Spatial Inequality, Geographical Specialization and Structural Change

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February 28, 2025

Abstract

This paper documents three facts about spatial income inequality across US local labor markets since 1950. First, the contribution of between-market to aggregate US inequality follows a U-shape over time: The share of total inequality accounted for by between-market inequality was high in the 1950s (16%), low between 1970-80 (6%) and is peaking today (18%). Second, the U-shape is accompanied by a change in the income ranking of markets - a reversal of fortunes. Third, a systematic relationship exists between markets' relative income path and their initial industrial specialization. I rationalize these findings in a two-state, two-sector model of structural change with non-homothetic preferences. Structural change affects markets heterogeneously based on their industrial specialization and generates a time-varying spatial composition of total inequality.

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1 Introduction

Until the 1980s, labor markets in the US provided clear evidence of convergence with per capita incomes growing faster in poorer markets. Since then, however, the process reversed and incomes across markets have become increasingly dissimilar. The spatial dispersion of incomes thus depicts a U-shape over time: between-labor market inequality was high in the 1950s, declined up until 1980 and is peaking today (Figure 1).

From a policy perspective, understanding how this U-shape emerges is important as income disparities create social tensions and many policies are explicitly designed to reduce spatial inequality.[1] From a theoretical perspective, it further poses a puzzle: Classical growth theories (e.g. Solow (1956) and Barro and Sala-i-Martin (1992)) generally predict monotone convergence across regions with different income levels that contradicts the divergence since 1990. More recent studies point at sorting differences between highly-skilled metropolitan areas and the rest of the US to explain the divergence but do not rationalize the convergence until 1990 (e.g. Eckert (2019) and Lhuillier (2023)). A unifying mechanism leading to both con- and divergence over time is yet to be discussed.

In this paper, I therefore ask two main questions: What drives the U-shaped dispersion of incomes across US labor markets and how much does it matter for total inequality over time? Answering these questions I provide two main contributions. First, I document novel empirical evidence on spatial inequality and geographical specialization using micro and macro data across US labor markets. Each local labor market thereby corresponds to on of 741 mutually exclusive and exhaustive commuting zones defined by Dorn (2009). Second, I develop a multi-state, multi-sector model with non-homothetic preferences and structural change that rationalizes these facts.

In short, I show that - under certain circumstances - structural change from manufacturing to services-based industries gives rise to both con- and divergence of markets. The process is accompanied by a change in the income ranking of markets creating winner and loser markets. It further affects aggregate inequality through a within- and between market channel by a varying degree depending on the time. As a result, optimal re-distributive policies aimed at counterbalancing effects of structural change need to accommodate for a time-varying composition of total inequality.

To start, I document that the U-shaped income dispersion across markets since 1950 comes with a change in the income ranking of states over time - a reversal of fortunes. Specifically, one can divide US labor markets into three groups with rising, constant and declining relative incomes.

Then, I provide evidence that relative income of labor markets over time is directly

[1] A large set of policies in multiple countries is explicitly designed with the aim of closing spatial gaps. Examples of this are the European Union's regional policy or the "levelling up" policy in the UK.

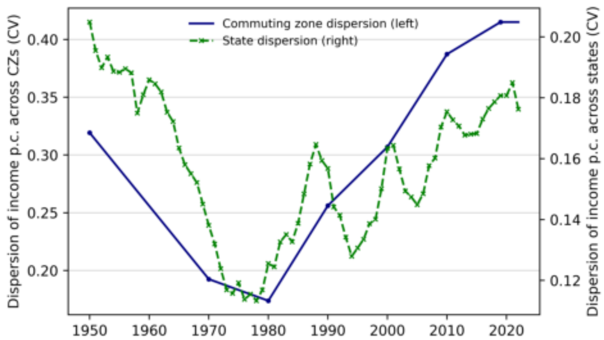


Figure 1: Dispersion of income p.c. across US labor markets

Notes: Figure 1 shows the dispersion of per capita incomes across US labor markets, both at the state level and more granular commuting zones. The dispersion is measured by the coefficient of variation (CV) computed as the ratio between the standard deviation σ_t and the mean μ_t at time t: $CV_t = \frac{\sigma_t}{\mu_t}$.

linked to initial specialization in certain industries.[2] While markets that specialize in manufacturing-based (services-based) industries have relatively high (low) income in the 1970s, they have relatively low (high) income today. The industrial specialization of markets is highly persistent over time and can be well predicted by their initial 1950 specialization. In fact, the relative specialization of markets appears to be increasing over time. If a market in 1950 had a relatively high employment share in, for example, car production (or manufacturing in general), in 2020 this market is likely to have an even higher relative employment share in that sector. This does not imply that manufacturing employment in that market has increased over time. Instead, it implies that the manufacturing share in that market has decreased by less than the manufacturing share in the whole economy - hence the relative specialization has risen.

I further use the initial specialization of markets to assess the heterogeneous impact of structural change across the US. As on aggregate the economy moves from manufacturing-based to services-based production, at the local labor market level this transition implies winners and losers depending on markets' industrial specialization: Using county-level industry data, I estimate that a 1% percent higher specialization in services-based industries in 1950 is associated with a 8ppt higher growth of relative labor market per capita income since 1950. Given the initial 1950 industrial specialization of a labor market one can thus predict its evolution of relative income until today. Moreover, given the persistent industrial specialization of labor markets, structural change in the US can be seen as happening mostly across rather than within markets. Specifically, the as on aggregate the economy moves from manufacturing-based to services-based production, it shifts production across markets that have a relative advantage in producing the goods (and services) in demand

[2] A market's specialization is defined by its revealed comparative advantage (RCA) which measures the share of employment (or value added) in an industry in the market relative to the country's share of employment in that industry.

at every point in time. The majority of local labor markets themselves, however, maintain their initial specialization.

Next, I use individual-level data to estimate the relevance of spatial income dispersion for aggregate US inequality over time. Using decennial Census data and cross-sectional Consumer Population Survey (CPS-ASEC) micro-data I document a U-shaped relevance of between-market income inequality for total inequality over time. A between-/ within market decomposition shows that the between-share accounts for 16% of total inequality in the 1950, about 6% in 1980 and 18% today. The time-varying spatial composition of total inequality highlights the importance of understanding the spatial impacts of structural change over time.

Finally, I construct a multi-state, multi-sector model of structural change with non-homothetic preferences to combine the spatial impact of structural change and its effect on total inequality through a within- and between market channel. The baseline model focuses on the transition from manufacturing to services-based production and consists of two main features. First, markets are equipped with heterogeneous comparative advantages that leads them to specialize into different industries. Second, non-homothetic preferences in line with Boppart (2014) imply that richer households consume more services as a share of their expenditure. They drive structural change and move consumption from manufactured to services-based industries as income increases. Together these two features give rise to a U-shaped dispersion of labor market incomes. The intuition goes as follows: Initially, aggregate income is low and non-homothetic preferences imply that the main share of demand goes towards sector 1 (e.g. manufacturing). Therefore, the region specialized in producing manufactured goods has relatively higher income - between regional inequality is high. As aggregate income increases over time, demand shifts towards the other good (e.g. services) and the region specialized in services relatively gains income: between-regional inequality declines. As aggregate income further increases, the services-market overtakes the manufacturing market and between inequality rises again. As a result, the income ranking of labor markets changes over time and total inequality has a time-varying within- and between market composition. I then use the model to decompose aggregate income inequality in the US into the between- and within market impacts of structural change over time. In the next steps of the paper, I intend to endogenize the industrial specialization of labor markets. This model will have two goals. First, to run a counterfactual exercise and analyse how total inequality had evolved if labor markets could change their industrial specialization. And second, to assess the effectiveness of common policies aimed at reducing income inequality. I provide further detail on these next steps in 4.

Related literature. I contribute to two strands of literature. The first one is the convergence and structural change literature (see, e.g. Barro and Sala-i-Martin (1992), Eichengreen et al. (1992), Acemoglu, Aghion, and Zilibotti (2006), Boppart (2014), Ding et al. (2022), Comin, Lashkari, and Mestieri (2021), and Herrendorf, Rogerson, and Valentinyi (2013)) with its recent advances in spatial economics. Most structural change studies seek to explain the process at the aggregate level (see, e.g. Allen and Arkolakis (2014), S. J. Redding and Rossi-Hansberg (2017), and Autor, Dorn, et al. (2020)). More recently, research has focused on regional implications, for example in terms of trade liberalization (Caliendo, Dvorkin, and Parro (2019) and Fajgelbaum and S. Redding (2022)) or misallocation (Fajgelbaum, Morales, et al., 2019; Ganong and Shoag, 2017), employment (Autor, Patterson, and Van Reenen, 2023; Bilal, 2023), innovation (Desmet and Rossi-Hansberg, 2014) and start-up location (Walsh, 2023). However, the link between heterogeneous impacts of structural change, convergence and income inequality has been much less discussed.

A notable exception is the work by Eckert and Peters (2022) who study the relationship between local economic development and aggregate structural change for the US between between 1880-1920. They show that regional convergence during the rise of the manufacturing sector in the US depends on both the regional sectoral specialization and the technological catch-up of rural areas. While my paper is closely linked to their findings, it differs in three key aspects. First, I consider a different time period (1970-today) and a different type of structural change: the structural change I consider relates to the move from manufactured-based industries to business services-based industries. Second, while they focus on the catch-up of regions in terms of industrialization, I focus on the implications of aggregate income inequality using individual-level income data. Third, I use aggregate production data to compute the specialization of states empirically.

The second strand of literature I contribute to is on the drivers of US income inequality. While the literature on inequality is vast, and has not reached full consensus yet (Heathcote, Perri, and Violante, 2010; Heathcote, Perri, Violante, and L. Zhang, 2023), I focus on one area where there is most agreement: individual wages and labor earnings. Both survey ad administrative data estimate a steady rise in wage dispersion that started in the early 1970s (Autor, Katz, and Kearney, 2008; McKinney, Abowd, and Janicki, 2022; Guvenen, Pistaferri, and Violante, 2022; Moffitt and S. Zhang, 2018). I follow these authors in using individual-level data to measure income inequality. I then contribute to their findings by making use of the geographic information available to estimate the between- and within state share of income inequality.

The rest of the paper is structured as follows. Section 2 provides the empirical evidence. Section 3 explains the main model mechanism using a simple, analytical two-state model. Section 4 points out the next steps I intend to take on this project. Finally, Section 5 concludes.

2 Empirical Analysis

I document three novel facts about income inequality in the US since 1950. I begin by showing that the U-shape dispersion of labor market incomes (Figure 1) is accompanied by labor markets moving in the income distribution over time. Specifically, one can group US labor markets by rising, constant and declining relative incomes. Then, I compute the industrial specialization of markets over time and show that the relative income path is directly linked to initial industrial specialization. Finally, I show that the contribution of between-market to overall inequality follows a U-shape over time.

Data. I assemble county-level US data on personal income per capita, employment, GDP across all industries since 1950 from the County Business Patterns (CPB). I further collect data on the firm population from the Business Dynamics Statistics (BDS) since 1978. Since the classification of industries changed from SIC to NAICS in 1998, I use the crosswalk from Eckert, Fort, et al. (2020) to match industries over time.

I further collect individual-level income data from two sources. I use decennial US Census data as a nationally representative sample of individuals. The survey is run every ten years between 1950 and 2010. It covers information on a range of economic, employment, demographics topics including income measures and information on the region of residence. I assign individuals to one of 741 mutually exclusive and exhaustive local labor markets that correspond to commuting zones defined by Dorn (2009). While many papers in the spatial economics literature focus on pre-defined Metropolitan Statistics Areas (MSAs), using commuting zones provides two key advantages. First, a commuting zone is the most precise way of defining a local labor market. In the analysis that follows, the definition of a local labor market is crucial as it implies that agents cannot move across markets free of costs and non-tradable prices are defined locally. In contrast, there is no reason why a local labor market should be bounded by county or even state-level borders. Second, the commuting zones used are mutually exclusively covering all of the US. Instead, MSA only cover the largest economic areas leaving some regions undocumented.

In constructing the baseline sample I follow Heathcote, Perri, Violante, and L. Zhang (2023) by focusing on all individuals aged between 25-60.[3] The baseline variable of interest is total individual pre-tax wage and salary income. Moreover, I deal with top-coded income variables in the same manner as described by Heathcote, Perri, Violante, and L. Zhang (2023). Crucially, however, I run the replacement of top-coded values on state-level rather than US-level income distribution.[4]

I further supplement the Census dataset with the Consumer Population Survey (CPS)

[3]Further studies I follow are Moffitt and S. Zhang (2018) and Heathcote, Perri, and Violante (2010).
[4]A more detailed explanation can be found in Appendix A.

together with its Annual Social and Economic Supplement (ASEC) starting in 2005. The CPS-ASEC is the source of official US government statistics on detailed income and labor force statistics. While the basic unit of observation is a housing unit, the survey does include all relevant information (i.e. demographic, income and labor force details) also on the individual level. I construct the baseline sample in the same way as for the Census data.

Fact 1: The U-shape dispersion of income across labor markets is accompanied by markets moving in the income ranking over time. As shown in Figure 1, the dispersion of per capita incomes by labor market exhibit a U-shape over time with high dispersion in the 1950s and today, and little dispersion between 1970-1980. While the U-shape shows that on aggregate income across labor markets con- and then diverge, the dispersion conceals whether the ranking of labor markets stays constant. For example, it could be that the dispersion shrinks with relatively rich labor markets remaining rich over time. On the other hand, it could be that rich labor markets become poor and poor labor markets become rich where the point of intersection of their relative income paths corresponds to the trough of the U-shape. To assess whether the ranking of markets within the income distribution remains the same or whether the change in dispersion is accompanied by a change in the income ranking, I compute the distance to median income as follows:

$$D_{c,t} = log(Inc_{c,t}) - log(\bar{Inc}_t) \tag{1}$$

where $Inc_{c,t}$ is the per capita income of market c at time t and $\bar{Inc}_t$ is the median income across all markets. The distance $D_{c,t}$ measures the relative income of markets over time as percentage deviation. I choose the median as the measure of comparison so that the distance is not biased by outlier markets that may face exceptional income shocks at any time.

In order to analyse potential changes in relative incomes I then compute the linear trend of the distance over time using the following regression:

$$D_{c,t} = \alpha_c + \beta_c Year_t + \epsilon_{c,t}$$

where a coefficient β_c significantly larger (smaller) than 0 indicates a rising (declining) relative income. Figure 2 shows the trend in distance for three local labor markets that exemplify that evolution of market incomes in the US.[5] While people living in one example labor market in Michigan had on average an income around 30% higher than the median income across labor markets in 1950, today they earn around 15% less than the median. On the other hand, the relative per capita income in labor markets Mississippi has risen

[5]Appendix **??** shows the results for all labor markets.

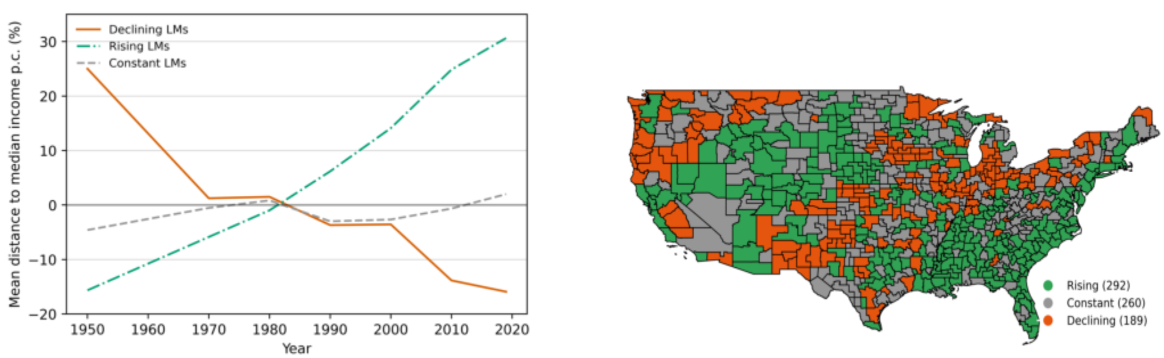
from around -30% to 30% of median income across labor markets today. The local labor market in Wisconsin exhibits a constant evolution of income relative to the US median.

(a) LM in Michigan (b) LM in Wisconsin (c) LM in Mississippi

Figure 2: Distance to median income p.c. over time

Notes: Figure 2 shows the distance of local labor market per capita income to the median per capita income across example commuting zones over time for Michigan, Wisconsin and Mississippi. The black line is the trend (linear fit) of the distance over time.

Finally, I rank states based on their β_c and divide them into three groups equal to one third each. Figure 3a shows the average distance to income over time with the corresponding commuting zones highlighted in 3b.



(a) Relative income over time (b) Labor market income groups

Figure 3: US local labor markets' relative income over time

Notes: Figure 3a shows the the average distance of per capita income to median income for three groups of states created by ranking countries β_c as computed in equation 2. Figure 3b shows the map of corresponding US states. I exclude Alaska, Hawaii, and Puerto Rico.

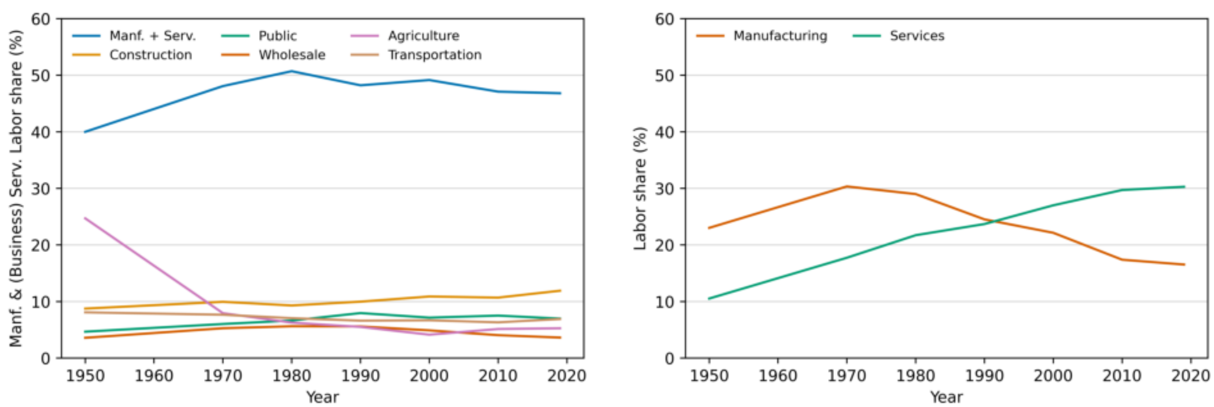
Figure 3 documents that the U-shaped dispersion of incomes across local labor markets is accompanied by a change in the ranking of markets. It is evident that the upper end of the distribution in the 1950s was driven by a group of states that are on the lower end of the distribution today and vice versa. This points out at a large-scale reversal of fortunes across US regions. Appendix A.4 provides further detail on the relationship between relative income of labor markets over time.

Fact 2: Labor markets' relative income over time is linked to their initial industrial specialization. In order to assess what causes the change in relative incomes I investigate the structural characteristics of labor markets in two steps. First, I analyse what industries labor markets specialize in in terms of employment, firms and GDP. Then, I estimate the relationship between labor markets specialization and their future income path.

For this I calculate the revealed comparative advantage (RCA) based on Ricardian trade theory. The RCA is defined as

$$RCA_{i,c,t} = \frac{X_{i,c,t}}{\sum_{i \in I} X_{i,c,t}} / \frac{X_{i,US,t}}{\sum_{i \in I} X_{i,US,t}} \tag{2}$$

where $X_{i,c,t}$ is employment (or GDP) in industry i in market c. The RCA measures the share of employment in one industry in on market relative to the share of employment in the industry in the US. Hence, a RCA larger than 1 indicates a revealed comparative advantage (or equivalently, a specialization) in that industry. In the baseline I calculate the RCA across 893 industries that I aggregate into manufacturing and (business) services. Together, these industries account for approximately 50% of total employment and GDP in the US.[6] The industries are based on the 1990 Census definition of industries that is available and comparable for all years since 1950. Appendix A.2 lists the considered industries.



(a) Employment shares

(b) Manufacturing vs. Services

Figure 4: US labor shares across industries over time

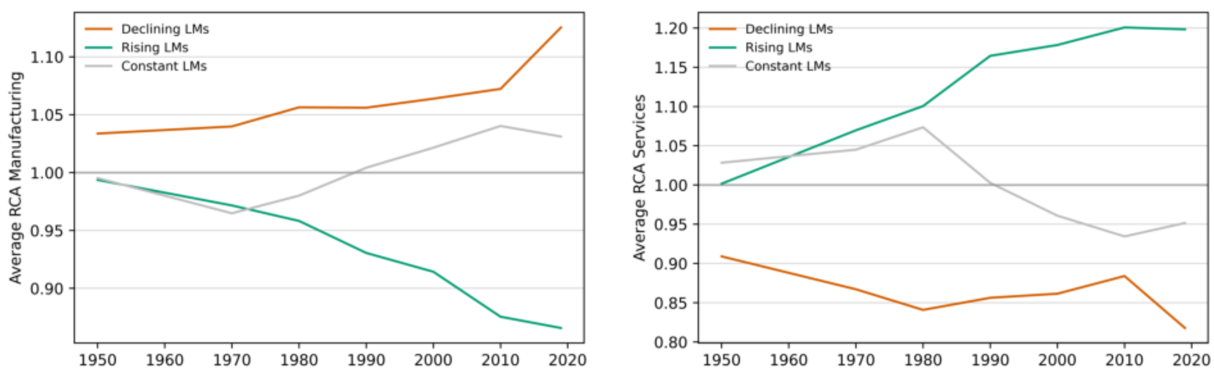
Notes: Figure 4 shows the labor shares across industries in the US over time. Appendix A.2 shows a detail list of industries included.

Figure 4 shows the labor shares across industries in the US over time. While all industries (except for agriculture) shows a relative constant share of labor, the employment

[6] I exclude Agriculture, Mining, Construction, Non-tradable services and Public services.

share in manufacturing and services shows the timing of the structural change. In particular, manufacturing starts declining around 1970 and services employment overtakes manufacturing employment around 1980.

In order to assess differences of RCAs across the income groups defined earlier, I calculate the average specialization of each group over time. Figure 6 shows the industrial specialization across labor markets in manufacturing and services industries over time. The graphs reveals two key findings. First, the three groups are specialized differently in 1950 already. While the group of declining labor markets is relatively specialized in manufacturing industries in 1950, the rising labor market seems to have an advantage in services industries. Second, the RCA increases for groups over time. The rising labor markets show an increasing advantage in services and a rise in their disadvantage in manufacturing. The declining labor markets depict the opposite. This result can be interpreted as a rising relative specialization of labor markets. While this does not imply that the declining labor market have a rise in their manufacturing employment over the time, it does mean that their manufacturing employment falls by less than that of the rising labor markets. Appendix A.5 shows the distirbution of RCAs in 1950 in further detail.



(a) Manufacturing (b) Services

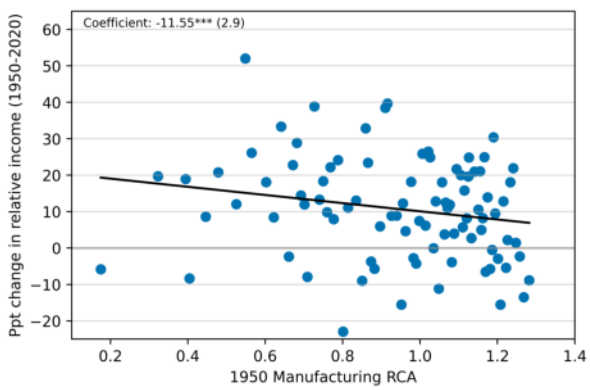
Figure 5: Industrial specialization across states

Notes: Figure 6 shows the industrial specialisation of markets. Specialization is calculated as the maximum RCA as given by equation 2.

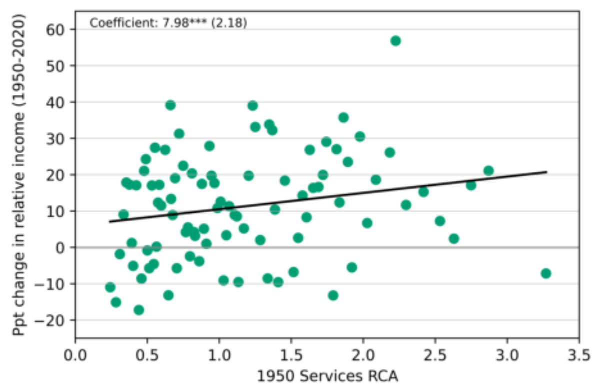
Having documented the evolution of industrial specialization across US labor markets, I now turn to estimating the relevance of industrial specialization for future income path of labor markets. Specifically, I regress the change in relative income of local labor markets on the initial specialization in 1950 as follows:

$$\Delta D_{c,1950-2020} = \alpha + \beta \gamma_{s,1950} + \epsilon_c$$

where $\Delta D_{c,1950-2020}$ is the growth of relative income of labor market c, and $\gamma_{c,1950}$ is the initial 1950 RCA in sector $s \in$ (Manf., Serv.). By using the initial specialization as the regressor, I avoid the typical endogeneity concerns. In particular, high income markets may be more able to attract future growth industries. In fact, I show that that is only partly the case above,. Instead, highly specialized markets only attract future industries in line with their specialization.



(a) Manufacturing



(b) Services

Figure 6: Regression results

Notes: Figure 6 shows the regression results in a scatter plot. The black line is the linear fit. Coefficients are reported in the top right corner.

The graphs shows a significant relationship between initial industrial specialization and future income paths. Two aspects are further interesting. First, this result complements the existing literature on convergence in to ways. First, instead of regressing future income growth on initial income level as usual in the convergence literature, I here provide a more granular analysis: one reason why labor markets in the US have converged (and then diverged again) is the different industrial specialization. Second, I show that in addition to occupational differences across regions as in Autor, Katz, and Kearney (2008) and skill heterogeneity as in Giannone (2017), industrial differences across regions also play a crucial role even when controlling for the other factors (see Appendix A.6).

The second aspect deals with the contemporaneous relationship of industrial specialization and income. In particular, as the specialization of labor markets increases over time, the relationship between relative income and industry becomes stronger. Appendix D shows these results.

While the empirical results so far provide indicative evidence for a link between the industrial specialization of a state and its relative income over time, the results cannot establish causality. In order to pinpoint the mechanism and fix the intuition on how specialization and relative income are related, I provide a model mechanism in the section 3.

Fact 3: The relevance of between-labor market inequality for total inequality is U-shaped over time. Having illustrated the link between incomes per capita at the labor market level and structural change, I now investigate how much between-labor market inequality matters for aggregate US income inequality over time. I show that the between-state share of aggregate inequality also depicts a U-shape accounting for around 16% in 1950s, about 6% between 1970-80 and close to 20% today. Finally, I combine the results with the findings from section 2 to show that structural change affects aggregate US inequality via different channels at different times.

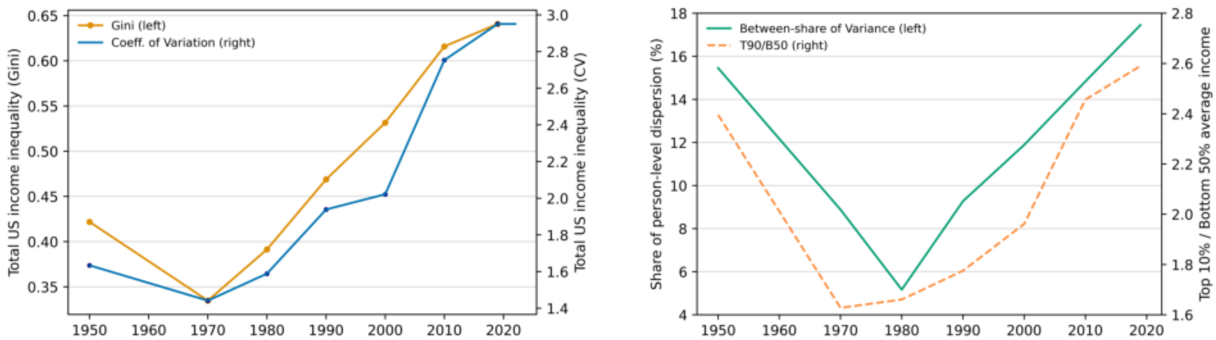
I decompose income inequality into a within - and between-regional share by splitting the log variance of income. The log variance is a special case of the additively decomposable general entropy classes that provides the most intuitive interpretation.[7] In particular, the log variance share calculates the ratio of the variance of log per capita income of labor markets over the variance of log income of all people in the US:

$$B_{CZ,t} = V_{CZ,t}/V_{Pop,t} \tag{3}$$

where $V_{CZ,t} = Var(log(Inc_{c,t}))$ for labor markets $c \in (1, ..., 741)$ and $V_{Pop,t} = Var(log(Inc_{i,t}))$ for individual $i \in (1, ..., N)$. Intuitively, the larger the dispersion of per capita incomes across labor markets keeping the overall inequality constant, the larger the between-share of total income inequality.

Figure 7 shows the evolution of aggregate US inequality and its between-labor market share over time. The left-hand panel compares the variance measure used for the decomposition exercise with the well-known Gini coefficient. It is evident that income inequality in the US has risen since 1950 with a small decline between 1950 and 1970. The right-hand panel plots the share of inequality accounted for by between local labor market inequality. The share depicts a clear U-shape declining until 1970 and rising since then. To provide further intuition I also calculate the ratio between the top 10% of labor market incomes over the bottom 50%. The dotted line shows that in 1950 the top 10% of labor markets had a per capita income about 2.4 times as high as the bottom 50%. The ratio declined to 1.7 in 1980. Today the top 10%of markets have an income 2.6 times as high. Combined with Fact 1, it is clear the a large share of the labor markets in the top 10% today were in the bottom 50% in 1950. One factor determining this change in ranking is the industrial specialization of markets. A further decomposition of between-regional inequality can be found in Appendix A.3 .

[7] The general entropy classes Theil index, MLD and CV are slightly more convoluted but provide similar results as shown in Appendix E.



(a) Aggregate inequality

(b) Between labor market inequality

Figure 7: Inequality decomposition

Notes: Figure 7 shows the decomposition of inequality as calculated in 3. The left-hand panel shows the evolution of aggregate income dispersion in the US using the Gini coefficient and the coefficient of variation.

3 Theory

In this section I provide a simple, tractable model of structural change across multiple local labor markets. The goal of the model is twofold: First, I illustrate how the combination of industrial specialization and structural change can give rise to a U-shape dispersion of incomes across labor markets and a change in the ranking of relative labor market income over time. Then I use the model to decompose aggregate inequality over time into within and between effects of structural change. In section 4, I the outline what next steps I intend to take on the modelling.

Consider a setup with two markets: $c \in (1, 2)$, two sectors: $i \in (S, M)$, i.e. Services and Manufacturing, and one factor: labor. The production side will feature different comparative advantages across sectors between the two markets. The demand side will feature non-homothetic preferences in line with Boppart (2014) to give rise to demand-driven structural change from manufacturing-based to sevices-based industries.[8]

Production. There is one firm per sector and market using the following production functions

$$Y_c^S = A_c (H_c^S)^\alpha \tag{4}$$
$$Y_c^M = B_c (H_c^M)^\beta \tag{5}$$

where Y_c^i is the final good for $i \in (S, M)$, A and B reflect market and sector-specific ag-

[8]Note that structural change can also be driven by relative productivity change as shown by Ngai and Pissarides (2007). Initial results show that the choice of driver does not make a difference. In the current version of the model, however, I abstract from this mechanism.

gregate productivity, and H is one efficiency unit of labor. Further assume that market 1 has a comparative advantage in producing the services good such that $A_1 > A_2$ and market 2 has the comparative advantage in the manufactured good $B_1 < B_2$. Following Stolper and Samuelson (1941), the markets specialize in the industries they maintain comparative advantages in and hence become net exporters of them respectively. Markets are perfectly competitive and firm price at marginal cost resulting in the following labor demand conditions:

$$w_c^S = \alpha P_c^S A (H_c^S)^{\alpha-1}, \qquad\qquad w_c^M = \beta P_c^M B_c (H_c^M)^{\beta-1}$$

where w_c^i is the wage and P_c^i is the price for $i \in (S, M)$.

Preferences. Individuals have non-homothetic preferences over consumption of services and manufactured goods characterized by the indirect utility function of Boppart (2014):

$$\frac{1}{\varepsilon}\left[\left(\frac{e}{P^S}\right)^{\varepsilon} - 1\right] - \frac{\nu}{\gamma}\left[\left(\frac{P^M}{P^S}\right)^{\gamma} - 1\right] \tag{6}$$

where e is the nominal expenditure, P^S is the price of services good and P^M is the price of manufacturing good with the parameters $\varepsilon, \gamma \in (0, 1)$ and $\nu \geq 0$. These preferences allow for non-homotheticity and for expenditure shares over services and manufacturing that vary in the level of total expenditure. The parameter ε characterizes the degree of non-homotheticity. For $\varepsilon > 0$, the expenditure share on manufactured goods is decreasing in the level of total expenditure. The parameter ν controls the level of demand for services. γ governs the elasticity of substitution between the two industries, which is not constant for $\gamma \neq 0$. These preferences embed homothetic Cobb-Douglas preferences with $\varepsilon = \gamma = 0$.

Individuals are subject to the following budget constraint:

$$P_c^S C_c^S + P_c^M C_c^M = y_c = e_c^i \tag{7}$$

giving rise to the first order condition

$$C^S = \frac{\big(1 - \nu\varpi(P^S, P^M, e)\big)}{\nu\varpi(P^S, P^M, e)} \frac{P^M C^M}{P^S} \tag{8}$$

where $\varpi(P^S, P^M, e) \equiv \left(\frac{P^S}{e}\right)^{\varepsilon}\left(\frac{P^M}{P^S}\right)^{\gamma}$. The preferences imply structural change as follows. While aggregate income is low, households consume a larger share of their income on manufactured goods. As income rises, the non-homothetic preferences imply that households decrease their expenditure share on manufactured goods and consume a larger fraction of services. As such, the aggregate demand moves from one industry to the other. The demand-induced structural change is well-documented by a large strand of literature including Engel's law, Kuznets (1955) and Boppart (2014). Alternative ways of achieving structural change include a change in relative productivity growth across industries (Ngai and Pissarides, 2007).

Sectoral labor supply. Individuals allocate across sectors and markets according to their preferences and expected wages. An individual worker within a market can supply H_s^i efficiency units to sector s that she draws from a sector-specific Fréchet distribution, $P(H_s^i \leq H) = F_s(H) = e^{-H^{-\theta}}$. The parameter θ captures the dispersion of efficiency units across workers in sector s. Each worker chooses a sector to maximize their income $y_s^i = \max_s\{H_s^i w_{s,c}\}$. As a result, the income distribution in each market inherits the Fréchet distribution of underlying efficiency units with average income by market given by

$$\bar{w}_c = \left((w_c^S)^\theta + (w_c^M)^\theta\right)^{\frac{1}{\theta}} \tag{9}$$

Following the standard result in the literature, the sector employment share can then be derived as

$$H_{s,c} = \frac{w_{s,c}^\theta}{\sum_s w_{s,c}^\theta} * \bar{H}_c = \frac{w_{s,c}^\theta}{\sum_s w_{s,c}^\theta} * \bar{H}_c \tag{10}$$

where $\bar{H}_c$ is total labor in market c. Here, the parameter θ obtains an additional interpretation. Intuitively, if θ goes to infinity, labor will fully move to the sector with the highest wage. As a result, wage will fall in that sector and eventually, labor will distributed to equalize wages across sectors - this reflects the perfect mobility case. If, however, θ tends to zero, individuals do not care about the relative wage they could earn and efficiency units are distributed equally across agents. As a result, labor will not move to equalize wage across sectors - the fully frictional case.

Regional mobility. At the beginning of each period, workers can also move to another location. Crucially, a worker learns about their efficiency in each sector only after arriving at a market. The indirect utility of a worker i in market c is given by

$$U_c^i = \int V(y) dF_r(y) * \gamma_c^i = \int \frac{1}{\eta} \Gamma_{\frac{\theta}{\eta}} \left(\bar{w}_c / P_M\right)^\eta - \nu ln(1/P_M) * \gamma_c^i \tag{11}$$

where $V(y)$ reflects agents expected utility taking into account their non-homothetic preferences uncertainty about efficiency units and Γ is the gamma function. In line with the literature, I assume that workers choose their location based on a location-specific preference shock that is drawn i.i.d from a Fréchet distribution with parameter ζ. Using the same properties derived early, I can express the share of workers in market c as

$$l_c = \frac{V_c^\zeta}{\sum_s V_c^\zeta} * \bar{L}$$

where $\bar{L}$ is total labor in economy. Here, the parameter ζ can be interpreted in line with θ above. In particular, if ζ is large, labor will move to equalise per capita income across markets. If ζ is small, labor will move inter-regionally and per capita income across markets will not be equalised.

Equilibrium. In the baseline model, I assume that trade in both manufactured goods and services is free implying the non-arbitrage nationwide prices $P_1^M = \tau^M P_2^M$, and $P_1^S = \tau^S P_2^S$ where $\tau^i = 1$ for $i \in (S, M)$. Goods and service markets clearing implies that

$$C_1^i + C_2^i = Y_1^i + Y_2^i \tag{12}$$

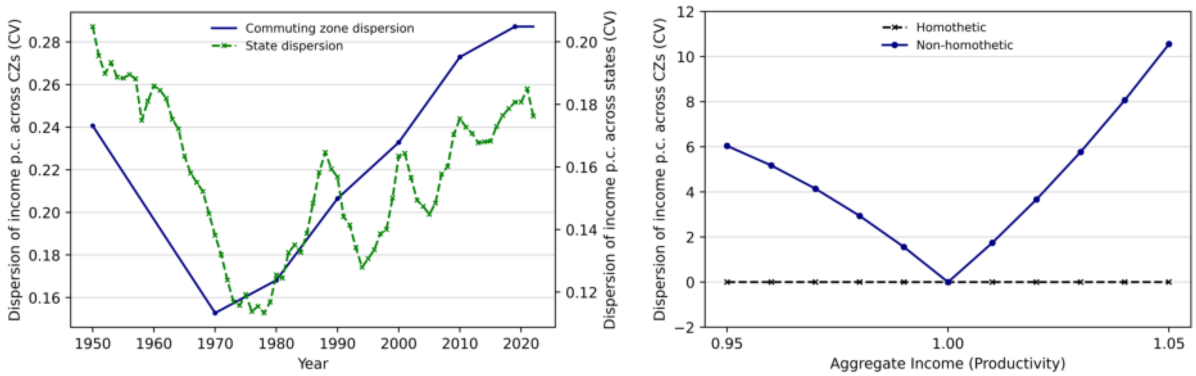
for $i \in (S, M)$, and labor markets clear such that

$$\sum_c \sum_s H_{s,c} = \bar{L} \tag{13}$$

.

Model implications and mechanism. I use this simple set-up to illustrate the link between labor markets' persistent specializations, their relative incomes over time and aggregate inequality. In this exercise, I simulate a rise in aggregate income proxied by a rise in aggregate productivity A and B. The income increase implies demand-driven structural change: As individuals have more money they gradually consume larger shares of services thereby forcing a change in production. In the baseline exercise, I allow for free sectoral labor movement (i.e. a high ζ) so that markets can specialize and allocate labor according to their comparative advantage. I further assume frictional spatial mobility (i.e. a low θ) so that wages across market can not fully equalise via labor reallocation. Note that without any frictions, no spatial inequality would every evolve as labor would perfectly adjust to equalize wages. Further note that this simple model is build for illustrative purposes and solves for the equilibrium wages statically in each period.

Figure 8 compares the dispersion of incomes across local labor markets over time in the model to the data. While without non-homothetic preferences, the rise in aggregate productivity does not translate into a change in income dispersion, with non-homothetic preferences the model replicates the U-shaped dispersion of incomes. The intuition goes as follows: Initially, overall income is low and non-homothetic preferences imply that the main share of demand goes towards sector 1 (e.g. manufacturing). Therefore, the region with the comparative advantage in producing manufactured goods has relatively higher income - between regional inequality is high. As overall income (or productivity) increases over time, demand shifts towards the other good (e.g. services) and the region with a comparative advantage in services relatively gains income: between-regional inequality declines. As aggregate income further increases, it overtakes the manufacturing sector region and spatial inequality rises again.



(a) Data

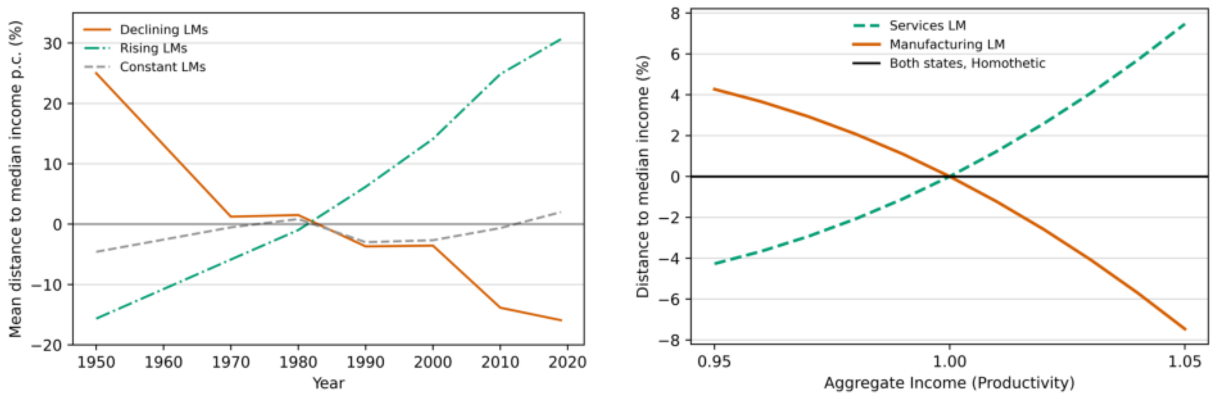
(b) Model

Figure 8: US labor markets' relative income

Notes: Figure 8 compares the dispersion of labor market incomes per capita in the data to the model output. The model output is generated by increasing aggregate productivity A and B in lockstep.

Figure 9 further shows the ranking of labor market incomes over time. The market specialized in manufactured goods has relatively high income in the beginning and declines over time as demand moves towards the services sector. The evolution mimics the development of the declining and rising labor markets in the data.

Despite its simplicity, the model further replicates the between-state inequality share of aggregate inequality over time. When decomposing aggregate US inequality into its within and between-regional share, the between-state share captures the extend to which differences in labor market incomes account for aggregate inequality. The decomposition is explained in further detail in Section **??**. In the model, inequality is a combination of the income dispersion between workers within a market, and the dispersion of mean incomes across markets. As aggregate productivity rises, aggregate inequality is affected via two channels. First, the "within effect" generates a wage premium between sectors as demand services rises. Second, the "between effect" creates as a difference between the income across the two markets as the manufacturing-specialised market experiences a decline in demand and the services-specialised market a rise in demand. The ratio of the between-inequality and the aggregate inequality (i.e. the effect of the within and between combined) illustrates the importance of between-market inequality for aggregate inequality over time.

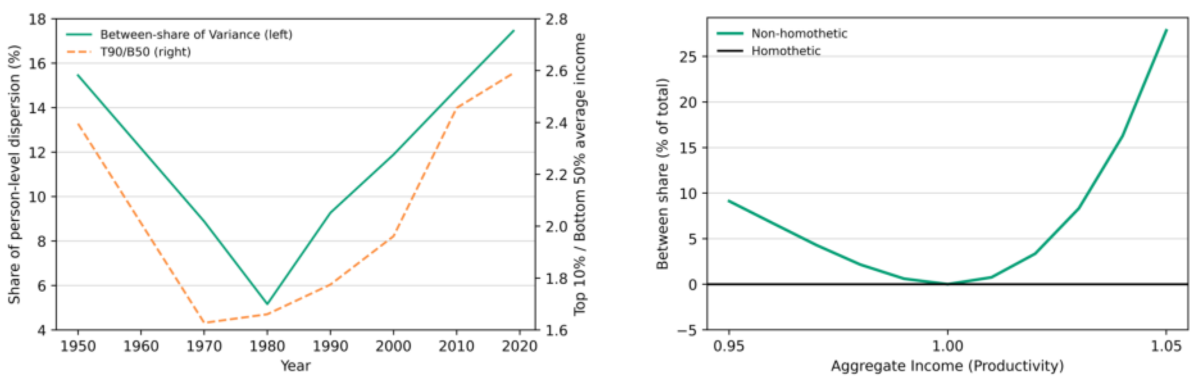


(a) Data (b) Model

Figure 9: US labor markets' relative income and structural characteristics

Notes: Figure 8 compares the dispersion of labor market incomes per capita in the data to the model output. The model output is generated by increasing aggregate productivity A and B in lockstep.

Figure 10 shows the model result for the between-share of inequality: As aggregate income increases and the economy moves from manufacturing-based to services-based production, the between-share of aggregate inequality depicts a U-shape. In other words, over time aggregate inequality is driven by different components affected by spatially heterogeneous impacts of structural change.



(a) Data (b) Model

Figure 10: US labor markets' relative income and structural characteristics

Notes: Figure 8 compares the dispersion of labor market incomes per capita in the data to the model output. The model output is generated by increasing aggregate productivity A and B in lockstep.

4 Next steps

In this section I point out the main next steps I intend to take on the modelling part of this paper. As shown above, a model without any frictions will never exhibit any kind of (spatial) inequality as labor and firms will reallocate until nominal wages equalise.[9] Incorporating the right frictions is therefore key in understanding the drivers of spatial inequality. In total, I would like to consider three main frictions: inter-sectoral, inter-regional reallocation frictions on the worker side plus an inter-regional friction on the firm side. Having introduced the former two already, as the next step, I will add the location decision of firms in line with Walsh (2023) as an additional friction. Although very stylized, each of these frictions can be interpreted as a wedge in the optimality conditions illustrating a deviation from the optimal, output-maximizing spatial allocation of labor and firms (Chari, Kehoe, and McGrattan, 2007). Estimating the simple model in an "accounting exercise" will allow me to quantify the relative importance of these wedges in driving spatial inequality. I will then build a large-scale model in which I endogenize the specialization of labor markets using the estimates from the simple model.[10]

The first goal of this model is to showcase why labor markets experience an increase in their relative specialization over time and are not able to change their specialization even in the light of structural change. For example, while the labor market around Detroit was very rich in 1950 based on manufacturing production, why was it not able to shift its specialization to services-based industries as structural change went on.

Second, I aim at using the model to run three exercises. I will first simulate a counterfactual economy to see how inequality would have evolved had (spatial) frictions and mechanisms had not played a role in driving labor market specialization over time. While in the empirical section, the decomposition of inequality into within and between shares will always add up to the full level of inequality, this counterfactual based on a model will be informative about realistic inequality paths in absence of the between-regional channel of structural change on inequality.

The second exercise will deal with the trade-off in having specialized local labor markets over time. The idea is the following. In the short-run, having industrially specialized regions maximizes output as each region produces a good according to its comparative advantage (Stolper and Samuelson, 1941). In the long-run, however, structural change takes place and the demand for good moves. If regions get locked into their initial specialization the amount of labor and firms in the new sector may deviate from the optimal allocation.

[9] This holds under the assumption that utility is derived purely from consumption and amenities play no first order role.

[10] If, for example, inter-sectoral allocation frictions appear important, I will incorporate sector-specific human capital (Porzio, Rossi, and Santangelo, 2022) in the model to show that the workforce within regions can only slowly move to new specializations.

While this idea is not novel (see e.g. Krugman (1979)), a quantification of this trade-off is yet to be discussed.

Finally, I would like to use the model to assess the role of policies aimed at reducing inequality. Place-based redistribution is a ubiquitous subject of debate among policymakers today. [11] Especially in the light of the currently ongoing structural change to a new type of services industry, having a model informed by structural change in the past to assess the effect of current structural change on inequality may be helpful. I therefore want to assess how common place-based re-distributive policies (e.g. housing subsidies) can affect inequality differently through a direct effect (i.e. reducing inequality within a region) and an indirect effect (e.g. making one region as a whole more/less wealthy relative to others).

5 Conclusion

I document three facts about the dispersion of income across local labor markets in the US since 1950. First, a U-shaped relevance of between-regional inequality for total inequality over time. Second, a change in the income ranking of labor markets - a reversal of fortunes. Third, a strong link between a state's relative income and its persistent industrial specialization.

I show that a two-market, two-sector model with differences in comparative advantages across industries and non-homothetic preferences can rationalize these findings. Labor markets that are specialized in manufacturing-based industries benefit from the relative high demand for manufactured goods in the 1950s and have relative high income. At the same time, between-market income inequality is high. As the economy undergoes structural change, demand moves towards the services-based industries which decreases the relative income of markets specialized in manufacturing and increase the income of services markets. As the services market overtakes the manufacturing market, between-market inequality first declines and then increases giving rise to the observed U-shape over time.

The model I present in this paper is an analytical one. The next logical step is to write a quantitative model that can be rigorously disciplined by micro data to assess the strength of the effect of structural change on inequality via its within- and between-regional channels. The quantitative model would both, aid in understanding the frictions causing spatial inequality as well as help to understand effects of re-distributive policy across labor markets.

[11] A large set of policies in multiple countries is explicitly designed with the aim of closing spatial gaps. Examples of this are the European Union's regional policy or the "levelling up" policy in the UK.

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A Appendix

A.1 Dispersion of state incomes accounting for transfers

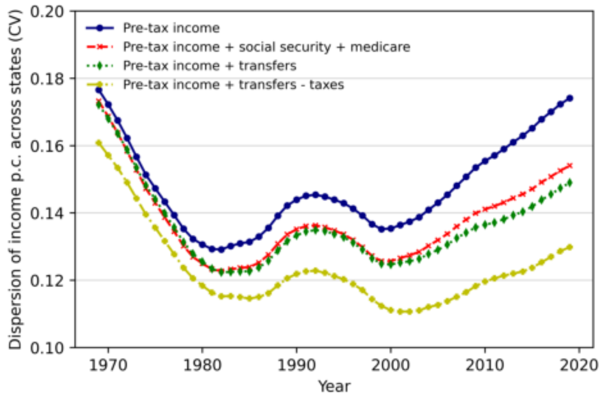


Figure 11: Dispersion of state income p.c. across US states

Notes: The figure shows the dispersion of nominal and real per capita incomes across US states as a 10-year moving average. The dispersion is measured by the coefficient of variation (CV) computed as the ratio between the standard deviation σ_t and the mean μ_t at time t: $CV_t = \frac{\sigma_t}{\mu_t}$.

A.2 Industry details

The following table show the labor shares across the 17 industries aggregate from 865 sub-industries defined in the decennial Census. The green highlighted industries are referred to as services, the red correspond to manufacturing industries.

	Industry	1950	1990	2020
1	Agriculture	20.71	3.61	3.46
2	**Business Services**	**2.96**	**4.43**	**7.61**
3	**Communication**	**0.61**	**1.52**	**1.36**
4	Construction	8.75	9.98	11.91
5	**Durable**	**13.53**	**15.88**	**10.77**
6	Entertainment	0.66	1.06	1.28
7	**Finance**	**2.2**	**4.47**	**4.79**
8	Mining	3.99	1.9	1.82
9	**Nondurable**	**9.48**	**8.64**	**5.77**
10	**Personal Services**	**2.37**	**1.39**	**1.6**
11	**Routine Prof. Serv.**	**4.39**	**11.26**	**13.19**
12	**Non-routine Prof. Serv.**	**0.37**	**2.02**	**3.33**
13	Public	4.67	7.96	6.98
14	Retail	11.84	11.15	13.26
15	Transportation	8.09	6.61	6.91
16	Utilities	1.8	2.53	2.34
17	Wholesale	3.59	5.6	3.63

Table 1: Labor shares

A.3 Cross-industries between-share

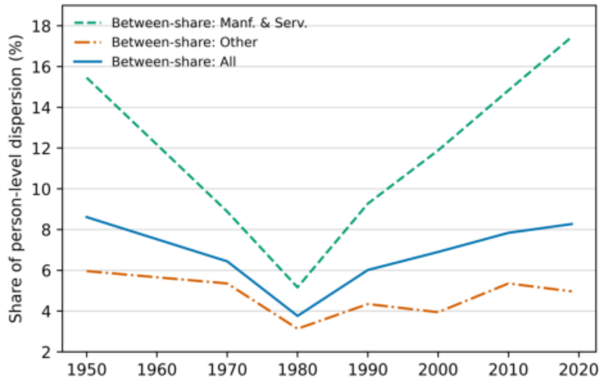
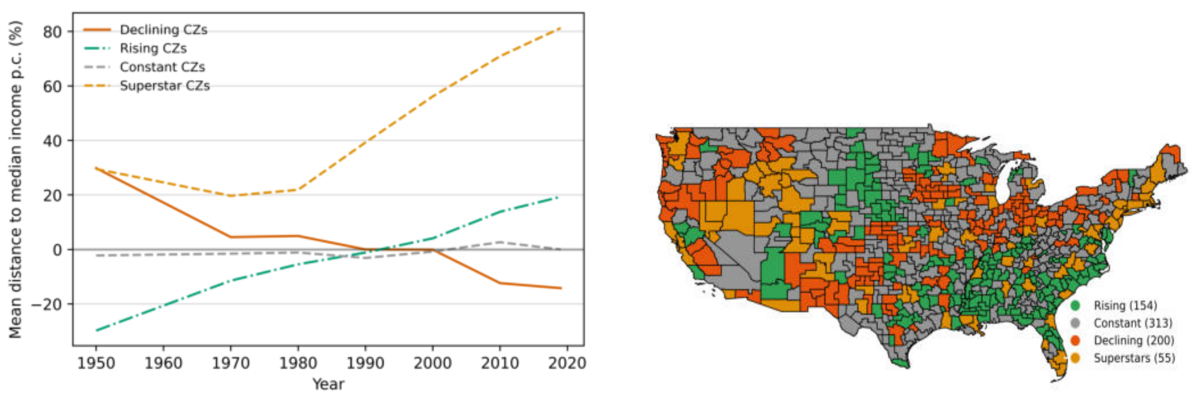


Figure 12: Spatial inequality share of aggregate inequality

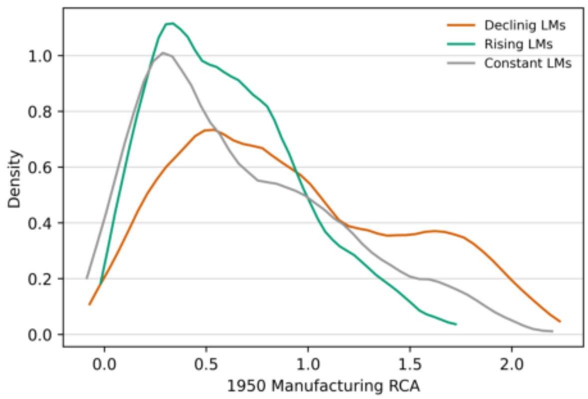
A.4 Granular Labor market income groups



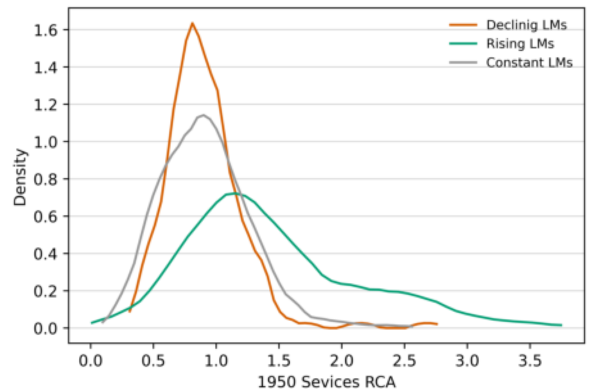
(a) Relative income by group (b) Corresponding Labor markets

Figure 13: US labor markets' relative income and structural characteristics

A.5 Spatial dispersion of industries in 1950



(a) Manufacturing



(b) Services

Figure 14: Spatial dispersion of industries in 1950

A.6 Income regression with for further variable controls

	1	2	3
Manf. RCA	-21.5***	-28.2***	-6.14
	(5.9)	(6.35)	(7.78)
College		-2.89***	3.07**
		(0.67)	(1.72)
Manf x College			-7.61***
			(2.1)
Serv. RCA	7.98***	10.45***	2.27
	(2.18)	(2.35)	(2.88)
College		-2.89***	-7.35**
		(0.67)	(1.43)
Serv x College			2.81***
			(0.77)
N	741	741	741

Table 2: Regression results

A.7 Persistence of comparative advantages over time

The persistence of revealed comparative advantages (RCA) can be computed using the location-quotient - the ranking of sectors comparative advantage in a state over time. The revealed comparative advantage for each sector i in state c is given by $RCA_{i,c} = \left(\frac{X_{c,i}}{\sum_{i \in I} X_{c,i}} / \frac{X_{US,i}}{\sum_{i \in I} X_{US,i}} \right)$. Second, one can rank $RCA_{i,c}$ for every state-year and auto-regress it over different horizons as follows:

$$Rank_{c,i,t} = \alpha + \rho_{c,h} Rank_{c,i,t-h} + \epsilon_{c,i,t}$$

The following table shows the regression results. The ranking is highly persistence over short, medium and long-run horizons.

Horizon	1	5	10	20
Persistence	0.961***	0.8962***	0.839***	0.8148***
	(0.002)	(0.003)	(0.004)	(0.025)

Table 3: RCA persistence