Europe Falling Behind:
Structural Transformation and Labor Productivity Growth Differences Between Europe and the U.S.*

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Abstract

This paper investigates the convergence and subsequent divergence of labor productivity between the U.S. and Europe through a quantitative general equilibrium framework that integrates endogenous changes in employment shares as a function of exogenous and unbalanced labor productivity growth rates across sectors. We calibrate our model to the U.S. and test it against Europe from 1970 to 2019. Our quantitative model accurately accounts for the structural transformation and the aggregate labor productivity paths. Leveraging a set of numerical experiments, we find that the reallocation of labor toward less productive sectors in response to sectoral productivity changes mitigates the potential effects that the productivity growth in market services may have on the aggregate labor productivity: The duality within services brings forth a Baumol cost disease whereby productive sectors lose ground despite their strong income effects.

JEL: E24, O41, O47;
Keywords: Structural transformation, services, labor productivity, long-run income effects, Baumol cost disease.

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1 Introduction

Around the mid-1990s, the differences in output per hour worked between Americans and Europeans nearly disappeared, with the remaining differences hinging more on working hours than productivity[1] (Prescott, 2004). Figure 1 (left panel) shows the labor productivity gap between the U.S. and four major European economies (Germany, France, Great Britain, and Italy) from 1970 to 2019. Whereas the Europeans produced about 72% per hour compared to American residents in 1970, by 1995, the gap had been closed. However, this convergence trend reverted; by 2019, the gap had widened to 86%. Europe is falling behind. A leading factor behind the overall productivity slowdown and Europe's relative decline has been the rise of services and their inherent lower labor productivity (Duarte & Restuccia, 2010; Timmer, Inklaar, O'Mahony, & van Ark, 2011). In particular, William Baumol and collaborators have stressed that while wages rise due to the dramatic productivity gains witnessed since the Industrial Revolution, *some* sectors, mainly services, grapple with a *cost disease* while gaining participation in the economy during the process of structural transformation. Figure 1 (right panel) shows that the United States and Eu-

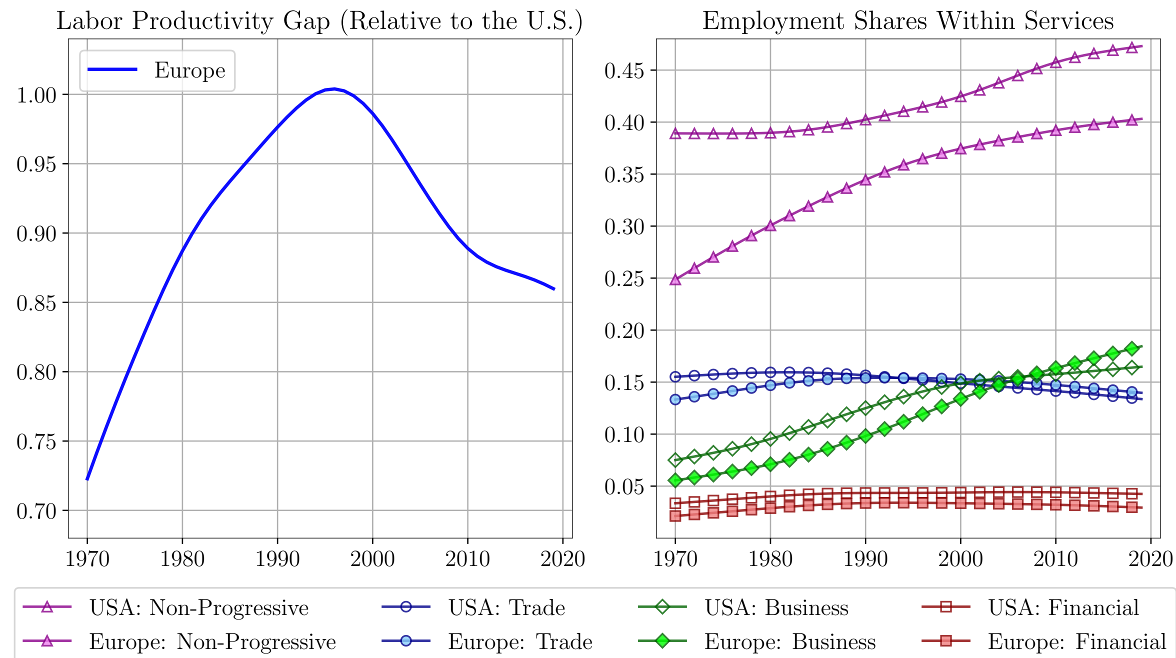

Figure 1: U.S. and Europe. Labor productivity gap and structural transformation. 1970–2009.

Notes: The left panel plots the ratio between the aggregate labor productivity in Europe and the U.S. from 1970 to 2019. Aggregate labor productivity is measured as PPP-adjusted GDP per hour using OECD data. The right panel of this figure plots the employment shares across sectors in Europe and U.S. from 1970 to 2019 using hours worked using KLEMS data. See the online appendix, section A, for details on how the data on labor productivity and employment shares are constructed.

[1]Throughout this paper, unless explicitly stated otherwise, we interchangeably refer to output per worker, labor productivity, and productivity as equivalent concepts.

rope have undergone significant reallocation of the labor force toward services. Notably, this shift involves substantial reallocation within services, with business and nonprogressive (or stagnant) services gaining participation while trade and financial services remain relatively stable.

Through the lenses of a structural transformation theory that allows for the presence of Baumol cost disease and income effects, this paper studies how the productivity of specific sectors has impacted the overall labor productivity in the U.S. and Europe during the rise of services. As Nordhaus (2008, p. 14) writes, "[p]erhaps the most interesting question from a social perspective is whether stagnant industries are gaining or losing shares of labor inputs". Motivated by a shift-share decomposition that highlights the importance of labor reallocation on the aggregate productivity deceleration, we construct a structural transformation model that accounts endogenously for changes in employment shares over the development path as a function of exogenous and unbalanced processes of labor productivity growth for an arbitrary number of sectors. Our framework combines a production technology linear in labor, as in Duarte and Restuccia (2010), with the CES non-homothetic preferences crafted by Comin, Lashkari, and Mestieri (2021). It is critical to introduce long-run Engel curves that shape the structural transformation to account for the Baumol cost disease in general equilibrium,[2] as changes in sectoral productivity affect relative prices *and* the overall household purchasing power. These effects run in opposite directions within services under empirically relevant parameter values.

We calibrate our model to the United States from 1970 to 2019 and test it against European data for the same period. After demonstrating that our model replicates the salient facts of the structural transformation and the aggregate productivity gap, we perform a series of numerical experiments: First, we input the observed growth rates for sectoral labor productivity in the U.S., one sector at a time, to assess how much Europe would have grown had they had the sectoral growth witnessed in America. Second, we exploit the employment shares observed in the final period to calculate each sector's implied "catch-up" annualized growth rate that eliminates the aggregate productivity gap in 2019 had the employment shares remained constant. Then, we compare the implied aggregate growth rates from this simulation with those obtained using our parameterized model economy by feeding these counterfactual "catch-up" growth rates while allowing labor to reallocate among sectors endogenously.

We find that leveraging on labor productivity growth in market services would result in less significant impacts on overall labor productivity than previously suggested[3] since labor reallocation mitigates the aggregate effects of sectoral productivity gains in line with the Baumol cost disease. Our numerical experiments show that the share of nonprogressive services would have absorbed the surplus labor resulting from enhanced productivity in market services. Specifically, in our first set of counterfactuals, if Europe were to match the pace of productivity growth seen in the American market services, we find that disregarding endogenous labor reallocation across

[2] The income effects generated by these preferences do not level off as countries grow wealthier, unlike parsimonious settings with Stone-Geary preferences (for more than two sectors) that fail to account for the steep rise in services observed at advanced stages of development.

[3] See, for instance, Timmer et al. (2011) and the references therein.

sectors would lead to an overestimation of about 30% of Europe's annualized aggregate labor productivity growth. Focusing on business services, where reallocation is substantial, we find that the overestimation would be particularly severe, at about 50%. In our second set of experiments, where we feed the "catch-up" growth rates for each sector computed under constant employment rates, one at a time, we find that a significant gap would persist if labor reallocation is allowed to respond endogenously to these growth rates. For example, by 2019, approximately 42% and 32% of the gap would persist if financial services and wholesale/retail trade in Europe had grown at the "catch-up" growth rates implied in our counterfactual. The reallocation of labor toward non-progressing services entirely drives the persistence of these gaps.

Our paper belongs to the literature that studies the role of rising services in aggregate productivity using general equilibrium quantitative frameworks. In particular, we study the Baumol cost disease within the context of structural transformation, focusing on the duality that persists within services in advanced economies, as not all services have negligible productivity growth. The foundational concept of the disease was introduced by Baumol (1967), and subsequently, Ngai and Pissarides (2007) formalized it as a principal catalyst of the structural transformation.[4] In a closely related vein, Nordhaus (2008) identifies robust evidence supporting both the deceleration of overall productivity growth through Baumol's key mechanisms: distinct rates of productivity across sectors translating into price differentials, alongside the growing presence of nonprogressive sectors. Moreover, the findings from Duernecker and Sanchez-Martinez (2023) suggest that the ongoing structural transformation process may continue to slow down the European aggregate productivity. In contrast, Oulton (2001) and Duernecker, Herrendorf, and Valentinyi (2023) offer more sanguine perspectives. The former's optimism is rooted in the role of business services as inputs for production, while the latter's is attributed to the potential for substitution within the services sector. Last, our paper complements Broadberry (1998), who posit that a significant factor contributing to the catching up and outpacing of Germany and the United States in relation to Great Britain (the dominant industrial nation) from 1870 to 1990 was the reallocation out of agriculture and the enhancement of labor productivity in the services. Whereas Broadberry (1998) explains the catch-up via reallocation from agriculture to manufacturing, we focus on the divergence observed in Europe from reallocating labor out of manufacturing and the duality persistent within services.

The rest of the paper is organized as follows. Section 2 documents the motivating facts. Section 3 describes the theoretical framework. Section 4 presents our calibration strategy and its results. Section 5 evaluates the model's predictions against the data. Section 6 presents a set of numerical experiments. Section 7 concludes.

[4]See Herrendorf, Rogerson, and Valentinyi (2014) for a comprehensive review of the main facts, the relevant literature and a workhorse structural transformation model. For the rise of services in the context of structural transformation, see Rogerson (2008), Duarte and Restuccia (2010), and Buera and Kaboski (2012). For further insights into the evolution of Baumol's ideas, Baumol (2012) is a valuable resource to consult.

2 Motivating Facts

This section documents facts on the aggregate and sectoral labor productivity growth and structural transformation in Europe and the U.S. from 1970 to 2019. We leverage on the OECD and KLEMS-type databases to build a panel of country-year data on aggregate and sectoral labor productivity and employment shares for agriculture (`agr`), manufacturing (`man`) and four service sectors – business (`bss`), financial (`fin`), wholesale and retail trade (`trd`) and non-progressive (`nps`) services – in Europe and the U.S. Throughout this paper, following Baumol (1967), we refer to business, financial, and trade services as market or progressive services to emphasize that these sectors display nonnegligible productivity growth, unlike stagnant (nonprogressive) services.[5]

Throughout this paper, Europe represents four main European economies (Germany, France, Great Britain, and Italy), and sectoral labor productivity is the weighted average of labor productivity using the labor market size in each country as weight. Similarly, the employment shares are computed as the sum of hours in a given sector for the main European economies divided by the total hours worked across all four countries.[6]

The average annualized labor productivity growth in the U.S. accelerated from 1.4% in the 1970–1995 period to almost 1.6% from 1995 to 2019, while the European countries, on average, experienced a labor productivity growth slowdown between these two time periods from 2.8 percent to 1% percent. These data imply a labor productivity gap in annualized growth rates between the U.S. and Europe of about 0.6% from 1995 to 2019. Hence, the falling behind pattern in Europe results from an acceleration in the U.S. and a European slowdown.

Turning to sectoral labor productivity, Europe has experienced a slowdown in labor productivity growth across all sectors since 1995. However, the slowdown was markedly deeper in the services sectors. The annualized European labor productivity growth in services (0.5%) was approximately one-third of that in the U.S. (1.3%) from 1995 to 2019. This gap in services between the two regions is particularly acute in business services, which grew only 0.4% in Europe compared to 2.4% in the U.S. Hence, the facts we document on aggregate and sectoral labor productivity growth between Europe and the U.S. are similar to those noted in older releases of

[5]Labor productivity is measured as value added in local currency at constant prices per hour. Sectoral employment shares are the hours worked in each sector divided by the total hours worked for a given country year. Since we focus on long-run trends, all the data are trended using the Hodrick-Prescott filter with a smoothing parameter $\lambda = 100$. See the Online Appendix A for details on how the data on labor productivity and employment shares are constructed. Our data has two measures of aggregate labor productivity. One is PPP-adjusted GDP per hour from OECD, and the other is real value added in local currency at constant prices per hour from KLEMS data. Even though both measures provide a similar picture of aggregate labor productivity growth in these two regions, we use each for different purposes. We use GDP per hour as our preferred measure because their levels are PPP-adjusted. However, we use KLEMS aggregate real value added to compute the sectoral decomposition of aggregate labor productivity because there are no PPP-adjusted sectoral gross output measures.

[6]To present our analysis more clearly and to directly align with the research conducted by Prescott (2004), we concentrate our investigation on the four major European countries. However, in the Online Appendix's Section B, we demonstrate that the growth of labor productivity in the EU15 closely resembles that of the prominent four European countries. Additionally, as outlined in Section C of the same appendix, we establish that all our findings remain consistent when considering all EU-15 countries.

KLEMS data in van Ark, O'Mahony, and Timmer (2008) and Timmer et al. (2011).[7] Concurrently, as shown in Figure 1, there has been a substantial reallocation of labor across sectors, particularly in non-progressive services and business services in Europe, which saw their employment shares rise five and seven percentage points, respectively.

To address the importance of labor reallocation, we employ a shift-share analysis to quantify how labor movements across sectors impact the aggregate labor productivity in each region from 1970 to 2019. Let Y_t denote real aggregate output in time t and L_t denote the total hours worked. The aggregate labor productivity is

$$A_t = \frac{Y_t}{H_t} = \frac{\sum_i y_{it}}{L_t} = \sum_i \frac{y_{it}}{h_{it}} \frac{l_{it}}{L_t} = \sum_i A_{it} s_{it}, \tag{1}$$

where y_{it}, l_{it}, A_{it} and s_{it} are real value added, hours worked, labor productivity, and employment share, respectively, of sector i at time t. This sectoral decomposition implies that the change in aggregate labor productivity between time 0 and time T is a function of change in sectoral labor productivity and labor reallocation across sectors given by

$$A_T - A_0 = \sum_i A_{iT} s_{iT} - \sum_i A_{i0} s_{i0}. \tag{2}$$

The contribution of an individual sector i to aggregate labor productivity changes is given by $A_{iT}s_{iT} - A_{i0}s_{i0}$. Hence, the contribution of sector i to aggregate labor productivity changes is a function of changes in labor productivity A_i and employment share s_i in that specific sector between time 0 and T. In addition, by algebraic manipulation of equation (2), one can decompose the change in aggregate labor productivity into changes coming directly from within-sector labor productivity growth (growth effect) and those coming from labor reallocation across sections (shift effect) according to

$$A_T - A_0 = \underbrace{\sum_i (A_{iT} - A_{i0}) s_{i0}}_{\text{Growth effect}} + \underbrace{\sum_i (s_{iT} - s_{i0}) A_{i0} + \sum_i (s_{iT} - s_{i0})(A_{iT} - A_{i0})}_{\text{Shift effect}}. \tag{3}$$

Table 1 reports the sectoral decomposition and the shift-share analysis of the aggregate labor productivity growth at an annualized rate from 1970 to 2019. Labor reallocation across sectors significantly and negatively contributed to aggregate labor productivity, especially in Europe. The shift effect in Europe is more than five times that of the U.S. Also, the services sector is by far the main contributor to aggregate labor productivity growth in both regions. However, in the U.S. this is primarily due to labor productivity growth in services rather than the reallocation toward services, in contrast to Europe where reallocation matters the most. Breaking down services into subsectors, we find that the significant reallocation effect in Europe is driven by reallocation to business and non-progressive services.[8]

[7] See online appendix for more details on aggregate and sectoral labor productivity statistics.

[8] We obtain similar conclusions if we restrict the use of the shift-share decomposition to the subsample period

Table 1: Shift-share analysis and sectoral decomposition of annualized aggregate labor productivity growth in Europe and the U.S. for 1970–2019.

	$g_A^{1970-2019}$ (%)		Shift-share decomposition			
			Growth effect		Shift effect	
	US	Europe	US	Europe	US	Europe
Total	1.37	1.53	1.56	2.57	-0.19	-1.04
Sectoral Decomposition						
`agr`	0.04	0.08	0.17	0.92	-0.13	-0.84
`man`	0.12	0.31	0.54	1.11	-0.42	-0.80
`ser`	1.22	1.14	0.86	0.49	0.36	0.65
`bss`	0.44	0.34	0.15	0.05	0.29	0.29
`fin`	0.10	0.03	0.07	0.01	0.03	0.02
`trd`	0.42	0.29	0.52	0.27	-0.10	0.02
`nps`	0.26	0.48	0.12	0.16	0.14	0.32

Notes: Columns 1 and 2 report the aggregate and sectoral contribution of each sector to the annualized growth rate of aggregate labor productivity during the period 1970–2019 in the U.S. and Europe, respectively. Columns 3 to 6 report the shift-share decomposition of the annualized labor productivity growth rate for each region and sector. Note that for each region, the growth effect plus the shift effect add up to the aggregate labor productivity. We compute the sectoral decomposition by using equation (2) to find the relative contribution of a given sector to the change in aggregate labor productivity from 1970 to 2019 and then multiply the relative contribution by the aggregate labor productivity annualized growth rate. The shift-share decomposition is computed in a similar fashion using equation (3) to find the relative contribution of the growth and shift effects to the change in aggregate labor productivity. Hence, column (1) = (3) + (5) and column (2) = (4) + (6). The table also reports the sectoral decomposition of aggregate labor productivity across the three broad sectors of the economy (agriculture, manufacturing and services) and a disaggregation of some sectors within services. The addition of the contributions from oagriculture, manufacturing and services add up the aggregate labor productivity in the first row; the summation of disaggregated services amounts to the contribution of total services (row 4) to aggregate labor productivity. Hence, across all columns, row (1) = (2) + (3) + (4), and row (4) = (5) + (6) + (7) + (8).

Table 1 demonstrates that labor reallocation is a critical component of the overall growth in labor productivity. The decomposition suggests that this reallocation exerts considerable negative impacts on productivity growth, aligning with the Baumol cost disease, as labor shifts away from sectors with high productivity. Nevertheless, the decomposition does not shed light on the mechanics of labor reallocation over the development path that gives rise to such a slowdown. The following section presents a structural transformation model that addresses the mechanics behind labor movements across sectors over the development path.

during which Europe is lagging behind the United States. See Online Appendix's Table C.1.

3 A Model of Structural Transformation

This section presents a model of structural transformation where the reallocation of labor across an arbitrary number of sectors is a function of income and price effects. The model borrows the production technology from Duarte and Restuccia (2010) and the preferences from Comin et al. (2021). The model generates endogenous employment shares as a function of exogenous labor productivity paths.[9] The production technology is linear in labor (hours worked); thus, the residual output not explained through labor input is understood as labor productivity, and the absence of capital implies that all production is consumed each period as there is no savings motive.[10] The equilibrium allocations are sequences of static choice, updated each period depending on the exogenous labor productivity path.[11]

3.1 Environment

An infinitely lived stand-in household of measure L supplies labor inelastically to perfectly competitive labor markets.[12] There are I sectors, each producing output using labor as the only production input.

3.1.1 Preferences

The household has preferences over its consumption stream over time. Since we are not dealing with an inter-temporal choice in our model (*i.e.* there are no savings), there is no need to formalize the structure of preferences toward the inter-temporal substitution of consumption. We abstract from time subscripts when defining intra-temporal allocations, but we will use time subscripts later in the exposition of the calibration. The preferences for consumption are defined implicitly through the constraint

$$\sum_{i=1}^{I}(\Omega_i \tilde{C}^{\epsilon_i})^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1, \tag{4}$$

where $\tilde{C}$ is an unobservable aggregate consumption index, c_i is the consumption from output produced in sector $i \in I$, σ is the price elasticity of substitution, ϵ_i is the income elasticity for good i (i.e. a relative Engel curve), and $\Omega_i > 0$ are constant CES weights for each good

[9]This model, therefore, generates endogenously the weights needed to compute the aggregate labor productivity from sectoral data.

[10]Building upon the work of Duarte and Restuccia (2010), we simplify our analysis by excluding various factors that could account for variations in labor productivity across regions, such as capital, factor intensity, input quality, etc. While considering these factors might provide insights into the underlying causes of productivity differences, treated here as exogenous, Timmer et al. (2011) show in a growth accounting setting that the Solow residual remains substantial even after accounting for capital and input quality. Moreover, their research indicates that the primary contributors to labor productivity differences between Europe and the U.S. stem from multi-factor productivity rather than variations in input utilization.

[11]A period in our model is a year in the data.

[12]The labor endowment L changes over time in the empirical counterpart of our theory to match the evolution of total hours supplied to the marketplace.

i, where $\sum_{i \in I} \Omega_i = 1$. There are two main reasons for using this particular non-homothetic CES preference structure: First, it is trivial to extend the model for any arbitrary number of sectors, which is not a feature of other types of preferences such as Boppart (2014), Herrendorf, Rogerson, and Valentinyi (2013) and Duarte and Restuccia (2010), among many others. Second, these preferences give rise to heterogeneous sectoral log-linear Engel curves that are consistent with the empirical evidence as income effects do not level off as the economy grows wealthier.[13] This is critical to study the rise of services observed at advanced stages of development.

3.1.2 Technology

There are I different sectors in the economy, each producing a consumption good to be sold in competitive markets. Within each sector, there is a continuum of homogeneous firms that use a production technology linear in labor described by

$$y_i = A_i l_i, \quad i \in I, \tag{5}$$

where y_i represents the output produced by a representative firm of sector i, A_i stands for the labor productivity, and l_i is the labor input demanded by firm i. The firm hires labor at the prevailing economy-wide wage W.

3.2 Household's Problem

Given prices, the household problem is to minimize its budget subject to constraint (4), namely

$$\min_{c_i} p_i c_i \quad \text{subject to} \quad \sum_{i=1}^{I} (\Omega_i \tilde{C}^{\epsilon_i})^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1. \tag{6}$$

Assuming interior solutions, the FONCs yield the following Hicksian demand

$$c_i = \Omega_i \left(\frac{p_i}{E} \right)^{-\sigma} \tilde{C}^{\epsilon_i}, \tag{7}$$

where the output demand of sector i is defined in terms of the observables E (total nominal expenditure) and sectoral prices p_i, and the unobservable real consumption index aggregator $\tilde{C}$. Defining the expenditure shares as $\omega_i = \frac{p_i c_i}{E}$, where $E = \sum_{i=1}^{I} p_i c_i$, and using (7) to solve for ω_i yields the sectoral expenditure shares as

$$\omega_i = \Omega_i \left(\frac{p_i}{E} \right)^{1-\sigma} \tilde{C}^{\epsilon_i}. \tag{8}$$

3.3 Firm's problem

The firm's problem is a standard static maximization of profits through labor demand, given competitive prices. Formally,

[13] See, for instance, the motivating facts presented in Aguiar and Bils (2015) and Comin et al. (2021)

$$\max_{l_i}\{p_i A_i l_i - W l_i\} \qquad \forall i \in I. \tag{9}$$

Assuming interior solutions, the FONCs yield

$$p_i = \frac{W}{A_i}. \tag{10}$$

Equation 10 shows that increases in sectoral labor productivity are mapped one-to-one to price reductions, whereas the economy-wide wage W does not affect relative prices across sectors.

3.4 Market Clearing Conditions

In every period, the demand for each consumption good or service is supplied by each sector, namely

$$y_i = c_i \quad \forall i \in I. \tag{11}$$

Labor markets also clear: The total demand for labor, the sum of all sectoral labor demand, must be equal to the labor endowment in every period. That is

$$L = \sum_{i=1}^{I} l_i. \tag{12}$$

3.5 Equilibrium

Having completed the description of endowments, preferences, technology, and market clearing conditions, we proceed to define the equilibrium concept of our model economy of the structural transformation.

Definition 1. *A Competitive Equilibrium is a collection of prices $\{p_i, W\}$, household allocations $\{c_i\}$ and firm's allocations $\{l_i\}$, such that for each sector i:*

(α) Given prices, c_i^* solve the household's problem defined in (6);

(β) Given prices, l_i^* solve the firm's problem defined in (9);

(γ) Market are cleared, as defined in (11) and (12).

Combining equations (8), (10), the market clearing conditions (11) and (12), and the definition of ω_i one gets the following expression for the sectoral labor demand

$$l_i = \left(\frac{E}{W}\right)^{\sigma} \Omega_i \tilde{C}^{\epsilon_i} A_i^{\sigma-1}. \tag{13}$$

Finally, adding equation (13) across all sectors to obtain the aggregate labor demand and taking the ratio to obtain the employment shares, one gets the following expression that defines the structural transformation in the economy in terms of parameters, observables, and the unobservable real consumption index.

$$\frac{l_i}{L} = \frac{\Omega_i \tilde{C}^{\epsilon_i} A_i^{\sigma-1}}{\sum_{j=1}^{I} \Omega_j \tilde{C}^{\epsilon_j} A_j^{\sigma-1}}. \tag{14}$$

Equation (14) illustrates our theory's two main drivers of labor reallocation. The income and price effects, working through the parameters ϵ_i and σ, respectively. Whereas ϵ_i describes how sensitive labor demand in sector i toward changes in the (unobserved) real consumption index, i.e., the relative Engel curve for sector i, σ reflects the sensitivity of the expenditure shares to changes in prices. A higher ϵ_i compared to sector's j income elasticity ($\epsilon_i > \epsilon_j$) implies that more labor will be demanded to produce goods in sector i relative to sector j. On the other hand, and for the empirically relevant case of $\sigma < 1$ when goods are gross complements, a drop in p_i due to an increase in productivity of sector i causes an increase in demand for this good less than proportional when compared to the price change.

The price effect illustrates the Baumol cost disease, formalized by Ngai and Pissarides (2007), in which labor is continuously allocated toward less productive sectors in the long run, as the drop in price (and thus cost) is not met by a proportional increase in labor demand. The total impact on the sector's size depends on combining these two effects, as sectoral productivity changes simultaneously affect real income (and thus $\tilde{C}$) and relative prices.[14]

Equation (14), however, is not sufficient to define the structural transformation in terms of the time series for $\{A_i\}$ and parameter values for ϵ_i and σ for every sector i due to the unobservable aggregate real consumption index $\tilde{C}$.

To derive a system of demand equations in terms of parameters and observables, the following section presents our calibration strategy, where we exploit the implicit Marshallian demand system and then use these parameters to compute an unobservable real consumption index consistent with our theory to later feed in the sectoral labor productivity time paths in equation (14) and evaluate the main predictions of the model.

4 Calibration

We calibrate our model to the structural transformation and aggregate labor productivity data in the U.S. Then, with parameter values for price and income elasticities, we use European country-specific CES weights to match the initial employment shares, and feed in the observed European country-specific labor productivity paths to evaluate the model's capacity to generate the structural transformation and aggregate labor productivity patterns observed in Europe.[15]

[14] In our theory, these effects are one-to-one if one uses value-added instead of employment shares.

[15] This approach is similar to the quantitative strategy employed by Buera, Kaboski, Rogerson, and Vizcaino (2022)

Our calibration strategy proceeds in four steps. Following Comin et al. (2021), we derive a system of Marshallian demand equations relative to manufacturing as a function of observables. Then, we use the initial and final observations in the U.S. for the period 1970–2019 to calibrate the parameters that define the preferences jointly. Third, we use the parameter values obtained in the previous step to compute an unobserved real consumption index consistent with our theory. Last, we feed in the time paths for labor productivity and the unobservable consumption index in (14) to obtain predictions for the structural transformation and the aggregate labor productivity.[16]

4.1 Parameterization

Our calibration delivers a value for $\sigma = 0.79$, which is below one and consistent with the Baumol's cost disease. Our algorithm also delivers parameter values that rank $\epsilon_{\mathtt{agr}} < \epsilon_{\mathtt{man}} = 1$, whereas the Engel curve for sectors within services are above one, consistent with Comin et al. (2021).[17] We find that business services has the strongest income effect ($\epsilon_{\mathtt{bss}} = 1.35$), whereas financial and non-progressive services have Engel curves ($\epsilon_{\mathtt{fin}} = 1.20$ and $\epsilon_{\mathtt{nps}} = 1.19$) that are virtually the same than the Engel curve for services as a whole. Last, we find that, albeit bigger than one, the Engel curve in wholesale and retail trade ($\epsilon_{\mathtt{trd}} = 1.11$) is the weakest among all services.[18] Having finalized the calibration, the next section evaluates the predictions of our model.

5 Model Evaluation

This section tests the model's predictions for the structural transformation and the evolution of aggregate labor productivity. We contrast the model predictions for the sectoral employment shares and the aggregate real output per hour. Since we calibrated the model to the U.S. structural transformation, the sectoral employment data is not insightful to evaluate the model's performance. Recall, however, that we did not match employment shares in the last period by construction. Instead, we use (13) to match labor demand in each sector relative to manufacturing, as shown by (D.2) in Appendix D. The model replicates well – by construction – the salient facts of the American structural transformation, with the biggest distance between the model and the data arising at the last period in nonprogressive services (47.3% in the data vs. 50.2% in the model.[19]) Our model predicts an annualized labor productivity growth rate of 1.26%, while the annual growth rates from OECD and KLEMs are 1.53% and 1.36%, respectively. Most of the

[16]Online appendix D describes in detail our calibration algorithm.

[17]Note that the parameter space is not restricted in the algorithm. Compared to Comin et al. (2021), we found bigger values for σ, implying a lower degree of complementary across all goods, and a significantly stronger Engel curves in agriculture, although still below one. The reason is that our model is calibrated to the U.S., which has virtually completed the transformation out-of-agriculture for the period we study, thus there is not much room for drastic drops in agricultural employment. For our purposes, this calibration is more suited to account for the role of structural transformation on aggregate productivity at later stages of development, as we are interested primarily in the rise of sectors within services.

[18]Table D.1 in the Online Appendix presents the values for the entire parameter space in our model economy.

[19]See Figure C.1 (left panel) in Online Appendix C.3. In a working version of this paper, we documented that most of these discrepancies arose during the 90s in health services.

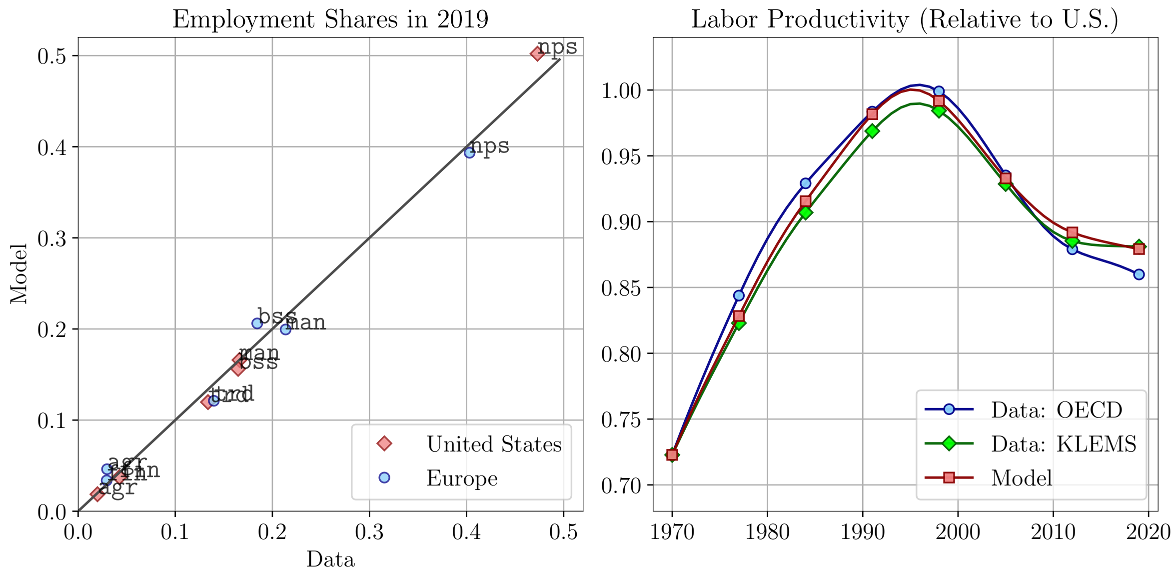

Figure 2: Model predictions vs. data of aggregate labor productivity and sectoral employment shares in 2019 for Europe and U.S.

Notes: Europe groups the countries discussed in Section 2. The aggregations are weighted averages using the size of each country's labor market as weight. The left panel compares the predictions for each sector's final employment share to the data in the U.S. and Europe. The right panel compares the predictions for aggregate labor productivity relative to the U.S. to the labor productivity gap from the OECD and KLEMs. The initial levels of the time series in the right panel start at the labor productivity gap from the OECD in 1970. From this level, the time series from KLEMS is constructed with the observed annual growth rates.

difference between our model and the data comes from the weighted average itself rather than the predictions for the structural transformation (the annualized growth rate of the weighted average is 1.31%).[20]

Figure 2 presents the main test of the theory. The left panel compares the model predictions for the employment shares in U.S. and Europe by plotting a scatter between each observed sectoral employment share in 2019 and our model prediction for the same period. It also plots a solid line representing the 45-degree line starting at the origin of the y and x-axis. It is remarkable how close the pairs between data (y-axis) and model (x-axis) are to the 45-degree line. Recall that, unlike the U.S. employment shares, the European employment shares in 2019 are untargeted. This suggests that our theory is a good measurement instrument for studying the structural transformation in Europe.

The right panel of Figure 2 compares our model prediction for the aggregate labor productivity gap between the U.S. and Europe. We compare our results to the labor productivity gap reported by the OECD, which is PPP-adjusted, and to the labor productivity gap from KLEMs

[20]The right panel of Figure C.1 Online Appendix C.3 contrasts our predictions for aggregate productivity against two data sources: KLEMs and OECD.

using the OECD's initial productivity gap for the initial value of the time series.[21] Regardless of the data source, Figure 2 shows that our model, through its success in accounting for the structural transformation in Europe, can explain the evolution of the labor productivity gap between the U.S. and Europe: The model generates the catch-up witnessed in Europe between 1970 and 1995 and its further divergence after 1995.[22] The model also captures well the transition timing from convergence to divergence.

Having established the quantitative success of the theory, the next section presents a set of numerical experiments to study the role of sectoral productivity on aggregate labor productivity, emphasizing on the sectors that belong to services.

6 Counterfactual Exercises

This section uses our parameterized model economy to study how the productivity of specific sectors affects the overall labor productivity. Section 2 shows, through a decomposition exercise, that addressing labor reallocation is critical. In particular, the decomposition suggests that if one ignores the reallocation of labor, one will overestimate a sector's role in aggregate productivity. This intuition aligns with Baumol's cost disease, as more productive sectors lose participation in the economy while stagnant sectors gain more weight.

To understand the role of sectoral productivity on aggregate productivity growth, we use our quantitative general equilibrium framework to account for labor reallocation via changes in relative prices (Baumol) and changes in income (Engel curves). We compare our results with a dynamic shift-share analysis, whereby the entire observed employment shares time series are the weights used to compute the counterfactual aggregate labor productivity path.[23] This type of analysis ignores, by construction, the general equilibrium effects brought by counterfactual changes in sectoral productivity.

We propose two sets of counterfactual experiments. First, we study what would have happened had Europe experienced the sectoral productivity growth witnessed in the U.S. between 1970 and 2019 (counterfactual 1). Second, we use the employment shares in 2019 to compute the implied growth rate needed in one sector from 1970 to 2019 to close the aggregate productivity gap with the U.S. entirely. We then compute the gap predicted by our model when feeding this counterfactual "catch-up" growth rate in our model (counterfactual 2).

Table 2 shows the counterfactual results. The exercises reveal that, except for financial services in counterfactual 1, endogenous reallocation across sectors reduces the contribution of

[21] As explained in Online Appendix D.4, our model is also targeted to the initial productivity gap in Europe.

[22] Timmer et al. (2011, p. 8) document that "[s]ince the mid-1990s, the patterns of productivity growth in Europe and the United States changed dramatically. In the United States, average annual labour productivity growth accelerated from 1.3 per cent during the period 1973–95 to 2.1% during 1995–2007. Comparing the same two time periods, annual labour productivity growth in the European Union declined from 2.7 to 1.5 per cent."

[23] We prefer the dynamic shift-share analysis because it considers the entire time series of employment reallocation and sectoral labor productivity growth between 1970 and 2019, as opposed to a static shift-share analysis, which uses changes in employment shares and sectoral labor productivity between 1970 and 2019. See Barff and Knight III (1988) for a careful comparison between static and dynamic shift-share analysis.

Table 2: Numerical experiments: counterfactual change in Europe's annualized aggregate labor productivity growth (percentage points) for 1970–2019.

	g_A^{cf} - $g_A^{baseline}$ (percentage points difference)		Difference
	Model (1)	Dynamic shift-share (2)	(1) - (2) (3)
Counterfactual 1: U.S. sectoral growth rates			
`agr`	-0.12	-0.08	-0.03
`man`	-0.12	-0.15	0.02
`bss`	0.04	0.06	-0.02
`fin`	0.04	0.03	0.01
`trd`	0.07	0.09	-0.02
`nps`	-0.10	-0.10	-0.00
`bss`, `fin`, `trd`	0.13	0.18	-0.04
Counterfactual 2: Implied "catch-up" sectoral growth rates			
`agr`	0.58	0.65	-0.07
`man`	0.51	0.65	-0.14
`bss`	0.55	0.65	-0.10
`fin`	0.39	0.65	-0.27
`trd`	0.44	0.65	-0.21
`nps`	0.59	0.65	-0.06

Notes: The table shows how annualized aggregate labor productivity growth between 1970 and 2019 in Europe changes when feeding different counterfactual sectoral labor productivity growth rates. Counterfactual 1 feeds the U.S. sectoral labor productivity growth of the indicated sectors. Counterfactual 2 feeds the sectoral labor productivity growth needed in each indicated sector to close the aggregate labor productivity gap between Europe and the U.S. by 2019. The first column reports how Europe's annualized aggregate labor productivity growth changes using our model relative to that given by the baseline (1.57%). The second column reports how Europe's annualized aggregate labor productivity growth changes when keeping the employment shares fixed, as in the data from 1970 to 2019, relative to that given by the data (1.53%). Finally, the third column reports the difference between the change implied by the model, which considers endogenous employment shares, vs. the counterfactual keeping employment shares fixed.

market services to aggregate labor productivity in Europe from 1970 to 2019. For instance, our model predicts that annual aggregate labor productivity growth between 1970 and 2019 in Europe would increase by 0.04 percentage points when feeding higher labor productivity growth into business services. Dynamic shift-share, which ignores changes in sectoral labor relocation, predicts an increase of 0.06 percentage points instead. The two models' predictions diverge by 0.02 percent annualized growth rate. Ignoring the reallocation brought by counterfactually changing the productivity of business services results in a 50% overestimation of the change in annualized aggregate labor productivity growth. Similarly, the model predicts a smaller impact for counterfactual labor productivity growth in wholesale and retail trade, with annual growth in labor productivity being 0.02 percentage points below that predicted by shift-share. In this case, however, the overestimation of dynamic shift-share analysis is relatively less severe but still substantial (30%). Note that these results show how sensitive aggregate labor productivity is concerning changes in the sectoral productivity paths when one accounts for the endogenous reallocation of labor.

In counterfactual 2, under more dramatic changes in labor productivity, the labor reallocation effect coming from higher productivity in market services is evident in all sectors. In this second experiment, since each sectoral counterfactual productivity closes the aggregate productivity gap in 2019 – by construction –*if all* the employment shares remain unaltered, we find that Europe's annualized aggregate labor productivity would increase by 0.65 percentage points. However, when labor reallocation responds to these counterfactual changes, we find that the aggregate impact is not the same in *all* sectors, and their effect on aggregate productivity is substantially lower. For market services, we find an annualized aggregate productivity growth rate difference of 0.10, 0.27, and 0.21 percentage points in business, finance, and trade services, respectively. These large differences imply that the productivity gap would not have been closed in 2019: The model predicts a significant productivity gap would persist: 42% and 32% of the observed gap in 2019 for financial and trade services. For business services, however, the gap would be lower as some of the reallocation out of this sector is mitigated by its strong income effect, although the net effect is still non-negligible.

To grasp better the endogenous reallocation brought by counterfactual 2 in market services, Figure 3 plots the baseline and counterfactual employment shares for the entire structural transformation. Two aspects are worth highlighting. First, most of the response to a counterfactual productivity enhancement takes place in the sector that experiences this direct effect by pushing labor out of it. The income effects, albeit strong, are insufficient to compensate for the price effect in market services. Second, the lion's share of this reallocation out of productive sectors is absorbed by nonprogressive services, the least productive sector in the economy. These two mechanisms are an integral part of the Baumol cost disease and explain the slowdown in aggregate productivity and the rising (relative) costs in nonprogressive services in the aftermath of productivity gains when the price effect dominates the income effect.[24]

In sum, our numerical experiments imply that although there is potential for enhanced productivity in European market services, in line with the observations of Timmer et al. (2011), one must carefully consider the broader impact of these advancements on overall economic performance due to the onset of the Baumol cost disease resulting from these potential productivity increments. This phenomenon, as explained by Baumol (1967), is an inherent attribute of the macroeconomics of unbalanced growth.

[24]These findings are consistent with Nordhaus (2008) and Baumol, Blackman, and Wolff (1985) and the rising costs of nonprogresive services documented in Baumol (2012), mostly in health care and education.

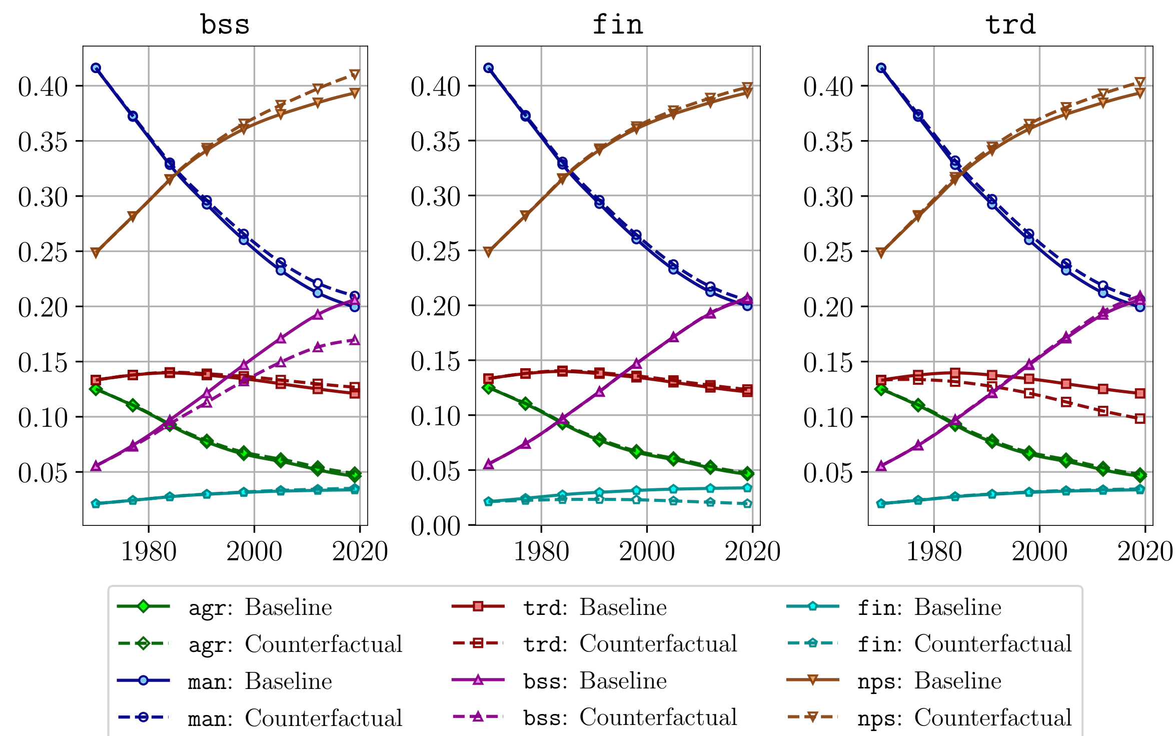

Figure 3: Labor reallocation across sectors in the baseline vs. counterfactual 2 exercises for wholesale and retail trade, business, and financial services.

Notes: The figure plots the model baseline employment shares using color-filled markers and solid lines vs. model counterfactual 2 employment shares using empty-filled markers and dashed lines. Each panels represents the employment shares predicted from feeding the catch-up growth rate in business services (left panel), financial services (middle panel), and wholesale and retail trade (right panel).

7 Conclusion

This paper underscores the importance of structural transformation in shaping aggregate productivity growth even at advanced stages of economic development. Using a structural transformation model calibrated to the U.S., we quantitatively examine the influence of labor reallocation across sectors on aggregate labor productivity through income and price effects. We use the model to study the convergence and divergence patterns in output per hour between Europe and the U.S. from 1970 to 2019. Our findings emphasize that the reallocation witnessed in the long run over the process of economic transformation is critical for understanding the deceleration in aggregate productivity, as the duality within services brings forth a Baumol cost disease whereby productive sectors lose ground despite their strong income effects.

Our results indicate that the divergence between market and nonprogressive services may hinder the potential for overall economic performance through productivity gains in market services. As Rodrik (2013) documents, manufacturing has historically been a source of unconditional convergence. However, the convergence unleashed at the early stages of economic development is insufficient to keep the European economy performing on par with the U.S. As countries grow and transform into service-oriented economies, the dichotomy between progressive and nonprogressive services might usher in a new stage of the Baumol cost disease.

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Online Appendix

A Data Construction Details

Aggregate data We use two measures of aggregate labor productivity. The first is PPP-adjusted GDP per hour from OECD data from 1970 to 2019. The second is the total industry real value added in local currency at constant prices from EUKLEMS 2023 release (Bontadini, Corrado, Haskel, Iommi, & Jona-Lasinio, 2023) from 1995 to 2019. We then use the growth rates of total real value added in local currency at constant prices growth rates from EUKLEMS 2009 release (O'Mahony & Timmer, 2009) to extend the KLEMS aggregate labor productivity series back to 1970 for all European countries and back to 1977 for the U.S. Finally, we use World KLEMS 2013 release (Jorgenson, Ho, & Samuels, 2013) growth rates to extend the U.S. KLEMS aggregate labor productivity in the U.S. from 1977 to 1970. Total hours worked are from KLEMS data, and we use the same procedure above to extend the hours series back to 1970.

Sectoral data We combine data from the EUKLEMS 2023 (Bontadini et al., 2023) and 2009 (O'Mahony & Timmer, 2009) release with the World KLEMS 2013 (Jorgenson et al., 2013) release to build a country-industry-year panel data on labor productivity—real value added per hour worked—and employment shares for the EU15 countries and the U.S. in agriculture, manufacturing and services—disaggregated into business services, financial services, wholesale and retail trade, and non-progressive services—from 1970 to 2019. The EUKLEMS databases have country-industry-year harmonized data on nominal value-added, price deflator and hours worked. We construct sectoral labor productivity as real value added—sectoral nominal value added divided by sectoral price deflator—divided by hours worked and employment shares as the share of hours worked in each sector divided by total hours worked. Again, the EUKLEMS 2023 release only goes back to 1995, and we use the same procedure as in the aggregate data to extend the sectoral series back to 1970. We classify our sectors as aggregates of ISIC Rev. 3 and ISIC Rev. 4 industries as shown in table A.1. The classify industries with low labor productivity growth into non-progressive services. In B.1 in section B, we show that labor productivity growth is insignificant in the non-progressive sector between 1970 and 2019.

Table A.1: Sectoral classification and KLEMS data ISIC Rev. 3 and 4 industries correspondence.

Abbreviated Name		Name	ISIC Rev. 3 – NACE Rev. 1 (EUKLEMS 2009 and World KLEMS)	ISIC Rev. 4 – NACE Rev. 2 (EUKLEMS 2023)
agr		Agriculture	A, B	A
man		Manufacturing	C, D, E, F	B, C, D, E, F
ser	bss	Business services	64, 71–74	J, M, N
ser	fin	Financial services	J	L
ser	trd	Wholesale and retail trade services	G	G
ser	nps	Non-progressive services	H, 60–63, 70, L, M, N, O, P	I, H, L, O, P, Q, R, S, T

Notes: the table shows the mapping between the ISIC Rev. 3 and 4 industry classification and the sectoral classification used in this paper. In addition, it shows the aggregate classifications of total services (ser).

B Data Descriptive Statistics

In this section, we provide descriptive statistics of the data in Table B.1. We discuss these statistics in section 2 of the paper. Additionally, we note here that both OECD and KLEMS measures provide a similar picture of aggregate labor productivity growth in all regions. Second, the aggregate and sectoral labor productivity growth and employment shares are approximately between EU4 and EU15.

Table B.1: Labor productivity growth and employment shares in EU4, EU15 and U.S.

	LP annualized growth rate						Employment share								
	1970-1995			1995-2019			1970			1995			2019		
	U.S.	EU4	EU15	U.S.	EU4	EU15	U.S.	EU4	EU15	U.S.	EU4	EU15	U.S.	EU4	EU15
Total (OECD)	1.45	2.79	2.79	1.60	0.95	1.01									
Total (KLEMS)	1.20	2.54	2.56	1.58	0.95	0.85									
agr	2.20	5.30	5.52	3.37	2.27	2.54	0.04	0.13	0.15	0.03	0.05	0.06	0.02	0.03	0.04
man	1.18	3.04	3.01	2.16	1.39	1.46	0.30	0.41	0.39	0.23	0.28	0.28	0.17	0.21	0.20
ser	0.84	1.52	1.55	1.29	0.48	0.37	0.65	0.46	0.46	0.75	0.67	0.66	0.81	0.76	0.76
nps	0.42	1.25	1.30	0.38	0.23	0.02	0.39	0.25	0.25	0.41	0.36	0.36	0.47	0.40	0.41
bss	1.08	1.49	1.54	2.44	0.37	0.40	0.08	0.06	0.05	0.14	0.11	0.11	0.16	0.18	0.18
fin	1.78	0.91	1.16	2.10	0.75	1.19	0.03	0.02	0.02	0.04	0.03	0.03	0.04	0.03	0.03
trd	2.04	2.18	2.02	2.40	1.48	1.31	0.15	0.13	0.14	0.15	0.15	0.16	0.13	0.14	0.15

Notes: the table shows in the first six columns the total and sectoral labor productivity (LP) annualized growth rate in the U.S. EU4 and EU15 in the 1970–1995 and 1995–2019 periods. The last nine columns show the sectoral employment share in the U.S. EU4 and EU15 regions in 1970, 1995 and 2019. We use the OECD data to calculate the aggregate labor productivity growth rates and KLEMS-type databases to compute the total and sectoral labor productivity growth rates and employment shares. The industry codes agr, man, ser, nps, bss, fin, and trd correspond to agriculture, manufacturing, services, non-progressive services, business services, financial services, and wholesale and retail trade, respectively.

In Figure B.1, we plot the labor productivity growth in all sectors in the U.S. from 1970 to 2019. The largest increases in worker productivity were seen in the agricultural sector, followed by market services, including wholesale and retail trade, financial services, and business services. Additionally, we observe that labor productivity improvements in non-progressive services are in fact almost nonexistent. The only sector in which labor productivity growth is less than total labor productivity growth is non-progressive services. Additionally, because of its relatively large size, it alone causes the labor productivity growth in the total services sector to be less than the labor productivity growth in the overall sector. Therefore, the non-progressive services sector is specifically affected by the Baumol cost illness, which slows the growth of total labor productivity as its relative size rises.

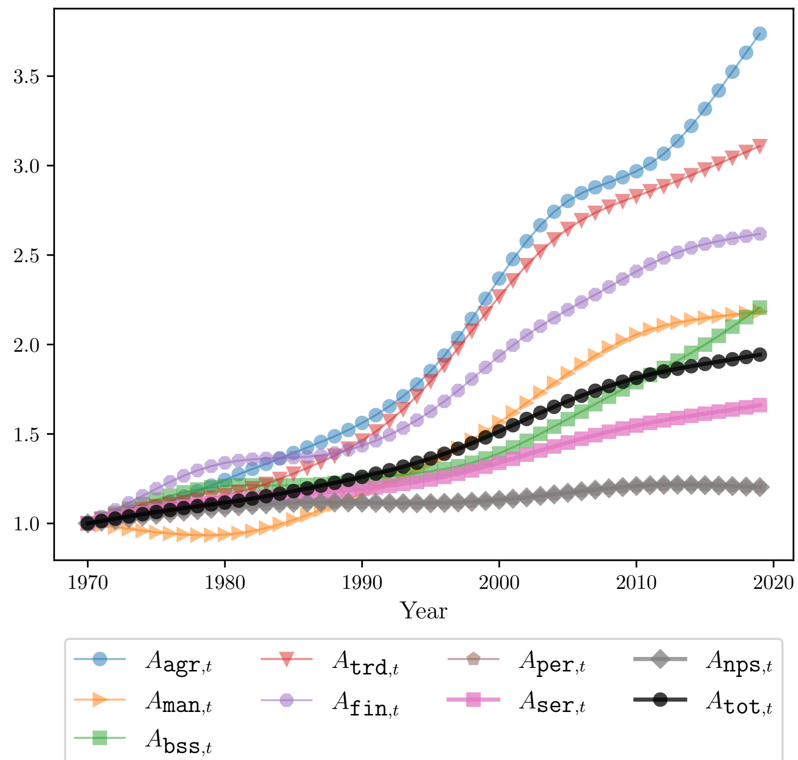

Figure B.1: U.S. sectoral labor productivity growth from 1970 to 2019.

Notes: This figure plots sectoral labor productivity growth in the U.S. using KLEMS data. To facilitate interpretation, we fix all the initial sectoral labor productivity indexes, $A_{i,1970}$, to 1.

C Additional Analysis and Results

The supplementary analysis and findings in this section support the analysis in the main text and serve as robustness tests. To begin, we compute a shit-share decomposing for the 1995—2019 period, which concentrates on the time when labor productivity growth in Europe is diverging from that in the U.S. Next, instead of merely using the big four European nations as in the baseline, we apply the same decomposition for both the diverging period (1995-2019) and the baseline period (1970-2019) of Europe defined as a weighted average of all EU15 countries. Third, we illustrate how the calibrated model can generate the structural transformation and aggregate labor productivity path observed in the U.S. and in Europe, defined as a weighted average of all EU15 nations, in order to give additional tests of the theory. Finally, we calculate exactly the same counterfactual experiments for EU15 as those described in the paper and compare them with our baseline results.

C.1 Shift-share analysis of EU4 for the 1995-2019 period

Table C.1 presents the shift-share decomposition for the 1995–2019 period. The results are similar to those obtained for the entire 1970–2019 period in the main text. Both regions continue to see a considerable labor reallocation effect, but Europe is more affected. The primary distinction is the reduced growth effect in Europe, which was previously larger than the U.S. in the full sample but is now smaller during the period of falling behind.

Table C.1: Shift-share analysis and sectoral decomposition for the 1995–2019 period.

	LP growth		Shift-share decomposition			
			Growth effect		Shift effect	
	US	Europe	US	Europe	US	Europe
Total	2.04	1.21	2.33	1.92	-0.30	-0.71
Sectoral Decomposition						
`agr`	0.10	0.04	0.20	0.50	-0.10	-0.46
`man`	0.24	0.11	0.62	0.83	-0.38	-0.72
`ser`	1.70	1.06	1.53	0.59	0.17	0.47
`bss`	0.66	0.48	0.46	0.06	0.20	0.42
`fin`	0.14	0.00	0.14	0.00	0.00	0.00
`trd`	0.55	0.28	0.80	0.41	-0.25	-0.13
`nps`	0.35	0.30	0.13	0.12	0.22	0.18

Notes: Columns 1 and 2 report the aggregate and sectoral contribution of each sector to the annualized growth rate of aggregate labor productivity during the period 1995–2019 in the U.S. and Europe, respectively. Columns 3 to 6 report the shift-share decomposition of the annualized labor productivity growth rate for each region and sector. Note that for each region, the growth effect plus the shift effect sum to the aggregate labor productivity. We compute the sectoral decomposition by using equation (2) to find the relative contribution of a given sector to the change in aggregate labor productivity from 1970 to 2019 and then multiplying that relative contribution by the aggregate labor productivity annualized growth rate. The shift-share decomposition is computed in a similar fashion using equation (3) to find the relative contribution of the growth and shift effects to the change in aggregate labor productivity. Hence, column (1) = (3) + (5) and column (2) = (4) + (6). The table also reports the sectoral decomposition of aggregate labor productivity across two levels of aggregation. First by agriculture, manufacturing and services, and second in which we disaggregate services. The summation of agriculture, manufacturing and services contributions to labor productivity amount to the aggregate labor productivity in the first row, and the summation of disaggregated services amount to the contribution of total services (row 4) to aggregate labor productivity. Hence, across all columns, row (1) = (2) + (3) + (4), and row (4) = (5) + (6) + (7) + (8).

C.2 Shift-share analysis of EU15 for the 1970-2019 period and for the 1995-2019 period

In Table C.2, we present the results for the shift-share and sectoral decomposition when we use all EU-15 countries instead of the big four European economies. Comparing this table with Table 1, we find that the values are virtually unchanged. The general message is the same, but Europe as the EU15 has a slightly larger shift effect and a smaller growth effect. The overall labor productivity in Europe was dramatically and adversely affected by the reallocation of labor across sectors. By breaking services down into its component parts, we discover that reallocation to business and non-progressive services is what is responsible for the considerable reallocation effect in Europe.

Table C.2: Shift-share analysis and sectoral decomposition for the 1970–2019 period.

	LP growth		Shift-share decomposition			
			Growth effect		Shift effect	
	US	EU-15	US	EU-15	US	EU-15
Total	1.37	1.57	1.56	2.79	-0.19	-1.22
Sectoral Decomposition						
`agr`	0.04	0.14	0.17	1.26	-0.13	-1.12
`man`	0.12	0.32	0.54	1.06	-0.42	-0.74
`ser`	1.22	1.12	0.86	0.47	0.36	0.65
`bss`	0.44	0.34	0.15	0.05	0.29	0.29
`fin`	0.10	0.04	0.07	0.02	0.03	0.02
`trd`	0.42	0.28	0.52	0.25	-0.10	0.03
`nps`	0.26	0.46	0.12	0.15	0.14	0.31

Notes: Columns 1 and 2 report the aggregate and sectoral contribution of each sector to the annualized growth rate of aggregate labor productivity during the period 1970–2019 in the U.S. and EU-15, respectively. Columns 3 to 6 report the shift-share decomposition of the annualized labor productivity growth rate for each region and sector. Note that for each region, the growth effect plus the shift effect sum to the aggregate labor productivity. We compute the sectoral decomposition by using equation (2) to find the relative contribution of a given sector to the change in aggregate labor productivity from 1970 to 2019 and then multiplying that relative contribution by the aggregate labor productivity annualized growth rate. The shift-share decomposition is computed in a similar fashion using equation (3) to find the relative contribution of the growth and shift effects to the change in aggregate labor productivityX. Hence, column (1) = (3) + (5) and column (2) = (4) + (6). The table also reports the sectoral decomposition of aggregate labor productivity across two levels of aggregation. First by agriculture, manufacturing and services, and second in which we disaggregate services. The summation of agriculture, manufacturing and services contributions to labor productivity amount to the aggregate labor productivity in the first row, and the summation of disaggregated services amount to the contribution of total services (row 4) to aggregate labor productivity. Hence, across all columns, row (1) = (2) + (3) + (4), and row (4) = (5) + (6) + (7) + (8).

In Table C.3, we present the shift-share decomposition for the 1995—2019 period in EU15. The results are, again, similar to those obtained when using EU4 countries. Both regions continue to see a considerable labor reallocation effect, but Europe is more affected. The primary distinction

Table C.3: Shift-share analysis and sectoral decomposition for the 1995–2019 period

	LP growth		Shift-share decomposition			
			Growth effect		Shift effect	
	US	EU-15	US	EU-15	US	EU-15
Total	2.04	1.23	2.33	2.12	-0.30	-0.89
Sectoral Decomposition						
agr	0.10	0.08	0.20	0.75	-0.10	-0.67
man	0.24	0.11	0.62	0.85	-0.38	-0.74
ser	1.70	1.04	1.53	0.54	0.17	0.50
bss	0.66	0.50	0.46	0.07	0.20	0.43
fin	0.14	0.02	0.14	0.06	0.00	-0.04
trd	0.55	0.27	0.80	0.36	-0.25	-0.09
nps	0.35	0.25	0.13	0.05	0.22	0.20

Notes: Columns 1 and 2 report the aggregate and sectoral contribution of each sector to the annualized growth rate of aggregate labor productivity during the period 1995–2019 in the U.S. and EU-15, respectively. Columns 3 to 6 report the shift-share decomposition of the annualized labor productivity growth rate for each region and sector. Note that for each region, the growth effect plus the shift effect sum to the aggregate labor productivity. We compute the sectoral decomposition by using equation (2) to find the relative contribution of a given sector to the change in aggregate labor productivity from 1970 to 2019 and then multiplying that relative contribution by the aggregate labor productivity annualized growth rate. The shift-share decomposition is computed in a similar fashion using equation (3) to find the relative contribution of the growth and shift effects to the change in aggregate labor productivity. Hence, column (1) = (3) + (5) and column (2) = (4) + (6). The table also reports the sectoral decomposition of aggregate labor productivity across two levels of aggregation. First by agriculture, manufacturing and services, and second in which we disaggregate services. The summation of agriculture, manufacturing and services contributions to labor productivity amount to the aggregate labor productivity in the first row, and the summation of disaggregated services amount to the contribution of total services (row 4) to aggregate labor productivity. Hence, across all columns, row (1) = (2) + (3) + (4), and row (4) = (5) + (6) + (7) + (8).

continues to be the reduced growth effect in Europe, which was previously larger than the U.S. across the whole sample but is now smaller during the period of falling behind.

C.3 Additional Tests to the Theory

In this subsection, we provide additional tests to the theory by, first, testing our model predictions against the U.S. data not used in the calibration of the model and, second, by comparing the model predictions to European data when using the full set of EU15 countries.

C.3.1 U.S.

Figure C.1 (left panel) demonstrates that the model effectively reproduces the significant aspects of the American structural transformation. Notably, the largest disparity between the model and the empirical data occurs in the final period of Non-progressive services, with a discrepancy of 47.3 percent in the data compared to 50.2 percent in the model. The right panel of Figure C.1 presents a comparison between our predicted aggregate productivity and data from two sources, namely KLEMs and OECD. The model presented in our study estimates a labor productivity growth rate of 1.26 percent per year. In comparison, the annual growth rates reported by the OECD and KLEMs stand at 1.53 percent and 1.36 percent, respectively. The primary source of disparity between our model and the empirical data arises from the discrepancy between the aggregate data and the sectoral productivity's weighted average. However, it is comforting to see that the model is capable of generating a labor productivity trajectory that closely aligns with the aggregate data for the United States, which was not used during the calibration process.

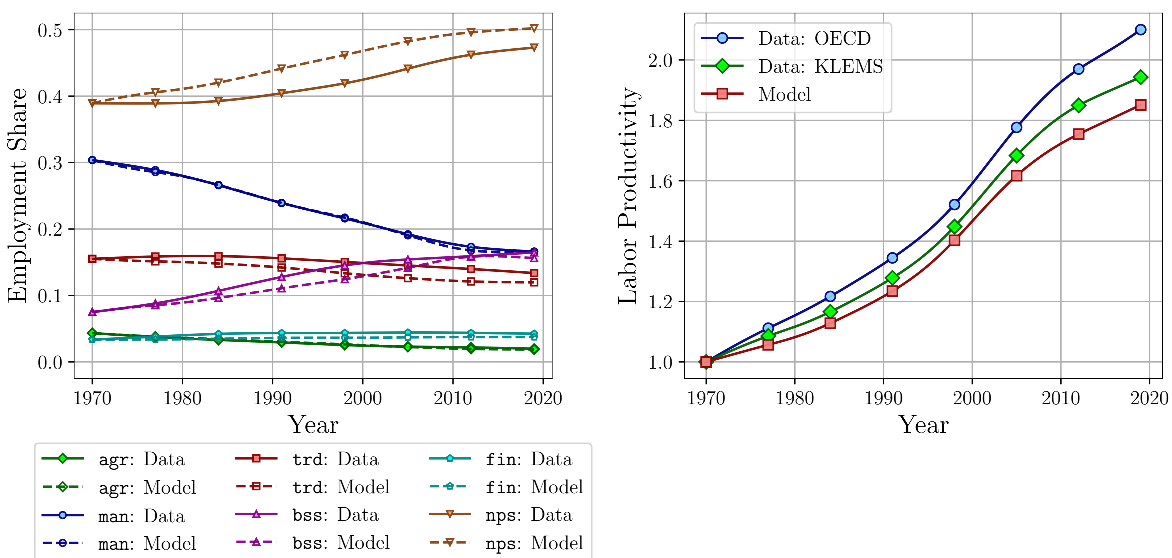

Figure C.1: Aggregate Labor Productivity and Structural Transformation in the U.S. 1970–2009. Model predictions vs. data.

Notes: The left panel of this figure shows the employment shares predicted by the model (dashed lines vs. data (solid lines). The right panel shows the model's prediction (red) vs. two different data measurements of aggregate labor productivity growth: OECD (blue) and KLEMS (green).

C.3.2 EU15

In Figure C.2, we show that our model that the model effectively reproduces the significant aspects of labor reallocation in Europe when using the full set of EU15 countries. Notably, the model fit is even better for the employment shares of business and non-progressive services in 2019. Additionally, when employing EU15, the model replicates the patterns of data on relative aggregate labor productivity growth between Europe and the U.S., although there is a somewhat larger gap between the model and the data. However, the majority of this discrepancy results from the gap between the total data and the sectoral productivity weighted average.

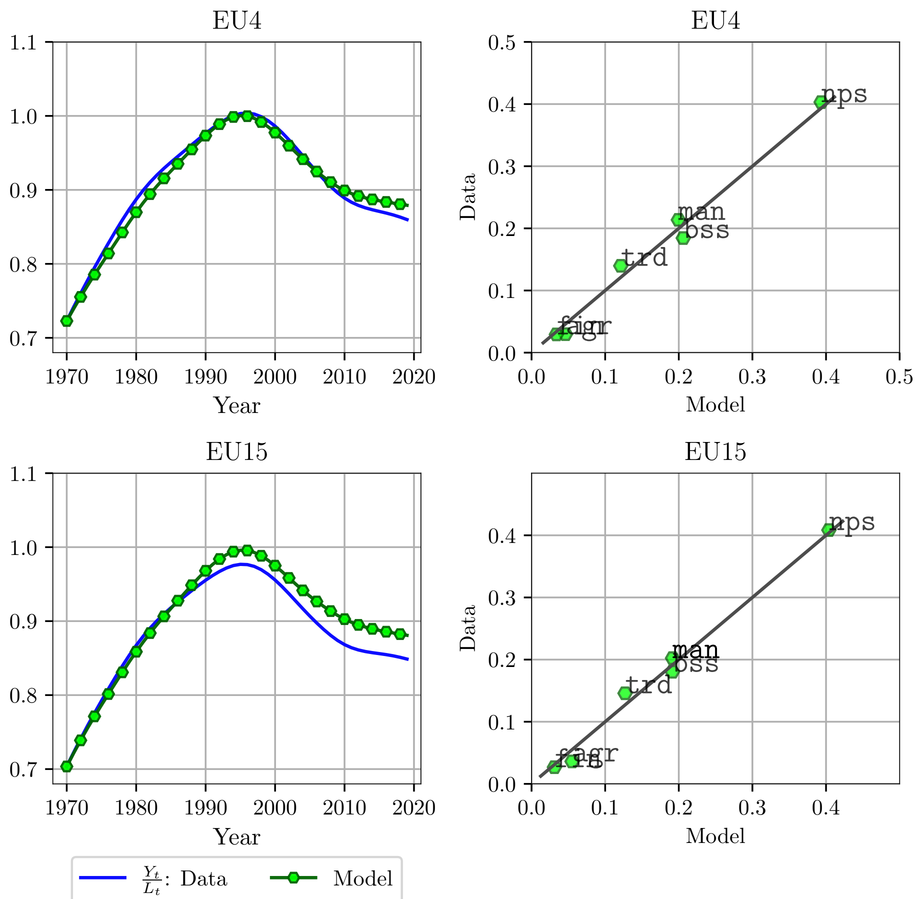

Figure C.2: Model predictions vs. data of aggregate labor productivity sectoral employment shares in 2019 in EU4 and EU15.

Notes: The left panels show the model's prediction (green) vs. OCDE data on aggregate labor productivity growth for EU4 (top panel) and EU15 (bottom panel). The right panels of this figure show the scatter plots of the employment shares predicted by the model (x-axis vs. data (y-axis) for EU4 (top panel) and EU15 (bottom panel).

C.4 Counterfactual Experiments When Using EU15 as Europe

In Table C.4, we present the counterfactual change in Europe's annualized aggregate labor productivity growth (pp) for 1970–2019 using EU4 and EU15 as Europe. It is reassuring to observe that our counterfactual results hold true despite the greater alignment in business services and non-progressive services employment shares shown in the previous subsection when utilizing EU15.

Table C.4: Numerical experiments: counterfactual change in Europe's annualized aggregate labor productivity growth (pp) for 1970–2019 using EU4 (main paper) and EU15 as Europe.

	g_A^{cf} - $g_A^{baseline}$ (percentage points difference)			
	Model		Dynamic shift-share	
	EU4	EU15	EU4	EU15
Counterfactual 1: U.S. sectoral growth rates				
`agr`	-0.12	-0.17	-0.08	-0.11
`man`	-0.12	-0.15	-0.15	-0.17
`bss`	0.04	0.04	0.06	0.07
`fin`	0.04	0.03	0.03	0.02
`trd`	0.07	0.08	0.09	0.11
`nps`	-0.10	-0.09	-0.10	-0.09
`bss`, `fin`, `trd`	0.13	0.13	0.18	0.20
Counterfactual 2: Implied "catch-up" sectoral growth rates				
`agr`	0.58	0.70	0.65	0.74
`man`	0.51	0.57	0.65	0.74
`bss`	0.55	0.63	0.65	0.74
`fin`	0.39	0.44	0.65	0.74
`trd`	0.44	0.48	0.65	0.74
`nps`	0.59	0.66	0.65	0.74

Notes: The table shows how annualized aggregate labor productivity growth between 1970 and 2019 in Europe changes when feeding different counterfactual sectoral labor productivity growth rates. Counterfactual 1 feeds the U.S. sectoral labor productivity growth of the indicated sectors. Counterfactual 2 feeds the sectoral labor productivity growth needed in each indicated sector to close the aggregate labor productivity gap between Europe and the U.S. by 2019. The first and second columns report how Europe's annualized aggregate labor productivity growth changes using our model relative to that given by the baseline using Europe as a weighted average of EU4 and EU15. The third and fourth columns report how Europe's annualized aggregate labor productivity growth changes when keeping the employment shares fixed, as in the data from 1970 to 2019, relative to that given by the data using Europe as a weighted average of EU4 and EU15.

D Calibration Algorithm

D.1 Marshallian Demand System

The expenditure shares in equation (8) are defined in terms of preferences, observables, and the unobservable real consumption index aggregator $\tilde{C}$. To define a demand system in terms of parameters and observables, consider the equation (8) for manufacturing and solve for $\tilde{C}$. This yields

$$\tilde{C} = \frac{\omega_{\mathtt{man}}}{\Omega_{\mathtt{man}}} \left(\frac{E}{p_{\mathtt{man}}} \right)^{1-\sigma}. \tag{D.1}$$

Plugging (D.1) in (8), and using the market clearing conditions, one obtains sectoral labor demand relative to manufacturing in terms of observables. Taking logs on both sides, one gets

$$\begin{aligned} \log\left(\frac{l_i}{l_{\mathtt{man}}}\right) = \log\left(\frac{\Omega_i}{\Omega_{\mathtt{man}}}\right) + (1-\sigma)\log\left(\frac{p_i}{p_{\mathtt{man}}}\right) + (1-\sigma)(\epsilon_i - 1)\log\left(\frac{E}{p_{\mathtt{man}}}\right) \\ + (\epsilon_i - 1)\log\left(\frac{\omega_{\mathtt{man}}}{\Omega_{\mathtt{man}}}\right). \end{aligned} \tag{D.2}$$

D.2 Initial and Final Data to Parameterize Price and Income Elasticities

With the system of Marshallian demands at hand, the first step of the parameterization is to normalize the initial productivity levels $A_{i,t=1970} = 1$ and the initial level of the real consumption index $\tilde{C}_{t=1970} = 1$. As $\tilde{C}$ is an object of the preferences, we are free to determine its level. With this normalization, and using the fact that $\sum_{i \in I} \Omega_i = 1$, one gets parameter values for each Ω_i from equation (14) with the observed initial, namely $\Omega_i = \frac{l_{i,t=1970}}{L_{t=1970}}$.

Using the parameter values for each $\Omega_{i \in I}$, we exploit the relative sectoral demands for the last period observed in the U.S. data (2019) using (D.2). To obtain the empirical counterparts of (D.2), we use World KLEMs data for the U.S. to construct sectoral labor demand relative to manufacturing, $\frac{l_{i,t=2019}}{l_{\mathtt{man},t=2019}}$, sectoral prices relative to manufacturing, $\frac{p_{i,t=2019}}{p_{\mathtt{man},t=2019}}$, total nominal expenditures relative to manufacturing prices, $\frac{E_{t=2019}}{p_{\mathtt{man},t=2019}}$, and the manufacturing expenditure share, $\omega_{\mathtt{man},t=2019}$. With these data, and normalizing the Engel curve in manufacturing $\epsilon_{\mathtt{man}} = 1$, we need a external value for either σ or *one* of the income elasticities outside manufacturing, or we would need an additional moment in the data to discipline *one* of these parameters. We borrow from Comin et al. (2021, Table VIII, p. 350) the parameter value for the Engel curve in services ($\epsilon_{\mathtt{ser}} = 1.2$) to discipline σ and $\epsilon_{i \in I, i \neq \{\mathtt{man},\mathtt{ser}\}}$ according to the following steps:

1. Conditional on an external value for the Engel curve in services, use (D.2) for $i = \mathtt{ser}$ and solve for σ.

2. Conditional of the value for σ associated with the $\epsilon_{\mathtt{ser}}$, use (D.2) to obtain values for rest of income elasticities $\epsilon_{i \in I, i \neq \{\mathtt{man},\mathtt{ser}\}}$.

D.3 Computation of the Unobserved Real Consumption Index

Albeit unobserved, we can compute a time path for $\tilde{C}_t$ consistent with the theory. In principle. there are $I+1$ equations in the model that one can use to compute the evolution of $\tilde{C}_t$. Thus far, we have used the real consumption index for base good man expressed in equation (D.1) to obtain the Marshallian demand system. In addition, one can solve for the expenditure share in any sector i relative to manufacturing. This yields $I-1$ equations, one for each $i \neq \texttt{man}$, namely

$$\tilde{C} = \left[\frac{\Omega_{\texttt{man}}}{\Omega_i}\frac{l_i}{l_{\texttt{man}}}\left(\frac{p_i}{p_{\texttt{man}}}\right)^{\sigma-1}\right]^{\frac{1}{\epsilon_i-1}}, \quad i \neq \texttt{man}, \quad i \in I. \tag{D.3}$$

Since we use an external value for the Engel curve in services, we also compute $\tilde{C}$ using the equation for services relative to manufacturing from (D.3) as well. Although one could use a weighted average for all I sectors, including equation (D.1), we chose not to use this approximation since we already have used (D.1) to obtain the Marshallian Demand System, and more importantly, because it is arbitrary what weights ought to be used to compute this average. In principle, one could use the employment shares of each sector as weights, but this approximation is not fruitful if one wants to use the model to perform numerical experiments since these weights are a function of labor productivity.[25]

Alternative, one could use the definition of aggregate expenditure $E = \left[\sum_{i\in I}\Omega_i\tilde{C}^{\epsilon_i}p_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ and solve the fixed point problem every period to obtain $\tilde{C}$. We do not follow this approach in the baseline calibration, but we use it in our numerical experiments to compute the counterfactual growth for $\tilde{C}$, as this approach does not exploit observations for relative employment that depend on the labor productivity time paths.

D.4 Feed in Observed Sectoral Productivity Time Paths

To complete the calibration, the last step is to feed in $\tilde{C}_t$ constructed in the previous step and the observed paths for $\{A_{i,t}\}$ in equation (14) to compute both the model's prediction for the structural transformation and the aggregate labor productivity. For the United States, all the sectoral productivity indexes start at one, and the time series is completed using growth rates. For the European countries, the time series starts at the initial aggregate productivity gap reported by the OECD, which is PPP adjusted. This also implies that the CES weights $\Omega_i, i \in I$ must be country-specific to match the initial employment shares in each European country and in Europe as a whole. Last, following Duarte and Restuccia (2010), we map from sectoral to aggregate productivity by weighting each sector's labor productivity using the predicted employment share of each sector as weight, namely $A_t = \sum_{i\in I}\frac{l_{i,t}}{L_t}A_{i,t}$. In our model, therefore, weighted productivity

[25]However, our baseline predictions are virtually unaltered if we use (D.3) instead for each $i \neq I$ to compute $I-1$ paths for $\tilde{C}_t$, and then take the weighted average across sectors with each sector's employment share as weight, or even if one uses a simple average. This is an useful approximation to generate theoretical predictions of our theory, but not to perform numerical experiments.

averages can be mapped directly to the evolution of the aggregate productivity gap.

D.5 Parameterization: Summary

Table D.1: Parameterization. The model is calibrated to the U.S. (1970–2019.)

Parameter	Comment/Target	Value
σ	Price elasticity of substitution.	0.79
$\epsilon_{\texttt{agr}}$	Engel curve for agriculture.	0.97
$\epsilon_{\texttt{man}}$	Engel curve for manufacturing (normalization.)	1
$\epsilon_{\texttt{ser}}$	Engel curve for services (Comin et al. (2021, Table VIII, p. 350).)	1.2
$\epsilon_{\texttt{trd}}$	Engel curve for whole sale and retail trade.	1.11
$\epsilon_{\texttt{bss}}$	Engel curve for business services.	1.35
$\epsilon_{\texttt{fin}}$	Engel curve for financial services.	1.20
$\epsilon_{\texttt{nps}}$	Engel curve for non-progressive services.	1.19
$\Omega_{\texttt{agr}}$	Initial emp. share in agriculture.	0.04
$\Omega_{\texttt{man}}$	Initial emp. share in manufacturing	0.30
$\Omega_{\texttt{ser}}$	Initial emp. share in services.	0.65
$\Omega_{\texttt{trd}}$	Initial emp. share in wholesale and retail trade.	0.15
$\Omega_{\texttt{bss}}$	Initial emp. share in business services.	0.07
$\Omega_{\texttt{fin}}$	Initial emp. share in financial services.	0.03
$\Omega_{\texttt{nps}}$	Initial emp. share in non-progressive services.	0.39