Reassessing Spatial Labor Misallocation: A Decade Beyond Hsieh and Moretti (2019)

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Abstract

This study revisits Hsieh and Moretti's (2019) research, extending the original 1964-2009 timeframe to 1964-2019. Using kernel density estimation for land use regulations, housing costs, and employment, we observe improvements in spatial labor misallocation from 2009 to 2019. Also, our study critically reviews the counterfactual estimation procedure of Hsieh and Moretti (2019) and proposes a potential enhancement: iterating the estimation until the indirect utility level equalizes across all locations. Using this new algorithm, we find a significant overstatement in the original estimation of aggregate output growth over 1964-2009 if housing costs were fixed at the 1964 level. Lastly, holding housing costs at the 2009 level, our counterfactual results indicate a 13.9 percentage point smaller output growth for the 1964-2019 period, confirming that spatial misallocation has indeed improved in the recent years.

(JEL R12, R14, R23)

Keywords: Spatial Labor Misallocation; Housing Costs; Land Use Regulations.

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1. Introduction

The misallocation of scarce resources has long been recognized as a crucial factor hindering the maximization of the aggregate output of an economy, as well as the profitability of a firm, in the various fields of economics, and the spatial misallocation of labor is no exception to this discussion (Caballero et al., 2008; Hopenhayn, 2014; Hsieh and Klenow, 2009). Hsieh and Moretti (2019) document a significant increase in spatial distortion in labor allocation over the 1964-2009 period, attributing the growth of misallocation to housing constraints in cities with high TFP shock. In particular, they find these constraints lowered aggregate US growth by 36 percent from 1964 to 2009.

Our research is motivated by the work of Hsieh and Moretti (2019), and utilizes their mechanism on how increased distortion in labor allocation ultimately lowers the aggregate output of the US. In larger cities, such as New York City, San Francisco, and San Jose, firms are more productive because those cities promote interactions that increase productivity and foster competition, forcing firms to be more productive (Combes et al., 2010). However, spatial misallocation arises when the number of workers who can access such highly productive cities decline due to unaffordable housing costs. Indeed, in combination with stricter regulation, the decreased elasticity of housing supply resulting from property-right changes has significantly increased the housing prices of those large and productive cities in the US over the past few decades.[1] The labor misallocation caused by high housing costs are reported to be sufficient enough to reduce the aggregate output in the US from 1964 to 2009 (Hsieh and Moretti, 2019).

[1] While those cities were lightly regulated until the late 1960s, since the large reassignment of property rights in the 1970s from landowners to wider communities, the supply of new buildings has significantly decreased due to the growing power of anti-growth political movement and environmentalism (Glaeser and Gyourko, 2018).

Our paper extends the timeframe of Hsieh and Moretti (2019) to examine recent changes in the allocation of labor and evaluate the consistency of the mechanism. This extension is specifically motivated by the possible relaxation of urban regulations in large cities over the last 10 years. As illustrated in Figure 1, which depicts the kernel density estimation result of the Wharton Land Use Regulation Index (WRLURI), the right tail of the WRLURI in 2018 has significantly contracted, and the distribution is more concentrated around the median, compared to the 2008 WRLURI distribution. This change suggests that the spatial misallocation may have been alleviated over the 10 years.

From the kernel density estimation of housing cost and employment, we find that the housing cost of high-productivity cities has constantly increased from 1964 to 2019 (see Figure 2). The employment misallocation, on the other hand, worsened from 1964 to 2009 but has improved from 2009 to 2019 (see Figure 3). Since the housing cost is determined by both the demand and supply of the housing market, the increased housing cost between 1964 and 2009 can be explained by the stringent land use regulation that reduced the housing supply over the period. However, the increased housing cost from 2009 to 2019 can only be explained by the increased housing demand, because the regulation stringency reduced from 2009 to 2019, increasing the housing supply. This implies that the housing cost increase from 2009 to 2019 is due to the reduced labor misallocation which enabled the increase in housing demand to fully reflect the productivity growth, despite the increase in housing supply.

Motivated by the kernel density estimation results, the study conducts counterfactual analyses to understand the impact of housing cost on the aggregate output growth. Specifically, we take a critical stance on Hsieh and Moretti's (2019) estimation process: their estimation procedure is too simplified, since they do not consider the feedback loop by the adjusted wage on the resulting labor share changes. As a result, their equilibrium does not equalize the utility level of individuals across different cities.

Thus, in our counterfactual exercise, we continuously adjust the labor share distribution across cities until the utility level of every individual across different location becomes the same.[2] Using the labor share and wage found at the fixed point, we calculate the counterfactual output and compare this with the actual output in 2009. We find that the aggregate output growth would have been 15.6 percentage points greater than the actual realized output growth over the 1964-2009 period, if the housing costs had been fixed at the 1964 level. This indicates that the estimated effect of Hsieh and Moretti (2009), which is reported to be 103.5 percentage points, significantly overstates the actual counterfactual outcomes.

Moreover, we confirm that the problem caused by spatial misallocation has been indeed alleviated by the recent relaxation of land use regulation in large and high productivity cities. Our findings show that the aggregate output growth would have been 7.7 percentage points greater than the actual realized output growth over the 1964-2019 period if the housing cost distribution had been held constant at the 1964 level. This percentage difference is smaller in magnitude than the percentage difference in output growth over the 1964-2009 period holding the house prices at the 1964 level (i.e., 15.6 percentage points), implying there has been less distortion in the spatial allocation of labor.

We further confirm this finding by fixing the housing cost distribution at the 2009 level and comparing the counterfactual output growth for the 1964-2019 period to the actual growth. The results indicate that the aggregate output growth over the period would have been 13.9

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[2] Further detail of this process is summarized in appendix A.

percentage points smaller if the housing cost distribution had been fixed at the 2009 level. Thus, the recent relaxation of land use regulations in large cities has mitigated the spatial misallocation problem caused by high housing costs.

The rest of the paper proceeds as follows. Section 2 discusses the model and estimation process. Section 3 presents data. Section 4 discusses kernel density estimation and decomposed aggregate output growth results. Section 5 concludes.

2. Model and Estimation Process

This section revisits Hsieh and Moretti's (2019) model framework to understand the mechanism through which the spatial misallocation of labor affects the aggregate output and the estimation process to calculate the aggregate output.

2.1. Model

This paper uses the Rosen-Roback spatial equilibrium model to calculate the GDP of the country as an aggregate output of all cities. To find equilibrium, this paper considers each city as a firm that maximizes profit, and workers as perfectly mobile with a homogeneous taste that moves across cities to maximize their utility. Each worker freely moves to a city with a higher wage, higher amenities, and lower housing prices until the equilibrium is reached.

(1) $Y_i = A_i L_i^{\alpha} K_i^{\eta} T_i^{1-\alpha-\eta}$

In this production function, A_i is productivity, L_i is employment, K_i is capital and T_i is land available for business use, where subscript i represents each city. $\alpha,$ and η are production function elasticities that are the same across the cities. In this equation, T_i, K_i, T_i, α, and η are all exogenously given. Using the first-order condition for both labor and capital, equate the marginal product of labor and capital to nominal wage, and rent respectively. Solve the wage, W_i, equation for K_i, and plug K_i into the capital rent, R, equation, then solve this equation for L_i to get labor demand, equation (2).

$$(2) \quad L_i = \left(\frac{\alpha^{1-\eta}\eta^{\eta}}{R^{\eta}} \cdot \frac{A_i}{W_i^{1-\eta}}\right)^{\frac{1}{1-\alpha-\eta}} \cdot T_i$$

Equation (2) shows that labor demand is increasing in A_i, and T_i, but decreasing in W_i. Also, it is important to note that this paper will refer to $A_i^{\frac{1}{1-\alpha-\eta}} \cdot T_i$ as a local TFP throughout the paper.

$$(3)\ V = \frac{W_i Z_i}{P_i^{\beta}}$$

To derive the labor supply, this paper uses the indirect utility function of workers that is given in equation (3). In equation (3), β is the expenditure share on housing, Z_i is the amenity, and P_i is the housing price, which can be written as equation (4).

$$(4)\ P_i = \bar{P}_i L_i^{\gamma_i}$$

In equation (4), P_i is explained by two parts, $\bar{P}_i$, the part of local housing price that is exogeneous of employment, and $L_i^{\gamma_i}$, where γ_i is the inverse elasticity of housing supply with respect to the number of employees in the city. Since the scarce land availability and the stringent regulations cause the housing supply to be inelastic, the impact of change in the L_i on P_i is larger in the city where the housing regulations are more stringent (γ_i is large).[3] Substitute P_i in equation (3) with equation (4), then solve for W_i to get equation (5).

$$(5)\ W_i = V \cdot \frac{\bar{P}_i^{\beta} L_i^{\beta\gamma_i}}{Z_i}$$

Equation (5) is the labor supply equation solved for W_i. This equation shows that the nominal wage is increasing with the city's employment and decreasing with the amenity. It also means that when the level of employment and amenities are the same in different cities, the nominal wage is lower in the city with a more elastic housing supply (γ_i is small) because the wage compensates for the housing price of the city. Solving equa tion (5) for L_i, and equating it with labor demand from equation (2), equilibrium employ ment from equation (6) is derived.

$$(6)\ L_i = \left(\frac{\alpha^{1-\eta}\eta^{\eta}}{R^{\eta}V^{1-\eta}} \cdot A_i T_i^{1-\alpha-\eta} \cdot \left(\frac{Z_i}{\bar{P}_i^{\beta}} \right)^{1-\eta} \right)^{\frac{1}{1-\alpha-\eta+\beta\gamma_i(1-\eta)}}$$

In this equilibrium employment, in equation (6), excluding all the variables that are given exogenously, the local employment is increasing with the productivity, and the amenity of the city. Moreover, γ_i in the power increases the local employment when the housing supply elasticity is higher in that city. This implies that the cities with fewer housing restrictions have higher employment.

To find the aggregate output, equate the aggregate labor demand with the aggregate labor supply normalized to 1. Normalizing labor supply to 1 allows this paper to look at the effect of v

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[3] See Glaeser et al. (2006); Glaeser and Ward (2009); and Saiz (2010).

ariables as a proportion of aggregate output, which is useful when the labor supply grows over time. Since the labor share α of output from city i is paid as a wage, $\alpha Y_i = W_i \cdot L_i$. Solving for the sum of Y_i for all i, the aggregate output, equation (7) is derived.

$$(7)\ Y = \left(\frac{\eta}{R}\right)^{\frac{\eta}{1-\eta}} \left[\sum_i \left(A_i^{\frac{1}{1-\alpha-\eta}} \cdot \left[\frac{\bar{Q}}{Q_i}\right]^{\frac{1-\eta}{1-\alpha-\eta}} \right) \cdot T_i \right]^{\frac{1-\alpha-\eta}{1-\eta}}$$

In this equation, $Q_i \equiv {P_i^{\beta}}/{Z_i}$, and $\bar{Q} \equiv \sum_i L_i Q_i$, where Q_i is the local price, and $\bar{Q}$ is the employment weighted average of local price, Q_i, across the cities. Therefore, ${\bar{Q}}/{Q_i}$ can be interpreted as an inverse dispersion of local price, and, since ${1-\eta}/{1-\alpha-\eta} > 1$, the aggregate output decreases with the size of dispersion in local price. Notably, the large labor share of the city can amplify the degree of decrease in aggregate output, because the city with more employment is weighted heavily.

3. Data

This paper utilizes panel data of county level employment, wage, demographic, education, rent in 1964, 2009 and 2019. County level data is aggregated by Metropolitan Statistical Area (MSA) level as employment weighted average. The 1999 crosswalk defined by Population Division of US Census Bureau is used to match each county with MSA. Excluding all counties with unavailable education attainment and aggregating each county by MSA, there are 274 MSAs in 1964, 2009, and 2019.[4]

Demographic data is categorized by age, sex, and race, where age is the mean of the age distribution, and race classified as white or non-white. Education attainment is categorized by high school drop out if less than high school diploma is attained, high school graduates if high school diploma or GED is attained, some college if some college education is attained but did not get a college degree, and college or more if college degree or higher education is attained. Rent is a median of the aggregate monthly rent.

All employment and wage data are from County Business Patterns (CBP), however, to increase the sample size and reduce the measurement error, this paper combines 1964 with 1965, and 2008 with 2009 CBP for 1964 and 2009 employment and wage data, per Hsieh and Moretti in 2019. 1964 demographic data is from 1960 Census of Population, but 1964 education, rent data is from 1970 Census of Population. Different year's data is used for 1964 data due to the availability of data that contains all counties as a sample size. 2009 demographic, education, and rent are from 2007 - 2011 5-year American Community Survey (ACS), and 2019 demographic, education, and rent are from 2016 - 2020 5-year ACS.

The time frame of the research is selected as 1964, 2009, and 2019 because 1964 is the earliest available data of County Business Patterns (CBP), which provides the aggregate number of employment and aggregate payroll of each county. 2019 is the latest year unaffected by COVID-19 with available demographic, and education attainment data. The availability of demographic and education data is important because aggregate employment and wage data from CBP does not

[4] Dropped MSA 380 and 3320, in which the 1964 data was unavailable.

include the difference in workers' education level across counties, which affects the wage level (Krueger 1993). Therefore, demographic and education data can augment the limitations of CBP.

To find the city-specific average wage conditional on worker characteristics, this paper runs a regression of log wage on the individual worker's age, sex, race, and education attainment using the 1964, 2009, and 2019 Current Population Survey (CPS). By subtracting the sum product of the coefficient and the corresponding variable from the log wage in each MSA using the main data, this paper finds the average residual wage, which eliminates the difference in the average wage caused by the composition of workers' characteristics (Hsieh, Jones, and Klenow, 2019).

We also use land use regulations and housing supply elasticity data to find the relationship between housing constraints and housing prices. We utilize the Wharton Land Use Regulation Index from Gyourko et al. (2008) and local housing supply elasticity data from Saiz (2010) for each data.

4. Results

In this section, the paper utilizes kernel density estimation to illustrate the distribution of land use regulation, housing costs, and labor forces across geography. By doing so, we aim to gain insight into how labor resources are spatially misallocated, and how the misallocation has changed over time.

4.1. Kernel Density Estimation

4.1.1. Land Use Regulation

We begin by documenting changes in the extent to which land use is regulated in each city.

The WRLURI is displayed in Figure 1, indicating that the distribution of WRLURI narrowed in 2018 compared to 2008. Since strict land use regulation were pointed as the primary reason for higher housing costs hindering the efficient inflow of labors to highly productive areas (Hsieh and Moretti, 2019), the decrease in dispersion of WRLURI suggests a potential improvement in labor misallocation over the last decade.

4.1.2. Housing Costs

Figure 2 shows the distribution of housing prices in 1964, 2009, and 2019. To draw this figure, we calculate the logarithm of employment-weighted average of 1-year median rent. Most notably, we can observe consistent increase in the housing costs in the in the right tail. The expansion of right tale may reflect either the supply side factor, i.e., decreases in housing supply due to stricter land use regulation, or the demand side factor, i.e., excessive inflow of labors due to the TFP and amenity value growth, as suggested in Equation (4). Considering the substantial increase in land use regulation between 1964 and 2009 (Glaeser and Gyourko, 2018), the shift in the distribution of housing costs during this period can be attributed to factors on the supply side. On the other hand, since we observe the relaxation of land use regulation from 2008 to 2018, it is more likely that the housing cost change in the 2009-2019 period is driven by the demand side factor.

4.1.3. Employment

Lastly, and most importantly, figure 2 depicts the distributions of demeaned log employment across cities in 1964, 2009, and 2019 to visualize the spatial allocation of labor. From 1964 to 2009, dispersion has significantly shrunk as in the original Hsieh and Moretti (2019) paper. However, interestingly the dispersion has increased again from 2009 to 2019. In particular, the considerable length of the left tail from 1964 disappeared in 2009, but in 2019, some of the left tail has re-appeared. Also, the right tail shrunk minimally from 1964 to 2009 and has not shrunk anymore.

The change in the shape of the distribution suggests that there has been a significant spatial misallocation of labor from 1964 to 2009, while some mitigation is observed from 2009 to 2019. All else being equal, individuals move to cities with higher productivity that offer greater wages to maximize their utility. However, the choice of migration is also influenced by housing costs. If housing costs are prohibitively high in those cities, people may choose not to relocate, as observed over the 1964-2009 period. In contrast to the change from 1964 to 2009, the movement of labor over the 2009-2019 period indicates that the relative attractiveness of high productivity cities, characterized by wages and housing costs, is greater than that of low productivity cities, which, in turn, alleviates the spatial misallocation of labor.

5. Counterfactual Analyses

The kernel density estimation of land use regulation, housing costs, and employments suggests that the potential that the spatial misallocation has been mitigated over the recent period. Motivated by these results, this section reports the counterfactual analyses to study the net impact of unaffordable housing costs on the aggregate output.

Specifically, to compare the counterfactual output in 2009 to the actual 2009 output level, we fix the housing price distribution at the 1964 level and adjust the labor share distribution across cities until the utility level of every individual across different location equalizes.[5] Using the labor share and wage found at the fixed point, we calculate the counterfactual output and compare this with the actual output at 2009. We implement the same procedure to calculate the counterfactual output level in 2019, with the housing price distribution fixed at the 1964 and 2009 level.

5.1. Critics of Hsieh and Moretti's (2019) Estimation Procedure

Before showing the results, we first review Hsieh and Moretti's (2019) estimation procedure.[6] Although the authors describe that they obtain the general equilibrium of spatial equilibrium model, their counterfactual analyses actually do not equalize the utility level of individuals across different locations. Rather, their estimation procedure is simple: the code replaces the distribution of housing costs (i.e., P_i) in Equation (6) and obtain the new labor share distribution (i.e., L_i). Then, they plug the new L_i into Equation (5) to get the new, counterfactual wage distribution (i.e., W_i). Using these counterfactual L_i and W_i, combined with other fixed values including TFP_i, Z_i, and P_i distributions, they obtain the counterfactual aggregate output.

However, a severe problem arises from the fact that the equilibrium labor equation in Equation (6) is a function of utility, V, which, in turn, depends on the wage, W_i. Thus, not only does the adjustment of labor share affect the wage distribution, but also the change in wage distribution influences the spatial distribution of labor share. Due to this feedback loop between labor share and wage distributions, we must continuously adjust the labor share until we reach the fixed point, in which the distribution of labor makes the utility of all the individuals the same across different cities. In this regard, their counterfactual exercise is merely the implementation of

[5] Further detail of this process is summarized in appendix A.

[6] The replication code of Hsieh and Moretti (2019) is posted in the following link: https://www.aeaweb.org/articles?id=10.1257/mac.20170388.

one iteration of the fixed-point algorithm.

5.2. Aggregate Output Growth in 2009 Fixing Housing Costs at the 1964 Level

Holding the housing cost distribution fixed at the 1964 level, we reach to the counterfactual spatial equilibrium after 94 iterations. The finding in Table 1 indicates that the aggregate output growth would have been 15.6 percentage points greater than the actual realized output growth over the 1964-2009 period if the housing costs remained at the 1964 level. This result is surprising, given that the estimated outcome of Hsieh and Moretti (2009)'s spatial equilibrium overstates the actual counterfactual outcomes by 6.63 times, reported to be 103.5 percentage points in their paper. In other words, the continuous adjustment between the labor share and the wage level leads to the long-run stable equilibrium, significantly lowering the initial overshooting in labor and wage distributions.

5.3. Aggregate Output Growth in 2019 Fixing Housing Costs at the 1964 and 2009 Levels

We repeat the same exercise in Section 5.2 to calculate the counterfactual aggregate output in 2019, with the housing cost distribution fixed at the 1964 level. The findings show that the aggregate output growth would have been 7.7 percentage points greater than the actual realized output growth over the 1964-2019 period if the housing cost distribution were held constant at the 1964 level. The smaller magnitude of the 2019 counterfactual result, compared to the 2009 result (15.6 percentage points), aligns with our narrative that spatial misallocation has been mitigated in the recent 10 years.

To further validate our argument, we fix the housing cost distribution at the 2009 level and compare the counterfactual output growth for the 1964-2019 period to the actual growth for the same period. The results indicate that the aggregate output growth over the period would have been 13.9 percentage points smaller if the housing cost distribution were fixed at the 2009 level. In summary, our findings suggest that the relaxation of land use regulations in large and highly productive cities in the recent period has alleviated the spatial misallocation problem caused by high housing costs.

6. Conclusion

The benefits of land use regulation are already well known, however, the study on the cost of the regulation is not yet widely known. This paper finds that housing constraints cause labor misallocation across cities, which is costly to aggregate growth in the US. This paper uses kernel density estimation to observe how housing price and employment has responded to stricter regulation between 1964 and 2009 and more relaxed regulations between 2009 and 2019. The result shows that between 1964 and 2009, labor dispersion decreased across cities with stricter regulation, leading to increased labor misallocation, which absorbed the housing demand growth from the productivity shock in the city. During the same period, housing prices increased due to the reduced supply from the constrained housing market. From 2009 to 2019, the housing supply increased, but decreased labor misallocation due to the relaxed regulation increased the housing demand growth which led to increased demand growth, and housing prices still increased.

This paper also found the cost of labor misallocation on aggregate output through comparing the counter factual aggregate output growth and the actual aggregate output growth using the general equilibrium estimation process. The result shows that aggregate output growth would have been 7.7 percentage points greater than the actual output growth from 1964 to 2019, and 15.6 percentage points greater between 1964 and 2009 period if the housing cost was held at the 1964 level. This result reflects the relaxation in the regulation between 2009 and 2019. In addition, this paper also finds that the aggregate output growth between 1964 and 2019 would have been 13.9% lower if the housing cost was held at 2009 level. This proves our argument that labor misallocation caused by the housing constraint reduces the aggregate output.

Appendix A: Counterfactual Estimation Procedure

We utilize a general equilibrium estimation process to calculate the net effect of changing the housing price, and amenities, changing the cities' aggregate output at the spatial equilibrium of Rosen-Roback model. We regard the following variables and parameters as given: local TFP, $A_i^{\frac{1}{1-\alpha-\eta}} \cdot T_i$, local housing price exogeneous of employment, $\bar{P}_i$, local amenities, Z_i, and inverse elasticity of housing supply, γ_i, and production function elasticities α, and η from and expenditure share on housing, β.[7]

To find general equilibrium, we first calculate the labor share distribution, L_i by plugging the counterfactual local housing price, $\bar{P}_i$, into Equation (8):

$$(8)\ L_i = \left(\frac{\alpha^{1-\eta}\eta^{\eta}}{R^{\eta} V^{1-\eta}} \cdot A_i T_i^{1-\alpha-\eta} \cdot \left(\frac{Z_i}{\bar{P}_i^{\beta}} \right)^{1-\eta} \right)^{\frac{1}{1-\alpha-\eta+\beta\gamma_i(1-\eta)}}$$

Then, we calculate the wage from Equation (9):

$$(9)\ W_i^1 = \left[\frac{1}{L_i^1} \cdot \left(\frac{\alpha^{1-\eta}\eta^{\eta}}{R^{\eta}} \right)^{\frac{1}{1-\alpha-\eta}} \cdot A_i^{\frac{1}{1-\alpha-\eta}} \cdot T_i \right]^{\frac{1-\alpha-\eta}{1-\eta}}.$$

Using the calculated wage from Equation (8), and all the variables and parameters assumed above to be fixed, we find indirect utility function, V_i^1 across cities given by Equation (10) and the average utility, $\bar{V}^1$.

[7] We use the following parameter values: $\alpha = 0.65$, $\eta = 0.25$ (Piketty et al., 2014; Karabarbounis and Neiman, 2014), $\beta = 0.32$ (Albouy, 2008).

$$(10) \qquad V_i = \frac{W_i Z_i}{P_i^{\beta}}$$

If the initial calculation of utility in city i, V_i^1, is higher than the average utility, $\bar{V}^1$, workers will relocate to city i, lowering the wage in city *i*. On the other hand, if V_i^1 is lower than $\bar{V}^1$, workers will leave the city i, which will increase the wage level of the city. Either case, as long as $V_i^1 \neq \bar{V}^1$, the employment adjusts to $L_i^2 = L_i^1 \cdot \frac{V_i^1}{\bar{V}^1}$. Note that L_i^2 is normalized to a proportion of total employment as it eliminates the impact of total employment growth on comparing the aggregate output growth over time. Using the normalized $L_i^2,$ repeat the series of calculation until $V_i^n = \bar{V}^n$ for all *i*'s. Therefore, L_i^n reaches at the spatial equilibrium.

Finally, at the equilibrium, we can calculate the aggregate output, using Equation (10).

$$(11) \qquad Y = \sum_{i=1}^{N} Y_i = \sum_{i=1}^{N} \frac{W_i L_i}{\alpha}$$

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Figure 1: Change in Wharton Land Use Regulation Index (WRLURI)

This figure draws the spatial distribution of WRLURI in 2008 and 2018.

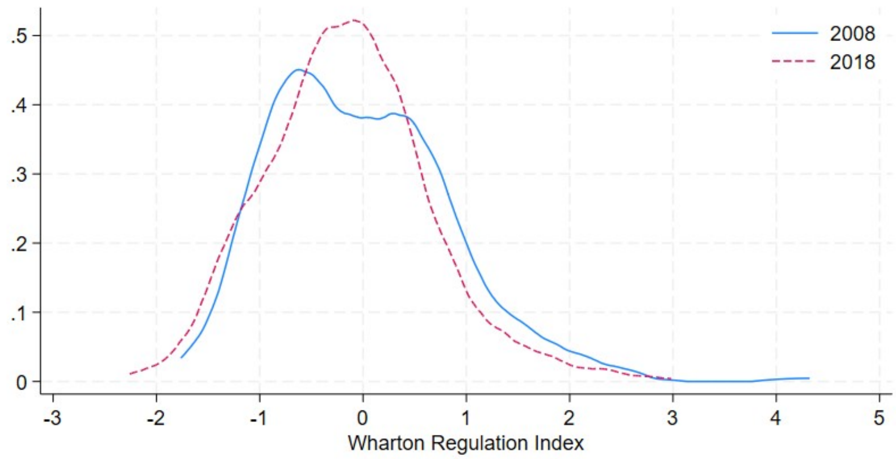

Figure 2: Spatial Distribution of Employment

This figure draws the spatial distribution of (log) employment in 1964, 2009, and 2019.

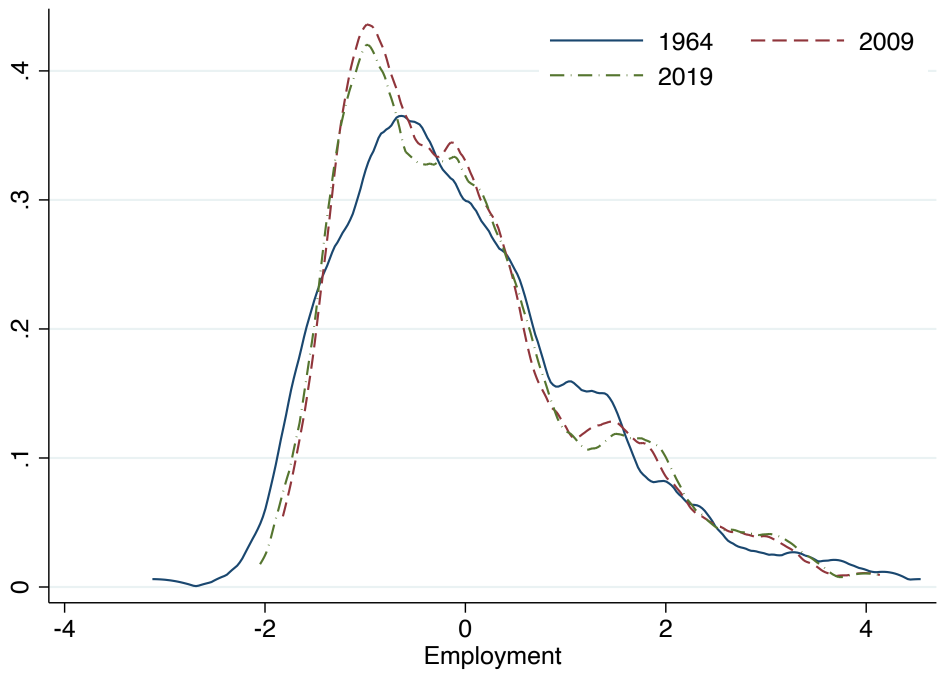

Figure 3: Spatial Distribution of Housing Costs

This figure draws the spatial distribution of (log) housing costs in 1964, 2009, and 2019.

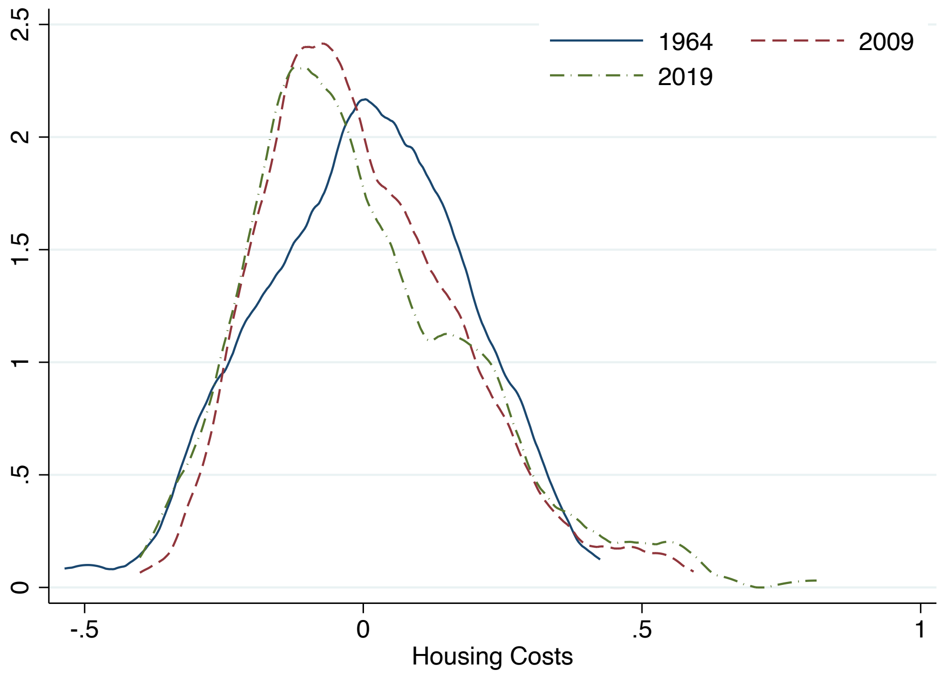

Figure 3: Change in Wages

This figure draws the spatial distribution of (log) wage in 1964, 2009, and 2009.

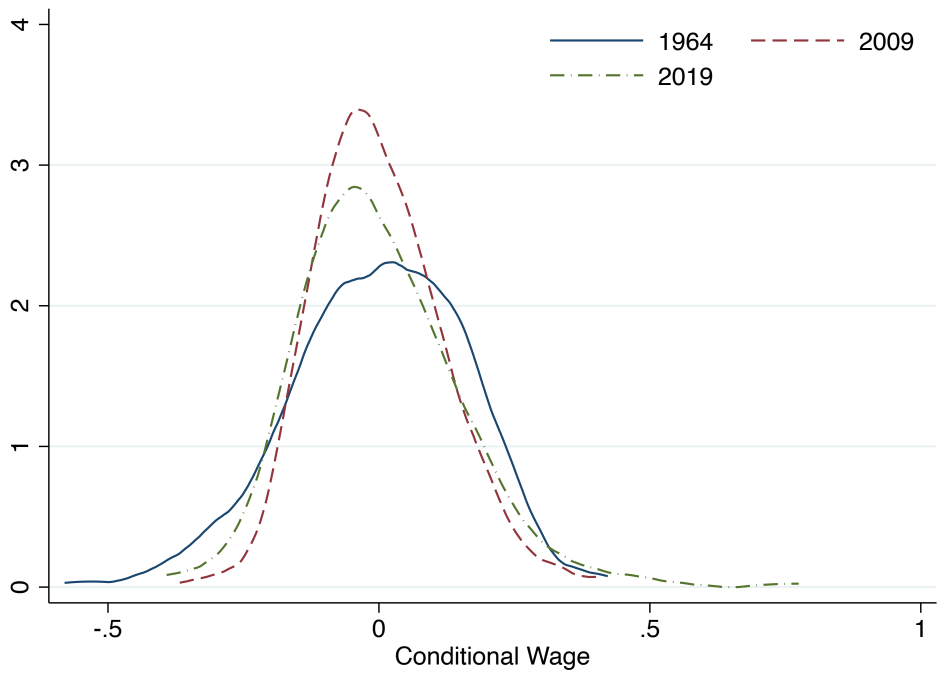

Table 1: Output Growth Difference between Counterfactual and Actual
This table shows the difference between counterfactual aggregate output growth and the actual aggregate output growth.

Percentage Difference from the Actual Output Growth	(1) Holding Housing Cost at the 1964 Level	(2) Holding Housing Cost at the 2009 Level
1964-2009	15.6	-
1964-2019	7.7	-13.9