Macroeconomic Development, Rural Exodus, and Uneven Industrialization*

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Abstract

Economic development and industrialization are typically led by a few regions within a country. The initially laggard regions may catch up and industrialize —as in the US 1880 to 1940— or they may fail to industrialize, experience a population exodus, and help industrialization elsewhere —as in Spain 1940 to 2000. To understand the relationship between internal migrations and uneven industrialization, we build a model of structural change with multiple locations and sectors where both internal migration and internal trade are costly. In the model, internal migrations change the relative labor demand across sectors at the local level and hence act as a force of within-region structural change and uneven paths to industrialization. We calibrate our economy to the development experience of Spain, and find that internal migrations fully explain the lack of industrialization in laggard areas, while increasing growth at the aggregate level. Furthermore, we show that the large rural exodus was driven by a decline in migration costs towards the most industrialized areas and an early divergence in regional productivity.

JEL classification: O41, O11, F16, N10, R11

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1 Introduction

The economic development of nations is characterized by a shift of employment away from agriculture and a slow cycle of industrialization and de-industrialization, see Herrendorf et al. (2014) for details. A salient feature of this process is that, at its early stages, agricultural and non-agricultural activities tend to happen in different locations within a country. For instance, industrialization was initially more intense in the North of France, the Northeast of the US, the Basque Country and Catalonia in Spain, or the Guangdong, Jiangsu, and Shanghai regions in China.

As a few regions in a country start to industrialize, different patterns of development may follow. On the one hand, the initially agrarian regions may experience large outmigration flows towards the leading industrial hubs —a rural exodus— and fail to industrialize. We show this to be the case for Spain between 1940 and 2000, and we additionally document other development episodes with a large rural exodus like France (1872-1975) or China (2000-2015). On the other hand, the initially agrarian regions may not suffer large outmigration flows, manage to catch up with the leaders, and also industrialize. Eckert and Peters (2022) show this to be the case for the US between 1880 and 1940, and we additionally document other development episodes without a rural exodus, like Indonesia (1971-2010).

The goal of this paper is to understand the role of internal migrations in shaping the sectoral composition of local economies. Migrations are usually seen as shifts in labor supply across regions. We emphasize that they also shift the level and composition of labor demand. In particular, outmigration lowers local labor demand more in sectors that rely heavily on local consumers. In addition, outmigration raises local wages, which erodes the competitiveness of the region's most tradable sectors. We study how these demand changes may help determine where industrialization takes place.

Our case study is the relatively recent development experience of Spain, which provides invaluable sector- and location-specific data over a complete process of economic development. We start by documenting that, from the 1950s, Spain experienced fast growth in income per capita, a strong reallocation of employment across sectors and space, a lack of industrialization in many regions, and an inverted-U-shaped evolution of spatial inequality. In particular, initially rural regions lost population in net terms (while the country almost doubled in size) and failed to create industrial jobs. At the same time, these initially rural regions created jobs outside agriculture in the (less tradable) services sector, and they eventually (partially) converged in income per capita with the rest.

Next, we build a model of structural change with multiple locations and sectors, where both the reallocation of workers across regions and the trade of goods and services are costly. In particular, we start from a simple model of structural change similar to Duarte and Restuccia (2010) where we add costly migration as in Artuç et al. (2010) and costly trade as in Eaton and Kortum (2002). This framework provides a high degree of tractability and is amenable to quantitative work.

We first use the model to show theoretically how internal migration flows represent an engine of structural change at the local level by changing the sectoral composition of local labor demand. First, holding local wages fixed, we show that the elasticity of sectoral labor demand with respect to a population change is given by the importance of local demand in the sector's total sales. This implies that, in areas losing (gaining) population, labor is reallocated away from (toward) sectors that are more dependent on local consumers.[1] Second, a population outflow generates a local wage increase because, with costly internal trade, the decline in labor demand is smaller than the decline in labor supply —since part of labor demand depends on consumers elsewhere. We demonstrate that the wage increase reduces labor demand more in sectors that are more exposed to trade, thereby inducing a reallocation of employment away from more tradable sectors. Conversely, in areas receiving migrants, wages decline, which generates a comparative advantage in tradables. And third, the wage increase leads to sectoral reallocation due to the different income elasticity of sectoral demands. Ultimately, which force dominates is a quantitative question.

We then bring the model to the data through the development experience of Spain. We have time series data at the province and sector level for value added, prices, and employment, plus data on bilateral migration flows across provinces. These data allow us to recover the time paths for province-sector productivity, province-sector export costs, and bilateral migration costs. Our strategy to achieve this identification represents a methodological contribution. The use of models with costly internal trade in the macro-development literature has been halted by the lack of time series data for internal bilateral trade flows, which is the information typically used to recover bilateral trade costs. We argue that in multi-sector models, for given province-sector productivity, the difference between sectoral employment shares and sectoral expenditure shares at the regional level reveals information about the tradability of each sector. Our strategy, similar to Eckert (2019), builds on Gervais and Jensen (2019), who show how to use region-industry trade surpluses to infer the trade costs for different goods and services in the US. We extend this logic to identify both sector-specific and region-specific trade costs that vary over time.

Our main quantitative result is that the large rural exodus of workers looking for better economic opportunities had a first-order impact on the development process of each province, while having only moderate aggregate effects. To show this, we solve for two counterfactual economies without migration (infinite migration costs over the entire period), in which the distribution of workers across regions is fixed at its 1940 values. In the first one, region-specific sectoral productivity paths remain as in the benchmark economy and do not react to population movements. In the second one, we allow for agglomeration economies in industry and decreasing returns to scale in agriculture such that region-specific sectoral productivity paths are affected by migrations.

Starting with the simpler case, we find that absent migrations, laggard regions do industrialize and leading regions specialize less in manufacturing. Indeed, there is structural change everywhere,

[1] This relates to Burstein et al. (2020), who show how heterogeneity in the tradability of an occupation's output determines its exposure to the effects of immigration shocks.

and the economic structure of regions looks more similar to each other. This result implies that the evolution of region-specific sectoral productivity and trade costs was conducive to industrialization in the initially rural areas, but the rural exodus impeded it. The reason is twofold. On the one hand, the relatively unproductive manufactures of laggard areas were very much dependent on local demand, which declined due to the outmigration. On the other hand, migrations reduced the wage gap between leading and laggard regions, which allowed leading areas to remain competitive in the highly tradable manufacturing sector. This result is amplified when we allow for non-constant returns to scale in production because the rural exodus enhances industrial productivity in the leading regions at the expense of the laggard ones, an advantage that is inverted when there are no migrations. The aggregate effects of labor reallocation through the rural exodus are positive but modest. In the counterfactual economy with no migration, GDP per capita would have grown 36 percentage points less (in a period in which output increased eightfold). When we allow productivity to react to migrations, the aggregate effects are similar. Therefore, we conclude that outmigrations were the key determinant of the lack of industrialization in laggard regions and moderately accelerated growth at the aggregate level.

Finally, we study the determinants of the rural exodus and the uneven pattern of regional industrialization in Spain. We identify two main factors. The first one was the decline of the destination-specific component of migration costs in the leading regions, which we show empirically to be associated with large increases in their housing supply. The second one was the regional divergence in industrial and services productivity between 1940 and 1960. Absent these two factors, the spatial pattern of development in Spain would have been closer to the one in the US (1880-1940) —with initially agrarian regions not losing population in a systematic manner—, industrialization would have been more homogeneous across regions, and GDP growth would have been lower.

1.1 Related literature

Our work relates to the literature on growth and structural change with spatial frictions. This literature has traditionally focused on frictions to either internal migration —see Garriga et al. (2023) or Ngai et al. (2019)— or internal trade —see Adamopoulos (2011), Herrendorf et al. (2012), or Gollin and Rogerson (2014)— by use of stylized models with two sectors (agriculture and non-agriculture) and two locations (rural and urban). Compared to this literature, we emphasize the interactions between migration and trade frictions and consider a quantitative exercise with multiple regions, three sectors, and a lack of full sectoral specialization across regions.

Two recent papers are closely related to our research. First, Hao et al. (2020) study the growth episode in China between 2000 and 2015, which was characterized by large migrations from rural to urban locations and the reallocation of employment away from agriculture. Building on Tombe and Zhu (2019), they set up a model with both internal trade costs and migration costs as well as multiple locations. They show that the reduction in migration costs (the *hukou* system reform) and in internal trade costs account for a substantial fraction of the changes in aggregate outcomes

and in the spatial distribution of economic activity. Compared to this paper, we explore the impact of spatial frictions in the long run following a complete process of economic modernization (with a full cycle of industrialization and de-industrialization), and we emphasize the effects of migrations on the sectoral composition of local employment. The second one is Eckert and Peters (2022), who explore the role of migrations across US counties between 1880 and 1940. Different from Spain, they find that migration flows in the US do not follow any sectoral pattern. They write a model with constant spatial frictions and focus on the productivity catch-up between locations that makes rural areas industrialize instead of losing population. We allow both productivity and spatial frictions to change over time and discuss how they interact to generate the patterns of migrations and local industrialization observed in Spain.

Our paper is also linked to recent work showing that structural change need not be spatially equalizing. Chatterjee et al. (2025) document for a large set of countries since 1980 that regional convergence has declined as employment shifted towards high-skill services, which are geographically concentrated because of agglomeration effects. Similarly, Chen et al. (2026) show that the rise of tradable services in France between 1995 and 2018 disproportionately favored denser cities. These papers study how a sectoral shift towards services shapes the spatial distribution of economic activity. We instead focus on an earlier stage of development, the transition out of agriculture, and on the reverse channel: how the reallocation of population across regions shapes the spatial pattern of industrialization.

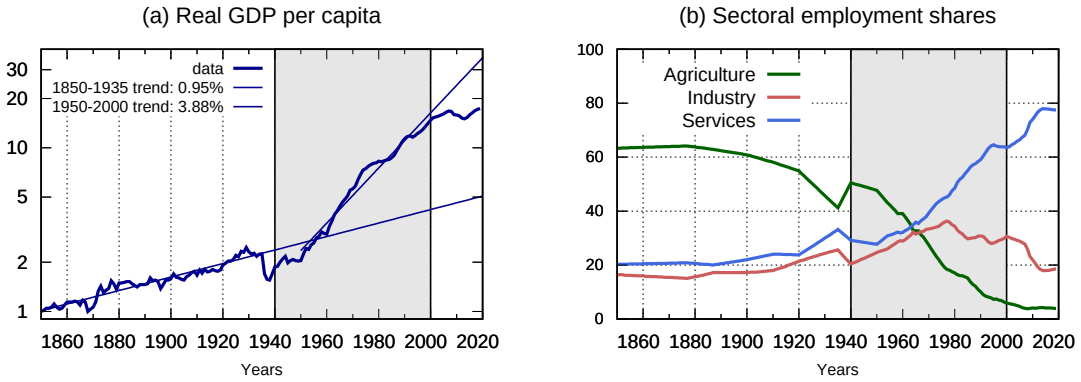
Lastly, our paper contributes to a recent strand of work zooming in on the development experience of selected countries. These country studies are useful for understanding specific factors affecting economic development and drawing lessons for current developing economies. For instance, Song et al. (2011) study the case of China; Uy et al. (2013) the case of South Korea; Cheremukhin et al. (2017) the case of Russia; Fajgelbaum and Redding (2022) the case of Argentina; and Fan et al. (2023) the case of India. The development experience of Spain is one of the few success stories in the second half of the 20th century outside Asia, and yet it has attracted little attention.

2 The Spanish development experience

Our period of study is 1940 to 2000. Spain started its industrialization process well before this, but it was only after 1950 that the process accelerated to become an episode of fast economic development leading to convergence with Europe.[2] Between 1850 and 1935, real GDP per capita increased steadily at an average rate of almost one percent per year, while the share of employment in agriculture fell from 63.3 to 41.2 percent, see Panels (a) and (b) in Figure 1. The Civil War between 1936 and 1939 interrupted this process. Economic development regained vigor in the 1950s: between 1950 and 2000 the average rate of growth increased to 3.88% per year, the share of

[2]We stop our analysis in 2000 because the process of economic modernization was already completed, and because of the peculiar characteristics in the years that followed, with the twin credit and housing booms and the ensuing severe recession.

FIGURE 1: The Spanish development experience



Notes: Panel (a) reports GDP per capita in real terms, normalized to 1 in 1850, and on a log scale. Panel (b) reports the share of employment in each sector. Data from Prados de la Escosura (2017). The grey areas represent our period of study.

employment in agriculture dropped from 47.7 to 5.9 percent, the share of employment in services increased from 27.7 to 63.5 percent, and the share of industrial employment experienced a classic hump over time, with an increase from 24.7 to 36.3 percent between 1950 and 1977, and a decline to 30.6 percent in 2000. Despite the Spanish political idiosyncrasies of the period, this pattern of sectoral reallocation is standard among development episodes, see Herrendorf et al. (2014).[3,4]

Next, we zoom in on the spatial dimension of the development process. To do so we consider data at the province level, which is the smallest administrative unit for which we can gather information on employment, productivity, and prices at the sectoral level.[5] We identify three main facts.

Fact 1: rural exodus

Between 1940 and 2000, the country experienced massive migrations across provinces, mainly from poor agrarian provinces towards richer and more industrial or service-intensive ones.[6] In Figure 2,

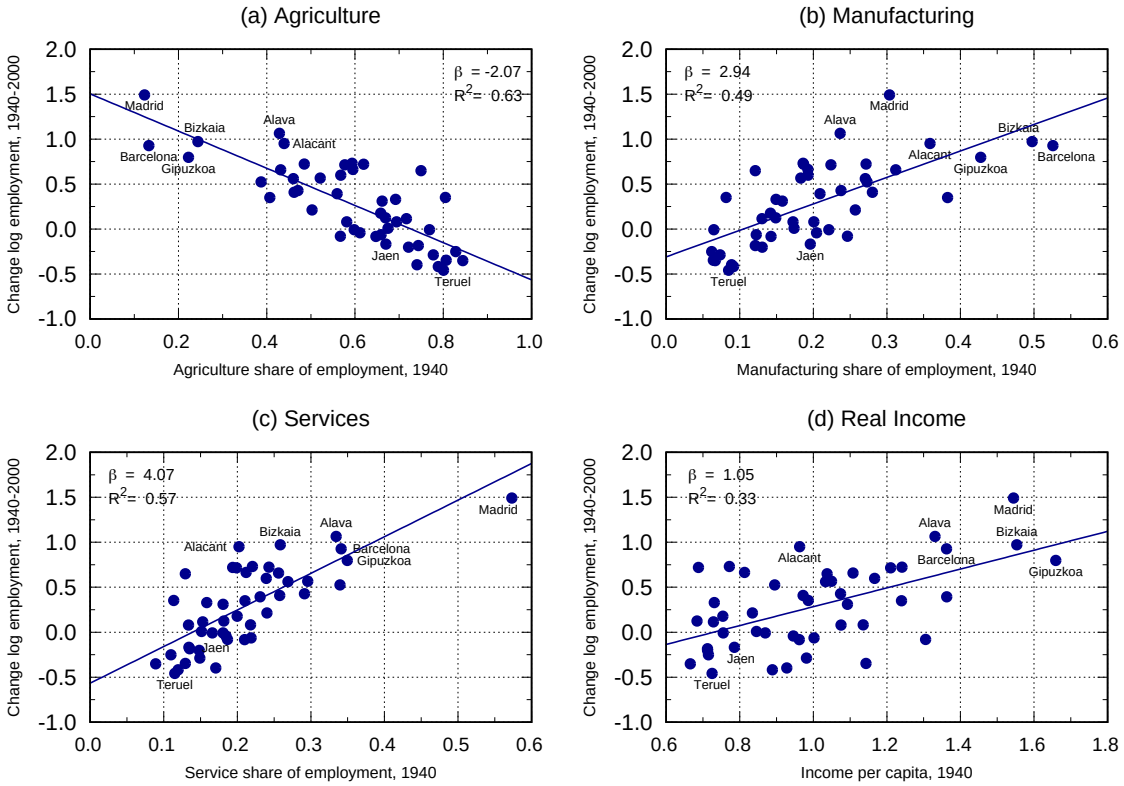
[3]See Prados de la Escosura and Rosés (2021) for a detailed account of the growth process in Spain since 1850.

[4]A salient feature of our period of study is a gradual opening to international trade. The process started in 1953 with the imports of machinery to modernize the industrial sector. In 1959, the "*Plan de Estabilización*" implemented a set of structural reforms, including the lifting of several restrictions to international trade. However, the recent work by Campos et al. (2023) estimates that the effective pace of trade liberalization in Spain between 1948 and 1985 was no different from the one experienced by other European countries, and in terms of levels, the Spanish border effect was comparable to that of the countries in the communist bloc. See Conesa et al. (2024) for a study of the role of international trade in the industrialization process of Spain since 1850.

[5]The territorial division of Spain into provinces dates back to 1833, with minimal changes since then. It is roughly equivalent to the NUTS3 classification of Eurostat. The median employment of Spanish provinces was 135,000 workers in 1940 (9.2 million for the whole country) and 208,000 in 2000 (16.3 million for the whole country). To be consistent with the calibrated model later on, we use data for the 47 mainland provinces in the Iberian Peninsula (i.e. dropping data for the Canary and Balearic Islands). Provinces are hence larger than local labor markets, and rural-to-urban migration also happened within provinces. This is a dimension that we overlook in our study.

[6]Richer provinces in 1940 had more labor in industry and services and less in agriculture, see Panels (a) to (c) in Figure E.1. We also note that in 1940 there was little relationship between income per capita and total employment across provinces, see Panel (d) in Figure E.1.

FIGURE 2: Employment growth and initial sectoral composition

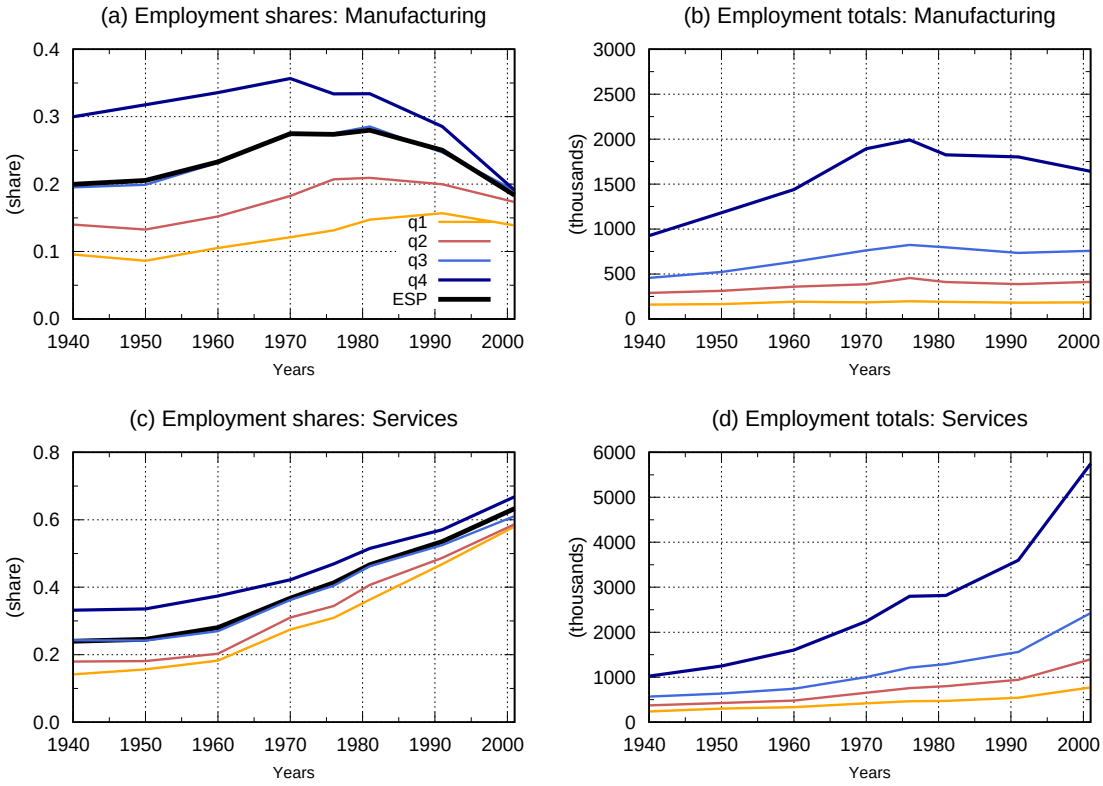


Notes: This figure plots the relative increase in employment between 1940 and 2000 (in logs) for all provinces, against the 1940 sectoral shares of employment, Panels (a) to (c), and against real income per capita (relative to the country average), Panel (d). Income per capita at the provincial level, deflated by the provincial price indices obtained with the model calibration of Section 4. Each panel also reports the slope of the relationship (β) and the share of variance in log employment growth explained by the corresponding x-axis variables (R^2).

we plot the relative increase in employment between 1940 and 2000 against its sectoral composition and income per capita in 1940. On the vertical axis of any panel we can see that there was a large heterogeneity in employment growth across provinces. Some provinces like Madrid, Álava, or Barcelona multiplied their total employment by a large factor, between two and four (employment grew between 100 and 150 log points), while others like Jaén or Teruel lost population over these 60 years.[7] The correlation between the initial sectoral employment composition and subsequent employment growth is strong: provinces with a larger share of agrarian employment lost population (Panel a) while provinces with a larger share of manufacturing or services grew in size (Panels b and c). Our estimated relationships imply that a province with a 10 percentage point higher share of employment in agriculture in 1940 experienced a 20% smaller population growth between 1940 and 2000. Remarkably, 63% of the variance in employment growth across provinces is related to their initial agricultural share of employment. We also note that the correlation between initial income per capita and employment growth is strong (Panel d), which should not be surprising given the correlation between income per capita and sectoral specialization in 1940.

[7]The process of internal migration in Spain over this period is well documented in Bover and Velilla (2005).

FIGURE 3: Industrialization and lack thereof, 1940-2000



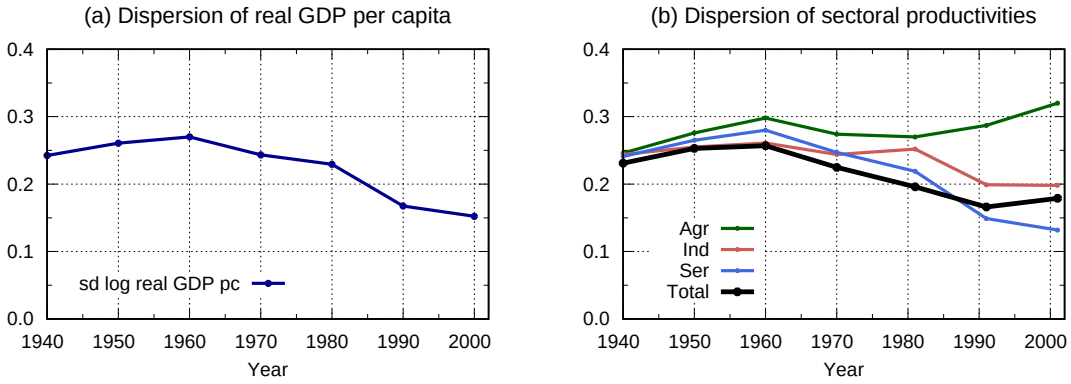
Notes: Panels (a) and (c) report the evolution of sectoral shares of employment in Manufacturing and Services, while Panels (b) and (d) report the evolution of the number of workers in the same sectors. Provinces are grouped into four quartiles in terms of the change in their relative employment size within the country between 1940 and 2000. q1 corresponds to the bottom quartile (these provinces moved from 26.7% to 14.2% of total employment), q2 to the second (from 17.1% to 11.2%), q3 to the third (from 19.1% to 17.7%), and q4 is the top quartile (from 37.1% to 56.8%).

We can compare this pattern of internal migration to that of the development experience of other countries. To do so, we resort to the IPUMS International Census Database (and other sources) and gather data on employment at the region-sector level for 27 countries that experienced a development episode. We find several development episodes with a rural exodus similar to Spain, as for instance France (1872 to 1975), Greece (1971 to 2011) and China (2000 to 2015). In contrast, in salient development episodes like the US (1880 to 1940), the Dominican Republic (1960 to 2010) or Indonesia (1971 to 2010), the initial sectoral composition of regions, while negatively related to regional employment growth, only explains a tiny fraction of its variation. In between, we have intermediate cases like India (1987 to 2011), Brazil (1980 to 2010), or Turkey (1985 to 2000). Further details can be found in Appendix A.5.

Fact 2: uneven industrialization

The country experienced a process of industrialization that was largely uneven across regions. It is easy to overlook this fact because the evolution of relative industrial employment within every

FIGURE 4: Dispersion of income and productivity across provinces, 1940-2000



Notes: Panel (a) reports the standard deviation of the log of real income per capita. Panel (b) reports the standard deviation of the log of provincial productivities in each sector. Income per capita at the provincial level is deflated using the provincial price indices obtained from the model calibration in Section 4.

province mimics the classic hump-shaped pattern. Yet, when we look at total rather than relative employment by sector, the initially agrarian regions did not industrialize; they simply lost agrarian workers who moved to non-agrarian sectors in other provinces. This is illustrated in Figure 3. We classify all provinces into four groups according to the change in their relative size (employment) within the country between 1940 and 2000, see Appendix A.3 for details. The provinces in the bottom quartile (q1) almost halved their size (shrinking from 26.7% to 14.2% of total employment in the country), while provinces in the top quartile (q4) experienced a large increase (from 37.1% to 56.8%). In Panel (a) we see how the four groups of provinces experienced a hump in the *share* of employment in manufacturing similar to the one for the overall country. Yet, in Panel (b) we see that provinces in the q1 and q2 groups hardly experienced any increase in the *levels* of manufacturing employment, so these provinces did not really industrialize. It is important to note that regions in the q1 and q2 groups did create non-agricultural jobs in net terms despite the outmigration, though job creation was concentrated in the much less tradable services sector. For instance, Panels (c) and (d) in Figure 3 show the evolution of relative and total employment in services. This shows net employment growth in services, even in provinces in the q1 and q2 groups. Figure D.4 in Appendix D shows the same pattern for selected provinces in the q1 and q2 groups.

Fact 3: the rise and fall of spatial inequality

Spatial inequality in income per capita followed a classic inverted-U shape over time, increasing until 1960 and declining afterward, see Panel (a) in Figure 4. This path of inequality was first conjectured by Kuznets (1955) for individual income and later documented by Williamson (1965) or Lessmann (2014) among others for regional income. We also find that measured sectoral productivity diverged across provinces in the early decades, but it started to converge after 1960. This was mostly apparent in aggregate and services productivity, while agricultural productivity started to diverge again in the 1990s, see Panel (b) in Figure 4.

3 Model

We consider an economy with three sectors $j = a, m, s$ (agriculture, manufacturing, and services), and several regions $r = 1, 2, ..., R$, where time is indexed by t. Within each sector there is a continuum of varieties indexed by $x \in [0, 1]$, which can be produced in any region by competitive producers that use labor L as the only input of production. Productivity is region-sector specific, and varieties are tradable across regions subject to trade costs. Both productivity and trade costs evolve exogenously over time. Within regions, labor can be freely reallocated across sectors.[8] Across regions, labor reallocation is costly, as there are migration costs. Hence, there is a unique labor market within regions but segmented labor markets across regions.

3.1 Consumption and migration

At any time t, the economy is populated by a mass N_t of identical, infinitely-lived workers. Workers are forward-looking and decide, at the beginning of every period, where to live, consume, and supply labor. Their location choice is determined by the path of real income in each region, their current location —as there are bilateral migration costs—, and their idiosyncratic preferences for each region. Workers have perfect foresight over the evolution of economic fundamentals, but receive preference shocks every period, which introduces idiosyncratic uncertainty. Workers cannot save or borrow. Hence, once established in a region, their only decision is how to allocate their income across the consumption of different sectoral goods. We first characterize this intratemporal consumption decision, and then their intertemporal location choice.

Consumption decisions. Workers in region r have preferences for the consumption of goods in each sector j, denoted c_{rjt}. Preferences over c_{rjt} are in turn characterized by a consumption basket c_{rt} that is implicitly defined by the following non-homothetic CES aggregator (Comin et al., 2021):

$$\sum_j \omega_{jt}^{\frac{1}{\nu}} \left(\frac{c_{rjt}}{\frac{c_j}{c_{rt}}} \right)^{\frac{\nu-1}{\nu}} = 1 \tag{1}$$

where $\omega_{jt} > 0$ are the CES taste parameters, $\nu \in (0, 1) \cup (1, \infty)$ is the constant elasticity of substitution between goods —controlling how changes in relative prices affect relative sectoral expenditures—, and $\epsilon_j > 0 \ \forall j$ are parameters that introduce non-homotheticities in demand — controlling how changes in real income affect relative sectoral expenditures. The budget constraint for a worker living in region r at time t is given by

$$\sum_j P_{rjt} c_{rjt} \leq w_{rt} \tag{2}$$

[8] We make this assumption due to the lack of sectoral wage and worker flow data needed to quantify the sector reallocation frictions. Underlying this assumption is the idea that, over a long enough period of time, workers can move easily across sectors within a region.

where P_{rjt} is the price index of the final good in sector j, c_{rjt}, and w_{rt} the nominal wage. Workers maximize utility $U = \left(c_{rt}^{1-\sigma} - 1\right) / (1-\sigma)$, with c_{rt} implicitly defined by (1), subject to their budget constraint (2). As a result, the expenditure share on sector j goods of region r consumers at time t is:

$$\frac{P_{rjt}c_{rjt}}{w_{rt}} = \omega_{jt}\left(\frac{w_{rt}}{P_{rjt}}\right)^{\nu-1} c_{rt}^{(1-\nu)\epsilon_j} \tag{3}$$

where, given the budget constraint (2), w_{rt} is both the wage and the total expenditure per worker in region r. Given w_{rt} and prices P_{rat}, P_{rmt}, and P_{rst}, the consumption basket c_{rt} and the sectoral demands c_{rat}, c_{rmt}, and c_{rst} can be found combining equations (1) and (3).[9] Then, substituting the consumption basket into the utility function delivers the indirect utility that workers derive from consumption in region r at time t:

$$\mathcal{V}(w_{rt}, P_{rat}, P_{rmt}, P_{rst}) = \frac{\left[c_{rt}(w_{rt}, P_{rat}, P_{rmt}, P_{rst})\right]^{1-\sigma} - 1}{1-\sigma}. \tag{4}$$

Migration decisions. At the beginning of each period, every worker in region ℓ decides to locate in the region r that offers her the highest migration value, solving the following problem:

$$\max_r \left\{V_{rt} - \mu_{\ell rt} + \kappa\xi_{rt}^i\right\}, \tag{5}$$

where V_{rt} is the value of residing in location r at time t, $\mu_{\ell rt}$ is a bilateral contemporaneous migration cost, capturing a notion of connectivity between regions ℓ and r, and ξ_{rt}^i is a taste shock that individual i experiences for region r at the beginning of period t. This idiosyncratic shock is i.i.d. across regions and over time, and captures the notion that workers may decide to live in a region for reasons unrelated to economic conditions. The extent to which idiosyncratic preferences determine migration patterns is therefore controlled by parameter κ.

The value of residing in region r at time t is given by

$$V_{rt} = \mathcal{V}(w_{rt}, P_{rat}, P_{rmt}, P_{rst}) + \beta\,\mathbb{E}[\max_\ell \{V_{\ell t+1} - \mu_{r\ell t+1} + \kappa\xi_{\ell t+1}\}] \tag{6}$$

where $\mathcal{V}(w_{rt}, P_{rat}, P_{rmt}, P_{rst})$ is the flow utility that workers derive from consumption in region r at time t, given by (4), β is the discount factor, and the expectation $\mathbb{E}$ is taken over future realizations of the idiosyncratic taste shocks $\xi_{\ell t+1}$.

Assuming that ξ_{rt} is drawn from a Gumbel distribution, the share of workers in region ℓ that

[9] Note that substituting equation (3) for each sector into equation (1) yields a single non-linear equation in c_{rt}:

$$\sum_j \omega_{jt}\left(P_{rjt}c_{rt}^{\epsilon_j}\right)^{1-\nu} = w_{rt}^{1-\nu}$$

move to region r between $t-1$ and t is given by

$$\rho_{\ell rt} = \frac{\exp\left\{\frac{1}{\kappa}\left(V_{rt} - \mu_{\ell rt}\right)\right\}}{\sum_{k}^{R} \exp\left\{\frac{1}{\kappa}\left(V_{kt} - \mu_{\ell kt}\right)\right\}}. \tag{7}$$

This expression illustrates that workers move towards regions offering them higher utility (higher current and future real income) and to which it is easier to arrive (lower migration costs). It also shows that κ limits the extent to which these economic forces determine the population of each region. The law of motion for the labor supply in each region is then given by

$$L_{rt} = (1 + n_t) \sum_{\ell}^{R} \rho_{\ell rt} L_{\ell t-1}, \tag{8}$$

where L_{rt} denotes region r population at time t, $L_{\ell t-1}$ denotes region ℓ population at time $t-1$, and n_t is the country-wide population growth between $t-1$ and t. The labor supply in region r at time t is thus given by the inflows of workers from all regions (including itself) that optimally choose to locate in r in period t plus population growth.

3.2 Production and trade

The sector j final good consumed by region r workers comes from the aggregation of tradable intermediate varieties $q_{rjt}(x)$. We consider a standard CES aggregator with an elasticity of substitution $\eta > 0$. One can micro-found this with a final good production sector, but we can as well think of it as a preference aggregator.

Production of varieties. Within each sector j of region r, varieties are produced with a constant returns to scale technology that uses labor as its only input, $y_{rjt}(x) = A_{rjt}(x) L_{rjt}(x)$, where $A_{rjt}(x)$ denotes the productivity of region r at producing variety x of sector j at time t. Following Eaton and Kortum (2002), productivity $A_{rjt}(x)$ is a random variable drawn from an independent region- and sector-specific Fréchet distribution with c.d.f. $F_{rjt}(A) = \exp\{-T_{rjt} A^{-\theta_j}\}$. The parameter T_{rjt} is region- and sector-specific and controls the average level of regional efficiency in the production of sector j varieties. Due to specialization, region r will tend to be a net exporter of sector j goods if T_{rjt} is high relative to T_{rkt} for $k \neq j$. The shape parameter θ_j is sector-specific and common across regions and over time, and governs the dispersion of productivity in the production of sector j varieties. More productivity dispersion in a given sector (lower θ_j) will provide room for further specialization, increasing intrasectoral trade across regions.

Optimization and trade. Regional trade is subject to iceberg trade costs. This means that $\tau_{r\ell jt} \geq 1$ units of sector j varieties must be shipped from region r to region ℓ such that one unit arrives at ℓ. Under perfect competition, cost minimization implies that the price of a variety x in sector j that is offered by region r producers to region ℓ consumers is $p_{r\ell jt}(x) = \frac{w_{rt}}{A_{rjt}(x)} \tau_{r\ell jt}$ —the

marginal cost of production times the cost of shipping sector j goods from r to ℓ. Consumers in region ℓ only purchase variety x of sector j from the region that can provide it at the lowest price, such that $p_{\ell jt}(x) = \min_{r\in\{1,...R\}} p_{r\ell jt}(x)$. Hence, the distribution of prices paid by region ℓ consumers is a distribution over minimum prices, i.e. an extreme value distribution. Taking advantage of the properties of the Fréchet distribution, Eaton and Kortum (2002) show that the price P_{rjt} of the sector j composite good (the price index of sector j varieties) in region r at time t is given by

$$P_{rjt} = \gamma_j \left[\sum_{\ell}^{R} \left(w_{\ell t} \tau_{\ell rjt} \right)^{-\theta_j} T_{\ell jt} \right]^{-1/\theta_j}, \tag{9}$$

where $\gamma_j = \Gamma\left(\frac{\theta_j+1-\eta}{\theta_j}\right)^{1/(1-\eta)}$, and $\Gamma(.)$ is the gamma function. It can be shown that the share of region ℓ's expenditure in sector j varieties produced by region r at time t is given by

$$\pi_{r\ell jt} = \frac{\left(w_{rt} \tau_{r\ell jt} \right)^{-\theta_j} T_{rjt}}{\sum_{k}^{R} \left(w_{kt} \tau_{k\ell jt} \right)^{-\theta_j} T_{kjt}}, \tag{10}$$

which is larger if region r has a low wage w_{rt}, low trade costs $\tau_{r\ell jt}$ or high productivity T_{rjt}.

Aggregation. In equilibrium, the relevant objects are magnitudes at the region-sector level. Aggregating over all varieties x, we can define total output Y_{rjt} of sector j in region r at time t (in units of the rj consumption composite good) as $Y_{rjt} \equiv \int y_{rjt}(x) p_{rjt}(x) dx / P_{rjt}$.

3.3 Equilibrium

As is common in the dynamic spatial economics literature (see, e.g., Caliendo et al., 2019), we first define a *static competitive equilibrium* as the set of prices that clears goods and labor markets at a given point in time, given fundamentals $\Upsilon_t \equiv \{T_{rjt}, \tau_{r\ell jt}, \mu_{r\ell t}, \omega_{jt}\}$ and the distribution of workers across regions $\{L_{rt}\}$ in that period. Then, we define a *sequential competitive equilibrium* as a sequence of static competitive equilibria over time, where the distribution of workers across regions —the endogenous state of the system— evolves according to the dynamics of labor supply given by equation (8). Finally, we define a *steady state competitive equilibrium* as a sequential competitive equilibrium in which the distribution of workers across regions does not change over time.

Definition 1. Given fundamentals Υ_t and a distribution of workers across regions $\{L_{rt}\}$, a *static competitive equilibrium* is a set of region-specific wages $\{w_{rt}\}$ such that: (a) workers and producers make optimal decisions in terms of consumption and production (equations (3), (9), (10) hold); (b) goods markets clear in each region-sector

$$P_{rjt} Y_{rjt} = \sum_{\ell}^{R} \pi_{r\ell jt} P_{\ell jt} C_{\ell jt} \quad \forall r, j\,; \tag{11}$$

where $C_{\ell jt} \equiv c_{\ell jt} L_{\ell t}$, and (c) labor markets clear in each region

$$L_{rt} = L_{rat} + L_{rmt} + L_{rst} \quad \forall r \,. \tag{12}$$

Definition 2. Given an initial distribution of workers across locations $\{L_{r0}\}$, and a sequence of fundamentals $\{\Upsilon_t\}_t$, a *sequential competitive equilibrium* is a sequence of wages and employment allocations $\{w_{rt}, L_{rt}\}_t$ and a sequence of value functions $\{V_{rt}\}_t$ in each region such that, for all time periods, workers solve their dynamic location choice problem (equations (6) and (7) hold) and the static competitive equilibrium conditions are satisfied.

Note that, in a sequential competitive equilibrium, the distribution of workers across regions at time t depends on the dynamic, forward-looking location choices that determine the labor supply in each region, as given by equation (8).

Definition 3. A *steady state competitive equilibrium* is a sequential competitive equilibrium in which fundamentals Υ_t, wages and employment allocations $\{w_{rt}, L_{rt}\}_t$, and value functions $\{V_{rt}\}_t$ do not change over time.

Steady state vs transitional dynamics. In a steady state equilibrium, workers move across regions due to their idiosyncratic shocks. However, net migration flows across regions are zero, the distribution of employment across regions is constant, there is no sectoral reallocation of labor, and the economy does not grow. Outside the steady state, the model features transitional dynamics where aggregate allocations change. Transitional dynamics arise due to changes in model fundamentals Υ_t, but also due to the slow changes in the distribution of employment across regions $\{L_{rt}\}$, as migration is costly.

Labor demand. At every point in time, the goods market clearing in equation (11) requires that the value of sector-j output produced in region r equals the value that all regions, including itself, purchase from region r, where aggregate consumption of the sector j good in region r is defined as $C_{rjt} \equiv c_{rjt} L_{rt}$. The labor market clearing in equation (12) requires that the labor supply in each region r, as given by equation (8), equals the labor demanded by region r producers of all three sectors. The labor demand in each region r and sector j can be easily characterized as follows. First, note that constant returns to scale and perfect competition in the production of varieties imply that total revenues must equal total costs for all producers in each sector and region. As labor is the only input of production, total costs are simply labor costs, and we can write $p_{rjt}(x) y_{rjt}(x) = w_{rt} L_{rjt}(x)$. Aggregating over producers we obtain,

$$P_{rjt} Y_{rjt} = w_{rt} L_{rjt} \,. \tag{13}$$

Next, one can use equation (13) to substitute total revenues by labor income in the goods market clearing condition (11) and obtain an expression for labor demand in sector j and region r as

$$L_{rjt} = \frac{1}{w_{rt}} \sum_{\ell}^{R} \pi_{r\ell jt} P_{\ell jt} C_{\ell jt} \quad \forall r, \forall j. \tag{14}$$

Balanced trade. Finally, note that the static nature of the consumer problem (workers in region r can neither save nor borrow so $\sum_j P_{rjt} Y_{rjt} = \sum_j P_{rjt} C_{rjt}$) and the goods market clearing conditions imply that trade balances in each region:

$$\sum_{j \in \{a,m,s\}} \sum_{\ell \neq r}^{R} \pi_{r\ell jt} P_{\ell jt} C_{\ell jt} = \sum_{j \in \{a,m,s\}} (1 - \pi_{rrjt}) P_{rjt} C_{rjt} \quad \forall r \,, \tag{15}$$

that is, the total value of exports must equal the total value of imports at the regional level. However, trade imbalances at the sectoral level, $Y_{rjt} - C_{rjt} \gtrless 0$, may exist in each region.

3.4 Structural change with spatial frictions

In order to study the process of spatial structural change, it will be useful to obtain production functions at the region-sector level.[10] Given region-sector output $Y_{rj} \equiv \int y_{rj}(x) p_{rj}(x) dx / P_{rj}$, we can write the region-sector production function as $Y_{rj} = B_{rj} L_{rj}$ by defining $B_{rj} \equiv Y_{rj}/L_{rj} = \int \frac{L_{rj}(x)}{L_{rj}} \frac{p_{rj}}{P_{rj}} A_{rj}(x) dx$. Hence, in equilibrium, the measured aggregate sectoral productivity B_{rj} in each region is obtained by averaging over the productivity of those varieties that survive country-wide competition (those with $L_{rj}(x) > 0$). Given this production function, equation (13) implies that in equilibrium

$$B_{rj} = \frac{w_r}{P_{rj}}, \tag{16}$$

which, given the expression for equilibrium prices P_{rj} in equation (9), can be expressed as

$$B_{rj} = \gamma_j^{-1} \left(\frac{T_{rj}}{\pi_{rrj}} \right)^{1/\theta_j}. \tag{17}$$

This expression highlights two components of region-sector measured productivity. The first component is the exogenous fundamental productivity T_{rj}, which determines the measured productivity B_{rj} of region r in producing goods in sector j. This would be the only relevant term if the region was closed to trade ($\pi_{rrj} = 1$) because region r would need to produce all varieties on its own. As trade increases (π_{rrj} declines) more goods are sourced from other regions, region r can specialize in the subset of intermediate varieties for which it has a comparative advantage, and productivity

[10] Throughout this section, we drop time subscripts t, as we focus on comparative statics.

increases due to selection.[11]

Closed economy. When our model economy is closed to internal trade and migration, each region is a closed economy independent of the others. Structural change within each region arises from the standard income and price effects due to symmetric and asymmetric sectoral productivity growth. Because $\pi_{rrj} = 1 \; \forall r, j$, this productivity growth just tracks the evolution of the exogenous productivity parameters T_{rj}, see equation (17). Structural change for the country is the sum of what happens in all its independent regions, while spatial income inequality is the result of asymmetric productivity growth across regions.

Trade and structural change. The effects of trade on structural change are well-studied in the literature on international trade and structural change cited in the Introduction. A symmetric decline in trade costs allows for regional specialization, which increases productivity due to selection (π_{rrj} declines in equation (17)) and hence generates structural change through income effects (as long as income elasticities are different from one). When the decline in trade costs is asymmetric across sectors, relative prices change, and structural change follows as long as price elasticities are different from one.

Migration and structural change. The effects of migration on structural change are far less studied. In our model, migrations generate structural change both at the aggregate and at the local level. At the aggregate level, there is the mechanical composition effect of moving people from agrarian regions to industrial ones. At the local level, things are more interesting because population movements between locations change the sectoral composition of labor demand in each region, which induces local structural change. In general, this migration-led sectoral reallocation of employment does not cancel across regions and may have aggregate consequences.

To see how internal migrations generate local structural change, recall that the labor demand of sector j in region r is given by equation (14). A fraction of this demand is local (the term $\ell = r$ on the right-hand side) and a fraction is country-wide (the terms $\ell \neq r$). Suppose there is an outmigration from region r (led by changes in either migration costs, trade costs, or productivity), and that region r is small enough such that we can abstract from the effect of outmigration on the country-wide fraction of labor demand. Then, we can state three theoretical results that we formally prove in Appendix B.1.

Proposition 1. *Holding prices fixed and assuming region r is small relative to the country size, a decline in population L_r in region r leads to (a) a fall in labor demand L_{rj} in all sectors j, and (b) a reallocation of labor away from sectors j where local purchases represent a larger fraction of value added.*

Equation (14) shows that labor demands L_{rj} in region r decline mechanically in all sectors j due

[11] See Finicelli et al. (2013), Sposi (2019) and our own derivations in Appendix B.1.

to the fall in population L_r. The labor demand elasticity to this fall is given by

$$\frac{\partial L_{rj}}{\partial L_r}\frac{L_r}{L_{rj}} = \frac{\pi_{rrj}P_{rj}C_{rj}}{P_{rj}Y_{rj}} \leq 1 \tag{18}$$

and hence it is larger in sectors where local demand $\pi_{rrj}P_{rj}C_{rj}$ represents a larger fraction of total production $P_{rj}Y_{rj}$. In particular, local employment is reallocated away from sectors where this elasticity is larger. That is, local employment is reallocated away from sectors j where region r is less competitive in the sense that $\tau_{r\ell j}^{-\theta_j}T_{rj}$ is lower, which is the case for sectors j in which region r is less productive or less able to export.

Proposition 2. *Holding prices fixed and assuming region r is small relative to the country size, a decline in population L_r in region r leads to (a) a fall in total labor demand $\sum_j L_{rj}$ that is lower than the fall in population L_r, and (b) an increase in the local wage w_r.*

The logic is clear. Without trade, all demand would be local. Then, if population leaves region r, the decline in labor demand is equal to the decline in labor supply and the regional wage does not change. With trade, at least a fraction of demand in each sector j comes from outside region r, and this demand does not change with outmigration, which means that outmigration reduces labor demand less than labor supply. Then, the wage has to increase to restore the equilibrium. Note the importance of the level of trade frictions for the quantitative effects of migration on the regional wage w_r.

In turn, the increase in the regional wage affects the sectoral employment composition in two different ways. First, it makes the local economy less competitive and lowers $\pi_{r\ell j}$ $\forall \ell$ in equation (14). This effect is larger when sectoral trade costs are smaller, that is, the increase in the regional wage lowers demand relatively more in sectors that are more tradable. This is stated in the next result.

Proposition 3. *Holding expenditure shares constant, an increase in region r wage w_r reduces labor demand in all sectors j of region r, more so in those sectors with lower trade costs, which reallocates labor towards less tradable sectors.*

Therefore, outmigration reallocates labor away from less tradable sectors due to the partial equilibrium effect (Proposition 1) but towards them due to the general equilibrium effect (Proposition 3), with the net effect being ambiguous. However, outmigration unambiguously reallocates labor away from less productive sectors due to the partial equilibrium effect only. For instance, if manufacturing is relatively less productive in initially laggard areas, outmigration from these areas will reallocate employment away from manufacturing.

Finally, the second effect of an increase in the regional wage is that it makes region r richer, which triggers changes in the composition of the local demand (the terms $P_{\ell j}C_{\ell j}$ on the right-hand side of equation (14) for $\ell = r$) due to the standard income effects.

4 Calibration

The calibration of the model requires choosing values for parameters σ and β, elasticities $\nu, \epsilon_j, \eta, \theta_j$ and κ, the rate of exogenous population growth n_t, and time-changing model fundamentals $\Upsilon_t = \{T_{rjt}, \tau_{r\ell jt}, \mu_{r\ell t}, \omega_{jt}\}$. We focus our analysis on the 47 contiguous provinces in mainland Spain ($R = 47$) and 7 different points in time (from 1940 to 2000 every ten years).

We start by setting $\sigma = 1$, $\eta = 4$ and $\beta = 0.6$. The log specification of the utility function implied by this value of σ is standard in both dynamic spatial models (see, e.g., Caliendo et al., 2019) and macroeconomic models of structural change (see, e.g., Herrendorf et al., 2014).[12] The elasticity of substitution across varieties η has no quantitative relevance, so we choose it to satisfy the technical condition $1 + (1 - \eta)/\theta_j > 0$. And a discount factor of $\beta = 0.6$ corresponds to an annual interest rate of around 5%. Next, we set $\theta_a = 8.8$, $\theta_m = 5.6$, and $\theta_s = 6.2$ based on the estimates of Sposi (2019). This implies that productivity dispersion, and hence the potential gains from trade, are highest in manufacturing and lowest in agriculture, with services in between. Finally, we choose $\{n_t\}$ to match aggregate employment growth at the country level for every decade.

Given these choices, the rest of the parameters and (time-changing) model fundamentals are recovered such that the transitional dynamics of the model match key time series of the data.[13] We proceed in three sequential steps. In the first step, we estimate the preference parameters $\{\nu, \epsilon_j, \omega_{jt}\}$ to match the aggregate evolution of sectoral employment shares over time. In the second step, trade costs and productivity parameters $\{\tau_{r\ell jt}, T_{rjt}\}$ are calibrated jointly to match, every period, data on employment and measured productivity at the region-sector level. Finally, in the third step, we recover the migration elasticity and migration cost parameters $\{\kappa, \mu_{r\ell t}\}$ that perfectly rationalize the observed bilateral migration flows.[14]

4.1 Data

We have data on (a) employment, nominal value added, and prices at region-sector level from 1940 to 2000 in 10-year periods; and (b) bilateral migration flows between all provinces from 1960 to 2000, also in 10-year periods (which we extend back to 1940, see Appendix A.2). All the data sources are detailed in Appendix A.1. We note that sectoral employment and value added shares at the province

[12] Moreover, with $\sigma = 1$, the elasticity of migration to real income differences is independent of the level of income, which is convenient in order to estimate the migration elasticity.

[13] This follows standard practices in the structural change literature, see Cheremukhin et al. (2017) or García-Santana et al. (2021).

[14] In principle, one may think that Steps 2 and 3 would need to be simultaneous, as the migration elasticity and costs $\{\kappa, \mu_{r\ell t}\}$ are needed to compute the labor supply for given wages in Step 2. However, observing the migration flows $\rho_{r\ell t}$ allows us to invert the labor supply equation (8), which means that we can take L_r as given when estimating sectoral productivity and trade costs in Step 2. The separation between labor supply and labor demand in the calibration stage also allows us to retrieve the productivity and trade cost parameters that are consistent with labor allocations in 1940, despite not having information on the 1930-1940 bilateral migration flows.

level are different from each other in the data, while they are restricted to be the same in the model. For consistency between the model and the data, we keep the sectoral split of employment. Hence, our sectoral value added at the province level is given by the sectoral employment share times the total value added in each province, that is, $P_{rjt}Y_{rjt} = \frac{L_{rjt}}{L_{rt}} P_{rt}Y_{rt}$. Then, using equation (13), we can infer regional wages from data on regional income per capita: $w_{rt} = P_{rjt}Y_{rjt}/L_{rjt} = P_{rt}Y_{rt}/L_{rt}$. Additionally, using equation (16), we can infer region-sector measured productivity from data on region-sector value added per worker and prices: $B_{rjt} = w_{rt}/P_{rjt} = \frac{P_{rt}Y_{rt}/L_{rt}}{P_{rjt}}$.[15]

4.2 First step: preferences

The preference parameters ν, ϵ_j, and ω_{jt} determine the sectoral composition of expenditure in each region, see equation (3). We do not have data on the sectoral composition of expenditure by province and, due to internal trade, the sectoral composition of employment or value added in each region is different from the sectoral composition of expenditure. Hence, we cannot directly use equation (3) to estimate the parameters governing the demand system. Instead, we aggregate equation (3) across regions to obtain an expression relating the country-level expenditure on sector j goods to regional-level wages and prices, which we do observe. Then, treating Spain as a closed economy (such that the total expenditure on sector j goods equals the total value of production of sector j goods), we can use data on sectoral value added at the country level to estimate the parameters of the demand system.[16] In particular, we obtain:

$$\frac{\text{VA}_{jt}}{\text{VA}_t} = \omega_{jt} \sum_r \left(\frac{w_{rt}}{P_{rjt}} \right)^{\nu-1} c_{rt}^{(1-\nu)\epsilon_j} \frac{\text{VA}_{rt}}{\text{VA}_t}, \tag{19}$$

where c_{rt} is implicitly defined by the aggregator (1), and w_{rt}, P_{rjt} and the value added aggregates $\text{VA}_{jt} \equiv \sum_r (P_{rjt}Y_{rjt})$, $\text{VA}_{rt} \equiv \sum_j (P_{rjt}Y_{rjt})$, and $\text{VA}_t \equiv \sum_{rj} (P_{rjt}Y_{rjt})$ all come from the data; see Appendix C.1 for details. This expression gives us 2 independent moment conditions per time period, 14 in total. To be able to estimate the income and price elasticities from time-series variation, we follow the literature and first hold the preference shifters constant, $\omega_{jt} = \omega_j$. This leaves us with 5 parameters to estimate: ω_a, ω_s, ϵ_a, ϵ_s, and ν (without loss of generality we normalize $\omega_m = 1$ and $\epsilon_m = 1$). We do so by non-linear least squares, solving for c_{rt} in each iteration by combining equations (1) and (3). Next, because we need the predicted aggregate sectoral expenditures to be consistent with aggregate sectoral labor incomes,[17] we recover the time-

[15] Note therefore that relative sectoral productivities are empirically recovered by the inverse of relative sectoral prices, $B_{rjt}/B_{rit} = P_{rit}/P_{rjt}$, as standard in the structural change literature. In turn, relative regional productivities are given by the inverse of relative regional prices times the ratio of income per capita across regions, $B_{rjt}/B_{\ell jt} = (P_{\ell jt}/P_{rjt}) \frac{P_r Y_r/L_r}{P_\ell Y_\ell/L_\ell}$.

[16] Exploiting the closed-economy assumption for estimation of preferences is standard in this literature, e.g. Herrendorf et al. (2013). The equality of sectoral value added and expenditure shares further requires that value added shares in investment are similar to those in consumption. This is also a standard assumption in the literature, but see García-Santana et al. (2021) and Herrendorf et al. (2021) for recent examples where they differ.

[17] Our calibration strategy in Step 2 takes the predicted local sectoral expenditure as given and looks for the productivity and trade costs that match the sectoral labor income observed in the data. To be able to match the

TABLE 1: Demand system parameters

ω_a	ω_m	ω_s	ν	ϵ_a	ϵ_m	ϵ_s	RMSE a	RMSE m	RMSE s
0.024	1.0	0.382	0.005	0.379	1.0	0.879	0.053	0.081	0.107
(0.006)		(0.163)	–	(0.045)		(0.08)			

Notes: The table reports the estimated parameters of the demand system restricted to have constant ω_j. The parameters are estimated by feasible generalized non-linear least squares using equation (19) and data on sectoral value added. The table also reports the root mean squared error (RMSE) for each sector as well as standard errors for the estimated parameters with the exception of ν, which is estimated to be very close to its lower bound.

varying ω_{jt} that perfectly match the aggregate sectoral value added shares at every decade given the estimated elasticities ν and ϵ_j.

Estimated parameters and model fit. The estimated demand system with constant ω_j reproduces well the aggregate sectoral shifts in the value added of the Spanish economy between 1940 and 2000, see Panel (a) in Figure C.1. The parameter estimates with their corresponding standard errors are reported in Table 1. We estimate an elasticity of substitution ν close to zero, which implies that goods from different sectors are poor substitutes. Hence, changes in relative prices have very small effects on relative quantities and translate almost one-to-one into changes in relative sectoral expenditure. The estimated value of the term ϵ_j, which controls the income elasticity of sectoral demand, is higher in services than in agriculture, and in both cases lower than in manufacturing. For the region with the average real income, these estimates generate income elasticities of 0.56, 1.47, and 1.29 for agriculture, manufacturing, and services, respectively, in 1940.[18] In the year 2000, these elasticities are 0.42, 1.10, and 0.97. This implies that income growth reallocates expenditure away from agriculture and towards manufacturing and, to a lesser extent, services. This force is more than offset by the decline in the price of manufactures relative to services, which shifts non-agriculture expenditure from manufacturing towards services.[19] While the estimated demand system provides a good fit to the evolution of value added shares over time, a perfect match requires time-varying ω_{jt}. The time-varying ω_{jt} that we recover from this correction procedure can be found in Table C.1. To grasp the importance of changes in ω_{jt} over time, Panel (b) in Figure C.1 plots the evolution of value added shares when only ω_{jt} changes, keeping wages and prices constant at their 1940 values. We can see that ω_{jt} slightly shifts expenditure away from agriculture and into services, particularly in the last decade of our data.[20]

sectoral labor income, the predicted aggregate sectoral expenditure has to perfectly match the observed aggregate sectoral labor income. Otherwise, we cannot recover productivity and trade costs that generate local sectoral labor incomes that, once aggregated, are consistent with the data.

[18]The income elasticity of sectoral demand is given by $\partial \log c_{rjt}/\partial \log w_{rt} = \nu+(1-\nu)(\epsilon_j/\bar{\epsilon})$ where $\bar{\epsilon} = \sum_j \frac{P_{rjt}c_{rjt}}{w_{rt}}\epsilon_j$ is the expenditure-weighted average of the non-homotheticity parameters.

[19]Preference estimates with sectoral value added data tend to find $\nu \simeq 0$ as we do here, see Herrendorf et al. (2013). Different from standard results, we find $\epsilon_m > \epsilon_s$ whereby income growth reallocates employment from services to manufacturing. We find similar results with Stone-Geary preferences.

[20]The increase in ω_{st}/ω_{at} in the 1990s may reflect an estimated income effect that is weaker in this decade than the observed reallocation from agriculture to services. One potential explanation is that the current account deficit increased sharply in the 1990s, which means that consumption expenditure increased more than GDP. Our closed economy model is fed with the increase in GDP, not consumption expenditure, so it misses part of the income effect.

4.3 Second step: trade costs and productivity

It is standard in models of international trade to calibrate the iceberg trade costs $\tau_{r\ell jt}$ using equation (10) and data on bilateral trade flows across countries. Data on bilateral trade flows across regions within countries, however, are not typically available for development episodes. Hence, the use of models with costly internal trade for macro-development questions requires a different empirical approach. We develop a novel strategy to calibrate together the trade costs $\tau_{r\ell jt}$ and fundamental productivity T_{rjt} using an exactly identified system based on (a) the observed difference between sectoral expenditure and production shares in each region and (b) measured productivity in each region-sector B_{rjt}. In particular, for a given set of fundamental productivities, the difference between sectoral employment and sectoral expenditure shares at the local level provides information on the magnitude of trade costs, see Gervais and Jensen (2019). This strategy, however, requires restricting the structure of the matrix of bilateral trade costs $\tau_{r\ell jt}$ in order to reduce its dimensionality.

Trade costs. We identify the trade cost parameters using the goods market clearing conditions in equation (11). This equation provides, for every year t, $3 \times R$ moment conditions, while we have $3 \times R \times (R-1)$ bilateral trade cost parameters $\tau_{r\ell jt}$ ($\tau_{rrjt} = 1 \; \forall j$). Therefore, we need to reduce the dimensionality of the matrix of trade costs. We do so as follows. First, we parameterize costs as $\log \tau_{r\ell jt} = (\hat{\tau}_{rjt} d_{r\ell})$, where $\hat{\tau}_{rjt}$ captures the ability of region r at exporting sector j goods at time t, and $d_{r\ell}$ is a time-invariant term capturing origin-destination fixed effects. This means that we allow the trade costs (a) to be asymmetric between origin-destination routes, $\tau_{r\ell jt} \neq \tau_{\ell rjt}$, and (b) to vary over time by sector-origin.[21] Second, we use data on road distance (normalized between 0 and 1) between r and ℓ capital cities in the year 2000 to calibrate the $d_{r\ell}$ terms outside the model. In this way, we are left with $3 \times R$ parameters $\hat{\tau}_{rjt}$ to be calibrated using $3 \times R$ moment conditions. In particular, using equation (10) to substitute away trade flows and equation (13) to replace value added by the wage bill, the sectoral goods market clearing condition (11) becomes:

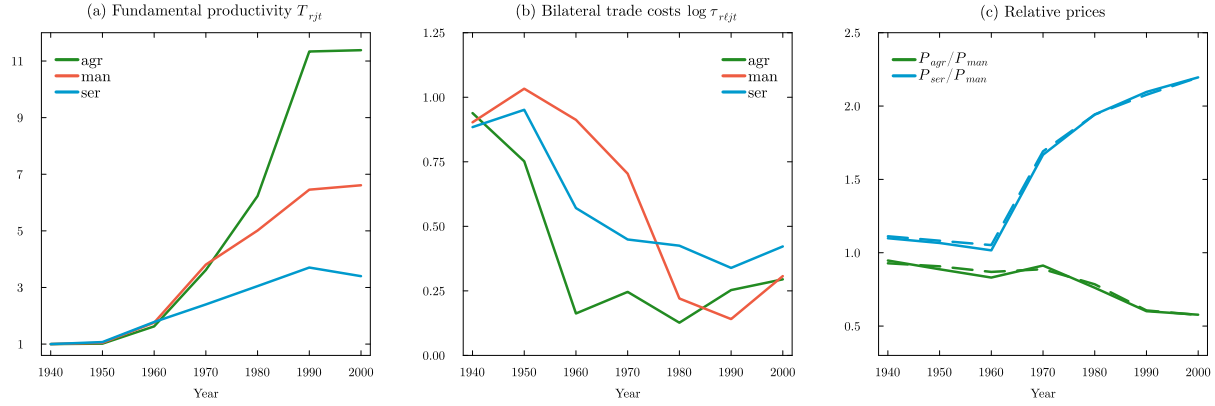
$$L_{rjt} w_{rt} = \sum_{\ell}^{R} \left[\sum_{k}^{R} \left(\frac{\exp\left(\hat{\tau}_{kjt} d_{k\ell}\right)}{\exp\left(\hat{\tau}_{rjt} d_{r\ell}\right)} \frac{w_{kt}}{w_{rt}} \right)^{-\theta_j} \frac{T_{kjt}}{T_{rjt}} \right]^{-1} P_{\ell jt} C_{\ell jt} \quad \forall r, \forall j. \tag{20}$$

To use equation (20), we have data on sectoral employment L_{rjt} and wages w_{rt} for each region, sectoral expenditure $P_{\ell jt} C_{\ell jt}$ is given by equation (3) using the preference parameters estimated in the first step, and the $3 \times R$ productivity parameters T_{rjt} can be identified using the $3 \times R$ equations for measured productivity B_{rjt} described in the next paragraph. In terms of identification, note that we can also write the goods market clearing condition (11) as

$$P_{rjt} Y_{rjt} - P_{rjt} C_{rjt} = \sum_{\ell \neq r}^{R} \pi_{r\ell jt} P_{\ell jt} C_{\ell jt} - \left(1 - \pi_{rrjt}\right) P_{rjt} C_{rjt} \, .$$

[21] The cost to pay is that we force trade costs changes to be symmetric across destinations for a given origin (e.g. trade costs in sector j from say Barcelona to Madrid and from Barcelona to Valencia change at the same rate $\hat{\tau}_{rjt}$).

FIGURE 5: Estimated trends



Notes: Panel (a) displays the estimated sectoral productivity parameters averaged across all provinces, normalizing 1940 to 1 in each sector. Panel (b) reports the average (across all origin-destination pairs) of the estimated trade cost parameters below the 75th percentile of their distribution. Panel (c) shows the relative price of agriculture and services to manufacturing averaged across provinces in the data (solid line) and in the model (dashed line).

This simply states that net exports of region r in sector j (left-hand side) are given by the difference between gross exports and gross imports (the first and second terms on the right-hand side, respectively). Because $\pi_{r\ell jt}$ decrease with $\hat{\tau}_{rjt}$ $\forall r \neq \ell$ and π_{rrjt} is invariant to $\hat{\tau}_{rjt}$, net exports decline monotonically with $\hat{\tau}_{rjt}$. Hence, other things equal, large differences between employment and expenditure sectoral shares in region r (high net exports) reveal low export costs $\hat{\tau}_{rjt}$.[22]

Fundamental productivity. We can recover T_{rjt} from the observed B_{rjt} using equation (17). In particular, we plug equation (10) into (17) to obtain

$$B_{rjt} = \gamma_j^{-1} \left(\sum_k^R \left(\exp\left(\hat{\tau}_{kjt} d_{kr}\right) \frac{w_{kt}}{w_{rt}} \right)^{-\theta_j} T_{kjt} \right)^{1/\theta_j} \qquad \forall r, \forall j \tag{21}$$

which gives us $3 \times R$ non-linear equations in as many unknowns T_{rjt} for every time period t (given the trade cost parameters $\hat{\tau}_{kjt}$ identified above, plus the distance matrix d_{kr}, the wage w_{rt}, and the measured productivity B_{rjt}). In terms of identification, note that measured productivity increases monotonically with T_{rjt}.

Estimation and model fit. We aim to find the values of $\hat{\tau}_{rjt}$ and T_{rjt} that solve the non-linear system of equations given by (20) and (21) for each region in each sector j, *separately for every period*. In practice, we minimize the sum of squared residuals of both equations, rather than trying to find the zero of the large non-linear system, as we find this strategy to work better. The model fit to the targeted data moments on employment and measured productivity in each region and sector is presented in Figures C.2 to C.5. Overall, the model fits the targeted moments very well.

[22] Note also that the correlation of sectoral expenditure and employment shares across provinces for a given sector j reveals information about the average values of $\hat{\tau}_{rjt}$ in sector j. In the data, there is a steady decline in this correlation for all three sectors after 1950, which helps recover declining trade costs (see Table C.2 in Appendix C.2).

Estimated parameters. In order to summarize all the information of the estimated parameters, we report the average (across all provinces r) of T_{rjt} for every sector j and year t in Panel (a) of Figure 5, and the average (across all origin-destination pairs $r\ell$) of all the values of $\tau_{r\ell jt}$ below the 75th percentile of their distribution for every sector j and year t in Panel (b) of Figure 5.[23] The estimated parameters display two important trends: an increase in sectoral productivity (mostly between 1950 and 1990) and a decline in trade costs (mostly between 1950 and 1980).[24] The productivity growth is largest in agriculture and smallest in services, while the decline in trade costs is larger and earlier in time for agriculture than for manufacturing and services. Both changes in productivity and trade costs affect relative prices across sectors, as reported in Panel (c) of Figure 5. The asymmetric productivity growth is the main driver of the increase in the price of services relative to manufacturing, while the decline in the price of agriculture relative to manufacturing is driven first by the asymmetric fall in trade costs and then by the asymmetric growth in productivity, see Figure D.1. The fall in trade costs and the changes in the dispersion of productivity also generate a rise in trade volumes across provinces, see Figure C.7 in Appendix C.2, which plots the evolution of both intrasectoral and intersectoral trade as a share of sectoral value added.

4.4 Third step: migration costs

In order to recover the migration elasticity κ and the bilateral migration costs $\mu_{r\ell t}$, we use our data on the bilateral migration flows $\rho_{r\ell t}$ for each decade. As is common in this literature —see, for instance, Artuç et al. (2010)— we start by estimating κ from the observed correlation between migration flows and differences in regional value functions. In particular, using equation (7), we can arrive at the following expression:

$$\log\left(\rho_{r\ell t}/\rho_{rrt}\right) = \frac{1}{\kappa}\log(c_{\ell t}/c_{rt}) - \frac{1}{\kappa}(\mu_{r\ell t} - \beta\mu_{r\ell t+1}) + \beta\log(\rho_{r\ell t+1}/\rho_{\ell\ell t+1}) \tag{22}$$

where we normalize $\mu_{rrt} = 0$, see Appendix C.3.1 for a detailed derivation. Intuitively, the gross flow between region r and region ℓ (relative to those who remain in r) at time t depends on the contemporaneous difference in real consumption, the bilateral migration costs, and the future value offered by each location, which is captured by next period's flows. The expression shows that κ regulates how differences in real consumption between any two regions translate into migration flows across them.

[23] We report the average of a left truncation of the distribution of trade costs because these are the values that are more relevant for trade, as very high trade costs are typically associated with routes with no trade. The patterns summarized by these averages are common to most provinces, see Figure C.6 in Appendix C.2.

[24] The productivity stagnation in the 1940s is consistent with the lack of economic development in that decade, see Figure 1 in Section 2. The productivity slowdown in the 1990s (and beyond) has already been documented by García-Santana et al. (2020) among others. The fall in trade costs can be understood as a result of large investments in transport equipment and infrastructure. For instance, a publicly-funded program to improve the surface and increase the width of the most-used 5,000 km of the road network was in place between 1967 and 1974, while the construction of the first highways (6,000 km) connecting the main cities of the country started in 1968, see Ventosa (2017).

With data on wages and prices, plus the parameters of the utility function estimated before, we can compute the index of real consumption in each location c_{rt} and construct $\log(c_{\ell t}/c_{rt})$. Next, with data on migration flows $\rho_{r\ell t}$ and a value for β, we can construct the dependent variable of the following expression

$$\log\left(\rho_{r\ell t}/\rho_{rrt}\right) - \beta \log(\rho_{r\ell t+1}/\rho_{\ell\ell t+1}) = \frac{1}{\kappa}\log(c_{\ell t}/c_{rt}) - \frac{1}{\kappa}(\mu_{r\ell t} - \beta\mu_{r\ell t+1}) \tag{23}$$

which we can use to directly estimate $\frac{1}{\kappa}$, treating the changes in migration costs $\mu_{r\ell t}$ as an unobserved residual. Estimating $\frac{1}{\kappa}$ by OLS produces a biased estimate, as differences in c_{rt} across regions are an equilibrium outcome that depends on the value of unobserved migration costs $\mu_{r\ell t}$. Hence, we look for an instrumental variable for $\log(c_{\ell t}/c_{rt})$. We use as an instrument the log difference in the fundamental productivity across regions, averaged across sectors and lagged by one period, $\log(\bar{T}_{\ell t-1}/\bar{T}_{rt-1})$. Fundamental productivity affects real consumption through its effects on local income. By assumption, it is orthogonal to migration costs, as it reflects the efficiency of a region in the production of sectoral varieties. Moreover, by using lagged productivity, which is estimated using data on measured productivity from the previous period, we do not use any contemporaneous information on migration flows, alleviating further endogeneity concerns.

Our estimation delivers $1/\kappa = 1.632$ (s.e. 0.159), see Appendix C.3.2 for further details. As we are using log utility, this number corresponds to the elasticity of migration flows to real income for the homothetic limit where ϵ_j are all equal to one.[25] Using this estimate of $1/\kappa$ and equation (23), we can recover the changes in bilateral migration costs $\mu_{r\ell t} - \beta\mu_{r\ell t+1}$ as the residuals of our regression for each decade t. To recover the levels of migration costs, we leverage the assumption that migration costs remain constant since the year 2000, which implies that the residuals of our regression for $t = 2000$ become $(1-\beta)\mu_{r\ell t}$. Using this information, we can back out the levels of migration costs $\mu_{r\ell t}$ for all decades by iterating backward from 2000 to 1940.

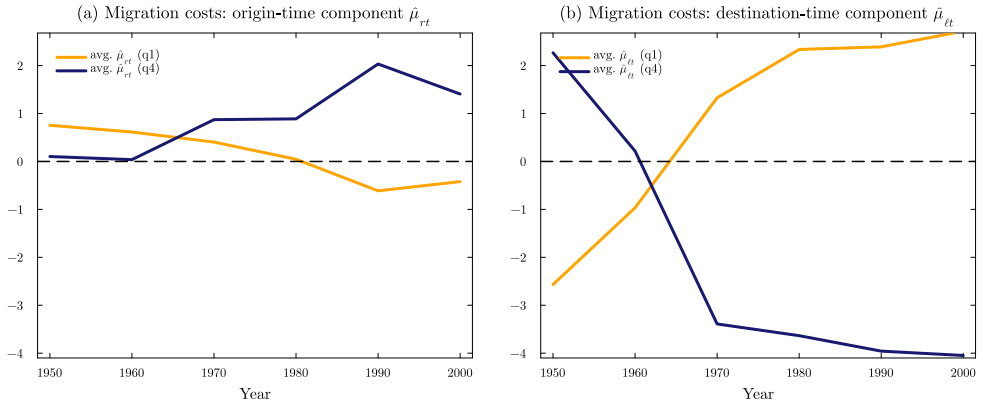
The raw migration costs recovered from this estimation procedure are useful as they perfectly match the data on migration flows and hence the labor supply in each region. This allows us to separate this part of the calibration from Step 2, in which the labor supply is taken as given. However, these migration costs are hard to interpret without further structure, which limits their usefulness for counterfactual exercises. For this reason, we decompose $\mu_{r\ell t}$ as follows

$$\mu_{r\ell t} = \hat{\mu}_t + \hat{\mu}_{rt} + \hat{\mu}_{\ell t} + \hat{\mu}_{r\ell} + \varepsilon_{r\ell t}\,, \tag{24}$$

where $\hat{\mu}_t$ is a common time effect, $\hat{\mu}_{rt}$, $\hat{\mu}_{\ell t}$, $\hat{\mu}_{r\ell}$ are origin-time, destination-time, and origin-destination fixed effects, and $\varepsilon_{r\ell t}$ captures any residual variation. Since the level of the origin-time and destination-time components cannot be separately identified in each period, we normalize both to have mean zero across provinces in every decade, so that $\hat{\mu}_t$ captures the common evolution of

[25] This implies a value of $\kappa = 1/1.632 = 0.613$, which is very close to the estimates found in other papers in the dynamic migration and occupational choice literatures, such as Artuç and McLaren (2015) for the case of occupational-industry flows ($\kappa = 0.62$) or Caliendo et al. (2021) for the case of migration across European countries ($\kappa = 0.55$).

FIGURE 6: Components of migration costs



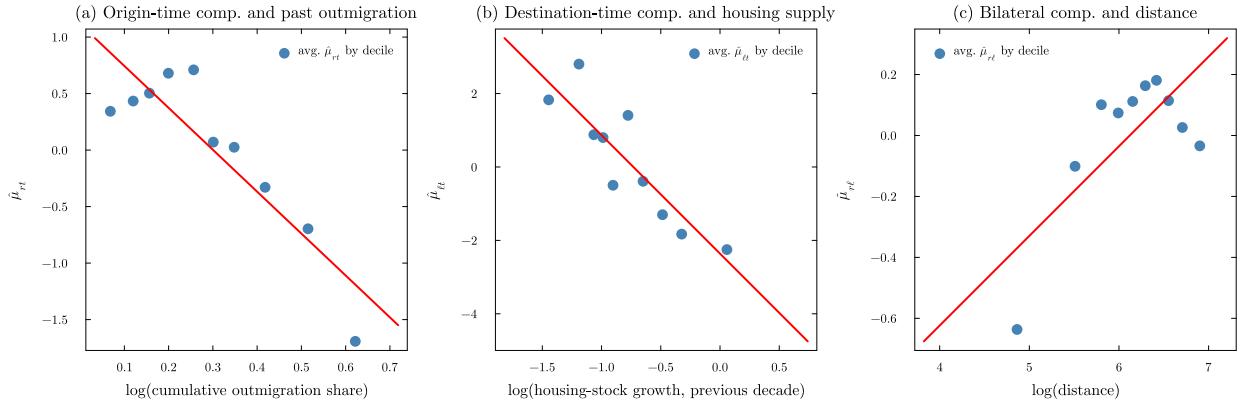
Notes: Panel (a) reports the average of the origin-time component of migration costs $\hat{\mu}_{rt}$ for provinces in the top (q4) and bottom (q1) quartiles of employment growth. Panel (b) reports the same statistics for the destination-time component of migration costs $\hat{\mu}_{\ell t}$. Dashed lines at zero represent the average of both components across all provinces in each decade.

migration costs over time. We estimate these components by OLS, pooling all the values of $\mu_{r\ell t}$ across decades. The resulting fixed effects ($\hat{\mu}_t$, $\hat{\mu}_{rt}$, $\hat{\mu}_{\ell t}$, $\hat{\mu}_{r\ell}$) account for 93% of the variation in the raw migration costs.

Next, to get a sense of the evolution of the origin ($\hat{\mu}_{rt}$) and destination ($\hat{\mu}_{\ell t}$) components of migration costs for different regions, we report in Figure 6 their averages for the provinces in the top and bottom quartiles of relative employment growth over 1940-2000. We can see that the origin component of migration costs is relatively higher for the provinces that lost the most population in earlier decades, but falls over time, while the opposite happens for the provinces that gained the most population (Panel a). This implies that laggard provinces became relatively easier to leave over time. The destination component of migration costs is higher for the provinces that gained the most population in earlier decades, but falls significantly over time, while the opposite is true for provinces that lost population (Panel b). This implies that leader provinces became easier to reach over time. In the Figure we can also see that the destination-time components of migration costs are much more dispersed than the origin-time components.

A natural question is whether the estimated migration cost components correlate with observables that are consistent with the interpretation of them as origin-time, destination-time, and origin-destination factors affecting migration costs. We provide some evidence that supports this interpretation. First, we correlate the origin-time component of migration costs $\hat{\mu}_{rt}$ with the stock of migrants that left region r in the decades prior to t relative to the population that remains in region r at t. This aims to capture a notion of the size of migration networks, which in principle should make leaving a region easier. Panel (a) of Figure 7 presents a binscatter that displays a negative relationship between $\hat{\mu}_{rt}$ and this measure of the size of the migration network, supporting this idea. Second, we correlate the destination-time component of migration costs $\hat{\mu}_{\ell t}$ with the change in housing stock of region ℓ in the previous decade, which we measure as the growth in dwelling surface built in the region. As our model does not feature a housing market, increases in

FIGURE 7: Correlates of migration cost components



Notes: Panel (a) is a binscatter of the origin-time component $\hat{\mu}_{rt}$ against the log migrant network of province r. Panel (b) is a binscatter of the destination-time component $\hat{\mu}_{\ell t}$ against the growth in dwelling surface in province ℓ in the previous decade. Panel (c) plots the bilateral component $\hat{\mu}_{r\ell}$ against log road distance between province capitals of regions r and ℓ.

housing supply that reduce housing prices in a given region may be reflected in the destination-time component of migration costs. Panel (b) of Figure 7 displays this correlation also in a binscatter form. The relationship is negative and statistically significant, showing that provinces that built more housing have on average lower values of $\hat{\mu}_{\ell t}$. Finally, we correlate the bilateral component of migration costs $\hat{\mu}_{r\ell}$ with the log road distance (in km) between the province capitals of each region. Panel (c) of Figure 7 shows that pairs of provinces that are further away tend to have higher values of $\hat{\mu}_{r\ell}$. Further details on this exercise can be found in Appendix C.4.

4.5 The calibrated economy *vs* the data

We report a selection of development statistics for the benchmark economy in Column (2) of Table 2. By construction of our estimation strategy, they are very close to the actual data, see Column (1). Real income grows by a factor of 8.31. The employment shares of agriculture and services decline and increase by 46 and 39 percentage points, respectively, while the employment share of manufacturing follows a hump shape, increasing by 14 percentage points until 1970 and declining by 7 percentage points afterward. The uneven industrialization across provinces can be seen by comparing the increase in manufacturing employment between 1940 and 1970 for q1 provinces (those that lose the most population) and q4 provinces (those that gain the most population). While for the q1 group this increase is only 8% of its total employment in 1940, it amounts to 43% for the q4 group. The rural exodus is summarized by three statistics: the increase in the coefficient of variation of employment across provinces of 62 percentage points, the regression coefficient of log regional employment growth between 1940 and 2000 on the initial agricultural share of -2.02 (the model counterpart of the slope of -2.07 in Panel (a) of Figure 2), and the R^2 of this regression of 0.61. The evolution of spatial inequality is described by the changes in the standard deviation

of regional income, which falls by 24 p.p. after 1960.

4.6 Engines of development

Given the calibrated model, one can analyze the sources of growth in Spain by decomposing how changes in productivity T_{rjt}, migration costs $\mu_{r\ell t}$, and trade costs $\tau_{r\ell jt}$ affect different long-run outcomes. This analysis is not the main goal of our paper, so we relegate it to Appendix D.1. As a summary, we mention that the growth in productivity generates most of the changes in relative prices and aggregate productivity that drive structural change and growth. Changes in trade costs complement productivity growth to complete the reallocation of employment out of agriculture. The effects of changes in migration costs are analyzed in the next Section.

5 Quantitative results

We start this Section by examining how the rural exodus shaped the development process of Spain (Section 5.1). To do so, we consider counterfactual economies where no migrations are possible. At the regional level, we find that internal migrations —and not the evolution of comparative advantage— are the main reason behind the asymmetric industrialization of Spain. At the aggregate level, we find that internal migrations accelerated growth by reallocating labor toward more efficient uses, yet the overall effect was moderate.

Next, we study the driving forces of the rural exodus in Spain. We find that the decline of migration costs towards the leading regions (Section 5.2.1) and the regional divergence in productivity (in manufacturing and services) during the first half of the development process (Section 5.2.2) were on their own powerful sources of migration and of uneven paths to regional industrialization, respectively.

5.1 The role of the rural exodus

To explore the role of the rural exodus in the development experience of Spain, we solve for a counterfactual economy in which workers cannot migrate (migration costs tend to infinity) and hence the relative size of provinces remains as in 1940. The main challenge in this exercise is what to assume about the evolution of labor productivity when the economy faces substantially different migration flows. In our first exercise, we assume that the region-specific sectoral productivity paths T_{rjt} evolve as in the calibrated economy and hence do not react to population movements. This is a strong assumption, but one that allows us to focus on the partial effect of migration flows on development. Second, we allow for agglomeration economies in industry and decreasing returns in agriculture, which results in industrial productivity growing more in areas receiving more

TABLE 2: Counterfactual exercises (changes between 1940 and 2000)

			No rural exodus		Migration costs		Early convergence	
	Data	Bench	CRS	Non-CRS	fixed $\hat{\mu}_{rt}$	fixed $\hat{\mu}_{\ell t}$	Man	Man, Ser
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real income pc	8.16	8.31	7.95	7.92	7.87	7.98	8.23	8.20
Agr share	−0.45	−0.46	−0.46	−0.47	−0.46	−0.46	−0.46	−0.46
Man share: 40-70	0.14	0.14	0.14	0.15	0.15	0.14	0.18	0.16
Man share: 70-00	−0.08	−0.07	−0.07	−0.07	−0.08	−0.07	−0.11	−0.08
Ser share	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39
Man emp q1: 40-70	0.07	0.08	0.19	0.26	0.01	0.17	0.48	0.39
Man emp q4: 40-70	0.44	0.43	0.27	0.25	0.60	0.31	0.20	0.23
$CV(L_r)$	0.65	0.62	0.00	0.00	1.29	0.15	0.40	0.24
$\hat{\beta}$	−2.07	−2.02	0.00	0.00	−1.75	−0.78	−1.35	−1.20
R^2	0.63	0.61	0.00	0.00	0.14	0.11	0.35	0.24
Sd($\log C_r$): 40-60	0.02	−0.02	−0.01	−0.01	−0.03	−0.01	−0.09	−0.12
Sd($\log C_r$): 60-00	−0.21	−0.24	−0.23	−0.23	−0.20	−0.23	−0.20	−0.18

Notes: Each column reports level changes in the corresponding variable between 1940 and 2000, unless another time frame is indicated in the corresponding row. For real income pc we report the ratio. "$\hat{\beta}$" and "R^2" are the coefficient and the share of explained variance of a regression of employment growth on initial agriculture share. "Man emp q1: 40-70" is employment change in manufacturing in q1 provinces relative to total employment of those provinces in 1940. Columns (1) and (2) correspond to the data and the calibrated economy, respectively. Columns (3) and (4) correspond to economies with no migration, with constant and non-constant returns to scale production functions, respectively. Columns (5) and (6) show the outcomes of economies in which the origin-time and destination-time components of migration costs are fixed at their initial values, respectively. Columns (7) and (8) show the outcomes of economies in which productivity converges across regions since 1940 in manufacturing and in manufacturing and services, respectively.

population.[26] Our results below show that the main insights for the effects of migration on local development are already apparent in the first case, although there are some interesting quantitative differences in the second one.[27]

5.1.1 Exogenous productivity paths

When productivity paths T_{rjt} evolve as in the calibrated economy (they do not depend on local employment), we find that without population movements the initially laggard regions do industrialize, while the initially leading regions specialize much less in manufacturing. In particular, absent migrations, provinces in the q1 and q4 groups would have increased their manufacturing employment between 1940 and 1970 by 19% and 27% of their initial total employment, while in the benchmark economy this increase is 8% and 43% respectively, see Column (3) in Table 2 (or

[26] Starting from Krugman (1991), many authors have used agglomeration economies to help explain the spatial concentration of economic activity. The literature on growth and structural change has also studied how agglomeration economies in urban locations increase the productivity of certain sectors, see for instance Michaels et al. (2012), Desmet and Rossi-Hansberg (2014), or Nagy (2023).

[27] Migrations may affect labor productivity for other reasons too. First, the allocation of capital across regions and time may depend on the allocation of labor, see for instance Kleinman et al. (2023). In this situation, capital stocks may follow population changes, increasing labor productivity in regions attracting more migrants. Second, there may be selection of individuals of better skills into migration as in Lagakos and Waugh (2013) such that regions attracting migrants receive more skilled workers (although for the case of Spain we show very little selection on education, see Appendix A.4). The results in this Section show that most of the interesting action already happens with productivity paths that are invariant to population movements.

Figures D.4 and D.5 in Appendix D for a few province-by-province examples). Therefore, we can conclude that the evolution of productivities and trade costs in the Spanish development episode was conducive to industrialization in the initially rural areas, but migrations prevented this from happening. The rural exodus is behind the uneven industrialization of Spanish regions. We discussed the economic mechanisms in Section 3.4. First, manufactures in initially laggard areas were not very competitive and hence depended very much on local demand, which the rural exodus depressed. Second, migration flows eroded the wage gap between leading and laggard regions, which made the manufactures of leading regions much more competitive country-wide, eventually taking over most of the market.

In the aggregate, the rural exodus contributed to real income growth, while having very limited effects on structural change. In particular, real income increases 36 percentage points more in the benchmark economy than in the no-migration counterfactual, as workers are forced to remain in regions that are less productive in manufacturing and services. Yet, the aggregate reallocation of employment across sectors remains unchanged. On the one hand, keeping workers in laggard regions makes the country poorer, which limits the reallocation of employment into manufacturing due to income effects. On the other hand, it hinders aggregate productivity growth in manufacturing, which limits the reallocation of employment out of manufacturing due to price effects. In the aggregate, these two opposing forces tend to compensate each other, and the overall effect of the rural exodus on structural change is limited.

5.1.2 Non-constant returns to scale

Next, we allow for non-constant returns to scale in sectoral production functions. Our quantitative model can easily accommodate this exercise. In particular, we can redefine the scale parameter T_{rjt} as $T_{rjt} \equiv \widetilde{T}_{rjt} L_{rjt}^{\theta_j \alpha_j}$, where $\widetilde{T}_{rjt}$ reflects the exogenous component of productivity and $L_{rjt}^{\theta_j \alpha_j}$ reflects departures from constant returns to scale whenever $\alpha_j \neq 0$. Then, output in each sector Y_{rjt} can be written as $Y_{rjt} = B_{rjt} L_{rjt}^{1+\alpha_j}$. With an estimate of α_j for each sector, the estimated productivity paths T_{rjt} from Section 4.3, and the observed allocation of workers L_{rjt}, we can recover the time paths $\widetilde{T}_{rjt}$ that are invariant to population changes. This allows us to separate productivity T_{rjt} into a "fundamental" exogenous component $\widetilde{T}_{rjt}$ and a component that varies with L_{rjt} in counterfactual exercises.

Estimating values for α_j is notoriously difficult as good instruments are needed to isolate exogenous variation in population. Lacking such instruments, we take some values from outside sources. In the macro-development literature, it is quite standard to set $\alpha_a < 0$, reflecting decreasing returns to scale in agriculture due to the fixed land factor. Typical values for α_a range from -0.30 (see Gollin et al. (2007) or Restuccia et al. (2008), who use estimates from Hayami and Ruttan (1985)) to -0.09 (Lagakos et al., 2023), so we decide to set an intermediate value of $\alpha_a = -0.15$. For manufacturing, we resort to the estimate of Desmet et al. (2018), a classic reference in the literature, and set $\alpha_m = 0.06$. Finally, for lack of a better alternative, we leave $\alpha_s = 0$ in services.

In Appendix D.2 we discuss the difference between the calibrated productivity paths T_{rjt} and the ones inferred with non-constant returns to scale production functions, $\widetilde{T}_{rjt}$.

Then, we revisit our counterfactual exercise of no migration with non-constant returns to scale production functions, see Column (4) in Table 2. Overall, we find that the qualitative effects are the same and that the quantitative results get reinforced. The initially laggard (leading) regions experience a stronger (weaker) industrialization when there is no migration compared to the CRS case because the increase (decrease) in manufacturing employment in these provinces improves (worsens) their manufacturing comparative advantage. Indeed, with agglomeration economies and no migration, q1 provinces experience a slightly stronger industrialization process than q4 provinces, as the manufacturing employment increase between 1940 and 1970 equals 26% and 25% of initial employment, respectively. This can be seen by comparing Figure D.6 (D.7) in Appendix D for the case with agglomeration with Figure D.4 (D.5) for the case with CRS. In terms of growth, the rural exodus is a slightly larger contributor to the increase in aggregate income when we allow for non-constant returns to scale, as migrations toward leading regions raise aggregate productivity beyond the mechanical increase due to shifting population from less to more productive regions.

5.2 The origins of the rural exodus

To uncover the economic forces leading to the rural exodus in Spain, we focus on the heterogeneous evolution of migration costs (Section 5.2.1) and sectoral productivity across regions (Section 5.2.2).

5.2.1 Changes in migration costs

Both the fall in the origin-time component of migration costs $\hat{\mu}_{rt}$ in laggard regions and in the destination-time component $\hat{\mu}_{\ell t}$ in leading regions (documented in Section 4.4) may help workers migrate from the former to the latter. To explore the importance of each of these changes, we solve for counterfactual economies in which either the origin-time or destination-time components are kept constant at their initial values. In both experiments, we let migration costs follow a common time trend $\hat{\mu}_t$ (see Figure C.8 in Appendix C.4), such that we just focus on the effects of how migration from (to) some regions has become relatively cheaper over time. The remaining time-changing fundamentals (productivity T_{rjt}, trade costs $\tau_{r\ell jt}$ and preference shifters ω_{jt}) also evolve as in the benchmark economy. We report the main results in Columns (5) and (6) of Table 2.

Our main finding is that the key driver of the rural exodus and uneven industrialization in Spain is the fall in the destination-time component of migration costs in the leading regions. In particular, when the destination-time component of migration costs $\hat{\mu}_{\ell t}$ is held fixed everywhere at its 1940 level, (a) the rural exodus is much smaller (the regression coefficient of employment growth on the initial agricultural share shrinks from -2.02 to -0.78, the R^2 from 0.61 to 0.11, and the dispersion of population across provinces increases by 15 percentage points instead of 62), and (b) industrialization is much more even across regions (the increase in industrial employment

represents 17 and 31 percent of initial employment in the q1 and q4 provinces respectively, compared to 8 and 43 percent in the benchmark).

Instead, when the origin-time component of migration costs $\hat{\mu}_{rt}$ remains fixed, the results are much less clear-cut. As in the previous experiment, we also find that the direction of migration is less rural-to-industrial than in the benchmark, although the change is smaller (the regression coefficient of employment growth on the initial agricultural share shrinks from -2.02 to -1.75, the R^2 from 0.61 to 0.14). However, different from before, population concentrates much more in leading regions (the overall dispersion of population across provinces increases by 129 percentage points instead of 62). These changes generate a more (rather than less) uneven pattern of industrialization (the increase in industrial employment represents 1 and 60 percent of initial employment in the q1 and q4 provinces, respectively, compared to 8 and 43 percent in the benchmark). This may seem surprising, as we saw that $\hat{\mu}_{rt}$ declined in laggard regions, making them easier to leave over time. However, $\hat{\mu}_{rt}$ also increased in leading regions (Figure 6, Panel a). This has two effects. First, fewer people leave leading regions, which helps them grow in population. Second, although more people leave laggard regions, this population outflow is not as much directed to leading regions, as workers anticipate that leaving them will be costlier in the future. In the counterfactual where $\hat{\mu}_{rt}$ is fixed, both effects are absent, and population concentrates more in leading regions, which shows that the second effect dominates.

Therefore, the key change is that the most prosperous regions became more accessible, which we related to the increase in housing supply in Section 4.4. This result is consistent with the findings of Hao et al. (2020) showing that the reform of the *hukou* system in China —an effective decline of migration costs towards the most prosperous regions— was an important driver of the Chinese rural exodus between 2000 and 2015.

5.2.2 Productivity convergence

Measured productivity in manufacturing and services diverged across provinces during the first two decades of the Spanish development episode but started to converge after 1960 (see Panel (b) in Figure 4). This pattern increased the gap between leading and laggard regions at the start of the development process, generating the inverted-U-shaped profile of inequality across provinces documented in Panel (a) in Figure 4. Our calibrated economy recovers productivity paths T_{rjt} that follow a similar pattern of regional inequality, see Panel (b) in Figure D.3. In this Section, we want to quantify the role played by the initial divergence of sectoral productivity across provinces in the development process of Spain, in particular on its rural exodus and uneven regional industrialization. To do so, we generate counterfactual sector-specific productivity paths T'_{rjt} for manufacturing and services in each Spanish province such that sectoral productivity starts converging in 1940 —at the same rate as services productivity converged between 1960 and 2000— while aggregate sectoral productivity still grows as in the data, see Appendix D.3 for details. We leave the evolution of productivity in the agriculture sector as in the benchmark calibrated economy.

We start by considering convergence only in manufacturing productivity —while letting services and agriculture productivity evolve as in the calibrated economy— and report the main results in Column (7) of Table 2. The convergence in manufacturing productivity is able to generate convergence in real income per capita across provinces before 1960 (the standard deviation of income per capita decreases 9 log points, compared to 2 log points in the benchmark) and to considerably reduce the rural exodus (the slope of the relationship between initial agriculture share and employment growth is -1.35 and the R^2 is 0.35, compared to -2.02 and 0.61 in the benchmark). Convergence in manufacturing productivity reverses the uneven pattern of industrialization across regions, as the relative increase in manufacturing employment in q1 provinces is higher than in q4 provinces. At the aggregate level, manufacturing experiences a bigger hump over the course of development than in the benchmark, as both the increase pre-1970 and the decline post-1970 of the manufacturing share are higher than in the benchmark. Before 1970, higher manufacturing productivity in q1 regions pushes employment towards manufacturing due to income effects; after 1970, it reallocates employment away from manufacturing due to price effects.

When we extend the convergence in productivity to both manufacturing and services (column 8), these results are amplified. First, convergence in real income per capita is stronger before 1960 (its standard deviation declines by 12 log points). This further diminishes the incentives to outmigrate from the initially rural areas, producing a smaller increase in the dispersion of population across provinces (a 24 percentage point increase in the coefficient of variation) and a smaller correlation between initial agriculture shares and employment growth (the slope of the relationship is -1.20 and the R^2 is 0.24). Eckert and Peters (2022) argue that early convergence of productivity across counties explains the lack of a rural exodus and homogeneous local industrialization in the US. Our results show that early convergence of sectoral productivity would have generated a more even pattern of industrialization in Spain and a weaker rural exodus.

6 Conclusions

As countries develop, their regions industrialize at an uneven pace. We have shown how migrations from laggard to leading regions help explain the lack of industrialization of the former and the fast path of industrialization of the latter. More generally, we have shown how these migrations contribute to the overall process of growth and macroeconomic development of a country.

We have started by looking at the development experience of Spain between 1940 and 2000, characterized by fast growth in income per capita, a large structural transformation, and mass migration from rural areas, which failed to industrialize, to early industrial hubs. Our simple model of structural change with multiple locations and sectors shows that the large rural exodus in Spain originated mainly from a decline in the migration costs towards the most prosperous regions during the 1950s, 1960s, and 1970s, complemented by a divergence of sectoral productivities across regions during these same decades. The rural exodus completely explains the lack of industrialization in

laggard areas, which shows how population movements can be a relevant force of local structural change.

We think of our paper as a first step towards understanding the role of the heterogeneous incidence of spatial frictions on economic development and structural change across countries. In this sense, this research agenda can help shed light on the heterogeneous paths of development documented by Rodrik (2016) and Huneeus and Rogerson (2024), among others. Our results focus on how population movements change local wages and prices, which in turn change the patterns of comparative advantage across regions. A limitation is that we take the estimated time paths of productivity, migration costs, and trade costs as exogenous. Further research can explore how to endogenize them, which would affect the counterfactual analyses. We took a first step in this direction by exploring how the time paths of region-specific sectoral productivity vary with employment due to agglomeration economies in manufacturing or decreasing returns to scale in agriculture. While qualitative results do not change, the quantitative effects of a rural exodus on the local development experience of regions are amplified. Future research could endogenize the joint evolution of migration costs and regional productivities, which is a promising explanation for the cross-country differences in local development patterns.

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Online Appendix

Macroeconomic Development, Rural Exodus, and Uneven Industrialization

Tomás Budí-Ors Josep Pijoan-Mas

November 2026

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Appendix A: Data

A.1 Data sources

Our analysis combines data from different sources, which we detail in the following paragraphs.

Employment. Data on regional employment for each sector between 1940 and 2000 comes from the Spanish Population Census, conducted every ten years by the National Statistics Office (*Instituto Nacional de Estadística*). We aggregate employment in agriculture, hunting, forestry and fishing and classify it as agriculture; employment in manufacturing, mining, construction and utilities and classify it as manufacturing; and employment in trade, transport, business, government and personal services and classify it as services.[28] In Figure 1 Panels (a) and (b) we use historical data from Prados de la Escosura (2017), which can be accessed here.

Migration flows. Information on bilateral migration flows is retrieved as well from the Census, which reports, for each province, the number of people that lived in a different province in the previous census wave, separating this number by migrants' region of origin since 1960 (i.e. we know, for instance, the number of people living in Barcelona in 1970 who were living in València in 1960, and the same for every pair of provinces). The procedure we follow to go from observed bilateral migration flows to our model-consistent bilateral migration flows is discussed in detail in Section A.2 of the Appendix.

Value added and prices. Data on regional value added and price indices by sector are obtained from the regional accounts prepared by the research department of BBVA.[29] To get a time series of regional price levels, we combine the regional price indices, which tell us how prices changed over time for each province and sector, with a cross-section of regional price levels for 1930. The latter is obtained from micro data on the prices of a common basket of goods across Spanish provinces, which were gathered by the *Instituto de Reformas Sociales*, a government institution in charge of assessing the material living conditions of the labor force at the time. We direct the interested reader to Gómez-Tello et al. (2019), to whom we are thankful for kindly sharing the data with us.

A.2 From data on migration flows to model counterparts

Our data on inter-regional migration flows $\hat{\rho}_{\ell rt}$ spans 1960 to 2000. We make two corrections to these data.

[28] For most years, we obtain the data at four-sector level (agriculture, manufacturing, construction, and services) directly from INE, which follows the aggregation criteria outlined above.

[29] Starting in 1957, the research department of BBVA published, every two years, a volume with the main economic aggregates of Spanish regions. In 2003, they released a volume with revised information and longer time coverage, with information dating back to 1930, which can be downloaded here.

The first one comes from the fact that the observed migration flows $\hat{\rho}_{\ell rt}$ do not perfectly square with the data on employment, that is, L_{rt} is not exactly equal to $(1+n_t)\sum_{\ell}^{R}\hat{\rho}_{\ell r}L_{\ell t-1}$.[30] To find the migration flows $\rho_{\ell rt}$ that are consistent with the data on employment, we simply minimize the Euclidean distance with respect to the observed $\hat{\rho}_{\ell rt}$ subject to the law of motion of employment being satisfied. In other words, we search for the most similar matrix to the observed matrix of bilateral migration flows that replicates the observed changes in the distribution of labor across regions. We further impose the constraints that the entries in $\rho_{\ell rt}$ are non-negative and that the elements in each row add up to 1. Then, the problem we solve is:

$$\begin{aligned}
\min_{\rho_{\ell rt}} \quad & \sqrt{\sum_{r=1}^{R}\sum_{\ell=1}^{R}(\rho_{\ell rt}-\hat{\rho}_{\ell rt})^2} & \\
\text{s.t.} \quad & L_{rt} = (1+n_t)\sum_{\ell=1}^{R}\rho_{\ell rt}L_{\ell t-1} & \forall r, \\
& \sum_{r=1}^{R}\rho_{\ell rt} = 1 & \forall \ell, \\
& \rho_{\ell rt} \geq 0 & \forall \ell, r.
\end{aligned} \tag{A.1}$$

The second correction comes from the fact that data on bilateral migration flows $\hat{\rho}_{\ell rt}$ is only available from 1960 onward, as in previous Census waves there is no question regarding workers' region of previous residence. Therefore, we cannot retrieve $\rho_{\ell rt}$ for 1950 and 1940 by solving (A.1). Instead, we look for $\rho_{\ell r1950}$ that minimize the Euclidean distance with $\rho_{\ell r1960}$ (which is based on observed migration flows), and similarly for $\rho_{\ell r1940}$ with $\rho_{\ell r1950}$ as target; with constraints as in (A.1). Additionally, we refine our strategy using data on net migration in each region for both 1950 and 1940, such that $\rho_{\ell r1950}$ and $\rho_{\ell r1940}$ are consistent with the volume of internal migration in

[30] This happens for two reasons. First, there may be measurement error in either the migration flows or the employment stocks. Second, regional employment growth in the model only depends on net internal migration and aggregate population growth. However, in the data it also depends on additional factors such as regional differences in the unemployment rate, in the fertility and mortality rates, or in the incidence of international migrations. Foreign immigration in Spain started in the 2000s, which does not affect our period of study. However, a significant number of workers in rural areas migrated abroad between 1960 and 1973 (mostly to Germany, France, and Switzerland). The exact numbers are unclear, see Bover and Velilla (2005) for details.

Spain in 1940 and 1950.[31] Specifically, we solve the following problem for $t = 1950$ and $t = 1940$:

$$\begin{aligned}
\min_{\rho_{\ell rt}} \quad & \sqrt{\sum_{r=1}^{R}\sum_{\ell=1}^{R}(\rho_{\ell rt} - \rho_{\ell rt+1})^2} \\
\text{s.t.} \quad & L_{rt} = (1+n_t)\sum_{\ell=1}^{R}\rho_{\ell rt}L_{\ell t-1} && \forall r, \\
& \sum_{r=1}^{R}\rho_{\ell rt} = 1 && \forall \ell, \\
& \rho_{\ell rt} \geq 0 && \forall \ell, r, \\
& NM_{rt} = \sum_{\ell \neq r}^{R}\rho_{\ell rt}L_{\ell t-1} - (1-\rho_{rrt})L_{rt-1} && \forall r\,.
\end{aligned} \tag{A.2}$$

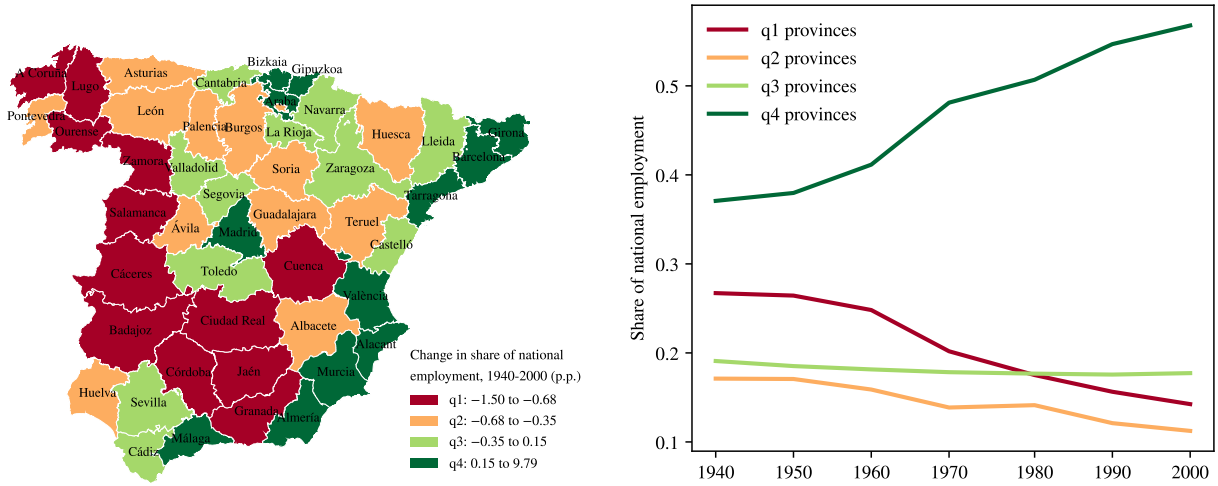
where NM_{rt} is the net migration in each region in period t.

[31] Net migration is defined as the difference between total migrant inflows and outflows. The data comes from the Census and is retrieved as a residual, given that for 1940 and 1950 we have information on births, deaths and population stocks for each province.

A.3 Regional employment growth in Spain, 1940-2000

Throughout the paper we stress the heterogeneity in employment growth across provinces and how this relates to the sectoral composition of regional employment in 1940 (Figure 2). For many statistics, we classify provinces in four quartiles based on the change in their relative size within the country (measured as the province share of total employment) over the period 1940-2000. The provinces corresponding to each group are shown in the left panel of Figure A.1. The share of total employment represented by each group over time is shown in the right panel of Figure A.1.

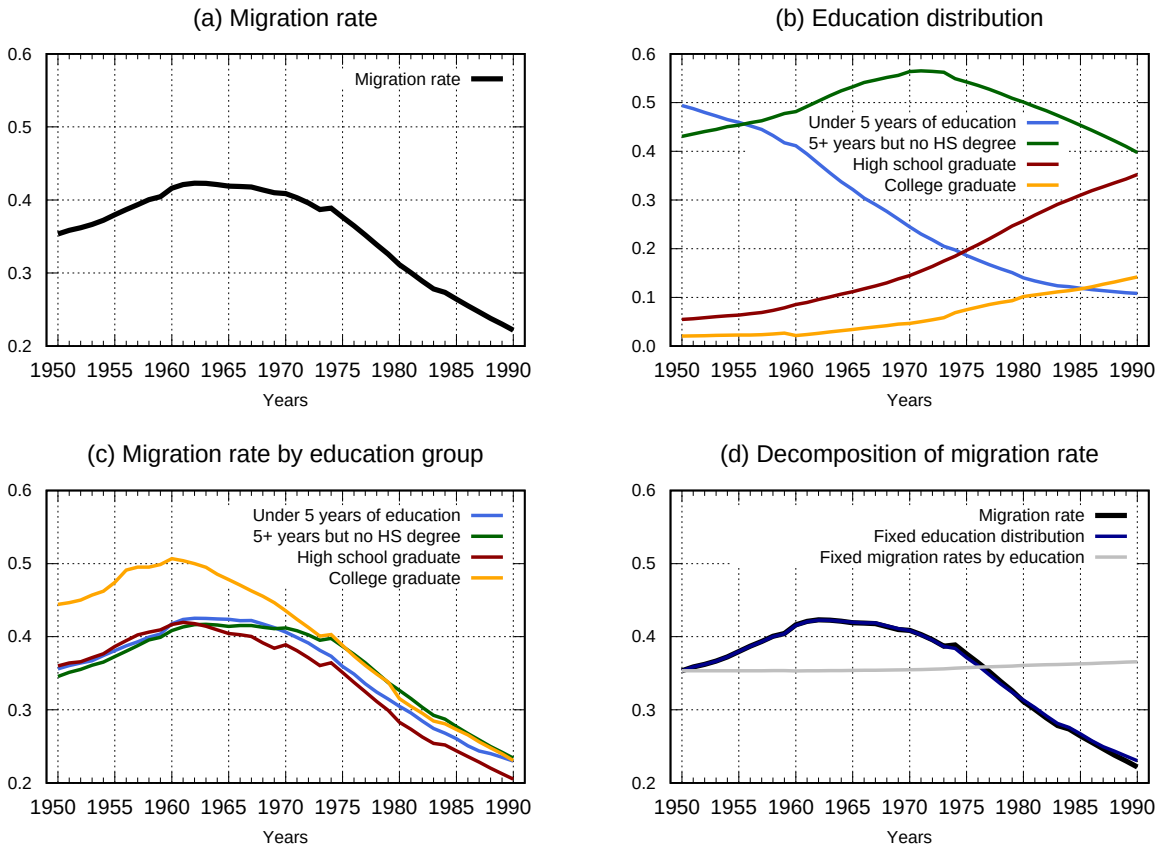
FIGURE A.1: Regional employment growth 1940-2000



Notes: The left panel groups provinces by quartiles of the change in their share of national employment between 1940 and 2000. Provinces in red are part of the bottom quartile (q1), in orange of the second quartile (q2), in light green of the third quartile (q3), and in dark green of the fourth quartile (q4). The right panel plots the evolution in the share of national employment of each group of provinces over time.

A.4 Education changes and migrations in Spain

FIGURE A.2: Migration and education, 1950-1979



Notes: Panels (a), (c), and (d) plot the fraction of people aged 18-25 in the given year that were observed as living in a province different from their birth province in some of the subsequent censuses (when they were aged between 26 and 56). Panel (b) plots the fraction of 18-25 year olds in the given year that hold each education level, also according to the subsequent censuses.

In this Appendix we document the small role played by changes in education in the rural exodus in Spain. To do so, we use microdata for the censuses of 1981, 1991, 2001, and 2011 (the only available ones).[32] From each census we select individuals that were aged 18 to 25 for each year between 1950 and 1979. We only use individuals that are observed in the census with ages between 26 and 56.[33] We classify these individuals as migrants if, when observed in the census, they reside in a different province from birth (and as non-migrants otherwise). The assumption is that most migrants moved in the age range 18 to 25 and hence the comparison of the two groups reveals

[32]The microdata comes from the IPUMS International Census Database. All cases correspond to 5% samples of the census, with the exception of 2011 which is a 10% sample.

[33]We do not use older individuals to limit biases due to differential mortality across education or migration groups, and also to minimize the incidence of return migrations, which in Spain are typically linked to retirement.

differences between migrants and non-migrants. We collect education data in four categories: less than five years of education (50% of 18-25 year olds in 1950), 5 or more years of education but no high school degree (43%), high school or vocational school degree (5%), and college degree (2%).

In Panel (a) of Figure A.2 we plot the migration rate for 18-25 year old individuals between 1950 and 1979. We see how the migration rate increases until the early 1960s and declines afterward. In Panel (b) we observe a clear educational transition over the period. The share of 18-25 year old individuals with less than 5 years of schooling falls steadily, the share of 18-25 year old individuals with 5 or more years but no high school degree increases first and declines later, and the shares of high school graduates and college graduates increase. Additionally, we note that the share of 18-25 year old college educated individuals is still very small in 1980, around 10% of the population in that age group. In Panel (c) we see that over this period migration rates were only partially linked to education: while the migration rate of college graduates is substantially larger than for the other education groups, there is no clear education gradient of migration among the non-college educated (the vast majority of young population). In particular, individuals with less than 5 years of schooling migrated at least as much (if not more than) more educated individuals without college. As a result, the educational transition did not mechanically produce a large change in migration rates. In Panel (d) we decompose the migration rate for the 18-25 year old individuals by isolating changes coming from changes in education while keeping migration rates by education constant, and changes in migration rates by education while keeping the education distribution constant. We see that if we keep the migration rates by education at their 1950 level and only let the distribution of education change over time, there is no increase in migration over the period. Rather, the change in migration comes from the change in migration within education groups.

A.5 International evidence on rural exodus

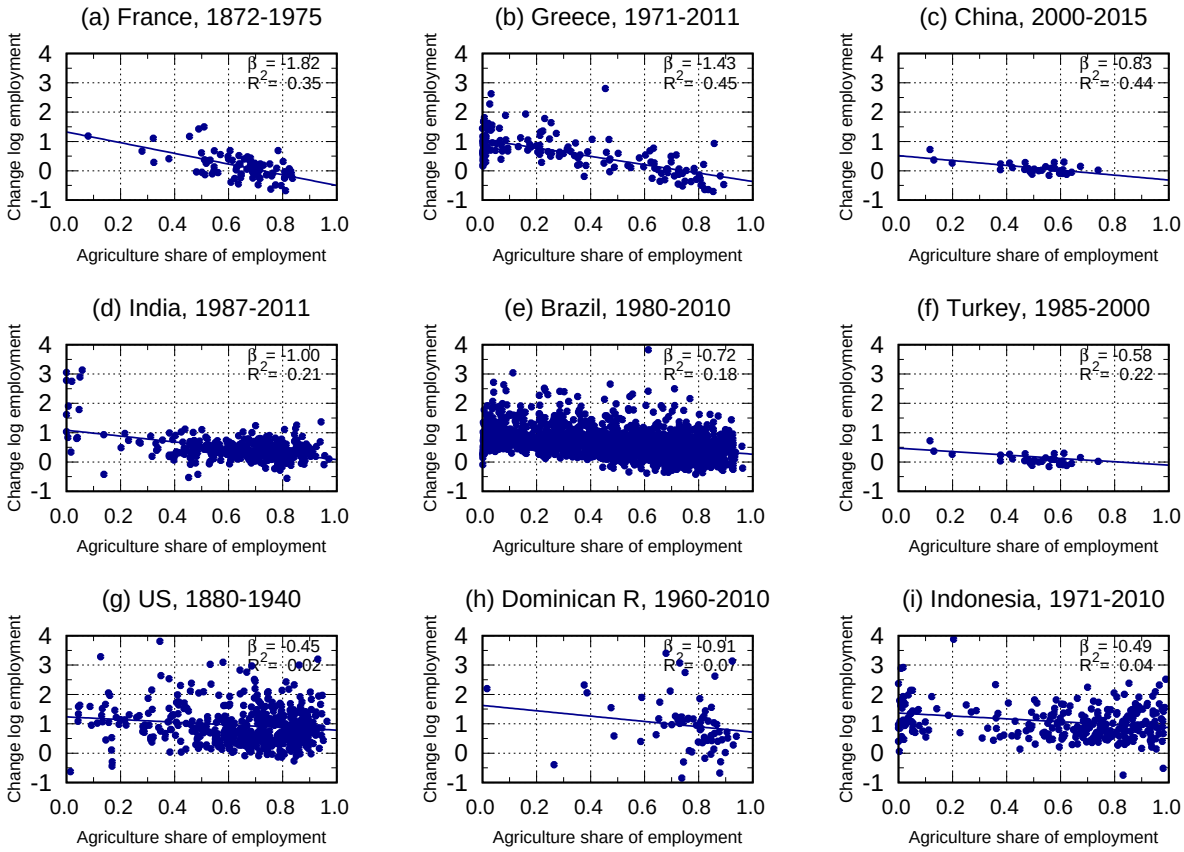
We use census data from several countries to explore the relationship between regional employment growth and the initial sectoral composition of regions. Our main data set is the IPUMS International Census Database. We complement these data with our own data for Spain, data from Hao et al. (2020) for China, data from García-Peñalosa and Bignon (2021) and Franck and Galor (2021) for France, data from Fan et al. (2023) for India, and data from Eckert and Peters (2022) for the US. We want to focus on development episodes, so we restrict the sample to countries such that (i) the time span between the first and the last year observed is larger than 10 years, (ii) the initial share of employment in agriculture is at least 25% and (iii) the fall in the country-level agricultural share in the period considered is larger than 10 percentage points. This gives us 27 development episodes. Then, for every country we run the regression,

$$\Delta \log L_r = \alpha + \beta \frac{L_{ra}}{L_r} + \varepsilon_r$$

where L_{ra}/L_r is the share of region r employment in sector a in the first year of the development episode and $\Delta \log L_r$ is total employment growth in region r between the first and last year of observation.

Table A.1 reports the results. For most countries $\beta < 0$, which means that more agrarian regions tend to lose population in relation to the rest (the only exceptions being Haiti, 1982-2003, and Honduras, 1961-2001). However, both the magnitudes of β and the R^2 vary substantially across countries. The magnitude of β is largest for Spain (1940-2000), with a value of -2.07, which means that a province with a 10-percentage-point higher share of employment in agriculture in 1940 experienced a 20% smaller population growth between 1940 and 2000. Remarkably, in the case of Spain, 63% of the variance in employment growth across provinces is related to the initial share of employment in agriculture. Other development episodes where the initial share of agriculture across locations is strongly related to employment growth are France (1872-1975), Greece (1971-2011), Bangladesh (1991-2011), Senegal (1988-2013), and China (2000-2015), with slopes equal to -1.82, -1.43, -1.36, -1.27, and -0.83, and R^2 equal to 35%, 45%, 44%, 60%, and 44% respectively. Some intermediate cases are India (1987-2011), Brazil (1980-2010), and Turkey (1985-2000) with slopes equal to -1.00, -0.72, and -0.58, and R^2 equal to 21%, 18%, and 22% respectively. In contrast, in some salient development episodes like the US (1880-1940), Indonesia (1971-2010), the Dominican Republic (1960-2010), or Costa Rica (1963-2011) migration flows are scarcely related to initial sectoral composition. For instance, the slope for these four countries is -0.45, -0.49, -0.91, and -0.70 respectively, but the R^2 of the regression is only 2%, 4%, 7%, and 9% respectively.

FIGURE A.3: Rural exodus across development episodes



Notes: This figure plots the relative increase in employment (in logs) across sub-national divisions against the initial sectoral shares of employment in agriculture for several countries. Each panel also reports the slope of the relationship (β) and the share of variance in log employment growth explained by the corresponding x-axis variables (R^2).

TABLE A.1: Rural exodus across development episodes

Country	Period	Ini Agr Sh	Δ Agr Sh	N	$\hat{\beta}$	R^2
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bangladesh	1991-2011	69.8	25.1	64	-1.36^{***}	0.44
Benin	1979-2013	59.4	16.8	77	-0.05	0.00
Bolivia	1976-2012	45.3	18.8	80	-0.83^{***}	0.15
Brazil	1980-2010	29.1	15.1	2040	-0.72^{***}	0.18
Cambodia	1998-2013	76.5	13.9	141	-0.40^{***}	0.05
China	2000-2015	52.9	24.6	30	-0.83^{***}	0.44
Costa Rica	1963-2011	48.1	35.1	55	-0.70^{*}	0.09
Dominican Rep.	1960-2010	62.1	52.8	65	-0.91	0.07
Ecuador	1962-2010	58.1	36.4	77	-1.74^{***}	0.21
El Salvador	1992-2007	35.0	18.5	103	-0.54^{***}	0.20
France	1872-1975	57.6	47.7	85	-1.82^{***}	0.35
Greece	1971-2011	38.7	30.1	156	-1.43^{***}	0.45
Guatemala	1964-2002	65.0	25.8	191	-1.27^{***}	0.14
Haiti	1982-2003	33.7	14.0	19	0.84^{**}	0.20
Honduras	1961-2001	66.2	24.6	96	1.20	0.05
India	1987-2011	63.9	16.9	368	-1.00^{***}	0.21
Indonesia	1971-2010	64.6	26.4	268	-0.49^{***}	0.04
Malaysia	1970-2000	52.5	37.3	101	-0.72^{***}	0.12
Mali	1987-2009	81.0	13.8	47	-0.40	0.08
Mexico	1970-2015	40.6	30.4	2321	-1.17^{***}	0.11
Nicaragua	1971-2005	48.1	14.4	68	-0.26	0.01
Panama	1960-2010	46.3	34.5	35	-1.14^{*}	0.11
Paraguay	1962-2002	54.1	28.1	60	-1.00^{**}	0.05
Senegal	1988-2013	61.5	35.2	27	-1.27^{***}	0.60
Spain	1940-2000	51.9	45.4	47	-2.07^{***}	0.63
Turkey	1985-2000	55.8	12.3	114	-0.58^{***}	0.22
United States	1880-1940	51.2	33.3	506	-0.45^{***}	0.02

Notes: This table shows the relationship between the initial agricultural share of regional employment and subsequent regional employment growth for a group of selected countries. Selected countries meet the following criteria: (i) the time span between the first and the last year observed is larger than 10 years, (ii) the initial share of employment in agriculture is at least 25% and (iii) the fall in the country-level agricultural share in the period considered is larger than 10 percentage points. For all countries except China, France, India, Spain and the US (see the text above) data comes from the IPUMS International Census Database. Regional-level employment is constructed by aggregating microdata on employed individuals between ages 20 and 59. The coefficient $\hat{\beta}$ reported in Column (6) is the point estimate of a regression of log employment growth at the regional level on the initial agricultural share of regional employment.

Appendix B: Model

B.1 Analytic results

Intersectoral and intrasectoral trade. The goods market clearing condition, equation (11), can be rewritten as

$$P_{rj}Y_{rj} - \pi_{rrj}P_{rj}C_{rj} = \sum_{\ell \neq r}^{R} \pi_{r\ell j}P_{\ell j}C_{\ell j} \quad \forall r, j \tag{B.1}$$

giving us the gross exports of sector-j goods by region r. Note that the gross imports of sector-j goods by region r are given by $(1 - \pi_{rrj})\, P_{rj}C_{rj}$ (the fraction of sector-j expenditure sourced from other regions). We can define intrasectoral trade as the sum of sectoral gross imports or exports across regions: $\sum_r (1 - \pi_{rrj})\, P_{rj}C_{rj}$ or $\sum_r [P_{rj}Y_{rj} - \pi_{rrj}P_{rj}C_{rj}]$, which are equal to each other because there is no international trade ($\sum_r P_{rj}C_{rj} = \sum_r P_{rj}Y_{rj}$). Then, net exports of sector-j goods by region r are given by the difference of gross exports and gross imports of that sector,

$$NX_{rj} = \left[P_{rj}Y_{rj} - \pi_{rrj}P_{rj}C_{rj}\right] - \left[\,(1 - \pi_{rrj})\, P_{rj}C_{rj}\right] = P_{rj}Y_{rj} - P_{rj}C_{rj} \tag{B.2}$$

which equals the difference between production and expenditure in that region-sector. We define intersectoral trade as the sum across regions of the positive sectoral net exports, which equals the sum of positive sectoral net imports because there is no international trade ($\sum_r P_{rj}C_{rj} = \sum_r P_{rj}Y_{rj}$). In particular, this would be $\sum_r \frac{1}{2} |P_{rj}Y_{rj} - P_{rj}C_{rj}|$

Trade balance equation. To derive the trade balance condition (15), note that the budget constraint of the households in equation (2) can be aggregated at the region level as

$$\sum_j P_{rj}C_{rj} = \sum_j w_r L_{rj} = \sum_j P_{rj}Y_{rj} \Rightarrow \sum_j \left[P_{rj}Y_{rj} - P_{rj}C_{rj}\right] = 0 \tag{B.3}$$

which says that sectoral net exports have to add up to zero at the regional level. Plugging the definition of net exports as the difference of gross exports and gross imports into equation (B.3), we obtain the equilibrium equation (15).

Proposition 1. *Holding prices fixed and assuming region r is small relative to the country size, a decline in population L_r in region r leads to (a) a fall in labor demand L_{rj} in all sectors j, and (b) a reallocation of labor away from sectors j where local purchases represent a larger fraction of value added.*

Proof. Holding prices fixed and assuming that region r is small enough to dismiss the effects of changes in demand coming from other regions, the derivative of L_{rj} in equation (14) with respect

to L_r can be written as

$$\frac{\partial L_{rj}}{\partial L_r} = \frac{\pi_{rrj} P_{rj} C_{rj}}{P_r Y_r} > 0 \tag{B.4}$$

which proves (a) as both numerator and denominator are strictly positive. To prove (b) note that multiplying and dividing the right-hand side of equation (B.4) by $P_{rj}Y_{rj}$ easily gives us equation (18). Equation (18) shows that the elasticity $\epsilon_{rj} \equiv \frac{\partial L_{rj}}{\partial L_r}\frac{L_r}{L_{rj}}$ of changes in the sector j labor demand L_{rj} with respect to changes in the population L_r is given by the ratio of $\pi_{rrj}P_{rj}C_{rj}$ to $P_{rj}Y_{rj}$. Actually, note that labor reallocation can be written as

$$\frac{\partial}{\partial L_r}\left(\frac{L_{rj}}{L_{ra} + L_{rm} + L_{rs}}\right) \propto \epsilon_{rj} - \bar{\epsilon}_r$$

where $\bar{\epsilon}_r \equiv \sum_i \epsilon_{ri}\frac{L_{ri}}{L_r}$, such that sectors where ϵ_{rj} is larger than the average elasticity $\bar{\epsilon}_r$ increase their relative size when there is a population inflow. □

Proposition 2. *Holding prices fixed and assuming region r is small relative to the country size, a decline in population L_r in region r leads to (a) a fall in total labor demand $\sum_j L_{rj}$ that is (weakly) lower than the fall in population L_r, and (b) a (weak) increase in the local wage w_r.*

Proof. Add up equation (B.4) over all sectors j to get,

$$\frac{\partial}{\partial L_r}\sum_j L_{rj} = \frac{\sum_j \pi_{rrj} P_{rj} C_{rj}}{P_r Y_r} \leq 1$$

where the weak inequality follows from the trade balance condition, $\sum_j P_{rj}C_{rj} = P_r Y_r$ and the amount of trade across regions, that is, $\pi_{rrj} \leq 1\ \forall j$. Indeed, note that without trade $\pi_{rrj} = 1\ \forall j$ and the decline in labor demand would be equal to the decline in labor supply, preventing changes in the equilibrium wage w_r. □

Proposition 3. *Holding expenditure shares constant, an increase in region r wage w_r decreases labor demand in all sectors j in region r, more so in those that are more tradable, that is, those with lower trade costs.*

Proof. The fraction of sector j goods that region ℓ buys from region r is given by the $\pi_{r\ell j}$ in equation (10). An increase in region r wage, w_r, will decrease this fraction $\forall \ell$ (including $\ell = r$) because region r becomes less competitive (the prices it offers to all regions ℓ are larger). To see this note that we can rewrite $\pi_{r\ell j}$ as $\pi_{r\ell j} = [1 + A_{r\ell j}]^{-1}$ where

$$A_{r\ell j} \equiv \sum_{k \neq r}\left(\frac{w_r}{w_k}\frac{\tau_{r\ell j}}{\tau_{k\ell j}}\right)^{\theta_j}\frac{T_{kj}}{T_{rj}} \tag{B.5}$$

is the inverse of how competitive region r is in selling sector j goods to region ℓ in relation to all other regions (including ℓ itself). Now, we can show that

$$\frac{\partial \pi_{r\ell j}}{\partial w_r} = -\theta_j \left[1 + A_{r\ell j}\right]^{-2} A_{r\ell j} \frac{1}{w_r} < 0$$

In addition, we can show that the loss of market share is larger in sectors that are more tradable. To see this, let's first decompose $\tau_{r\ell j} = \tau_j \tau_{r\ell}$ into a sector-specific term τ_j and a bilateral term $\tau_{r\ell}$. Then,

$$\frac{\partial^2 \pi_{r\ell j}}{\partial w_r \partial \tau_j} = \frac{\partial^2 \pi_{r\ell j}}{\partial w_r \partial A_{r\ell j}} \frac{\partial A_{r\ell j}}{\partial \tau_j} \propto -\left(1 - A_{r\ell j}^2\right) \frac{\partial A_{r\ell j}}{\partial \tau_j}$$

Now, to sign this derivative we need two pieces. First, $\frac{\partial A_{r\ell j}}{\partial \tau_j} > 0$ because the effect of an increase in τ_j cancels in all ratios $\frac{\tau_{r\ell j}}{\tau_{k\ell j}}$ in equation (B.5) except for the case $k = \ell$ where $\frac{\tau_{r\ell j}}{\tau_{k\ell j}} = \tau_{r\ell j}$ because $\tau_{\ell\ell j} = 1$. That is, an increase in τ_j decreases the ability of region r to sell sector j goods in region ℓ because the competition with local goods ℓ is tougher. Second, we have that $A_{r\ell j} > 1$ whenever $\pi_{r\ell j} < 1/2$. Hence, with region r small enough, this will be the case and hence we will have $\left(1 - A_{r\ell j}^2\right) < 0$. Therefore, whenever $\pi_{r\ell j} < 1/2$, the decline of $\pi_{r\ell j}$ with a wage increase is larger in sectors where trade costs are lower, that is, in sectors with lower τ_j. □

B.2 Solution algorithm

Starting from an initial distribution of workers across regions $\{L_{r0}\}_r$ and a converging sequence of fundamentals $\{\Upsilon_t\}_t$, such that $\Upsilon_t = \bar{\Upsilon}$ for all $t \geq T$, the solution algorithm to find equilibrium prices and allocations proceeds as follows:

1. Guess an initial sequence of wages $\left\{w_{r\,t}^{0}\right\}_{t=1,\ldots,T}$ in each region.
2. Given the last element of the sequence of wages $\left\{w_{r\,t}^{0}\right\}_{t=T}$, find the steady state value functions in each region $\{V_{r\,t}\}_{t=T}$.
3. Given the full sequence of wages and the value functions corresponding to the steady state, find the value functions for every period $t \leq T$ of the transition to the steady state $\{V_{r\,t}\}_t$ using the corresponding Bellman equations.
4. Given the full sequence of value functions, compute the labor supply in each region at every period of the transition using equation (8) and the initial distribution of workers across regions $\{L_{r0}\}_r$.
5. Given the labor supply at every period $\{L_{r\,t}\}_{t=1,\ldots,T}$, find the wage that clears the labor market in each region at every period using equation (12), obtaining $\left\{w_{r\,t}^{1}\right\}_{t=1,\ldots,T}$.

6. Compute a distance between the new wage sequence $\left\{w_{r\,t}^{1}\right\}_{t=1,...,T}$ and the initial wage sequence $\left\{w_{r\,t}^{0}\right\}_{t=1,...,T}$. If this distance is below some tolerance level, stop. Otherwise, update the wage sequence and go back to step 2.

In the calibration of the model, we recover the parameters that match the allocation of employment across regions and sectors at every decade between 1940 and 2000. When we compute the equilibrium of our benchmark economy, we keep these parameters constant from the year 2000 onwards, and allow the economy to slowly reach a steady state.[34] When we solve for the equilibrium of a counterfactual economy, we also keep the (counterfactual) sequence of fundamentals constant from the year 2000 onwards, so the economy reaches its corresponding counterfactual steady state.

[34] In practice, we solve for a steady state 10 periods (so 10 decades) after the year 2000, and obtain by backward induction the full sequence of value functions.

Appendix C: Calibration

C.1 First step: preferences

To obtain the estimation equation (19), let's start with the expenditure share on sector j goods by consumers in region r, equation (3), which we rewrite here for clarity (omitting time subscripts):

$$\frac{P_{rj}c_{rj}}{w_r} = \omega_j \left(\frac{w_r}{P_{rj}}\right)^{\nu-1} c_r^{(1-\nu)\epsilon_j} \tag{C.1}$$

with $w_r = P_{ra}c_{ra} + P_{rm}c_{rm} + P_{rs}c_{rs}$. We can multiply both sides by $w_r L_r$ and add up across regions r to obtain,

$$\sum_r P_{rj}C_{rj} = \omega_j \sum_r \left(\frac{w_r}{P_{rj}}\right)^{\nu-1} c_r^{(1-\nu)\epsilon_j} w_r L_r \tag{C.2}$$

On the left-hand side, $P_{rj}C_{rj} = P_{rj}c_{rj}L_r$ is total expenditure on sector-j goods by region-r consumers. In a closed-economy equilibrium, it must be that $\sum_r P_{rj}C_{rj} = \sum_r P_{rj}Y_{rj}$ (total expenditure in good j across provinces must equal total production of good j). On the right-hand side, $w_r L_r$ is total labor income in region r, which due to constant returns to scale and perfect competition in production, equals total value added in region r; that is, $w_r L_r = \sum_j P_{rj}Y_{rj}$. Therefore, replacing these two expressions and dividing both sides by total value added, we get:

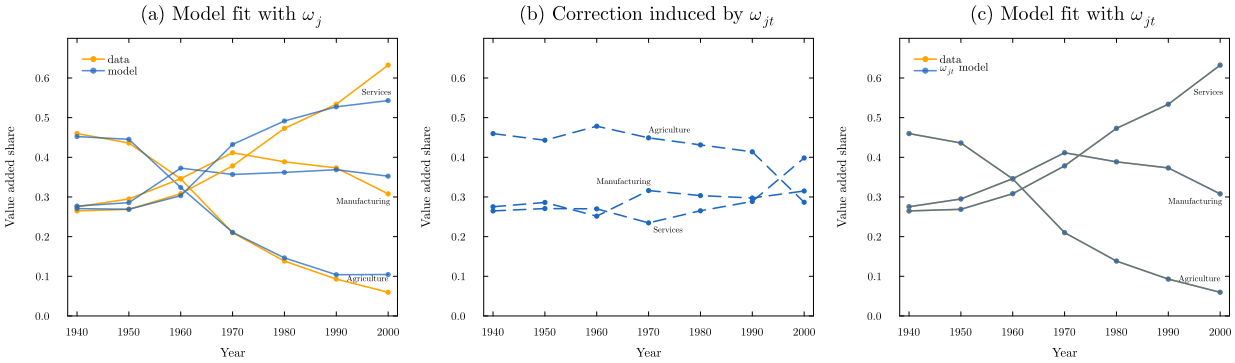
$$\frac{\sum_r P_{rj}Y_{rj}}{\sum_{rj} P_{rj}Y_{rj}} = \omega_j \sum_r \left(\frac{w_r}{P_{rj}}\right)^{\nu-1} c_r^{(1-\nu)\epsilon_j} \left(\frac{\sum_j P_{rj}Y_{rj}}{\sum_{rj} P_{rj}Y_{rj}}\right)$$

or more intuitively,

$$\frac{\text{VA}_j}{\text{VA}} = \sum_r \left(\frac{P_{rj}c_{rj}}{w_r}\right)\left(\frac{\text{VA}_r}{\text{VA}}\right)$$

where $\text{VA}_j \equiv \sum_r (P_{rj}Y_{rj})$, $\text{VA}_r \equiv \sum_j (P_{rj}Y_{rj})$, and $\text{VA} \equiv \sum_{rj} (P_{rj}Y_{rj})$ are all measured in the data. The left-hand side is the country-wide share of value added coming from sector j. The right-hand side is a weighted average of each region's expenditure share in good j, with the weights given by the weight of each region in the national GDP.

FIGURE C.1: Aggregate value added shares



Notes: Panel (a) plots the sectoral value added share in the data (yellow) and in the model (blue) using equation (19) with constant ω_j across time. Panel (b) plots the evolution of sectoral value added shares induced by the changes over time in ω_{jt}, keeping prices and wages at their 1940 levels. Panel (c) plots the sectoral value added share in the data (yellow) and in the model (blue) using equation (19) with time-varying ω_{jt}.

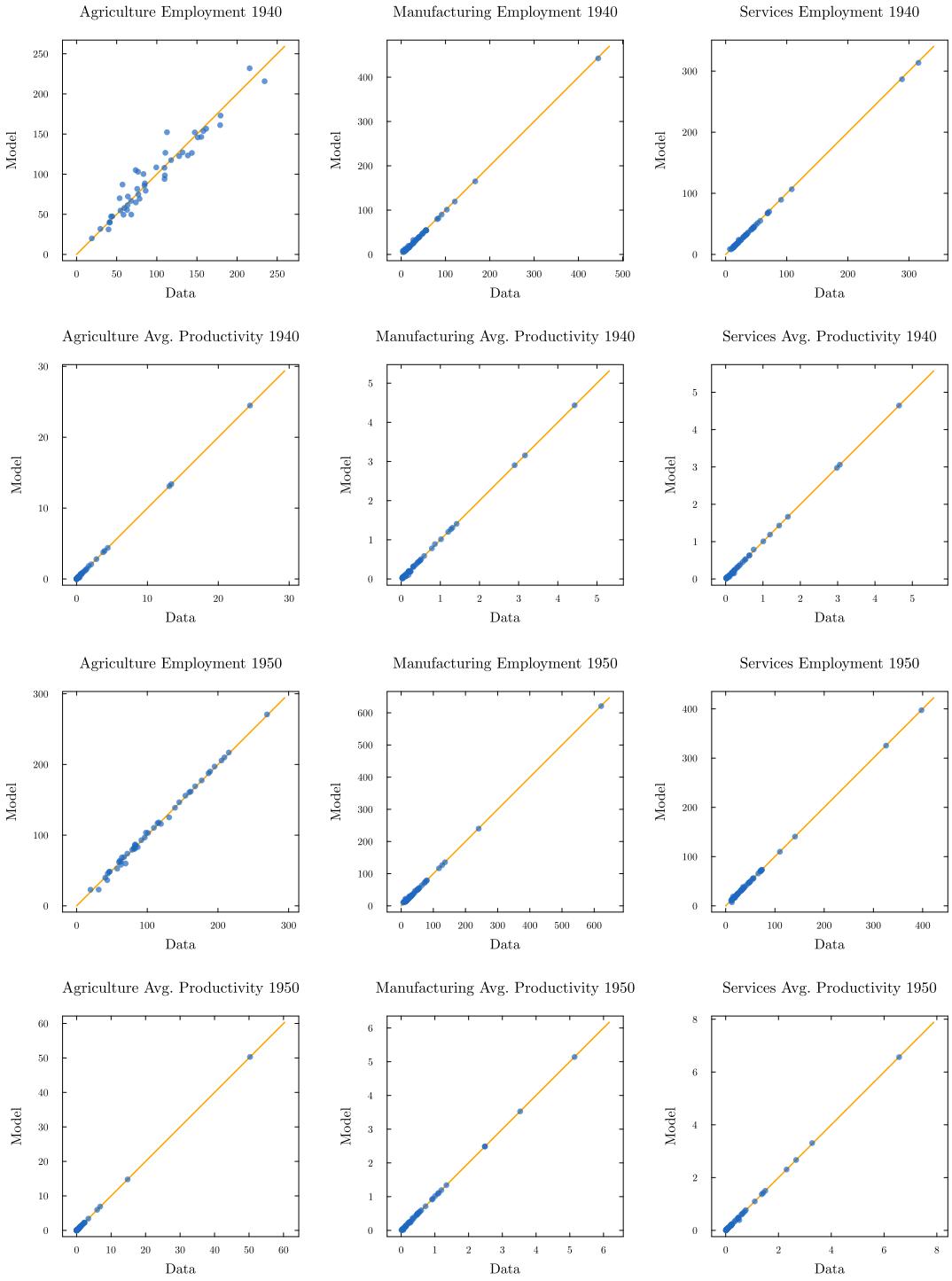
TABLE C.1: Time-varying ω_{jt}

	1940	1950	1960	1970	1980	1990	2000
ω_a	0.024	0.023	0.026	0.022	0.022	0.021	0.014
ω_m	1.0	1.0	1.0	1.0	1.0	1.0	1.0
ω_s	0.375	0.371	0.415	0.295	0.345	0.382	0.501

Notes: values for ω_{jt} obtained to perfectly match the data on aggregate sectoral value added shares over time.

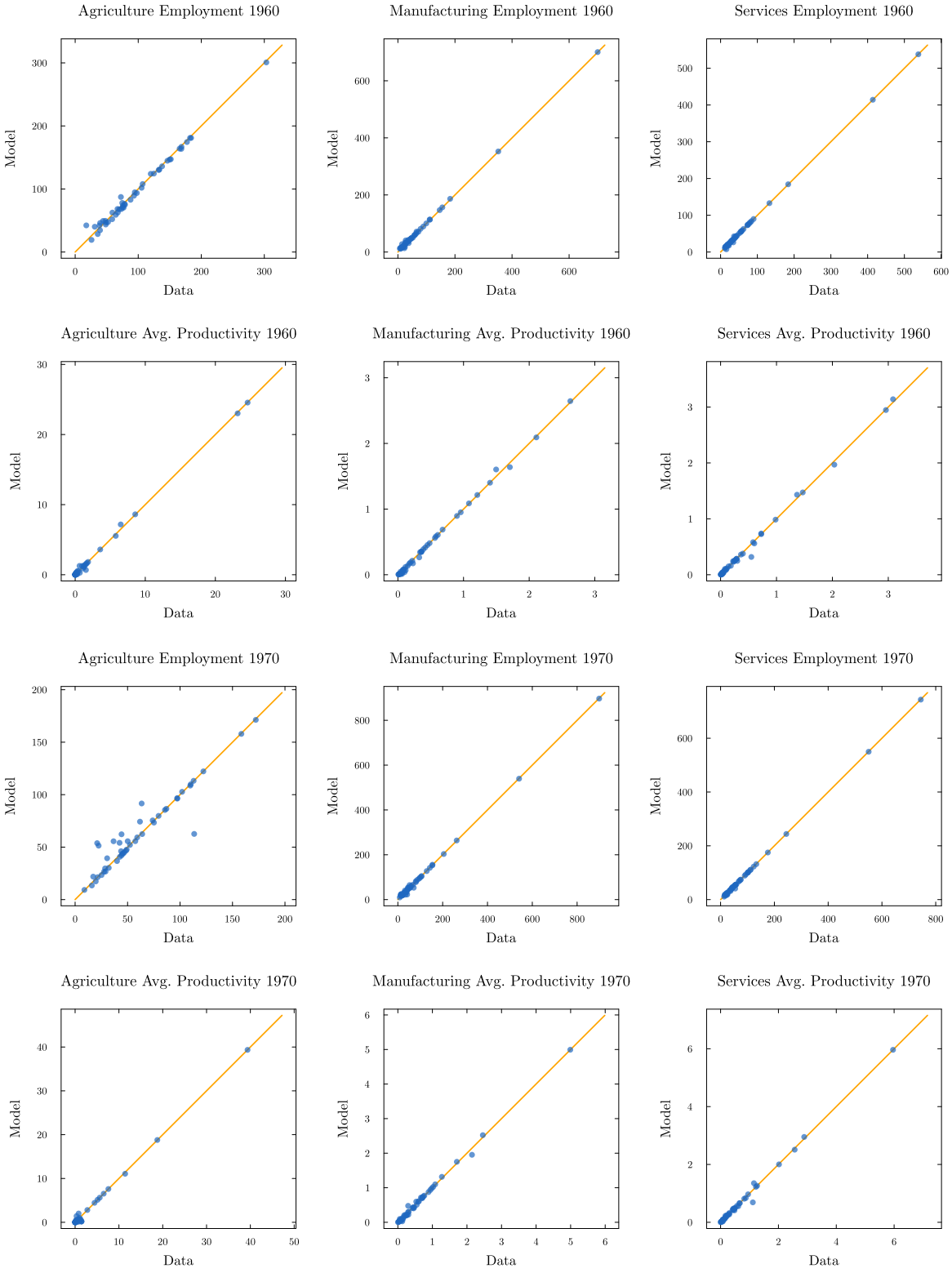
C.2 Second step: trade costs and productivity

FIGURE C.2: Model fit employment and productivity: 1940 and 1950



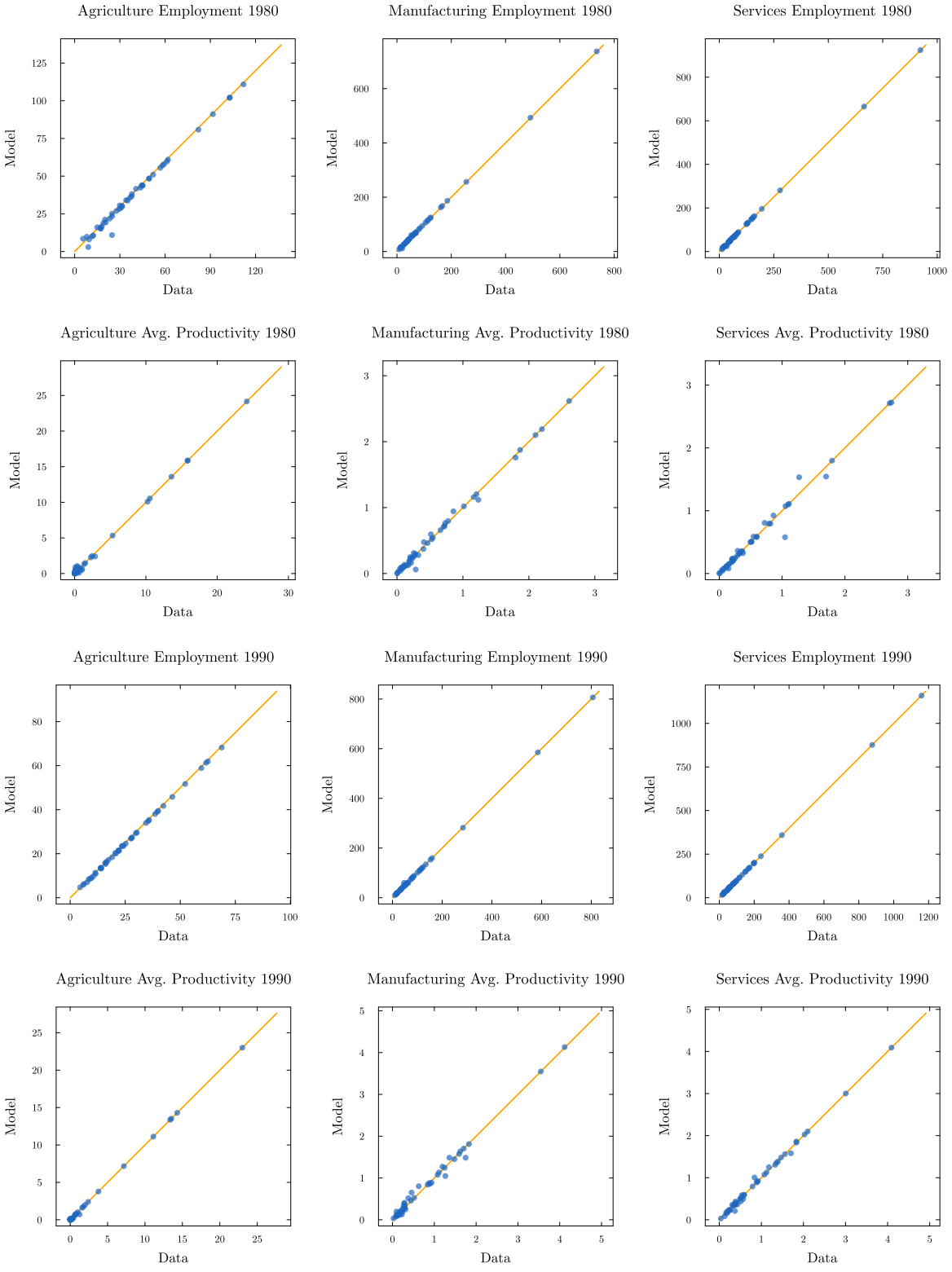
Notes: This figure compares the model-predicted values for employment and productivity in each sector for the 1940 and 1950 decades. Each dot represents a province. Employment moments are measured in thousands of workers; productivity moments are $\tilde{B}_{rjt} = (\gamma_j B_{rjt})^{\theta_j}$, where B_{rjt} is measured productivity (see equation (17)), relative to its employment-weighted national average in each year and sector.

FIGURE C.3: Model fit employment and productivity: 1960 and 1970



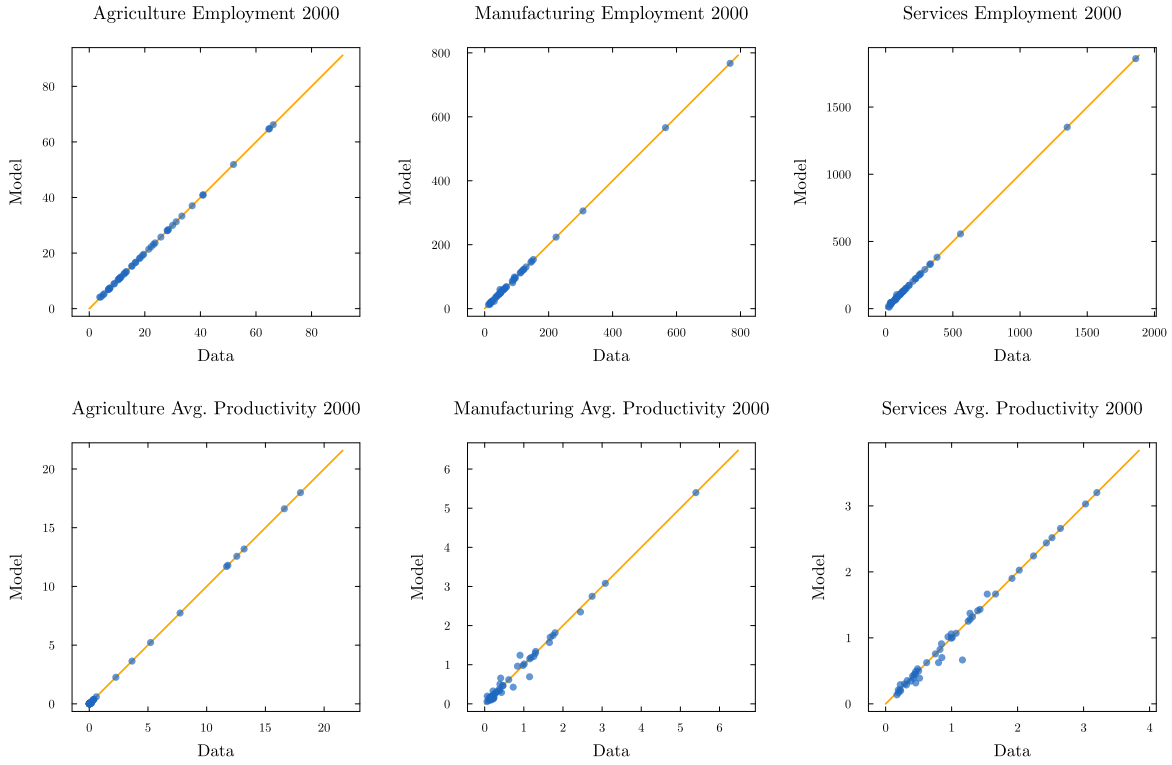
Notes: This figure compares the model-predicted values for employment and productivity in each sector for the 1960 and 1970 decades. Each dot represents a province. Employment moments are measured in thousands of workers; productivity moments are $\tilde{B}_{rjt} = (\gamma_j B_{rjt})^{\theta_j}$, where B_{rjt} is measured productivity (see equation (17)), relative to its employment-weighted national average in each year and sector.

FIGURE C.4: Model fit employment and productivity: 1980 and 1990



Notes: This figure compares the model-predicted values for employment and productivity in each sector for the 1980 and 1990 decades. Each dot represents a province. Employment moments are measured in thousands of workers; productivity moments are $\tilde{B}_{rjt} = (\gamma_j B_{rjt})^{\theta_j}$, where B_{rjt} is measured productivity (see equation (17)), relative to its employment-weighted national average in each year and sector.

FIGURE C.5: Model fit employment and productivity: 2000



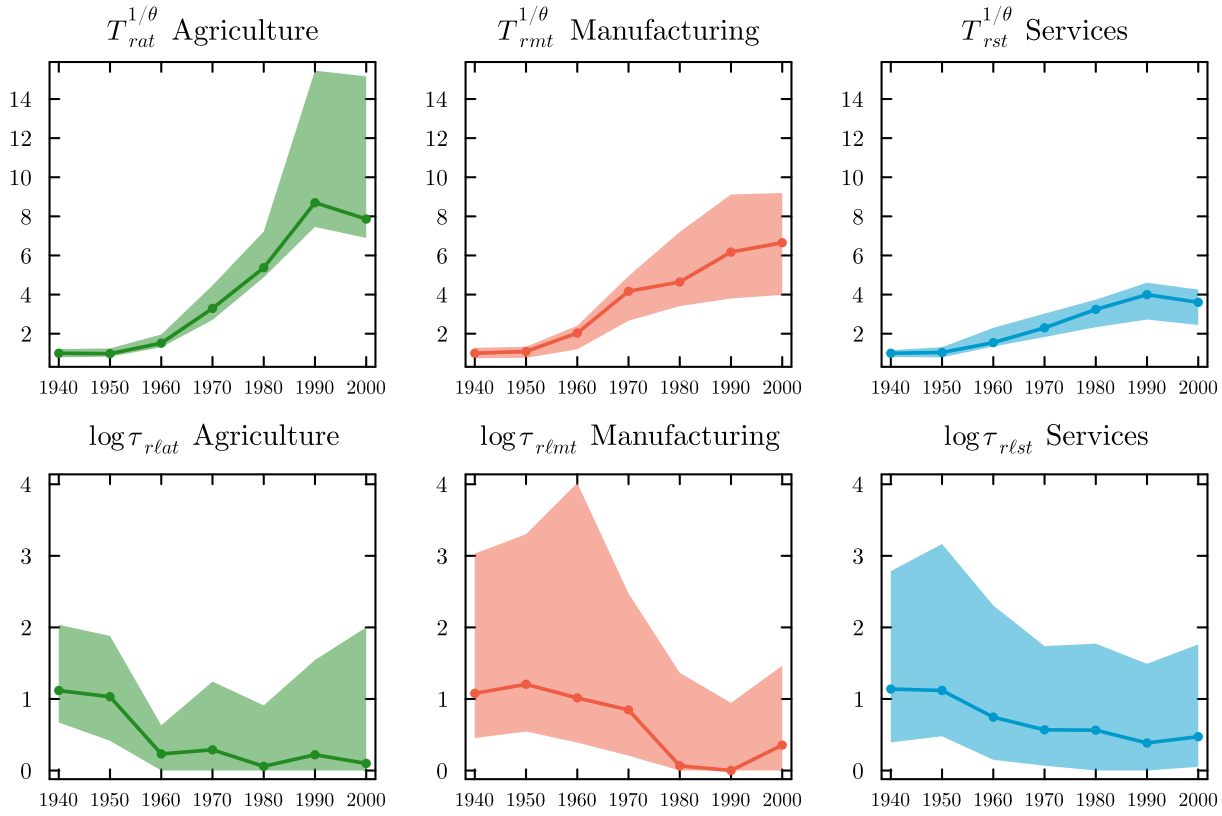
Notes: This figure compares the model-predicted values for employment and productivity in each sector for the 2000 decade. Each dot represents a province. Employment moments are measured in thousands of workers; productivity moments are $\tilde{B}_{rjt} = (\gamma_j B_{rjt})^{\theta_j}$, where B_{rjt} is measured productivity (see equation (17)), relative to its employment-weighted national average in each year and sector.

TABLE C.2: Correlation of employment and expenditure shares over time

	1940	1950	1960	1970	1980	1990	2000
Agriculture	0.55	0.68	0.69	0.34	0.56	0.13	−0.05
Manufacturing	0.52	0.63	0.65	0.37	0.11	−0.34	−0.37
Services	0.43	0.53	0.45	0.15	0.17	−0.07	0.06

Notes: Each entry is the correlation of sectoral employment and model-implied expenditure shares across provinces for every year and sector.

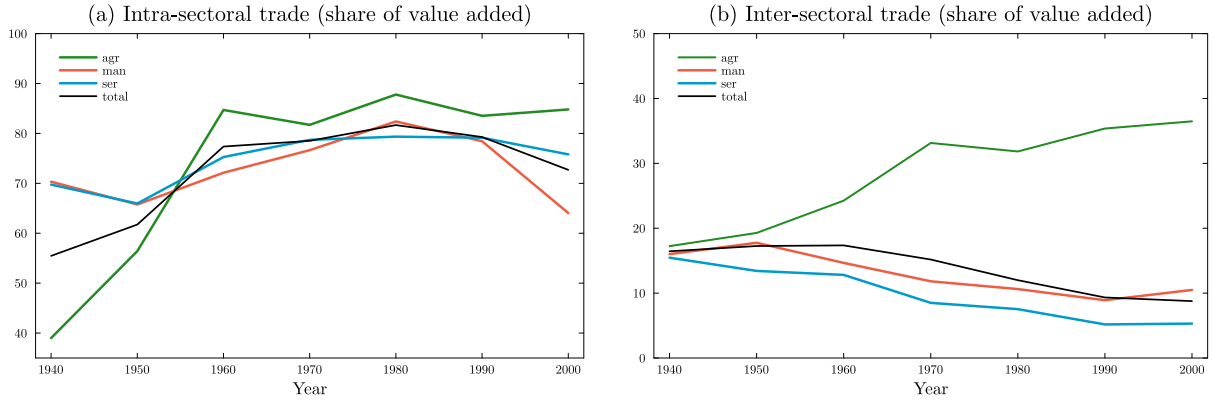
FIGURE C.6: Evolution of fundamental productivity and trade costs over time



Notes: The lines represent the median across provinces of the productivity parameters T_{rjt}^{1/θ_j} (top row), normalized by their 1940 median, and the median across province pairs of the log trade costs $\log \tau_{r\ell jt}$ (bottom row). The bands represent the 25th to 75th percentiles of the distribution of the same parameters.

Implied trade volumes. The fall in trade costs and changes in the dispersion of productivity generate a rise in trade volumes. We define intrasectoral trade as the fraction of sectoral expenditure not produced locally, $\sum_r (1 - \pi_{rrjt}) P_{rjt} C_{rjt}$, see Appendix B.1. This is the notion of trade in Eaton and Kortum (2002) whereby intrasectoral heterogeneity in productivity across provinces generates Ricardian trade. As we can see in Panel (a) of Figure C.7, intrasectoral trade as a share of sectoral value added increases in all three sectors until 1990. This increase is much more apparent for agriculture, while for manufacturing and services intrasectoral trade is hump-shaped, given that aggregate value added reallocates over time toward these sectors. We can additionally define intersectoral trade for sector j as the difference between sectoral expenditure and sectoral value added, $\sum_r \frac{1}{2} |P_{rjt} C_{rjt} - P_{rjt} Y_{rjt}|$, see Appendix B.1. In Panel (b) of Figure C.7 we see how intersectoral trade declines relative to sectoral value added in manufacturing and services, which reflects growing convergence between sectoral expenditure and value added shares across provinces in these sectors. Instead, intersectoral trade increases in agriculture due to the fact that the declining production of agriculture gets concentrated over time in fewer, specialized regions.

FIGURE C.7: Trade across provinces



Notes: Panel (a) reports predicted intrasectoral trade as a share of sectoral value added. Panel (b) shows predicted intersectoral trade as a share of sectoral value added.

C.3 Third step: migration costs

C.3.1 Derivation of estimating equation

To estimate the migration elasticity $1/\kappa$, we derive an expression that relates current migration flows to differences in real income and future migration flows, see equation (23). This appendix presents a step-by-step derivation starting from the migration probabilities, given by

$$\rho_{r\ell t} = \frac{\exp\left\{\frac{1}{\kappa}\big(V_{\ell t} - \mu_{r\ell t}\big)\right\}}{\sum_k^R \exp\left\{\frac{1}{\kappa}\big(V_{kt} - \mu_{rkt}\big)\right\}}.$$

Taking the ratio between the probability of migrating from region r to region ℓ and the probability of staying in region r, we get (in logs)

$$\log\left(\frac{\rho_{r\ell t}}{\rho_{rrt}}\right) = \frac{1}{\kappa}\Big[V_{\ell t} - V_{rt} - \mu_{r\ell t}\Big].$$

Replacing the value of living in regions ℓ and r using equation (6), we obtain

$$\begin{aligned}\log\left(\frac{\rho_{r\ell t}}{\rho_{rrt}}\right) = \frac{1}{\kappa}\Big[&\log(c_{\ell t}) + \beta\kappa \log\left(\sum_k \exp(V_{kt+1} - \mu_{\ell kt+1})^{1/\kappa}\right) \\ &- \left(\log(c_{rt}) + \beta\kappa \log\left(\sum_k \exp(V_{kt+1} - \mu_{rkt+1})^{1/\kappa}\right)\right) - \mu_{r\ell t}\Big].\end{aligned}$$

Next, adding and subtracting $\beta\kappa\big(\log(\exp(V_{\ell t+1})^{1/\kappa}) - \log(\exp(\mu_{r\ell t+1})^{1/\kappa})\big)$ and rearranging terms by using the definition of $\rho_{r\ell t+1}$ in equation (7), we get

$$\begin{aligned}\log\left(\frac{\rho_{r\ell t}}{\rho_{rrt}}\right) = \frac{1}{\kappa}\Big[&\log(c_{\ell t}) - \log(c_{rt}) \\ &+ \beta\kappa\left(\log(\exp(V_{\ell t+1})^{1/\kappa}) - \log(\exp(\mu_{r\ell t+1})^{1/\kappa}) - \log\left(\sum_k \exp(V_{kt+1} - \mu_{rkt+1})^{1/\kappa}\right)\right) \\ &- \beta\kappa\left(\log(\exp(V_{\ell t+1})^{1/\kappa}) - \log\left(\sum_k \exp(V_{kt+1} - \mu_{\ell kt+1})^{1/\kappa}\right)\right) \\ &+ \beta\kappa\log(\exp(\mu_{r\ell t+1})^{1/\kappa}) - \mu_{r\ell t}\Big] \\ = \frac{1}{\kappa}\Big[&\log(c_{\ell t}) - \log(c_{rt}) + \beta\kappa\big(\log(\rho_{r\ell t+1}) - \log(\rho_{\ell\ell t+1})\big) + \beta\mu_{r\ell t+1} - \mu_{r\ell t}\Big].\end{aligned}$$

Finally, rearranging terms gives us equation (23) in the main text:

$$\log\left(\rho_{r\ell t}/\rho_{rrt}\right) - \beta\log(\rho_{r\ell t+1}/\rho_{\ell\ell t+1}) = \frac{1}{\kappa}\log(c_{\ell t}/c_{rt}) - \frac{1}{\kappa}(\mu_{r\ell t} - \beta\mu_{r\ell t+1})$$

C.3.2 Estimation details

With data on regional wages and prices, plus the parameters of the demand system estimated in Step 1, we use equations (1) and (3) to compute real consumption per capita in each region c_{rt} and hence $\log(c_{\ell t}/c_{rt})$. Next, we construct the left-hand side of equation (23) using our data on migration flows across regions $\rho_{r\ell t}$ and the value we have assigned for the discount factor β. We then proceed with the estimation of equation (23), treating the term $(\mu_{r\ell t} - \beta\mu_{r\ell t+1})$ as an unobserved residual. Estimating $1/\kappa$ by OLS would produce biased estimates, as $\log(c_{\ell t}/c_{rt})$ is an equilibrium outcome that depends on the value of migration costs $\mu_{r\ell t}$. Hence, we look for an instrumental variable that affects current consumption while being orthogonal to changes in migration costs. We use as instrument the log difference in the fundamental productivity across regions, averaged across sectors and lagged by one period, $\log(\bar{T}_{\ell t-1}/\bar{T}_{rt-1})$, where

$$\bar{T}_{rt} = \left(\sum_j \omega_{jt} T_{rjt}^{\nu-1} \right)^{\frac{1}{\nu-1}}.$$

Fundamental productivity affects real consumption through its effects on local income. By assumption, it is also orthogonal to migration costs, as it reflects the efficiency of a region in the production of sectoral varieties. As fundamental productivity is retrieved using information on the allocation of labor across regions in that same period —see equations (20) and (21)—, which contains information on migration flows, we use lagged productivity as instrument. The instrument remains relevant as regional productivity is persistent over time, and endogeneity concerns are alleviated, as we do not use any contemporaneous information on migration costs $\mu_{r\ell t}$ in order to recover it.[35]

Estimates of $1/\kappa$ are presented in Table C.3. The first column reports OLS estimates, while the second column reports IV estimates using lagged fundamental productivity as instrument. We can see that the OLS estimate of $1/\kappa$ is *negative*, which is at odds with any reasonable economic logic, but not surprising given that differences in consumption $\log(c_{\ell t}/c_{rt})$ and changes in migration costs $(\mu_{r\ell t} - \beta\mu_{r\ell t+1})$ are likely to be positively correlated.[36] The IV estimate of $1/\kappa$ is instead positive and statistically significant, with a value of 1.632. This implies a value of $\kappa = 1/1.632 = 0.613$. This value is very close to the estimates found in other papers in the dynamic migration and occupational

[35] Several papers in the dynamic migration and occupational choice literatures (see, e.g. Caliendo et al. (2019) or Artuç et al. (2010)) use past values of real wages as instruments. Past values of real wages (which in our model are given by c_r) are not a good instrument in our case as they are affected by future changes in migration costs, given that agents have perfect foresight over the path of economic fundamentals.

[36] The intuition for this positive correlation is as follows. Consider the case where migration costs between region r and region ℓ increase at t, so that $\mu_{r\ell t} - \beta\mu_{r\ell t+1}$ rises. All else equal, this would prevent some workers from migrating from r to ℓ, keeping labor supply higher in r and lower in ℓ, which would reduce incomes in r relative to ℓ, increasing $\log(c_{\ell t}/c_{rt})$. Since $\mu_{r\ell t} - \beta\mu_{r\ell t+1}$ enters the error term with a negative sign, the regressor is negatively correlated with the error, and the OLS estimate of $1/\kappa$ is biased downward.

TABLE C.3: Estimates of migration elasticity $1/\kappa$

	(1) OLS	(2) IV
$\log(c_{\ell t}/c_{rt})$	-1.417***	1.632***
	(0.115)	(0.159)
N	10,810	10,810
1st stage F-stat		3,599.1

Notes: This table reports estimates of the migration elasticity $1/\kappa$ using equation (23). Column (1) reports OLS estimates, while Column (2) reports IV estimates using lagged fundamental productivity as instrument. Standard errors clustered at the origin-destination pair level in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

choice literatures, such as Artuç and McLaren (2015) for the case of occupational-industry flows ($\kappa = 0.62$) or Caliendo et al. (2021) for the case of migration across European countries ($\kappa = 0.55$).

C.3.3 Recovering migration costs

Next, using equation (23) and our estimate for κ, we recover the values of migration costs $\mu_{r\ell t}$ that perfectly rationalize the observed migration flows $\rho_{r\ell t}$ and hence the local labor supply L_{rt}. To be able to recover the level of migration costs, we leverage the assumption that fundamentals remain constant after the year 2000, such that equation (23) becomes

$$\log\left(\rho_{r\ell t}/\rho_{rrt}\right) - \beta \log(\rho_{r\ell t+1}/\rho_{\ell\ell t+1}) = \frac{1}{\kappa}\log(c_{\ell t}/c_{rt}) - \frac{1}{\kappa}(1-\beta)\mu_{r\ell t} \quad \text{for } t \geq 2000$$

Once we have recovered the level of migration costs for the year 2000, it is straightforward to recover the level of migration costs for previous years by using equation (23) recursively.

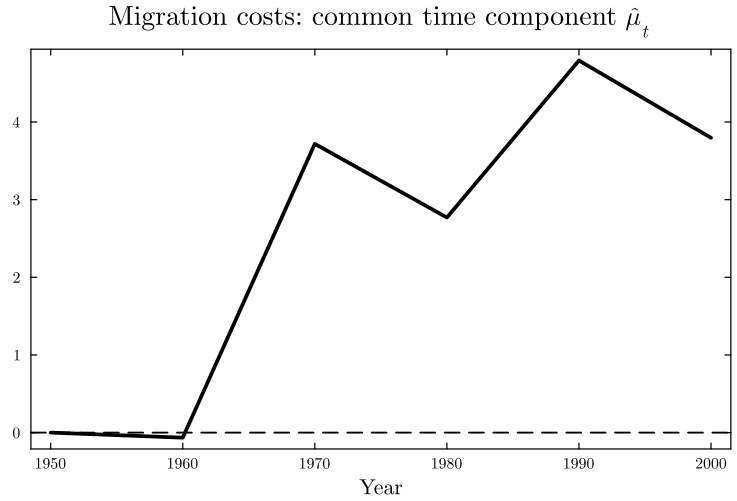
C.4 Interpreting migration cost components

In Section 4.4 of the main text, we decompose the variation in raw migration costs into a common time trend $\hat{\mu}_t$, origin-time and destination-time components ($\hat{\mu}_{rt}$, $\hat{\mu}_{\ell t}$), a bilateral component ($\hat{\mu}_{r\ell}$), and a residual, see equation (24). Figure 6 shows the evolution of the origin- and destination-time components for q1 and q4 provinces, and Figure C.8 below displays the evolution of the common time trend.[37] In this section, we provide evidence that the estimated components correlate

[37]The common time trend displays a generalized increase in migration costs over time. This is consistent with the fact that migration flows across provinces slowed down after 1970, while real income differences across provinces declined only gradually.

with observables consistent with their interpretation as origin-time, destination-time, and origin-destination factors affecting migration costs across regions.

FIGURE C.8: Common time component of migration costs



Notes: The line reports the common time component $\hat{\mu}_t$ of the decomposition of migration costs in equation (24), which is the same for all origin-destination pairs in each decade, relative to its initial value.

First, we correlate the origin-time component of migration costs $\hat{\mu}_{rt}$ with the stock of migrants that left region r in the decades prior to t relative to the population that remains in region r at t, that is

$$\text{Mig network}_{rt} = \frac{\sum_{s=2}^{t-1} \sum_{\ell \neq r} \rho_{r\ell s} \cdot L_{rs-1}}{L_{rt}}.$$

This measure aims to capture a notion of the size of migration networks of region r, which in principle should make leaving the region easier. The correlation between $\hat{\mu}_{rt}$ and $\log(\text{Mig network}_{rt})$ is -0.41, and an OLS regression generates a statistically significant coefficient of -3.71.

Second, we correlate the destination-time component of migration costs $\hat{\mu}_{\ell t}$ with the change in housing stock of region ℓ in the previous decade, which we measure as the growth in dwelling surface built in the region. The data on buildings comes from the Spanish official cadaster. For each building, we have information on the surface built for housing, its coordinates, and its construction year. We aggregate this information at the province level to obtain a measure of the housing stock, and then compute its decadal growth rate.[38] In this way, we try to capture increases in the housing supply. As our model does not feature a local housing market, increases in housing supply that reduce housing prices in a given region should be reflected in a lower destination-time component of migration costs. The correlation between $\hat{\mu}_{\ell t}$ and the log growth in the housing stock in the

[38]The provinces of Bizkaia, Gipuzkoa, Álava and Navarra are omitted from this exercise because they have their own cadastral office and hence their housing data is not included in the national cadaster.

previous decade is indeed negative, -0.35, and the coefficient of an OLS regression a significant -3.23.

Finally, we correlate the bilateral component of migration costs $\hat{\mu}_{r\ell}$ with the log road distance (in km) between the province capitals of each region. We would expect that pairs of provinces that are further away are associated with a higher bilateral component of migration costs. We find that the correlation between the log distance between provinces and $\hat{\mu}_{r\ell}$ is 0.23, and the coefficient of a regression 0.29 and statistically significant.

Appendix D: Quantitative analysis

D.1 Engines of development

Our model features four types of time-changing fundamentals: $\Upsilon_t \equiv \{T_{rjt}, \tau_{r\ell jt}, \mu_{r\ell t}, \omega_{jt}\}$ (productivity, trade costs, migration costs, sectoral tastes). Moreover, even if all these parameters remain constant, the economy features transitional dynamics because the initial spatial distribution of population is not necessarily the one of the corresponding steady state.

To understand the importance of the different engines for the Spanish development experience, we run a number of counterfactual exercises in which we allow these engines to change one by one. The main results of these exercises are presented in Table D.1.[39] First, we can see in Column (3) that population dynamics have almost no effect on real income per capita or the aggregate allocation of employment across sectors, despite implying substantial reallocation of employment across regions (the coefficient of variation of employment increases by 60 percentage points between 1940 and 2000, compared to 62 in the benchmark). Second, in Column (4), we can see that changes in preferences generate substantial structural change out of agriculture and into services, due to the fact that ω_{jt} increases over time for services relative to agriculture. This reallocation of employment across sectors combined with the spatial reallocations due to population dynamics increases real income per capita by a further 11%.

Productivity growth is the main engine of Spanish development between 1940 and 2000, see column (5). This follows from the fact that changes in productivity are the main driver of changes in relative prices and of changes in real income, see Figure D.1. Indeed, growth in real income is higher in the economy in which only productivity changes than in the benchmark economy. In terms of employment shares, changes in productivity cannot generate the pronounced hump-shaped pattern of the manufacturing employment share observed in the benchmark. Up to 1970, they do not generate enough changes in the relative price of agriculture-manufacturing to reallocate as much employment as in the benchmark. After 1970, they are the main driver of the decreasing relative price of manufacturing goods, which pushes employment away from manufacturing, but also of income growth, which pushes employment towards manufacturing. Interestingly, changes in productivity generate stronger industrial growth in laggard than in leading regions, with employment growth in manufacturing being 23% and 20% of the initial local employment for regions in

[39] We proceed as follows. First, we solve for a counterfactual economy in which all parameters stay constant at their 1940 values, such that model dynamics only come from the reallocation of population in the transition towards the steady state (Column 3). Then, we allow for sectoral tastes, productivity, and trade costs to vary over time one by one, and report how allocations change with respect to the economy in which parameters remain constant (Columns 4-6). Finally, we explore economies in which only migration costs change (their raw values, Column 7), only their common time-trend (Column 8), or only their origin- or destination-specific components (Columns 9 and 10), reporting as well the differences in allocations with respect to column 3.

TABLE D.1: Engines of development (changes between 1940 and 2000)

	Data (1)	Bench (2)	ΔPop. (3)	$\Delta\omega_{jt}$ (4)	ΔT_{rjt} (5)	$\Delta\tau_{r\ell jt}$ (6)	$\Delta\mu_{r\ell t}$ (7)	$\Delta\hat{\mu}_t$ (8)	$\Delta\hat{\mu}_{rt}$ (9)	$\Delta\hat{\mu}_{\ell t}$ (10)
Real income pc	8.16	8.31	1.15	1.11	7.89	1.22	1.17	0.95	1.02	0.64
Agr share	−0.45	−0.46	−0.03	−0.17	−0.39	−0.12	−0.04	0.01	−0.0	0.02
Man share: 40-70	0.14	0.14	0.01	0.04	0.08	0.05	0.01	−0.0	−0.01	0.03
Man share: 70-00	−0.08	−0.07	0.01	0.0	−0.02	0.01	0.01	−0.01	0.01	−0.04
Ser share	0.39	0.39	0.01	0.13	0.33	0.06	0.01	−0.0	0.0	−0.01
Man emp q1: 40-70	0.07	0.08	0.0	0.03	0.23	0.1	−0.05	−0.0	0.05	−0.15
Man emp q4: 40-70	0.44	0.43	0.15	0.07	0.05	0.0	0.11	0.0	−0.05	0.35
$CV(L_r)$	0.65	0.62	0.60	−0.05	−0.45	−0.31	0.72	−0.26	0.08	1.97
$\hat{\beta}$	−2.07	−2.02	−1.31	−1.14	0.38	−0.78	−4.66	−1.05	−1.31	−7.59
R^2	0.63	0.61	0.16	0.13	0.02	0.03	0.50	0.24	0.09	0.08
Sd($\log C_r$): 40-60	0.02	−0.02	−0.00	0.01	0.05	−0.04	−0.00	−0.00	0.00	0.02
Sd($\log C_r$): 60-00	−0.21	−0.24	−0.01	−0.07	−0.16	−0.01	−0.04	0.01	−0.01	0.17

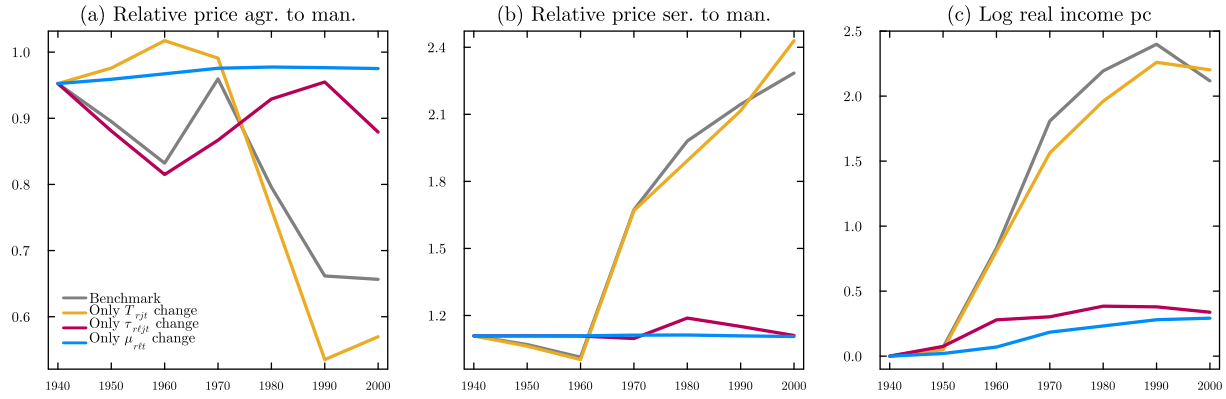
Notes: Each column reports level changes in the corresponding variable between 1940 and 2000, unless another time frame is indicated in the corresponding row. For real income per capita we report the ratio. "$\hat{\beta}$" and "R^2" are the coefficient and the share of explained variance of a regression of employment growth on initial agriculture share. "Man emp q1: 40-70" is employment change in manufacturing in q1 provinces relative to total employment of those provinces in 1940. Columns (1) and (2) are the data and the benchmark calibrated economy respectively. Column (3) is an economy in which all parameters stay put at their 1940 values. Columns (4)-(10) report the difference between economies in which only one set of parameters (CES demand shares, productivity, trade costs, migration costs or their components) changes with respect to Column (3), except for "$\hat{\beta}$" and "R^2", which are reported in levels.

the q1 and q4 groups of employment growth, compared to 8% and 43% in the benchmark economy. Consistently, in this economy there is no significant relationship between the initial agricultural share and local employment growth ($R^2 = 0.02$). While productivity growth generates a more even structural transformation across regions, it also increases regional inequality, as the standard deviation of real income increases more between 1940 and 1960 and falls less after 1960 than in the benchmark economy.

The effects of changes in trade costs are shown in Column (6). Trade costs move employment across sectors in the directions observed in the data, except for the manufacturing share after 1970. However, their effect is limited, consistent with their limited impact on relative prices and real income, see Figure D.1. The changes in inequality generated by changes in trade costs go in the opposite direction to the data, as they reduce inequality until 1960 and barely reduce it afterwards.

Finally, Columns (7) to (10) report the outcomes of several economies in which only migration costs or one of their components change over time. While changes in migration costs have a limited impact on aggregate structural change and income growth, they are the main driver of the diverging patterns of industrialization across regions. In fact, we can see that changes in migration costs (column 7) generate a relationship between the initial agricultural share and local employment growth much more negative than in the benchmark ($\hat{\beta} = -4.66$ compared to $\hat{\beta} = -2.02$), with a relatively similar R^2 (0.50 compared to 0.61). The main driver of this pattern is the change in the destination-specific time component of migration costs (column 10), which helps population reach

FIGURE D.1: Forces of structural change

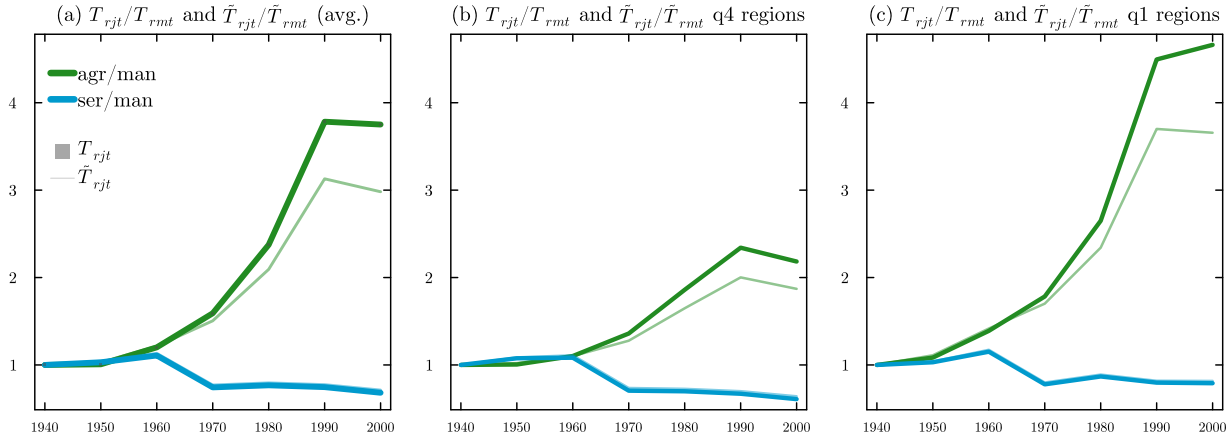


Notes: Relative price of agriculture with respect to manufacturing –Panel (a)–, of services with respect to manufacturing –Panel (b)–, and real income per capita –Panel (c)– for our benchmark economy and counterfactual economies in which only one engine of growth is allowed to change. Each line plots the population-weighted average across provinces.

the most dynamic regions and depresses industrial growth in initially agrarian regions. Indeed, this heterogeneous variation in migration costs across destinations contributes to the hump-shaped evolution of the manufacturing employment share. Changes in the origin-specific component of migration costs have opposite effects (column 9). Instead, when the change in migration costs is only driven by its common time trend (column 8), the dispersion of regional employment rises less than in the benchmark economy.

D.2 Productivity paths with non-CRS production functions

FIGURE D.2: Relative sectoral productivities



Notes: Panel (a) plots the average (across provinces) relative productivity of agriculture and services with respect to manufacturing. The thick line corresponds to the calibrated productivity parameters T_{rjt} under the CRS assumption, while the thin line corresponds to the underlying productivity $\widetilde{T}_{rjt}$ when we allow for non-constant returns to scale. Panels (b) and (c) report the same averages for provinces within the q4 (highest population growth) and q1 (lowest population growth) groups respectively.

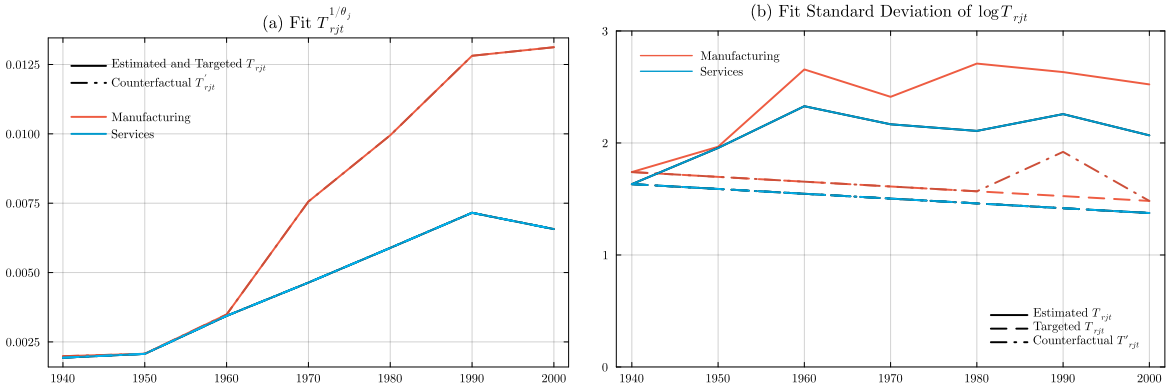
Here we compare the exogenous $\widetilde{T}_{rjt}$ with the calibrated productivity paths T_{rjt}. In Figure D.2, we plot the time paths of the relative sectoral productivity parameters for both cases, aggregated over all provinces (Panel a) and also aggregated over q4 and q1 provinces (Panels b and c), which are the 12 provinces with highest and lowest population growth respectively. We observe two patterns. First, the exogenous productivity of services relative to manufactures, $\widetilde{T}_{rst}/\widetilde{T}_{rmt}$, declines slightly less than the endogenous one, T_{rst}/T_{rmt}. This happens due to the increase in manufacturing employment, which raises T_{rmt} over time. We also observe that this pattern is stronger in q4 than in q1 provinces due to the stronger industrialization in the provinces within the q4 group. Second, the endogenous productivity of agriculture relative to manufacturing, T_{rat}/T_{rmt}, grows more than the exogenous one, $\widetilde{T}_{rat}/\widetilde{T}_{rmt}$. This happens because the decline of employment in agriculture raises T_{rat} more than the increase in employment in manufacturing raises T_{rmt}.[40] The pattern here is stronger for q1 provinces, which are the ones with a stronger decline in agriculture employment.

D.3 Convergence of sectoral productivities

Sectoral productivity diverged across provinces until 1960 and converged afterwards. A natural question is whether the patterns of migration could have been reversed had regional productivities started to converge from 1940. To explore this scenario, we want to generate alternative productiv-

[40] This result comes from the facts that (a) $|\alpha_a| > |\alpha_m|$ and (b) employment loss in agriculture is larger than the employment growth in manufacturing.

FIGURE D.3: Alternative productivity paths



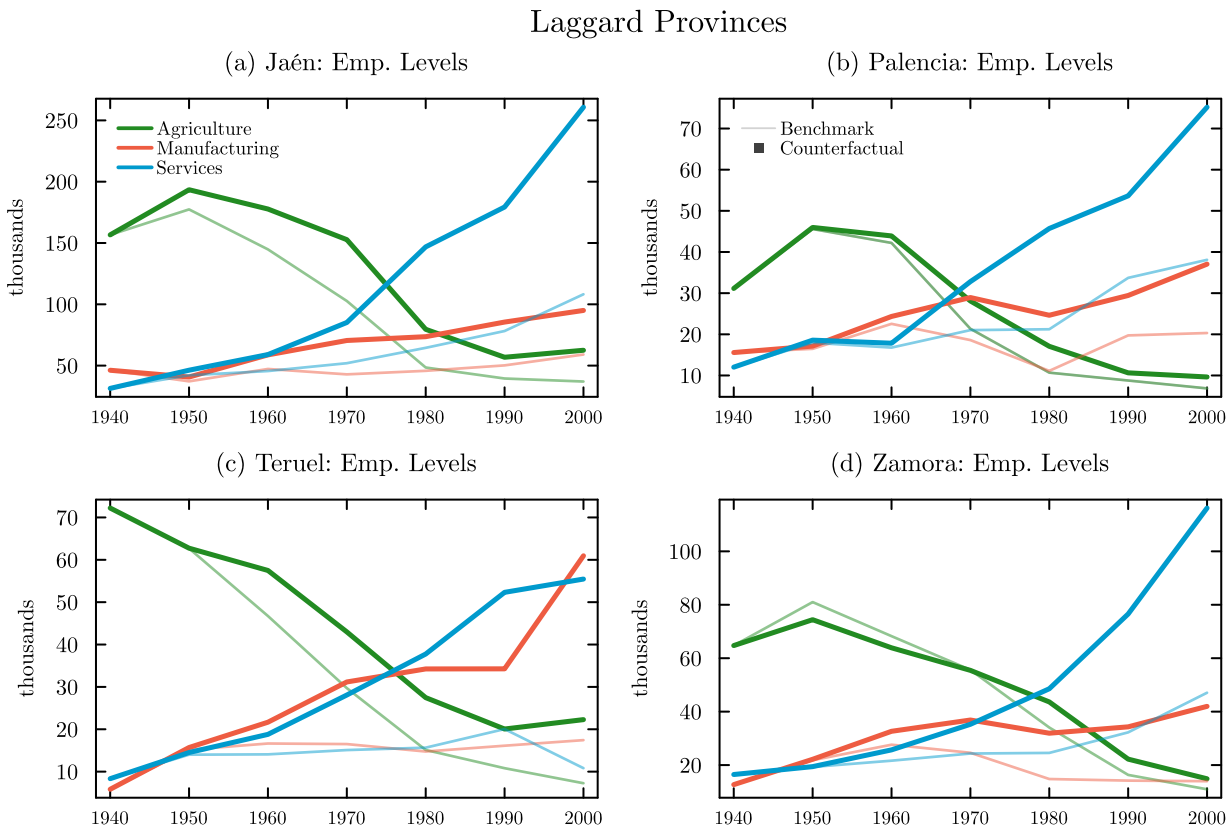
Notes: Panel (a) shows the level of mean $\log T_{rjt}$ (solid lines) and the level of mean $\log T'_{rjt}$ (dotted line) for manufacturing and services. Panel (b) shows the standard deviation of $\log T_{rjt}$ in the calibrated economy (solid lines), the targeted standard deviation of $\log T_{rjt}$ (dashed lines), and the dispersion of $\log T'_{rjt}$ (dotted line) obtained using equation (D.1) for manufacturing and services.

ity paths T'_{rjt} in each region r and for each sector j that preserve the evolution of average sectoral productivity across provinces as in the calibrated economy, but with a different evolution of dispersion across provinces. Of course, there are multiple ways of doing so. We proceed as follows. First, we parameterize the transformation from the calibrated T_{rjt} to the counterfactual T'_{rjt} with this simple function:

$$T'_{rjt+1} = T_{rjt+1}\,\lambda_{1jt}\left(\frac{T_{rjt}}{\bar{T}_{jt}}\right)^{\lambda_{2jt}} \tag{D.1}$$

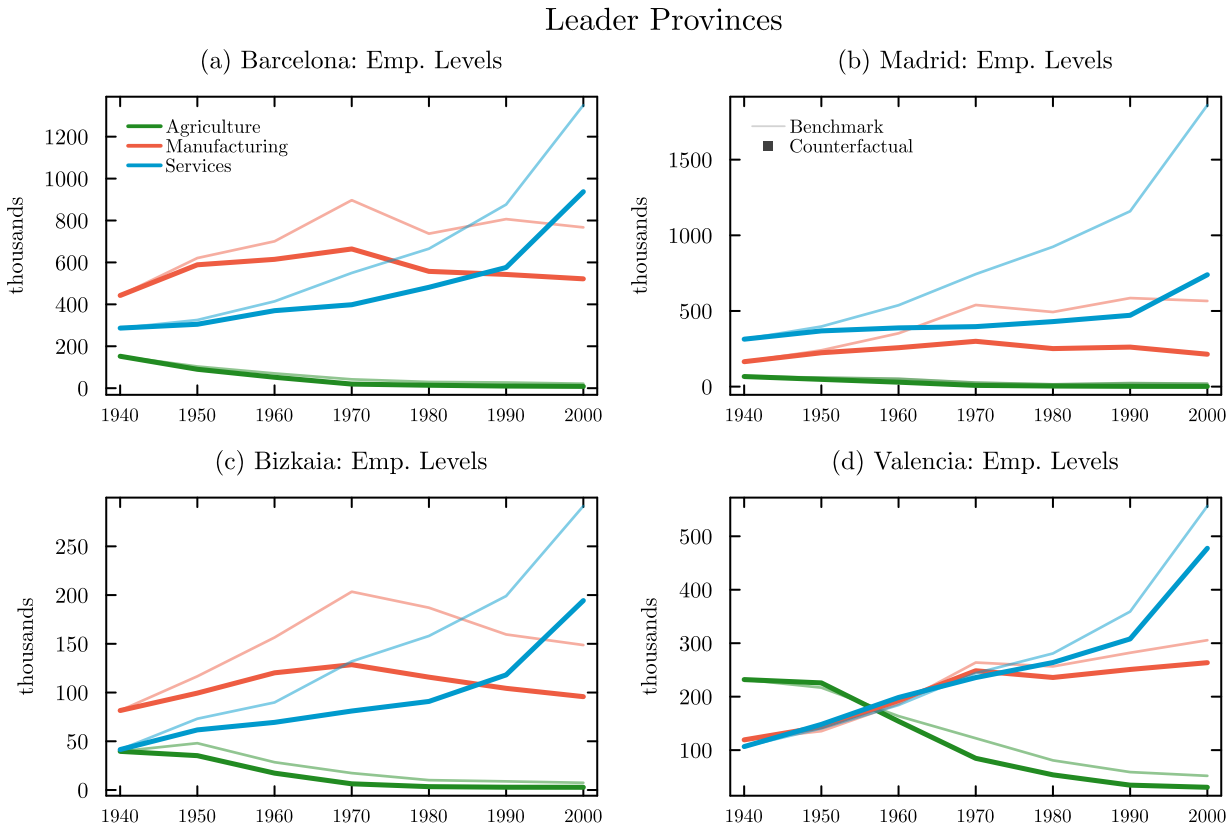
where $\bar{T}_{jt} = \sum_{r=1}^{R} T_{rjt}/R$. With this formulation, $\lambda_{1jt} > 0$ controls the average of T'_{rjt+1} and λ_{2jt} the dispersion. With $\lambda_{1jt} = 1$ and $\lambda_{2jt} = 0$ we recover the original productivity paths $T'_{rjt+1} = T_{rjt+1}$. With $\lambda_{2jt} < 0$, T'_{rjt+1} is relatively lower (higher) for high (low) productivity regions, which generates convergence across provinces and lowers dispersion. With $\lambda_{2jt} > 0$ the opposite is true. We then choose the time sequence of λ_{1jt} and λ_{2jt} for each sector j to match the desired counterfactual evolution of the average and the dispersion of sectoral productivity paths across provinces. In particular, for sectors $j = m, s$, we target (i) the actual time evolution of the average of sector j productivities across regions (solid lines in Figure D.3 Panel (a)); and (ii) the counterfactual time evolution of the dispersion of sector j productivity across regions. This arises from starting with the actual dispersion in sector j productivities in 1940 and letting it decline at the same average rate as the dispersion of services productivity T_{rst} between 1960 and 2000 (dashed lines in Figure D.3 Panel (b)). The choice of λ_{1jt} and λ_{2jt} matches the targets almost perfectly (see dotted lines in Figure D.3).

FIGURE D.4: Counterfactual exercises: no migrations



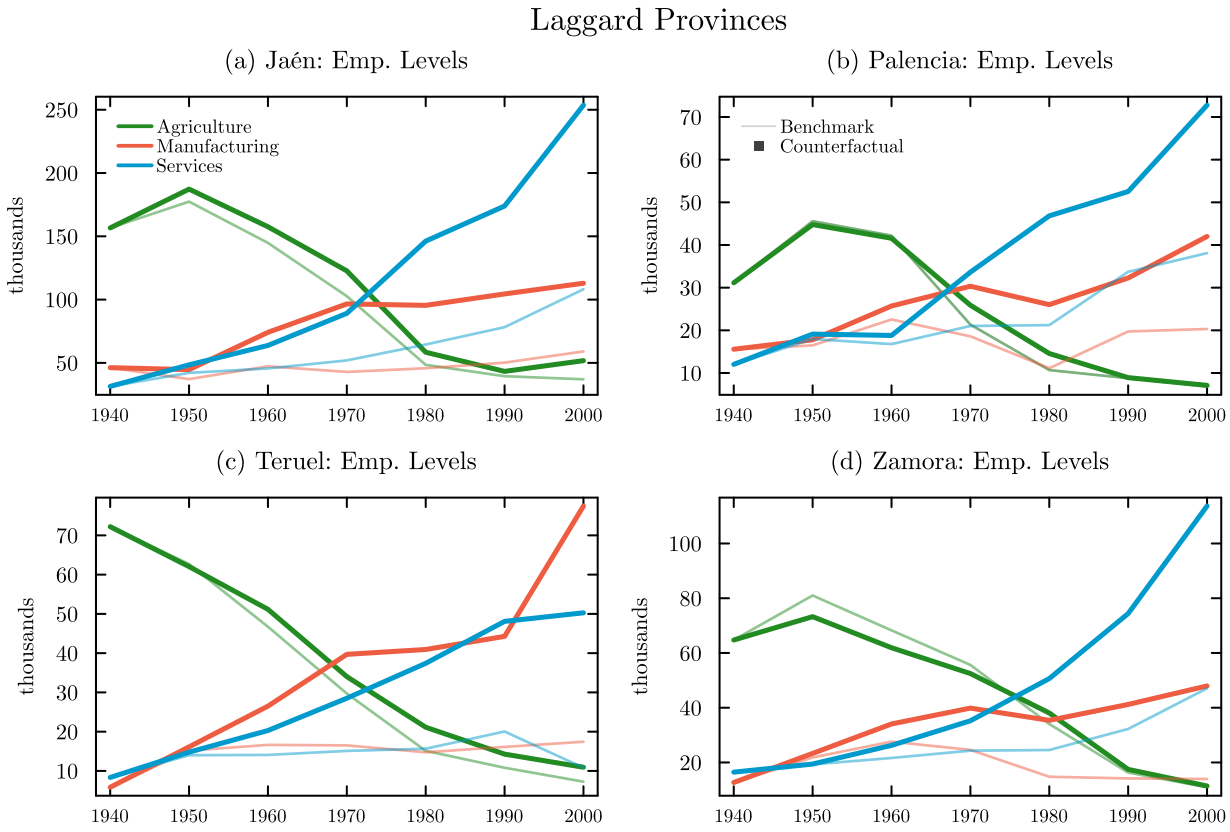
Notes: This Figure represents the time series evolution of employment levels in each sector for a group of selected provinces that lost population between 1940 and 2000. The thin lines correspond to the calibrated economy and the thick lines correspond to the counterfactual economy with no migration.

FIGURE D.5: Counterfactual exercises: no migrations



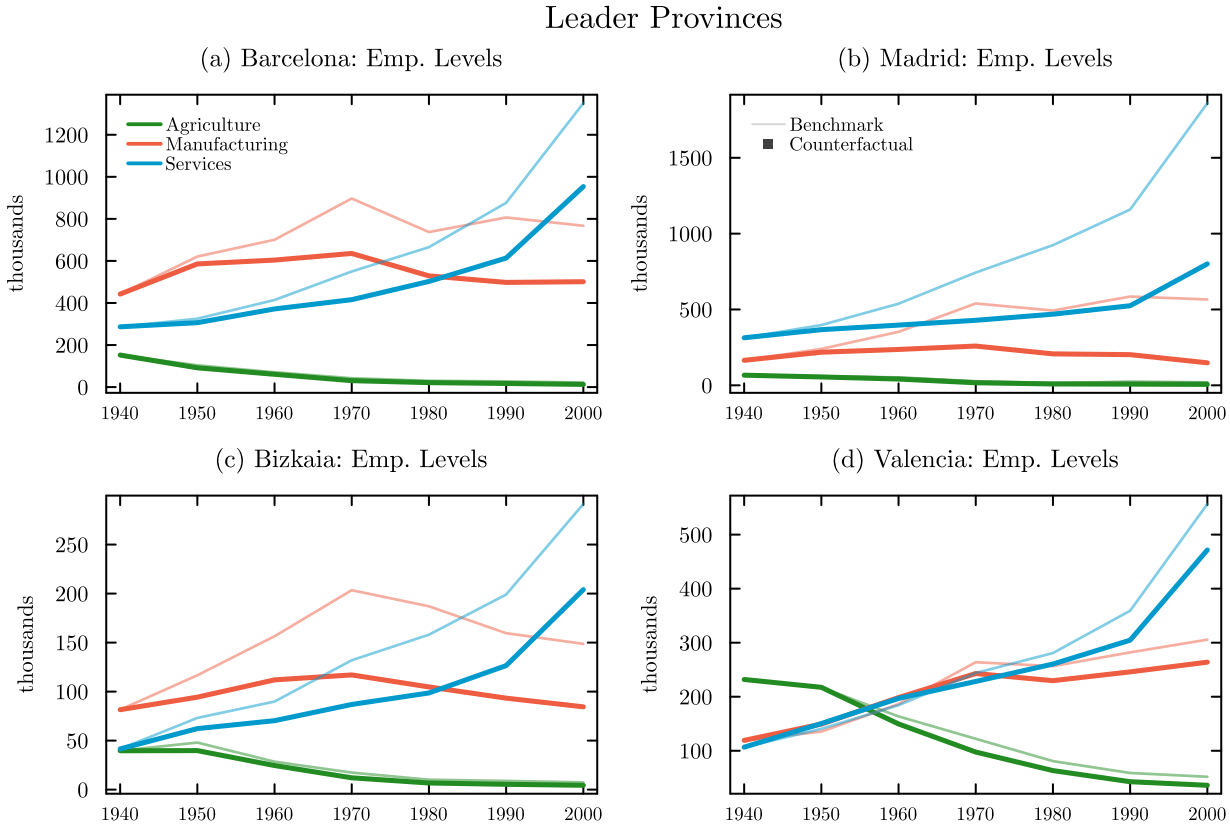
Notes: This Figure represents the time series evolution of employment levels in each sector for a group of selected provinces that gained population between 1940 and 2000. The thin lines correspond to the calibrated economy and the thick lines correspond to the counterfactual economy with no migration.

FIGURE D.6: Counterfactual exercises with agglomeration economies: no migrations



Notes: This Figure represents the time series evolution of employment levels in each sector for a group of selected provinces that lost population between 1940 and 2000. The thin lines correspond to the calibrated economy and the thick lines correspond to the counterfactual economy with no migration and agglomeration economies.

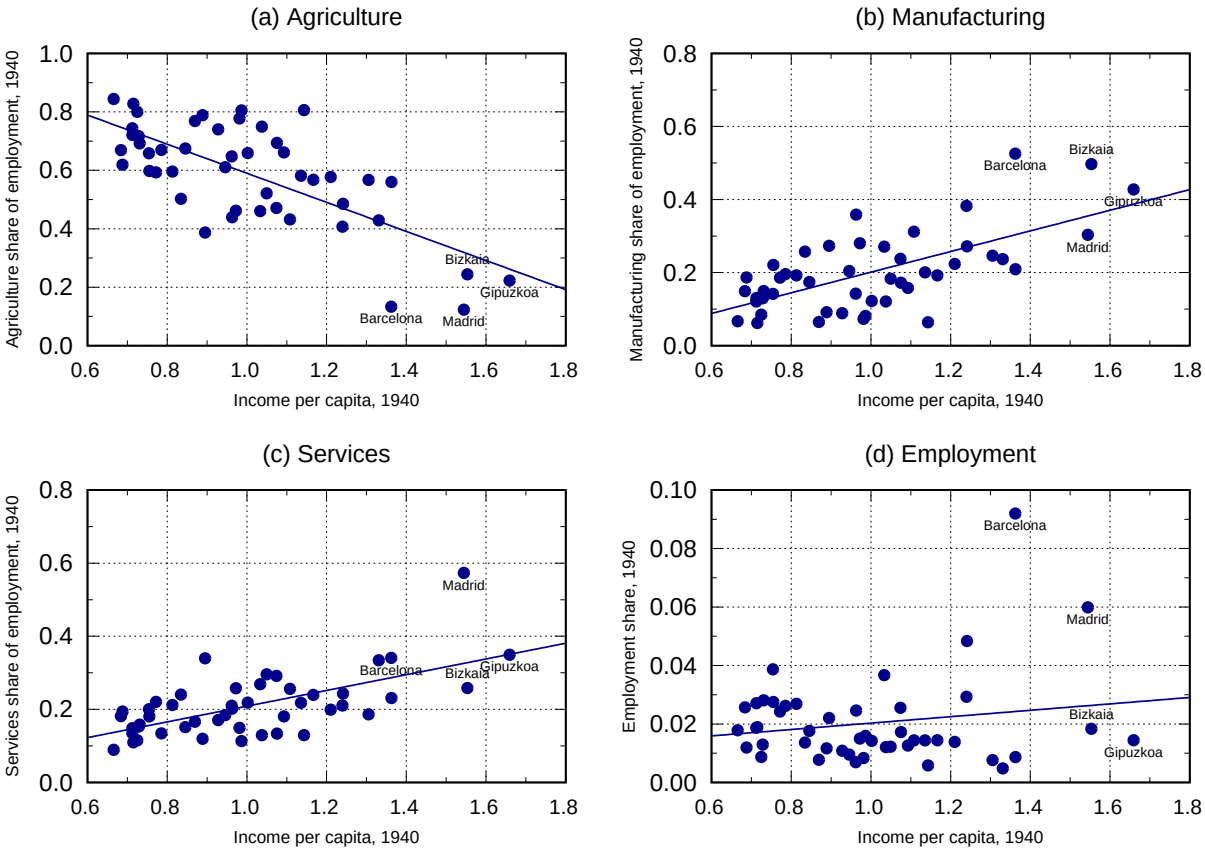
FIGURE D.7: Counterfactual exercises with agglomeration economies: no migrations



Notes: This Figure represents the time series evolution of employment levels in each sector for a group of selected provinces that gained population between 1940 and 2000. The thin lines correspond to the calibrated economy and the thick lines correspond to the counterfactual economy with no migration and agglomeration economies.

Appendix E: Extra figures

FIGURE E.1: Sectoral shares, 1940



Notes: Panels (a) to (c) plot the employment shares in Agriculture, Manufacturing, and Services against real income per capita in each province (relative to the country average). Panel (d) reports the relative size of each province (in terms of employment) against provincial income per capita. All panels for 1940.