two locations differ, commute costs erode earning. Worker's overall welfare is higher if locations with better job access are also those desirable to reside in.

I estimate the parameters, and recover the unobservables to rationalize the observed data as an equilibrium outcome of the model. Based on the commuting gravity equation, skill-specific commuting elasticities are estimated matching model's commute flows to those observed. Then a unique set of wages (up to some scale) can be recovered using the residential population distribution and sectoral job distribution in the data. Given wages, other wage-related parameters are calibrated targeting different empirical moments. Finally, a set of location fundamentals (sectoral productivity, skill-specific amenity, and floorspace supply) are selected so that they cohere with the sectoral revenue/demand distribution across space, residential choice probability and housing market clearing.

In the final part of the paper, I utilize the estimated model to perform several counterfactuals. First, to isolate model's sorting mechanism, I study the partial-equilibrium impact of an exogenous divergent income shock. Consistent with the theoretical predictions, college and non-college residents are sorted into different locations. The model endogenously generates the residence-workplace mismatch for the non-college: while city center witnesses largest increase in non-tradable service jobs, non-college workers relocate to far-off locations. The rise in welfare inequality ends up to be larger than the rise in income inequality. In the second quantitative counterfactual, I use the model to quantify the welfare implications of spatial mismatch from early 2000 to 2017. I endogenize the income growth in the previous counterfactual using the change of calibrated skill productivity. I further take into account the change of location fundamentals, and the adjustment of housing rents/floorspace supply and skill population in the city. The model generates the exact residential and job sorting patterns observed in the data and concludes a 23% increase in welfare inequality, exacerbating the increase in income inequality by 1%. Last, I conduct a policy counterfactual of relaxing residential zoning restriction in central locations. I allow a 10% increase in residential floor area ratio (FAR) in those locations. The policy has a more significant impact on non-college workers. It makes downtown desirable for both working and living purposes, and thus helps to attenuate the spatial mismatch faced by non-college workers. As a result, both the non-college job share and residential share expand in downtown, leading to a decline in welfare inequality.

Related Literature. The paper fits into several literature. First, a recent strand of literature studies how the nominal skill premium can induce even larger welfare inequality due to the endogenous response of residential amenities. Diamond (2016) shows that increased skill sorting across cities fuels up endogenous increases in amenities within higher skill cities, which exacerbates welfare inequality between non-college and college workers. Couture et al. (2019) follows this insight and studies the spatial sorting and welfare inequality with endogenous supply of neighborhood amenities within a city[3]. I contribute to this literature by noticing the fact that within a city, jobs to provide private amenities mostly belong to the non-tradable service sector, and are largely performed by non-college workers. Thus their wages are determined

[3]In addition, Couture and Handbury (2020) points out the rising tendency of young college graduates to reside inside the city center because they value the consumption of non-tradable services there. Hoelzlein (2019) highlights a large portion of the endogenous amenity spillover is due to the sorting of service establishments.

locally and endogenously. To evaluate the welfare in a comprehensive manner, I consider the worker's choice of both residential and working locations, and therefore fully endogeneize the non-college wage. The joint decision further motivates the key trade-off of the paper seriously faced by non-college workers: residence-workplace mismatch.

Second, the paper relates to the quantitative spatial economics literature where general equilibrium spatial model is used to evaluate economic shocks and policies. This includes Ahlfeldt et al. (2015), Redding and Rossi-Hansberg (2017), Tsivanidis (2019), Rossi-Hansberg et al. (2019), Balboni (2019), Su (2020), Heblich et al. (2020) etc. I perform the model's estimation following the methodology of model inversion developed in those papers. In addition, I enrich the model with heterogeneous skills having non-homothetic preferences and heterogeneous sectors having different trade frictions. I demonstrate that model's unobservables can still be recovered without much heavier data requirement.

Third, the paper relates to work that highlights the various structural changes happening within the U.S. labor market, including a rising skill premium (Eckert et al. (2019)), a rising urban premium and spatial divergence (Giannone (2017), Eckert et al. (2020)), polarization (David and Dorn (2013), Autor et al. (2019)) etc. This paper complements the existing literature by focusing on the structural relocation of jobs and residential population and thus the relevant change of commute patterns within a large U.S. urban area in the era of "Great Divergence".

Lastly, the paper complements a list of empirical work that focuses on poor inner-city job accessibility for minority workers and their subsequent unsatisfactory labor market outcome. This includes early papers such as Kain (1968), Kain (1992), Ihlanfeldt (1993), Ihlanfeldt and Sjoquist (1998) etc where the hypothesis of "spatial mismatch" was first raised and discussed, and more recent papers such as Hellerstein et al. (2008) and Andersson et al. (2018) that utilize detailed micro-data to verify the hypothesis.

The rest of the paper proceeds as follows. Section 2 discusses the data and the motivating facts. Section 3 presents a spatial equilibrium model of a city. Section 4.1 provides the quantitative analysis of the model. Section 5 quantifies the within-city welfare impact of spatial mismatch and performs policy counterfactuals. Section 6 concludes.

2 Data and Motivating Evidence

2.1 Data

In this subsection, I describe the dataset used in the paper for the empirical motivation and the quantitative analysis.

The major dataset used in the paper is the LEHD Origin-Destination Employment Statistics (LODES) of year 2002 and 2017. First, the OD file in the data provides counts of jobs whose residential and working locations belong to any given pair of census blocks, which can be aggregated onto the census tract level. This gives me information on commute flows associated with jobs[4]. Second, the RAC and WAC files in the data summarize counts of jobs by residential and working census block respectively. Jobs are further categorized by NAICS 2-digit sector and education level. However, educational attainment is only available after year 2009. Thus, I refer to National Historical Geographic Information System (NHGIS) for the tract-level residential population by skill in early 2000s. I use these combined information to characterize the residential and working location choices by skill and sector.

The rest tract- and CBSA-level data come from two standard sources: NHGIS and Integrated Public Use Micro-data Series (IPUMS). I use these data to construct aggregate statistics such as annual skill-specific earning at the tract level, CBSA-level (residual) skill premium and employment share by sector and skill from 2000 to 2017 etc. I also utilize the "Place to Work and Travel" section of IPUMS to obtain the commute patterns by skill since early 2000s. In addition, housing cost data in 2017 comes from Zillow Rent Index (ZRI). It provides the median value of the monthly residential rental prices per square foot by zip code. I match each census tract with its corresponding zip code, and use the Zillow Rent Index for residential housing rents in 2017[5]. For the housing cost in early 2000s, I use household's monthly contract rent payment and household geographic location (Public Use Microdata Area) provided in IPUMS to calculate PUMA-level average housing rent[6].

Finally, I use Bing Distance API to construct the commute costs between two census tracts. Based on the current traffic infrastructure, the Bing Distance API provides the average travel time between any two pairs of geographic coordinates under different transportation modes. I reply on 2010-2011 Regional Household Travel Survey conducted by New York Metropolitan Transportation Council for work and non-work trip information to estimate the disutility of long commute and commute frictions of consuming non-tradable services. I refer to MapPLUTO for the New York City's land use and zoning regulation information. I use the Consumer Expenditure Survey (CES) including both the aggregate reports and the public use micro-data sample to obtain household sectoral expenditure (manufacturing, service and housing) and to estimate household preferences.

[4] I don't observe the number of jobs *by skill* in each census block pair, and thus the commute flows by skill.

[5] Zip code is a broader geographic unit compared to census tract. I assume all the census tracts in each zip code share the same rent index.

[6] Public Use Microdata Area is a geographic unit larger than census tract, and used by the U.S. Census for providing statistical and demographic information. Each PUMA contains at least 100,000 people. PUMAs do not overlap, and are contained within a single state. I assume all the census tracts in each PUMA share the same housing rent.

2.2 Motivating Evidence

The analysis of the paper focuses on the most populated U.S. CBSA: New York-Newark-Jersey City Metropolitan area (New York metro area). As the largest urban agglomeration within U.S., it encompasses 26 counties and is further partitioned into 4,700 census tracts. Figure 7 shows the geographic outline of the city. Consistent with "Great Divergence", Figure 8 confirms that since 2000, the ratio of hourly wage between college- and non-college workers (skill-premium) within the New York metro area has increased from 1.8 to 2 by 2017[7]. In addition, during the same period, average college wage has increased by 5%, while average non-college wage has decreased by 7%. In what follows, I present some ongoing trends in the New York metro area together with the divergence of wages.

Sectoral Employment Reallocation. Along with the increase in skill premium, there is labor reallocation across sectors. Following Eckert et al. (2019), I classify all the 2-digit NAICS industries into 3 broad sectors: first, *low-skill non-tradable service* includes Accommodation and Food Services, Admin, Support and Waste Services, Retail etc; second, *high-skill tradable service* includes Professional Services, Finance and Insurance, Information etc; lastly, *manufacturing* groups together Resources (Agriculture, Mining, Utilities), Construction and Manufacturing[8]. Figure 1 illustrates the change of sectoral employment since 2000. In Panel (a), overall employment share in the manufacturing sector has been decreasing sharply while the non-tradable service sector is expanding over time. In Panel (b), I further decompose the sectoral employment by skill. The share of non-college employment in both manufacturing and tradable service sectors has declined, while non-tradable service sector becomes the largest employer of non-college workers. This is consistent with the finding in David and Dorn (2013) that overall non-college workers are shunted out of specialized middle-skill production occupations into low-wage non-tradable service occupations. Compared to non-college workers, the percentage increase of college employment share in the non-tradable service sector is only half.

Residential and Job Relocation. After describing the change of aggregate employment share, here I demonstrate that workers' choices of residential and working locations have also varied over time. First, Figure 9 in the Appendix reports the redistribution of residential population by skill since 2000. Panel (a) shows that tracts close to the city center (Upper Manhattan, Upwest Brooklyn, Jersey City etc) attracts larger share of college workers; however, at the same time, Panel (b) shows that non-college workers are residing out of those central locations into more distant locations. Figure 2 summarizes this change where 4,700 census tracts are divided into 8 groups according to their distances to the city center, which is defined

[7]After controlling for worker observables (gender, race, age, having had a child in the last year etc), residual wage premium increases from 1.6 to 1.78.

[8]Appendix A.2 provides a full list of sectors.

to be the New York City Hall located in Lower Manhattan. Switching to jobs, Figure 10 in the Appendix reports the geographic relocation of non-tradable service jobs. The city center attracts larger share of non-tradable service jobs over the period, where the college residential share is increasing. This echos the finding in Couture and Handbury (2020) that college workers value those non-tradable services in downtown, resulting in "urban revivial". However, if those non-tradable services are mainly provided by non-college workers, then this implies *residence-workplace mismatch* for the non-college as they are pushed to live outside the city center. Figure 3 summarizes the change of job share in different sectors across census tract groups[9].

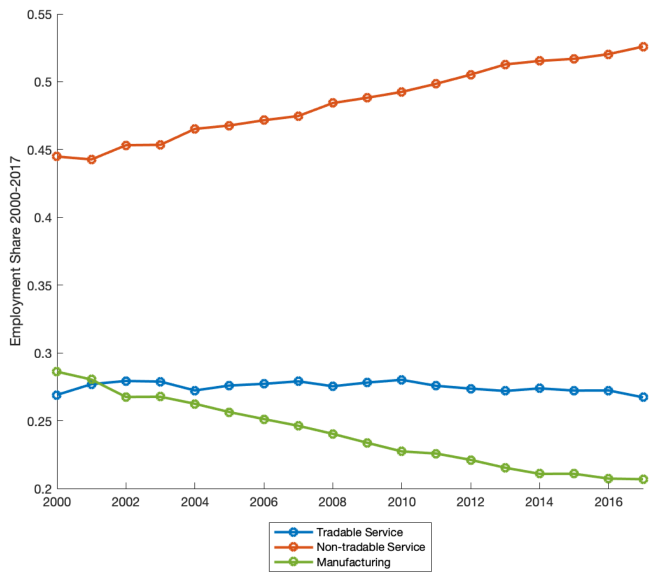
Commute Pattern. To provide micro evidence on residence-workplace choice, Table 3 in the Appendix compares the commute pattern by skill over time. In each column, I show the probability of commute time to work exceeding certain minutes for non-college workers relative to college workers, controlling for household demographics, transit mode choice etc. Both the linear and the probit specification imply that on average, non-college workers are less likely to commute long distances to work; however, more crucially, the gap has been decreasing over time, reflected by the positive significant coefficients in front of the interaction term (Non-College $\times$ Year). This emphasizes that compared to early 2000, non-college workers are travelling *relatively farther* from their residence to their workplace with respect to college workers[10].

In summary, the evidence shown above suggest the following story: in the era of "Great Divergence", non-college workers are pushed to find jobs in low-skill non-tradable service sectors; those jobs are more likely to be located in downtown, where larger share of college workers are residing; at the same time, non-college workers are moving out of downtown. Thus, even though the city center provides best job opportunities for non-college workers, there are forces, e.g. high cost-of-living, offsetting those job benefits; while it is less costly to reside in distant locations, longer commute distances to work and associated commute costs discount the earning. This fundamental trade-off imposes negative effect on non-college welfare. In the following section, I develop a spatial equilibrium model of a city that features the endogenous residential and job location choices of workers with different skills, and use the model to match those observed trends, and quantify the welfare consequences of spatial mismatch for non-college workers.

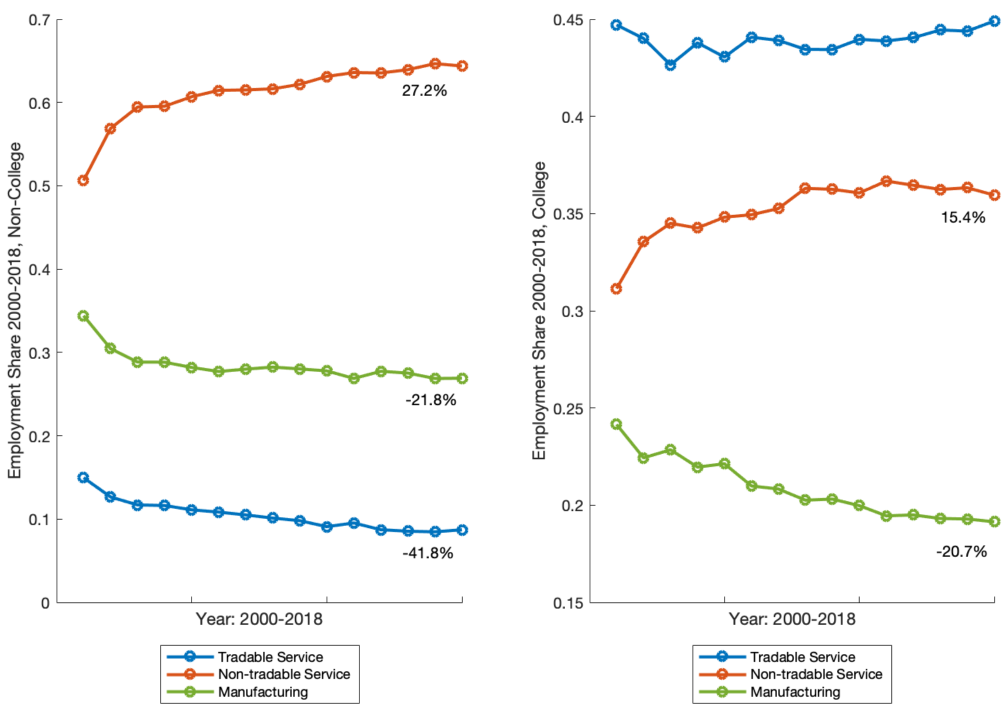
[9] Instead of showing the change of residential/job share, Figure 11 and 12 in the Appendix scatter the population/job growth (in total number) in different census tracts. There are large positive college population growth and non-tradable service job growth in the city center, while the non-college population growth is negative.

[10] This pattern is consistent with the finding in Su (2020) (See Figure 5 (b) of the paper) where the growth in commute time is decreasing in wage.

Figure 1: Employment Share By Sector and Skill



(a)



(b)

Figure 2: % Change of Residential Population Share By Skill (8 Census Tract Groups), 2000-2017

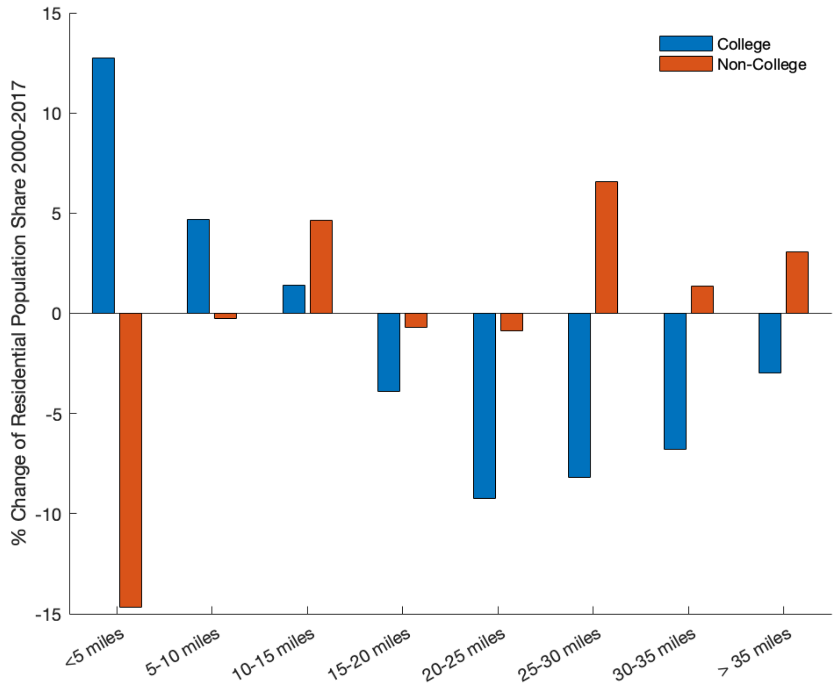
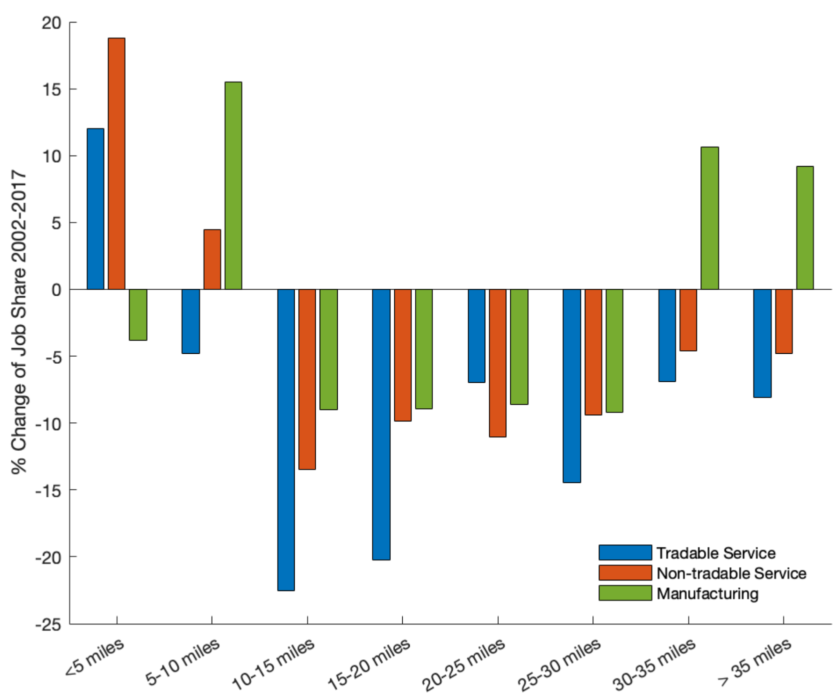


Figure 3: % Change of Job Share By Sector (8 Census Tract Groups), 2002-2017



3 A Spatial Model of City

Set-up. The modeled city (New York metro area) is embedded in a larger economy (U.S.) with a discrete set of geographic locations M. The city itself comprises a subset of those locations $N \subset M$, and each outside location alone represents another different city[11]. Locations differ in their amenities, productivities, (housing) floorspaces and commute time to every other location. There exists a fixed measure $\overline{L}_s$ of atomistic workers endowed with skill level s. Taking into account income, cost-of-living, residential amenity and commute cost, workers first decide whether to reside in the city; if yes, the optimal residence and workplace within the city. Commute costs are assumed to be *prohibitive* across the city boundaries as in Heblich et al. (2020). Firms produce in three sectors, manufacturing, tradable and non-tradable services, indexed by $g \in \{M, T, NT\}$. In the non-tradable service sector, monopolistically competitive firms enter freely into various locations and provide differentiated varieties (restaurants, night life, gyms etc) using effective labor, commercial housing, and output from other sectors under increasing returns to scale implied by the fixed cost of production. Demand for non-tradable services is located entirely within the city, and consuming the non-tradable service varieties outside the residence suffers from commute costs. Firms in the manufacturing/tradable service sector use the same factors to produce location-specific varieties in a perfectly competitive market. Manufacturing goods and tradable services can be freely traded within the city and costly traded across the city border[12]. In equilibrium, floorspace prices and skill-specific wages adjust to clear all the markets.

3.1 Workers

I first describe worker's preference and subsequent consumption choice. Then I characterize the commute and migration decision.

3.1.1 Consumption Choice

Preference. Consider a worker ω in skill group s who chooses to live in location n and work in location i, he derives utility from residential amenity u_{ns} and a consumption basket $C_{ns}(\omega)$ which is comprised of a manufacturing good bundle $C^M_{ns}(\omega)$, a service bundle $C^{Ser}_{ns}(\omega)$, and residential floorspace $H^R_{ns}(\omega)$ according to the following non-homothetic preference,

$$U_{ns}(\omega) = u_{ns} C_{ns}(\omega), \tag{3.1}$$

[11] Unless further notified, "the city" mentioned in Section 3 refers to the modelled city.

[12] In the quantitative analysis, I include a foreign economy to consider international trade of goods and services.

and the consumption basket $C_{ns}(\omega)$ is defined implicitly after Comin et al. (2015) and Ganong and Shoag (2017),

$$\rho^{M\frac{1}{\gamma}}\left(\frac{C_{ns}^{M}(\omega)}{C_{ns}(\omega)^{\zeta^{M}}}\right)^{\frac{\gamma-1}{\gamma}}+\rho^{Ser\frac{1}{\gamma}}\left(\frac{C_{ns}^{Ser}(\omega)}{C_{ns}(\omega)^{\zeta^{Ser}}}\right)^{\frac{\gamma-1}{\gamma}}+\rho^{Hou\frac{1}{\gamma}}\left(\frac{H_{ns}^{R}(\omega)-h}{C_{ns}(\omega)^{\zeta^{H}}}\right)^{\frac{\gamma-1}{\gamma}}=1,$$

$$h,\gamma,\{\rho^{k},\zeta^{k}\}_{k\in\{M,Ser,H\}}\geq 0,$$

where h represents the minimum housing requirement, γ governs the elasticity of substitution among the manufacturing good, service and residential housing consumption, and $\{\zeta^{k}\}$ controls the income elasticity of sectoral demand.

Within the service bundle $C_{ns}^{Ser}(\omega)$, I assume a Cobb-Douglas preference for tradable and non-tradable services, $C_{ns}^{Ser}(\omega)=C_{ns}^{NT}(\omega)^{\gamma^{NT}}C_{ns}^{T}(\omega)^{1-\gamma^{NT}}$, $\gamma^{NT}\in[0,1]$. The non-tradable service bundle $C_{ns}^{NT}(\omega)$ is a CES aggregator of non-tradable service varieties from various locations with elasticity of substitution $\sigma>0$,

$$C_{ns}^{NT}(\omega)=\left(\sum_{j\in M}\int_{\nu\in\Omega_{j}^{NT}}C_{ns}^{NT}(\nu;\omega)^{\frac{\sigma-1}{\sigma}}d\nu\right)^{\frac{\sigma}{\sigma-1}},$$

where Ω_{j}^{NT} is the set of differentiated non-tradeable service varieties available in location j. For a worker to consume a variety ν in location j, the total cost is $d_{nj}^{\delta}p_{j}^{NT}(\nu)$ with $\delta>0$, where d_{nj} captures the commute cost between the location n and j, and $p_{j}^{NT}(\nu)$ is the price of variety ν. Accordingly, the price index of non-tradable service bundle in residential location n is given by

$$P_{n}^{NT}=\left(\sum_{j\in M}\int_{\nu\in\Omega_{j}^{NT}}(d_{nj}^{\delta}p_{j}^{NT}(\nu))^{1-\sigma}d\nu\right)^{\frac{1}{1-\sigma}}.$$

A residential location has lower non-tradable service price if it is surrounded by a large number of low-cost varieties[13]. Similarly, the manufacturing good/tradable service bundle $C_{ns}^{M}(\omega)$/ $C_{ns}^{T}(\omega)$ aggregate location-specific varieties in a CES fashion with the same elasticity of substitution $\sigma>0$. Given the sectoral-specific trade cost $\{\tau_{nj}^{g}\}$, the price index of manufacturing good/tradable service bundle is $P_{n}^{g}=\left(\sum_{j\in M}(\tau_{nj}^{g}p_{j}^{g})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$, $g\in\{M,T\}$, where p_{j}^{g} is the price of sector g variety from location j.

Solving utility maximization given income $y_{nis}(\omega)$ and sectoral prices $\{P_{n}^{M},P_{n}^{Ser},r_{n}^{R}\}$ yields

[13]Notice even though workers try to source non-tradable service varieties from all the locations, prohibitive commute costs across the city boundaries prevent them from consuming the non-tradable services outside the city.

the following sectoral expenditure share

$$\overline{s}_{ns}^k(\omega) = \left(1 - \frac{r_n^R h}{y_{nis}(\omega)}\right)\rho^k \left(\frac{P_n^k}{y_{nis}(\omega) - r_n^R h}\right)^{1-\gamma} C_{ns}(\omega)^{\zeta^k(1-\gamma)} + \frac{r_n^R h}{y_{nis}(\omega)} 1\{k = H\}, k \in \{M, Ser, H\}, \tag{3.2}$$

with aggregate consumption $C_{ns}(\omega)$ solving

$$y_{nis}(\omega) - r_n^R h = \left(\sum_{k \in \{M, Ser, H\}} \rho^k P_n^{k(1-\gamma)} C_{ns}(\omega)^{\zeta^k(1-\gamma)}\right)^{\frac{1}{1-\gamma}}. \tag{3.3}$$

And the indirect utility takes a standard form except that the overall price index becomes non-homothetic and is given by

$$U_{ns}(\omega) = u_{ns} \frac{y_{nis}(\omega) - r_n^R h}{P_{ns}(\omega)}, \tag{3.4}$$

where the price index $P_{ns}(\omega)$ satisfies $P_{ns}(\omega) = \left(\sum_{k \in \{M, Ser, H\}} \rho^k P_n^{k(1-\gamma)} C_{ns}(\omega)^{(\zeta^k - 1)(1-\gamma)}\right)^{\frac{1}{1-\gamma}}$.

There are two sources of non-homothecity in worker's preference. First, in contrast to standard homothetic CES preferences, sectoral expenditure share depends on the aggregate consumption level, which from Equation 3.3, is positively related to net income (income after the minimum housing expenditure). The effect of income on the sectoral expenditure is governed by $\{\zeta^k\}$: when $\{\zeta^k\} = 1$, we retain the standard CES preference, where income is irrelevant to the substitution pattern; if instead we have e.g. $\zeta^{Ser} > 1$ with $\gamma < 1$, then as income grows, workers switch to more service consumption relatively given prices. Second, existence of minimum housing requirement implies that housing expenditure takes up a much larger budget share for low-income workers, and thus they have larger incentive to avoid high housing cost locations when choosing where to reside[14].

Income. Switching to the determination of income, first consider the case where the worker chooses to reside inside the city ($\{n, i\} \subset N$). His disposable income is given by

$$y_{nis}(\omega) = (1 + \lambda_s) \frac{w_{is} T_s \epsilon_{is}(\omega)}{d_{ni}}, \{\lambda_s\} \geq 0.$$

Workers are heterogeneous in their match-productivity with firms in different workplaces, which is reflected by $T_s \epsilon_{is}(\omega)$, the total efficiency units that can be supplied if worker ω works in location i. T_s captures the absolute productivity of skill s, and $\epsilon_{is}(\omega)$ is drawn i.i.d across

[14]It is important to have *positive* minimum housing requirement to rationalize the residential sorting pattern observed in the data after the income growth, where negative income growth pushes workers out of high housing cost locations (Ganong and Shoag (2017), Couture et al. (2019)). More details are explained later in worker's residential choice.

workers and working locations from the Frechet distribution with unit mean and dispersion parameter $\theta_s > 1$. The supply of efficient unit is discounted by the commute cost to work d_{ni}, capturing the the opportunity cost of time spent commuting. Given the wage per efficient unit of labor w_{is}, total wage earned by the worker is $w_{is}T_s\epsilon_{is}(\omega)/d_{ni}$. The adjustment factor λ_s then further takes into account that worker's other income sources (not explicitly modelled here). If the worker chooses to reside and work in an outside location (which itself alone is a different city)[15], his disposable income is simply $y_{ns}(\omega) = (1+\lambda_s)T_s w_{ns}$.

3.1.2 Location Choice

Regarding the timing assumption of location choice, first I assume that workers draw a vector of idiosyncratic migration tastes (one for each city), together with expected welfare of living in different cities, workers decide whether to reside inside the city ("migration choice"). Second, conditional on living inside the city, workers decide the optimal residence-workplace pair within the city ("commuting choice"). To ease the quantitative analysis, I assume the commuting choice is made by first choosing the residential location and then the working location. To be more specific, I augment worker's utility in Equation 3.1 with a vector of idiosyncratic residential tastes (one for each location inside the city), and assume the residential location choice is made after observing these residential tastes, but before the realization of efficient unit draws. Therefore, residential location is selected to maximize utility based on *expected income* workers that will earn. Then the efficient unit draws are realized, and workers choose to work in location that offers the highest total wage. This order of commuting choices greatly simplifies the model quantification, since it delivers a log-linear gravity equation for the commute flows, which can be utilized to estimate the commuting-related parameters ($\{\theta_s\}$) and unobservables (wage) [16]. I illustrate worker's location choice in reverse order.

[15]Recall that each outside location alone represents a different city, and since commuting to a job across the city boundaries is not allowed, the worker has to reside and work in the same location.

[16]If on the other hand, assuming there is only one taste shock over residence-workplace pair which follows Frechet distribution with unit scale and shape $\theta_s > 1$, and simultaneous decision of both locations as in Ahlfeldt et al. (2015), then the probability of choosing residential location n and working location i is given by

$$\pi_{nis} = \frac{(\frac{w_{is}}{d_{ni}P_{nis}}u_{ns})^{\theta_s}}{\sum_{n',i'}(\frac{w_{i's}}{d_{n'i'}P_{n'i's}}u_{n's})^{\theta_s}}.$$

Notice here the overall price index P_{nis} is both residential- and working-location specific. The reason is that worker's income depends on both locations due to the commute cost, and the overall price index depends on income due to non-homothetic preferences. Then conditional on living in location n, the probability of working in location i is

$$\pi_{i|ns} = \frac{\pi_{nis}}{\sum_{i'}\pi_{ni's}} = \frac{(\frac{w_{is}}{d_{ni}P_{nis}})^{\theta_s}}{\sum_{i'}(\frac{w_{i's}}{d_{ni'}P_{ni's}})^{\theta_s}}.$$

Compared to Equation 3.5, the appearance of price indices in the commute gravity equation complicates the process of estimating commuting elasticity θ_s and recovering unobserved wage $\{w_{is}\}$. The same timing

Workplace Choice. Given that a worker with skill s has decided to reside in location n inside the city, he chooses to work in location that offers the highest discounted wage. Frechet distribution implies that the probability of working in location i is given by

$$\pi_{i|ns} = \frac{(\frac{w_{is}}{d_{ni}})^{\theta_s}}{\sum_{i' \in N}(\frac{w_{i's}}{d_{ni'}})^{\theta_s}}. \tag{3.5}$$

Equation 3.5 implies a commute gravity equation with an elasticity determined by the dispersion parameter θ_s. When workers have similar productivity draws across different locations (high θ_s), working location choices are more sensitive to commute cost. Given θ_s, the probability of working in location i is larger if the wage per efficiency unit is higher or/and location i is relatively closer to residence. Defining inclusion value as $\Phi_{ns} = \left(\sum_i (w_{is}/d_{ni})^{\theta_s}\right)^{1/\theta_s}$, the expected wage prior to the efficiency unit draw is given by

$$\overline{w}_{ns} = T_s \Phi_{ns}.$$

The expected wage takes into account all possible working locations, and it is higher when worker is absolutely more productive (larger T_s), and when workers are surrounded by more high-paid jobs (higher inclusion value Φ_{ns}).

Residence Choice. Given expected wage $\overline{w}_{ns}$ and from Equation 3.4, worker's total indirect utility from living in location n is given by

$$V_{ns}(\omega) = U_{ns}(\omega) b_{ns}(\omega) = u_{ns} \frac{(1+\lambda_s)\overline{w}_{ns} - r_n^R h}{P_{ns}} b_{ns}(\omega),$$

where the residential taste shocks $\{b_{ns}(\omega)\}$ capture any idiosyncratic preferences towards location n. I assume that $b_{ns}(\omega)$ is drawn i.i.d across workers and residential locations from the Frechet distribution with unit scale and shape $\eta_s > 1$[17]. Frechet distribution implies that the probability of choosing location n is given by

$$\pi^R_{n|s} = \frac{B_{ns}^{\eta_s}\left((1+\lambda_s)\overline{w}_{ns} - r_n^R h\right)^{\eta_s}}{\sum_{n' \in N} B_{n's}^{\eta_s}\left((1+\lambda_s)\overline{w}_{n's} - r_{n'}^R h\right)^{\eta_s}}, \tag{3.6}$$

where $B_{ns} = u_{ns}/P_{ns}$. Equation 3.6 states that workers will be attracted to locations with higher amenities, lower cost-of-living, and higher net income. When the dispersion of taste shocks becomes lower (larger η_s), workers become more sensitive to those economic factors.

Consider the residential sorting after a hypothetical economy-wide skill-specific income

assumption is used in Tsivanidis (2019) as well.

[17]Unit scale is without loss of generosity due to the existence of amenity $\{u_{ns}\}$.

shock, the first-order effect is shaped by the following derivative

$$\left.\frac{\partial \ln \pi^R_{n|s}}{\partial \lambda_s}\right|_{\lambda_s=0} = \eta_s \left(\frac{\overline{w}_{ns}}{\overline{w}_{ns} - r^R_n h} - \sum_{n' \in N} \pi^R_{n'|s} \frac{\overline{w}_{n's}}{\overline{w}_{n's} - r^R_{n'} h} \right).$$

If $h > 0$, after a positive income growth, workers move more into high housing cost locations (locations with higher-than-average $\overline{w}_{ns}/(\overline{w}_{ns} - r^R_n h)$) [18]. Thus, given the positive/negative wage growth of high-/low-skilled over time in the data, the model predicts that high-skilled are sorted into the high housing cost locations (e.g. locations close to the city center), while the opposite is true for the low-skilled. The follow-up *amplification* effects then include: first, the general equilibrium response of r^R_n, as more high-skilled move into high housing cost locations, higher housing rents in those locations further push the low-skilled away; second, due to the non-homothetic preference, if $\zeta^{Ser} > 1$ with $\gamma < 1$, positive income growth induces the high-skilled to value more the consumption of services, and therefore to move into locations with lower service prices (e.g. locations close to the city center since they provide a large number of non-tradable service varieties, and the variety effect lowers the price index of non-tradable service.).

The overall expected welfare of living inside the city prior to the residential taste draw is given by

$$U^N_s = \Gamma_{\eta_s} \left(\sum_{n \in N} B^{\eta_s}_{ns} (\overline{w}_{ns} - r^R_n h)^{\eta_s} \right)^{1/\eta_s}, \tag{3.7}$$

where $\Gamma_{\eta_s} = \Gamma(1 - 1/\eta_s)$. Equation 3.7 highlights that if locations with low cost-of-living and high residential amenities are also those with better access to high-paid jobs, the overall welfare will be higher. On the other hand, if those two sets of locations differ, welfare will be discounted.

Migration Choice. The first-stage migration decision is shaped by choosing either the city or an outside location that maximizes the overall welfare given as follows,

$$V_s(\omega) = \max_{N, \{m \in M \setminus N\}} \{U^N_s v^N_s(\omega), U_{ms} v_m(\omega)\},$$

where the migration taste shocks $\{v_{ms}(\omega), v^N_s(\omega)\}$ is drawn i.i.d across workers and cities from the Frechet distribution with unit scale and shape $\eta_s > 1$[19]. U^N_s is the expected welfare of living inside the city given by Equation 3.7, and U_{ms} is the welfare of living in an outside location m

[18] This also highlights that if there is no minimum housing requirement, then such uniform aggregate income shock wouldn't affect the residential allocation.

[19] I assume the migration taste shock $\{v_{ns}(\omega)\}$ shares the same distribution as the residential taste shock within the city $\{b_{ns}(\omega)\}$.

given by $u_{ms}\big((1+\lambda_s)T_s w_{ms} - r^R_m h\big)/P_{ms}$. The share of skill s labor inside the city is given by

$$\frac{L^N_s}{\overline{L}_s} = \frac{(U^N_s)^{\eta_s}}{(U^N_s)^{\eta_s} + \sum_{m\in M\setminus N}(U_{ms})^{\eta_s}}. \tag{3.8}$$

3.1.3 Firm Access to Labor

Based on workers' commute choices, the supply of skill s labor into location i is given by

$$L_{is} = \sum_{n\in N}\pi_{i|ns}\pi^R_{n|s}L^N_s = w^{\theta_s}_{is}\sum_{n\in N}(\Phi_{ns}d_{ni})^{-\theta_s}\pi^R_{n|s}L^N_s. \tag{3.9}$$

On one hand, given wage w_{is}, firms in location i have better access to workers when i is close to locations with higher residential population and with worse access to jobs. On the other hand, firms entering locations that don't have good access to workers have to rely on higher wages to attract labor supply. Thus, Equation 3.9 highlights the following *"complementary"* effect: making residence and workplace closer for the low-skilled could also be beneficial for the high-skilled if the high-skilled values the product of a sector where the low-skilled has comparative advantage (e.g. non-tradable service). This is because firms don't need to offer high wage to attract low-skilled employees, and thus prices of non-tradable services are lower.

Since within each skill group, workers are heterogeneous in their efficiency unit draw, the total supply of effective labor to any location $\widetilde{L}_{is}$ depends on the average productivity of workers working in that location $\bar{\epsilon}_{is}$, and is given by $\widetilde{L}_{is} = L_{is}\bar{\epsilon}_{is}$ [20].

3.2 Firms

Non-tradable Service. A firm produces a variety ν using effective labor supplied by low-skilled and high-skilled workers $\widetilde{L}^{NT}_{is}$, commercial floorspace H^{NT}_i and sectoral output $Q^{g,NT}_i, g\in \{M,T,NT\}$ according to the following Cobb-Douglas production technology,

$$Y^{NT}_i(\nu) = A^{NT}_i N^{NT}_i(\nu)^{\alpha^{NT}} H^{NT}_i(\nu)^{\beta^{NT}} \prod_{g\in\{M,T,NT\}} Q^{g,NT}_i(\nu)^{\gamma^{g,NT}},$$

$$N^{NT}_i(\nu) = \left(\sum_s (\alpha^{NT}_s)^{\frac{1}{\xi}}\big(\widetilde{L}^{NT}_{is}(\nu)\big)^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}},$$

[20] The average productivity $\bar{\epsilon}_{is}$ is $\bar{\epsilon}_{is} = T_s\sum_{n\in N}\frac{(\pi_{i|ns})^{-1/\theta_s}}{d_{ni}}\frac{\pi_{i|ns}\pi^R_{n|s}L^N_s}{L_{is}}$. It is a weighted average of skill s workers' average productivities from different residences, where the average productivity of workers from location n is given by $T_s\frac{(\pi_{i|ns})^{-1/\theta_s}}{d_{ni}}$. When more and more workers from location n are self-selected to location i (high $\pi_{i|ns}$), the average productivity drops since more less efficient workers join the labor force.

$$\xi > 0, \{\alpha_s^{NT}, \alpha^{NT}, \beta^{NT}, \{\gamma^{g,NT}\}_{g\in\{M,T,NT\}}\} > 0, \alpha^{NT} + \beta^{NT} + \sum_{g\in\{M,T,NT\}} \gamma^{g,NT} = 1,$$

where ξ governs the skill substitution, α_s^{NT} reflects the comparative advantage of skill s, $\{\gamma^{g,NT}\}$ governs the input-output (I-O) linkages, and A_i^{NT} denotes the location-specific productivity.

Entry into any location is free, while production requires fixed costs in unit of the whole input bundle. In location i, the total fixed cost of production is given by $c_i^{NT} f^{NT}$, where $c_i^{NT} = \left((\sum_s \alpha_s^{NT} w_{is}^{1-\xi})^{\frac{1}{1-\xi}}\right)^{\alpha^{NT}} (r_i^F)^{\beta^{NT}} \prod_{g\in\{M,T,NT\}} (P_i^g)^{\gamma^{g,NT}}$ is the total unit cost of the input bundle. Firms compete with each other in a monopolistic competition fashion. Profit maximization implies that firms from the same location charge the same price, which is a constant mark-up over the marginal cost $p_i^{NT} = (\sigma/(\sigma-1))(c_i^{NT}/A_i^{NT})$. Free entry ensures the equilibrium number of varieties is such that all the entrants are earning zero profits. This implies that the equilibrium output of a firm is given by $d_i^{NT} = (\sigma-1)A_i^{NT} f^{NT}$. And the total equilibrium sectoral revenue in any location is proportional to the total variable/fixed cost of production

$$R_i^{NT} = \sigma N_i^{NT} c_i^{NT} f^{NT} = \frac{\sigma}{\sigma-1} \frac{\sum_s w_{is} \widetilde{L}_{is}^{NT}}{\alpha^{NT}}, \tag{3.10}$$

where N_i^{NT} is the endogenous measure of non-tradable firms in location i.

Manufacturing and Tradable Service. Firms in manufacturing/tradable service sectors produce using the same production technology as non-tradable service firms. I assume markets in both sectors are perfectly competitive, and firms in each location produces a location-specific variety valued by consumers living in other locations.

3.3 Agglomeration

When necessary, I decompose the city's unobserved productivity and amenity into an exogenous component and a component that depends on the endogenous location economic outcome. Following Tsivanidis (2019), I let a location's sectoral productivity depend endogenously on the total effective labor normalized by the location's physical area

$$A_i^g = A_{i,0}^g \left(\frac{\widetilde{L}_i}{K_i}\right)^{\mu^g}, g \in \{M, T, NT\}, \tag{3.11}$$

where $\widetilde{L}_i = \sum_s \widetilde{L}_{is}$, and K_i is the total area of location i. Sectoral-specific parameter $\{\mu^g\}$ governs the strength of the productivity externality in sector g. For a location's unobserved amenity, I assume that it depends endogenously on the college share of total residents,

$$u_{ns} = u_{ns,0}\left(\frac{L^R_{nH}}{L^R_n}\right)^{\mu_s}, \tag{3.12}$$

where $L^R_n = \sum_s L^R_{ns}$. I allow the strength of the amenity externality to be skill-specific.

3.4 Equilibrium

I can now define a spatial general equilibrium of the economy, for simplicity assuming exogenous productivity and amenity.

Definition. Given exogenous characteristics $\{\overline{L}_s, \overline{H}_n, A^g_i, u_{ns}, d_{ni}\}$, an equilibrium can be defined in terms of a set of endogenous factor prices $\{w_{is}, r^R_n, r^F_i\}$ such that: in each location,

1. Labor market clears: the supply of labor is shaped by worker's migration and commute choices characterized by Equation 3.5 – 3.8; the demand of labor is derived from the demand of sectoral output produced in each location; in locations with positive labor demand (e.g. $A^g_i > 0$), $\{w_{is}\}$ are such that labor demand equates labor supply.

2. Housing market clears: in locations with positive residential/commercial housing service demand (e.g. $u_{ns}/A^g_i > 0$), $\{r^R_n, r^F_i\}$ are such that demand of floorspaces equates supply of floorspaces.

4 Quantitative Analysis

4.1 Quantification

In this section, I take the model to the data, estimate the model parameters and recover the model unobservables. I consider the modelled city to be the New York-Newark-Jersey City Metropolitan Area, and include two outside hypothetical locations: one represents the other 99 largest U.S. Core-based Statistical Areas (CBSAs), and the other represents the rest U.S. CBSAs. I also include a hypothetical rest-of-world (RoW) to account for international flows of goods and services (see Appendix A.4). I group all the 2-digit NAICS industries into three broad sectors: manufacturing, tradable service and non-tradable service. I define two skill levels: high-skilled workers are those that have received at least some post-secondary education, and low-skilled workers are those without any. The model's equilibrium can be used to match any given year's data, and therefore in what follows, I consider a generic year and omit the year index unless necessary.

4.1.1 Parameters Determined Externally

A subset of parameters are determined externally without solving the model. In the preference, following Redding and Weinstein (2020), I set the within-sector elasticity of substitution to $\sigma = 6.5$. In the production technology, Ciccone and Peri (2005) summarizes that elasticity of substitution between skilled and unskilled labor is estimated to be between 1.36 and 2, and therefore I use an intermediate value $\xi = 1.68$. I determine the factor share in the production function following BEA I-O 15 industries Use Table and Valentinyi and Herrendorf (2008)[21].

Sectoral Income Elasticity $\{\zeta^k\}$. I normalize $\zeta^M = 1$ since only the ratio of ζs between two sectors matters for the expenditure share. From Equation 3.2, the log relative expenditure share of sector $k \in \{Ser, H\}$ with respect to the manufacturing sector satisfies[22]:

$$\log\left(\frac{\bar{s}^k - \frac{r^R h}{E} 1_{k=H}}{\bar{s}^M}\right) = \tilde{\rho}^k + (1-\gamma)\log\frac{P^k}{P^M} + (1-\gamma)(\zeta^k - 1)\log\frac{E - r^R h}{P^M} + (\zeta^k - 1)\log\left(\bar{s}^M \frac{E}{E - r^R h}\right),$$

where $\tilde{\rho}^k = \log\rho^k - \zeta^k \log\rho^M$, and E denotes the total expenditure. To estimate γ, ζ^k, I use a sample of urban households with a household head aging between 18 and 64 from the 2017 CES Public Use Micro Data. I augment the expenditure data with regional consumer price index from BLS's urban CPI-U. Following Comin et al. (2015), I construct the sectoral price index faced by each household using the household expenditure weighted average of the log-price of each of the expenditure categories belonging to the sector[23]. In the empirical implementation, I include household demographic controls such as age of household head, household size dummies, dummy for number of household earners and estimate parameters using GMM. I use household annual income after taxes and income quantiles of the household as instruments; in addition, to identify the minimum housing requirement h, I further include in the instruments a dummy variable indicating whether the household has income belonging to the lowest 1% quantile, since minimum housing requirement tilts up housing expenditure mainly for the low-income. Estimates in Table 5 shows that: first, $\gamma < 1$ implies housing, manufacturing goods and services are complements; second, $\eta^H < 1$ and $\eta^{Ser} > 1$ suggest that preferences are non-homothetic, and as income increases, households spend relatively less on housing and more on services compared to manufacturing good; third, $h > 0$ implies that there exists positive minimum housing expenditure and the magnitude of the estimate implies that it takes up on average

[21] I use the Compensation of Employees, Intermediate Use in the I-O table to determine $\{\alpha^g, \gamma^{g',g}\}$, and I use the income share of land in Valentinyi and Herrendorf (2008) to determine $\{\beta^g\}$.

[22] Here I omit the location and skill index to ease the expression.

[23] I group house outlays, utilities and fuels into the housing sector. The manufacturing sector is made up of food at home, beverages, tobacco, clothing, personal care item, vehicle outlays, housing furniture etc. The expenditure categories in the service sector include food away from home, entertainment, domestic service, public transportation etc.

12% of household income. Based on the estimates, I pick $\gamma = 0.45$, $\zeta^{Ser} = 1.5$, $\zeta^{H} = 0.57$, and h to ensure that minimum housing expenditure share is on average 12%.

Commute Cost $\{d_{ni}\}$. Following Ahlfeldt et al. (2015), I assume the commute cost between two locations takes an exponential function form $d_{ni} = \exp(\kappa \bar{t}_{ni})$, where κ denotes the disutility of longer commute, and $\bar{t}_{ni}$ is the average commute time under certain traffic condition. Appendix A.3 lays out a multinomial logit model of transit mode choice to estimate κ and average commute time $\bar{t}_{ni}$, where a car owner can choose to commute via car, public transit and walk, otherwise only the latter two modes are available. The logit model is estimated using 2010-2011 Regional Household Travel Survey. κ is identified from how mode choice probability responds to mode-specific travel time, and $\bar{t}_{ni}$ is the average travel time across modes using the mode choice probabilities predicted by the logit model[24]. Table 9 reports the results. Value of $\kappa = 0.015$ is slightly higher compared to 0.01 in Ahlfeldt et al. (2015) and 0.012 in Tsivanidis (2019).

Non-tradable Service Trade Cost $\{\delta\}$. The model implies that the relative expenditure on non-tradable services produced by any of the two locations $\{i, i'\} \subset N$ is given by

$$\frac{\bar{s}_{ni}^{NT}}{\bar{s}_{ni'}^{NT}} = \frac{N_i^{NT}}{N_{i'}^{NT}} \left(\frac{MC_i^{NT}}{MC_{i'}^{NT}}\right)^{1-\sigma} \left(\frac{d_{ni}^{\delta}}{d_{ni'}^{\delta}}\right)^{1-\sigma},$$

where MC_i^{NT} is the marginal cost of non-tradable service production in location i. After taking logs, I reach the following estimating equation

$$\log\left(\frac{\bar{s}_{ni}^{NT}}{\bar{s}_{ni'}^{NT}}\right) = \delta_i + \delta_{i'} - \delta(\sigma - 1)\kappa(\bar{t}_{ni} - \bar{t}_{ni'}) + \epsilon_{ii'},$$

where δ_i denotes the location fixed effect. To estimate δ, I use 2010-2011 Regional Household Travel Survey and focus on trips with purposes related to shopping, dining-out, recreation, entertainment, social activities etc. I proxy the relative expenditure using the relative number of trips. Given σ and κ, δ is identified from the sensitivity of relative number of trips with respect to the relative commute time. Estimate in Table 6 implies that $\delta = 0.14$. Thus, compared to the commute cost of work trips, commute cost of non-tradable service consumption is lower,

[24] To obtain the travel time between two census tracts under different travel modes, I use Bing Distance API. Given the large number of origin-destination pairs, it's costly to retrieve travel information for all the pairs directly from API. I resolve this issue by selecting 40 destinations for each origin tract, and obtain the travel information for those pairs from API. I then use the shortest path algorithm to calculate the travel duration for the rest pairs. See Appendix A.3 for further details on the selection of those 40 destinations and how computed travel durations match those in the data for a random sample. The travel duration obtained under the current traffic will be used to calculate the average commute time for year 2017. For the average commute time in 2002, I adjust the travel duration under current traffic using the self-reported travel time in 1997-1998 Regional Household Travel Survey.

residents are more willing to travel further to consume services.

Manufacturing/Tradable Service Trade Cost $\{\tau_{ni}\}$ I posit trade cost to be a log-linear function of bilateral distance $\tau_{ni}^g = (dist_{ni})^{\tau^g}$. I use the estimates obtained in Eckert et al. (2019) and set $\tau^T = 0.27$ and $\tau^M = 0.29$. Since I group CBSAs into two hypothetical locations, to obtain the distance between these two locations, and distance from those two locations to the NY Metro, I calculate the area-weighted average of bilateral distances, where the geo-location of a CBSA is defined by its centroid.

4.1.2 Parameters Determined Internally

In this subsection, I estimate the rest of the parameters using data and the model's equilibrium structure. The model's unobservables can be recovered to rationalize the data we observe.

Wage. The model's labor market clearing condition implies the following

$$\sum_n \frac{(w_{is}/d_{ni})^{\theta_s}}{\sum_i (w_{is}/d_{ni})^{\theta_s}} L_{ns}^R = \sum_{g\in\{M,NT,T\}} \frac{\alpha_s^g w_{is}^{-\xi}/\bar{\epsilon}_{is}}{\sum_s \alpha_s^g w_{is}^{-\xi}/\bar{\epsilon}_{is}} L_i^g, i \in N, \tag{4.1}$$

$$L_{is}^R = \sum_{g\{M,NT,T\}} \frac{\alpha_s^g w_{is}^{-\xi}/T_s}{\sum_s \alpha_s^g w_{is}^{-\xi}/T_s} L_i^g, i \in M \setminus N, \tag{4.2}$$

where L_i^g is the labor employed in sector g and location i, L_{ns}^R is the amount of skill s residents location n. The left-hand side of Equation 4.1-4.2 shows the total labor supplied into location i, while the right-hand side summarizes the total labor demand from different sectors in location i.

Proved in Tsivanidis (2019), given data $\{L_{ns}^R, L_i^g\}_{i\in N}$, commute cost $\{d_{ni}\}$ and parameter values, there exists a unique within-city wage vector $\{w_{is}\}_{i\in N}$ (up to a scale) that rationalizes the data as an equilibrium outcome of the model; from Equation 4.2, by the same logic, given data $\{L_{is}^R, L_i^g\}_{i\in M\setminus N}$, I can solve for wages outside the city (up to a scale)[25]. After recovering the wage, I can construct several wage-related moments implied by the model, including the bilateral commuting probabilities (Equation 3.5). This motivates the following calibration procedure: I select T_H to match the observed NY metro residual skill premium (normalize $T_L = 1$); I allow $\{\alpha_s^g\}$ to be city-specific to reflect the fact that the relative skill-sectoral productivity can be different in different cities, and calibrate the values to match the observed share of non-college wage in the total wage bill in each city (normalize $\sum_s \alpha_s^g = 1$); I choose θ_s

[25] To determine the scale of wages, I normalize the geometric mean of wages in the NY metro area to be 1. I determine the *level* of non-college wages in the outside locations to keep the relative non-college wages across cities in the model the same as those in the data. Then college wages in the outside locations are also determined.

to bring model's within-city commute flows as close as possible to those in the data[26]. Year 2017 estimates in Table 4 imply that in the NY metro area, non-college workers have comparative advantage in the non-tradable service sector; non-college are more sensitive to commute cost ($\theta_L > \theta_H$), and the estimates are within the range of values found in Ahlfeldt et al. (2015) and Tsivanidis (2019).

Given wages, additional endogenous variables can be computed, including worker's income, total expenditure, and sectoral revenue across space (given by $R_i^g = \sum_s w_{is} \widetilde{L}_{Fis}^g / \alpha^g$). From the CES Metropolitan Statistical Areas Tables, I obtain the city-level average expenditure share on manufacturing good, service and housing, which I use to obtain the total city-level sectoral demand. I allow the Cobb-Douglas share of the non-tradable service γ^{NT} to be city-specific, and select the values to ensure non-tradable service market clearing in the model[27].

Productivity. The idea of recovering location-specific sectoral productivity relies on rationalizing the distribution of sectoral revenue and sectoral demand across space. If a location is a net-exporter in one sector (sectoral revenue larger than own sectoral expenditure), the location must have lower marginal cost of production in that sector. With the knowledge of marginal cost, if we observe factor prices, productivity can be recovered. Under the assumption that manufacturing goods/tradable services are freely traded within the city, recovered sectoral revenue across space and city-level sectoral expenditure are enough to pin down the location-specific marginal costs in these two sectors. In the non-tradable service sector, however, the whole distribution of expenditure within the city is needed but not directly observed in the data. Therefore, I utilize a loop to recover the non-tradable marginal costs where I first guess the expenditure distribution, which allows me to recover the associated marginal costs; I then calculate the sectoral price indices using those marginal costs; together with the residential housing rents data, I solve utility maximization to update the expenditure distribution. I repeat this procedure until the convergence of expenditure distribution. Within the procedure, I also select the city-specific preference parameter $\{\rho^g\}_{g\in\{M,Ser,H\}}$ to match the city-level sectoral expenditure share in the data. Given marginal costs, and assuming that the commercial housing rents equate the observed residential housing rents[28], I could recover the unobserved

[26] Ideally, I want to estimate the commuting elasticity separately for non-college and college workers. However in LODES data, only aggregate bilateral commuting flows are observed. Thus, identification relies on the fact that different residential locations have different composition of skill. The estimates $\theta_L > \theta_H$ are consistent with the finding in Section 2.2 that on average, college workers commute longer.

[27] I group expenditure categories in the CES table into manufacturing, service and housing using the same criterion as in Section 4.1.1.

[28] This assumption is made because I only have residential housing rents data. However, LODES data shows that there is no census tract that has positive number of jobs but no residents. Thus, relative residential housing rent could be a good proxy for relative commercial housing rent if there exists some form of arbitrage in the real estate market.

productivity. More details are provided in Appendix A.5[29] .

Agglomeration and Residential Elasticity. To estimate the agglomeration parameters and skill-specific residential elasticity, using Equation 3.6, 3.11, 3.12 and taking the log change, I have

$$\Delta \log A^g_{n,0} = \Delta \log A^g_n - \mu^g \Delta \log \left(\frac{\widetilde{L}_n}{K_n} \right), \tag{4.3}$$

$$\Delta \log u_{ns,0} = \eta_s^{-1} \Delta \log \left(\frac{L^R_{ns}}{L^R_n} \right) - \mu_s \Delta \log \left(\frac{L^R_{nH}}{L^R_n} \right) - \Delta \log C_{ns}. \tag{4.4}$$

All the endogenous variables on the right-hand side of Equation 4.3-4.4 could be either observed or recovered from the data, and thus given any parameter values of $\{\mu^g, \mu_s, \eta_s\}$, changes of "exogenous" productivity and amenity can be calculated as the model's structural residuals. I estimate parameters via GMM using two Bartik instruments, *predicted* earning and employment change in each census tract. They are calculated by projecting the average earning and employment changes in 10 largest CBSAs (excluding NY metro) for each industry ($\{M, T, NT\}$) projected on each census tract's industry mix in 2002. The change of earning drives the residential sorting while the change of employment affects the supply of effective labor. The logic of instruments is that I aim to select a best set of parameters so that the change of productivity and amenity is mainly explained by the endogenous economic forces, leaving the structural residuals uncorrelated with predicted earning/employment change[30]. Table 7 reports the results. Estimates for residential elasticities $\eta_L = 3.3$ and $\eta_H = 3.6$ are consistent with the values obtained in Couture et al. (2019) and as in Tsivanidis (2019), college workers have larger elasticity. Agglomeration parameters imply college workers benefit more when surrounded by more college share of residents, and firms in the non-tradable service sector enjoy larger endogenous productivity from denser labor supply.

Amenity and Housing. Unobserved amenities are selected to exactly fit the residential population distribution across space in the data using the residential and migration choices (Equation 3.6 and 3.8). Finally, total amount of housing/floorspace endowment in each location is recovered from the housing market clearing condition.

4.2 Model Fit

Commute Pattern. Figure 13 contrasts model's commute flows $\pi^R_{i|n}$ aggregated onto the PUMA level with those in the data. Due to the fact that commuting gravity equation may not perfectly capture all the factors influencing the real-life commute decision, the model's

[29] I also recover the measure of non-tradable service varieties given by $N^{NT}_i = \frac{R^{NT}_i}{\sigma c^{NT}_i f^{NT}}$ (normalize $f^{NT} = 1$).

[30] In the empirical implementation, I further divide each variable on the right-hand side by its geometric mean so that selection of normalization doesn't influence the estimates.

predictions can differ from the data; nevertheless, I find a strong correlation (0.91) between these two sets of commuting probabilities. In recovering wages, I only utilize the residential population distribution by skill (L^R_{ns}) and the job distribution by sector (L^g_i) in the data. From 2017 LODES, I also observe the job distribution by skill. Figure 14 compares that distribution in the data with the model's prediction. The correlation is very high for both non-college (0.95) and college (0.96).

Wage. Figure 15 contrasts model's residential wage with the tract-level annual aggregate earning in 2017 NHGIS. Overall, there is a strong relationship (0.72) between these two sets of wages. Figure 16 further compares the residential wage by skill at the PUMA level using data from 2017 ACS in IPUMS. Skill-specific wages in the data are both positively correlated with the wages in the model, although the model matches non-college wages better.

Productivity, Amenity and Housing. Figure 17 plots the skill-specific unobserved amenity $\{u_{ns}\}$ across space. To perfectly fit the observed residential location choices in the data, in addition to endogenous economic forces, the model requires higher amenity in tracts close to the city center (Manhattan) and those quite far away (especially for the college amenity). Table 8 shows the regression result of recovered amenities on a set of variables that reflect the desirability of locations. Overall, the recovered amenity is higher in tracts with more street trees and better access to public open space (e.g. children's playground, waterfront etc). Figure 20 reports the sectoral productivity across space. In the non-tradable service sector, Manhattan area has the highest productivity. Tradable service and manufacturing productivites are relatively higher in both the urban core and those city areas in New Jersey, while there are also some distant locations that share high productivities in the manufacturing sector. Figure 18 plots the recovered residential/commerical floorspaces in each census tract. Locations with more floorspaces are those having either high sectoral productivities or high residential amenities. Figure 19 contrasts the recovered floorspaces with those observed in the data for the census tracts that belong to the New York City. They are highly correlated (0.70).

4.3 Equilibrium Characteristics

The estimated model implies following equilibrium characteristics illustrated in Figure 21-24: first, wage per effective labor is relatively higher in the city center for both skill groups, while in those more distant tracts, non-college workers attain relatively higher wages compared to college workers. This is because those locations have higher productivity in the manufacturing sector, where non-college workers have comparative advantage; second, since residential wage of a location takes into account nearby job access (whereas earnings from jobs far away are discounted by commute cost), they are also relatively higher in the city center for both skill groups, especially for college workers; third, due to high factor prices, input cost of non-tradable services is higher in the city center, but the non-tradable price index turns out to be lower there crucially because (i) downtown has higher non-tradable service productivity; (ii) there are more varieties available there and CES preference features "love-of-variety"; finally, the overall non-homothetic price index is higher in the city center for both skill groups, especially for non-college workers. This is due to the fact that college workers have higher residential wages, and hence spend relatively more on services instead of manufacturing goods and housing. And downtown exactly exhibits lower non-tradable service prices.

To further understand the model's sorting mechanism, in Appendix A.6, I study the effect of an exogenous income in a partial equilibrium scenario. Specifically, I adjust income adjustment factor $\{\lambda_s\}$ so that everything else equal, moving from the counterfactual equilibrium to the 2017 equilibrium, non-college and college workers experience an *exogenous* 20% negative and positive income growth respectively. Workers take into account both the endogenous change of residential wage (job opportunities) and this exogenous income adjustment. I keep the housing rents *fixed* at the 2017 value and the city border *closed*.

The model's prediction is consistent with what implied by the theory in Section 3.1, where more college workers reside in downtown after positive income growth, while those far-off locations receive an increasing number of non-college workers after negative income growth. Non-homothetic preference *amplifies* the sorting via the adjustment of cost-of-living: although larger demand of non-tradable services downtown raises the input cost, entry of more varieties offsets the higher cost, and the price index increases by the least amount in the downtown area; since college workers spend more on services and become increasingly so after the income shock, the rise of their cost-of-living in downtown is much less significant; non-college workers, on the other hand, spend even more on housing services, which are indeed most costly downtown. Despite the expansion of non-tradable service job opportunities, non-college workers are priced out of their ideal workplaces. The model endogenously generates more pronounced trade-off between ideal residence and ideal workplace for non-college workers. This trade-off leads to the negative welfare consequences of income shock: the rise in welfare inequality exacerbates the rise in income inequality by 3.8%.

5 Counterfactual Analysis

5.1 Welfare Effect of Non-College Residence-Workplace Mismatch (2000-2017)

In this section, I utilize the estimated model to measure the welfare implications of residence-workplace mismatch for non-college workers. The model is used to match key data features of New York metro area in both early 2000 and year 2017. Compared to the exogenous income shock considered in Appendix A.6, first, estimated change of $\{T_s, \lambda_s, \alpha_s^g\}$ captures the wage/income growth and change of comparative advantage in the data from early 2000 to 2017, where non-college wage and income have declined by 7% and 10% respectively. Second, estimated change of location fundamentals (productivity and amenity) shown in Figure 30 and 31 in the Appendix captures additional residential and job sorting that are not explicitly explained by income growth. Increase of non-tradable productivity and college amenity in areas close to downtown contributes to the expansion of non-college job access in those locations. Third, change of housing rents in the data implies the change of residential and commercial floorspace supply. Figure 32 and 33 illustrate that limited supply of residential floorspaces in central locations to which college workers have moved raises the cost-of-living there for non-college workers.

The model matches the residential and job sorting shown in Section 2.2 exactly. Figure 4 further highlights the economic forces behind the relocation. Panel (a) highlights that after shutting down the exogenous change of income adjustment factor and endogenous adjustment of prices, both non-college and college workers would have moved to locations close to downtown for better job access. For non-college workers, this is due to the expansion of non-tradable service sector there, where non-college labor have comparative advantage. Comparing the colorful bars in Panel (a) and (b) shows that negative income growth prices non-college out of downtown while college workers are sorted into downtown. Finally, Panel (b) shows that despite the improvement of residential amenity, endogenous adjustment of cost-of-living (including rents and sectoral price indices) reduces the desirability of downtown in general; however, the effect is much more pronounced for non-college workers. Figure 34 and 35 map the change of job access (measured by Φ_{ns}) and average commute cost across different residential locations. Compared to the change of residential share in Figure 9, we observe clearly that locations with expanded job access and reduced commute costs are those central places that non-college workers have largely moved out.

Table 1 reports the change of aggregate variables moving from the 2000 equilibrium to the 2017 equilibrium. Even though there exists large inflow of college workers into the New York metro area, increase of college productivity widens the wage inequality by 13.8%. Once taking into account other income sources, income inequality exacerbates wage inequality by an additional 8%. The surge in housing rents over this period implies that both non-college and college welfare decrease. However, it disproportionately hurts non-college workers more, leading to larger increase in welfare inequality compared to the increase in income inequality.

Table 1: % Change of Aggregates, Residence-Workplace Mismatch

	Non-College	College	Inequality
Population	−11.61%	+23.08%	+39.25%
Residential Wage	−7.25%	+5.57%	+13.81%
Income	−10.82%	+8.83%	**+22.03%**
Welfare	−36.81%	−22.25%	**+23.04%**

Note: The percentage changes are calculated using the 2000 equilibrium as base. Residential wage $\overline{w}_{ns}$ considers only the effective wage, while income takes into account the income adjustment factor λ_s. Skill-specific welfare is defined in Equation 3.7.

5.2 Housing Constraint

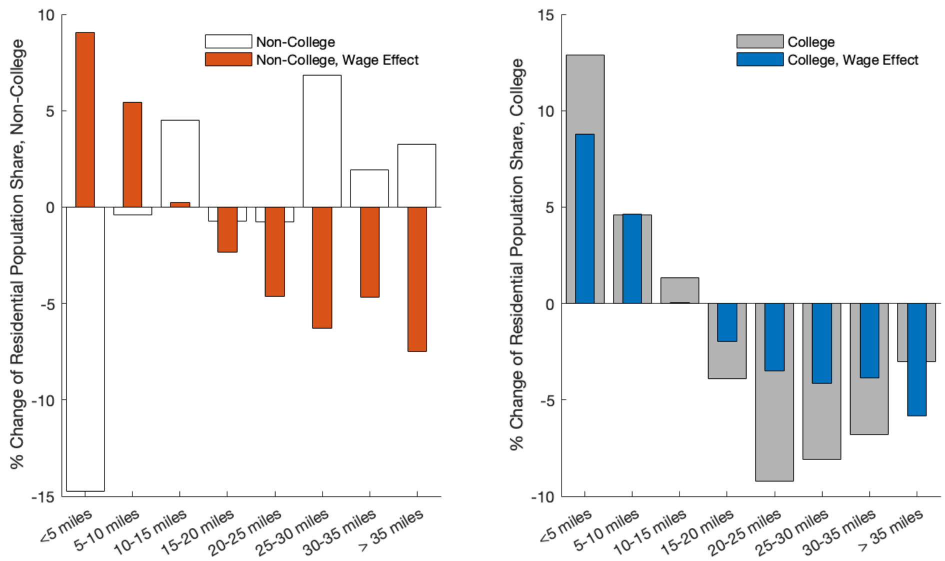
5.2.1 Residential Zoning

As is pointed out by Hsieh and Moretti (2019), stringent housing constraints in high productive U.S. cities limit the number of workers that can have access to such high productivity, generating spatial misallocation. One source of housing constraints in U.S. cities including the New York City is the residential zoning regulation[31]. In general, zoning is a law that organizes how land may be used. It establishes an orderly pattern of development across neighborhoods and the city by identifying what may be built on a piece of property. Residential zoning districts accommodate an variety of residential building forms, ranging from single-family homes to soaring residential high-rises. In New York City, there are 10 basic residential zoning codes where R1-R2 districts are designated to single-family houses, R3-R5 districts allow low-density multi-story multi-family buildings, while R6-R10 districts further accommodate medium-/high-density apartment buildings. Figure 36 and 37 in the Appendix illustrate the geographic distribution of residential zoning districts and tract-level average maximum allowable residential floor area ratio (FAR) implied by zoning[32]: overall, there is limited amount of high-density residential areas with average maximum FAR exceeding 5, and those areas are only concentrated in Manhattan; part of Brooklyn and Queens are designated to be medium-density residential zones with maximum FAR around 3. Figure 38 shows the ratio between the actual average building FAR and maximum allowable FAR in tracts within the 10-mile radius around the city center. In a large number of census tracts, building FAR is binding at the maximum allowable

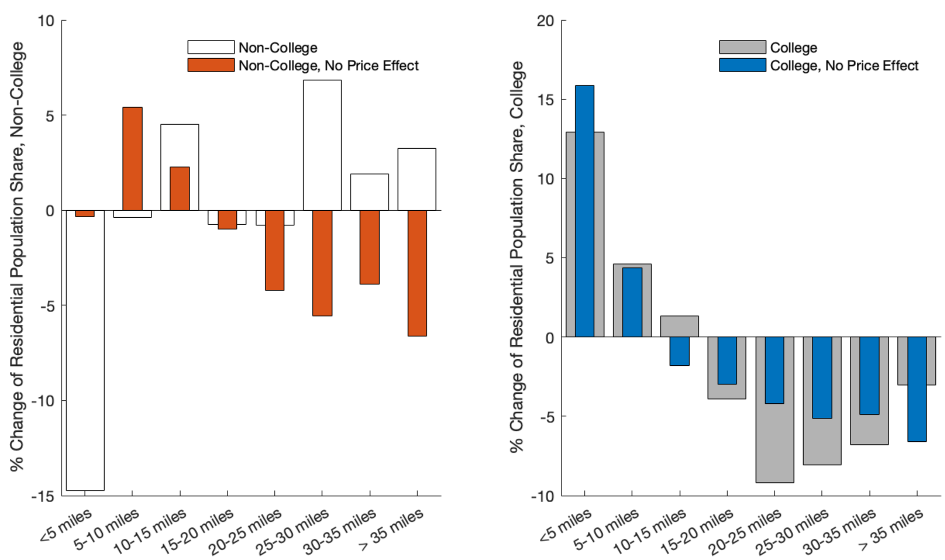
[31] The details of NYC zoning policy is provided on the city planning website (https://www1.nyc.gov/site/planning/zoning/about-zoning.page.).

[32] Floor area ratio is the ratio between the building floorspace area and the lot/land area. It limits the height of the building.

Figure 4: Price and Wage Effect, Residence-Workplace Location Mismatch



(a) Wage Effect



(b) Price Effect

Note: The percentage changes are calculated using the 2000 equilibrium as base. In the version with "Wage effect", I only allow effective wage and thus residential wage to change from the 2000 value to 2017 value. In the version with "No price effect", I further take into account the exogenous change of income adjustment factor, while the overall price index is fixed at the 2017 value.

limit, suggesting incentive to have more residential supply if zoning regulation is relaxed[33].

To embed the residential zoning into the current spatial framework, I consider a simple model of the city's residential housing sector. As in Desmet et al. (2018), infinite number of residential developers bid for each unit of land owned by the government. The winner transforms land into residential floorspaces. I assume the variable cost associated with producing h_n^R units of residential floorspace per unit of land in location n is given by $\frac{1}{A_n^H}\frac{(h_n^R)^{1+\frac{1}{\epsilon_n}}}{1+\frac{1}{\epsilon_n}}, \epsilon_n > 0$. In addition, there exists restriction on the maximum allowable floorspace that can be supplied on each unit of land $\overline{h}_n^R$. Thus each developer solves

$$\pi_n^R = \max_{h_n^R} r_n^R h_n^R - \frac{1}{A_n^H}\frac{(h_n^R)^{1+\frac{1}{\epsilon_n}}}{1+\frac{1}{\epsilon_n}}, s.t. h_n^R \leq \overline{h}_n^R.$$

Hence, the optimal supply of residential floorspace in location n is given by

$$H_n^R = K_n \min\{\overline{h}_n^R, (A_n^H)^{\epsilon_n}(r_n^R)^{\epsilon_n}\}, \tag{5.1}$$

where K_n is the total land area of location n. And developers would bid for land until their profits (after covering the variable costs) reach zero. For the census tracts within the boundary of New York City, I observe the land area and maximum allowable FAR $\{K_n, \overline{h}_n^R\}$ from the MapPLUTO data. With the housing rent data and recovered residential floorspaces, I can obtain the lower bound of the residential development productivity $\underline{A}_n^H$ from Equation 5.1[34]. In the commercial housing sector and locations outside the New York City, I posit a reduced-form elastic floorspace supply function $H_i = H_{i,0}(r_i)^{\epsilon_i}$, where $H_{i,0}$ potentially captures both the land area and zoning restriction. Given the recovered commercial floorspaces, $\{H_{i,0}\}$ can be easily obtained. Following Saiz (2010), I set ϵ_i to be 0.76 for locations within the New York metro area, and $1.5, 2$ for two hypothetical outside locations taking into account the average of housing supply elasticities in Saiz (2010).

5.2.2 Relaxing Housing Constraint

Misallocation due to housing constraints in this paper is reflected by the spatial mismatch of desirable residence and workplace. Due to high cost-of-living, non-college workers are unable to reside in central locations with best job access. In this subsection, I consider a policy counterfactual of relaxing housing constraints in areas close to downtown. To be more

[33] There have been heated policy discussions on relaxing the zoning restrictions in the New York City. In 2018, a proposed State bill (S6760) seeks to give City broad flexibility to increase floor area ratio in residential developments, which includes allowing exceptions to the 12.0 FAR cap in high-density residential neighborhoods.

[34] In locations where residential FAR is not binding at the maximum FAR, the lower bound is the true underlying residential development productivity.

specific, based on the current zoning restriction, I increase the maximum allowable residential FAR by 10% in census tracts within the 10-mile radius around the city center. To make this policy effective, I let residential development productivity be 20% larger than the recovered lower bound $\{\underline{A}_n^H\}$[35]. Throughout the counterfactual, I keep the city open, and allow location productivity and amenity to respond endogenously to the change of demographic composition[36].

Due to relaxed residential zoning restriction, Panel (a) of Figure 5 shows that housing rents drop universally in the city, and more notably in areas close to the city center. Panel (b) illustrates the resulting residential relocation, where the city center receives larger share of both skill groups, but the effect is much more significant for non-college workers. This is due to the fact that minimum housing requirement takes up a larger share in non-college worker's budget. They respond more significantly when housing cost is reduced. Figure 6 illustrates the change of job distribution across space. Relaxing housing constraint triggers a concentration of non-tradable service jobs in the city center while the effects in the manufacturing and tradable service sectors are muted. This is because there exist commute costs for consuming non-tradable services in locations different from residence. Thus, when downtown has more residents, more non-tradable service jobs are relocated there. Figure 39 in the Appendix further confirms that non-college workers indeed are moving into locations where jobs are closer (locations that commute costs have reduced most).

Relaxing the housing constraints makes central locations desirable for both living and working. Table 2 shows that moving from the 2017 equilibrium to the counterfactual equilibrium, New York metro area attracts relatively more non-college workers. Larger supply of non-college labor lowers the non-college residential wage and widens the income inequality by 0.11%. However, once taking into account the effect of policy on cost-of-living, welfare inequality has decreased by 0.16%. This again emphasizes the role of spatial mismatch in driving the welfare inequality, and how relaxing the housing constraints may help to reduce it by easing the trade-off faced by non-college workers.

[35]This is crucial, otherwise private developers wouldn't respond to the policy change. Isomorphically, this can also be motivated by government providing tax relief incentive for residential development.

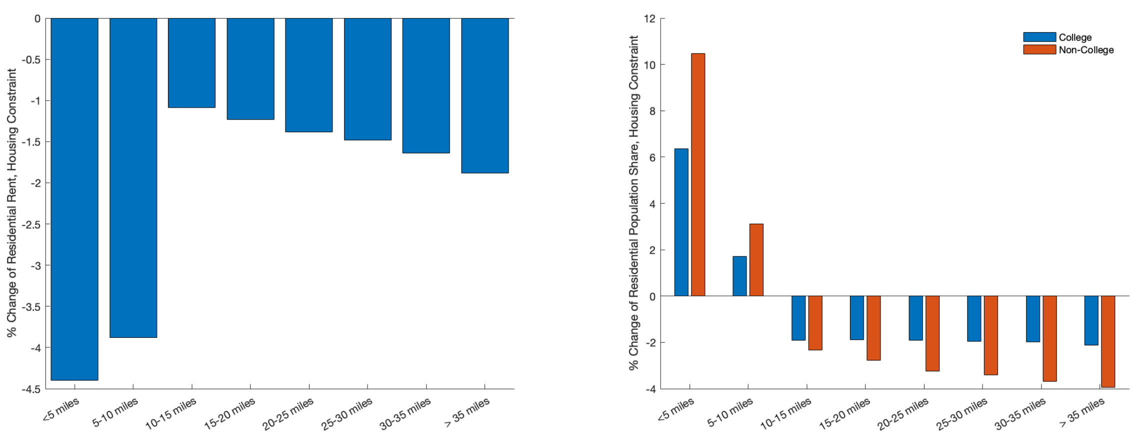
[36]The introduction of endogenous productivity and amenity raises the potential of multiple equilibria. As in Ahlfeldt et al. (2015), I focus on the counterfactual equilibrium that is closest to the 2017 equilibrium. Namely, in finding the counterfactual equilibrium I use the 2017 equilibrium as the initial guess.

Table 2: % Change of Aggregates, Housing Constraint

	Non-College	College	Inequality
Population	$+1.39\%$	$+0.98\%$	-0.41%
Residential Wage/Income	-0.36%	-0.25%	$+0.11\%$
Welfare	$+0.49\%$	$+0.30\%$	**-0.16%**

Note: The percentage changes are calculated using the 2017 equilibrium as base. Residential wage $\overline{w}_{ns}$ considers only the effective wage, while income takes into account the income adjustment factor λ_s. Skill-specific welfare is defined in Equation 3.7.

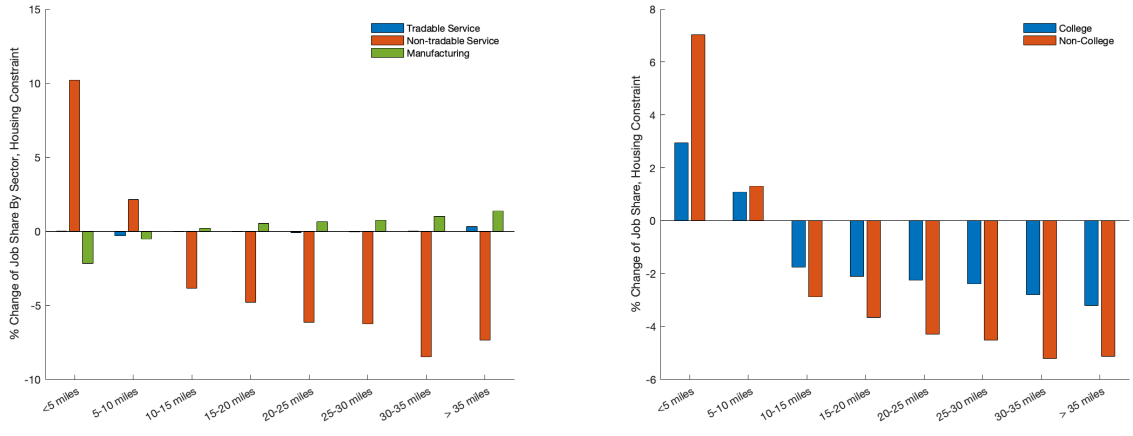
Figure 5: Residential Sorting, Housing Constraint



(a) Housing Rent (b) Residential Change

Note: The percentage changes are calculated using the 2017 equilibrium as base.

Figure 6: Job Sorting, Housing Constraint



(a) By Sector (b) By Skill

Note: The percentage changes are calculated using the 2017 equilibrium as base.

6 Conclusion

This paper studies the welfare implications of non-college residence-workplace mismatch caused by the wage growth and the change of location fundamentals within the largest urban area in US, New York-Newark-Jersey City Metropolitan Area from early 2000 to 2017. First, empirically, I show that since early 2000s, along with increasing skill premium, within the NY metro area, there is sectoral employment reallocation where non-college workers are shunted from the manufacturing sector into the non-tradable service sector. In addition, while the number of non-tradable service jobs mainly grows in downtown, non-college workers are residing outside the city center in those more distant locations. Second, I develop and estimate a spatial general equilibrium city model that features endogenous choices of residence and workplace from workers with heterogeneous skills, where demand of labor comes from firms producing in three sectors: manufacturing, tradable and non-tradable service. The model features non-homotheticity due to the preference specification and the existence of minimum housing requirement, which is crucial to match the residential and job sorting patterns observed in the data. Last, I perform several counterfactual exercises. I find that moving from the 2000 equilibrium to the 2017 equilibrium, welfare inequality has risen by 23%, 1% higher than the increase in income inequality. This is exactly due to the trade-off faced by non-college workers that desirable working locations (downtown) become less attractive for residence due to higher cost-of-living. In the policy counterfactual, I relax the residential zoning restriction in downtown, this on the other hand helps to reduce the welfare inequality.

A Appendix

A.1 Figures and Tables

A.1.1 Data and Motivating Evidence

Figure 7: New York-Newark-Jersey City Metropolitan Area

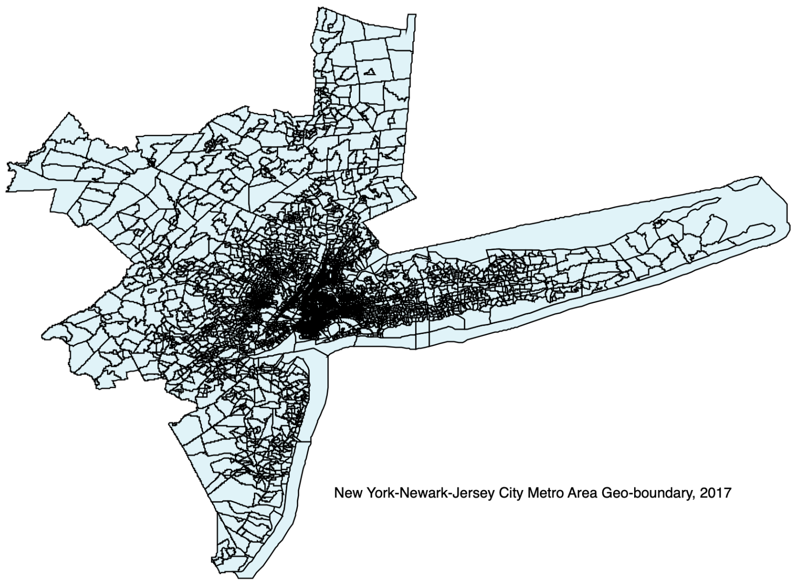


Figure 8: Skill Premium 2000-2018

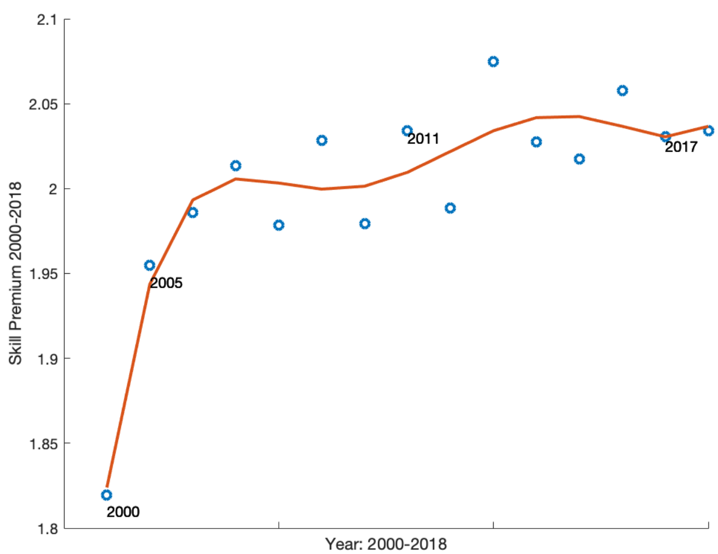
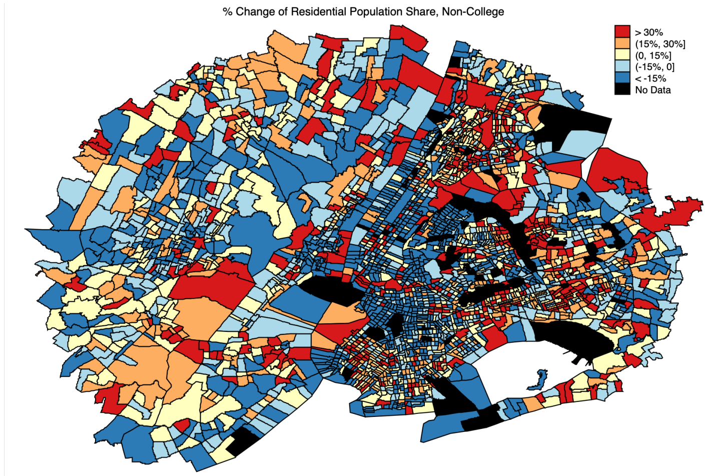
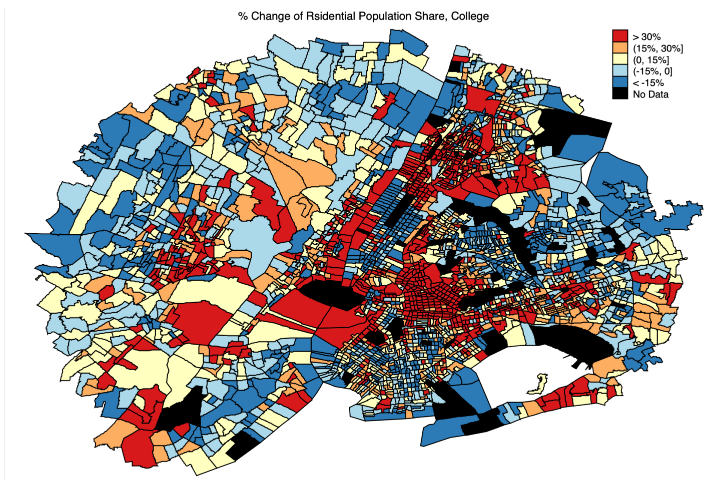


Figure 9: % Change of Residential Population Share By Skill, 2000-2017



(a) Non-College



(b) College

Figure 10: % Change of Non-tradable Service Job Share, 2002-2017

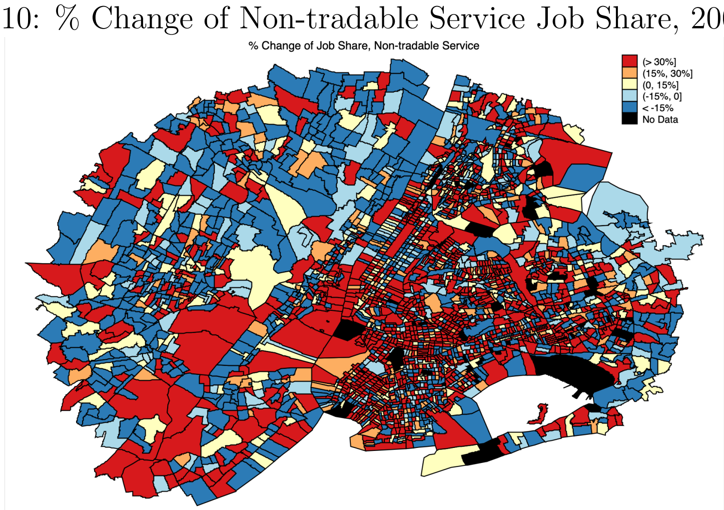


Table 3: Commute Time 2000-2015, College vs Non-College

	(1) Time15	(2) Time15	(3) Time30	(4) Time30	(5) Time45	(6) Time45	(7) Time60	(8) Time60
Non-College	-0.045^{***}	-0.177^{***}	-0.063^{***}	-0.191^{***}	-0.048^{***}	-0.166^{***}	-0.031^{***}	-0.170^{***}
	(0.004)	(0.016)	(0.005)	(0.014)	(0.004)	(0.015)	(0.003)	(0.018)
Non-College × Year 2005	0.003	0.005	0.002	0.003	-0.001	-0.005	-0.002	-0.048
	(0.010)	(0.041)	(0.012)	(0.036)	(0.011)	(0.039)	(0.008)	(0.049)
Non-College × Year 2010	0.022^{***}	0.084^{***}	0.027^{***}	0.079^{***}	0.010	0.027	-0.002	-0.052
	(0.008)	(0.036)	(0.010)	(0.032)	(0.009)	(0.033)	(0.006)	(0.041)
Non-College × Year 2015	0.017^{**}	0.056^{*}	0.035^{***}	0.106^{***}	0.016^{*}	0.053^{*}	-0.005	-0.046
	(0.008)	(0.035)	(0.010)	(0.031)	(0.009)	(0.032)	(0.006)	(0.040)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Transit Mode Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit
Observations	95,693	95,693	95,693	95,693	95,693	95,693	95,693	95,693
R^2	0.204		0.220		0.156		0.068	

Dependent variable is the probability of commute time to work exceeding 15/30/45/60 minutes. Data covers 2000, 2010 and 2015 American Community Survey 1-Year Sample from IPUMS. Observation is a person, and only persons who work fully through out the year and no fewer than 35 hours per week are included. Non-college is a dummy variable equal to 1 if the person doesn't receive any post-secondary education. Demographic controls include sex, race, age, citizenship, English fluency, marital status, and dummy of having children under age 5. Transit Mode controls include dummies of commuting via car and public transit. Standard errors are clustered at the household level. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Figure 11: Residential Population Growth By Skill 2000-2017

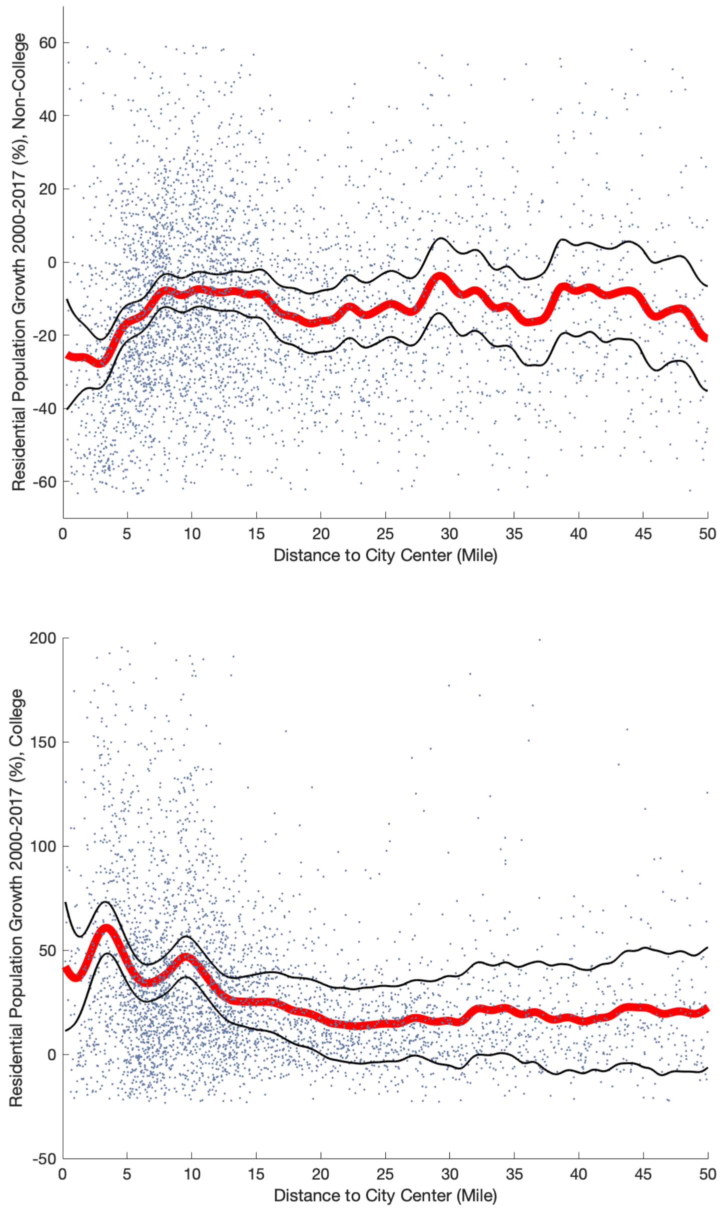
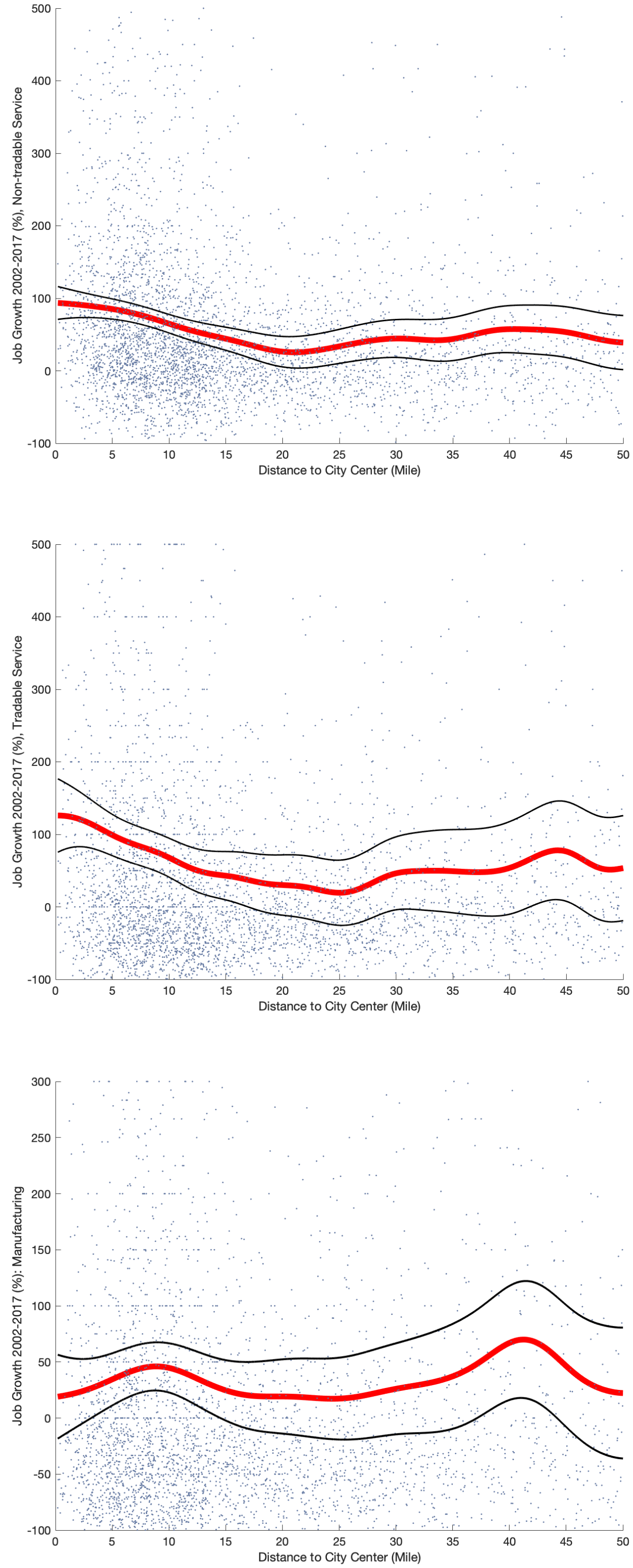


Figure 12: Job Growth By Sector 2002-2017



A.1.2 Estimation

Table 4: Parameter Values

Parameters	Value	Source
	Panel A: Preference and Production	
σ	6.5	Redding and Weinstein (2020)
γ	0.45	2017 CES
ζ^{Ser}, ζ^{H}	$1.5, 0.57$	2017 CES
γ^{NT} (city-specific)	$0.83; 0.94; 0.98$	2017 CES
ρ^{Ser}, ρ^{H} (city-specific)	$0.37, 0.56; 0.35, 0.22; 0.25, 0.08$	2017 CES
h	1.4	2017 CES
T_L, T_H (year-specific)	**2017**: $1, 4.65$	IPUMS
	2002: $1.06, 4.32$	
$\alpha_L^g, g = M, T, NT$ (city-year-specific)	**2017**: $0.46, 0.09, 0.60; 0.43, 0.14, 0.49; 0.57, 0.27, 0.54$	IPUMS
	2002: $0.59, 0.26, 0.69; 0.54, 0.26, 0.58; 0.63, 0.39, 0.61$	
θ^H, θ^L	$4.75, 3.84$	2017 LODES
ξ	1.68	Ciccone and Peri (2005)
$\alpha^g, \beta^g, \gamma^{g,g'}$		2018 BEA-IO; Valentinyi and Herrendorf (2008)
	Panel B: Trade Cost	
κ	0.015	2010-2011 Regional Household Travel Survey
δ	0.14	2010-2011 Regional Household Travel Survey
τ^T, τ^M	$0.27, 0.29$	Eckert et al. (2019)
	Panel C: Agglomeration and Residential Elasticity	
μ^M, μ^T, μ^{NT}	$0.1, 0.16, 0.21$	GMM
η_L, η_H	$3.3, 3.6$	GMM
μ_L, μ_H	$0.21, 0.31$	GMM

Table 5: Non-homothetic Preference

	(1)	(2)
γ	0.499^{***}	0.415^{***}
	(0.071)	(0.073)
$\zeta^{Hou} - 1$	-0.427^{***}	-0.438^{***}
	(0.089)	(0.095)
$\zeta^{Ser} - 1$	0.426^{***}	0.599^{***}
	(0.150)	(0.149)
$\overline{h}$	3.206^{***}	3.179^{***}
	(0.203)	(0.206)
Instrument:		
Annual Income Quantile	Yes	Yes
Annual Income	No	Yes
Income < 1% Percentile	Yes	Yes
Demographic Controls	Yes	Yes
Region Fixed Effects	Yes	Yes
Quarter Fixed Effects	Yes	Yes
Observations	14,304	14,304

Dependent variable is log of household relative sectoral expenditure. Data comes from 2017 Consumer Expenditure Survey Public-Use Microdata. Household demographic controls include age of household head, household size dummies, dummy for number of household earners. Regions refer to US Census Regions (West, Midwest, South, Northeast). Observation is a household. Standard errors are calculated using bootstrap with sampling weight equal to the household weight in the survey. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 6: Non-tradable Service Trade Cost

	ln Relative No. Trips
Reported Travel Time (min)	-0.012^{***}
	(0.001)
Destination Fixed Effects	Yes
Observations	1,877
R^2	0.358

Dependent variable is the relative number of trips between two destination PUMA. Data comes from 2010-2011 Regional Household Travel Survey. Observation is a pair of two non-tradable service consumption destinations. Robust standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 7: Agglomeration and Residential Elasticity: GMM Estimates

Productivity		Residential Elasticity		Amenity	
μ^{NT}	0.209^{***}	η_L	3.343^{***}	μ_L	0.208^{**}
	(0.004)		(0.879)		(0.092)
μ^{M}	0.101^{**}	η_H	3.621^{***}	μ_H	0.309^{***}
	(0.050)		(0.644)		(0.090)
μ^{T}	0.162^{***}				
	(0.045)				

Observation is a census tract. Estimates are obtained via GMM estimation using Bartik earning and employment change in each census tract. Standard errors are reported in parentheses.
$*p < 0.1; **p < 0.05; ***p < 0.01$.

A.1.3 Model Fit

Figure 13: Bilateral Commute Flows 2017: Model vs Data

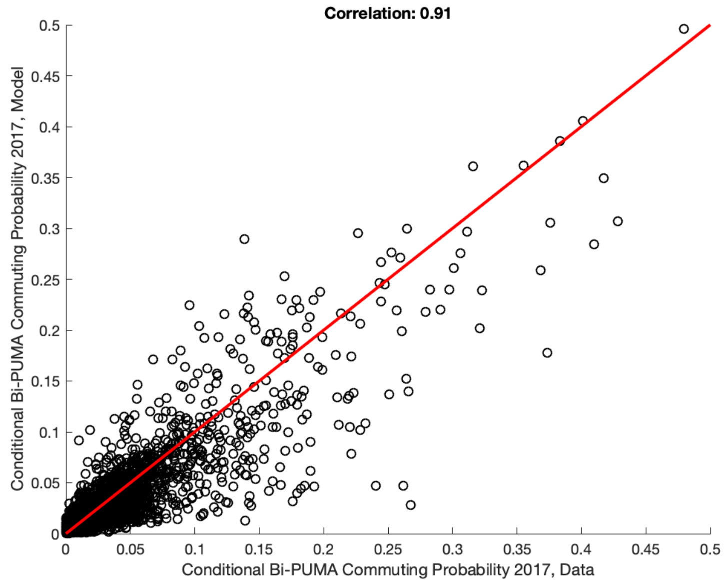


Figure 14: Job Distribution By Skill 2017: Model vs Data

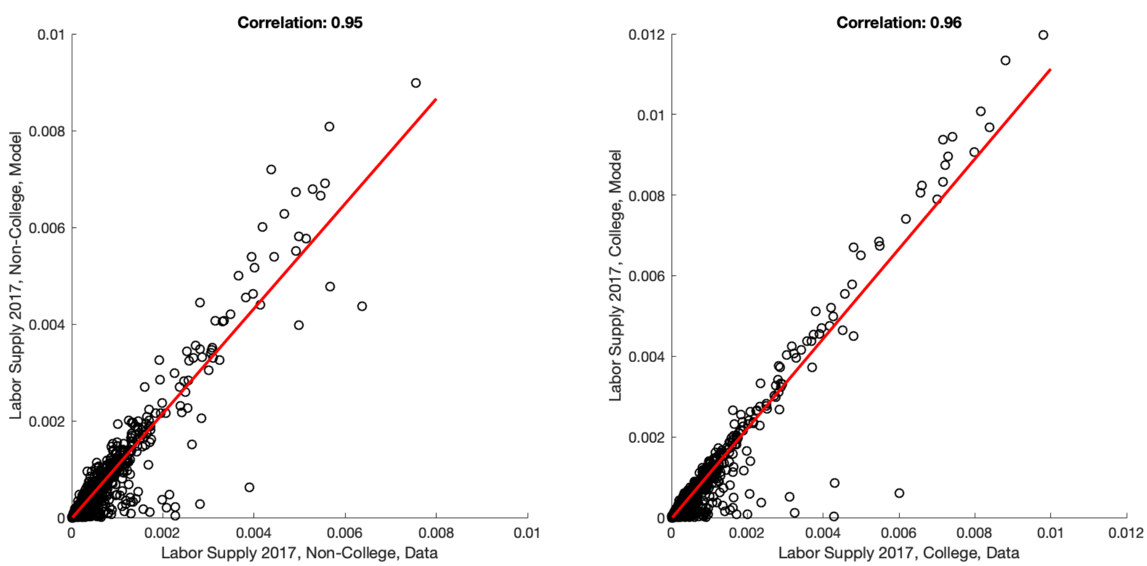
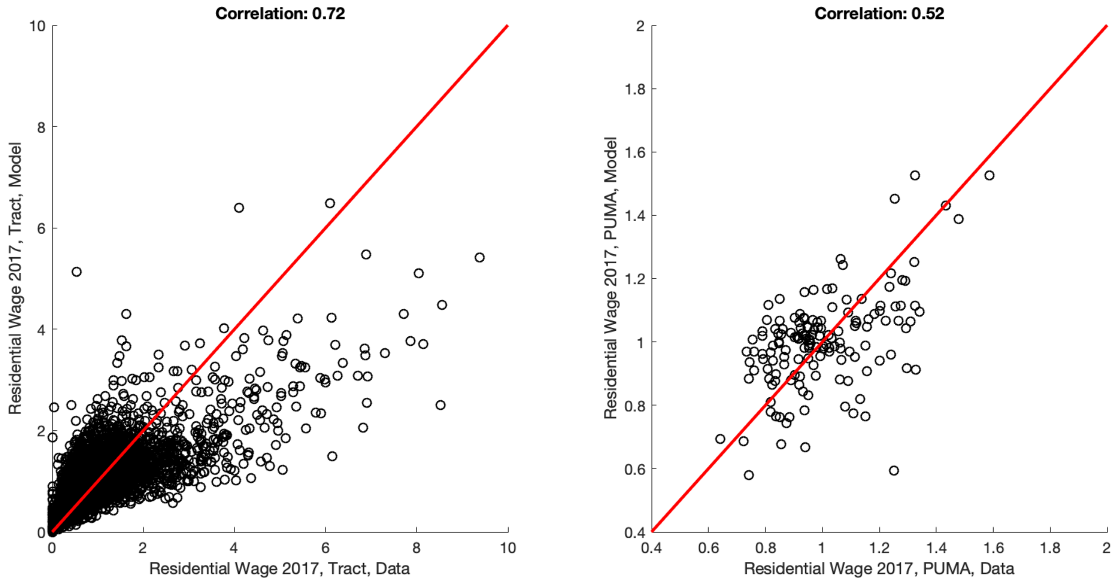
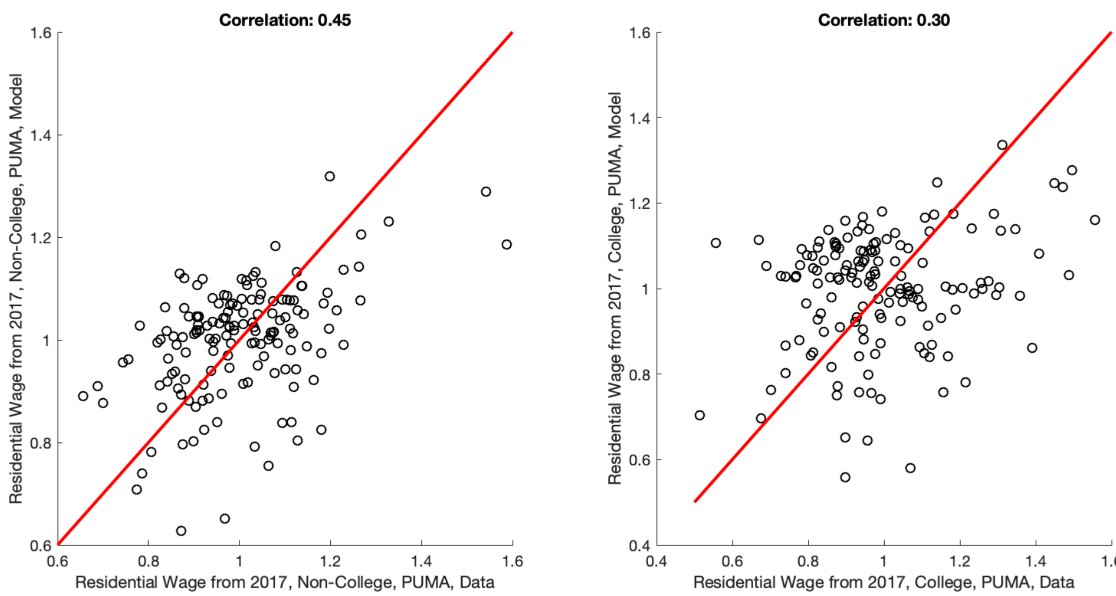


Figure 15: Residential Wage 2017: Model vs Data



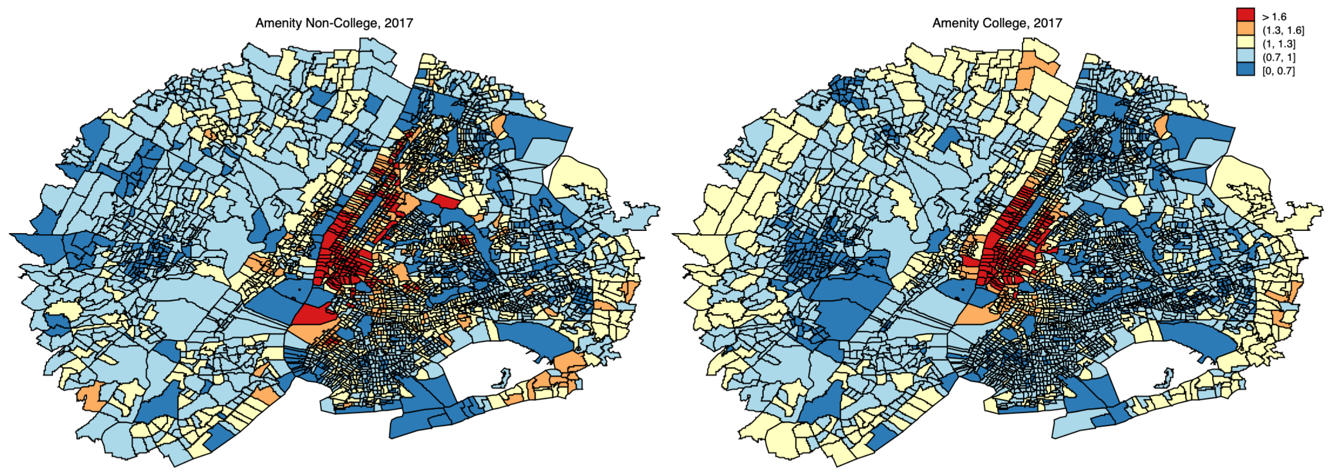
Note: The mean of residential wages is normalized to be one.

Figure 16: Residential Wage By Skill 2017: Model vs Data



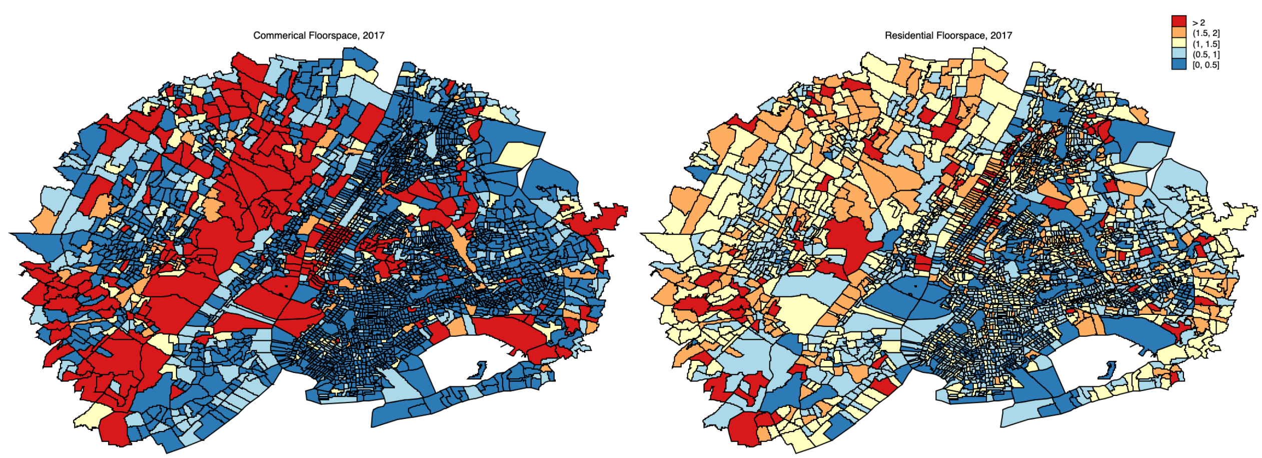
Note: The mean of residential wages is normalized to be one.

Figure 17: Amenity 2017



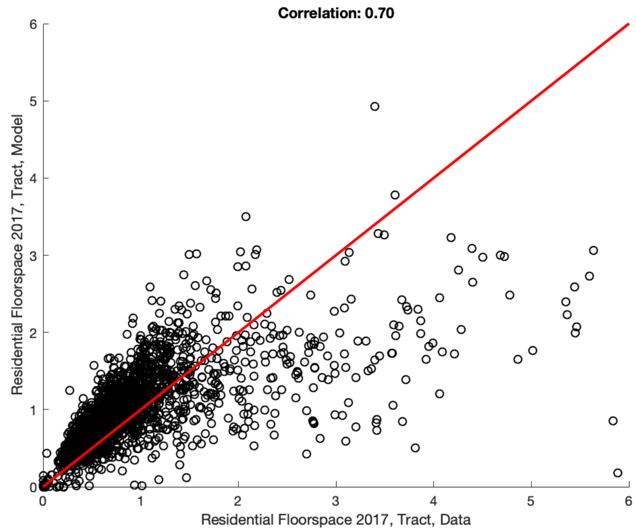
Note: The mean of amenities by skill is normalized to be one. The figure considers census tracts that are within 20-mile radius around the city center defined as the New York City Hall.

Figure 18: Housing 2017



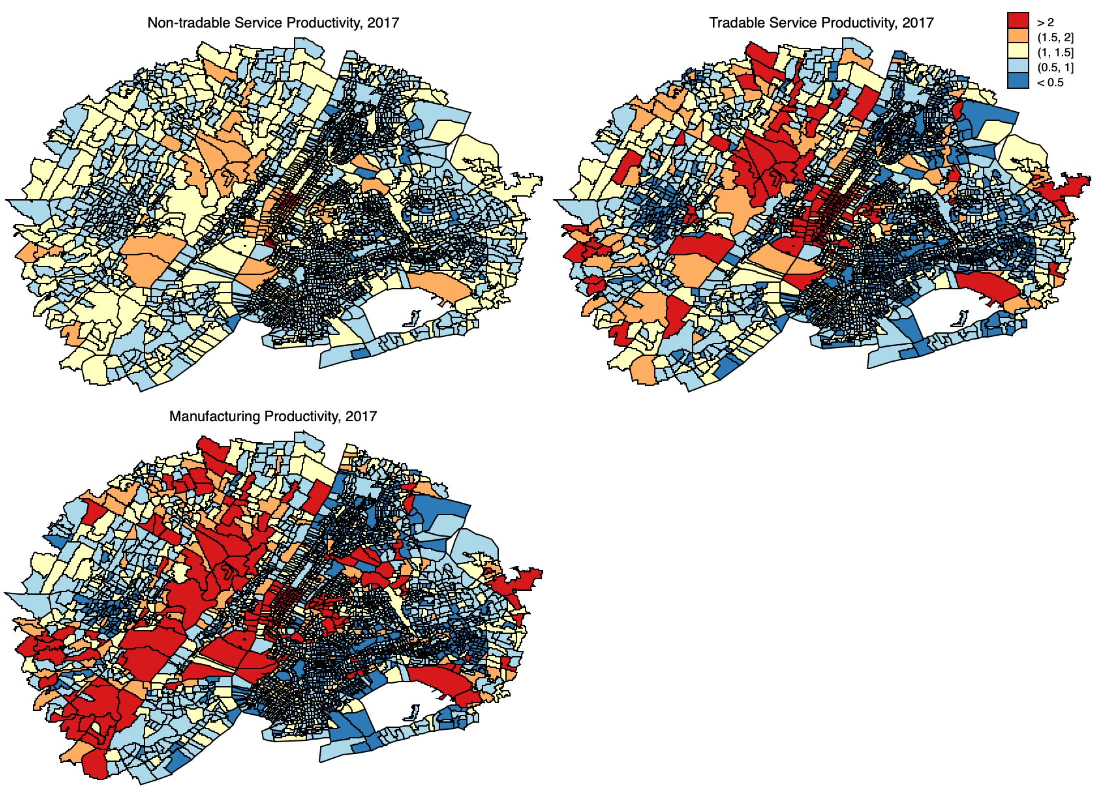
Note: The mean of floorspaces is normalized to be one. The figure considers census tracts that are within 20-mile radius around the city center defined as the New York City Hall.

Figure 19: Floorspace Area 2017: Model vs Data



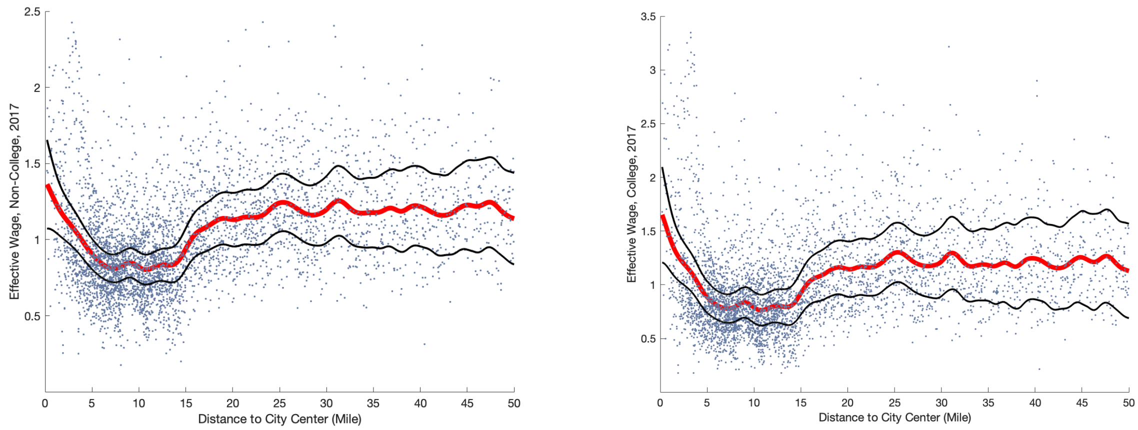
Note: The mean of floorspace is normalized to be one.

Figure 20: Productivity 2017



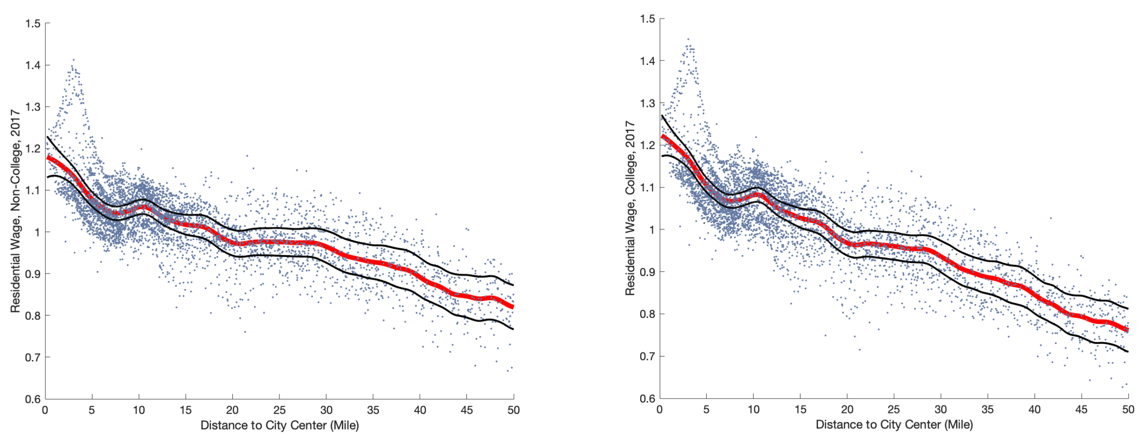
Note: The mean of productivities in each sector is normalized to be one. The figure considers census tracts that are within 20-mile radius around the city center defined as the New York City Hall.

Figure 21: Effective Wage 2017



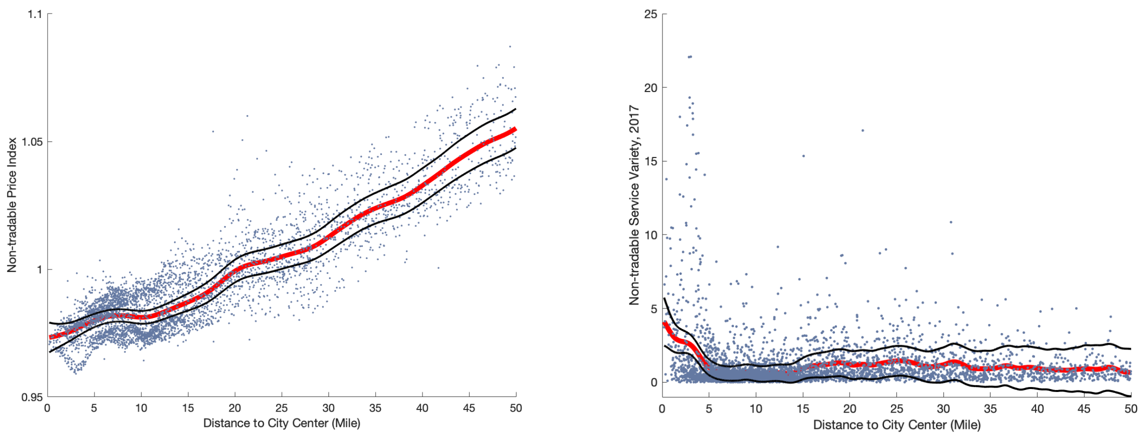
Note: The mean of effective wages is normalized to be one. The city center is defined to be the New York City Hall.

Figure 22: Residential Wage 2017



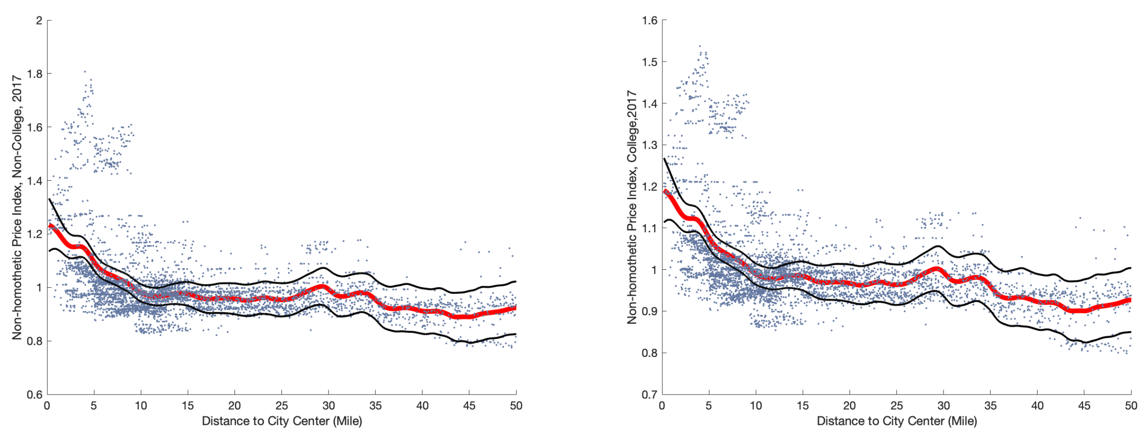
Note: The mean of residential wages is normalized to be one. The city center is defined to be the New York City Hall.

Figure 23: Non-tradable Price 2017



Note: The mean of price index and the mean of non-tradable measure are both normalized to be one. The city center is defined to be the New York City Hall.

Figure 24: Non-homothetic Price Index 2017



Note: The mean of price indices is normalized to be one. The city center is defined to be the New York City Hall.

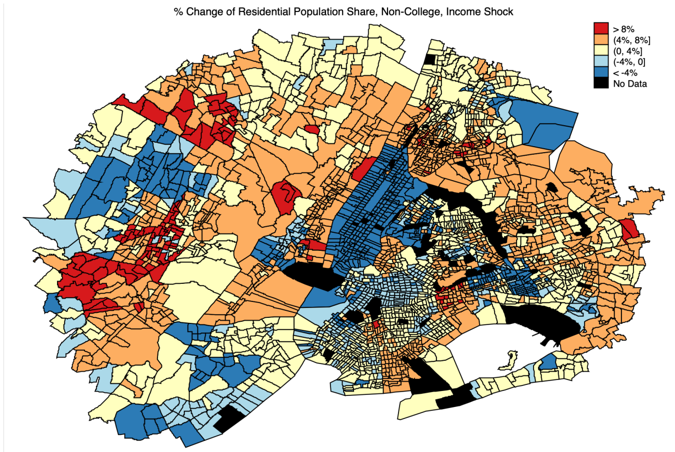
Table 8: Recovered Amenity

	(1)	(2)
	ln Amenity, Non-College	ln Amenity, College
ln No. street trees	0.145^{***}	0.171^{***}
	(0.021)	(0.019)
ln Dist to closest open space	-0.1706^{***}	-0.117^{***}
	(0.021)	(0.019)
Observations	2,158	2,158

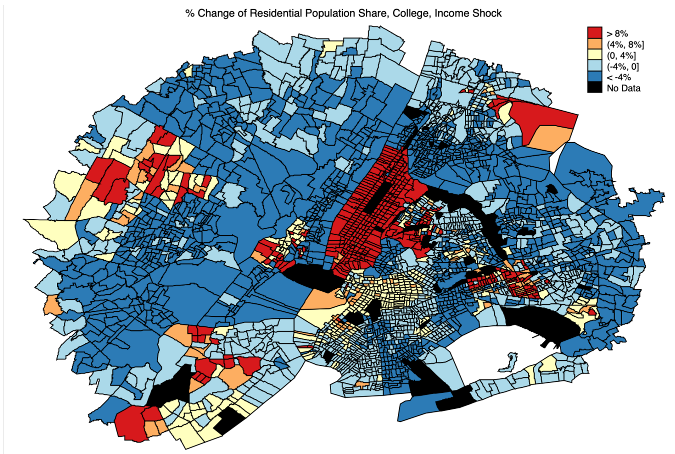
Observation is a census tract within the New York City. Estimates are obtained from regressing recovered log amenity on observables: log total number of street trees within a tract, and log distance to the closest open space from the tract centriod. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

A.1.4 Counterfactual: Exogenous Income Shock

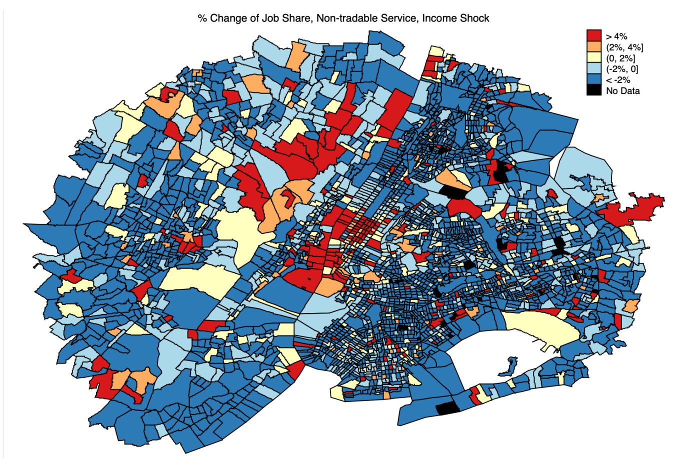
Figure 25: % Change of Residential Population/Job Share, Income Shock



(a) Non-College



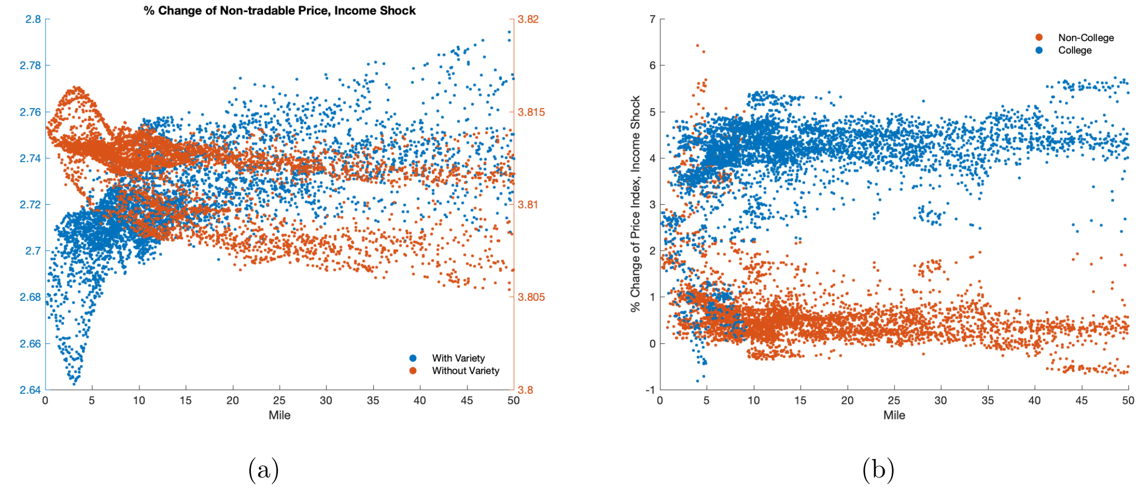
(b) College



(c)

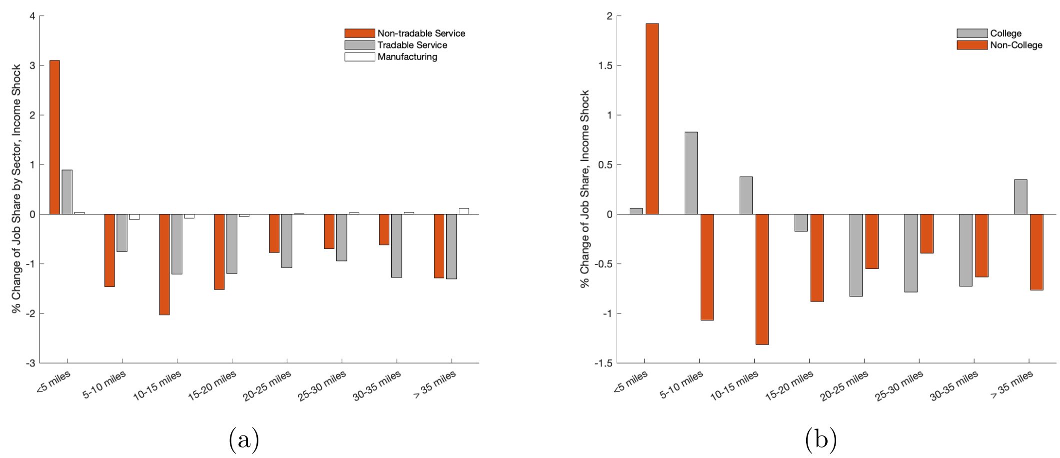
Note: The percentage changes are calculated using the counterfactual equilibrium as base.

Figure 26: Price Effect in Residential Sorting, Income Shock



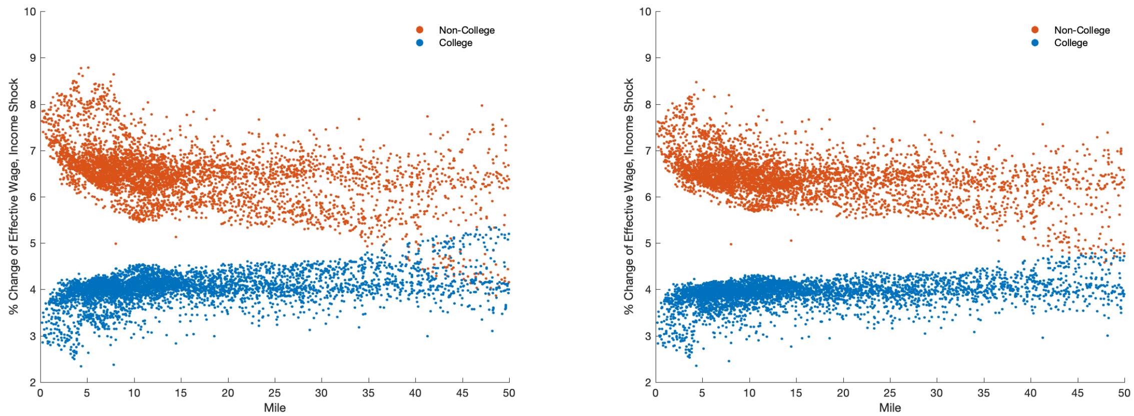
Note: The percentage changes are calculated using the counterfactual equilibrium as base.

Figure 27: Job Sorting, Income Shock



Note: The percentage changes are calculated using the counterfactual equilibrium as base.

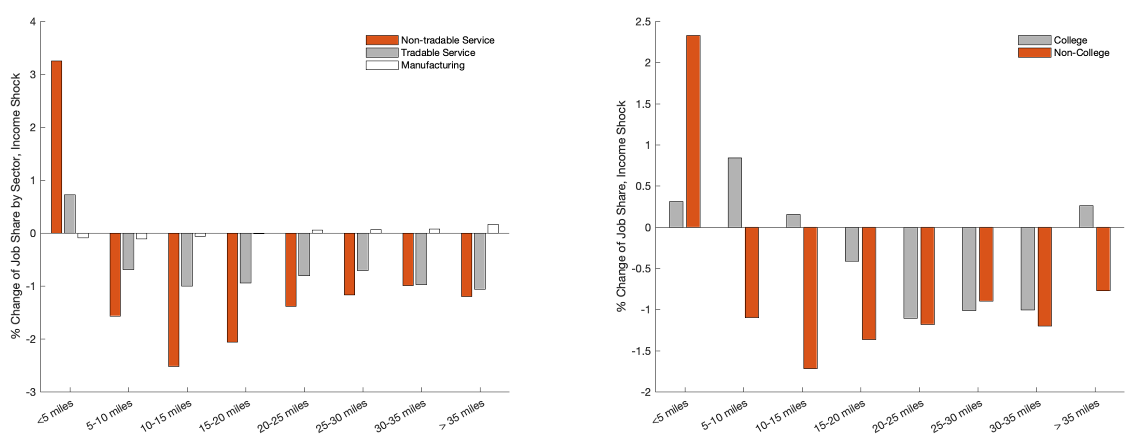
Figure 28: % Change of Effective Wage, Income Shock



(a) (b) Non-College: No Minimum Housing

Note: The percentage changes are calculated using the counterfactual equilibrium as base. In the version with "Non-College: No Minimum Housing", I set the minimum housing requirement $\overline{h}$ to 0 for non-college workers.

Figure 29: Job Sorting (Non-College: No Minimum Housing Requirement), Income Shock

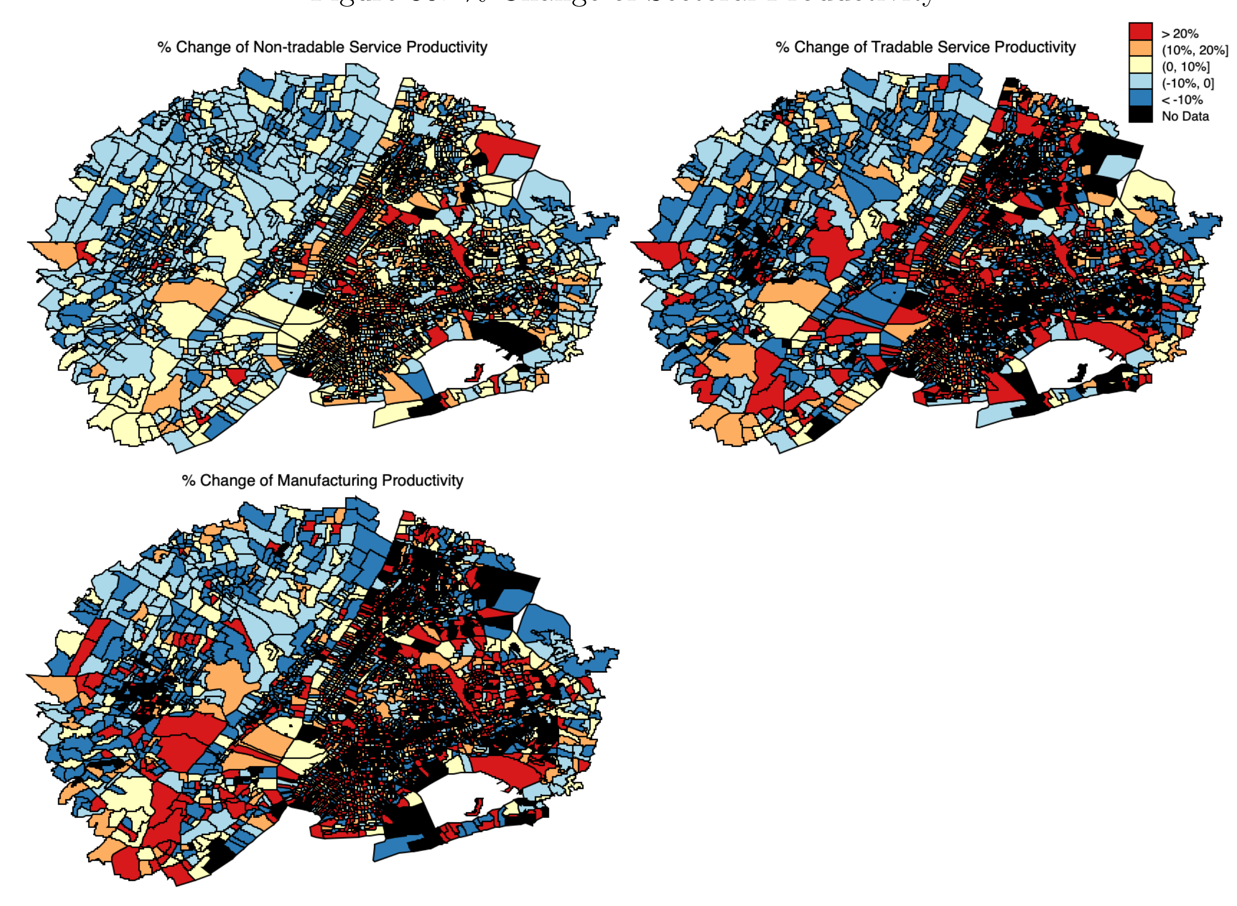


(a) (b) Non-College: No Minimum Housing

Note: The percentage changes are calculated using the counterfactual equilibrium as base. In the version with "Non-College: No Minimum Housing", I set the minimum housing requirement $\overline{h}$ to 0 for non-college workers.

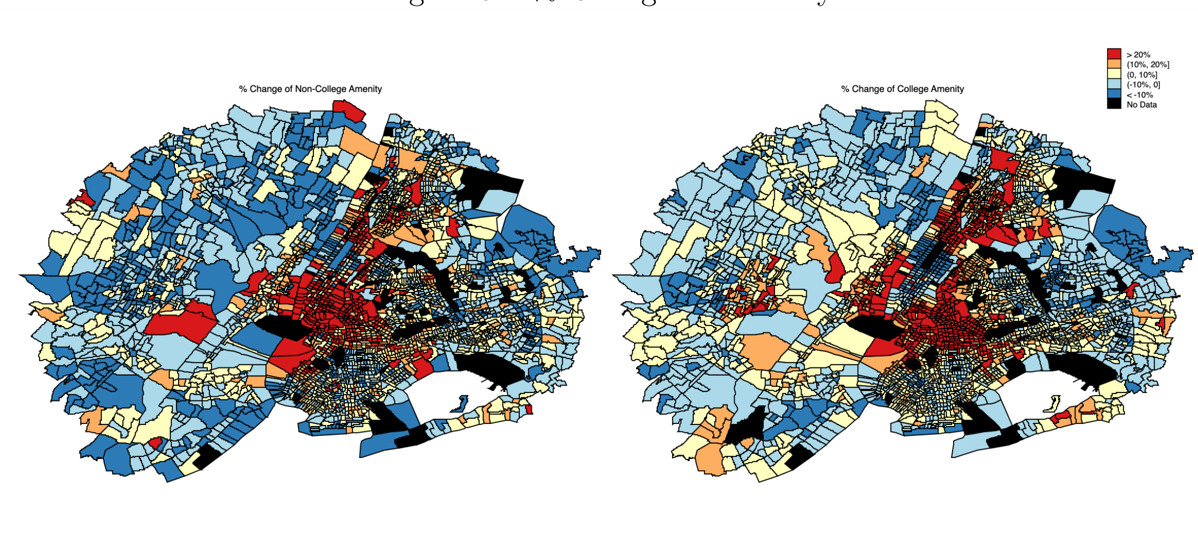
A.1.5 Counterfactual: Residence-Workplace Mismatch

Figure 30: % Change of Sectoral Productivity



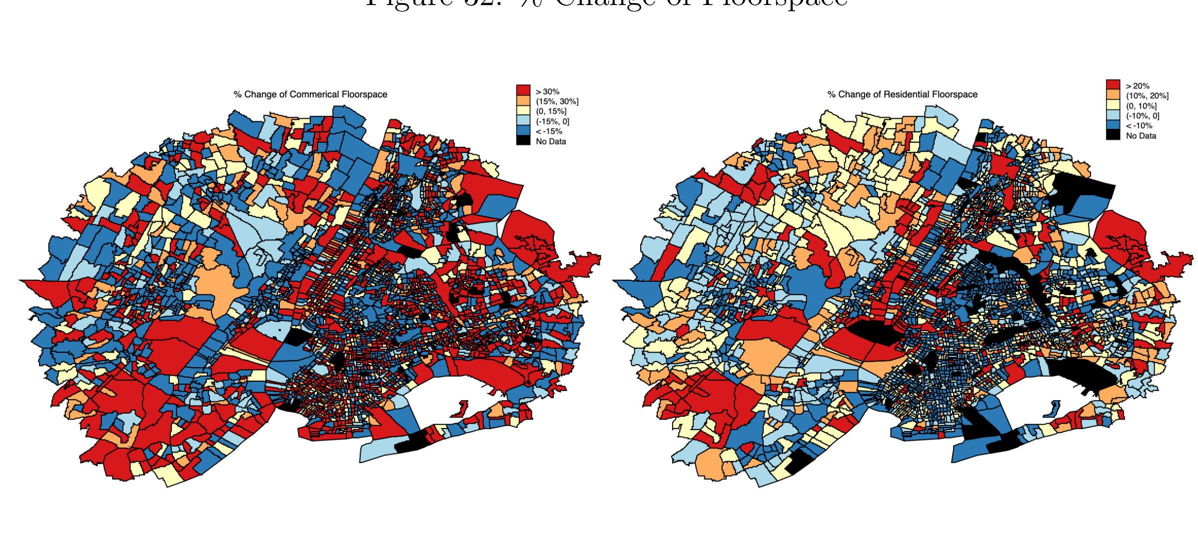
Note: The percentage changes are calculated using the 2000 equilibrium as base. The mean of productivity in both years is normalized to be 1.

Figure 31: % Change of Amenity



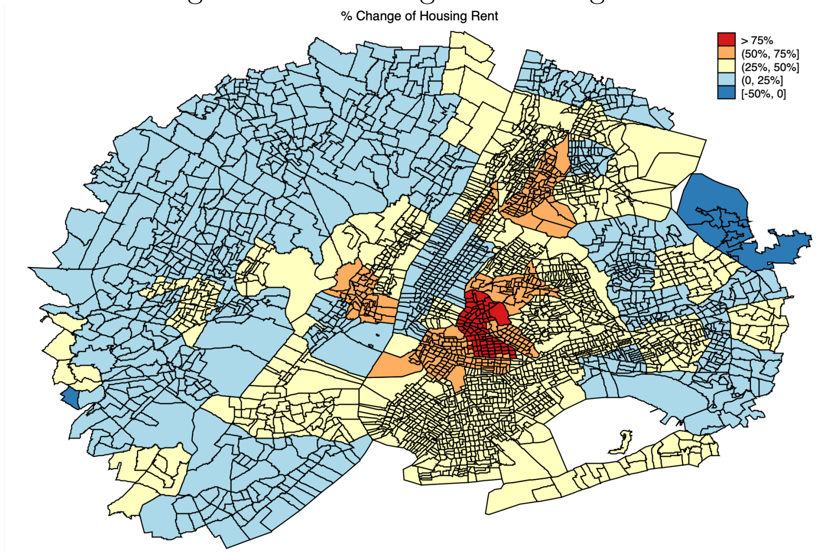
Note: The percentage changes are calculated using the 2000 equilibrium as base. The mean of amenity in both years is normalized to be 1.

Figure 32: % Change of Floorspace



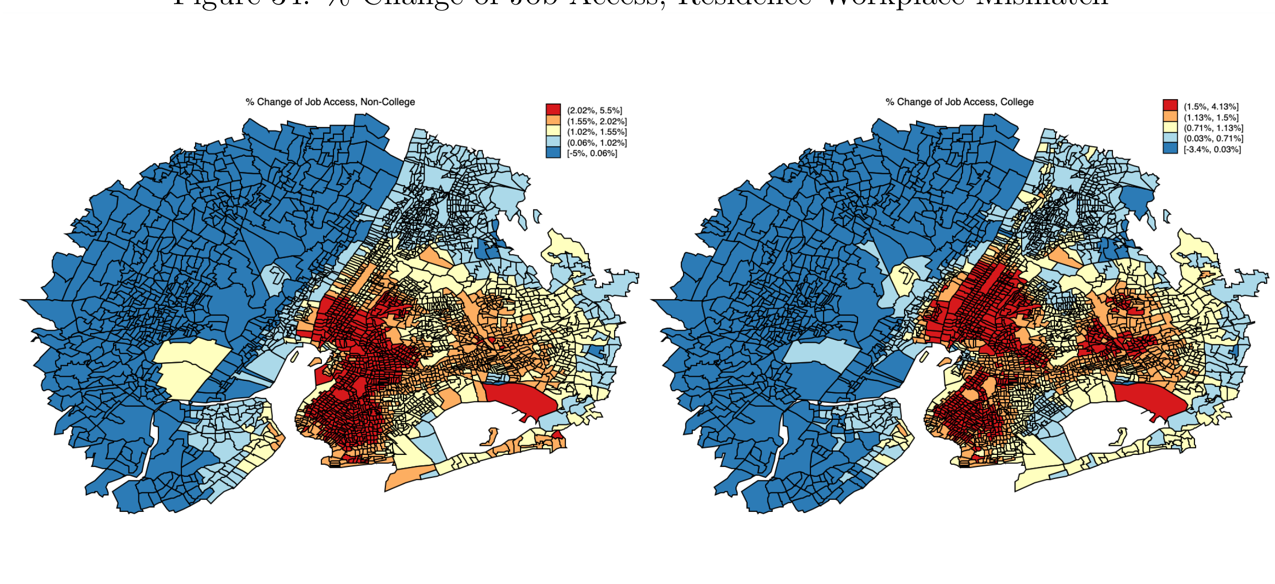
Note: The percentage changes are calculated using the 2000 equilibrium as base. The mean of floorspace in both years is normalized to be 1.

Figure 33: % Change of Housing Rent



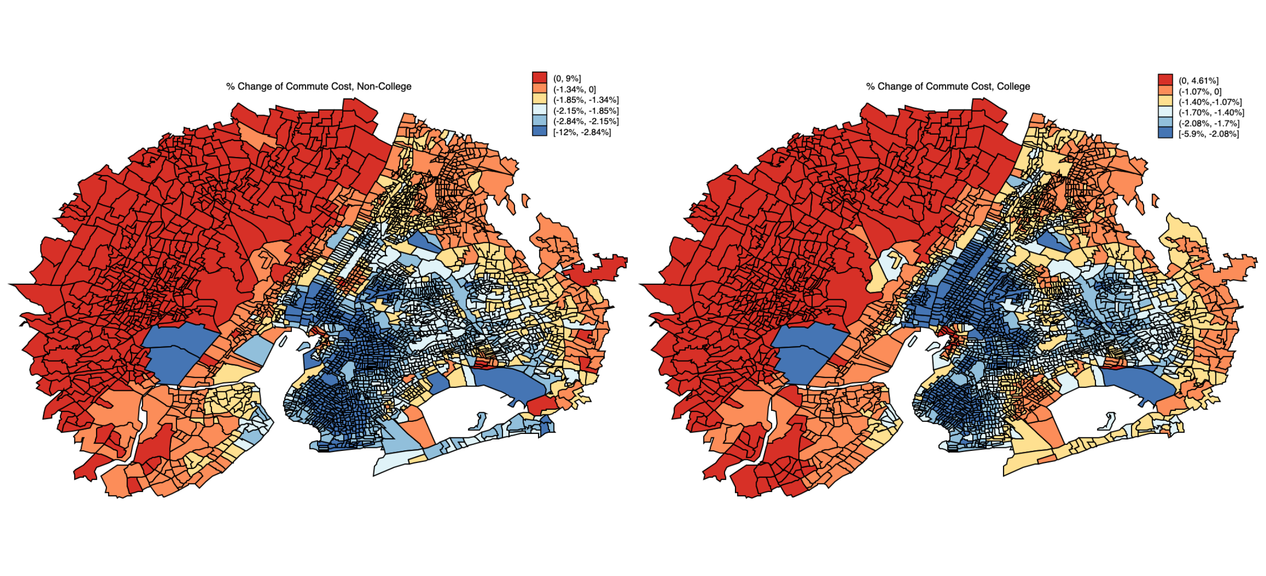
Note: The percentage changes are calculated using the 2000 equilibrium as base. The changes of rent are those observed in the data.

Figure 34: % Change of Job Access, Residence-Workplace Mismatch



Note: The percentage changes are calculated using the 200 equilibrium as base. Job access in each residential location is defined as Φ_{ns} in Section 3.1.2.

Figure 35: % Change of Residential Commute Cost, Residence-Workplace Mismatch



Note: The percentage changes are calculated using the 2000 equilibrium as base. The average commute cost in each residential location is defined as $\sum_i d_{ni}\pi_{i|ns}$, where commuting probability $\pi_{i|ns}$ is given by Equation 3.5.

A.1.6 Counterfactual: Residential Zoning

Figure 36: New York City Residential Zoning

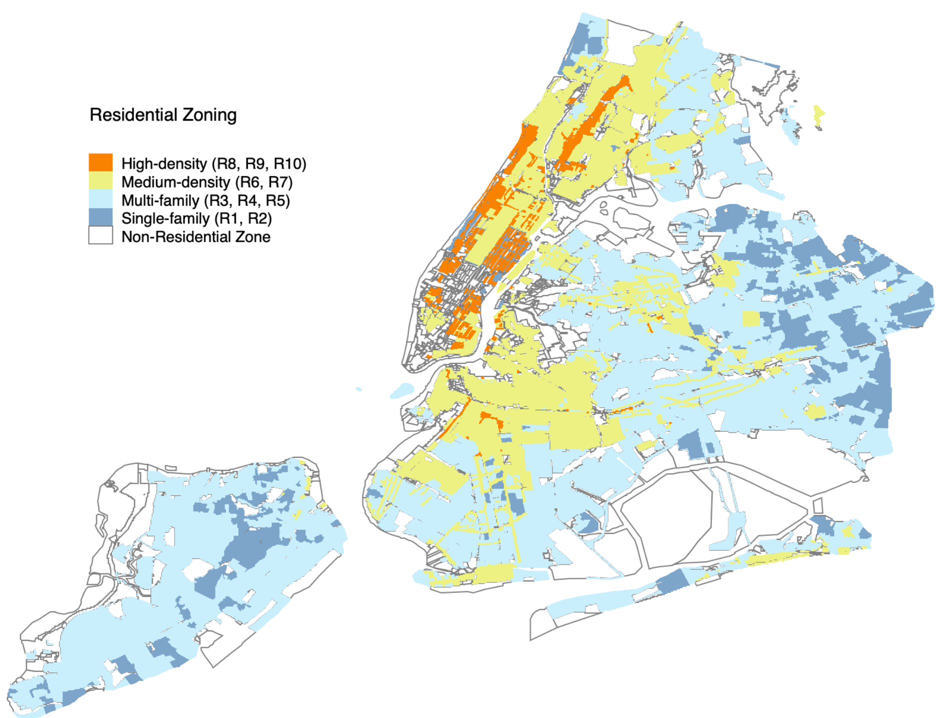


Figure 37: New York City Residential Floor Area Ratio (FAR)

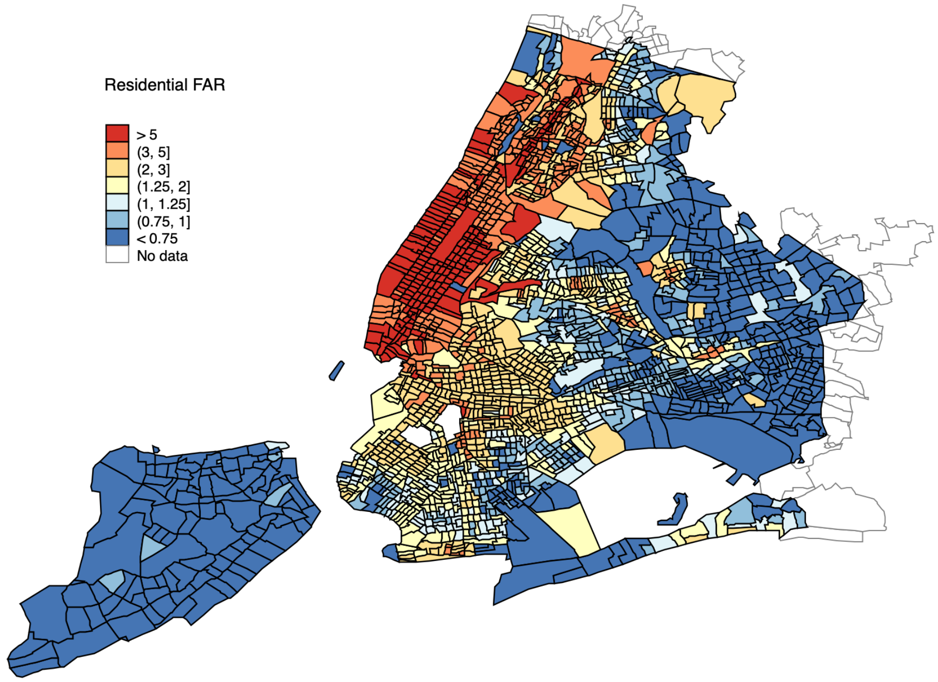


Figure 38: Policy Change: Relaxing Housing Constraint

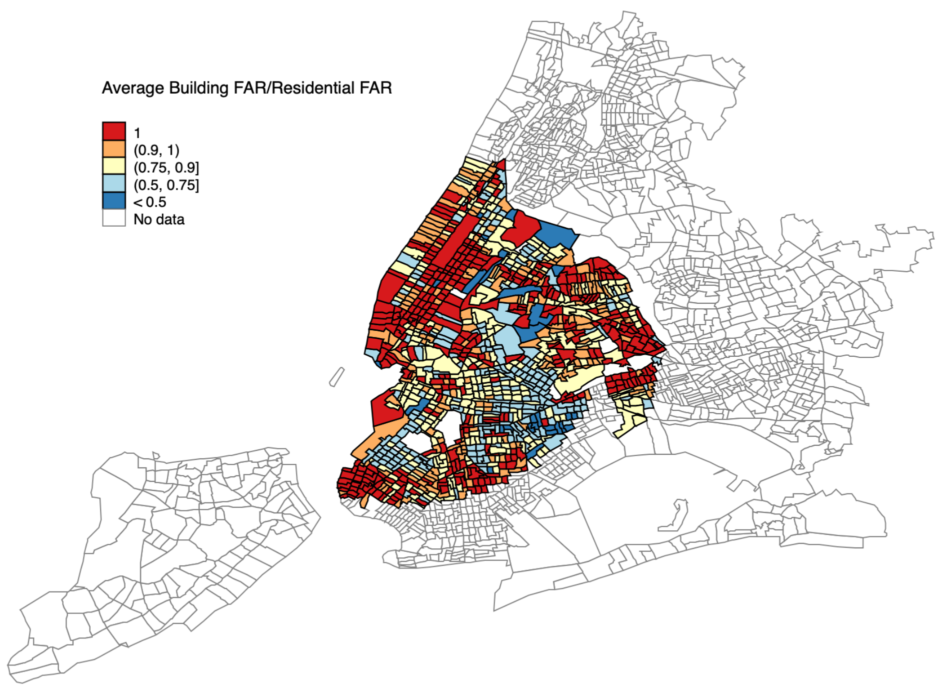
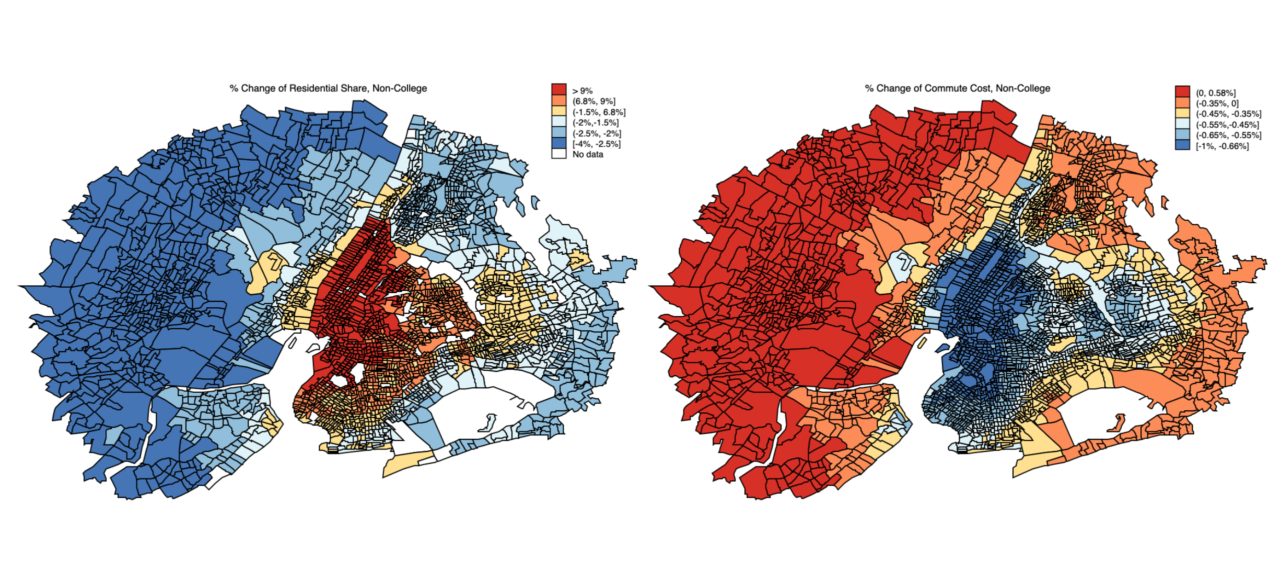


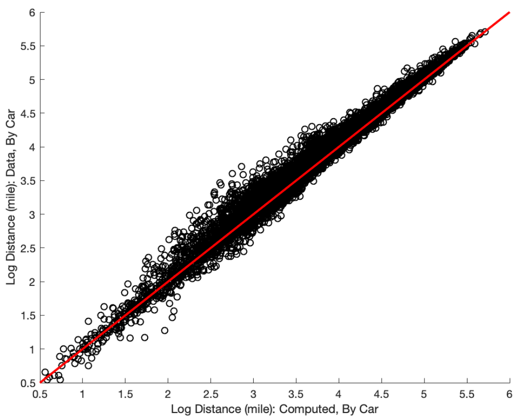
Figure 39: % Change of Residential Share/Commute Cost, Residential Zoning



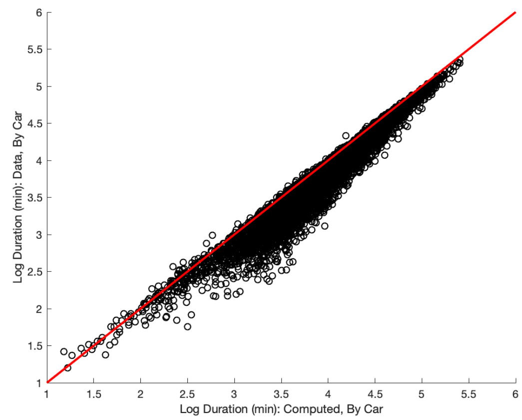
Note: The percentage changes are calculated using the 2017 equilibrium as base. The average commute cost in each residential location is defined as $\sum_i d_{ni}\pi_{i|ns}$, where commuting probability $\pi_{i|ns}$ is given by Equation 3.5.

A.1.7 Appendix Figures and Tables

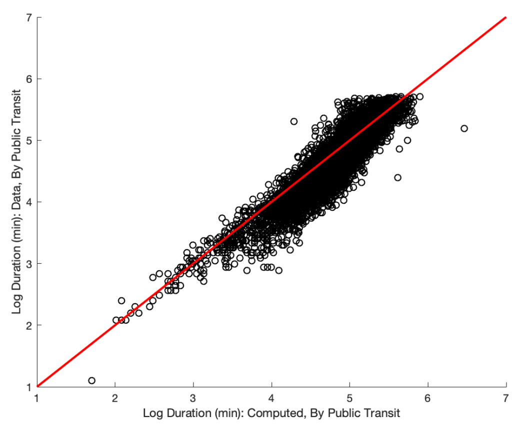
Figure 40: Travel Distance and Duration Predicted vs Data



(a)



(b)



(c)

Figure 41: Travel Duration Predicted vs Data, PUMA, Mode Choice Model

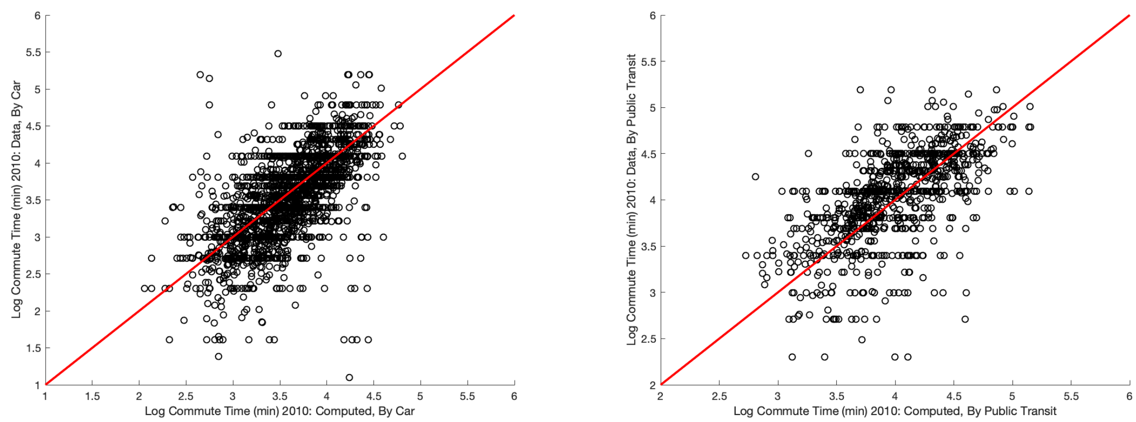


Table 9: Mode Choice

	Logit Estimate
κ	0.015***
	(0.001)
ξ^{car}	0.261***
	(0.093)
$\xi^{publictransit}$	−0.069*
	(0.053)
Observations	7,554

Distuility of walk ξ^{walk} is normalized to 0. Data comes from 2010-2011 Regional Household Travel Survey. Observation is a commute between home and workplace of a full-time employed sampled person. Robust standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

A.2 Industry Classification

I classify all the 2-digit NAICS industries into 3 broad sectors.

High-skill tradable service: Information (51); Finance and Insurance (52); Professional, Scientific, Technical Services (54); Management of Companies and Enterprise (55)

Low-skill non-tradable service: Administrative and Support and Waste Management and Remediation Services (56); Real Estate and Rental and Leasing (53); Arts, Entertainment, and Recreation (71); Accommodation and Food Services (72); Retail Trade (44-45); Construction (23)

Manufacturing: Agriculture, Forestry, Fishing and Hunting (11); Mining, Quarrying, and Oil and Gas Extraction (21); Utilities (22); Manufacturing (31-33); Wholesale Trade (42); Transportation and Warehousing (48-49)

A.3 Commute Cost

I estimate the commute cost between two census tracts (d_{ni} in the main text) following the steps listed here. I use tract centroid geo-coordinates to define the geographic location of a tract. I obtain the travel distance (in mile) by car, and travel duration (in min) by both car and public transit[37] under the current average traffic condition from Bing Distance API.

Given the large number of origin-destination pairs ($\frac{1}{2} \times 4,700 \times 4,699 \approx 11,000,000$), it's not feasible to retrieve the travel information for all the pairs. To resolve this issue, for each origin tract, I first calculate its surface distance to all other tracts using Haversine formula. Then, based on surface distance, I select 20 closest destinations, and another 20 destinations that lie evenly between the 25^{th} and 95^{th} distance quantiles. Finally, I obtain the travel information for those 40 selected pairs via Distance API for each origin tract. Selecting those specific pairs provides enough traffic network information around a tract. To compute the travel distance and duration for all the remaining pairs, I uses Djikstra's algorithm to calculate the least cost paths connecting any origin and destination. To verify that computed travel distance and duration match those in the real traffic, I further retrieve the travel information of $10,000$ randomly selected origin-destination pairs, Figure 40 shows that they are in line with each other.

As in Ahlfeldt et al. (2015), I assume the exponential functional form for the commute cost, that is, $d_{ni} = \exp(\kappa \bar{t}_{ni})$, where $\bar{t}_{ni}$ denotes the average commute time between tract n and tract i over different possible transit modes and κ is the disutility of longer commute time. To provide estimates of both, I consider a simple multinomial logit model of transit mode choice. For a commuter travelling between location n and i, if he owns a car, then the possible

[37] Travel duration by public transit includes the walk time to reach the public transit.

modes include walk, public transit and car, otherwise only walk and public transit are available. Choice probabilities of mode m are modelled as

$$\pi_{ni}^{m} = \frac{\exp(-\kappa t_{ni}^{m} + \xi^{m})}{\sum_{m'} \exp(-\kappa t_{ni}^{m'} + \xi^{m'})},$$

where t_{ni}^{m} is the commute time if the commuter chooses mode m, and ξ^{m} captures the mean preference for mode m, capturing all other features that commuter cares about besides the commute time.

I utilize 2010-2011 Regional Household Travel Survey conducted by New York Metropolitan Transportation Council to estimate the mode choice model, where in total $143,925$ linked trips were derived from a sample of $18,965$ households and $43,558$ individuals. From the survey's person file, I observe each interviewed person's work and residential census tracts, total travel time and transit mode to work, and a set of demographic variables include whether the household that the person belongs to owns a car or not[38]. To obtain more accurate estimates in the mode choice model, I aggregate work trips onto the PUMA level. I construct the commute time between any two PUMA (t_{ni}^{m}) as follows: first, for car and public transit modes, I take the area-weighted average of the commute time calculated above between each census tract pair within the PUMA pair; second, since commute time obtained above reflects the current traffic speed, I scale those commute time to best match the observed travel duration reported in the travel survey[39]; last, I set walk speed to 0.052 mile/min (Ahlfeldt et al. (2015)). Given the speed, I use the travel distance to compute the travel duration under walk between two census tracts, which are then averaged to obtain the commute time by walk for each PUMA pair. The mode choice model is estimated via standard maximum likelihood, and Table 9 shows the result. Estimate of $\kappa = 0.015$ is higher compared to 0.01 in Ahlfeldt et al. (2015) and 0.012 in Tsivanidis (2019).

After estimating the mode choice model, for year 2017 and for each census tract pair, I compute the average commute time as

$$\bar{t}_{ni} = \sum_{m} \pi_{ni}^{m} t_{ni}^{m},$$

where t_{ni}^{m} is the calculated commute time under mode m constructed above, and π_{ni}^{m} is the mode choice probability implied by the logit estimates. I consider three modes, car, public transit and walk, to compute $\bar{t}_{ni}$. The commute cost then is given by $d_{ni} = \exp(\kappa \bar{t}_{ni})$. For year

[38]However, the survey doesn't contain the education level of the respondents. I assume both skills share the same preference towards transit modes.

[39]Figure 41 shows the comparison between the predicted travel duration and those observed. They are highly correlated.

2002, I need to adjust the commute time t_{ni}^{m} calculated under current traffic condition to reflect the traffic in early 2000s. To achieve that, I use the travel time reported in the trip file of the 1997-1998 Regional Household Travel Survey. For each mode, I scale the commute time to best match the reported travel time in the survey.

A.4 RoW

I assume the size of rest-of-world (RoW) to be 5 times larger than the size of US. To account for trade deficit, following Eckert et al. (2019), I assume there exists an income subsidy τ distributed to U.S. workers (thus the final income of a worker with skill s in location n is given by $(1+\tau)y_{ns}$) and this subsidy is financed by an income tax of RoW workers (τ_{RoW}). I select τ to match the U.S. trade deficit over income ratio. I assume there is only one skill type in RoW.

To match the 2017 data, I normalize the wage of RoW to be 1, and τ_{RoW} is selected to ensure the subsidy budget balance. Let the preference of RoW workers to be Cobb-Douglas over manufacturing goods, tradable services and non-tradable services. The production technology in all three sectors are assumed to be Cobb-Douglas using labor and output from other sectors. I use the same labor share and I-O parameters as U.S.. Sectoral market clearing then implies:

$$E_{US}^{g} - R_{US}^{g} = R_{RoW}^{g} - E_{RoW}^{g} = (\alpha^{g})^{-1} w_{RoW} L_{RoW}^{g} - \rho_{RoW}^{g}(1-\tau_{RoW}) w_{RoW} L_{RoW}$$
$$- \sum_{g'} (\alpha^{g'})^{-1} w_{RoW} L_{RoW}^{g'} (1-\alpha^{g'}) \gamma^{g',g}, \{g, g'\} \in \{M, T, NT\},$$

where $\{\rho_{RoW}^{g}\}$ is the expenditure share in the preference. Notice when $g = NT$, $E_{US}^{NT} = R_{US}^{NT}$. I assume that the employment share in all three sectors is equal to $\frac{1}{3}$ and solve for ρ_{RoW}^{g} that ensures market-clearing. To match the 2002 data, I again normalize the wage of RoW to be 1. Then fixing the calibrated preference parameter ρ_{RoW}^{g}, I solve for the labor allocation L_{RoW}^{g} to clear the market. In any counterfactual equilibrium, I fix calibrated τ and ρ_{RoW}^{g}, while wage w_{RoW} and labor allocation L_{RoW}^{g} are endogenously determined in the model.

A.5 Sectoral Productivity

Manufacturing/Tradable Service Marginal Cost. Recall that both manufacturing goods and tradable services are freely traded within the city, all the locations in the city thus share the same sectoral price. Then sectoral market clearing implies that

$$R_i^g = \sum_{n \in \{N, m \backslash N\}} E_n^g \frac{(MC_i^g \tau_{ni}^g)^{1-\sigma}}{\sum_{i' \in M} (MC_{i'}^g \tau_{ni}^g)^{1-\sigma}}, g \in \{M, T\},$$

where E_n^g is the total expenditure on sector g output in location n (if $n = N$, it reflects the total expenditure in the city as a whole). City-level expenditure $\{E_n^g\}$ is obtained using the recovered wage, aggregate average expenditure share from CES Metropolitan Statistical Areas Tables [40], and calibrated γ^{NT} that ensures the non-tradable service market clearing at the city level. Now given $\{R_i^g, E_n^g\}$ and trade cost $\{\tau_{ni}^g\}$, we can recover (up to a scale) the sectoral marginal cost of production across space. Then, the sectoral price index is simply $P_n^g = (\sum_{i' \in M}(MC_{i'}^g \tau_{ni}^g)^{1-\sigma})^{\frac{1}{1-\sigma}}$.

Non-tradable Service Marginal Cost. To recover the distribution of non-tradable service productivities within the city, I again utilize the sectoral market clearing,

$$R_i^{NT} = \sum_{n \in N} \frac{(\widetilde{MC}_i^{NT} d_{ni}^{\delta})^{1-\sigma}}{\sum_{i \in N}(\widetilde{MC}_i^{NT} d_{ni}^{\delta})^{1-\sigma}} E_n^{NT}, \widetilde{MC}_i^{NT} = (N_i^{NT})^{\frac{1}{1-\sigma}} MC_i^{NT},$$

where $E_n^{NT} = \sum_s \bar{s}_{ns}^{NT}(1+\lambda_s) w_{ns} L_{ns}^R$. The complication compared to above is that we cannot directly obtain E_n^{NT} from the data. Thus, I use the following loop to recover the marginal cost:

- Step 1: I guess the distribution of $\{E_n^{NT}\}$ and at the same time ensure city-level average expenditure share is consistent with data.
- Step 2: Given $R_i^{NT}, E_n^{NT}, d_{ni}$, I recover a vector of marginal cost (up to a scale) $\{\widetilde{MC}_i^{NT}\}$, and construct the non-tradable price index as $P_n^{NT} = (\sum_{i \in N}(\widetilde{MC}_i^{NT} d_{ni}^{\delta})^{1-\sigma})^{\frac{1}{1-\sigma}}$.
- Step 3: Given the recovered sectoral price indices and residential housing rents data, I solve the utility maximization problem, and select $\{\rho^M, \rho^{Ser}, \rho^H\}$ to match the city-level average expenditure share in the data. I then update $\{E_n^{NT}\}$ using the calculated expenditure. I repeat Step 1-Step 3 until expenditure distribution $\{E_n^{NT}\}$ converges.

Using the algorithm listed above, I both recover the marginal cost of production in the non-tradable service sector and also the calibrate preference parameter $\{\rho^M, \rho^{Ser}, \rho^H\}$ to match the aggregate city-level sectoral expenditure share in the data.

Productivity. Once I recover the sectoral marginal cost of production across space, given recovered wages, price indices, and commercial housing rents, I can obtain the location-specific sectoral productivity. To be more specific, in the manufacturing/tradable service sector, for $g \in \{M, T\}$,

$$A_i^g = \frac{w_i^{g\,\alpha^g} r_i^{F\,\beta^g} \prod_g P_i^{g'\,\gamma^{g',g}}}{MC_i^g},$$

[40]For the first hypothetical location where I group 99 largest U.S. CBSAs except New York, I use the population-weighted average of the sectoral expenditure shares in those selected CBSAs listed in the table. For the second hypothetical location that represents the rest CBSAs, I use the average of Mid-west and Southern regional sectoral expenditure share to approximate.

where $w_i^g = (\sum_s \alpha_s^g w_{is}^{1-\xi})^{\frac{1}{1-\xi}}$.

In the non-tradable service sector, however the recovered marginal cost is confounded by the endogenous measure of firms. But the measure of firms can be easily recovered from the zero-profit condition,

$$N_i^{NT} = \frac{R_i^{NT}}{\sigma c_i^{NT} f^{NT}},$$

where the cost of the input bundle c_i^{NT} is known, and I normalize $f^{NT} = 1$. This normalization wouldn't influence the counterfactual behavior of the model, since the level of f^{NT} only scales the measure of firms up or down, leaving the percentage deviation unchanged. Once I obtain the measure of firms, I can obtain the true marginal cost of production MC_i^{NT} and recover A_i^{NT} as above. Notice the choice of scale for marginal costs determines the scale of productivities we recover. For the outside locations, I simply set the non-tradable price index equal to the housing rent and recover the associated productivity. This is harmless because we cannot separately identify the non-tradable price index and ρ^{Ser} in the outside locations.

Finally notice that in general, I cannot separately identify the ρ^g and the overall level of A_i^g. To match the year 2017 data, I normalize the geometric mean of sectoral marginal cost of production to be one, and this determines the scale of corresponding productivity. Then ρ is selected to match the sectoral expenditure share. To match the year 2002 data, instead, I keep ρ fixed, and adjust the scale of productivity to match the sectoral expenditure share.

A.6 Understanding the Model: Exogenous Income Shock

In this section, I consider an exogenous skill-specific income shock to understand the model's sorting mechanism. I adjust income adjustment factor $\{\lambda_s\}$ so that everything else equal, moving from the counterfactual equilibrium to the 2017 equilibrium, non-college and college workers experience an *exogenous* 20% negative and positive income growth respectively[41]. Workers take into account both the endogenous change of residential wage (job opportunities) and this exogenous income adjustment. To make the model's prediction clear, I keep the housing rents *fixed* at the 2017 value and thus ignore the general equilibrium effect of housing market clearing. I also assume the city border is *closed*.

Figure 25 in the Appendix plots the relocation of residents and non-tradable service jobs within the city. After the income shock, more college workers reside in downtown, while those far-off locations receive an increasing number of non-college workers. This pattern is consistent with the theoretical predictions illustrated in Section 3.1, where the first-order effect of an

[41] To be more specific, I divide $(1+\lambda_H)$ by 1.2, and $(1+\lambda_L)$ by 0.8. The size of the shock is chosen without any quantitative reason, and is only meant to illustrate the qualitative predictions of the model. Since effective wages change endogenously after the shock, the ultimate changes of income will not equal the size of the shock.

income shock is that the skill group receiving a positive/negative income growth moves into high/low housing cost locations. Due to the non-homothetic preference, college workers value more the consumption of non-tradable services and become increasingly so after the positive income growth. Hence, both the residential sorting and the shock itself expand the demand of non-tradable services in downtown. This is shown in Panel (c) that area close to downtown witnesses largest increases of non-tradable service jobs, especially those locations with high productivity in producing non-tradables.

To understand the economic forces shaping the magnitude of residential sorting, Panel (a) of Figure 42 decomposes the relocation due to the endogenous responses of prices. Those responses substantially *amplify* the first-order effect of the income shock. Non-college workers reside outside downtown not only because of the shock itself, but also the higher cost-of-living (overall price index) there, while the opposite is true for college workers. Figure 26 in the Appendix shows that: first, although larger demand of non-tradable services in downtown raises the effective wage and input cost, entry of more varieties offsets the higher cost, and the price index increases by the least amount in downtown; second, since college workers spend more on services, the rise of cost-of-living in downtown is much less significant. Non-college workers, on the other hand, spend even more on residential housing, which are most costly in downtown. Switching to jobs, Figure 27 and Figure 28 in the Appendix confirm that non-college job opportunities are mostly improved in downtown due to the concentration of non-tradable service jobs.

To highlight the residence-workplace *mismatch* for the non-college, in Panel (a) of Figure 43, I contrast the total residential sorting with the portion predicted only by the change of effective wage. We observe that the model endogenously generates the *mismatch* of ideal residence and ideal workplace for non-college workers: they would have stayed in downtown for better job opportunities, if cost-of-living hasn't increased that much. One key factor that is responsible for this trade-off is the existence of minimum housing requirement. In Panel (b) of Figure 42 and 43, I consider the same income shock but in a fictional economy where there is no minimum housing requirement for the non-college. Now, non-college workers suffer much less trade-off and are more willing to remain in downtown[42]. This benefits the college workers as well, since now firms don't need high wages to attract non-college labor, shown in Panel (b) of Figure 28. This implies lower prices of non-tradable services, more entry of varieties, large increase of non-college job share and college residential share in downtown (Figure 29 in the Appendix).

The welfare implications of the income shock is reported in Table 10. Panel A shows that average non-college residential wage increases by 6.6%, 2.6% large than the increase of college

[42]Although it is still true that the endogenous responses of non-homothetic price index implies largest increase of cost-of-living for the non-college in downtown.

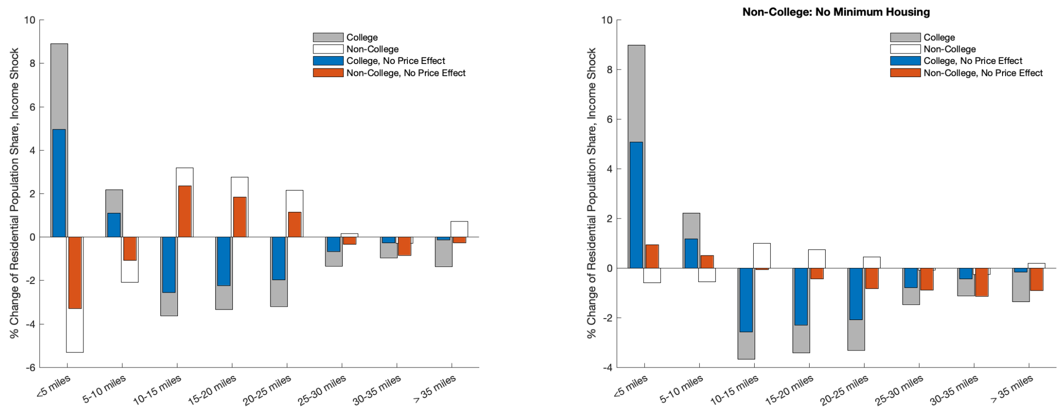
wage. This is consistent with the fact that non-college workers have comparative advantage in producing non-tradable services. Accounting for the exogenous income shock, non-college income declines by 14.7%, while college income increases by close to 25%. Once accounting for cost-of-living, non-college welfare drops by 3% larger than income decrease. As a result, the rise in welfare inequality exacerbates the rise in income inequality by 3.8%. However, in Panel B, after the non-college minimum housing requirement is removed, non-college wage is not much affected, but there is significantly smaller drop in non-college welfare due to lower cost-of-living. In the end, the rise in welfare inequality is smaller than the rise in income inequality. This counterfactual highlights the importance of the non-homotheticity created by the preference specification and the minimum housing expenditure in driving the residential and job sorting that are consistent with the data, and how it determines the welfare consequences.

Table 10: % Change of Aggregates, Income Shock

	Non-College	College	Inequality
Income Shock	−20%	+20%	
Panel A			
Residential Wage	+6.63%	+4.04%	−2.43%
Income	−14.70%	+24.85%	**+46.36%**
Welfare	−17.88%	+23.29%	**+50.13%**
Panel B: Non-College: No Minimum Housing			
Residential Wage	+6.70%	+3.98%	−2.56%
Income	−14.64%	+24.77%	**+46.17%**
Welfare	−15.30%	+23.29%	**+45.55%**

Note: The percentage changes are calculated using the counterfactual equilibrium as base. Residential wage $\overline{w}_{ns}$ considers only the effective wage, while income takes into account the income adjustment factor λ_s. Skill-specific welfare is defined in Equation 3.7.

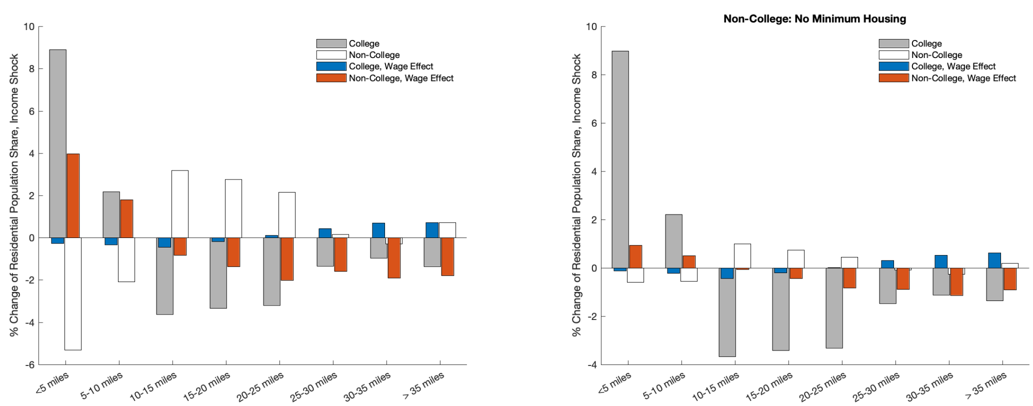
Figure 42: Residential Sorting, Price Effect, Income Shock



(a) (b)

Note: The percentage changes are calculated using the counterfactual equilibrium as base. In the version with "No price effect", I allow residential income to change (including both residential wage and income adjustment factor) while fixing the overall price index at the 2017 value. In the version with "Non-College: No Minimum Housing", I set the minimum housing requirement $\overline{h}$ to 0 for non-college workers.

Figure 43: Residential Sorting, Wage Effect, Income Shock



(a) (b)

Note: The percentage changes are calculated using the counterfactual equilibrium as base. In the version with "Wage effect", I only allow effective wage and thus residential wage to change. Income adjustment factor and overall price index are fixed at the 2017 value. In the version with "Non-College: No Minimum Housing", I set the minimum housing requirement $\overline{h}$ to 0 for non-college workers.

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