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 model accurately captures structural transformation and aggregate labor productivity paths, as well as the timing of Europe's transition from convergence to divergence relative to the U.S. 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 heterogeneous productivity observed within services brings forth a Baumol cost disease whereby productive sectors gain less employment share than their productivity growth would imply under constant shares, despite their strong income effects. An extended version of our model that accounts for international trade suggests that it is implausible for Europe to export its way out of the aggregate stagnation unleashed by labor reallocation toward unproductive sectors.

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1 Introduction

Around the mid-1990s, output per hour worked in Europe nearly converged to U.S. levels, with the remaining differences in overall output largely attributable to differences in hours worked rather than hourly 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 nearly been closed. However, this convergence trend reverted; by 2019, European labor productivity had fallen back to 86% of the U.S. level. 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 nonprogressive services (health, education, public administration, and real estate), grapple with a *cost disease* while gaining partic-

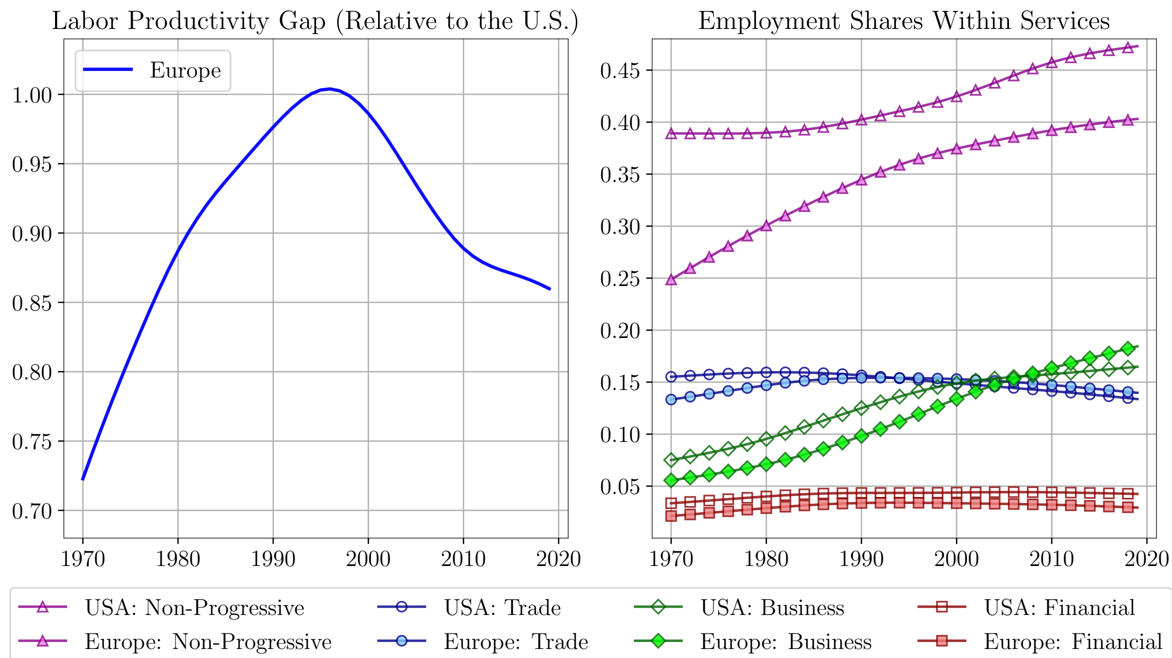

Figure 1: U.S. and Europe. Labor productivity gap and structural transformation. 1970–2019.

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 online Appendix A for details on how the data on labor productivity and employment shares are constructed.

[1]Throughout this paper, unless explicitly stated otherwise, "labor productivity" and "productivity" refer to output per hour worked.

ipation in the economy during the process of structural transformation. Nonprogressive services are characterized by stagnant labor productivity, while progressive services experience labor productivity growth comparable to that in agriculture and manufacturing. Figure 1 (right panel) shows that the United States and Europe have undergone significant reallocation of the labor force toward services. Notably, this shift involves substantial reallocation within services, with business and nonprogressive 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 for 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 pull the employment shares of productive services in opposite directions under empirically relevant parameter values.

We calibrate our model to the United States from 1970 to 2019 using OECD national accounts and the EUKLEMS 2023 release (Section 2), and test it against European data for the same period. After showing that our model accurately reproduces the key aspects of structural transformation and the overall productivity disparity, we conduct several numerical experiments to examine the impact of sector-specific labor productivity and labor redistribution on total labor productivity in Europe. To begin, we examine how sector-specific labor productivity and labor shift between sectors contributed to the labor productivity gap between Europe and the U.S. since the late 1990s using two hypothetical scenarios. In the first scenario, we feed the US sectoral labor productivity growth to Europe from 1990 onward. In the second scenario, we entirely halt labor reallocation in Europe after 1990, keeping the sectoral employment shares unchanged post-1990. Our analysis reveals that the changes in labor allocation in Europe played a major role—the shift effect accounts for -1.04 percentage points of annualized aggregate labor productivity growth in Europe, more than five times the -0.19 in the U.S. (Table 1)—in the reversal of labor productivity observed between Europe and the U.S.

Although previous exercises show that labor reallocation is crucial for overall labor produc-

[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.

tivity, they do not explicitly explain how shifts in sectoral productivity impact aggregate productivity. To study the endogenous reallocation of labor unleashed by changes in sectoral labor productivity, we conduct two additional numerical exercises. First, we input the observed growth rates for sectoral labor productivity in the U.S., one sector at a time, and now over the entire 1970–2019 period 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 labor productivity growth in market services would result in less significant impacts on overall labor productivity than previously suggested (Timmer et al., 2011). The main mechanism behind this finding is that when labor productivity increases in market services, labor is reallocated from these productive sectors to less productive services. There are two main effects—price and income effects, captured by our theory, that induce this reallocation of labor from productive into less productive sectors. i) Price effects: Improved labor productivity has led to a reduction in the prices of these services, allowing consumers to allocate a smaller portion of their total spending to them, ultimately decreasing the demand for employment in these sectors, since—as our calibration confirms ($\sigma = 0.79$)—sectors produce goods that are gross complements and the drop in price is more than proportional to the increase in demand. ii) Income effects: Enhanced labor productivity in market services boosts overall income, which raises demand for all services with income elasticity above one. Since nonprogressive services have a high income elasticity ($\epsilon_{\texttt{nps}} = 1.19$), they absorb a significant share of this additional demand. The income effect within services is sector-specific and can partially offset the price effect—for instance, business services benefit from the strongest income effect ($\epsilon_{\texttt{bss}} = 1.35$)—but the net reallocation still favors nonprogressive services because the price effect dominates in the shocked sector.

The reallocation of labor brought by income and price effects mitigates the aggregate effects of sectoral productivity gains in line with the Baumol cost disease, which posits that the cost of some services tends to rise faster than more productive sectors, including manufacturing and some services with non-negligible productivity gains, and the economy reallocates its resources in the long-run to the least productive sectors. Our numerical experiments show that the share of nonprogressive services, which are services with limited productivity gains, 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 would overestimate the counterfactual gain in Europe's annualized aggregate labor productivity by about 30%. Focusing on business services, where reallocation is substantial, the overestimation reaches about 50%. In our second set of experiments, where we feed the "catch-up" growth rates for each sector computed under constant employment shares, 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 aggregate EU–US labor productivity 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 nonprogressive services largely drives the persistence of these gaps.

These findings are robust along several dimensions. The Baumol cost disease within services is present in Great Britain—which never adopted the euro, testing whether the results are specific to Euro Area membership—the EU15 as a whole, and across both core and peripheral economies, where the core–periphery classification of Bayoumi and Eichengreen (1992) tests whether the capital misallocation documented in the periphery (Gopinath, Kalemli-Özcan, Karabarbounis, & Villegas-Sanchez, 2017) alters the mechanism. Disaggregating services into progressive and nonprogressive subsectors is essential: a standard three-sector model cannot capture the within-services reallocation that drives our main results. Our model uses a production technology linear in labor and maps sectoral labor productivity directly to relative prices. We show formally that this holds under standard assumptions: in a more general technology with capital, relative prices still depend on labor productivity, not TFP separately. As a direct test, replacing model prices with observed sectoral price deflators produces virtually identical employment share predictions (Table 3), confirming that the model's ability to match the data comes from the non-homothetic income effects and relative productivity movements, not from the particular mapping between productivity and prices. Although our framework does not require decomposing the sources of labor productivity, the growth rates of sectoral labor productivity and TFP are substantially correlated across EU countries ($\rho = 0.64$–0.87), consistent with Timmer et al. (2011), who document that TFP accounts for the primary share of labor productivity variation between Europe and the U.S.

We extend the model to allow exports to respond endogenously to sectoral productivity, calibrating sector-level export elasticities from observed export growth since 1995. This open-economy extension serves a dual purpose: it tests the robustness of the closed-economy identification, and it reveals a new mechanism through which trade interacts with the Baumol cost disease. Higher productivity always raises real export quantities, but the labor absorbed by exports—the ratio of export quantities to productivity—increases only when the sector-specific export elasticity exceeds one, i.e., when the quantity expansion outweighs the labor-saving efficiency gain. For most services, and especially business services ($\xi = 2.59$), this condition holds: productivity-driven exports sustain sectoral labor demand and partially offset the Baumol reallocation toward nonprogressive services, amplifying the role of progressive services in closing the productivity gap. Agriculture ($\xi = 0.74$) and manufacturing ($\xi = 0.91$) are the only sectors where the elasticity falls below one in Europe: higher productivity erodes export value added, and trade reinforces rather than offsets the cost disease. Repeating our main counterfactual under endogenous trade confirms the central identification: progressive services account for approximately two-thirds of the total gap explained in sector-by-sector counterfactuals. Since the results are virtually identical under no export response (exogenous trade, 19.7% of the gap explained) and under the full response estimated from the data (endogenous trade, 19.5%), the identification of key sectors is robust to the treatment of the export channel. While productivity-driven exports substantially reduce the trade surplus required for Europe to close the gap, the required magnitudes remain non-trivial, and, under the trade specifications explored in this paper, Europe cannot plausibly export its way out of the Baumol cost disease.

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 in the context of structural transformation, focusing on the heterogeneity 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 differential productivity growth as a catalyst of structural transformation.[3] 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. Our value-added framework addresses the former concern: since A_i is value added per hour, each calibrated ϵ_i absorbs both final and derived demand, embedding the intermediate-input channel in the model's employment share predictions (Section 3). Our six-sector disaggregation with heterogeneous income elasticities captures the within-service demand responses central to Duernecker et al.'s argument, but the net reallocation still favors nonprogressive services when $\sigma < 1$. 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 heterogeneity that persists 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

[3] 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.

results. Section 5 presents our results: we first evaluate the model's predictions against the data, then conduct a set of numerical experiments, and conclude with a robustness analysis along four dimensions—alternative European aggregations, applicability beyond the Euro Area, a three-sector model, and the model's pricing assumption—followed by a discussion of the relationship between labor productivity and TFP. Section 6 extends our framework to an open-economy setting. Section 7 concludes.

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 OECD national accounts and the EUKLEMS 2023 release 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 nonprogressive (`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.[4][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. Following Prescott (2004), we concentrate on these four major economies; Section 5.3 demonstrates that all findings are robust to defining Europe as the EU15 and to distinguishing between core and periphery regions.

Using OECD GDP per hour, the average annualized labor productivity growth in the U.S. accelerated from 1.5% 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

[4] Nonprogressive services include public administration, education, health, and real estate (see Table A.1 in the Online Appendix). Public sector output is often measured as input costs by statistical convention, and real estate value added is influenced by imputed rents. These measurement challenges are common to all studies using KLEMS-type data at this level of aggregation. Importantly, the three-sector robustness check in Section 5.3—which does not rely on isolating nonprogressive services from other services—confirms that the Baumol cost disease operates across the manufacturing–services margin as well.

[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 have 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.

these two time periods from 2.8% to 1%. 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 KLEMS data in van Ark, O'Mahony, and Timmer (2008) and Timmer et al. (2011). Concurrently, as shown in Figure 1, there has been a substantial reallocation of labor across sectors, particularly in nonprogressive services and business services in Europe, which saw their employment shares rise approximately fifteen and twelve 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

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

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 sectors (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 positive shift effect within services in Europe (0.65) is driven by reallocation toward business services (0.29, the same as in the U.S.) and, more distinctively, nonprogressive services (0.32 vs. 0.14 in the U.S.). These conclusions are robust to restricting the shift-share decomposition to the post-1995 subsample (Online Appendix, Table B.2).

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	0.97	-0.13	-0.89
`man`	0.12	0.31	0.53	1.10	-0.41	-0.79
`ser`	1.22	1.14	0.87	0.49	0.35	0.65
`bss`	0.44	0.34	0.15	0.05	0.29	0.29
`fin`	0.10	0.03	0.08	0.01	0.02	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 agriculture, 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). Individual entries are independently rounded to two decimal places; displayed column sums may differ by 0.01 from the sum of displayed entries.

Table 1 demonstrates that labor reallocation is a critical component of the overall growth in labor productivity. The negative shift effect is largely driven by labor exiting agriculture and manufacturing—a well-documented pattern of structural transformation. Note that the negative sign is an accounting property of the decomposition in equation (3): sectors whose employment shares decline contribute negatively to the shift term, regardless of the economic desirability of such reallocation. Within services, the positive shift effect is driven primarily by reallocation toward business and nonprogressive services, consistent with the Baumol cost disease operating within the service sector.

Further evidence consistent with the Baumol cost disease is provided by the evolution of labor compensation. Using EUKLEMS 2023 data on nominal compensation per hour from 1995 to 2019, we find that nominal wages grew at broadly similar rates across all sectors in Europe—ranging from 2.5% to 3.7% per year—despite wide differences in labor productivity growth. This is a direct manifestation of the cost disease: sectors with stagnant productivity, such as nonprogressive services, experience rising labor costs at rates comparable to the economy-wide average, driven by the need to compete for workers in a common labor market. As a result, the relative cost of nonprogressive services rises over time, consistent with the mechanisms that drive labor reallocation in our model.

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.

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—the weights needed to compute aggregate labor productivity from sectoral data—as a function of exogenous labor productivity paths. The production technology is linear in labor (hours worked), so labor productivity A_i is the sole exogenous input, and the absence of capital implies that all production is consumed each period as there is no savings motive. The equilibrium allocations are sequences of static choice, updated each year depending on the exogenous labor productivity path.

3.1 Environment

An infinitely lived stand-in household of measure L supplies labor inelastically to perfectly competitive labor markets. In the empirical counterpart of our theory, L changes over time to match the evolution of total hours supplied to the marketplace. 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 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 straightforward in 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.[6] 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.

The production technology (5) is linear in labor and abstracts from capital. The key observation is that our theory does not ask what determines A_i—it asks what observed A_i paths *do* to employment shares and aggregate labor productivity. The mechanism operates through relative prices: equation (11) below maps A_i to prices ($p_i = 1/A_i$), which together with the preference structure determine employment shares. Relative prices are the central force driving structural transformation, and modeling them as the inverse of labor productivity is the standard approach:

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

Baumol (1967), Ngai and Pissarides (2007), and Duarte and Restuccia (2010) all use the linear-in-labor technology, and Herrendorf et al. (2014) present it as the benchmark model. As Duarte and Restuccia (2010, fn. 15, p. 9) put it: "There are many features that can explain differences over time and across countries in labor productivity such as capital intensity and factor endowments... Our analysis abstracts from the sources driving labor productivity observations." Whatever forces shape A_i in practice—TFP, capital deepening, human capital, institutional factors, or measurement conventions (such as input-cost valuation of public sector output)—are already embedded in the observed A_i paths, and the model need not decompose them. The model's predictions are tested against observed employment shares and aggregate productivity that are subject to the same measurement conventions, ensuring internal consistency.

To see why this holds under standard assumptions, consider a more general technology $y_i = Z_i k_i^{\alpha} l_i^{1-\alpha}$ with a common capital share α across sectors, as in Ngai and Pissarides (2007). Under competitive labor markets with free capital mobility, capital-labor ratios equalize across sectors at a common ratio κ, so labor productivity in each sector is $A_i \equiv y_i/l_i = Z_i \kappa^{\alpha}$ and the equilibrium wage satisfies $W = p_i(1-\alpha)A_i$. Relative sectoral prices thus satisfy

$$\frac{p_i}{p_j} = \frac{A_j}{A_i}, \tag{6}$$

and the model with capital collapses to the labor-only version. When capital shares differ across sectors (Acemoglu & Guerrieri, 2008), the true price becomes $p_i \propto 1/[(1-\alpha_i)A_i]$. However, if sector-specific capital shares α_i are approximately constant over time, the factor $(1-\alpha_i)^{\sigma-1}$ enters the employment share equation as a sector-specific constant absorbed by the calibrated CES weights Ω_i. To see this, note that the employment share equation involves terms $\Omega_i \tilde{C}^{\epsilon_i} A_i^{\sigma-1}$; replacing A_i with $(1-\alpha_i)A_i$ merely rescales each Ω_i by a time-invariant constant, which is absorbed when we calibrate Ω_i to match observed initial employment shares. The *dynamics* of structural transformation—which depend on the time paths of A_i—are unaffected.

Factor compensation shares from the EUKLEMS growth accounts confirm that this condition holds in our data: within-country standard deviations of sectoral capital shares range from 2 to 6 percentage points over 1996–2019, with no systematic trend. Even so, one can bound the bias from residual time variation: if α_i drifts by $\Delta\alpha_i$ over the sample, the resulting error in the log employment share ratio $\ln(l_i/l_j)$ equals $|1-\sigma| \times |\Delta \ln(1-\alpha_i) - \Delta \ln(1-\alpha_j)|$. With $\sigma \approx 0.79$ and the observed within-sector variation, this error is approximately 0.02 in logs over 25 years (for $\bar{\alpha} \approx 0.30$ and $\Delta\alpha \approx 0.06$, $\Delta \ln(1-\alpha) \approx 0.09$; the cross-sector difference is at most 0.09, giving $|1-0.79| \times 0.09 \approx 0.02$), compared with log employment share changes of 0.5–1.0 that the model explains—roughly 25 to 50 times smaller. As a direct test: if the simplification $p_i = 1/A_i$ were consequential, feeding actual observed prices instead should change the model's predictions. Section 5.3 shows that it does not—replacing $1/A_i$ with observed sectoral price deflators produces virtually identical employment share predictions.

Although our question does not require decomposing A_i, one may ask what drives sectoral labor productivity differences. Section 5.4 shows that the growth rates of sectoral labor productivity and TFP are substantially correlated across EU countries ($\rho = 0.64$–0.87), consistent with the findings of Timmer et al. (2011), who document that multi-factor productivity accounts for the primary share of labor productivity differences between Europe and the U.S.

3.2 Household's Problem

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

$$\min_{c_i} \sum_{i=1}^{I} p_i c_i \quad \text{subject to} \quad \sum_{i=1}^{I} (\Omega_i \tilde{C}^{\epsilon_i})^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1. \tag{7}$$

Assuming interior solutions, the first-order conditions yield the following Hicksian demand

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

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 (8) to solve for ω_i yields the sectoral expenditure shares as

$$\omega_i = \Omega_i \left(\frac{p_i}{E}\right)^{1-\sigma} \tilde{C}^{\epsilon_i}. \tag{9}$$

3.3 Firm's problem

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

$$\max_{l_i} \{p_i A_i l_i - W l_i\} \qquad \forall i \in I. \tag{10}$$

In equilibrium, the zero-profit condition requires

$$p_i = \frac{1}{A_i}, \tag{11}$$

where W is set as the *numéraire*. Equation (11) shows that increases in sectoral labor productivity are mapped one-to-one to price reductions, whereas the economy-wide wage 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

$$y_i = c_i \quad \forall i \in I. \tag{12}$$

This condition implies that all output is consumed as final goods. In practice, several sectors—including manufacturing and business services—are partly intermediate inputs (Oulton, 2001). The justification for abstracting from input-output linkages is that our model operates with value-added measures: labor productivity A_i is value added per hour, and employment shares are constructed from hours worked. Value added, by construction, nets out intermediate consumption, so the observed employment share of sector i reflects the labor needed to produce that sector's contribution to final expenditure, regardless of whether its gross output also serves as an input to other sectors. Each income elasticity ϵ_i is calibrated to match these value-added employment shares, absorbing both final and derived demand channels. Herrendorf et al. (2013, Section 3) show formally that the final-goods framework is appropriate for structural transformation models estimated from value-added data, precisely because the value-added lens already incorporates the input-output structure.[7]

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

$$L = \sum_{i=1}^{I} l_i. \tag{13}$$

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 $\{p_i\}$, household allocations $\{c_i\}$ and firm's allocations $\{l_i\}$ for each sector i, such that:*

(α) Given prices, c_i^* solve the household's problem defined in (7);

(β) Given prices, l_i^* solve the firm's problem defined in (10);

(γ) Markets clear, as defined in (12) and (13).

Combining equations (9), (11), the market clearing conditions (12) and (13), and the definition of ω_i one gets the following expression for the sectoral labor demand

[7] The value-added approach requires that input-output coefficients are approximately stable over time, so that changes in sectoral employment shares are driven by final demand and productivity rather than shifts in IO linkages. This condition is satisfied in our data: the OECD ICIO tables show that within-country standard deviations of sectoral intermediate-use shares are between 1 and 3 percentage points over 1995–2019, with the sectors most central to our analysis—manufacturing, business services, and nonprogressive services—among the most stable ($\leq$2 percentage points). A full integration of input-output linkages with nonhomothetic CES preferences at the six-sector level remains an open direction for future research.

$$l_i = E^{\sigma}\Omega_i \tilde{C}^{\epsilon_i} A_i^{\sigma-1}. \tag{14}$$

Proposition 1. *The employment share for sector i is calculated by dividing the value of (14) for that sector by the total sum of this equation across all sectors, resulting in:*

$$\frac{l_i}{L} = \frac{\Omega_i \tilde{C}^{\epsilon_i} A_i^{\sigma-1}}{\sum_{j=1}^{I} \Omega_j \tilde{C}^{\epsilon_j} A_j^{\sigma-1}}. \tag{15}$$

Equation (15) provides a closed form solution that directly maps how structural transformation in the economy takes place as a function of parameters, exogenous sectoral labor productivity, and unobservable real consumption index. It 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 is to changes in the (unobserved) real consumption index, i.e., the relative Engel curve for sector i, σ reflects the sensitivity of expenditure shares to changes in prices. On one hand, a higher ϵ_i compared to the 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 the productivity of the sector i causes an increase in the demand for this good less than proportional compared to the change in price.

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, since the drop in price (and thus cost) is not met by a proportional increase in labor demand. The total impact on the size of the sector depends on combining these two effects, since changes in sectoral productivity simultaneously affect real income (and thus $\tilde{C}$) and relative prices.[8]

Equation (15), however, is not sufficient to define the structural transformation in terms of 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 (15) 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

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

country-specific labor productivity paths to evaluate the model's capacity to generate the structural transformation and aggregate labor productivity patterns observed in Europe, an approach 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 (15) to obtain predictions for the structural transformation and the aggregate labor productivity. Online Appendix E describes our calibration algorithm in detail.

The mapping from observables to parameters is as follows. The CES weights Ω_i are set to match 1970 U.S. employment shares (one moment per sector). The Engel curve for manufacturing is normalized to $\epsilon_{\texttt{man}} = 1$, and the Engel curve for aggregate services is set to $\epsilon_{\texttt{ser}} = 1.2$ following Comin et al. (2021). Given $\epsilon_{\texttt{ser}}$, the price elasticity σ is identified from the 2019 U.S. services-to-manufacturing relative labor demand via (15). Conditional on σ, the remaining Engel curves ϵ_i are identified from each sector's 2019 relative labor demand, one equation per sector. The full parameter space thus requires $2I + 1$ moments (initial shares, endpoint relative labor demands, the normalization $\epsilon_{\texttt{man}} = 1$, and the external $\epsilon_{\texttt{ser}}$) to pin down $2I + 1$ parameters (I weights, I income elasticities, and σ). The European evaluation uses none of these moments: only country-specific Ω_i (from European initial shares) and the European $\tilde{C}_t$ path are country-specific inputs.

4.1 Parameterization

Our calibration delivers a value for $\sigma = 0.79$, which is below one and consistent with the Baumol cost disease. The qualitative mechanism underlying our results—the price effect pushing labor out of productive sectors toward nonprogressive services—requires only $\sigma < 1$, a condition that is robustly established in the literature. Comin et al. (2021) estimate σ between 0.25 and 0.63 across multiple specifications using household-level micro data from the U.S. and India and cross-country aggregate data from 39 countries (their Tables I, III, V, and X); all estimates reject $\sigma \geq 1$. Their cross-country aggregate estimates—methodologically closest to our identification—yield σ between 0.25 and 0.63 depending on the subsample (Table III), with a point estimate of 0.57 for the full world sample. Our value of 0.79 implies a weaker degree of complementarity—and thus a weaker price effect—than any of their estimates, making our quantitative results conservative: lower values of σ would strengthen the Baumol cost disease and amplify the dampening of aggregate productivity through endogenous labor reallocation.[9] Our algorithm also delivers

[9]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 complementarity 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

parameter values that rank $\epsilon_{\texttt{agr}} < \epsilon_{\texttt{man}} = 1$, whereas the Engel curves for sectors within services are above one, consistent with Comin et al. (2021). We find that business services has the strongest income effect ($\epsilon_{\texttt{bss}} = 1.35$), whereas financial and nonprogressive services have Engel curves ($\epsilon_{\texttt{fin}} = 1.20$ and $\epsilon_{\texttt{nps}} = 1.19$) that are virtually the same as the Engel curve for services as a whole. Last, we find that, albeit bigger than one, the Engel curve in wholesale and retail trade ($\epsilon_{\texttt{trd}} = 1.11$) is the weakest among all services (Table E.1 in the Online Appendix presents the complete parameter space). These income elasticities will remain constant when we test and simulate our model in Europe. The only parameters that vary between different regions are the sectoral Ω_i, which are always adjusted to ensure the model is able to match the initial sectoral employment shares in each region. Having finalized the calibration, the next section presents the results of our model.

5 Results

5.1 Model Evaluation

This subsection 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.

For the U.S., two elements are matched by construction: the initial (1970) employment shares, which pin down the CES weights Ω_i, and the relative labor demand between services and manufacturing at the endpoint, which—together with an external Engel curve for services—identifies σ and the remaining ϵ_i (see Appendix E). The time path of the non-homothetic consumption index $\tilde{C}_t$ is then computed from the services-to-manufacturing employment ratio using (E.3). Given these inputs, the model predicts all six employment shares at every intermediate date, the 2019 level of each share, and the aggregate productivity path—none of which are directly targeted. The model replicates the salient facts of the American structural transformation well, 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; see Figure F.1 in Online Appendix F). Nonprogressive services is left out of the scatter plot in Figure 2 because, once the other five shares are determined, the sixth is pinned down by the adding-up constraint—not because it is directly targeted. 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 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%).

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 sec-

structural transformation on aggregate productivity at later stages of development, as we are interested primarily in the rise of sectors within services.

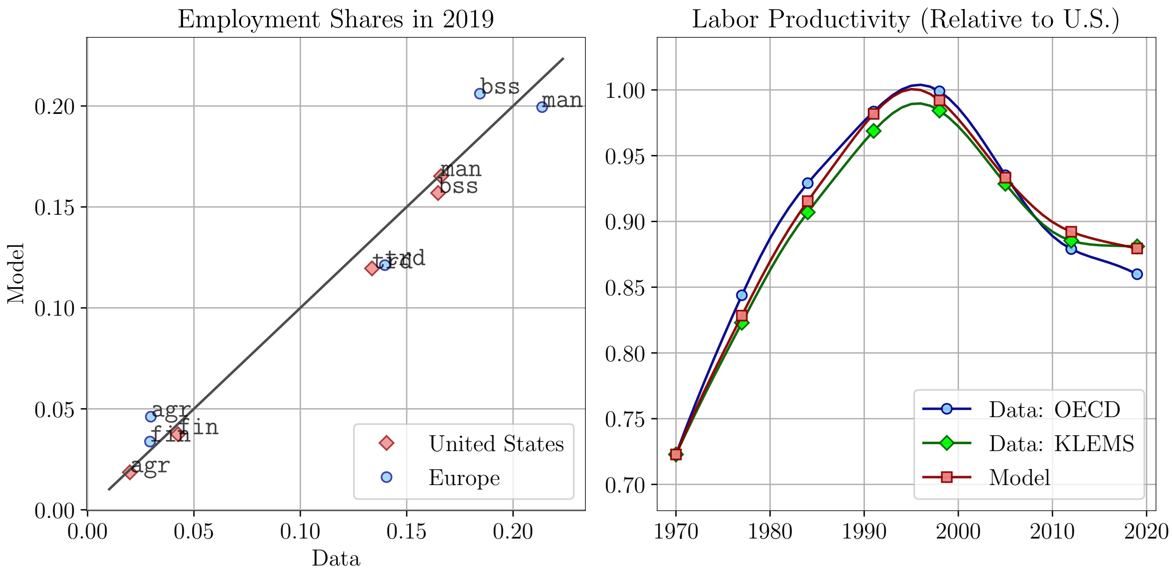

Figure 2: Model predictions vs. data: sectoral employment shares in 2019 (left) and aggregate labor productivity, 1970–2019 (right), for Europe and the U.S.

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. We leave out `nps` from the plot since it is a residual by construction. The predictions for this sector are close to the 45-degree line for the U.S. and Europe as well.

toral 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. For Europe, the only inputs that use European data are (i) the country-specific CES weights Ω_i, which match the initial employment shares, and (ii) the $\tilde{C}_t$ path, which is computed from the observed European services-to-manufacturing employment ratio using (E.3) with the U.S.-calibrated parameters. This construction pins down the time path of $\tilde{C}_t$ using the aggregate services-to-manufacturing employment ratio. However, the model operates at the six-sector level: it predicts each of the four service subsector shares independently, each governed by its own income elasticity ϵ_i and productivity path $A_{i,t}$. The aggregate services share in the model is the sum of these four independently predicted shares and is *not* constrained to equal the observed aggregate used to compute $\tilde{C}_t$.[10] The genuine out-of-sample test is the model's ability to match the *composition*

[10]To see why, note that the six-sector employment shares are determined by equation (15) with sector-specific ϵ_i and $A_{i,t}$. The sum of the four service subsector shares collapses to the three-sector aggregate only if all service subsectors have identical ϵ_i and identical productivity paths—a restriction that is strongly rejected by our estimates ($\epsilon_{\texttt{bss}} = 1.35$ vs. $\epsilon_{\texttt{nps}} = 1.19$; see Table E.1). Each subsector share is therefore a genuine prediction that could fail independently.

within services—the allocation across business, financial, trade, and nonprogressive services—and the aggregate productivity path, none of which are targeted. The tight fit in Figure 2 indicates that the U.S.-calibrated income and price elasticities accurately predict the within-service reallocation observed in Europe. 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 using the OECD's initial productivity gap for the initial value of the time series (our model is also targeted to the initial productivity gap in Europe, as explained in Online Appendix E.4). 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. Crucially, the model also captures well the timing of the transition from convergence to divergence.

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

5.2 Counterfactual Exercises

This subsection uses our parameterized model economy to study the role of sectoral labor productivity growth and labor reallocation in aggregate labor productivity growth. We begin by employing our model to examine the relative importance of sectoral labor productivity and labor reallocation in the reversal of the convergence trend between Europe and the United States that occurred in the late 1990s. To do so, we run three counterfactual exercises. In the first exercise, we keep Europe's observed sectoral labor productivity growth for the entire 1970–2019 period, but we assume that the labor reallocation from 1990 onward in Europe evolves as in the US. In the second exercise, we feed the US sectoral labor productivity growth to Europe from 1990 onward, while keeping the reallocation endogenous. Finally, in the third exercise, we shut down the labor reallocation process in Europe after 1990. In other words, the sectoral employment shares in Europe after 1990 remain at the same level as in 1990. These exercises allow us to grasp the relative importance of gaps in sectoral productivity growth and in labor reallocation on the aggregate labor productivity performance of Europe relative to the US.

Figure 3 illustrates the simulated comparative European aggregate labor productivity against the U.S. from 1970 to 2019 in the baseline model and under the three different counterfactual exercises. It reveals that both sectoral labor productivity deceleration and labor reallocation in Europe are crucial in explaining the reversal in Europe's aggregate labor productivity convergence process. Had Europe matched the sectoral labor productivity growth rate observed in the U.S., it would have circumvented the entire phase of divergence. Furthermore, the figure illus-

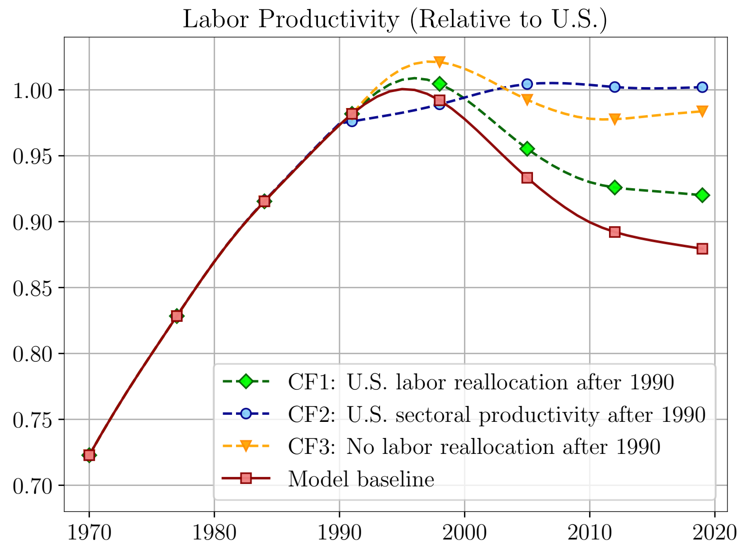

Figure 3: Aggregate labor productivity in Europe under alternative counterfactual scenarios

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 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 model's simulated annual growth rates.

trates that even if Europe had maintained its observed sectoral labor productivity deceleration, merely halting the labor reallocation process would have significantly reduced the observed divergence with respect to the U.S. Finally, on a more nuanced point, given that the U.S. completed its shift toward nonprogressive services earlier—and thus reallocated fewer workers into that sector over this period—if Europe had undergone a labor reallocation similar to that of the U.S., the disparity in Europe would be significantly less pronounced.

Although the earlier numerical exercises highlight the importance of labor reallocation in overall labor productivity, they still do not clearly demonstrate how labor reallocation, driven by shifts in sectoral labor productivity, influences aggregate labor productivity. 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, in which all observed employment share time series are the weights used to compute the counterfactual aggregate labor productivity path.[11] This type of analysis ignores, by construction, the general equilibrium effects brought by counterfactual changes in sectoral productivity.

We propose two additional sets of counterfactual experiments. First, we study again what would have happened had Europe experienced the sectoral productivity growth witnessed in

[11] 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 II: 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 4: U.S. sectoral growth rates after 1970			
`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 5: 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 4 feeds the U.S. sectoral labor productivity growth of the indicated sectors. Counterfactual 5 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. Column (3) is computed from unrounded values of columns (1) and (2); displayed entries are rounded to two decimal places, so differences may differ by 0.01 from arithmetic on displayed entries.

the U.S., now between 1970 and 2019 (counterfactual 4). Second, we use the employment shares in 2019 to compute the implied growth rate needed in each sector, one at a time, 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 5).

Table 2 shows the counterfactual results. The exercises reveal that, except for financial services in counterfactual 4, endogenous reallocation across sectors reduces the contribution of 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 reallocation, predicts an increase of 0.06 percentage points instead. The two models' predictions diverge by 0.02 percentage points in the 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 to changes in the sectoral productivity paths when one accounts for the endogenous reallocation of labor. As we demonstrate in the robustness analysis below, these results can only be obtained by disaggregating services into progressive and nonprogressive subsectors.

In counterfactual 5, 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.[12] 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 better grasp the endogenous reallocation brought about by counterfactual 5 in market services, Figure 4 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. To see why, note that a productivity increase in a single sector raises $\tilde{C}$ only modestly—the gain is shared across all sectors through the denominator of (15)—so the income-driven increase in labor demand is spread thinly, whereas the direct price effect $A_i^{\sigma-1}$

[12] These results take observed labor productivity paths as model inputs and do not depend on what drives A_i—TFP, capital deepening, or measurement conventions (see Section 3). The three-sector robustness check in Section 5.3, which does not isolate nonprogressive services, confirms that the Baumol mechanism operates across the manufacturing–services margin as well.

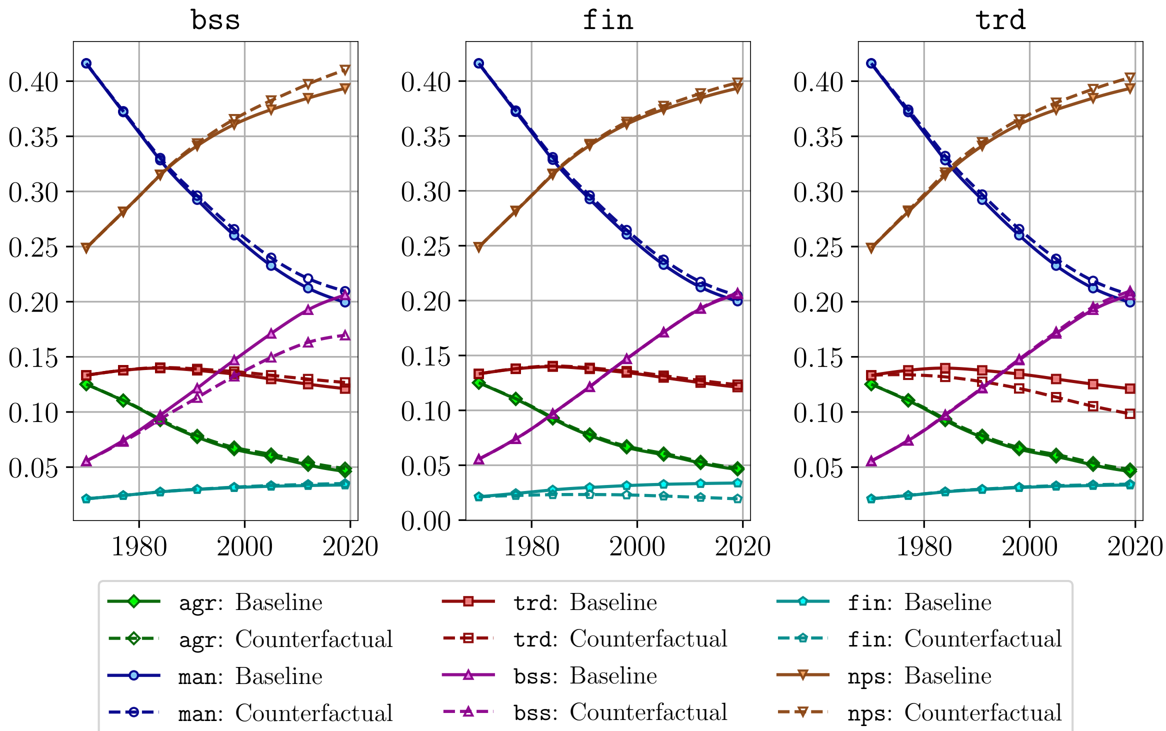

Figure 4: Labor reallocation across sectors in the baseline vs. counterfactual 5 exercises for business, financial, and wholesale and retail trade services.

Notes: Each panel plots employment shares for *all* sectors—agriculture, manufacturing, and the four service subsectors—under the baseline (color-filled markers, solid lines) and counterfactual 5 (empty markers, dashed lines). The panels differ by which sector's catch-up productivity path is imposed: business services (left), financial services (middle), and wholesale and retail trade (right).

with $\sigma < 1$ concentrates the employment reduction in the shocked sector. 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—mostly in health care and education—in the aftermath of productivity gains when the price effect dominates the income effect, consistent with Nordhaus (2008), Baumol, Blackman, and Wolff (1985), and Baumol (2012).

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 advances on overall economic performance due to the onset of Baumol cost disease resulting from these potential productivity increases. This phenomenon, as Baumol (1967) hypothesized, is an inherent attribute of the macroeconomics of unbalanced growth. Before extending our framework to account for international trade, we turn to the robustness of these findings.

5.3 Robustness

The numerical experiments above rely on a model calibrated to the U.S. structural transformation and tested against European data for the four largest economies. This subsection examines the robustness of our findings along four dimensions: (a) the choice of European aggregation, (b) applicability outside the Euro Area, (c) the level of sectoral disaggregation, and (d) the model's pricing assumption.

Great Britain, EU15, and core vs. periphery. A natural concern is whether our results are driven by Euro Area membership, given that three of the four EU4 countries adopted the euro in 1999—precisely when the productivity reversal occurred. To address this, we repeat the full analysis—shift-share decomposition, model evaluation, and counterfactual experiments—for Great Britain in isolation. The model captures the hump-shaped pattern in British aggregate labor productivity, and the counterfactual exercises yield results consistent with those for the EU4 (Online Appendix D, Figure D.1 and Table D.2). We also verify that the results extend to the EU15 as a whole and hold across the core and periphery classification of Bayoumi and Eichengreen (1992). Reassuringly, the Baumol cost disease within services is present in all aggregations, with especially pronounced effects in peripheral economies where faster catch-up growth rates amplify the labor reallocation toward nonprogressive services.

Three-sector model. Our baseline model disaggregates services into four subsectors. One might ask whether this disaggregation is essential or whether a standard three-sector model (agriculture, manufacturing, and an aggregate services sector) would deliver similar conclusions. Online Appendix C shows that while a three-sector model accurately reproduces the broad patterns of structural transformation and aggregate labor productivity, it misses the within-service reallocation that drives our main findings. In the three-sector model, endogenous labor reallocation has virtually no effect on aggregate labor productivity when services experience a counterfactual productivity increase—because labor simply remains within the single services sector. By contrast, our baseline model reveals that productivity gains in progressive services trigger substantial reallocation toward nonprogressive services, dampening the aggregate impact. The three-sector model thus overlooks precisely the mechanism that generates the Baumol cost disease within the service sector.

Model prices vs. observed price deflators. The pricing equation $p_i = 1/A_i$ follows from competitive factor markets with labor as the sole input. We assess this assumption by comparing the price inputs directly and then examining whether replacing them affects employment share predictions.

Since the model normalizes the wage to unity ($W = 1$), the model price $1/A_i$ is expressed in units of labor per unit of output. To compare on the same footing, we deflate the observed implicit price deflator $P_i = \mathrm{VA}_i/\mathrm{VA}_{Q,i}$ by economy-wide nominal value added per hour, $W = \mathrm{VA}_{\mathrm{tot}}/H_{\mathrm{tot}}$.[13] For each of the 96 sector-country pairs in the EUKLEMS 2023 database (6 sec-

[13] In the model, with labor as the sole input and competitive markets, $\mathrm{VA}_{\mathrm{tot}}/H_{\mathrm{tot}}$ equals the wage. We HP-filter ($\lambda = 100$) the level of each series and extract the trend component; both trends are then normalized to unity at the

tors $\times$ 16 countries, spanning the U.S. and all EU15 economies), we compute the time-series correlation between the normalized paths of $1/A_i$ and P_i/W. The median correlation is 0.97 (interquartile range: 0.92 to 0.99), with 78 out of 90 European pairs and all 6 U.S. pairs exceeding 0.80. Performance is comparable across the U.S. (median 0.98) and Europe (EU15 median 0.97). The approximation is weakest in business services and financial services—sectors where the gap between labor productivity and prices is largest—with mean correlations of 0.65 and 0.81 across EU15 countries; only 6 of 96 pairs fall below 0.50.

Table 3 asks whether these discrepancies matter for employment shares. We replace $A_i^{\sigma-1}$ with $(P_i/W)^{1-\sigma}$ in the employment share equation (15), holding all calibrated preference parameters fixed. The two specifications produce nearly identical predictions: the average correlation of cumulative employment share changes with data is 0.90 under both specifications (0.897 and 0.902 before rounding), and neither systematically dominates. The robustness reflects two reinforcing forces. First, the high correlations between $1/A_i$ and P_i/W documented above (median 0.97) imply that the two price inputs trace nearly identical paths. Second, whatever residual discrepancy exists is further attenuated by the low exponent ($|\sigma - 1| \approx 0.21$), which dampens the sensitivity of employment shares to the price specification. Both the relative-price and the non-homothetic income channels of the Baumol cost disease remain operative under either specification.

Table 3: Employment share predictions: model prices ($1/A_i$) vs. observed price deflators.

	Corr. with data		MAE (pp)	
Country	$1/A_i$	Observed P_i	$1/A_i$	Observed P_i
United States	0.956	0.949	1.07	1.14
Germany	0.956	0.957	1.93	1.98
France	0.863	0.879	3.36	3.01
Great Britain	0.959	0.954	2.09	2.23
Italy	0.750	0.771	4.24	3.85
Average	0.897	0.902	2.54	2.44

Notes: Each entry compares model-predicted and observed *cumulative changes* in sectoral employment shares from the base year, pooled across all six sectors and all years within each country. "$1/A_i$" uses the model's pricing equation $p_i = 1/A_i$; "Observed P_i" uses sectoral price deflators computed as nominal value added divided by real value added from EUKLEMS. Both specifications use identical calibrated preference parameters (σ, ϵ_i, Ω_i). Mean absolute errors (MAE) are in percentage points. Year-to-year employment share changes under the two specifications have a pooled correlation of 0.99.

first sample year (1995). The correlation thus captures whether the trend path of model prices tracks that of observed prices. The implicit price deflator is a well-defined accounting object at any level of sectoral aggregation, so the comparison uses the same six sectors as the model.

Table 4: Correlation between growth rates of labor productivity and total factor productivity across EU15 countries, 1996–2019.

Sector	Correlation ($\Delta \ln A_i$, $\Delta \ln \mathrm{TFP}_i$)
Agriculture (agr)	0.87
Wholesale & retail trade (trd)	0.87
Financial services (fin)	0.86
Manufacturing (NACE C)	0.64
Total economy (tot)	0.73

Notes: Each entry reports the Pearson correlation between the growth rates of sectoral labor productivity and total factor productivity, pooled across 15 EU countries and the 1996–2019 period. Labor productivity growth is the log-difference of real value added per hour from KLEMS data. TFP growth is the variable LP2TFP_I from the EUKLEMS 2023 release growth accounts, which measures the residual of labor productivity growth after removing the contribution of capital deepening. Both series are HP-filtered ($\lambda = 100$) before log-differencing. Correlations are reported for the three model sectors whose definitions correspond to a single NACE category in the EUKLEMS growth accounts, plus NACE C (manufacturing proper), which is the largest component of our broader manufacturing sector. The remaining model sectors—business services and nonprogressive services—each aggregate multiple NACE categories, and because TFP is an estimated residual it cannot be aggregated across industries without imposing additional structure on the production function.

5.4 Labor productivity and TFP

Our model takes sectoral labor productivity $A_i = Y_i/L_i$ as the exogenous driving force and does not require taking a stand on what determines it. As we argue in Section 3, under the maintained assumption that sector-specific capital shares are approximately stable over time, labor productivity is a sufficient statistic for the structural transformation channel: relative prices and employment shares depend on A_i regardless of whether differences in A_i arise from TFP, capital deepening, or other factors. One may nonetheless ask—as a separate and complementary question—what forces are behind observed sectoral labor productivity differences.

Table 4 provides an initial answer. We compute the correlation between the growth rates of sectoral labor productivity and TFP across EU15 countries over 1996–2019. Labor productivity growth is the log-difference of real value added per hour from our baseline KLEMS data; TFP growth is the variable LP2TFP_I from the EUKLEMS 2023 growth accounts, which measures the residual of labor productivity growth after removing the contribution of capital deepening (both ICT and non-ICT capital). Both series are HP-filtered ($\lambda = 100$) to focus on trend variation. Correlations are computed by pooling all country-year observations within each sector. We report results for the three model sectors that map to single NACE categories—agriculture, wholesale and retail trade, and financial services—as well as NACE C (manufacturing proper, the largest component of our broader manufacturing sector) and the total economy. The remaining model sectors each aggregate multiple NACE categories, and because TFP is an estimated residual it cannot be aggregated across industries without imposing additional structure on the production function.

The correlations range from 0.64 for manufacturing—where capital deepening has been particularly pronounced—to 0.87 for agriculture and wholesale and retail trade. The lower manufacturing correlation is consistent with the well-documented role of capital deepening in that sector, but even there the two growth rates remain substantially correlated. The somewhat lower aggregate correlation (0.73) reflects heterogeneous capital dynamics across sectors, but the sectoral correlations—the relevant unit of analysis for our model—are uniformly above 0.6. These results are consistent with Timmer et al. (2011), who document that multi-factor productivity accounts for the primary share of labor productivity differences between Europe and the U.S. A full causal analysis of what determines sectoral labor productivity is beyond the scope of this paper, but these correlations point to TFP as a promising candidate for future work on the sources of the European productivity slowdown.

6 International Trade and the Baumol Cost Disease

In this section, we examine the importance of international trade for our main findings. We are interested in understanding first how important trade is to account for the structural transformation patterns observed in the U.S and Europe. In addition, this section explores how counterfactual changes in productivity at the sector level can be augmented via trade, and how these changes affect the aggregate labor productivity. We are particularly interested in assessing whether exports in productive sectors can cure the Baumol cost disease by alleviating the stagnation predicted by the main mechanisms of our closed-economy model through income and price effects.

To account for the role of trade in the structural transformation and the relative performance of the U.S. *vis-à-vis* Europe, we use data on exports and imports at the sector level from the OECD Inter-Country Input-Output (ICIO) tables, 2021 edition, which cover 66 economies at 45 industries (ISIC Rev. 4) since 1995. The OECD ICIO classification separately identifies real estate, business services, financial services, transport, and communications—which is essential for mapping trade flows to our six-sector model, and in particular for distinguishing progressive from nonprogressive services (see Table A.1).[14] Fortunately, 1995 is when Europe reversed its catching-up trend, which allows us to study the period of European divergence using the most reliable sectoral trade data available.

Figure 5 illustrates that trade is a non-negligible force in advanced economies by plotting the ratio of exports plus imports to GDP for each sector. Although it is not exclusively a manufacturing phenomenon, manufacturing trade does represent the lion's share of international

[14] The Long-run World Input-Output Database (?, ?) extends inter-country I-O tables back to 1965 for 25 countries, but its coarser 23-sector classification (ISIC Rev. 3.1) bundles real estate with business activities (sector K: ISIC 70–74) and transport with communications (sector I: ISIC 60–64), preventing a clean mapping to our six-sector model. Earlier sources such as UN Comtrade provide gross trade flows before 1995 but lack the input-output structure needed for sectoral consistency with value-added data. Austria and Great Britain have data on sectoral net exports as early as 1968, while The Netherlands, Denmark, France, and the U.S. have data since 1972, but these data contain substantial gaps before 1995.

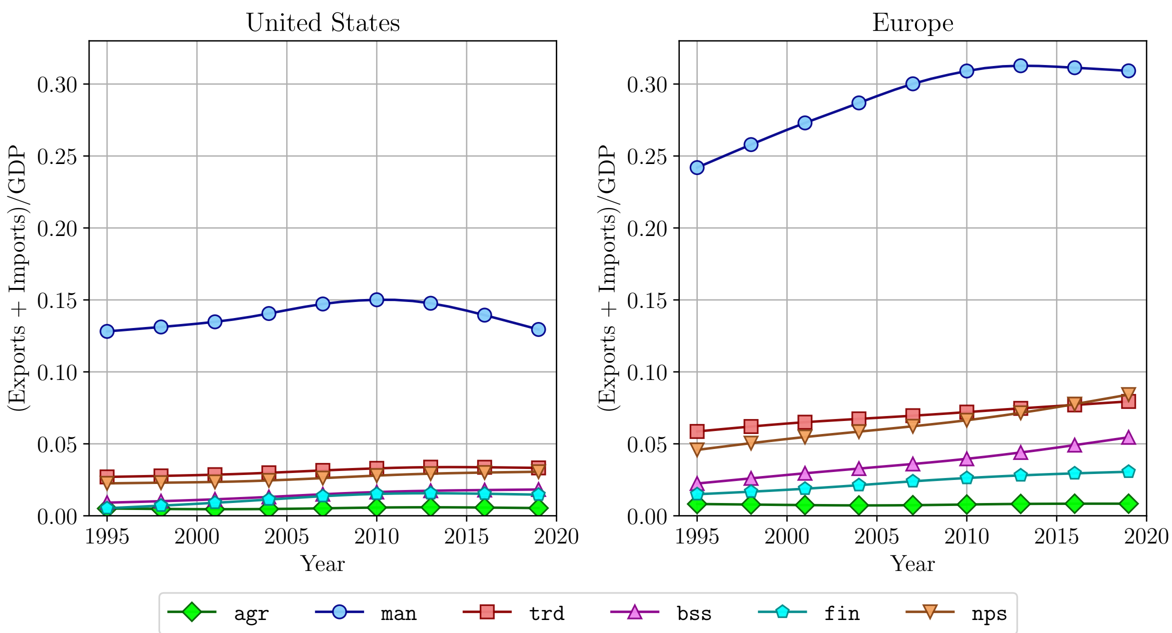

Figure 5: (Exports + Imports)/GDP at the sector level.

Notes: Source: Input-Output tables from the OECD. Europe groups the countries discussed in Section 2. The aggregations are weighted averages using the size of each country's labor market as weight.

trade in the United States and the four main European economies. Nevertheless, Figure 5 shows that trade in services is rising, particularly in `trd` and `nps`, and services as a whole in 2019 were about two-thirds of the manufacturing trade volume in the U.S. and Europe.[15] Motivated by this evidence, we extend our framework to address the quantitative importance of trade in understanding why Europe is falling behind.

6.1 Open Economy Model: The Role of Market Clearing Conditions

To account for the role of trade in structural transformation, we follow Comin et al. (2021) and Sáenz (2022), who adjust employment and value-added shares using the accounting identity $p_i c_i = p_i(y_i - xn_i)$ implied by market clearing, where xn_i denotes real net exports in sector i. We allow for international trade in final goods while keeping input markets closed (labor, in our case).

A full assessment of the role of trade would require modeling sector-level trade patterns with the "rest of the world" to capture how productivity differences shape comparative advantages and, in turn, structural transformation. We instead follow Rodrik (2016), who advocates for what he calls a "shortcut" by making one of two extreme assumptions: either taking the small-open economy route, treating prices as exogenous and letting net exports be determined endogenously, or letting domestic conditions in the home economy determine prices while treating net flows of

[15]For a careful taxonomy on the degree of openness within services, see Lee (2024).

trade as exogenously given.

The small-open-economy framework is appealing in many applications. However, in our context, it is not a suitable approximation for two reasons. First, in a small open, price-taking economy, the mapping from productivity to sectoral price differences would be lost, and with it the price-side mechanism underlying structural transformation (see Sáenz (2022), Section 3.6, for a detailed discussion). Second, our objective is to understand the productivity paths of Europe vis-à-vis the United States at advanced stages of development—large, post-industrial economies with expanding service sectors.

Instead of taking the net export flows in its entirety as exogenous, we adopt a mild version of Rodrik's shortcut. While we continue treating import flows (quantities) as given, we allow export quantities to respond to domestic productivity changes. This reduced-form assumption partially captures the key link between productivity and export performance emphasized in the trade literature—namely, that productivity improvements lead to export expansion and sectoral reallocation—while abstracting from an explicit modeling of sector-level domestic and foreign market shares.

Although this framework cannot trace cross-country interdependence via comparative advantages at the sector level, it does allow productivity changes to affect domestic employment through sectoral labor demand in export markets. In other words, this reduced-form export specification allows us to trace the effects of sectoral productivity gains via trade, and how these gains shape the aggregate productivity dynamics.[16]

In an open-economy model, the market-clearing condition for sectoral output is

$$y_i = c_i + xn_i, \tag{16}$$

where $xn_i = x_i - m_i$ denotes net exports. We assume that import flows are exogenous, while exports evolve according to

$$x_i = x_{0,i} A_i^{\xi_i}, \tag{17}$$

where ξ_i is the sector-level elasticity of exports with respect to productivity. This parameter captures, in reduced form, the net effect of productivity on export demand; for all estimated sectors, $\xi_i > 0$ (an unconstrained empirical finding), so higher productivity increases foreign demand. We refer to (17) as the *endogenous export* specification to distinguish it from the fully exogenous case where net exports do not respond to productivity; it is a reduced-form device

[16] The key technical obstacle to a fully structural approach is that the nhCES aggregator $\tilde{C}$ is implicitly defined and enters each sector's demand with a distinct income elasticity ϵ_i, making expenditure shares depend jointly on the full price vector and aggregate real income—unlike standard CES, where expenditure shares depend only on relative prices. In a multi-country trade model this coupling is consequential: changes in trade alter income, which shifts $\tilde{C}$ and reallocates demand across sectors, feeding back into trade—a fixed-point problem whose dimensionality scales steeply with the number of sectors and countries. Existing open-economy models of structural transformation manage this either by working at coarser (three-sector) aggregation or by adopting demand specifications—such as Stone-Geary—whose income effects are explicit but level off at high incomes, making them less suited for the advanced, post-industrial economies in our sample. Our identification requires both the persistent income effects that nhCES delivers and the six-sector disaggregation needed to isolate which service sectors drive the EU–US divergence.

that disciplines the first-order productivity–export link, not a structural trade model with cross-country equilibrium.

Combining (16) with (5), (8), and (17) yields

$$l_i = \underbrace{\frac{\Omega_i}{A_i}\left(\frac{p_i}{E}\right)^{-\sigma}\tilde{C}^{\epsilon_i}}_{\text{Domestic demand}} + \underbrace{x_{0,i}A_i^{\xi_i-1}}_{\text{Exports}} - \underbrace{\frac{m_i}{A_i}}_{\text{Imports}} . \tag{18}$$

Equation (18) decomposes labor demand in sector i into three components. In addition to the domestic demand forces present in the closed-economy framework, (18) shows how trade affects sectoral labor demand.

The second term captures *export-related labor demand*. An increase in productivity has two opposing effects on labor used to serve foreign markets. On the one hand, higher productivity reduces the amount of labor required to produce a given quantity of exports. On the other hand, it raises export demand through the term $A_i^{\xi_i}$. The quantity channel dominates whenever $\xi_i > 1$, in which case higher productivity increases labor demand in the export sector.

The third term captures the exogenous flow of *imports*. Since imports substitute for domestic production, they reduce sectoral labor demand. However, the magnitude of this reduction depends on productivity. In more productive sectors, a given volume of imports displaces less labor, as fewer workers are required per unit of output.

Taken together, the last two terms illustrate how productivity determines the magnitude and sign of the impact of net exports on sectoral labor demand. Productivity growth can foster job creation in export-oriented sectors when the expansion of foreign demand outweighs the labor-saving effect of higher efficiency. At the same time, sectors that are net importers experience a decline in labor demand, with the magnitude of this decline depending on their productivity level: less productive sectors lose more labor for a given volume of imports.

It is worth highlighting an asymmetry in the export channel that becomes salient in the counterfactual analysis below. Real export quantities, $x_{0,i}A_i^{\xi_i}$, are unambiguously increasing in productivity since $\xi_i > 0$. Yet the labor absorbed by export production—the ratio of quantities to productivity, $x_{0,i}A_i^{\xi_i-1}$—can either rise or fall with A_i depending on whether ξ_i exceeds or falls below unity. When $\xi_i < 1$, higher productivity reduces the labor absorbed by exports even as real quantities expand: the price decline more than offsets the quantity expansion, and export value added falls. This creates a trade-mediated reinforcement of the Baumol cost disease. Conversely, when $\xi_i > 1$, the export channel partially offsets the Baumol mechanism by sustaining labor demand from foreign markets. The open economy thus introduces an additional propagation channel absent from the closed-economy framework: counterfactual productivity changes in a sector propagate not only through domestic income and price effects but also through the export margin, with the sign of the trade effect determined by ξ_i.

Importantly, as long as imports and domestic production coexist, an arbitrage condition implies that domestic labor productivity determines the domestic price at which imports are valued.[17]

Dividing (18) by its sum across sectors implies the following structural transformation equation for the open-economy model:

$$\frac{l_i}{L} = \frac{\Omega_i \tilde{C}^{\epsilon_i} A_i^{\sigma-1} + E^{1-\sigma}\Theta_i}{\sum_{j=1}^{I}\left(\Omega_j \tilde{C}^{\epsilon_j} A_j^{\sigma-1} + E^{1-\sigma}\Theta_j\right)}, \tag{19}$$

where $E = \left[\sum_{i=1}^{I} \Omega_i A_i^{\sigma-1} \tilde{C}^{\epsilon_i}\right]^{\frac{1}{1-\sigma}}$ and $\Theta_i = \frac{p_i xn_i}{E} = \frac{x_{0,i} A_i^{\xi_i - 1} - m_i/A_i}{E}$.

The difference between (15) and (19) is in the role of net exports (as a share of total expenditures) in the structural transformation, represented by Θ_i.

Note that (19) is flexible to yield Rodrik's (2016) original shortcut. Instead of using (17) to discipline exports, one can simply hold the sectoral net exports xn_i at their observed data values throughout the sample period, and trade flows would enter in the labor demand equation as $\frac{xn_i/A}{E}$ instead of Θ_i term in equation (19) above—and these trade flows would not respond to counterfactual productivity changes. This provides a lower bound on the trade response: the exogenous specification attributes zero net-export adjustment to counterfactual productivity changes.

6.2 Quantitative Assessment

Our quantitative approach proceeds as follows. First, we adopt the parameterization from the closed-economy framework to discipline income and price effects, and choose the CES weights to match the initial calibration year, 1995. Alternatively, one could apply our calibration algorithm to recover the preference parameters using data starting in 1970. We prefer the closed-economy parameterization for income and price effects because trade data before 1995 contain substantial gaps, and interpolating them would introduce measurement error into the calibration.

We impose sector-level trade balance only in the initial period. We parameterize ξ_i by matching (17) to sectoral real export growth between 1995 and 2019 endpoints, and choose $x_{0,i}$ to match initial sectoral exports as a share of expenditure, consistent with the normalization of A_i in the initial period. Given the assumption of initial trade balance, $x_{0,i}$ also determines the initial level of imports.[18] As with the closed-economy framework, the model is estimated for each country

[17] In models where productivity determines trade patterns endogenously, a net-exporting sector's labor demand is ultimately disciplined by the same productivity forces that make it competitive abroad, while a net-importing sector experiences a substantial contraction in labor demand precisely because of its relatively low productivity. See Uy, Yi, and Zhang (2013), Swiecki (2017), Cravino and Sotelo (2019), Sposi (2019), and Sposi, Yi, and Zhang (2024) for open-economy models of structural change in which trade patterns arise endogenously.

[18] The initial trade balance is a normalization that pins down $x_{0,i}$ and $m_{0,i}$ from the same moment; relaxing it to match observed initial sectoral net exports would shift the level of the trade terms Θ_i in (19) but not the dynamics driven by ξ_i and the productivity paths. Moreover, the exogenous-trade specification already provides a direct test of this closure: it feeds the *entire observed time path* of sectoral net exports into the model, thereby matching observed initial (and subsequent) trade imbalances by construction. Since the exogenous- and endogenous-trade results are virtually identical (19.7% vs. 19.5% of the gap explained), the initial balance assumption is innocuous for the counterfactual conclusions.

separately, and the European results are employment-weighted averages of country-level outcomes.

Table 5 reports the estimated export elasticities for the U.S. and EU4. Two sectors have $\xi_i < 1$ at the EU4 level: agriculture and manufacturing. For these sectors, real export quantities grow with productivity, but the price decline more than offsets the quantity expansion, so that export value added—and thus export-related labor absorption—falls. For all service sectors, $\xi_i > 1$ and the quantity channel dominates. The large elasticity in nonprogressive services reflects rapid export growth from a negligible base in 1995.

Table 5: Export elasticity parameters (ξ_i).

	agr	man	trd	bss	fin	nps
U.S.	1.32	0.83	1.76	2.17	3.25	7.36
EU4	0.74	0.91	1.26	2.59	2.01	9.28

Notes: Each ξ_i is estimated by matching equation (17) to sectoral real export growth between 1995 and 2019 endpoints. The EU4 values are computed from employment-weighted aggregate exports across the four main European economies.

To compute the equilibrium paths, we feed into the model the observed time series for sectoral productivity and real imports for each sector. To account for the income effects generated by trade, we modify (E.3) by replacing $\frac{l_i}{l_m}$ with $\frac{p_i(y_i - xn_i)}{p_m(y_m - xn_m)}$, and by setting aggregate expenditure to $E = \sum_{i=1}^{I} p_i c_i = \text{VA}_{\text{tot}} - \sum_{i=1}^{I} p_i xn_i$, where $xn_i = x_i - m_i$ denotes real net exports (positive for net exporters), in the computation of the non-homothetic CES aggregator $\tilde{C}$.

Figure 6 compares the main predictions of the closed and open economy models since 1995. Note that despite allowing trade to alter the labor demand in each sector, the predictions for the structural transformation are remarkably similar. The closed and open economy model predictions are both close to the 45-degree line in the left panel (which plots predicted versus actual sectoral employment shares), with only minor differences across sectors. The right panel shows that both models can replicate the dramatic drop in aggregate productivity since 1995, with virtually identical predictions. Figure 6 implies that our closed-economy framework, despite abstracting from trade, captures the structural transformation and aggregate productivity dynamics well. The main reason for the similarity is that the trade terms Θ_i in equation (19) are quantitatively small relative to the domestic demand component: even in manufacturing, the sector with the largest trade volumes, observed net exports as a share of expenditure remain modest (Table 6, Panel B).

However, different frameworks address different questions. Given the success of our open-economy model in explaining the structural transformation in Europe, we are now in a position to assess whether it is plausible for Europe to export its way out of the Baumol cost disease.

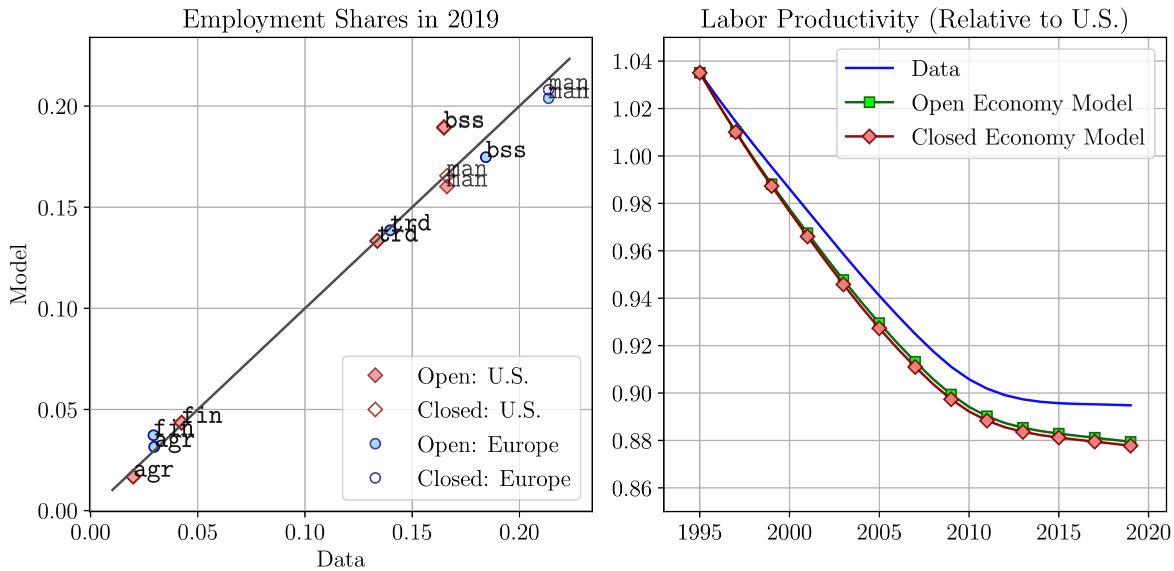

Figure 6: Closed- and open-economy model predictions vs. data of aggregate labor productivity and sectoral employment shares in 2019 for Europe and the U.S.

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 KLEMS. The initial levels of the time series in the right panel start at the labor productivity gap from the OECD in 1995. From this level, the time series from KLEMS are constructed with the observed annual growth rates. We leave out nps from the plot since it is a residual by construction. The predictions for this sector are close to the 45-degree line for the U.S. and Europe as well.

6.3 Can Trade Cure the Baumol Cost Disease?

To answer this question we proceed in two steps. First, we repeat counterfactual 4—feeding U.S. sectoral productivity growth into the European economy—in the open-economy framework with endogenous exports, to test whether the identification of key sectors is robust to the trade channel. Second, for each sector, we compute the net exports needed to close the aggregate productivity gap with the U.S. entirely, and assess whether these magnitudes are plausible.

Table 6 presents the results. A clear dichotomy emerges from the estimated export elasticities in Table 5. Recall that at the EU4 level, agriculture and manufacturing are the only sectors with $\xi_i < 1$, so that export value added—and thus export-related labor absorption—falls with productivity in these sectors. Agriculture is quantitatively negligible (accounting for only 1.1 of the 19.5 percentage points in Panel A), so the key sector where this mechanism operates is manufacturing ($\xi_{\mathtt{man}} = 0.91$ for EU4). It is worth noting that ξ_i is not a structural trade elasticity; it is a reduced-form elasticity of real value-added export quantities with respect to domestic labor productivity, estimated by matching equation (17) to sectoral real export growth between 1995 and 2019 endpoints. The estimate $\xi_{\mathtt{man}} < 1$ reflects the empirical fact that European manufacturing real exports grew more slowly than manufacturing labor productivity over this

Table 6: Open-economy counterfactuals with endogenous exports, 1995–2019.

	agr	man	trd	bss	fin	nps
Panel A: Counterfactual 4 — % of EU–US gap explained						
	1.1	4.7	3.7	7.6	1.1	1.3
Panel B: Trade cure — net exports (% of expenditure)						
Observed (2019)	−0.27	−0.25	0.17	0.28	0.12	−0.37
Exogenous trade	0.91	4.07	5.19	10.80	1.42	11.54
Endogenous trade	0.58	4.85	1.87	2.26	0.49	−5.85

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. Export elasticities ξ_i are reported in Table 5. In Panel A, each column is a separate experiment that feeds U.S. sectoral labor productivity growth from 1995 onward into the indicated sector and reports the percentage of the EU–US aggregate productivity gap explained under the open-economy model with endogenous exports. The total (19.5%) is the arithmetic sum of the one-sector-at-a-time experiments. Since each experiment perturbs only one sector's productivity, the non-linearity of the GE model is limited to the interaction between the shocked sector and the endogenous reallocation response; the arithmetic sum is therefore an approximation whose accuracy depends on the degree of cross-sector interaction. The robustness of this approximation is supported by the near-identity of totals across trade specifications: the exogenous-trade model yields 19.7% vs. 19.5% under endogenous trade. Panel B computes, for each sector separately, the level of net exports (as a percentage of total expenditure) needed to equalize European aggregate labor productivity to the U.S. by 2019. Each column in Panel B represents a separate experiment. Under exogenous trade, all non-cure sectors' net exports remain at their observed 2019 values. Under endogenous trade, non-cure sectors' exports respond to observed productivity via the estimated ξ_i, while imports remain at observed levels.

period. Manufacturing is the most globally traded sector and faces the most intense international competition; productivity gains in a sector exposed to rising import penetration from lower-cost producers need not translate one-for-one into export expansion if market share is simultaneously eroded. In service sectors, where trade barriers remain higher and international competition was expanding from a smaller base, export quantities responded more than proportionally to domestic productivity gains. For all service sectors, $\xi_i > 1$ and the quantity channel dominates, with EU4 elasticities ranging from 1.26 in wholesale and retail trade to 9.28 in nonprogressive services. The large elasticity in nonprogressive services reflects rapid export growth from a small base—services trade in health care, education, and public administration was negligible in 1995 and grew substantially over the sample period, amplifying the estimated ξ_i. As shown below, the core counterfactual results do not depend on this outlier: nonprogressive services account for only 1.3 of the 19.5 percentage points in Panel A. More broadly, the near-identity of the total gap explained under endogenous trade (19.5%) and exogenous trade (19.7%) implies that the results are robust to the precise values of ξ_i, since both specifications—one with no export response and one with the full response estimated from the data—deliver virtually the same result. Since the entire export channel shifts the total by only 0.2 percentage points, the precise value of any individual ξ_i, including the outlier $\xi_{\texttt{nps}}$, is immaterial for the counterfactual 4 identification.

Panel A presents the open-economy counterfactual 4 results. Although the trade analysis covers 1995–2019 (reflecting trade data availability) while the closed-economy counterfactual spans 1970–2019, the sectoral composition of the gap is consistent across both exercises: progressive services—wholesale and retail trade, business services, and finance—account for nearly two-thirds of the total gap explained (12.4 of 19.5 percentage points), with business services alone responsible for 7.6 percentage points. The total gap explained under endogenous trade is 19.5%. For comparison, the same exercise under exogenous trade—holding net exports at their observed values—yields 19.7%, with a sector-by-sector average absolute difference of 0.4 percentage points. Since the results are virtually identical under no export response (exogenous trade) and under the full response estimated from the data (endogenous trade), the identification of key sectors is robust to the treatment of the export channel. The endogenous trade channel does sharpen the sectoral composition: manufacturing's contribution is dampened by the $\xi < 1$ export response (from 5.6 percentage points under exogenous trade to 4.7), because higher manufacturing productivity erodes export labor demand ($x_{0,i} A_i^{\xi_i - 1}$ falls when $\xi_i < 1$), whereas the exogenous specification holds net exports fixed and thus does not penalize labor demand through this channel. Conversely, business services' contribution is amplified by the $\xi > 1$ response (from 6.5 to 7.6 percentage points), as productivity-driven export expansion sustains labor demand in that sector. The central finding that Europe's productivity shortfall originates in service sectors is robust to the trade specification.

Panel B addresses the trade cure. The experiment proceeds as follows. For each sector i separately, we solve for the counterfactual net export level—as a fraction of total expenditure—in that sector that equalizes European aggregate labor productivity to the U.S. by 2019. Sectoral productivity paths and import levels are held at their observed values throughout; only the net export level in the cure sector is adjusted. The two trade specifications differ in how non-cure sectors' trade flows are treated. Under exogenous trade, all non-cure sectors' net exports remain at their observed 2019 values. Under endogenous trade, non-cure sectors' exports respond to observed productivity via the estimated export elasticities in equation (17), while imports remain at observed levels. Each column is an independent exercise, and the results are not additive across sectors due to general equilibrium interactions.

This distinction explains why the required net export levels differ across the two specifications. Under endogenous trade, the export responses of non-cure sectors—particularly in high-ξ service sectors—already generate additional labor demand that partially offsets the Baumol reallocation effect. As a result, the net export adjustment needed in the cure sector is smaller. For business services, the counterfactual net exports fall from 10.80% of expenditure under exogenous trade to 2.26% under endogenous trade, compared with an observed level of 0.28%. For wholesale and retail trade, the required adjustment falls from 5.19% to 1.87%, compared with 0.17% observed. The mechanism reduces the *residual net-export adjustment* relative to the exogenous-trade benchmark—not the Baumol cost disease itself: because productivity-driven exports in high-ξ sectors already absorb labor into those sectors, the additional trade surplus needed to close the gap is a fraction of what would be required if exports did not respond to productivity. Nonprogressive services is an explicit exception to this pattern. Under endogenous trade, the non-cure service sectors—all with $\xi_i > 1$—generate substantially more export labor demand in progressive sectors than under the exogenous specification. This additional labor absorption into productive sectors closes much of the aggregate gap before the cure sector contributes at all. For nonprogressive services the combined effect is large enough that the cure requires *reducing* net exports—from $+11.54\%$ of expenditure under exogenous trade to -5.85% under endogenous trade—to prevent aggregate productivity from overshooting the U.S. target. In other words, productivity-driven exports in high-ξ service sectors already do the work that would otherwise fall on nonprogressive trade, and the cure must compensate by shrinking nonprogressive net exports.

The exception is manufacturing, where $\xi < 1$. Because higher manufacturing productivity reduces export value added, the trade cure must compensate not only for the domestic Baumol effect but also for the erosion of export labor demand. Europe would need net exports of approximately 4.85% of expenditure, from an observed deficit of -0.25%—a swing of over 5 percentage points.[19] This required adjustment is implausibly large. Moreover, this conclusion does not hinge on the precise value of $\xi_{\texttt{man}}$. Even if $\xi_{\texttt{man}}$ were modestly above one, the required net-export swing would remain several percentage points—the dominant force is the sheer magnitude of the productivity gap that manufacturing trade must single-handedly compensate, not the sign of the export-labor-demand response. The $\xi < 1$ estimate amplifies the required adjustment but is not its source. More broadly, the near-identity of the total gap explained under endogenous trade (19.5%) and exogenous trade (19.7%) in Panel A demonstrates that the entire export channel—including the sign of $\xi_{\texttt{man}}$—shifts the aggregate results by only 0.2 percentage points.

Two conclusions emerge. First, the endogenous export channel does not overturn the Baumol cost disease. The required trade adjustments in manufacturing remain implausibly large, and even in service sectors, the residual adjustments—while substantially reduced—are non-trivial. Under the trade specifications considered here, it is not plausible that Europe exports its way out of the Baumol cost disease. This conclusion is robust to the modeling choices: it holds under both exogenous trade (observed net exports, no response to productivity) and endogenous trade (export quantities responding via ξ_i), regardless of whether the initial period imposes sectoral trade balance or matches observed net exports, and it does not rely on any particular value of ξ_i (since the total gap explained differs by only 0.2 percentage points across specifications). The implausibility is structural—it reflects the sheer magnitude of the trade surplus that any single sector would need to generate to compensate for the economy-wide productivity shortfall,

[19] Consider the case of Germany, the largest European manufacturing exporter, with manufacturing net exports of about 1.4% of aggregate expenditure by 2019 (from our calibrated data). Under the EU4-average trade cure of 4.85%, the German manufacturing sector would need to more than triple its net export position; the Germany-specific requirement is even larger.

not the details of the trade closure.[20] While the total gap explained is invariant to the trade specification, the sectoral composition is not: endogenous trade dampens manufacturing's contribution (from 5.6 to 4.7 percentage points, because $\xi_{\texttt{man}} < 1$ erodes export labor demand) and amplifies business services' contribution (from 6.5 to 7.6 percentage points, because $\xi_{\texttt{bss}} > 1$ sustains it). If anything, allowing exports to respond to productivity strengthens the paper's central finding that progressive services—not manufacturing—are the key sectors driving the EU–US divergence. Second, the endogenous trade channel reveals that trade is not merely an external lever but an endogenous component of the structural transformation mechanism. For service sectors with $\xi > 1$, productivity improvements simultaneously generate labor reallocation through domestic demand *and* labor retention through export demand. The relevant policy question is not whether Europe can generate sufficient trade surpluses but whether the productivity–export channel in progressive services can be strengthened.

7 Conclusion

This paper underscores the importance of structural transformation in shaping aggregate productivity growth even in the 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 heterogeneity within services generates a Baumol cost disease, whereby productivity gains in progressive sectors are partially offset by endogenous labor reallocation toward less productive services, despite the strong income effects that favor progressive sectors. Furthermore, counterfactual experiments in our open-economy extension show a limited potential for trade to realistically mitigate the Baumol cost disease.

Quantitatively, disregarding endogenous labor reallocation would overestimate the counterfactual gains from matching U.S. productivity in market services by 30–50%, and for financial and trade services the aggregate EU–US gap would persist at 42% and 32% even under catch-up productivity growth. These results are robust across alternative European aggregations, a three-sector model, and alternative price specifications, and the open-economy extension confirms that the identification is virtually unchanged across trade specifications (19.5% of the gap explained under endogenous trade vs. 19.7% under exogenous trade, both for 1995–2019).

Our results indicate that the divergence between market and nonprogressive services may hinder the potential for overall economic performance through productivity gains in market ser-

[20] A structural multi-country trade model with endogenous terms-of-trade effects would further discipline large counterfactual export expansions: deteriorating terms of trade would raise the required export *quantities* even further, reinforcing rather than overturning the implausibility result. Our reduced-form approach is thus conservative in this regard.

vices, since our counterfactual exercises show that endogenous labor reallocation substantially dampens the aggregate impact of sector-specific productivity improvements. As Rodrik (2013) documents, manufacturing has historically been a source of unconditional convergence. However, our results suggest that the within-services Baumol mechanism generates a persistent drag on aggregate productivity in advanced economies, so that manufacturing convergence alone may be 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 may constitute the dominant channel of the Baumol cost disease in post-industrial economies.

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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 nonprogressive 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. The splicing procedure uses growth rates from earlier vintages rather than levels, so the 1995 splice point does not introduce a level discontinuity. Importantly, the mid-1990s productivity divergence between Europe and the U.S. is present in the unspliced OECD aggregate series (left panel of Figure 1), which is a single internally consistent source over the full 1970–2019 period. The model's ability to match the timing of the turning point is thus not an artifact of the sectoral splicing. We classify our sectors as aggregates of ISIC Rev. 3 and ISIC Rev. 4 industries as shown in Table A.1. We classify industries with low labor productivity growth into nonprogressive services. In Figure B.1 in Section B, we show that labor productivity growth is insignificant in the nonprogressive 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	K
`ser` `trd`	Wholesale and retail trade services	G	G
`ser` `nps`	Nonprogressive 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 rates and employment shares are very similar for EU4 and EU15, so the choice of European aggregation does not drive the descriptive facts.

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, nonprogressive 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 nonprogressive services are in fact almost nonexistent. The only sector in which labor productivity growth is less than total labor productivity growth is nonprogressive 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 nonprogressive services sector is specifically affected by the Baumol cost illness, which slows the growth of total labor productivity as its relative size rises.

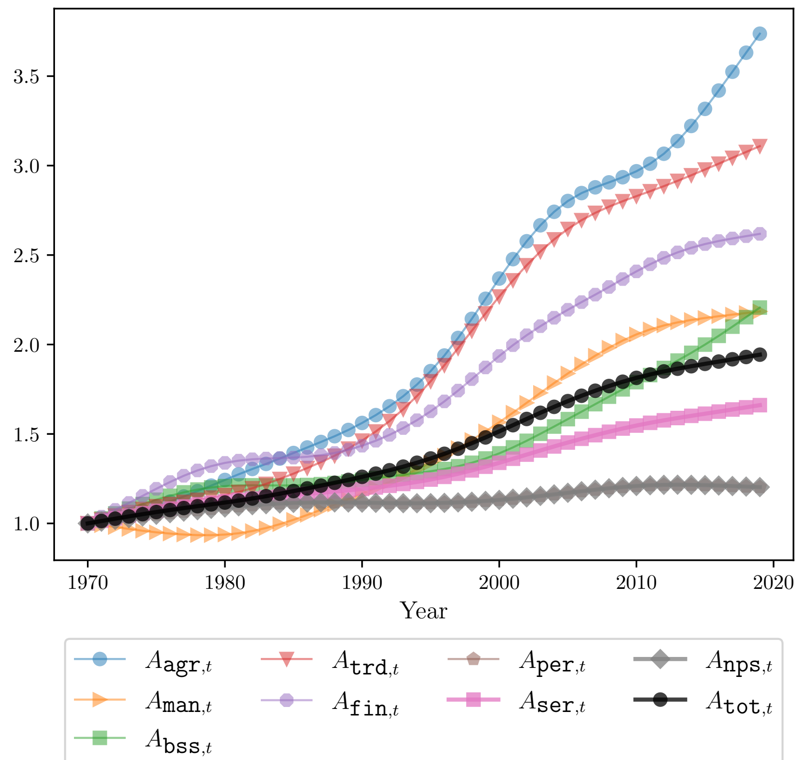

Figure B.1: U.S. sectoral labor productivity growth from 1970 to 2019.

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.

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

Table B.2 presents the shift-share decomposition for the 1995–2019 period. The "Total" row reports the annualized growth rate of the sectorally reconstructed aggregate, $A_t = \sum_i A_{it}s_{it}$, computed from KLEMS sectoral data using equation (1). This measure differs from the direct OECD and KLEMS aggregates reported in Table B.1 (1.60% and 1.58% for the U.S., respectively) because the sectorally reconstructed aggregate is built from sectoral real value added in constant local-currency prices, whereas the direct aggregates use economy-wide deflators and, in the OECD case, PPP-adjusted GDP per hour. The same distinction applies to Table 1 in the main text. The results are similar to those obtained for the entire 1970–2019 period. 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 B.2: 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	0.19	0.49	-0.09	-0.45
`man`	0.24	0.11	0.63	0.82	-0.39	-0.71
`ser`	1.70	1.06	1.52	0.61	0.18	0.45
`bss`	0.66	0.48	0.46	0.06	0.20	0.42
`fin`	0.14	0.00	0.14	0.03	0.00	-0.03
`trd`	0.55	0.28	0.79	0.40	-0.24	-0.12
`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 1995 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 Results from a Three-Sector Model

When we aggregate services, we miss the diversity among services in terms of labor productivity growth and labor reallocation. In terms of productivity, some services exhibit high growth in labor productivity, and others exhibit low growth in labor productivity. As demonstrated in Table B.1, certain services, such as wholesale and retail trade, financial, and business services, exhibit significant labor productivity growth, whereas others show very slow increases in productivity. In terms of labor reallocation, nonprogressive services see an increase in their employment share over time, whereas the situation is more complex for progressive ones. Employment shares in wholesale and retail trade and financial services remain stable or decrease slightly, while the employment share in business services increases over time.

To formally test the implications of abstracting from this rich heterogeneity in our analysis, in this section, we apply our structural transformation theory to a three-sector economy consisting of agriculture, manufacturing and a single aggregated sector for services. The goal of this application is to identify what we overlook in the analysis when services are not disaggregated.

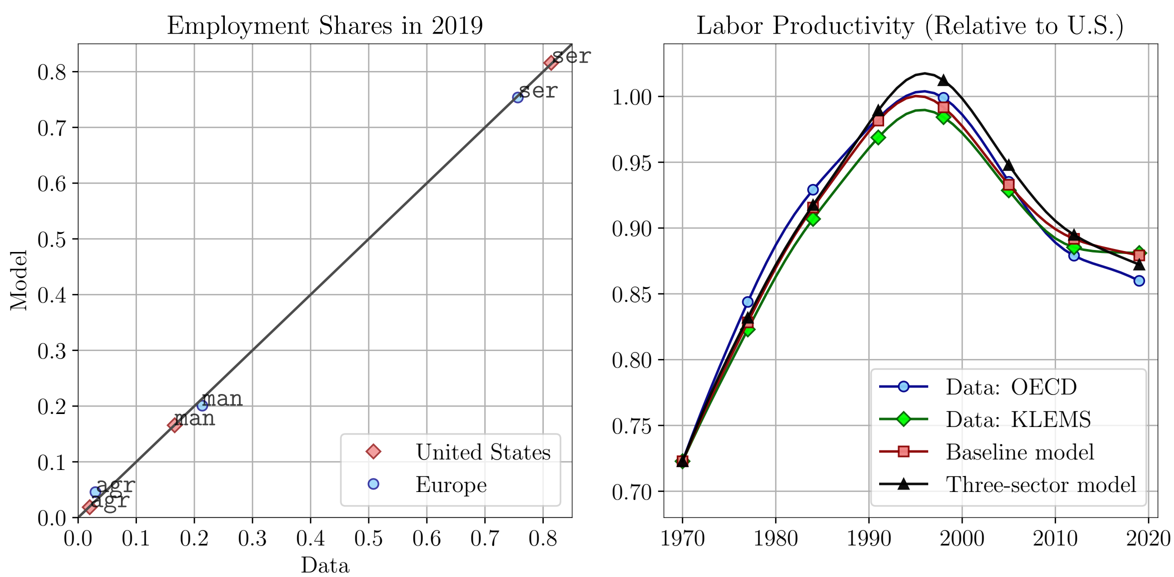

Figure C.1: Model predictions vs. data of aggregate labor productivity and sectoral employment shares in 2019 for Europe and U.S.

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. We leave out `ser` from the plot since it is a residual by construction. The predictions for this sector are close to the 45-degree line for the U.S. and Europe as well.

We begin by exploring if the three-sector model can accurately represent labor reallocation and aggregate labor productivity in both Europe and the U.S. Figure C.1 examines the theory using baseline and three-sector models. The left panel, similar to the main text, illustrates a comparison of employment share predictions for the U.S. and Europe. Specifically, it plots a scatter diagram for observed sectoral employment shares in 2019 against our three-sector model predictions for the same year, alongside a 45-degree reference line originating from the axes' intersection. The right panel of Figure C.1 contrasts baseline and three-sector model predictions concerning the aggregate labor productivity gap between the U.S. and Europe. The analysis reveals that the three-sector model effectively explains the convergence and subsequent divergence in Europe's aggregate labor productivity compared to the U.S. This demonstrates that our structural transformation theory is versatile enough to accommodate various levels of sectoral aggregation while capturing key patterns in labor reallocation and aggregate labor productivity growth.

Next, we conduct the sectoral counterfactual analyses, specifically counterfactuals 4 and 5, using our three-sector model. Table C.1 displays the results. In counterfactual 4, the outcomes for agriculture and manufacturing are as anticipated, while those for services differ. Our analysis indicates that endogenous reallocation has no adverse impact on aggregate labor productivity when comparing the model prediction with the shift share analysis in services. This finding aligns with the main text's examination of nonprogressive services but contrasts with our observations in progressive services. In the baseline model, when progressive services exhibit increased productivity, labor shifts from these sectors to nonprogressive sectors, negatively affecting aggregate labor productivity growth. The three-sector model overlooks this crucial result. Lastly, in the catch-up counterfactual exercise, enhancing labor productivity growth in services would only slightly boost aggregate labor productivity (model: 0.16 versus dynamic shift-share: 0.76). The large negative difference in column (3) reflects the endogenous reallocation triggered by the counterfactual productivity increase: because services has the highest income elasticity of demand ($\epsilon_{\texttt{ser}} = 1.2$), the income gains from higher services productivity raise the employment share of services *relative to the baseline scenario*, drawing labor out of agriculture and manufacturing—sectors with higher productivity levels—and thereby dampening the aggregate productivity gain relative to the fixed-employment-share benchmark. This deviation is not observed in the baseline model, where changes in individual service subsectors lead to labor reallocation not only to nonprogressive services but also to some progressive services, particularly business services, which exhibit the highest income elasticity of demand across all sectors ($\epsilon_{\texttt{bss}} = 1.35$). In sum, while the three-sector model is able to account for the stylized facts, it misses mechanisms of labor reallocation within services that occur between progressive and nonprogressive services that have an important role in shaping labor productivity growth.

Table C.1: Numerical experiments using the three-sector model: 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	Dynamic shift-share	(1) - (2)
	(1)	(2)	(3)
Counterfactual 4: U.S. sectoral growth rates after 1970			
`agr`	-0.12	-0.08	-0.04
`man`	-0.14	-0.15	0.02
`ser`	0.04	0.04	-0.00
Counterfactual 5: Implied "catch-up" sectoral growth rates			
`agr`	0.58	0.76	-0.18
`man`	0.53	0.76	-0.23
`ser`	0.16	0.76	-0.59

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 4 feeds the U.S. sectoral labor productivity growth of the indicated sectors. Counterfactual 5 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. Column (3) is computed from unrounded values of columns (1) and (2); displayed entries are rounded to two decimal places, so differences may differ by 0.01.

D Robustness of Results to the Definition of Europe

In this section, our aim is to validate whether our main findings, using EU4 as a European proxy, are valid across different regions and countries within the continent. Therefore, we revisit the primary analysis, focusing on the UK, EU15, and both core and peripheral EU nations.[21] The comparison involving Great Britain helps determine whether the EU4 results are mainly driven by Euro Area countries, as three out of the four EU4 nations joined the Economic and Monetary Union in 1999. By examining the EU15, we assess whether our results are unique to these four major countries or have wider applicability. Finally, analyzing the core versus peripheral nations enables us to test the robustness of our findings in relation to more peripheral countries, which have diverged more significantly since the late 1990s. As shown below, it becomes clear that the Baumol cost disease identified within the services sector using EU4 in the main text is consistent across various aggregations of regions in Europe, including those that fall outside of the EU4.

D.1 EU4 vs. EU15 vs. Great Britain

D.1.1 Shift-share Decomposition

In Table D.1, we show the results for the shift share and sectoral decompositions for all EU15 countries, and for Great Britain in isolation, as opposed to just the big four European economies. Comparing this table with Table 1 reveals that the patterns for the EU15 closely mirror those of the EU4. However, there are notable distinctions for Great Britain. In Great Britain, both the shift and growth effects are smaller compared to EU4 and EU15. Another significant contrast is that while the EU4 and EU15 experienced lower labor productivity growth in business services compared to the US, Great Britain saw its labor productivity growth in this sector double that of the US during the 1970–2019 period.

D.1.2 Test of the Theory

In Figure D.1, we demonstrate that our model accurately captures key elements of labor reallocation in Europe, be it considering the entire EU15 or focusing solely on Great Britain. Crucially, the model accurately gets the timing of the reversal in aggregate labor productivity convergence with the US for both the EU15 and Great Britain right. However, it quantitatively underestimates the increase in labor productivity for Great Britain, mainly because it undervalues the labor share in business services, which experienced substantial productivity improvements.

[21] The first attempt to detect a core-periphery pattern in the run-up to the EMU was that of Bayoumi and Eichengreen (1992). They evaluated the degree of synchronization between supply and demand shocks using data from 1963 to 1989 and the classic Aggregate Demand-Aggregate Supply framework. According to their work, supply-side shocks are highly associated in the core (Germany, France, Belgium, Netherlands, and Denmark) and less so in the periphery (Greece, Ireland, Italy, Portugal, Spain and the UK). We follow this same classification of the core and periphery countries in our analysis in this section.

Table D.1: Shift-share analysis and sectoral decomposition for EU1-15 and Great Britain in the 1970–2019 period.

	LP growth			Shift-share decomposition					
				Growth effect			Shift effect		
	US	EU15	GBR	US	EU15	GBR	US	EU15	GBR
Total	1.37	1.57	1.46	1.56	2.79	1.92	-0.19	-1.22	-0.46
Sectoral Decomposition									
`agr`	0.04	0.14	0.07	0.17	1.26	0.22	-0.13	-1.12	-0.15
`man`	0.12	0.32	0.12	0.53	1.06	1.29	-0.41	-0.74	-1.17
`ser`	1.22	1.12	1.27	0.87	0.47	0.41	0.35	0.65	0.86
`bss`	0.44	0.34	0.81	0.15	0.05	0.23	0.29	0.29	0.58
`fin`	0.10	0.04	0.04	0.08	0.02	0.01	0.02	0.02	0.03
`trd`	0.42	0.28	0.11	0.52	0.25	0.10	-0.10	0.03	0.01
`nps`	0.26	0.46	0.31	0.12	0.15	0.07	0.14	0.31	0.24

Notes: Columns 1, 2 and 3 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., EU15 and Great Britain, respectively. Columns 4 to 9 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) = (4) + (7), column (2) = (5) + (8) and column (3) = (6) + (9). 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 disaggregating 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).

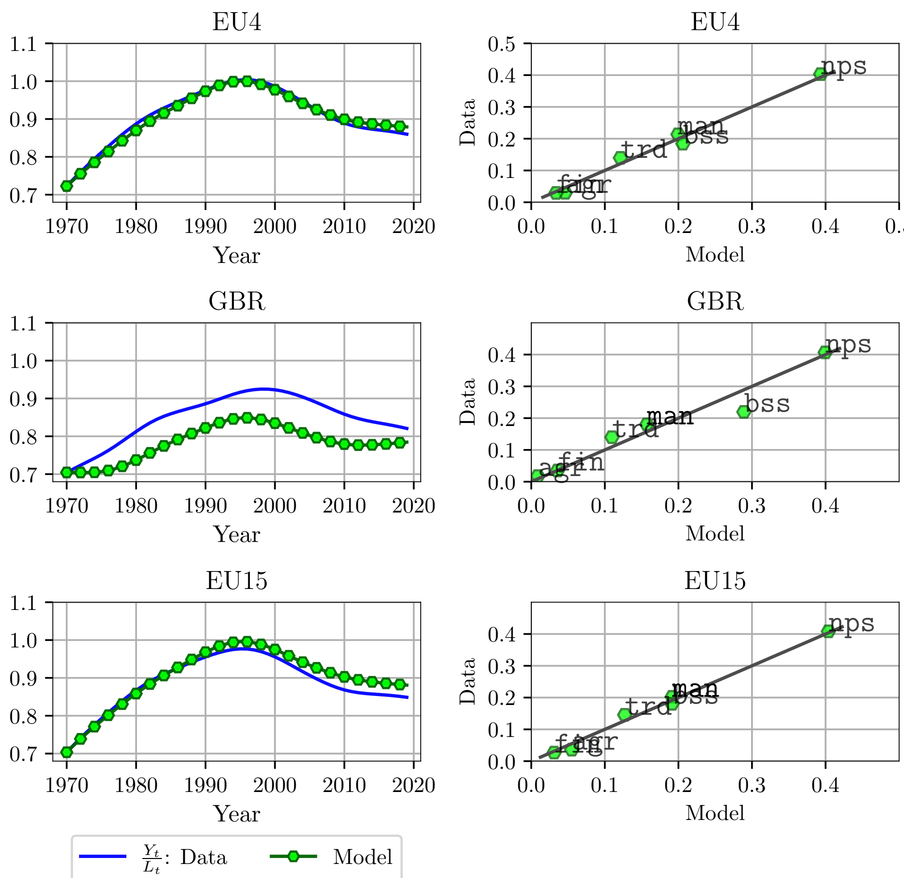

Figure D.1: Model predictions vs. data of aggregate labor productivity sectoral employment shares in 2019 in EU4, EU15 and Great Britain.

Notes: The left panels show the model's prediction (green) vs. OECD data on aggregate labor productivity growth for EU4 (top panel), Great Britain (middle 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), Great Britain (middle panel) and EU15 (bottom panel).

D.1.3 Counterfactual Experiments

In Table D.2, we present the results of the numerical counterfactual experiments in Europe's annual aggregate labor productivity growth (pp) from 1970 to 2019 for the EU4, the EU15 and Great Britain. The core mechanism is consistent across regions: in both counterfactual exercises, endogenous labor reallocation dampens the aggregate impact of counterfactual productivity changes, as the Baumol cost disease pushes labor from more productive sectors into nonprogressive services.

These results extend to European countries outside the Euro Area, such as Great Britain, confirming that the mechanism is not an artifact of Euro Area membership. The direction of individual sectoral effects can differ across regions: for example, Great Britain's business services productivity grew faster than the U.S. over this period, so feeding U.S. business services growth rates into Great Britain *reduces* rather than increases aggregate productivity (counterfactual 4, -0.23 vs. $+0.04$ for EU4). This sign reversal is expected and confirms that the model correctly reflects regional productivity differences. The underlying mechanism—that endogenous reallocation dampens the aggregate impact of sector-specific productivity changes—operates in both directions.

Table D.2: Numerical experiments: counterfactual change in EU4 (main paper), EU15 and Great Britain's annualized aggregate labor productivity growth (pp) for 1970–2019

	g_A^{cf} - $g_A^{baseline}$ (percentage points difference)					
	Model			Dynamic shift-share		
	EU4	EU15	GBR	EU4	EU15	GBR
Counterfactual 4: U.S. sectoral growth rates						
`agr`	-0.12	-0.17	-0.01	-0.08	-0.11	-0.02
`man`	-0.12	-0.15	-0.12	-0.15	-0.17	-0.15
`bss`	0.04	0.04	-0.23	0.06	0.07	-0.18
`fin`	0.04	0.03	0.04	0.03	0.02	0.04
`trd`	0.07	0.08	0.15	0.09	0.11	0.21
`nps`	-0.10	-0.09	0.01	-0.10	-0.09	0.01
`bss, fin, trd`	0.13	0.13	-0.03	0.18	0.20	0.09
Counterfactual 5: Implied "catch-up" sectoral growth rates						
`agr`	0.58	0.70	0.25	0.65	0.74	0.81
`man`	0.51	0.57	0.60	0.65	0.74	0.81
`bss`	0.55	0.63	0.85	0.65	0.74	0.81
`fin`	0.39	0.44	0.48	0.65	0.74	0.81
`trd`	0.44	0.48	0.50	0.65	0.74	0.81
`nps`	0.59	0.66	0.75	0.65	0.74	0.81

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 4 feeds the U.S. sectoral labor productivity growth of the indicated sectors. Counterfactual 5 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 three columns report how annualized aggregate labor productivity growth changes using our model relative to the baseline for EU4, EU15, and Great Britain, respectively. The last three columns report how 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 for EU4, EU15, and Great Britain, respectively.

D.2 Core vs. Periphery

In this subsection, we assess whether our results from the four largest economies in Europe remain consistent when compared to both core and peripheral economies. We employ the classification scheme of European economies outlined by Bayoumi and Eichengreen (1992), which divides them into core and periphery. The core includes Germany, France, Belgium, the Netherlands, and Denmark, while the periphery consists of Greece, Ireland, Italy, Portugal, Spain, and the UK.

D.2.1 Shift-share Decomposition

Table D.3 displays the shift-share and sectoral decomposition results. When compared with the figures in Table 1, we observe that the values remain almost identical. The overall conclusion persists: labor reallocation has substantially negatively impacted aggregate labor productivity in both core and peripheral countries.

Table D.3: Shift-share analysis and sectoral decomposition for the 1970–2019 period.

	LP growth			Shift-share decomposition					
				Growth effect			Shift effect		
	US	EU Core	EU Peri.	US	EU Core	EU Peri.	US	EU Core	EU Peri.
Total	1.37	1.78	1.37	1.56	2.98	2.81	-0.19	-1.20	-1.44
Sectoral Decomposition									
`agr`	0.04	0.12	0.15	0.17	1.18	1.42	-0.13	-1.06	-1.27
`man`	0.12	0.37	0.31	0.53	1.14	1.10	-0.41	-0.77	-0.79
`ser`	1.22	1.28	0.91	0.87	0.66	0.29	0.35	0.62	0.62
`bss`	0.44	0.37	0.32	0.15	0.06	0.04	0.29	0.31	0.28
`fin`	0.10	0.05	0.03	0.08	0.04	0.01	0.02	0.01	0.02
`trd`	0.42	0.35	0.22	0.52	0.36	0.17	-0.10	-0.01	0.05
`nps`	0.26	0.51	0.34	0.12	0.20	0.07	0.14	0.31	0.27

Notes: Columns 1, 2 and 3 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., EU Core and EU periphery, respectively. Columns 4 to 9 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) = (4) + (7), column (2) = (5) + (8) and column (3) = (6) + (9). 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 disaggregating 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).

D.2.2 Test of the Theory

In Figure D.2, we show that our model effectively reproduces the significant aspects of labor reallocation in countries belonging to the core and to the periphery of Europe.

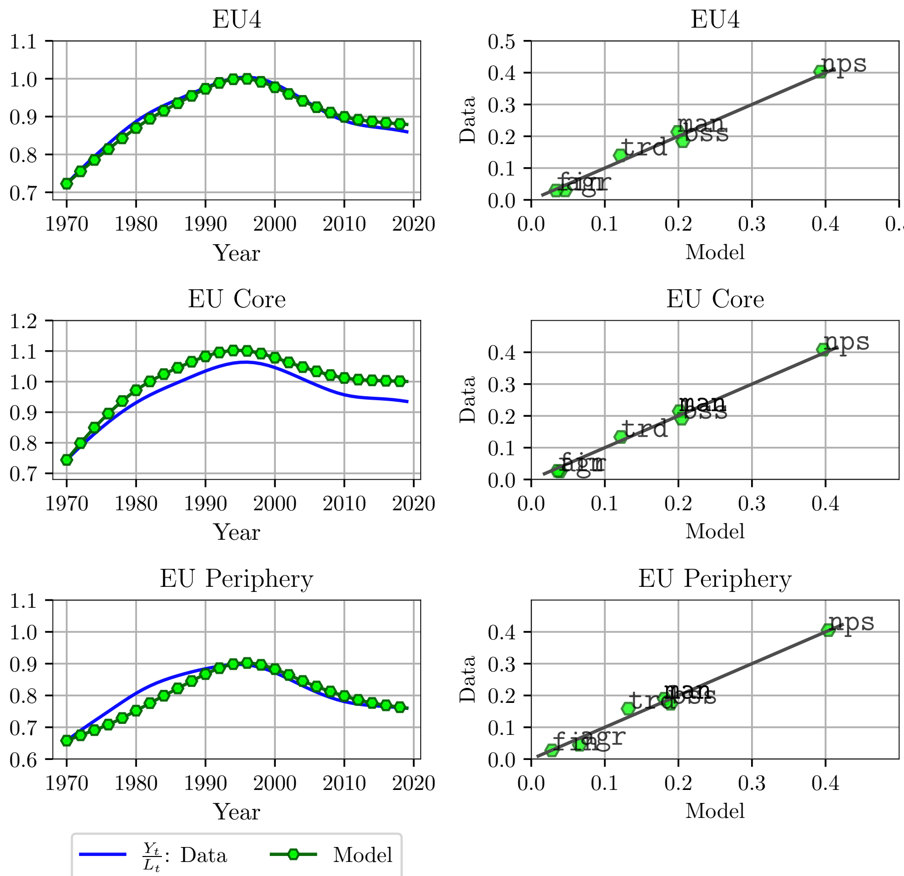

Figure D.2: Model predictions vs. data of aggregate labor productivity sectoral employment shares in 2019 in EU4, EU Core, and EU Periphery.

Notes: The left panels show the model's prediction (green) vs. OECD data on aggregate labor productivity growth for EU4 (top panel), EU Core (middle panel) and EU Periphery (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), EU Core (middle panel) and EU Periphery (bottom panel).

D.2.3 Counterfactual Experiments

Table D.4 presents the counterfactual annualized aggregate labor productivity growth (pp) for the EU4, EU Core, and EU Periphery from 1970 to 2019. It is reassuring that our counterfactual outcomes are stable across different regions. Furthermore, as anticipated, our theory forecasts a more significant manifestation of Baumol's cost disease in peripheral areas compared to core regions. This happens because peripheral areas need a quicker pace of sector-specific labor productivity growth to match that of the US compared to core areas, resulting in comparatively greater labor shifts into nonprogressive services.

Table D.4: Numerical experiments: counterfactual change in EU4 (main paper), EU Core and EU Periphery's annualized aggregate labor productivity growth (pp) for 1970–2019

	g_A^{cf} - $g_A^{baseline}$ (percentage points difference)					
	Model			Dynamic shift-share		
	EU4	EU Core	EU Periphery	EU4	EU Core	EU Periphery
Counterfactual 4: U.S. sectoral growth rates						
`agr`	-0.12	-0.13	-0.19	-0.08	-0.09	-0.13
`man`	-0.12	-0.19	-0.09	-0.15	-0.21	-0.12
`bss`	0.04	0.09	0.05	0.06	0.07	0.08
`fin`	0.04	0.02	0.03	0.03	0.01	0.03
`trd`	0.07	0.01	0.16	0.09	-0.00	0.22
`nps`	-0.10	-0.22	0.01	-0.10	-0.21	0.01
`bss, fin, trd`	0.13	0.11	0.23	0.18	0.08	0.32
Counterfactual 5: Implied "catch-up" sectoral growth rates						
`agr`	0.58	0.40	0.92	0.65	0.33	1.09
`man`	0.51	0.28	0.81	0.65	0.33	1.09
`bss`	0.55	0.33	0.88	0.65	0.33	1.09
`fin`	0.39	0.26	0.59	0.65	0.33	1.09
`trd`	0.44	0.25	0.66	0.65	0.33	1.09
`nps`	0.59	0.30	0.93	0.65	0.33	1.09

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 4 feeds the U.S. sectoral labor productivity growth of the indicated sectors. Counterfactual 5 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, EU Core and EU Periphery. 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, EU Core and EU Periphery.

E Calibration Algorithm

E.1 Marshallian Demand System

The expenditure shares in equation (9) 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 (9) for manufacturing and solve for $\tilde{C}$. This yields

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

Plugging (E.1) in (9), 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

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

E.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 (15) 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 (E.2). To obtain the empirical counterparts of (E.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 (E.2) for $i = \mathtt{ser}$ and solve for σ.

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

E.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 $\mathtt{man}$ expressed in equation (E.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 $i \neq \mathtt{man}$, namely

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

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 (E.3) as well. Although one could use a weighted average for all I sectors, including equation (E.1), we chose not to use this approximation since we already have used (E.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.[22]

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.

E.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 (15) 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

[22]However, our baseline predictions are virtually unaltered if we use (E.3) instead for each $i \neq \mathtt{man}$ 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. Note that the exponent $1/(\epsilon_i - 1)$ in (E.3) is large for sectors with ϵ_i near unity (e.g., agriculture, where $\epsilon_{\mathtt{agr}} = 0.97$ implies an exponent of approximately -33). In practice, numerical stability is preserved because the underlying employment-share and price ratios in (E.3) evolve smoothly over time, yielding similar $\tilde{C}_t$ paths across sectors, and agriculture's small employment share gives it a low weight in the average. This is a useful approximation to generate baseline predictions—where the employment-share weights used to average $\tilde{C}_t$ across sectors are taken from the data—but not to perform counterfactual experiments, where the employment-share weights are endogenous to the counterfactual productivity paths.

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

E.5 Parameterization: Summary

Table E.1: Parameterization. The model is calibrated to the U.S. (1970–2019). Values are independently rounded to two decimal places; displayed Ω_i may not sum exactly to 1.00.

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 nonprogressive 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 nonprogressive services.	0.39

F Additional Tests to the Theory

In this subsection, we provide additional tests to the theory by testing our model predictions against the U.S.

Figure F.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 nonprogressive services, with a discrepancy of 47.3 percent in the data compared to 50.2 percent in the model. The right panel of Figure F.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.

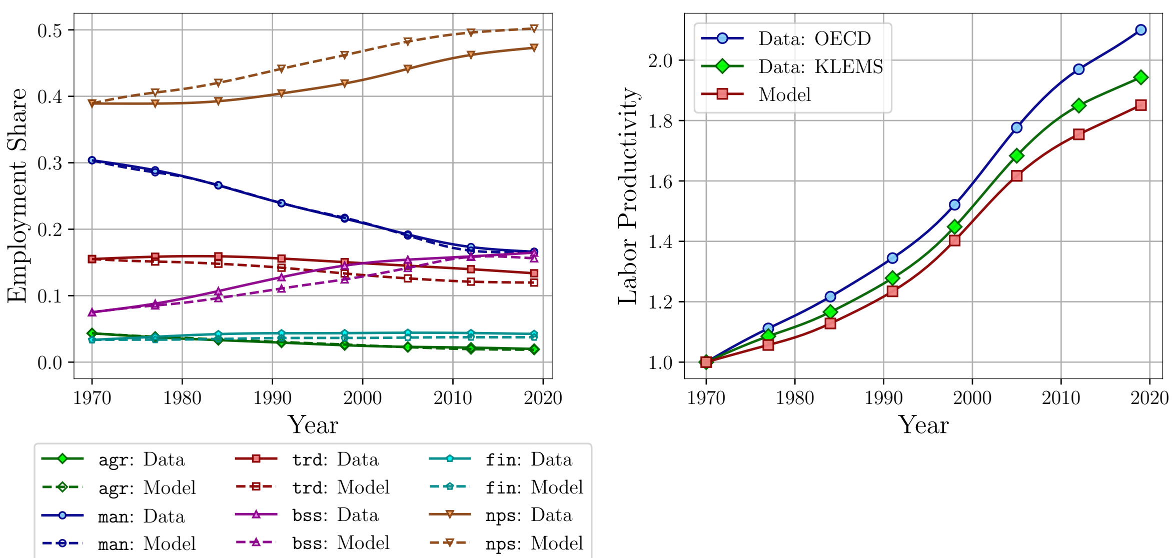

Figure F.1: Aggregate Labor Productivity and Structural Transformation in the U.S. 1970–2019. Model predictions vs. data.

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).