# Spatial Structural Change*

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**Abstract**

Between 1880 and 1920, the US agricultural employment share fell from 50% to 25%. However, despite aggregate demand shifting away from their sector of specialization, rural labor markets saw faster wage growth and industrialization than non-agricultural parts of the US. We propose a spatial model of the structural transformation to analyze the link between aggregate structural change and local economic development. The calibrated model shows that rural areas adapted to the decline of the agricultural sector by adopting technologies already in use in urban locations. Without such catch-up growth, economic development would have been urban-biased and spatial inequality would have increased.

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# Introduction

The secular decline of the agricultural sector is an essential regularity of modern economic growth and a key aspect of structural change. In this paper, we study the spatial dimension of this process and ask whether the structural transformation systematically benefits or hurts particular locations. Are rural labor markets bound to fall further behind when the agricultural sector becomes less important? Or does the process of industrialization offer opportunities for such areas to catch up with their more developed urban peers? In short, is the structural transformation urban- or rural-biased?

We study these questions in the context of the first phase of the structural transformation in the US. The US economy changed dramatically between 1880 and 1920: average income grew by 60%, and the agricultural employment share halved from 50% to 25%. Unknown to popular belief, however, is that this economic growth was decidedly pro-rural. Using data on local earnings and sectoral employment shares at the level of counties and commuting zones, we find that poor agricultural locations experienced faster wage growth and rapid industrialization and that regional living standards converged. Hence, rural locations were the primary beneficiaries of economic growth despite aggregate demand shifting away from their sector of specialization.

To explain this pattern of rural-biased growth, we propose a novel theory of spatial structural change. Our approach combines insights from the macroeconomic literature on structural change with recent advances in quantitative spatial models. Consumers have non-homothetic preferences, making agricultural spending shares decline as incomes grow. Locations differ in their sectoral productivity, amenities, and the supply of agricultural land. Agricultural production requires land, leading to decreasing returns at the local level. Workers can move between locations and sectors subject to reallocation costs.

At the heart of our theory is a flexible process of regional productivity that captures the possibility that different locations might be on different growth trajectories. Specifically, we model local productivity as evolving on a sector-specific, spatial productivity ladder. This formulation lets us parsimoniously capture the spatial evolution of absolute and comparative advantage. If locations at the bottom of the ladder grow faster and catch up with locations close to the technological frontier, the cross-sectional dispersion of productivity declines, and so does spatial inequality. If, by contrast, locations at the top of the ladder experience faster growth, spatial fortunes tend to diverge.

Our theory makes precise predictions about the spatial bias of the structural transformation. Whether growth is urban or rural biased is a horserace between two forces. On the one hand, falling agricultural demand hurts rural locations. The intuition is similar to that of Bartik instruments: because rural labor markets have a large share of their workforce in the agricultural sector, they have high exposure to a reallocation of spending away from agriculture. All else equal, this demand-side channel makes the structural transformation urban-biased. Moreover, this force is stronger, the more specific workers' skills are to a particular sector, making it difficult to move them out of agriculture.

On the other hand, regions differ in their position on the spatial productivity ladder and, consequently, their future growth prospects. If agriculturally specialized locations are (on average) located at the bottom rungs of the ladder and productivity is subject to catch-up growth, rural labor markets benefit (on average) from faster productivity growth. This supply-side channel has the potential to make the structural transformation rural-biased. The overall spatial bias thus depends on the elasticity of sectoral labor supply, the correlation between absolute and comparative advantage, and the extent of catch-up growth.

We structurally estimate our model using time-series and regional data for the US between 1880 and 1920. Regions' initial positions on the spatial productivity ladder, the strength of spatial convergence, and the sectoral substitutability of labor supply are essential for the spatial bias of economic growth. Our model provides an intuitive way to estimate these objects. First, we can infer the sectoral productivity ladder in 1880 from the joint distribution of local wages and sectoral employment shares (while controlling for the size of the local population and the availability of agricultural land in a model-consistent way). Second, we estimate the extent of catch-up growth and the labor supply elasticity by targeting the empirical relationships between initial agricultural specialization and subsequent wage growth and industrialization.

Our central finding is that catch-up growth was most important in shielding rural labor markets from the adverse impacts of structural change. First, we estimate that rural locations had low productivity in both sectors in 1880: their initial agricultural specialization reflected a comparative disadvantage in manufacturing, not an absolute advantage in agriculture. Second, the spatial productivity distribution converged, and agricultural areas were the primary beneficiaries since they were, on average, at the bottom of the ladder. We estimate that annual productivity growth in both sectors was roughly two percentage points higher in rural locations relative to urban regions close to the technological frontier. While faster productivity growth in agriculture explains why rural locations experienced faster wage growth, technological catch-up in manufacturing triggered rural regions' swift industrialization.

What is the importance of catch-up growth in shaping the spatial evolution of economic development during the first phase of the structural transformation? To answer this question, we compare our baseline calibration with an alternative "macro-calibration" in which we shut down the possibility of catch-up growth. Notably, the "macro-calibration" of the model matches the same macroeconomic time-series evidence as the baseline calibration by adjusting the aggregate rates of productivity growth in each sector. However, this alternative "macro-calibration" fails to capture the spatial dimension of the structural transformation in important ways: it implies that growth is urban-biased, generates spatial wage divergence rather than convergence, and makes counterfactual predictions for the correlation between initial agricultural specialization and future industrialization.

In addition to this model-based perspective, we also provide direct evidence for the empirical relevance of catch-up growth. We document that various canonical development indicators, such as educational attainment, capital-deepening, firm size, and financial development, grew substantially faster in rural America between 1880 and 1920. In sum, rural productivity convergence was a central driving force behind the observed patterns of spatial structural change during the first structural transformation in the US.

Although many aspects of our theory are specific to the transition out of agriculture, our analysis also provides insights into the spatial incidence of the second structural transformation toward services. Unlike in 1880-1920, spatial inequality in the US has increased in the last few decades, and regions specializing in the declining manufacturing sector have experienced slower growth. Our analysis suggests that changes in the regional productivity process might be responsible for these differences. While frontier technologies in manufacturing were embodied in physical capital and easy to move into rural regions, the human capital required in high-skill service production may be unwilling to settle in declining manufacturing towns outside big cities. As a result, economically backward locations today might have more difficulty catching up.

**Related Literature** We contribute to the large macroeconomic literature on structural transformation - see Herrendorf et al. [2014] for a survey.[1] Models in this literature are ag-

[1] The macroeconomics literature on structural change highlights both the role of non-homothetic demand (see, e.g., Kongsamut et al. [2001], Comin et al. [2021], and Boppart [2014]) and supply-side explanations such as unbalanced technological progress, capital-deepening, and human capital accumulation (see, e.g., Ngai and Pissarides [2007], Acemoglu and Guerrieri [2008], Alvarez-Cuadrado et al. [2017], and Porzio

gregative and hence silent on the spatial dimension of structural change. In contrast, our theory combines elements of a standard macroeconomic model with recent advances in spatial economics (e.g., Allen and Arkolakis [2014], Redding and Rossi-Hansberg [2017]) to study the spatial aspects of the structural transformation.[2]

A set of closely related papers studies aspects of spatial structural change: an important early contribution is Caselli and Coleman II [2001],, who use a stylized two-region model to highlight that the structural transformation went hand-in-hand with regional convergence. In a recent contribution, Nagy [2016] examines the transformation of rural labor markets as part of the process of city formation in the US before 1860. Michaels et al. [2012] also study the implications of agricultural specialization on subsequent development in the US since 1880. Relative to our paper, they focus on population growth rather than wage growth and industrialization. More recently, a growing number of papers study the spatial dimension of the structural transformation towards services (see, e.g., Desmet and Rossi-Hansberg [2014], Eckert et al. [2020a], Fan et al. [2022], Budí-Ors and Pijoan-Mas [2022] or Hsieh and Rossi-Hansberg [2019]) and structural change within the agricultural sector in developing countries (e.g., Pellegrina and Sotelo [2021], Sotelo [2020], Farrokhi and Pellegrina [2020]).

On the theoretical side, we follow Boppart [2014] in using a price-independent generalized linear (PIGL) demand structure. This demand structure has more potent income effects than the widely used Stone-Geary specification and can generate the large declines in agricultural employment observed in the data (see Alder et al. [2022] and Buera and Kaboski [2009]). We show how these preferences can be tractably integrated into a general equilibrium trade model, making them a natural choice in our setting.

A crucial element of our theory is the spatial productivity ladder and the possibility of regional convergence. Several studies document technological convergence across countries (see, e.g., Acemoglu et al. [2006] or Desmet et al. [2018]) and across regions within countries (see, e.g., Barro and Sala-i Martin [1992] or Desmet and Rossi-Hansberg [2009]). We add to this literature by showing that regional convergence played a key role in the structural transformation. In particular, our theory highlights why these benefits of backwardness accrued to agricultural regions in the past and why the structural transforma-

et al. [2022]).

[2]The quantitative spatial literature has studied topics such as spatial misallocation (Hsieh and Moretti [2019], Fajgelbaum et al. [2019]), the local effects of trade opening (Tombe and Zhu [2019], Coşar and Fajgelbaum [2016], Fajgelbaum and Redding [2022], Caliendo et al. [2019]), the importance of market access (Redding and Sturm [2008], Ahlfeldt et al. [2015]), and the role of dynamic innovation and investment decision for spatial growth (Desmet et al. [2018], Walsh [2019], Peters [forthcoming], Kleinman et al. [2021]).

tion today might lead to regional divergence (see, e.g., Austin et al. [2018] and Chatterjee and Giannone [2021]).

The rest of the paper is structured as follows. Section 1 presents two facts on spatial structural change in the US that motivate our analysis. Section 2 contains our theory. Section 3 draws on that theory to characterize the spatial incidence of structural change. We describe the calibration of our model in Section 4 and quantify the link between catch-up growth and rural-biased growth in Section 5. Details on both our theoretical derivations and our empirical analysis are contained in an Appendix.

# 1. Structural Change Across US Commuting Zones, 1880-1920

In this section, we document a set of patterns of spatial structural change that guide the development of our theory and inform our calibration. We focus on the time period between 1880 and 1920, and use data on agricultural employment from the full-count Decennial Census files and on average earnings from the Census of Manufacturing.[3] Throughout the paper, we aggregate county-level observations to constant-boundary "commuting zones" (Tolbert and Sizer [1996]) which serve as a consistent spatial unit of observation.[4]

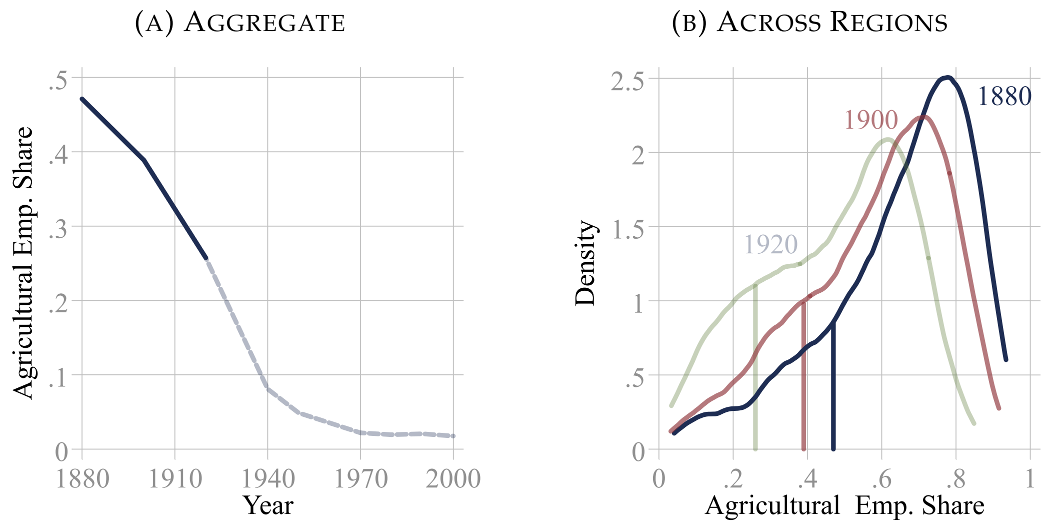
,The relative importance of agricultural employment in the US economy declined dramatically between 1880 and 1920. The left panel of Figure 1 shows the time series of the agricultural employment share of the US economy. Starting in 1880, the aggregate agricultural employment share declined from 50% to essentially 0% today. Half of that decline occurred between 1880 and 1920, the time period of our study.

The decline in agricultural employment was a "within labor market" phenomenon affecting *all* locations. This is seen in the right panel, which shows the distribution of agricultural employment shares across commuting zones in our years of study. In 1880, regions differed widely in their reliance on agricultural employment: many localities had over 75% of their workers engaged in the agricultural sector. Between 1880 and 1920, there was a pronounced left-ward shift in this distribution indicating that agricultural employ-

[3] We focus on the years between 1880 and 1920 because consistent data are not available earlier and to avoid the Great Depression.

[4] We create this time-invariant measure of geography using the crosswalk of Eckert et al. [2020b]. See Section 4 for details on the data.

FIGURE 1: SPATIAL STRUCTURAL CHANGE




Notes: The left panel shows the aggregate agricultural employment share in the US since 1880. The right panel shows the distribution of agricultural employment shares across commuting zones in 1880, 1900, and 1920. The vertical lines in the right panel depict the aggregate agricultural employment share in the respective year. Both panels use data from the full-count US Decennial Census files available from IPUMS (see Ruggles et al. [2017]).

ment fell in all regions.[5]

In Figure 2 we document the importance of spatial convergence during the same time period. Initially more agricultural regions started out poor, but saw faster wage growth and industrialization during the first phase of the structural transformation. The left panel shows the negative correlation between wages and agricultural employment in 1880: agricultural locations were poor, and average earnings between more and less industrialized regions differed by up to one log point. The red line (right-axis) in the right panel, shows average wage growth between 1880 and 1920 as a function of their initial agricultural employment share. The figure shows a clear pattern of rural-biased growth: rural locations saw faster wage growth than urban locations.

Regions in the intermediate range of agricultural employment shares industrialized the fastest. The blue line (left axis) in the right panel of Figure 2 graphs the change in the

[5]To see this formally, note that we can decompose the change in the agricultural employment share between 1880 and 1920 into a within location component, a spatial reallocation component, and a covariance term as follows:

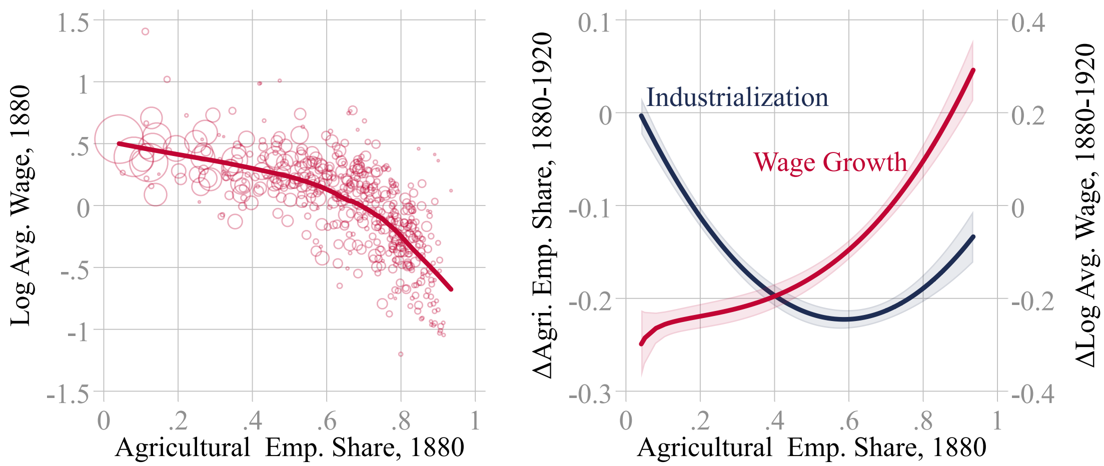
$$\underbrace{s_{A1920} - s_{A1880}}_{-0.21} = \underbrace{\sum_r (s_{rA1920} - s_{rA1880})\, l_{r1880}}_{-0.17} + \underbrace{\sum_r s_{rA1880}\,(l_{r1920} - l_{r1880})}_{0.04} + \underbrace{\sum_r (s_{rA1920} - s_{rA1880})\,(l_{r1920} - l_{r1880})}_{0.01}.$$

Quantitatively, the within component along accounts for almost 80% of the entire decline in agricultural employment between 1880 and 1920.

FIGURE 2: THE PATTERNS OF SPATIAL STRUCTURAL CHANGE

(A) RURAL POVERTY

(B) RURAL CATCH-UP




Notes: The left panel shows a scatter plot between commuting zones' agricultural employment shares and average earnings in 1880 and a Lowess fit line. The size of the points is proportional to the total workforce in each commuting zone. The right panel shows two fitted fractional polynomial curves along with 95% confidence intervals. They show the relationship between commuting zones' agricultural employment share in 1880 and (1) their average earnings growth between 1880 and 1920 (left axis) relative to the nationwide average and (2) the change in the agricultural employment share between 1880 and 1920 (right axis). In fitting the polynomials, we weight by commuting zones' total employment in 1880.

agricultural employment share as a function of its level in 1880. While more agricultural locations industrialized faster than regions with little reliance on agricultural employment, the relationship is not monotone, but $U$-shaped: subsequent industrialization was fastest in commuting zones that had agricultural employment shares between 0.5 and 0.7 in 1880.

Throughout the paper, we refer to the correlations presented in Figure 2 as the "patterns of spatial structural change" and use them to inform our theory and identify model parameters in our calibration. These patterns are robust to changes in the spatial unit of observation and more formal statistical analysis. In Section B.2 in the Appendix, we replicate our results at the county-level and also provide them in regression form.

The key takeaway from this section is that even though rural locations saw aggregate demand shifting away from their sector of specialization, rural areas caught up with urban centers and experienced rapid industrialization. As a result, the first phase of the structural transformation in the US was an episode of regional convergence. In the remainder of the paper, we show that these patterns are consistent with a spatial theory of structural change in which productivity convergence allowed rural locations to catch-up with their technologically more advanced non-agricultural counterparts.

# 2. A Theory of Spatial Structural Change

Our theory of spatial structural change combines the workhorse model of economic geography (see, e.g., Redding and Rossi-Hansberg [2017]) with a macroeconomic theory of structural change (see, e.g., Herrendorf et al. [2014]). We provide detailed derivations in Section A of the Appendix.

## 2.1 Environment

The economy consistent of a set of discrete locations, indexed by $r = 1, ..., R$, and two sectors, agriculture and non-agriculture, indexed by $s = A, M$, respectively. At time $t$, the economy is inhabited by a mass $\bar{L}_t$ of workers. We suppress time subscripts when describing the static elements of our model.

**Preferences** Individuals value the consumption of agricultural and non-agricultural goods. Preferences for these sectoral outputs are non-homothetic to generate the shifts in sectoral demand associated with the structural transformation. Following Boppart [2014], we assume preferences fall in the non-homothetic "PIGL" (Price-Independent Generalized Linear) class. As we show in detail in Section 2.2, these preferences have convenient aggregation properties that make them a natural choice for models of trade and economic geography. PIGL preferences do not have an explicit utility representation, but are defined implicitly via the indirect utility function. We parametrize the indirect utility of an agent with expenditure $y$ facing final good prices $(P_{rA}, P_{rM})$ as:

$$V(y, P_{rA}, P_{rM}) = \frac{1}{\eta}\left(\frac{y}{P_{rA}^{\phi}P_{rM}^{1-\phi}}\right)^{\eta} - \nu \ln\left(\frac{P_{rA}}{P_{rM}}\right), \tag{1}$$

where $\eta, \phi \in (0,1)$ and $\nu > 0$ are the structural preference parameters.

For now, we assume trade costs are zero for the agricultural good. Doing so allows us to treat the agricultural good as the numeraire, that is, $P_{rA} = P_A = 1$, and to simplify the notation. Our quantitative exercise below features trade costs in both sectors.

Applying Roy's Identity yields the following expression for an individual's expenditure share on the agricultural good:

$$\vartheta_A(y, P_M) \;=\; \phi + \nu\left(y/P_{rM}^{1-\phi}\right)^{-\eta}. \tag{2}$$

Equation (2) shows that the demand system is akin to a Cobb-Douglas specification with a non-homothetic adjustment.[6] Conveniently, the term $y/P_{rM}^{1-\phi}$, which we also sometimes refer to as "real income," emerges as a summary statistic for such non-homotheticities. Consumers reduce their relative agricultural spending as they grow richer, since $\nu > 0$ and $\eta > 0$ and the expenditure share asymptotes to $\phi$ as incomes grow large. If $\nu = 0$ and $\eta = 1$, equation (1) reduces to a Cobb Douglas utility function with constant expenditure shares and utility fully determined by real income.[7] We refer to the elasticity parameter $\eta$ as the "Engel elasticity" because it determines the shape of consumers' Engel curves. The larger $\eta$, the stronger the effect of real income on consumer demand.

Our preferences imply that the elasticity of substitution between the value added generated in the two sectors,

$$\varrho = 1 + \eta \frac{(\vartheta_A - \phi)^2}{\vartheta_A (1 - \vartheta_A)}, \tag{3}$$

is not a structural parameter, but varies across space and across the income distribution. The agricultural spending share $\vartheta_A$ emerges as a sufficient statistic for the variation in income and prices. Moreover, $\varrho$ is increasing in $\vartheta_A$ (that is, decreasing in real income) and satisfies $\lim_{\vartheta_A \to \phi} \varrho = 1$. Poor individuals, who spend a large fraction of their income on agricultural goods, consider food and non-agricultural products substitutes. Consequently, as non-agricultural prices fall, they increase their consumption of non-agricultural goods. As incomes increase, preferences approach a Cobb-Douglas utility function with constant expenditure shares and a unitary elasticity of substitution.

**Technology** Each region can produce agricultural and non-agricultural goods. A representative local firm produces the agricultural good using the following technology:

$$Y_{rA} = Z_{rA} H_{rA}^{1-\alpha} T_r^{\alpha}, \tag{4}$$

where $Z_{rA}$ is the local productivity in agricultural production, $H_{rAt}$ is agricultural labor (measured in efficiency units), and $T_r$ denotes agricultural land. We assume that agri-

[6] In Section B.3.7 in the Appendix, we show, using micro data on expenditure from the CEX in 1936, that the specification in equation (2) describes the cross-sectional relationship between sectoral spending shares and income well.

[7] In our quantitative application, we choose the level of regional productivity to ensure expenditure shares are between 0 and 1. This amounts to assuming consumers are sufficiently rich to be willing to consume non-agricultural goods in positive quantities.

cultural land is in fixed supply in each region. As result, the land share, $\alpha$, indexes the strength of decreasing returns to scale.

We model the non-agricultural sector in the standard "CES-monopolistic-competition"way. Individual firms pay a fixed cost of entry, $f_E$, denoted in units of manufacturing labor. Upon entering, each firm produces a differentiated variety, indexed by $\omega$, using the same constant-returns-to-scale, labor-only production technology with productivity $Z_{rM}$. Firms operate for a single period, which we define as 20 year in our empirical application. We assume free entry, so that new firms enter until their profits equal their fixed costs. Total demand for non-agricultural labor in region $r$, $H_{rM}$, is therefore the sum of entry and production labor, $H_{rE}$ and $H_{rP}$, respectively. The market for non-agricultural varieties is monopolistically competitive.

In each location, a representative firm assembles the differentiated non-agricultural varieties into a final consumption good:

$$Y_{rM} = \left( \int_0^N y(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} = \left( \sum_{j=1}^{R} \int_0^{N_j} y(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}. \tag{5}$$

Here, $N$ is the total number of varieties available and $N_r$ denotes the number of varieties produced in region $r$. Non-agricultural varieties are subject to the usual iceberg trade costs. The presence of such trade costs implies that the composition and price of the final non-agricultural good differs across locations.

**Productivity Growth and the Spatial Productivity Ladder** Productivity growth is the fundamental driver of economic development in our model, both at the regional and aggregate level. We model the evolution of the region- and sector-specific productivity terms productivity in a parsimonious way and assume they evolve on a *spatial productivity ladder*. Specifically, let $\overline{Z}_{st}$ denote a sector-specific productivity shifter that grows at the constant rate $g_s$. Assume $Z_{rst} \leq \overline{Z}_{st}$ so that we also refer to $\overline{Z}_{st}$ as the sectoral frontier. We assume the following process for the evolution of the local productivity terms in each sector:

$$d \ln Z_{rst} = g_s + \lambda_s \ln \left( \frac{\overline{Z}_{st}}{Z_{rst}} \right) \text{ for } s = A, M. \tag{6}$$

Equation (6), which is similar to Acemoglu et al. [2006] and Desmet et al. [2018], allows us to capture regional divergence, regional convergence, and balanced productivity growth parsimoniously through one sector-specific parameter, $\lambda_s$. If $\lambda_s = 0$, sectoral productivity grows at the same rate in all regions and the spatial productivity distribution in sector $s$ is stationary. If $\lambda_s > 0$, less productive regions benefit from their backwardness and grow at a faster rate. If $\lambda_s < 0$, the opposite is the case and technologically backward locations fall further behind.[8]

Our interpretation of the local productivity terms $Z_{rAt}$ and $Z_{rMt}$ is intentionally broad. A region's "benefit of backwardness" could be due to actual spatial technology diffusion, where lagging localities adopt existing techniques to catch up to the technological frontier. But, catch-up growth could also be driven by infrastructure investments, capital deepening, or other institutional changes that spatially diffuse with a time lag and reach less productive locations at later stages of economic development. Below, we provide direct empirical evidence for this pattern of catch-up growth for a variety of development indicators.

Importantly, equation (6) does *not* hardwire local productivity growth to local sectoral specialization. Whether agriculturally specialized locations experience faster growth depends on *why* they specialize in the agricultural sector. If agricultural locations have, on average, lower physical productivity $Z_{rAt}$ or $Z_{rMt}$, they benefit from catch-up growth. However, a comparative advantage in agriculture is also consistent with an absolute advantage in both sectors, or could be entirely due to an abundance of agricultural land $T_r$. As a result, our model does not mechanically produce a systematic relationship between sectoral specialization and future growth.[9]

**Sectoral Labor Supply** Structural change exerts pressure on local economies to reallocate labor across industries. Workers' ability to move out of agriculture depends on the extent to which their skills are substitutable across sectors. To capture this reallocation margin, we model sectoral labor supply using the typical Roy-type machinery.

An individual worker $i$ in region $r$ can supply $z_s^i$ efficiency units to sector $s$ that are drawn from a sector-specific Fréchet distribution, $P\left(z_s^i \leq z\right) = F_s\left(z\right) = e^{-z^{-\zeta}}$. The parameter $\zeta$ captures the dispersion of efficiency units across workers in sector $s$.

[8]If $\lambda_s > 0$, equation (6) implies regional productivity differences disappear in the long run. This is for simplicity only. Suppose equation (6) was given by $d \ln Z_{rst} = g_s + \lambda_s \ln\left(\overline{Z}_{st}/Z_{rst}\right) - \mu_{rs}$, where $\mu_{rs} \geq 0$. Then, $Z_{rst} \to e^{-\mu_{rs}/\lambda_s}\overline{Z}_{st}$. For the case of $\mu_{rs} = 0$, we recover $Z_{rst} \to \overline{Z}_{st}$. In our empirical application, which covers a 40-year period, this long-run result is not consequential.

[9]The diffusion process itself does not reflect any geographic attributes. Note, however, that local productivity growth will be correlated across labor markets if the initial cross-sectional distribution of productivity, $\{Z_{rst}\}_{rs}$ , are spatially correlated.

We denote total payments per efficiency unit of labor in region $r$ and sector $s$ by $w_{rs}$ and assume the payments to agricultural land in a location are distributed to local agricultural workers and included in $w_{rA}$.[10] Workers choose a sector of employment to maximize their income, $y_r^i = \max\left\{z_A^i w_{rA}, z_M^i w_{rM}\right\}$. As a result, the income distribution in each location inherits the Fréchet distribution of the underlying efficiency units, that is,

$$F_r(y) = e^{-(y/\overline{w}_r)^{-\zeta}} \quad \text{where} \quad \overline{w}_r = \left(w_{rA}^{\zeta} + w_{rM}^{\zeta}\right)^{1/\zeta}, \tag{7}$$

where the term $\overline{w}_r$ denotes average earnings in region $r$. Similarly, sectoral employment shares and aggregate labor supply are given by:

$$s_{rs} = (w_{rs}/\overline{w}_r)^{\zeta} \quad \text{and} \quad H_{rs} = \Gamma_{\zeta} L_r (w_{rs}/\overline{w}_r)^{\zeta-1}, \tag{8}$$

where $\Gamma_x \equiv \Gamma(1-1/x)$ and $\Gamma(\cdot)$ is the gamma function.

Equation (8) highlights that $\zeta$ governs the sectoral-labor-supply elasticity: the higher $\zeta$, the higher the elasticity of labor supply. As $\zeta \to \infty$, the heterogeneity in efficiency units disappears and labor is fully elastic across industries. This limiting case is the benchmark of most macroeconomic models of the structural transformation. We show below that the parameter $\zeta$ is a crucial determinant of the *spatial* distribution of wages and sectoral employment shares in the presence of aggregate growth.

**Spatial Mobility** At the beginning of each period, workers can move to another location. We denote the distribution of workers across regions at the beginning and at the end of a period by $\{L_{rt}^{Y}\}_r$ and $\{L_{rt}\}_r$, respectively.

We assume that worker learn their labor productivity in each sector only after arriving in a destination. The indirect utility of worker $i$ from location $r$ in location $r'$ at time $t$ is thus given by:

$$\mathcal{U}_{rr't}^i \equiv \mathcal{V}_{rt}\mathcal{B}_{rt}\mu_{rr'}u_{rt}^i, \text{ where } \mathcal{V}_{rt} \equiv \int V(y, p_{rt})\, dF_{rt}(y) \text{ and } \mathcal{B}_{rt} = B_r L_{rt}^{-\rho} \tag{9}$$

The term $\mathcal{V}_{rt}$ denotes expected consumption utility reflecting a worker's uncertainty about the efficiency units of labor drawn upon arrival in a region. The term $\mathcal{B}_{rt}$ is an amenity

[10] If we denote the skill price in agriculture by $\tilde{w}_{rA}$, then $w_{rA} \equiv \frac{1}{1-\alpha}\tilde{w}_{rA}$. With non-homothetic preferences, the income distribution is consequential for aggregate sectoral spending. Distributing land payments to local workers instead of immobile local land owners (see, e.g., Redding and Rossi-Hansberg [2017]) implies we have to keep track of only one income distribution.

term, which comprises an exogenous and endogenous part. The parameter $\rho > 0$ indexes the strength of congestion forces such as the scarcity of local housing or other non-traded goods. The parameter $\mu_{rr'} \in (0, 1]$ reflects the cost of moving: destination utility is discounted depending on a worker's region of origin. We assume that workers who stay put enjoy the full local utility, i.e., $\mu_{rr} = 1$. Finally, $u^i_{rt}$, reflects a worker-location-specific preference shifter, which is drawn prior to choosing a region, i.i.d. from a Fréchet distribution with shape parameter $\varepsilon$.

Using standard properties of the Fréchet distribution, the share of workers moving from location $r$ to $r'$ can be written as

$$m_{rr't} = \frac{\left(\mu_{rr'} \mathcal{V}_{r't} \mathcal{B}_{r't}\right)^{\varepsilon}}{\sum_j \left(\mu_{rj} \mathcal{V}_{jt} \mathcal{B}_{jt}\right)^{\varepsilon}}. \tag{10}$$

Changes in the local labor force are not only the result of internal migration, but also due to factors we do not model explicitly. In particular, international immigration was substantial during the time period of our study and local birth rates varied considerably. To capture these factors, we follow Cruz and Rossi-Hansberg [2021] and allow for an exogenous component of population growth, $n_{rt}$, that links the beginning-of-period distribution of workers, $\{L^Y_{rt}\}_r$, to the end-of-period workforce of the previous period, $\{L_{rt-1}\}_r$, according to $L^Y_{rt} = n_{rt-1} L_{rt-1}$. As a result, the law of motion for the local population takes the following form:

$$L_{rt} = \sum_{r'} m_{r'rt} L^Y_{r't} = \sum_{r'} m_{r'rt} n_{r't-1} L_{r't-1}, \tag{11}$$

where $m_{r'rt}$ is given in equation (10). The size of region $r$ is thus determined by its relative attractiveness $(m_{r'rt})$, its size in the past $(L_{rt-1})$, and exogenous local population growth $(n_{rt-1})$. Allowing for population growth is important because decreasing returns in agriculture imply that the size of the labor force has real effects.

## 2.2 Aggregate Demand and Spatial Welfare

To compute the equilibrium, we need to characterize workers' expected utility $\mathcal{V}_{rt}$ and the aggregate demand system. As we detail in Section A.3 in the Appendix, the combination of PIGL preferences and the Fréchet distribution of individual income allows us to derive closed-form expressions for these objects, despite the fact that consumer demand is non-homothetic.

First, the *aggregate* expenditure share on agricultural goods in region $r$, $\vartheta_{rA}$, is given by

$$\vartheta_{rA} \equiv \frac{\int \vartheta_A (y, p_r)\, y dF_r (y)}{\int y dF_r (y)} \;=\; \phi + \nu^{\mathrm{RC}} \left(\overline{w}_r / P_{rM}^{1-\phi}\right)^{-\eta}, \tag{12}$$

where $\nu^{RC} = \nu \frac{\Gamma_{\zeta/(1-\eta)}}{\Gamma_{\zeta}}$ is a composite parameter that depends on the underlying micro preference parameter $\nu$, the second moment of the income distribution $\zeta$, and the Engel elasticity $\eta$. Hence, the aggregate demand system is akin to the one generated by a representative agent who earns the average wage, $\overline{w}_{rt}$, and has a preference parameter $\nu^{RC}$. The aggregate demand system is still non-homothetic: an increase in average real income reduces the aggregate spending share on agricultural goods. Furthermore, the macro-elasticity of expenditure shares to real income coincides with the corresponding micro-elasticity, $\eta$. Importantly, local wages and prices are enough to compute the aggregate spending share and thus aggregate demand.

Second, we can also derive an intuitive expression for consumption utility in region $r$, $\mathcal{V}_r$:

$$\mathcal{V}_r = \int V(y, p_r)\, dF_r(y) = \frac{1}{\eta} \Gamma_{\frac{\zeta}{\eta}} \left(\overline{w}_r / P_{rM}^{1-\phi}\right)^{\eta} - \nu \ln (1/P_{rM}). \tag{13}$$

Expected utility in region $r$ resembles the indirect utility of a representative agent who earns average income $\overline{w}_{rt}$ and has a "taste" parameter $\Gamma_{\zeta/\eta}$ determining the relative importance of real income and relative prices. The indirect utility in equation (13) presents a non-homothetic generalization of the location-utility in the workhorse economic geography model (see, e.g., Allen and Arkolakis [2014] or Redding and Rossi-Hansberg [2017]).

## 2.3 Equilibrium: Local Wages and Industrialization

We are now in the position to characterize the equilibrium.

**Definition.** *Let $\{L_{r0}, Z_{rA0}, Z_{rM0}\}_r$ be the initial distribution of workers and productivity and $\{\overline{Z}_{At}, \overline{Z}_{Mt}\}_t$ be a path of the technological frontier. An equilibrium is a sequence of prices $\{P_{rAt}, P_{rMt}\}_{rt}$, wages $\{w_{rAt}, w_{rMt}\}_{rt}$, rental rates $\{R_{rt}\}_{rt}$, non-agricultural varieties $\{N_{rt}\}_{rt}$, employment allocations $\{H_{rAt}, H_{rEt}, H_{rPt}\}_{rt}$, local populations $\{L_{rt}\}_{rt}$, and individual consumption choices $\{c^i_{rAt}, [c^i_{rMt}(\omega)]_{\omega}\}^i_{rt}$, and productivity processes $\{Z_{rAt}, Z_{rMt}\}_{rt}$, such that (i) consumers' consumption and location choices maximize utility, (ii) the creation of local varieties is consistent with free entry, (iii) firms maximize profits, (iv) all markets clear, and (v) productivity evolves according to equation (6).*

We highlight a useful characterization of our main outcomes of interest: local wages and sectoral specialization and relegate a discussion of the full equilibrium system of equations to Appendix A.4.

Our model allows us to represent the non-agricultural sector within each location in a simple way. Under free entry, the mass of firms is proportional to non-agricultural production labor, who receive a fixed fraction of sectoral revenue. As a result, a location's non-agricultural revenue, $\mathcal{R}_{rM}$, is given by

$$\mathcal{R}_{rM} = \tilde{f}_E \mathcal{D}_r^{\frac{1}{\sigma}} Z_{rM}^{\frac{\sigma-1}{\sigma}} H_{rM}, \text{ where } \quad \mathcal{D}_r \equiv \sum_j \tau_{rjM}^{1-\sigma} P_{jM}^{\sigma-1} \vartheta_{jM} \Gamma_\zeta L_j \overline{w}_j, \tag{14}$$

where $\mathcal{D}_r$ is a measure of the effective *demand* for non-agricultural products and $\tilde{f}_E$ is a composite constant. Hence, non-agricultural revenue is similar to a constant-returns-to-scale production function, with revenue TFP being a combination of local physical productivity, $Z_{rM}$, and the endogenous demand term, $\mathcal{D}_r$. The presence of the demand term in sectoral revenue highlights the endogenous link between structural change and sectoral productivity: as incomes rise and spending shifts towards non-agricultural goods, the increase in market size leads to higher revenue productivity in the non-agricultural sector.

The production side of each local economy can thus be represented as a two-sector economy, with decreasing returns to scale in agriculture and constant returns in manufacturing. This representation is useful to derive the equilibrium factor prices and sectoral employment shares.

**Proposition 1.** *Define "population density," $\ell \equiv L_r/T_r$, and the following "effective" sectoral productivity terms in region $r$:*

$$\mathscr{Z}_{rM} \equiv \tilde{f}_E^{-1} \mathcal{D}_r^{\frac{1}{\sigma}} Z_{rM}^{\frac{\sigma-1}{\sigma}} \quad \text{and} \quad \mathscr{Z}_{rA} \equiv Z_{rA} \left(\Gamma_\zeta \ell_r\right)^{-\alpha}.$$

*Local wages $w_{rMt}$ and $w_{rAt}$ and sectoral employment shares $s_{rAt}$ are then determined by*

$$w_{rM} = \mathscr{Z}_{rM}; \qquad \left(\left(\frac{\mathscr{Z}_{rM}}{w_{rA}}\right)^{\zeta} + 1\right)^{\frac{\zeta-1}{\zeta}} \left(\frac{\mathscr{Z}_{rA}}{w_{rA}}\right)^{\frac{1}{\alpha}} = 1; \qquad \frac{s_{rA}^{1+(\zeta-1)\alpha}}{1-s_{rA}} = \left(\frac{\mathscr{Z}_{rA}}{\mathscr{Z}_{rM}}\right)^{\zeta}. \tag{15}$$

*Proof.* See Section A.5 in the Appendix. □

Proposition 1 characterizes local factor prices and sectoral specialization in terms of the two sufficient statistics, $\mathscr{Z}_{rM}$ and $\mathscr{Z}_{rA}$. We refer to these terms as "effective" sectoral productivities. While both $\mathcal{D}_r$ and $\ell_r$ are endogenous and intrinsically linked to the way locations spatially interact on the market for goods ($\mathcal{D}_r$) and in terms of inter-regional migration ($\ell_r$), Proposition 1 shows that as far as wages and sectoral specialization are concerned, they are isomorphic to sectoral productivity.

Equation (15) highlights that the two sectors differ in their exposure to these effective productivity terms. Manufacturing wages only depend on $Z_r$ and $\mathcal{D}_r$ and are independent of agricultural productivity $Z_{rA}$ and population density $\ell_r$. By contrast, agricultural wages are increasing in both $\mathscr{Z}_{rM}$ and $\mathscr{Z}_{rA}$. Moreover, the elasticity of agricultural wages to either productivity term varies across locations and depends on the elasticity of labor supply, $\zeta$, and the share of land, $\alpha$. These properties are direct implications of the sectoral differences in the returns to scale. Given that agriculture has decreasing returns, the marginal product of labor depends on the quantity of agricultural labor and hence sectoral labor supply. By contrast, as highlighted in equation (14), the marginal product of labor in the non-agricultural sector is constant and only depends on aggregate sectoral revenue TFP, $\mathscr{Z}_{rM}$. Finally, sectoral specialization is entirely determined by agricultural productivity $\mathscr{Z}_{rA}$ *relative* to non-agricultural productivity $\mathscr{Z}_{rM}$. The ratio $\mathscr{Z}_{rA}/\mathscr{Z}_{rM}$ thus plays the role of endogenous comparative advantage.

The expressions in Proposition 1 speak directly to the patterns of spatial structural change documented in Section 1. More specifically, the joint distribution of wages and agricultural employment shares in Figure 2 identifies the distribution of the effective productivity terms, $\mathscr{Z}_{rM}$ and $\mathscr{Z}_{rA}$. Rural locations have, by definition, a comparative advantage in the agricultural sector, that is a large $\mathscr{Z}_{rA}/\mathscr{Z}_{rM}$. Rural labor markets also have most of their labor force in agriculture. As a result, their low levels of average income suggest they have low effective agricultural productivity, $\mathscr{Z}_{rA}$, and even lower effective non-agricultural productivity, $\mathscr{Z}_{rM}$.

Similarly, Proposition 1 also stresses that *changes* in the effective productivities, $\mathscr{Z}_{rM}$ and $\mathscr{Z}_{rA}$, are at the heart of local wage growth and industrialization. Although the static equilibrium allocations do not depend on whether effective non-agricultural productivity, $\mathscr{Z}_{rM}$, is low because of low market access, $\mathcal{D}_r$, or low physical productivity, $Z_{rM}$, the distinction becomes important to predict the *change* in effective productivity. If differences in physical productivity drive most of the variation in effective industrial productivity, $\mathscr{Z}_{rM}$, rural labor markets benefit from catch-up growth in the non-agricultural sector. If, by contrast, most of the variation in revenue productivity is due to market access, the benefit for a rural location from productivity convergence is limited. Similarly, if most of the variation in agricultural effective productivity, $\mathscr{Z}_{rA}$, is driven by differences in population density, $\ell_r$, then the agricultural productivity ladder, $Z_{rA}$, must be compressed and the potential for catch-up growth limited. By contrast, if rural locations are on average poor because their physical agricultural productivity, $Z_{rA}$, is low, they have substantial potential for catch-up growth.

# 3. The Drivers of Spatial Structural Change

In Section 1, we presented the key patterns of spatial structural change in the US between 1880 and 1920: agricultural locations experienced faster wage growth and industrialization exhibited a $U$-shape as a function of initial agricultural specialization. We now leverage Proposition 1 to derive predictions for these patterns of wage growth and industrialization.

Local wage growth and industrialization vary across space for two reasons. First, regions differ in their *exposure* to changes in effective productivity $\mathscr{Z}_{rM}$ and $\mathscr{Z}_{rA}$ depending on their sectoral specialization. Second, effective productivity itself might grow faster in some regions than in others, that is, regions could differ in the *incidence* of growth.

We now consider a single region $r$ that takes aggregate prices as given. Using the results in Proposition 1, local wage growth and industrialization in such a region $r$ are given in the following Proposition.

**Proposition 2.** *Local wage growth and local industrialization are given by*

$$\begin{aligned} d\ln\overline{w}_{rt} &= \phi\left(s_{rA}\right)d\ln\mathscr{Z}_{rMt}+\left(1-\phi\left(s_{rA}\right)\right)d\ln\mathscr{Z}_{rAt} \\ ds_{rAt} &= \psi\left(s_{rA}\right)\left(d\ln\mathscr{Z}_{rAt}-d\ln\mathscr{Z}_{rMt}\right), \end{aligned}$$

*where the two exposure elasticities are given by*

$$\phi_r\equiv\phi\left(s_{rA}\right)=\frac{\left(\gamma+1\right)\left(1-s_{rA}\right)}{\gamma\left(1-s_{Ar}\right)+1};\qquad \psi_r\equiv\psi\left(s_{rA}\right)=-\frac{s_{rAt}\left(1-s_{rAt}\right)\zeta}{\gamma\left(1-s_{rAt}\right)+1},$$

*with* $\gamma\equiv\alpha\left(\zeta-1\right)$. *The regional incidence of effective productivity growth can be decomposed as*

$$d\ln\mathscr{Z}_{rMt}=\frac{\sigma-1}{\sigma}d\ln Z_{rMt}+\frac{1}{\sigma}d\ln\mathcal{D}_{rt};\qquad d\ln\mathscr{Z}_{rAt}=d\ln Z_{rAt}-\alpha d\ln\ell_{rt}.$$

*Proof.* See Section A.5.2 in the Appendix. □

Proposition 2 summarizes the patterns of spatial structural change in the model. Local wage growth is a simple average of sectoral effective productivity growth, with the weight of non-agricultural productivity growth given by the wage-exposure elasticity $\phi_r$. Similarly, changes in comparative advantage, $d \ln \mathscr{Z}_{rMt} / \mathscr{Z}_{rAt}$, map into local industrialization with the semi-elasticity $\psi_r$.

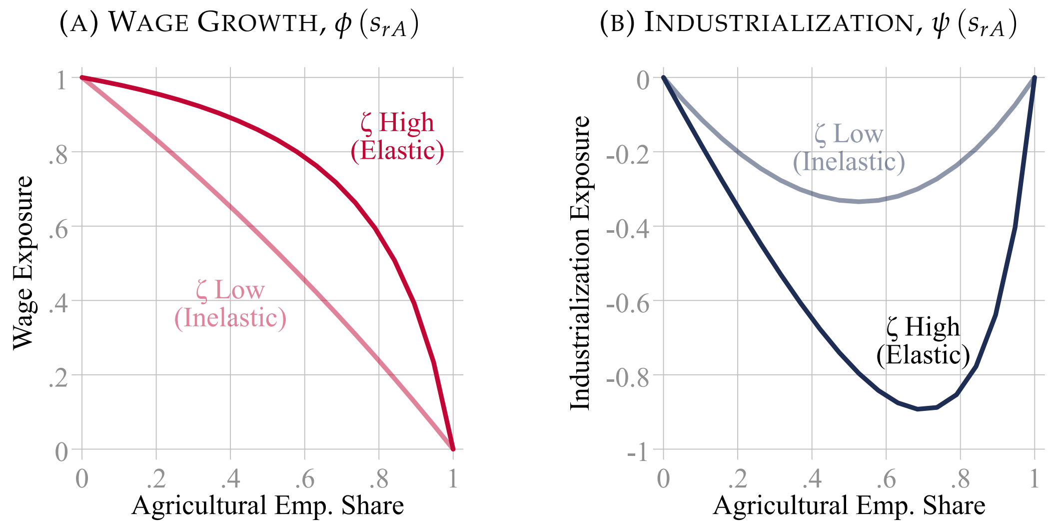
Importantly, Proposition 2 highlights the distinct roles of regional differences in incidence and exposure. Differences in exposure are summarized by the elasticities $\phi_r$ and $\psi_r$, which, crucially, are region-specific: a given change in effective productivity $\mathscr{Z}_{rMt}$ and $\mathscr{Z}_{rAt}$ will have a bigger impact in a location where $\phi_r$ and $\psi_r$ are large. Interestingly, the local agricultural employment share $s_{rA}$ emerges as the sufficient statistic for the regional heterogeneity in exposure.

Furthermore, our theory highlights the possibility of spatial differences in the incidence of growth, whereby effective productivity changes differentially across localities. Such differences in growth could be due to (i) the presence of technological catch-up ($d \ln Z_{rMt}$ and $d \ln Z_{rAt}$), (ii) local population growth $(d \ln \ell_{rt})$, and (iii) differential changes in market access $(d \ln \mathcal{D}_{rt})$.

**Spatial Heterogeneity in Exposure** In Figure 3, we depict the two exposure elasticities, $\phi_r$ and $\psi_r$, as a function of the agricultural employment share. As seen in the left panel, the sensitivity of local wages with respect to productivity growth in the manufacturing industry decreases in $s_{rA}$. Hence, whereas industrial areas benefit especially from growth in non-agricultural effective productivity, rural location are affected disproportionately by effective productivity growth in agriculture. Similar to the logic of "Bartik-style" instruments, Proposition 2 thus highlights that the sectoral origins of growth have direct spatial implications and that the current employment share determines regional exposure. Note, in particular, that rural locations benefit little from rising aggregate demand for non-agricultural products $\mathcal{D}_{rt}$. This formalizes the intuition that the demand shifts of the structural transformation have an inherent urban bias.

The right panel shows that the industrialization elasticity, $\psi_r$, is a $U$-shaped function of the agricultural employment share. Changes in comparative advantage, $d \ln \mathscr{Z}_{rMt} - d \ln \mathscr{Z}_{rAt}$, therefore induce industrialization everywhere. but especially at intermediate levels of agricultural specialization. Intuitively, the most urban locations cannot reduce their agricultural employment share, because they already are - effectively - fully specialized. By contrast, the most rural counties have such a strong comparative advantage in the agricultural sector that labor reallocation is limited. As we have shown in Figure 2 above, this

FIGURE 3: SPATIAL HETEROGENEITY IN EXPOSURE




Notes: The figure shows the exposure elasticities $\phi\,(s_{rA})$ and $\psi\,(s_{rA})$ given in Proposition 2 as a function of the agricultural employment share. We depict the case of relative inelastic supply (low $\zeta$) as a darker line and the case of relative elastic supply (high $\zeta$) as a more lightly-shaded line.

*U*-shape in local industrialization was one of the key patterns of spatial structural change in the US.

Proposition 2 also highlights that these exposure elasticities depend on the supply elasticity $\zeta$. This is because $\zeta$ captures the ease of sectoral reallocation and hence the ability of local labor markets to adjust to changes in the economic environment. As shown in Figure 3, the higher sectoral substitutability of skills $\zeta$, the higher the weight of non-agricultural productivity growth in determining local wages. As labor becomes very substitutable across sectors, the regional heterogeneity in wage exposure disappears. This is because sectoral wages equalize within a location and agricultural wages inherit the constant-returns-to-scale property of the non-agricultural sector, i.e., $\lim_{\zeta\to\infty}\phi_r = 1$. The inherent urban bias of falling agricultural demand is thus a symptom of the imperfect sectoral substitutability of workers *within* regions. Expectedly, the right panel shows that (the absolute value of) $\psi_r\,(s_{rA})$ is also increasing in $\zeta$: the higher the sector labor elasticity, the stronger the sectoral reallocation induced by changes in comparative advantage and the more pronounced the *U*-shape.

Finally, the exposure elasticities are tightly linked to the returns to scale in agriculture. If agricultural production was not reliant on land and had constant returns-to-scale, $\lim_{\alpha\to 0}\phi_r = 1 - s_{rA}$. Local wage growth would then simply be an employment-share weighted average of sectoral-revenue-productivity growth.

**Spatial Heterogeneity in Incidence** The discussion above highlights the spatially unbalanced impact of aggregate technological progress. This raises the natural question whether differences in exposure *alone* are able to explain the patterns of *spatial* structural change? The answer is no.

Suppose that the growth rate of the effective productivity terms $\mathscr{Z}_{rAt}$ and $\mathscr{Z}_{rMt}$ is common across regions and given by $\iota_A$ and $\iota_M$ respectively.[11] In this case, local development varies across regions only due to differences in exposure. In particular, using Proposition 2, the patterns of spatial structural change would then be given by:

$$d \ln \overline{w}_{rt} = \iota_A + \phi\left(s_{rA}\right)\left(\iota_M - \iota_A\right); \qquad ds_{rAt} = \psi\left(s_{rA}\right)\left(\iota_M - \iota_A\right). \tag{16}$$

Since $\psi\left(s_{rA}\right) < 0$, the aggregate agricultural employment declines if and only if $\iota_M > \iota_A$. However, wages in rural locations would grow *less* because $\phi\left(s_{rA}\right)$ is declining in $s_{rA}$. Hence, if effective productivity growth had been balanced, growth would have been urban-biased during the structural transformation. This is clearly at odds with the actual patterns of spatial structural change we documented in Section 1.[12]

The empirically observed rural bias thus directly implies that agricultural locations must have experienced faster growth in effective productivity. Proposition 2 highlights that such faster wage growth can be achieved in three ways: (i) out-migration, so that population density $\ell_{rt}$ falls in rural location raising the marginal product of labor, (ii) increases in market access $\mathcal{D}_{rt}$, stimulating additional firm entry and associated job-creation in rural locations, and (iii) faster growth of physical productivity $Z_{rMt}$ and $Z_{rAt}$. Next, we examine which of these factors were most influential in the US economy between 1880 and 1920.

# 4. Quantitative Analysis

We now apply our framework to understand why economic growth in the US between 1880 and 1920 was pro-rural. In this section, we estimate the structural parameters of our model before studying the role of catch-up growth in generating the patterns of spatial structural change in Section 5.

[11] For example, if population were fixed, sectoral productivity $Z_{rMt}$ and $Z_{rAt}$ grew at the same rate in all locations, and trade was free, so that the market-access term was common across space (i.e., $\mathcal{D}_{rt} = \mathcal{D}_t$).

[12] Note that this result holds regardless of why the agricultural employment share is declining. As long as agricultural employment is declining and the proportional change in effective productivity is spatially balanced, this aggregate reallocation will lead to urban-biased growth.

## 4.1 Data Description

To map our model to the data, we define locations in the model as commuting zones in the data. We map historic counties to modern-day commuting zones using the crosswalk in Eckert et al. [2020b] and drop commuting zones in states that were not in the Union by 1880. Our final sample consists of a balanced panel of 495 commuting zones (see B.1 in the Appendix for a map). We assume a period in the model corresponds to 20 years in the data.

Our analysis relies on the following sources of data. We obtain total employment by sector and county from the U.S. Census Bureau's Decennial Full Count Census files (via IPUMS; see Ruggles et al. [2015]). These data also contain information on children and immigrants, which we use to estimate the exogenous component of local population growth, $n_{rt}$. We supplement these data with information on average earnings at the county level from the Census of Manufacturing (via NHGIS; see Manson et al. [2017]).[13] We draw average values of farmland and buildings per acre for each decade from the Census of Agriculture (via NHGIS; see Manson et al. [2017]). We use longitudinal data at the individual level from the linked version of the Decennial Census data to measure migration flows across commuting zones (via IPUMS; see Ruggles et al. [2015]). Finally, to connect our model with macroeconomic aggregates, we rely on time-series data from the "Historical Statistics of the United States" (see Carter et al. [2006]) on real GDP per capita and the sectoral price indices. In Appendix B.1, we provide more details on data sources, data construction, and sample selection.

## 4.2 Estimation Strategy

We estimate a set of structural parameters via indirect inference using eleven empirical moments: the two catch-up parameters $\lambda_M$ and $\lambda_A$, the labor supply elasticity $\zeta$, consumers' preferences $\nu, \phi, \eta$, and $\varepsilon$ and the growth rates of the sectoral productivity frontiers $g_M$ and $g_A$. In addition, we estimate the elasticities of migration and trade costs with respect to distance from gravity relationships of trade and migration flows outside of the model. Finally, given these structural parameters, we infer the distribution of local fundamentals, that is the initial productivity ladder in 1880, $[Z_{rs1880}]_r$, the endowment of agricultural land $[T_r]$, and local amenities $[B_r]$, to perfectly rationalize the data on wages,

[13] In the model, average earnings in manufacturing exactly coincide with average regional earnings, $\overline{w}_{rt}$, which we compute as manufacturing payroll divided by manufacturing employment.

population, land rents and sectoral employment shares in 1880.

In Table 1 below, we provide an overview of all the parameters of our model and the empirical moments we use for identification. Even though most parameters are calibrated jointly, we discuss our calibration strategy for particular structural parameters in terms of the most informative empirical moments. The Appendix provides more details.[14]

**Regional Fundamentals:** $[T_r]$**,** $[B_r]$**, and** $[Z_{rs1880}]$ We choose regions' initial sectoral productivity, $[Z_{rs1880}]_{rs}$, and land endowments, $[T_r]$, to exactly match the distribution of average earnings $\{\overline{w}_{r1880}\}_r$, agricultural employment shares $\{s_{rA1880}\}_r$, and land rents $\{R_{r1880}\}$, given the observed population in 1880. A virtue of this approach is that the initial spatial productivity ladder in 1880 is directly taken from the data. So instead of assuming that agricultural regions are necessarily backward and hence benefit from catch-up growth, the correlation between a region's sectoral productivity and its initial agricultural employment share in our calibrated model *comes directly from the data*.

As we show below, we find that agricultural regions in 1880 had *both* low agricultural productivity, $Z_{rA1880}$, and low manufacturing productivity, $Z_{rM1880}$. Agricultural specialization was thus only a reflection of comparative advantage in agriculture, and not of an absolute agricultural advantage. The fact that rural locations were technologically behind the frontier in both industries implies that they benefitted from catch-up growth in both sectors.

For each sector separately, we set the level of the economy's technological frontier , $[\overline{Z}_{s1880}]_s$, to the highest regional productivity level of any region in 1880. Finally, we infer the exogenous component of regional amenities, $[B_r]_r$, to ensure the population distribution would be stationary between 1880 and 1920, if regional productivities and aggregate population stocks were fixed at their 1880 levels.[15]

**Technological Catch-Up (**$\lambda_s$**) and Skill Substitutability (**$\zeta$**)** The key empirical patterns motivating our analysis are the positive relationship between agricultural specialization and wage growth, and the $U$-shaped relationship of agricultural specialization and subsequent industrialization (cf. Section 1). In Section 3, we showed that the extent of technological catch-up $(\lambda_s)$ and the sectoral substitutability of skills $(\zeta)$ are important deter-

[14]Note the fixed costs $f_E$ can be normalized to unity without loss of generality.

[15]Note also that such calibrated amenities implicitly control for differences in the size of commuting zones. For given wages, commuting zones with a larger area and correspondingly larger population are associated with a higher amenity term.

minants of these patterns. We therefore estimate $(\zeta, \lambda_A, \lambda_M)$ by explicitly targeting these cross-sectional relationships.

Specifically, we summarize the empirical relationships from Figure 2 in the regressions

$$(17) \qquad d \ln \bar{w}_{rt} = \delta_t + \beta_w \, s_{rAt} + \nu_{rt}; \qquad ds_{rAt} = \delta_t + \beta_{s_A} \, s_{rAt} + \gamma_{s_A} \, s_{rAt}^2 + u_{rt},$$

where $\bar{w}_{rt}$ and $s_{rAt}$ denote average annual earnings and the agricultural employment share in commuting zone $r$ in 1880 and 1900, respectively, and $\delta_t$ is a time fixed effect. We then estimate $(\zeta, \lambda_A, \lambda_M)$ through indirect inference by matching the three coefficients $\beta_w$, $\beta_{s_A}$ and $\gamma_{s_A}$ in our model. In Table A.1 in the Appendix, we report the results of estimating equation (17) in our panel of commuting zones.

The coefficients $\beta_w$, $\beta_{s_A}$, and $\gamma_{s_A}$ are informative about $\lambda_A$, $\lambda_M$, and $\zeta$ because rural locations have an absolute disadvantage in agriculture and non-agriculture and benefit from catch-up growth in both industries. Hence, $\beta_w$ increases in both $\lambda_A$ and $\lambda_M$. At the same time, $\lambda_A$ and $\lambda_M$ have opposite effects on rural industrialization: if most catch-up growth occurs in agriculture, local agricultural specialization would *increase* in rural regions. If, by contrast, rural wage growth is mostly driven by catch-up in manufacturing, we would see a comovement between wage growth and industrialization in rural locations. In addition, Figure 3 above showed that a larger supply elasticity, $\zeta$, leads to a more pronounced $U$ shape in industrialization. As such, parameter $\gamma_{s_A}$ is informative about $\zeta$.

In addition to the parameters $\beta_{s_A}$ and $\gamma_{s_A}$, we also target the change in agricultural employment shares between 1880 and 1920 among the most rural location. In doing so, our model captures the $U$-shaped relationship of local industrialization and initial agricultural specialization. Specifically, we target the change in the agricultural employment share between 1880 and 1920 among locations with at least 80% of their 1880 workforce in agriculture.

**The Spatial Labor Supply Elasticity $\epsilon$** The sensitivity of spatial reallocation with respect to local factor prices is mainly governed by the Fréchet parameter $\epsilon$. However, unlike in models with homothetic preferences, the parameter $\epsilon$ is not the sole determinant of the spatial labor supply elasticity. In particular, the non-homotheticity of preferences implies that the elasticity varies endogenously across labor markets. In particular, using equation (10), the partial elasticity of migration flows from $r$ to $r'$ with respect to wages in $r'$ is given by

$$\frac{\partial \ln m_{rr'}}{\partial \ln \overline{w}_{r'}} = \varepsilon\eta \left(1 + \nu \frac{\ln\left(P_{r'A}/P_{r'M}\right)}{\frac{1}{\eta}\Gamma_{\zeta/\eta}\left(\overline{w}_{r'}/\left(P_{r'A}^{\phi}P_{r'M}^{1-\phi}\right)\right)^{\eta} - \nu \ln\left(P_{r'A}/P_{r'M}\right)}\right), \tag{18}$$

which, in addition to the parameter $\varepsilon$, depends on the Engel elasticity $\eta$, the taste parameter $\nu$, and a set of endogenous variables.

We estimate $\epsilon$ using two data moments. First we target an average labor-supply elasticity of two, a consensus estimate in the literature (see e.g. Allen and Donaldson [2020], Monte et al. [2018] or Peters [forthcoming]). Second, similar to equation (17), we match the observed correlation between initial agricultural specialization and future population growth. Specifically, we estimate the regression

$$d \ln L_{rt} = \delta_t + \beta_l \, s_{rAt} + \nu_{rt} \tag{19}$$

both in the data and in the model and target the coefficient $\beta_l$. Empirically, we find that $\beta_l = -0.36$ (see Table A.1 in the Appendix).

**Aggregate Productivity Growth ($g_A$ and $g_Z$) and Sectoral Preferences ($\eta$, $\nu$, and $\phi$)** We estimate the growth rates of the agricultural and non-agricultural frontier, $g_A$ and $g_{NA}$, and consumers' preferences, $\eta$ and $\nu$, to ensure that the model matches three macroeconomic time-series moments: (i) aggregate GDP growth between 1880 and 1920, (ii) the change in relative price of agricultural products between 1880 and 1920, and (iii) the evolution of the agricultural employment share. Given our estimates of $[Z_{rs1880}]_{rs}$ and $[T_r]$, we match the agricultural employment share in 1880 by construction. We thus target six macroeconomic moments: two growth rates (1880-1900 and 1900-1920) for each of the three outcomes. The remaining preference parameter, $\phi$, corresponds to the asymptotic spending share on agricultural value added for very high incomes. We set $\phi = 0.01$, which is close to the agricultural employment share in the US in 2020.

**Other Parameters** In our quantitative model, both people and goods are subject to moving costs. We parameterize these costs as power functions of distance. Migration and trade costs increase in distance with elasticity $\kappa > 0$ and $\theta > 0$, respectively. If we denote the geographic distance between regions $r$ and $r'$ by $d_{rr'}$, migration cost are $\mu_{rr'} = d_{rr'}^{-\kappa}$, and trade costs in both sectors are $\tau_{rr'} = d_{rr'}^{-\theta}$.

To estimate the "distance elasticity" of migration costs, $\kappa$, we use the following log linear relationship for interregional migration flows our model implies:

$$\log m_{rr't} = \delta^o_{rt} + \delta^d_{r't} - \kappa\epsilon \log d_{rr'}. \tag{20}$$

In the equation, $\delta^o_{rt}$ and $\delta^d_{r't}$ are origin and destination fixed effects, respectively, that are functions of endogenous location-specific objects and parameters. We estimate equation (20) using commuting-zone-to-commuting-zone migration flows that we constructed with the linked Census data. In specific, we use the Poisson Pseudo Maximum Likelihood estimator proposed by Silva and Tenreyro [2006] since the data contain many zero values. As we show in Section B.3.3 in the Appendix, our finding that $\kappa\varepsilon \approx 2.8$, is consistent with Allen and Donaldson [2020] who find a distance elasticity of 2.16 across counties during the same time period in the US. For the elasticity of trade flows to distance, $(1-\sigma)\theta$, Allen and Donaldson [2020] report an estimate of $-1.35$.[16]

We take the remaining parameters from various sources in the literature. Most related economic literature assumes an elasticity of substitution $\sigma$ between 3 and 8; we set $\sigma = 6$. Valentinyi and Herrendorf [2008] find the value-added share of land is roughly one third as large as the one of labor; consequently, we set the land share in agriculture, $\alpha$, to 0.4. We also borrow the congestion elasticity of $\rho = 0.15$ from Allen and Donaldson [2020] which is estimated using the same time period and Census data used in our study.

**The Exogenous Component of Local Labor Force Growth $n_{rt}$** In Section B.3.2 in the Appendix, we show that between 1880 and 1920 rural locations had substantially higher birth rates, while urban locations received more international immigrants. To capture both the aggregate level and spatial heterogeneity in population growth through fertility and international migration, we allow for an exogenous component of local population growth $n_{rt}$ - see equation (11). We choose the region- and period-specific parameter $n_{rt}$ to match the net effect of the cross-sectional variation in immigration and fertility rates for each commuting zone, as well as the overall aggregate rate of population growth between 1880 and 1920. In Section B.3.2, in the Appendix, we describe this procedure in more detail.

Importantly, since workers at the beginning of each period have the option to migrate before becoming economically active, employment growth in each location remains en-

[16] Monte et al. [2018] find a similar elasticity of $-1.29$. Disdier and Head [2008] show this elasticity is roughly constant in international trade data in the 20th century.

Table 1: Structural Parameters and Model Fit

| Structural Parameters | | | Estimation Method | | |
|---|---|---|---|---|---|
| | Description | Value | Panel A: In-Model (Moment, Data,Model) | | |
| $\zeta$ | Labor Supply Elasticity | 6.9 | $\gamma_{sA}$ in regression (17) | 0.45 | 0.51 |
| | | | $E[s_{rA1920} - s_{rA1880} \| s_{rA1880} > 0.8]$ | -0.20 | -0.20 |
| $\lambda_A$ | Catch-Up in Agricult. | 0.21 | $\beta_w$ in regression (17) | 0.25 0.16 | |
| $g_A$ | Growth of Agricult. Frontier | 0.07 | Ag. Empl. Share 1900 | 0.39 | 0.35 |
| | | 0.12 | Ag. Empl. Share 1920 | 0.26 | 0.25 |
| $\lambda_M$ | Catch-Up in Non-agricult. | 0.05 | $\beta_{sA}$ in regression (17) | -0.48 | -0.57 |
| $g_M$ | Growth of Non-agricult. Frontier | 0.09 | GDP growth 1880-1900 | 1.43 | 1.50 |
| | | | GDP growth 1900-1920 | 2.04 | 2.05 |
| $\epsilon$ | Location Taste Heterogeneity | 3.80 | Avg. Migration Elasticity | 2 | 2.03 |
| | | | $\beta_l$ in regression (19) | -0.36 | -0.04 |
| $\eta$ | Engel Elasticity | 0.93 | Rel. price $P_M/P_A$ 1900 | 0.94 | 1.01 |
| $\nu$ | PIGL preference parameter | 0.12 | Rel. price $P_M/P_A$ 1920 | 0.89 | 0.87 |
| | | | Panel B: Out-of-Model (Strategy) | | |
| $\kappa$ | Migration Cost Distance Elasticity | 2.8 | Gravity relationship of migration flows | | |
| $\theta$ | Trade Costs Distance Elasticity | 1.35 | Gravity relationship of trade flows | | |
| | | | Panel C: Exogenously-Set (Source) | | |
| $\sigma$ | Elastictiy of Substitution Mfg Good | 6 | NA | | |
| $\rho$ | Amenity Congestion Elasticity | 0.15 | Allen and Donaldson [2020] | | |
| $\alpha$ | Land Share in Production Function | 0.4 | Valentinyi and Herrendorf [2008] | | |
| $\phi$ | Asy. Exp. Share on Agricult. Goods | 0.01 | NA | | |

Notes: The table contains the values for all structural parameters and targeted moments of our model. The eight parameters in the upper panel are estimated within the model, targeting the eleven moments on the right. The two distance elasticities are estimated from gravity equations outside of the model. The remaining four parameters are set exogenously.

dogenous in our theory.

## 4.3 Estimates and Model Fit

Table 1 presents our parameter estimates and their loosely-associated moments in the calibrated model and the data. We differentiate parameters estimated within the model by matching moments (Panel A) parameters estimated outside the model (Panel B), and parameters that are set exogenously (Panel C). Overall, the calibrated model successfully captures the most important empirical features of spatial structural change in the US between 1880 and 1920.

The calibrated model produces the time-series patterns of the three aggregate "macro" moments: it successfully captures the large decline in agricultural employment, the increase in GDP per capita, and the small increase in the relative price of agricultural goods between 1880 and 1920. These time series moments mostly informed the rates of aggregate productivity growth and preference parameters. We estimate that the productivity frontier in non-agriculture ($\overline{Z}_{Mt}$) grew at a rate of 0.09, and the frontier in agriculture ($\overline{Z}_{At}$) at 0.07 over a 20-year time period. The estimates of the preference parameters imply an important role of the demand-side non-homotheticicities: we find an Engel elasticity $\eta$ of 0.93 and $\nu = 0.12$, which implies that agricultural value added is a necessity.[17]

Given the estimated preference parameters, we can compute the implied elasticity of substitution $\varrho$ via equation (3). Because $\varrho$ increases in the spending share on food, it is lower in urban areas and decreases over time. Our estimates imply that the median substitution elasticity declines from 2 in 1880 to 1.52 in 1900 and 1.31 in 1920. Similarly, the 10% and 90% quantiles of $\rho$ across regions in 1900 range from 1.3 to around 2.[18] This pattern of declining substitution elasticities along the development path is qualitatively consistent with the cross-country data reported in Comin et al. [2021].

Most importantly, the calibrated model matches the patterns of spatial structural change from Section 1. In particular, our model can rationalize the relationships between agricultural employment shares and future wage growth and industrialization. The cross-sectional estimates of the parameters $\beta_w, \beta_{sA}$, and $\gamma_{sA}$ from the two regression in equations (17) are very similar in the model and the data. In Figure 4, we replicate the non-linear relationships between agricultural employment shares and wage growth (left panel), and industrialization (right panel) introduced in Section 1 in both the data (grey) and our model (red and blue, respectively). Although we only targeted three regression coefficients and the change in agricultural employment among rural locations, our model reproduces the rural-bias of wage growth and the *U*-shape of industrialization very well.

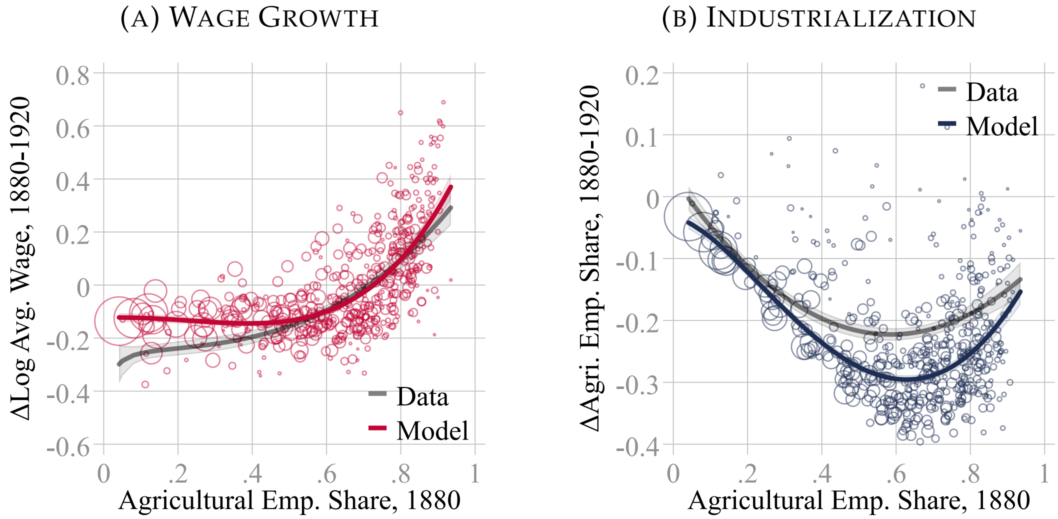
To fit these patterns of spatial structural change, our parameter estimates point towards the importance of catch-up growth in rural areas. Recall that local productivity growth depends both on a region's position on the spatial productivity ladder (i.e., $\overline{Z}_{s1880}/Z_{rs1880}$) and the strength of catch-up, i.e., the parameters $\lambda_A$ and $\lambda_M$. Our estimates of $\lambda_A = 0.21$ and $\lambda_M = 0.05$ indicate that there was significant catch-up growth and spatial convergence between 1880 and 1920. Moreover, because we estimate sectoral productivity in 1880, $Z_{rs1880}$, to be negatively correlated with the agricultural employment share, $s_{rA1880}$, rural labor markets were the main beneficiaries of such catch-up growth.

The quantitative impact of these patterns is depicted in Figure 5. In the left panel we dis-

[17] In Section B.3.7 in the Appendix, we compare this estimate from time-series data to cross-sectional estimates.

[18] In Section B.3.6 in the Appendix, we display the entire distribution.

FIGURE 4: RURAL GROWTH AND INDUSTRIALIZATION – MODEL AND DATA



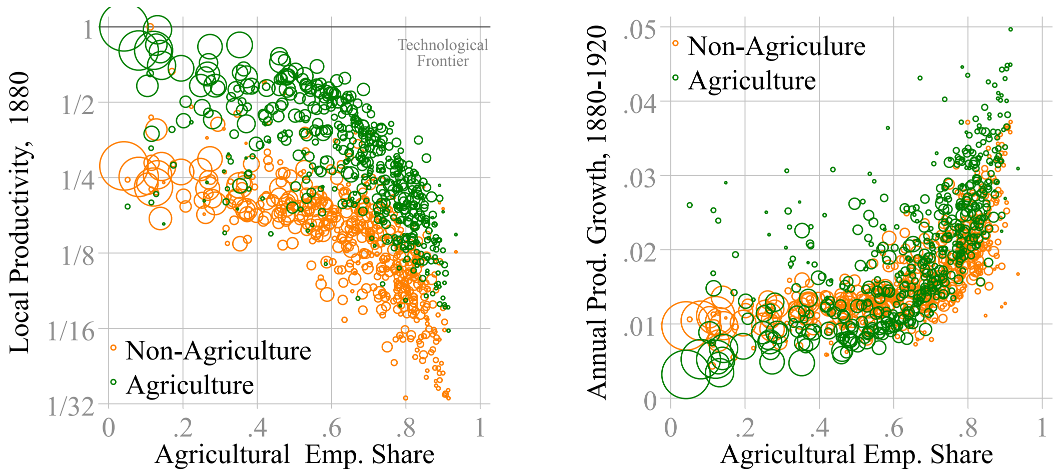

Notes: The figure displays the correlation of wage growth (left panel) and industrialization (right panel) with the agricultural employment share. We show the data in lighter-shaded colors and model output in darker shades.

play the productivity ladder in 1880 as a function of the agricultural employment share. Agriculturally specialized labor markets are, on average, less productive in *both* sectors. Locations with an agricultural share of 80% in 1880 operate, on average, with manufacturing technology that is only 20% as productive as the frontier technology at the time. In the agricultural sector, these differences are less pronounced but still sizable: although rural regions specialize in agriculture, TFP in the agricultural sector is only half that of more developed urban centers. These within-country productivity differences are comparable to estimates of relative TFP across countries [Jones, 2016].

Given that we found $\lambda_A, \lambda_M > 0$, the absolute technological disadvantage of agricultural regions in both sectors implies that they stand to enjoy the "benefits of backwardness" through catch-up growth. In the left panel of Figure 5, we show the implied heterogeneity in productivity growth across regions. In the four decades following 1880, rural labor markets experienced a growth premium of around two percentage points. The similarity in productivity growth in both sectors reflects the combination of two aspects of our theory. First, there is less regional dispersion in agricultural productivity, reducing the opportunities for productivity catch-up. Second, our structural estimation showed that $\lambda_A > \lambda_M$, that is, the process of catch-up is faster in agriculture (which, in turn, might be why agricultural productivity in 1880 is less dispersed). In terms of their regional growth implications, these two forces roughly balance out.

Figure 5: The Spatial Productivity Ladder and Local Catch-Up

(a) The Productivity Ladder in 1880 (b) Catch-Up Growth: 1880-1920



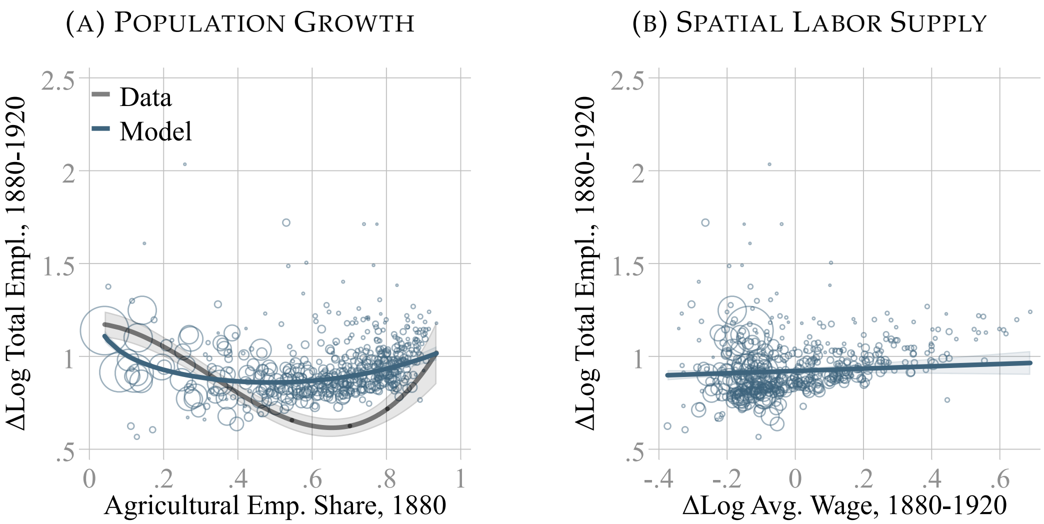

Notes: The left panel displays the correlation of initial backwardness, $\overline{Z}_{1880}/Z_{r1880}$ and $\overline{A}_{1880}/A_{r1880}$, with the agricultural employment share in 1880. As a measure of the frontier $\overline{Z}_{1880}$ and $\overline{A}_{1880}$, we take the 98% quantile of the distribution $Z_{r1880}$ of $A_{r1880}$. The right panel displays the correlation of the estimated rate of annual local productivity growth between 1880 and 1920, i.e., $\frac{1}{40}\ln\left(Z_{r1920}/Z_{r1880}\right)$ and $\frac{1}{40}\ln\left(A_{r1920}/A_{r1880}\right)$, with the agricultural employment share in 1880.

In Figure 6, we turn to the implications for spatial mobility. In the left panel, we show the cross-sectional relationship between local population growth and initial agricultural specialization, that is, the data underlying regression (19). The empirical relationship is non-monotone and, on average, relatively flat, indicating that population growth and agricultural specialization are not very strongly correlated. The $R^2$ of regression (19) is only 0.17, indicating that the agricultural employment share in 1880 is a weak predictor of future population growth.[19] As suggested by the pronounced leftward shift of the regional employment share distributions in Figure 2, the structural transformation in the US was mostly a within-labor-market phenomenon. Accordingly, the net-reallocation of labor from rural to urban commuting zones played a less important role for the structural transformation.[20] Our calibrated model captures the qualitative relationship reasonably well: the overall correlation of local population growth and initial agricultural

[19]This, of course, does not imply that spatial reallocation was not important. Presumably there was ample spatial reallocation within counties or commuting zones from rural areas to the local town. This view is consistent with the fact that most urbanization in the United States between 1880 and 1920 occured within commuting zones.

[20]Interestingly, Budí-Ors and Pijoan-Mas [2022] show that this pattern was different in the case of Spain between 1950 and 2000. They document a strongly negative correlation between population growth and agricultural employment shares and argue that migration costs might have been lower. Using data across countries, they show that for most countries, the relationship between population growth and agricultural specialization is similar to the case of the US shown in Figure 6.

FIGURE 6: POPULATION GROWTH AND LOCAL INDUSTRIALIZATION IN MODEL AND DATA, 1880-1920




Notes: In the left panel, we show the relationship between population growth and the agricultural employment share. We show the data in grey and our model in orange. The size of the markers reflect the relative size of different commuting zones. The solid lines show the best non-linear fit. In the right panel we display the correlation between wage growth and population growth in the model.

employment shares is small. However, we slightly overestimate (underestimate) population growth for very rural (urban) communities.[21]

At first glance, the weak relationship between agricultural employment shares and population growth seems at odds with the strong rural-bias of wage growth. After all, regional utility $\mathcal{V}_{rt}$ depends directly on regional wages and our model generates an empirically reasonable migration elasticity of two. We observe that these patterns are consistent with each other in the right panel of Figure 6, which - expectedly - shows a positive correlation between wage growth and population growth in the model. However, the relationship is noisy because (i) goods prices change at different rates due to trade costs, (ii) the current population distribution matters directly for future population growth because of moving costs, and (iii) the exogenous part of population growth $n_{rt}$ due to differential fertility and immigration inflows is not perfectly correlated with future wage growth. This, together with the fact that wage growth is not perfectly correlated with the agricultural employment share, rationalizes the weak relationship between agricultural specialization and future population growth shown in the left panel of Figure 6.

[21] In addition, population growth is less dispersed compared to the data. This is not surprising given that our analysis abstracts from idiosyncratic shocks to local productivity or to amenities.

## 4.4 Rural Catch-Up: Direct Evidence

Figure 5 showed that rural labor markets benefitted systematically from catch-up growth in both sectors. In this section, we complement these model-based estimates with direct empirical evidence for the presence of faster rural productivity growth.

Our theory summarizes all factors leading to catch-up growth in the reduced-form process of technological convergence. We view this parametrization as a modeling device for various technological and institutional developments in the US between 1880 and 1920 that benefitted rural locations. In Table 2, we provide evidence for such developments from multiple data sources. Specifically, we run a set of bivariate regressions where we regress the growth of different outcomes between 1880 and 1920 against the agricultural employment share in 1880. We differentiate between outcomes we expect are correlated with general productivity growth, and those we expect are correlated with sector-specific productivity growth.

In columns 1 and 2, we report two examples of general developments that benefitted rural locations. In Column 1, we show rural locations experienced faster financial development, as measured by the growth of the number of banks per capita. In the second column, we provide evidence for the pronounced catch-up in educational attainment, proxied by the share of children attending school. As a result, we find that the school attendance rate increased much faster in agriculturally specialized labor markets between 1880 and 1920.

In the remaining columns, we present additional evidence for sector-specific factors. In particular, rural locations saw faster growth in the capital stock in both sectors (columns 3 and 5) and experienced a faster increase in scale: the growth in both average farm and firm size is positively correlated with the initial agricultural employment share (columns 4 and 6).[22]

We view these results as an empirical description of the general transformation of rural labor markets between 1880 and 1920. Rising educational attainment, changes in the scale and capital intensity of production, and financial deepening are often seen as markers of economic development across countries. Table 2 shows that the same patterns were also present across local labor markets in the US during the first phase of the structural transformation.

[22] Desmet and Rossi-Hansberg [2009] provide direct estimates of manufacturing TFP convergence across regions in the US between 1900 and 1920; their estimates are of a similar magnitude (cf. Figure 6 in their paper).

TABLE 2: DRIVERS OF RURAL CATCH-UP

| | Growth in... | | | | | |
|---|---|---|---|---|---|---|
| | General | | Sector-specific Factors | | | |
| | Banks pc | School Attendance | Agri. Machinery | Farm Size | Non-agri. Machinery | Plant Size |
| Agri. Emp. Share | 0.117*** | 0.007*** | 0.032*** | 0.012*** | 0.039*** | 0.032*** |
| | (0.006) | (0.001) | (0.002) | (0.003) | (0.009) | (0.007) |
| $R^2$ | 0.723 | 0.331 | 0.359 | 0.107 | 0.090 | 0.242 |
| N | 495 | 495 | 495 | 495 | 495 | 495 |

Notes: The dependent variables are the growth rate in the number of banks per capita from Jaremski and Fishback [2018] (Column 1), the change in the share of children attending school from the Decennial Census (Column 2), and the growth rates of the sectoral capital stocks and average employment per farm/firm from the Census of Manufacturing (Columns 5 and 6) and the Census of Agriculture (Columns 3 and 4). All regressions are employment weighted.

# 5. CATCH-UP AND RURAL-BIASED GROWTH

In this section, we use our calibrated model to quantify the importance of catch-up growth in generating the patterns of spatial structural change introduced in Section 1.

## 5.1 The Sources of Rural-Biased Growth

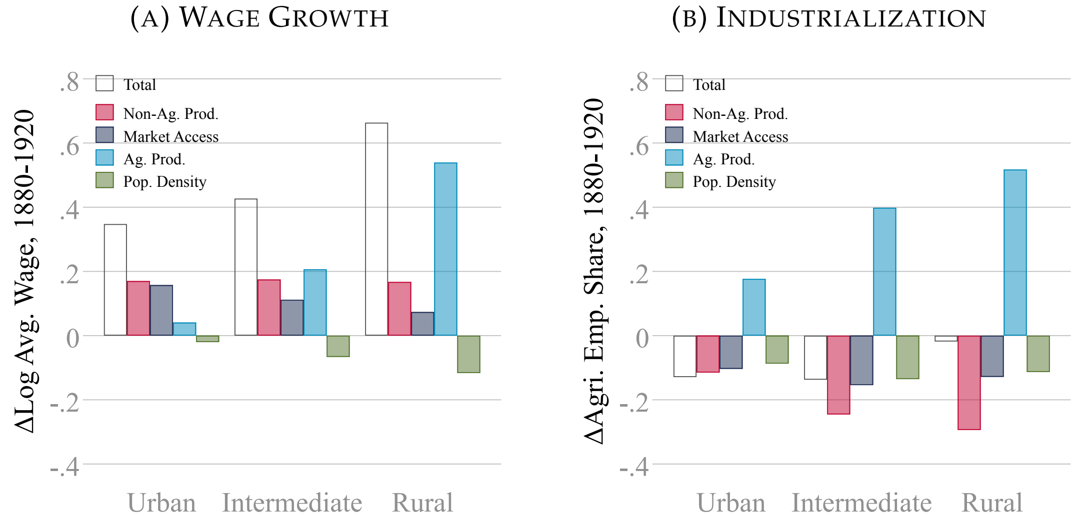
In Proposition 2, we decomposed local wage growth and industrialization into four components: demand growth ($d \ln \mathcal{D}_{rt}$), sectoral productivity growth ($d \ln Z_{rst}$), and changes in population density $(d \ln \ell_{rt})$.

In Figure 7, we implement this decomposition in our calibrated model.[23] Specifically, for each commuting zone, we compute the impact of each component separately for local wage growth and local industrialization. We then aggregate these results among urban, intermediate, and rural locations which we define as all regions below, within, and above the interquartile range of agricultural employment shares in 1880.

The left panel of Figure 7 presents the decomposition of wage growth. The white bars represent the total wage growth in each group of commuting zones, and exhibit the previously-documented pattern of rural-biased growth. The remaining bars show that re-

[23] Proposition 2 relies on a first-order approximation. In Section B.3.8 in the Appendix, we compare these predictions with the full non-linear solution in our model and show they are close.

FIGURE 7: THE MECHANISMS OF SPATIAL STRUCTURAL CHANGE




Notes: The figure reports the decomposition of local wage growth, $d \ln \overline{w}_{rt}$, and local industrialization, $ds_{rA}$, (see Proposition 2) into non-agricultural demand $\left(\phi_r \frac{1}{\sigma} d \ln \mathcal{D}_{rt}\right)$, local productivity growth ($\phi_r \frac{\sigma-1}{\sigma} d \ln Z_{rMt}$ and $(1-\phi_r)\, d \ln Z_{rAt}$), and changes in local population density ($-\phi_r \alpha d \ln \ell_{rt}$). We define urban (rural) locations as regions in the lower (upper) quartile of the distribution of agricultural employment share in 1880 and intermediate locations in the interquartile range. We refer to all commuting zones in the interquartile range as "intermediate."

gions differed substantially in *why* their wages grew. In rural labor markets, agricultural productivity growth was the dominant factor. By contrast, industrial revenue productivity growth through increasing demand ($\mathcal{D}_{rt}$) and non-agricultural growth ($Z_{rMt}$) had a positive, but small effect. This is because a small fraction of local workers is employed in non-agriculture, making $\phi\left(s_{rA}\right)$ small. Population growth reduced wage growth, especially in rural locations, whose sectoral structure exposes them to decreasing returns in the agricultural sector.

These patterns differ in urban areas. Revenue productivity growth in the non-agricultural sector played a dominant role for wage growth, and almost half of all wage growth stemmed from increased demand. Even though manufacturing productivity growth is slower in urban areas (see Figure 5), their outsized exposure to this sector implies that the total impact is comparable to rural locations. Rising agricultural productivity did not meaningfully affect wages in urban labor markets. Finally, increased population density also reduced wages in urban areas. Still, this reduction was far less than in rural labor markets in which a large fraction of workers is employed in the agricultural sector that is subject to decreasing returns.

Overall, the decomposition highlights the importance of exposure versus incidence in shaping the spatial bias of of growth. The impact of non-agricultural productivity growth is balanced across regions since exposure and incidence are inversely correlated: productivity growth is faster in rural regions where exposure is lower, since most workers belong to the agricultural sector. The opposite is true for urban regions. By contrast, rural regions are both more exposed to and benefit from faster agricultural productivity growth, making it a powerful source of rural-biased growth.

The right panel of Figure 7 displays the same decomposition for local industrialization. Rural locations industrialized because of rising relative productivity in the manufacturing sector and increasing population density. By contrast, productivity growth in the agricultural sector was a strong counteracting force that kept workers in agriculture. Intermediate locations saw a slightly faster decline in agricultural employment shares (the "$U$ shape"), primarily due to a less pronounced increase in agricultural productivity. Finally, in urban centers, rising demand, nonagricultural productivity growth, and rising population density are equally important contributors to the decline in agricultural employment.

## 5.2 Catch-up Growth and Spatial Structural Change

The accounting decomposition in Figure 7 highlights the pivotal role of rural-biased productivity growth to explain the patterns of spatial structural change. We now quantify the full impact of this form of productivity convergence.

To do so, we consider an alternative calibration of our model that does not feature catch-up growth. Specifically, we keep all preference parameters the same but consider a different parametrization of the productivity process: we assume that the spatial productivity ladder is stationary, i.e., $\lambda_A = \lambda_M = 0$, and re-estimate the growth rates of the respective technological frontiers, $g_A$ and $g_M$, to match the growth of aggregate income per capita and the change in relative prices since 1880. Hence, this scenario resembles a baseline macroeconomic model in which local labor markets are spatially segmented, but technologies grow at the same rate across regions. We thus refer to this parametrization as the "no-catchup" calibration of our model.

We report the resulting parameters of the productivity process (Columns 1 - 4) and the implied macro moments (Columns 5 - 10) in Table 3. All parameters except for $g_s$ and $\lambda_s$ are held fixed.[24] Table (3) shows that the overall rate of frontier productivity growth in

[24]Note that this implies that the location fundamentals, that is, the initial productivity ladder, the land

TABLE 3: THE MACRO CALIBRATION

| | TECHNOLOGY PARAMETERS | | | | MACRO MOMENTS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Agri. | | Non-Agri. | | Agri. Emp. Share | | GDP pc | | $P_M/P_A$ | |
| Calibration | $g_A$ | $\lambda_A$ | $g_M$ | $\lambda_M$ | 1900 | 1920 | 1900 | 1920 | 1900 | 1920 |
| No-Catchup | 0.41 | 0 | 0.34 | 0 | 0.34 | 0.24 | 1.41 | 2.03 | 0.98 | 0.88 |
| Baseline | 0.07 | 0.21 | 0.08 | 0.05 | 0.34 | 0.25 | 1.5 | 2.05 | 1.01 | 0.87 |

Notes: The table reports the technology parameters and the macro moments for the baseline model and the "macro-calibration." All other parameters are the same in both calibrations and reported in Table 1.

each sector, $g_s$, is substantially faster in the macro calibration to compensate for the absence of catch-up growth. In terms of the macro moments, however, both calibrations are indistinguishable and replicate the time-series patterns of the structural transformation equally well.

In contrast to these aggregate patterns, Figure 8 shows that the "no-catchup" calibration makes counterfactual predictions about the patterns of spatial structural change. The left panel shows that catch-up growth is essential to rationalize the empirically observed features of rural growth - both quantitatively and qualitatively. In the absence of productivity catch-up, growth would have been urban biased, and rural labor markets would have fallen even further behind their urban counterparts. This pattern resembles the theoretical results in equation (16) when differential exposure was the only form of spatial heterogeneity. Quantitatively, this form of differential exposure leads to a meaningful urban bias in wage growth: urban locations experience roughly 20% faster wage growth than rural locations.

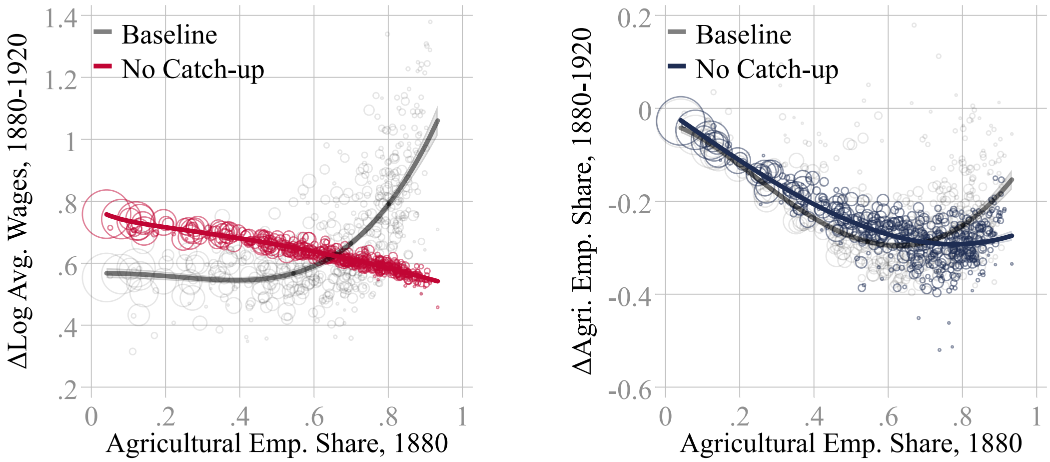
The right panel summarizes the implications for local industrialization. Without catch-up growth, the initially most agricultural locations would have industrialized the fastest -- in sharp contrast to the $U$-shaped industrialization pattern in the data. This is because the initially more agricultural regions benefitted substantially from relatively fast productivity growth in agriculture. This mechanism, which is absent without catch-up growth, increased the comparative advantage of initially more agricultural locations and kept workers in agriculture.

An important implication of these findings is that catch-up growth played a key role for the spatial convergence of living standards. We document this finding in Figure 9. In

endowment, and the local amenities in 1880, are exactly the same in both calibrations because they are estimated from static equilibrium conditions and therefore independent of $g_s$ and $\lambda_s$.

FIGURE 8: THE ROLE OF RURAL PRODUCTIVITY CATCH-UP

(A) WAGE GROWTH (B) INDUSTRIALIZATION

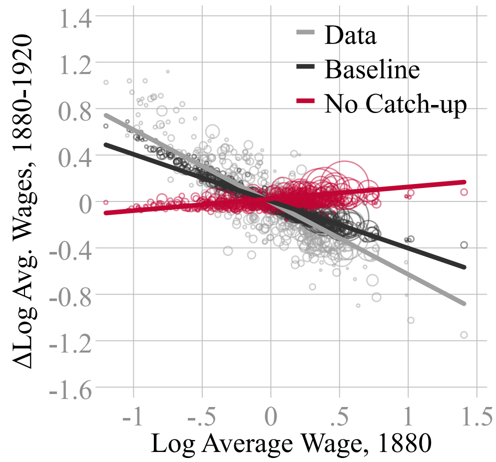



Notes: In the left (right) panel we show local wage growth (local industrialization) as a function of the initial agricultural employment share. We depict the baseline calibration in grey and the macro calibration with no catch-up in red and blue respectively. The size of the markers reflect the relative size of different commuting zones.

both the baseline model (black) and the data (grey), there is a strong negative correlation between wage growth and initial wages. Given our model is only disciplined by the relationship between wage growth and agricultural specialization, Figure 9 suggests that the mechanism of our theory, whereby *agriculturally* specialized labor markets caught up with the productivity frontier, played a key role in the evolution of regional living standards and the regional convergence highlighted in other studies of the period (e.g., Barro et al. [1991]). In the absence of catch-up growth, there is no indication of wage convergence. In fact,, wage growth is slightly faster in locations with higher initial wages reflecting the urban bias shown in Figure 8.

In sum, Figures 8 and 9 highlight that it is difficult to make sense of the patterns of spatial structural change between 1880 and 1920 without the possibility of productivity convergence in rural areas. Faster productivity growth in rural America played a key role for rural-biased growth, and can rationalize why industrialization was faster in intermediate localities relative to the rural fringe and why spatial inequality declined. Without productivity convergence, growth would have been biased towards the already rich urban areas of the country. Catch-up growth thus saved rural America from the perils of the first phase of the structural transformation.

FIGURE 9: WAGE CONVERGENCE




Notes: The figure shows commuting zone wage growth between 1880 and 1920 as a function of local average wages in 1880 in the calibrated model in grey. The dark red line shows the wage growth to initial wage relationship in the model without catch-up growth, i.e., when $\lambda_A = \lambda_M = 0$.

# 6. CONCLUSION

Economic growth systematically reallocates resources out of the agricultural sector. In this paper, we examine the spatial implications of this process. For the case of the US, we document a surprising finding: between 1880 and 1920, when agricultural employment fell from 50% to 25%, rural locations experienced substantially faster wage growth than their more developed urban peers. Moreover, almost all of the decline in agricultural employment took place within labor markets. Hence, the shrinking agricultural sector did not lead to a demise of rural labor markets, but rather seemed to offer opportunities for these locations to reinvent themselves.

These patterns are quantitatively consistent with a parsimonious model of spatial structural change that features a converging spatial productivity ladder. Since rural locations were, on average, concentrated on lower rungs of the ladder, the possibility of catching up with the frontier allowed them to successfully navigate the structural transformation. Without the possibility of catch-up growth, the structural transformation would have been decisively urban biased and rural locations would have fallen further behind.

Interestingly, the structural change toward services seems to have taken a different turn: spatial inequality has increased and the decline of manufacturing seems to have taken a toll on manufacturing-intensive labor markets. Our theory suggests that these differences reflect a changing spatial productivity ladder, whereby technologies in the service sector might be harder to adopt, for example, because they are not embodied in spatially mobile capital goods. Investigating the systematic differences in regional development during the first and second phase of the structural transformation would be a fruitful direction for future research.

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