Divergent Transformation Paths: An Anatomy of the Baumol Cost Disease*

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Abstract

We propose a novel explanation for secular stagnation that is linked to the process of structural transformation in post-industrial economies. We merge several data sources on sectoral production and innovation activities to document that while production workers move out of manufacturing and into non-research-intensive services, researchers move out of manufacturing and into research-intensive services, exhibiting divergent paths. We build a general equilibrium model of structural transformation and directed technical change where the sectoral allocation of productive and innovative resources is determined endogenously. We enrich this framework by allowing for heterogeneous, time-varying markups across sectors. The model mimics key features of structural change in employment, expenditure and innovation activity, including the divergent paths in production and innovation. We find that in the absence of structural change and the prevailing demographic trends, TFP would have grown by 62% between 1947 and 2010 in the US, as opposed to the observed TFP growth of 30%, with 87% of the slowdown due to structural change in production and innovation and the remaining 13% due to demographic forces.

JEL: O11, O14, O33, O41.

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1 Introduction

In the aftermath of the global financial crisis of 2007-2008, renewed attention has been directed toward the concept of secular stagnation: a prolonged period characterized by sluggish economic growth and sustained low interest rates.

The literature has proposed alternative explanations for this phenomenon. While Eggertsson et al. (2019) argue that demographic trends, notably an ageing population and the decline in birth rates have restricted labour force expansion, Piketty (2014) highlights the role of increased inequality, affecting demand dynamics due to concentrated wealth. Furthermore, the savings glut hypothesis posits an excess of global savings, leading to persistently low interest rates and reduced investment incentives (Caballero et al. 2008). Focusing on the case of the US case, Gordon (2012) relates lower economic growth due to a combination of factors, including demographic changes, education, and, notably, lower returns to innovation.

We propose an alternative explanation linked to the characteristics of the process of structural transformation in post-industrial economies. This idea was first introduced by Baumol in his cost disease hypothesis, which posited that economies face a growth slowdown as economic activity moves from fast-productivity-growing sectors like agriculture and manufacturing to slow-productivity-growing services (Baumol (1967);Baumol et al. (1985)) along the process of structural change. More recently, Duernecker et al. (2024) revisit Baumol's hypothesis focusing on its long-run effects. In their framework services are heterogeneous and can be split into dynamic and stagnant sectors. They find that these service sectors are substitutes in preferences, a force that prevents the Baumol cost disease from driving the economy to a permanent slowdown.

In this paper, we study in detail the anatomy of Baumol's cost disease by analyzing in depth the sectoral allocation of innovation activity along the development path of the US. We collate multiple data sources together. These include industry-level US patent and R&D employment data enabling us to track the sectoral composition of innovation activity across time as well as KLEMS and input-output tables which allow us to map expenditure and employment shares as well as TFP and relative prices over time. We then proceed by splitting services into research-intensive and non-research-intensive industries and find that the traditional process of structural change in economic activity goes from manufacturing to service sectors where R&D is almost absent. Additionally, we report that there is also structural change in R&D workers that presents the opposite trajectory, moving from manufacturing to highly-innovative service industries. These two facts together characterize the process of productivity slowdown in advanced economies, as production R&D workers move in opposite directions out of manufacturing.

To shed light on the mechanisms driving the sectoral reallocation of productive and innovative activities, we build a general equilibrium model of structural transformation and directed technical change, whereby the sectoral allocation of productive and innovative resources is determined endogenously. As in traditional directed technical change models, incentives to innovate in sector-specific technologies are determined by the size of sectors and relative prices, which are themselves influenced by the process of structural change. Our model also allows for markups that are heterogeneous across sectors and vary over time, potentially distorting the incentives to innovate stemming from off-the-shelf models that rely on monopolistic competition. We use a combination of calibration and structural estimation to match the main trends in sectoral employment, expenditure, and total factor productivity, among others, in the United States (US) between 1947 and 2010. We use our rich quantitative model as a laboratory to perform two quantitative exercises.

In the first exercise, we study the effects of structural change on TFP growth slowdown. We group competing forces leading to structural change and growth slowdown into three main groups: (i) drivers of structural change in employment and expenditure, including substitution and income effects together with sectoral-biased labour-augmenting technological change, (ii) drivers of structural change in innovation, which group knowledge spillovers between and across sectors and heterogeneous-time-varying sectoral markups, and (iii) a demographic channel that accounts for population growth slowdown. We find that these forces altogether led to a TFP growth slowdown of 32 percentage points (p.p.) between 1947 and 2010, with the structural change channels explaining 82% of the growth decline and the demographic channel the remaining 18%. That is, in the absence of structural change in employment, expenditure, and innovation, total factor productivity would have grown 56% between 2010 and 1947 in the US, as opposed to the growth of 30% observed in this period. If the slowdown in population growth had been absent, cumulative TFP growth would have been 62%, fully accounting for the 32 p.p.

difference.

In our second quantitative exercise, we simulate a future path for the economy going until 2075 and study the evolution of TFP growth, together with structural change in innovation, employment, and expenditure. We find that TFP growth is likely to accelerate in this period, accumulating an additional growth of 88% between 2075 and 2010 on top of the 30% observed between 2010 and 1947. Key to this result is a predicted reallocation of economic innovation activity towards sectors that generate quantitatively important knowledge spillovers across sectors.

The paper is organised as follows. Section 2 documents motivational facts on the movement of scientists between manufacturing and services and the parallel evolution of value added and employment shares over time. We try to rationalise these facts in Section 3 through our quantitative model of structural change in employment, expenditure, and innovation. Section 4 presents the model's calibration together with the main quantitative results of the paper, while Section 5 concludes.

2 Empirics

2.1 Data

Our empirical facts are built using various industry-level data sources from the US. We begin by documenting trends in R&D activity over the last few decades, relying primarily on R&D employment and patent data. For R&D employment, we build a time series of the sectoral allocation of the number of full-time equivalent R&D scientists & engineers in for-profit public and privately-held non-farm businesses in the US. This data comes from the US Business Enterprise Research and Development Survey (BERD) annual reports produced by the National Center for Science and Engineering Statistics (NCSES) and collected by the Census Bureau (NCSES 1985-2021). The level of granularity varies over time. For instance, R&D employment before 2000 offers minimal disaggregation of R&D employment within non-manufacturing, preventing us from studying longer-term disaggregated trends in R&D employment.

For patent data, we use the historical patent data masterfile produced by Marco et al. (2015). This database contains detailed information on US patents[1], spans back to 1840 and contains data on the US Patent Classification (USPC) of each of these patents as well as the publication and disposal dates. It is publicly available and can be accessed through the US Patent and Trademark Office (USPTO) website. We then proceed by applying a patent-industry classification crosswalk produced by Goldschlag et al. (2016). This crosswalk allows us to map the aggregate number of patents in each USPC category into an aggregate number of patents in any ISIC/NAICS category. Thus, we are able to compute a time series of the share of patents produced at the industry-year level in the US. Finally, we rely on the OECD Citations Database for data on patent and non-patent cross-citations (Webb et al. 2005). Similarly, we apply the USPC-industry crosswalk produced by Goldschlag et al. (2016) to the database.

For broader economic activity, we document trends in value added, employment and consumption as well as trends in relative prices, labor productivity and TFP. All of these variables excluding consumption are compiled using the US April 2013 release of the World KLEMS database (Jorgenson et al. 2012). This database benefits from coverage between 1947 and 2010 allowing us to document long-term trends in US economic activity. Meanwhile, consumption data is built using the long-run World Input-Output Tables (WIOD) (Woltjer et al. 2021) spanning from 1965 to 2000 and the 2016 release WIOD spanning from 2000 to 2014 (Timmer et al. 2015).

2.2 Structural Change in Innovation

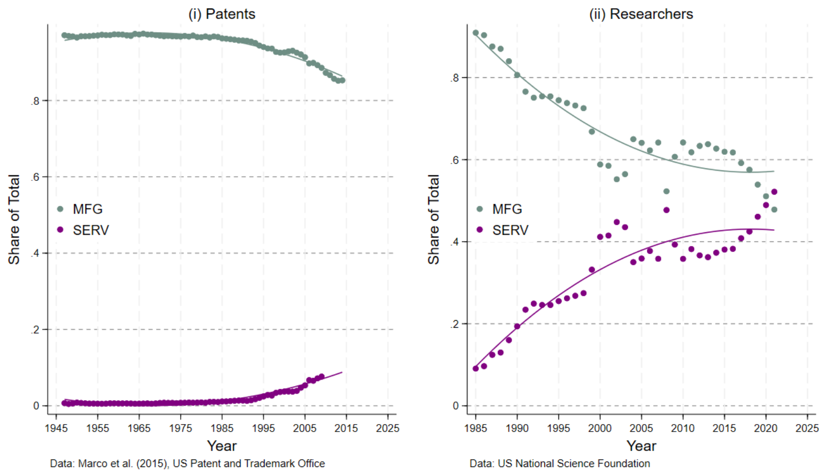
The Kuznets facts document changes in the sectoral composition of value added, employment and consumption away from manufacturing and into services over the development process (Herrendorf et al. 2014). We contribute to these observations by documenting similar trends in R&D activity. Figure 1 shows changes in the sectoral composition of both patents and researchers over time in the US[2]. The LHS chart shows that virtually all patents that were issued up until around 1985 belonged to the manufacturing sector, with no patents in services. Thereafter, we start to observe a shift in composition in

[1]This includes published and publicly-available non-published applications, though we restrict our attention to issued patents leaving us with a total of over 89 million observations.

[2]The sectoral composition of patents is produced by applying the Goldschlag et al. (2016) crosswalk on issued US patents.

favour of services. The share of patents produced in services has been gradually rising from the 1980s with a mirrored decline in the manufacturing share of patents. We see a similar trend in the sectoral composition of R&D employment across US businesses. Starting 1985, almost the entirety of R&D employment was concentrated in the manufacturing sector. Since then however, the services share of R&D employment has risen somewhat dramatically to the extent that R&D employment in the US is now evenly split between both sectors. Taken together, it is clear that there is evidence of structural change innovation activity away from manufacturing and into services. These trends appear to coincide together, with these structural changes in patent production and R&D employment starting at roughly similar time periods.

Figure 1: US Sectoral Composition of Patents & Researchers



2.3 Innovation Within Services

We proceed by splitting services at the 2-digit level into two categories: research-intensive and non-research-intensive services. To do so, we collect data on R&D intensity from the Business Enterprise Research and Development (BERD) database on R&D employment per 1,000 workers – our measure of R&D intensity. Table 1 shows the average R&D intensity between 2004 and 2020 for 2-digit services industries as well as for non-manufacturing as a whole [3]. The table showcases the heterogeneity in R&D intensity within services. While non-manufacturing as a whole has an R&D intensity of 66.3, some industries like Information have an R&D intensity of 125.8 while others like Transport & Warehousing have an intensity of just 7.3. Nevertheless, there appears to be a noticeable discontinuity across industries in terms of intensity. This is particularly true with the current industry groupings where the lowest intensity in the research-intensive group is 90.7 while the highest intensity in the non-research-intensive group is 51.5. For the remainder of the paper, we apply this grouping of services industries.

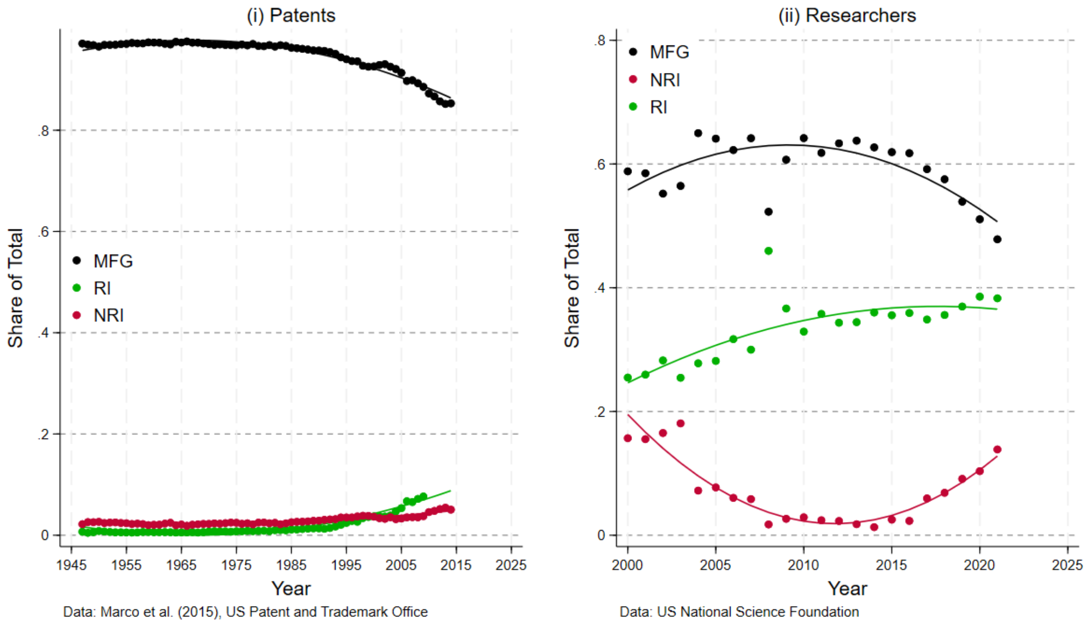
[3] We are aware of heterogeneity in R&D intensities at finer levels of disaggregation (like 4- or 5-digit level). For instance, within Wholesale Trade and Retail Trade, some industries such as Household Appliances & Electronic Merchants and Electronic Shopping & Mail-Order houses have R&D intensities similar to those of research-intensive services in the years where this level of disaggregation is available. Nevertheless, we stick with the two-digit disaggregation as this is consistent across the historical time series of R&D employment.

Table 1: 2004-2020 Average Research Intensity

Code	Industry	R&D Intensity
	Non-manufacturing	66.3
	Research-Intensive	
51	Information	125.8
53	Real Estate and Rental and Leasing	90.7
54	Professional, Scientific & Technical Services	171.5
	Non-Research-Intensive	
42	Wholesale Trade	51.5
44-45	Retail Trade	12.2
48-49	Transport and Warehousing	7.3
52	Finance & Insurance	25.6
621-623	Healthcare Services	26.1
	Other Non-Manufacturing	15.1

Next, we repeat Figure 1 but add a layer of disaggregation within services to better understand how R&D activity evolves within services. Figure 2 shows that while the absolute level of patent production in the non-research-intensive sector was historically (marginally) higher than that of research-intensive services, this trend reversed in the early 2000s when the latter overtook the former. Indeed, the rise in patent production in research-intensive services started roughly in the early 1980s, coinciding with the time we start to observe structural change in innovation suggesting that the process of structural change in innovation is largely being driven by the reallocation of R&D activity from manufacturing to research-intensive services. Similarly, the RHS of Figure 2 shows that the decline in manufacturing R&D employment is being consistently offset by an increase in R&D employment in research-intensive services, with R&D employment in non-research-intensive services displaying a U-shaped pattern with time. Between 2000 and 2020, the share of R&D employment in research-intensive services rises from roughly 25% to 40% while the share of R&D employment in manufacturing has fallen from around 60% to about 45% during the same time period.

Figure 2: US Sectoral Composition of Patents & Researchers

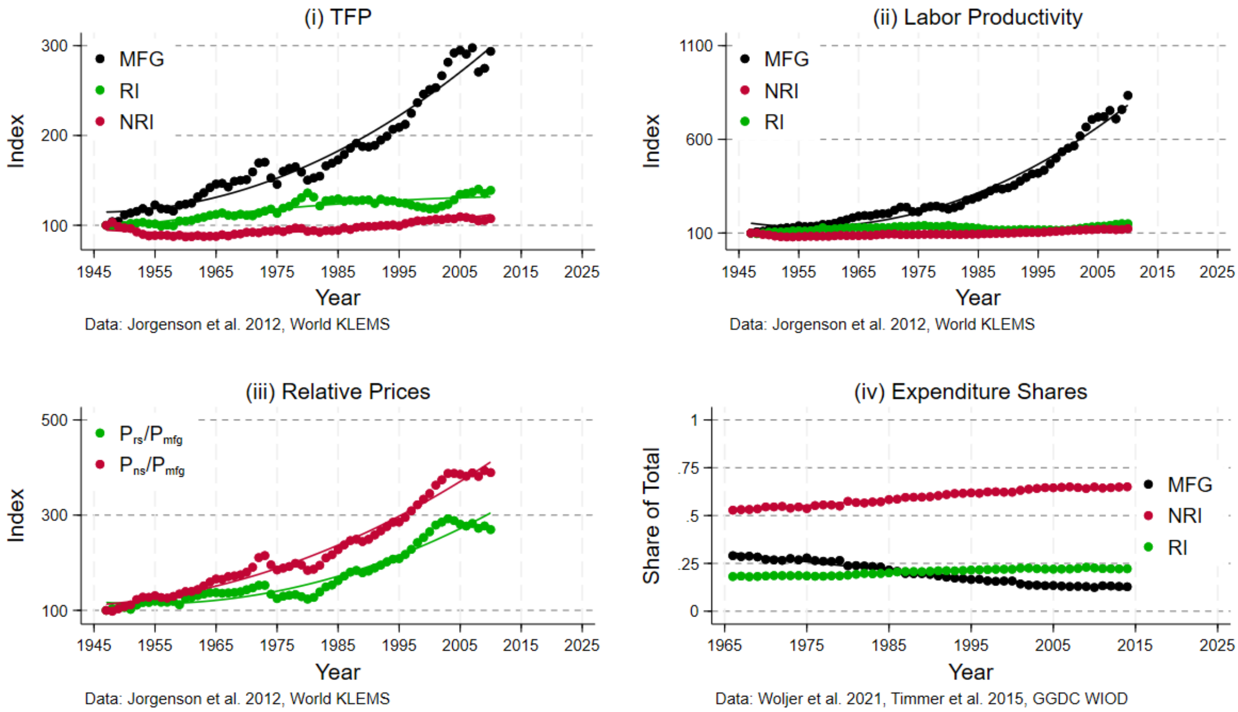


The reallocation of R&D activity across sectors is likely to have implications on sectoral productivity growth and, by extension, relative prices (Ngai & Pissarides 2007). Figure 3 plots the expenditure shares as well as the relative price, TFP and labor productivity indices over time for manufacturing and the 2 services sectors in the US. Computing relative prices involves taking the ratio between nominal and real value added while labor productivity is calculated as the ratio between real value added and employment for the different sectors. TFP of the different sectors, meanwhile, refers to the employment-weighted sector average. These data are obtained from the World KLEMS database (Jorgenson et al. 2012). Expenditure shares are computed using the long-run WIOD (Woltjer et al. 2021) as well as the 2016 release (Timmer et al. 2015), allowing a time series from 1965 to 2014.

In line with the sectoral composition of R&D activity, the manufacturing sector's TFP and labor productivity growth consistently outpace those of services – both research-intensive and non-research-intensive services. Productivity growth appears to be faster in the research-intensive sub-industries according to both the TFP and labor productivity indices. Indeed, the labor productivity and TFP indices (normalised to 100 in 1947) reached roughly 149 and 139, respectively, by 2010. This is noticeably larger than the 123 and 107 recorded by non-research-intensive services, respectively[4]. This is in line with the observation that R&D activity is reallocating into research-intensive services as opposed to non-research-intensive services. In terms of relative prices, it is clear that the relative price of non-research-intensive services has been consistently rising faster than that of research-intensive services since the mid-1940s. Expenditure shares exhibit a slightly different pattern, with the manufacturing share falling from 1945 onwards. While the research-intensive services share has been rising, the non-research-intensive services share has captured most of the gains observed in services. Indeed, between 1965 and 2016 the latter's share has risen by almost 20 percentage points. This is not surprising given that the relative price of non-research-intensive services has risen faster than that of research-intensive services. Overall, Figure 3 confirms that the reallocation of US R&D activity away from manufacturing and into research-intensive services is accompanied by differing paths of productivity growth, relative prices and expenditure shares at the sector level within services.

[4] In the Appendix we show that growth in the non-research-intensive sector's labor productivity and TFP is in some instances driven by productivity growth in some 5-digit industries within the sector that occupy small employment shares and therefore do not materially affect the 2-digit level research intensities. For instance, within Retail Trade both Electronics & Appliance Stores and Electronic Shopping & Mail-Order Houses (which have research intensities similar to research-intensive services) see labor productivity growth exceeding that of manufacturing. However, since they occupy minimal employment shares, they do not materially affect Retail Trade's overall labor productivity growth and potentially explain the higher-than-expected R&D intensities. We show a similar trend in Wholesale Trade. While we would prefer to account for these finer-level heterogeneities in our analysis, we are unable to do so given that this level of granularity is not persistently present in the R&D employment data.

Figure 3: US Sectoral Productivity, Relative Price Indices & Expenditure Shares



A useful exercise that will inform our subsequent analysis is to explore the role of between- and within-sector knowledge spillovers across sectors. We rely primarily on the OECD Citations Database for this exercise (Webb et al. 2005) and use this data to compute the probability of a citing sector (column) will cite a cited sector (row) – a measure that we will refer to as knowledge spillovers for the remainder of the paper.

Table 2: Patent Sector Cross-Citations

	MFG	RI-SERV	NRI-SERV
MFG	0.92	0.57	0.72
RI-SERV	0.04	0.27	0.10
NRI-SERV	0.05	0.16	0.18

Notes. Columns are the citing sectors while the rows are the cited sectors. The decimals indicate the probability of a citing sector citing patents produced in a cited sector.

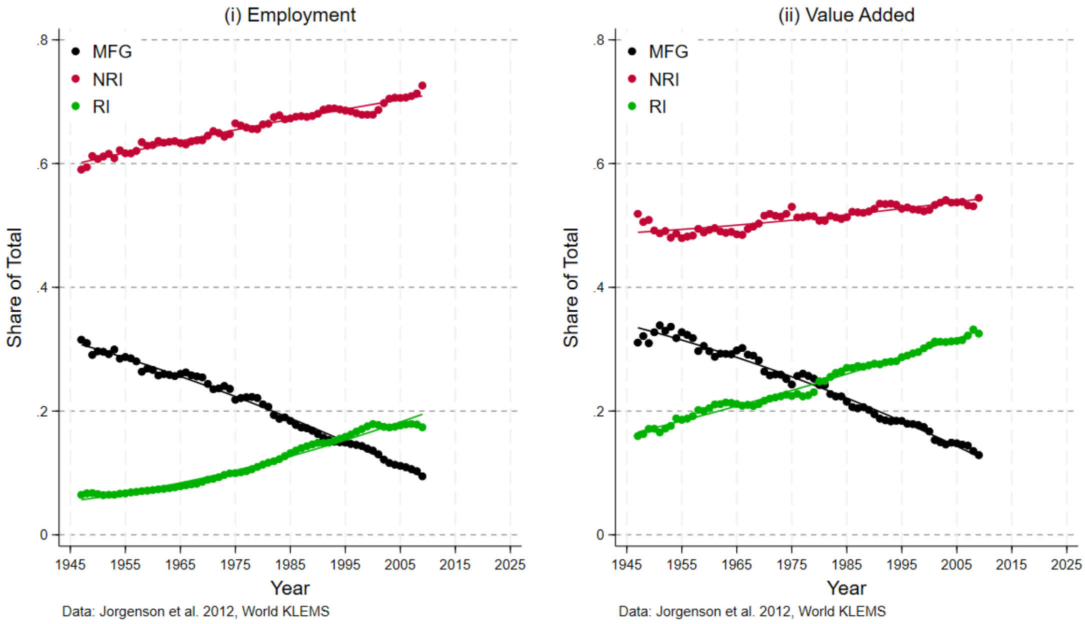
The results are presented in Table 2. Perhaps the most noticeable observation is that patents produced in manufacturing are not only important for subsequent patents produced in manufacturing, but also for patents produced in services – particularly non-research-intensive services. This is evidenced by the 57% and 72% probabilities that a manufacturing patent will be cited by a patent produced in research-intensive and non-research-intensive services sectors, respectively. A less surprising observation is that there is a somewhat strong degree of within-sector spillovers as shown by the fact 92%, 27% and 18% of patents produced in manufacturing, research- and non-research-intensive sectors cite patents in the same sector, respectively. These spillovers shed light on the innovation process in different sectors that will prove useful in the next two sections of the paper.

2.4 Divergent Transformation Paths

Finally, we check if the trends in R&D activity – namely the reallocation of R&D activity away from manufacturing and into research-intensive services – hold when we look at production activity. Figure

4 plots the US employment and value added shares from 1947 to 2010 using the same classification for research- and non-research-intensive services. As documented by the Kuznets facts, the manufacturing share of employment and value added fall consistently over time period. The manufacturing employment share falls from about a third to less than a tenth over the 6 decades while the manufacturing value added share falls also from roughly a third to less than 15% during the same time period. While the fall in manufacturing share of value added was mostly offset by increases in the value added share of research-intensive services – from 16% in 1947 to 31% in 2010 – the non-research-intensive sector was the sector that made the most gains in terms of employment. The share of employment in non-research-intensive services grew by almost 14 percentage points compared to less than 11 percentage points in research-intensive services.

Figure 4: US Sectoral Employment & Value Added Shares



This motivates our divergent transformations hypothesis: the observation that R&D employment moves towards research-intensive services industries while production employment moves largely towards non-research-intensive services industries. In the next section, we present a general equilibrium model that allows us to quantitatively decompose the forces at play and draw implications on future US productivity growth.

3 Model

3.1 Environment

3.1.1 Demographic Structure and Preferences

The economy is populated by an infinitely lived representative household composed of a continuum of individuals of mass $N(t)$. There are two types of individuals in the household: workers, of measure $L(t)$, and scientists, of measure $S(t)$, such that $N(t) = S(t) + L(t)$. The representative household has CIES preferences such that the intertemporal utility function is given by

$$\int_0^{\infty} e^{-\rho t} N(t) \left(\frac{c(t)^{1-\chi} - 1}{1-\chi} \right) dt$$

where ρ is the discount factor and χ is the inverse of the intertemporal elasticity of substitution. $c(t)$ is per-capita consumption. The population size evolves according to

$$N(t) = N(0)e^{\int_{s=0}^{t} n(s)ds}$$

where $N(0)$ is the initial population which we normalize to 1 from now on while $n(t)$ is the population growth rate in period t, with $n(t) < \rho$. The intertemporal utility function can therefore be written as

$$\int_{0}^{\infty} N(0)e^{-\int_{s=0}^{t}(\rho - n(s))ds} \left(\frac{c(t)^{1-\chi} - 1}{1-\chi}\right) dt$$

Per-capita consumption takes on a nested non-homothetic CES structure. The first layer combines the consumption of manufacturing $c_m(t)$ and services $c_s(t)$ with income elasticities ζ_m and ζ_s according to

$$\left[\theta_m \left(c(t)^{-\zeta_m} c_m(t)\right)^{\left(\frac{\sigma-1}{\sigma}\right)} + \theta_s \left(c(t)^{-\zeta_s} c_s(t)\right)^{\left(\frac{\sigma-1}{\sigma}\right)}\right]^{\left(\frac{\sigma}{\sigma-1}\right)} = 1$$

where σ measures the elasticity of substitution between the consumption of manufacturing and services final goods. In turn, services consumption $c_s(t)$ aggregates between research-intensive services $c_{rs}(t)$ and non-research-intensive services $c_{ns}(t)$ with income elasticities ζ_{rs} and ζ_{ns} according to the following CES structure

$$\left[\psi_{rs} \left(c_s(t)^{-\zeta_{rs}} c_{rs}(t)\right)^{\left(\frac{\epsilon-1}{\epsilon}\right)} + \psi_{ns} \left(c_s(t)^{-\zeta_{ns}} c_{ns}(t)\right)^{\left(\frac{\epsilon-1}{\epsilon}\right)}\right]^{\left(\frac{\epsilon}{\epsilon-1}\right)} = 1$$

where we allow for the elasticity of substitution between research-intensive and non-research-intensive services, represented by ϵ, to vary between aggregators. Setting the price of aggregate consumption as the numeraire ($p(t) = 1$), the household budget constraint is given by

$$p(t)C(t) + p(t)X(t) + \dot{A(t)} \leq w_l(t)L(t) + w_s(t)S(t) + r(t)A(t) + \Pi(t)$$

where $C(t)$ is aggregate consumption, $X(t)$ is aggregate investment, $A(t)$ is the household's stock of assets, $w_l(t)$ is the wage for production workers, $w_s(t)$ is the wage for R&D scientists, $r(t)$ is the real interest rate, and $\Pi(t)$ is aggregate profits. The household's initial stock of assets is given by $A(0) > 0$. Expressing the budget constraint in per-capita terms, we obtain

$$c(t) + x(t) + \dot{a(t)} = w_l(t)l(t) + w_s(t)s(t) + (r(t) - n(t))\, a(t) + \pi(t)$$

where $l(t)$ and $s(t)$ represent the shares of production and R&D workers (scientists) respectively, in the total population.

3.1.2 Sectoral Output

There is a representative firm in each sector operating competitively both in the final product and in the input market with the following technology

$$Y_j(t) = \left(\frac{1}{1-\beta}\right) X_j(t)^{1-\beta} \left(B_j(t)L_j(t)\right)^{\beta} \quad \text{for} \quad j \in \{m, rs, ns\}$$

where $L_j(t)$ represents labor used in sector j in period t and $B_j(t)$ is a labor-augmenting technology parameter. Additionally, $X_j(t)$ measures total output produced by machines in sector j and time t, implicitly defined by the following Kimball aggregator

$$\int_{0}^{N_j(t)} \Upsilon\left(\frac{x_j(\nu, t)}{X_j(t)}\right) d\nu = 1$$

where $x_j(\nu, t)$ is the number of machines of type ν used in sector j, $N_j(t)$ represents the measure of machines varieties in sector j and period t, and $\Upsilon(q)$ is a strictly increasing and strictly concave function that satisfies $\Upsilon(1) = 1$.

3.1.3 Intermediate Goods Producer

The producer of a machine type ν in sector j has access to the following technology

$$x_j(\nu,t) = z_j(\nu)Y_j^x(\nu,t)$$

where $z_j(\nu)$ represents the productivity of the the producer of variety ν and $Y_j^x(\nu,t)$ is the amount of final good used to produce machines of type ν in sector j. We assume that z_j is drawn from a Frechet distribution with a shape parameter ι

$$z_j \sim F(\iota)$$

3.1.4 Research & Development

The R&D sector produces sector-specific machine blueprints. It is composed of a large number of research labs that can freely enter. When a research lab discovers a new machine blueprint, it receives a fully enforced perpetual patent to produce a machine of a given type that can only be used in sector j. These patents are then sold to machine producers, who gain the right to reproduce them at will.

At any given period of time t, a research lab hires scientists to produce sector-specific machine blueprints and chooses a sector to direct its research efforts. The aggregate research efforts of the research labs in the economy lead to the following blueprint arrival rates at the aggregate level

$$\dot{N_m}(t) = \eta_m \Lambda_m(t)^\gamma S_m(t)^{(1-\alpha)} \quad \text{with} \quad \Lambda_m(t) = N_m(t)^{\delta_{mm}} N_{rs}(t)^{\delta_{mr}} N_{ns}(t)^{\delta_{mn}} \quad \text{and} \quad (\delta_{mm} + \delta_{mr} + \delta_{mn})=1$$

$$\dot{N_{rs}}(t) = \eta_{rs} \Lambda_{rs}(t)^\gamma S_{rs}(t)^{(1-\alpha)} \quad \text{with} \quad \Lambda_{rs}(t) = N_m(t)^{\delta_{rm}} N_{rs}(t)^{\delta_{rr}} N_{ns}(t)^{\delta_{rn}} \quad \text{and} \quad (\delta_{rm} + \delta_{rr} + \delta_{rn})=1$$

$$\dot{N_{ns}}(t) = \eta_{ns} \Lambda_{ns}(t)^\gamma S_{ns}(t)^{(1-\alpha)} \quad \text{with} \quad \Lambda_{ns}(t) = N_m(t)^{\delta_{nm}} N_{rs}(t)^{\delta_{nr}} N_{ns}(t)^{\delta_{nn}} \quad \text{and} \quad (\delta_{nm} + \delta_{nr} + \delta_{nn})=1$$

where $S_j(t)$ and η_j for $j \in \{m, rs, ns\}$ are the sector-specific number of scientists and arrival rates of new blueprints per unit of effective research effort, respectively. In turn, $\Lambda_j(t)$ is a Cobb-Douglas aggregator that captures the degree with which the economy-wide stock of knowledge impacts the production of new machine blueprints in sector j, with $\delta_{ji} \in [0,1]$ governing the impact of knowledge spillovers within (δ_{jj}) and between (δ_{j-j}) sectors.

3.1.5 Market Value of Patents

Suppose that machines fully depreciate after one period and that a variety of type ν in sector j can be sold to the final goods producer at price $p_j^x(\nu,t)$. The value of owning a patent to produce a machine type ν in sector j is

$$V_j(\nu,t) = \int_t^\infty e^{-\int_t^s r(s')ds'} \pi_j(\nu,s)ds \quad \text{for} \quad j \in \{m, rs, ns\} \quad \textit{with}$$

$$\max_{\{p_j^x(\nu,t), x_j(\nu,t), Y_j^x(z_j(\nu),t)\}} \pi_j(\nu,t) = p_j^x(\nu,t)x_j(\nu,t) - p(t)Y_j^x(z_j(\nu),t) \quad \text{for} \quad j \in \{m, rs, ns\} \quad \text{and}$$

$$x_j(\nu,t) = z_j(\nu)Y_j^x(\nu,t)$$

where $r(t)$ and $p(t)$ are the real interest rate and the price of the final good, both at time t. The corresponding Hamilton-Jacobi-Bellman (HJB) equation is

$$r(t)V_j(\nu,t) - \dot{V}_j(\nu,t) = \pi_j(\nu,t) \quad \text{for} \quad j \in \{m, rs, ns\}$$

3.1.6 Resource Constraints

The resource constraints for workers are given by

$$L(t) = L_m(t) + L_{rs}(t) + L_{ns}(t) \quad \text{and}$$

$$S(t) = S_m(t) + S_{rs}(t) + S_{ns}(t)$$

The total amount of resources used for machine production in period t is

$$X(t) = \kappa \int_0^{N_m(t)} x_m(\nu, t) d\nu + \kappa \int_0^{N_{rs}(t)} x_{rs}(\nu, t) d\nu + \kappa \int_0^{N_{ns}(t)} x_{ns}(\nu, t) d\nu$$

It follows that the sectoral resource constraints are

$$Y_m(t) = c_m(t) N(t) \quad \text{for} \quad j \in \{m, rs, ns\}$$

Finally, since in any given period t there is a positive net supply of patents, it must be the case that the household owns them. Thus

$$A(t) = a(t)N(t) = N_m(t)V_m(t) + N_{rs}(t)V_{rs}(t) + N_{ns}(t)V_{ns}(t)$$

3.2 Equilibrium

3.2.1 Consumption

The household faces both an intratemporal problem where it chooses the sectoral quantities of consumption in every period and an intertemporal problem where it faces the standard aggregate consumption-investment trade-off. In equilibrium, per-capita consumption levels can be written as

$$c_m(t) = \frac{c(t)}{p_m(t)} e_m(t) \quad \text{where} \quad e_m(t) = \left(\frac{p_m(t)\theta_m c(t)^{\zeta_m}}{c(t)} \right)^{(1-\sigma)}$$

$$c_j(t) = \frac{c(t)}{p_j(t)} e_s(t) e_j(t) \quad \text{where} \quad e_s(t) \equiv \left(\frac{p_s(t)\theta_s c(t)^{\zeta_s}}{c(t)} \right)^{1-\sigma} \quad \text{and} \quad e_j(t) \equiv \left(\frac{p_j(t)\theta_j c_s(t)^{\zeta_j}}{p_s(t) c_s(t)} \right)^{1-\epsilon} \quad \forall \quad j = \{ns, rs\}$$

As in the canonical structural change model, sectoral consumption levels are determined by both the relative price and income effects. The relative price effect is driven by the presence of p_m and p_j. The effect of a higher relative price is regulated by the parameters governing the elasticity of substitution σ and ϵ. Meanwhile, the income effect is present in the aggregate per-capita consumption level $c(t)$ and is regulated by the sectoral income elasticities ζ_m and ζ_j. We also obtain the following Euler Equation that determines the rate of per-capita consumption growth

$$\frac{\dot{c(t)}}{c(t)} = \left(\frac{1}{\chi - \sigma} \right) \left(r(t) - n(t) - \rho + \left(\frac{\dot{e_s}}{e_s} \right) \left\{ \frac{\zeta_s - \zeta_m (e_m / e_s)}{\zeta_s e_s + \zeta_m e_m} \right\} \right)$$

The consumption growth rate is increasing in the interest rate $r(t)$ and decreasing in both the population growth rate and the discount factor $n(t)$ and ρ, respectively. The intertemporal elasticity of substitution χ determines sensitivity of per-capita consumption growth to changes in the interest rate. Finally, the intertemporal problem requires that the transversality condition to hold

$$lim_{t \to \infty} \left[a(t) e^{\int_0^t (r(s) - n(s)) ds} \right] \geq 0$$

This boundary condition rules out a scenario of infinite borrowing.

3.2.2 Final Goods Producer

The final goods producer in each sector chooses the quantities of production labor and machine quantities of variety ν such that profits are maximised. This yields the following wage rate for production workers as a function of labor quantity

$$w_j(t) = p_j(t)\left(\frac{\beta}{1-\beta}\right) X_j(t)^{1-\beta} L_j(t)^{\beta-1} B_j(t)^{\beta}$$

Since $\beta < 1$, the wage rate is intuitively falling in the quantity of labor but increasing in the relative price of the sector and the labor-augmenting technology parameter p_j and $B_j(t)$, respectively. The inverse of the quantity of machines of type ν can be expressed as

$$p_j^x(q_j, t) = \Upsilon'(q_j)\left(\frac{p_j(t)Y_j(t)D_j(t)}{X_j(t)}\right)$$

where $\quad q_j = \frac{x_j(\nu,t)}{X_j(t)}$ and

$$D_j(t) = \left(\int_0^{N_j(t)} \Upsilon'\left(\frac{x_j(\nu,t)}{X_j(t)}\right)\frac{x_j(\nu,t)}{X_j(t)}d\nu\right) \quad \text{and} \quad \Upsilon'(q_j) = \frac{\omega-1}{\omega} exp\left[\frac{1-q_j^{\nu/\omega}}{\nu}\right]$$ [5]

3.2.3 Intermediate Goods Producer

Given the price of machines taken from the final goods producer and the linear technology for machines, the intermediate goods producer chooses how many machines of each variety to produce. The first order conditions produce a cut-off for $z_{j,min}$ at which intermediate goods producers with a larger z_j will produce while intermediate goods producers with a z_j lower than $z_{j,min}$ will prefer not to produce. The cut-off can be expressed as

$$z_{j,min} = \left(\frac{\omega}{\omega-1}\right)\frac{p(t)X_j(t)e^{-(1/\upsilon)}}{p_j(t)Y_j(t)D_j(t)}$$

Profits can be written as

$$\pi_j(q_j, t) = \frac{p(t)X_j(t)}{z_j(\nu)}\left(\frac{q_j{}^{(\upsilon/\omega)}}{\omega - q_j{}^{(\upsilon/\omega)}}\right)$$

where profits are strictly increasing in q_j. Meanwhile, markups can be written as

$$\mathcal{M}(q_j) = \left(\frac{\omega}{\omega - q_j{}^{\left(\frac{\upsilon}{\omega}\right)}}\right)$$

[5] We have assumed the Klenow & Willis (2016) specification for the Kimball aggregator where

$$\Upsilon(q) = 1 + (\omega-1)\, exp\left(\frac{1}{\upsilon}\right)\epsilon^{\frac{\sigma}{\upsilon}-1}\left[\Gamma\left(\frac{\omega}{\upsilon}, \frac{1}{\upsilon}\right) - \Gamma\left(\frac{\omega}{\upsilon}, \frac{q_j^{\upsilon/\omega}}{\upsilon}\right)\right]$$

with $\omega > 1$ representing the average demand elasticity and $\nu > 0$ dictating the firm's demand elasticity relative to q_j. Furthermore, $\Gamma(s,x)$ is an upper incomplete Gamma function

$$\Gamma(s,x) = \int_x^{\infty} t^{s-1}e^{-t}dt$$

.

3.2.4 Production Labour Market

Given free sectoral labor mobility in the production labour market, wages will equalise across sectors

$$w_{l,m} = w_{l,ns} = w_{l,rs}$$

Applying this yields the following expressions for relative prices

$$\frac{p_{ns}(t)}{p_m(t)} = \left(\frac{\tilde{Z_m}(t)B_m(t)}{\tilde{Z_{ns}}(t)B_{ns}(t)}\right)^{\beta}$$

$$\frac{p_{rs}(t)}{p_m(t)} = \left(\frac{\tilde{Z_m}(t)B_m(t)}{\tilde{Z_{rs}}(t)B_{rs}(t)}\right)^{\beta}$$

where it is clear that the relative price of the sectoral good j is inversely related to its productivity values $\tilde{Z_m}(t)$ and $B_m(t)$. The former represents a measure of the aggregate productivity across all intermediate goods producers operating in the sector

$$\tilde{Z_j}(t) = \left(\frac{1}{1-\beta}\right)^{(1/\beta)} Z_j(t)^{\left(\frac{1-\beta}{\beta}\right)} \quad \text{where} \quad Z_j(t) = \left(\frac{N_j(t)}{1-G(z_{j,min})}\right) \int_{z_{j,min}}^{+\infty} \frac{q_j(\nu,t)}{z_j(\nu)} dG(z_j)$$

3.2.5 Research & Development

Free entry into the innovation sector implies that the expected benefit must be equal to the cost of entering sector j:

$$\dot{N_j}(t)V_j(t) \geq w_s(t)S_j(t) \qquad j = \{m, rs, ns\}$$

In the case of the marginal firm in sector j we get

$$\eta_j \Lambda_j(t)^{\gamma} S_j(t)^{-\alpha} V_j(t) = w_{j,s}(t)$$

Free labor mobility of scientists between sectors yields

$$w_{s,m} = w_{s,ns} = w_{s,rs}$$

from which we can obtain the following ratios of scientist allocations

$$S_{ns}(t) = S_m(t)\left(\frac{\eta_{ns}}{\eta_m}\frac{\Lambda_{ns}(t)}{\Lambda_{ns}(t)}\frac{V_{ns}(t)}{V_m(t)}\right)^{1/\alpha} \quad \text{and} \quad S_{rs}(t) = S_m(t)\left(\frac{\eta_{rs}}{\eta_m}\frac{\Lambda_{rs}(t)}{\Lambda_{ns}(t)}\frac{V_{rs}(t)}{V_m(t)}\right)^{1/\alpha}$$

In equilibrium, the HJB equation must hold

$$r(t)V_j(\nu,t) - \dot{V_j}(\nu,t) = \pi_j(\nu,t)$$

Since research labs do not ex-ante observe productivity of z_j of the intermediate goods producer that they will sell their blueprint to, they take expectation over their productivity draw. Thus, the HJB can be re-written as

$$r(t)V_j(t) - \dot{V_j}(t) = p(t)Z_j(t)Y_j^x(t)\int_{z_{j,min}}^{\infty} \frac{1}{z_j(\nu)}\left(\frac{q_j^{(\nu/\omega)}}{\omega - q^{(\nu/\omega)}}\right) dG(z)$$

3.2.6 Market Clearing

Using the sectoral goods market clearing condition, we obtain the sector labor allocations

$$\frac{L_m(t)}{L(t)} = e_m(t) \quad \frac{L_{rs}(t)}{L(t)} = e_s(t)e_{rs}(t) \quad \text{and} \quad \frac{L_{ns}(t)}{L(t)} = e_s(t)e_{ns}(t)$$

Intuitively, the labor allocations have a one-to-one mapping with expenditure shares. Substituting the labor shares into the production labor market clearing condition yields an expression for consumption

$$c(t) = \frac{L(t)}{N(t)} p_m(t)^{(1/\beta)} \tilde{Z_m}(t) B_m(t)$$

which is naturally increasing in the productivity terms $\tilde{Z_m}(t)$ and $B_m(t)$. Equating this with the household's Euler equation yields an expression for the real interest rate in equilibrium

$$r(t) = (\chi - \sigma)\left(\frac{\dot{s_l}(t)}{s_l(t)} + \left(\frac{1}{\beta}\right)\left(\frac{\dot{p_m}(t)}{p_m(t)}\right) + \frac{\dot{B_m}(t)}{B_m(t)} + \frac{\dot{\tilde{Z_m}}(t)}{\tilde{Z_m}(t)}\right) + n(t)\left(\frac{(\chi - \sigma)}{s_l(t)} - \chi + \sigma + 1\right) + \rho - \left(\frac{\dot{e_s}}{e_s}\right)\left\{\frac{\eta_s - \eta_m(e_m/e_s)}{\eta_s e_s + \eta_m e_m}\right\}$$

Similarly, we can obtain the allocation of scientists in manufacturing using the scientist market clearing condition

$$S_m(t) = \frac{S}{\left(\left(\frac{\eta_{rs}\Lambda_{rs}(t)^{\gamma}V_{rs}(t)}{\eta_m\Lambda_m(t)^{\gamma}V_m(t)}\right)^{(1/\alpha)} + \left(\frac{\eta_{ns}\Lambda_{ns}(t)^{\gamma}V_{ns}(t)}{\eta_m\Lambda_m(t)^{\gamma}V_m(t)}\right)^{(1/\alpha)} + 1\right)}$$

The expression shows that a higher relative arrival rate of innovation, value function and spillovers in the manufacturing sector will draw more scientists into that sector.

Finally, using the equilibrium condition

$$w_l(t)s_l(t) = w_s(t)s_s(t)$$

along with the resource constraint $s_s(t) + s_l(t) = 1$ – where s_s and s_l are the share of scientists and production workers in the economy, respectively – yields the following expression

$$s_s(t) = \left(\frac{p_m(t)^{\frac{1}{\beta}}\tilde{Z_m}(t)B_m(t)}{\eta_{ns}\Lambda_{ns}(t)^{\gamma}S_{ns}(t)^{-\alpha}V_{ns}(t) + p_m(t)^{\frac{1}{\beta}}\tilde{Z_m}(t)B_m(t)}\right)$$

which suggests that the occupational choice is driven by the value of scientist and production worker wages at any given time

4 Quantitative Results

4.1 Calibration

The model produces 30 parameters of interest to be estimated. These include 7 preference parameters $\{\sigma, \epsilon, \chi, \rho, \zeta_m, \zeta_{rs}\zeta_{ns}\}$, 10 knowledge spillover intensities $\{\gamma, \delta_{mm}, \delta_{nn}, \delta_{rr}, \delta_{mnj}\delta_{rn}\delta_{mr}\delta_{nr}\delta_{rm}\delta_{rn}\}$, 4 innovation technologies $\{\eta_m, \eta_{rs}, \eta_{ns}, \alpha\}$, 3 Pareto distribution parameters $\{k_m, k_{rs}, k_{ns}\}$, 3 growth rates for labor-augmenting technologies $\{g_m, g_{rs}, g_{ns}, \alpha\}$, 2 Kimball aggregator parameters $\{\omega, \upsilon\}$, and the labor intensity parameter $\{\beta\}$. We recover these parameters through a combination of external and internal calibrations.

4.1.1 External Calibration

We calibrate the following 16 parameters externally $\{\delta_{mm}, \delta_{nn}, \delta_{rr}, \delta_{mnj}\delta_{rn}\delta_{mr}\delta_{nr}\delta_{rm}\delta_{rn}, \rho, \chi, \beta, \sigma, \gamma, \omega, \upsilon, \}$. The results are presented in Table 3. Starting with the labor intensity β, we assume a value of 0.65 which is broadly in line with the results from Gollin (2002). For the intertemporal elasticity of substitution χ, we recognise that the literature attempting to estimate this parameter is large and growing and so we assign a value of 2 for this parameter which is largely consistent with the latest developments in this literature focusing on advanced economies (Hall (1988); Evans (2005); Groom & Maddison Pr (2019)). We match an annual discount factor of 0.98 per year implying a discount rate of 0.02. This is also in line with the broader macroeconomics literature. Finally, for the between- and within-sector knowledge spillover intensities $\delta_{mm}, \delta_{nn}, \delta_{rr}, \delta_{mnj}\delta_{rn}\delta_{mr}\delta_{nr}\delta_{rm}\delta_{rn}$, we obtain these from our computations presented in Table 2 which use patent citation from Webb et al. (2005). For σ and γ which represent the elasticity of substitution between manufacturing and services and the spillover elasticity, we fix these to 0.1 and 0.5 respectively and run robustness checks in the appendix. For ω and υ, we fix the values at 2.50 and 2.00 respectively for all sectors. These values allow for flexibility when calibrating the Pareto distribution parameters in the next sub-section.

Table 3: Externally Calibrated Parameters

Parameter	Interpretation	Value	Source
β	labor intensity	0.65	macro literature
χ	intertemporal elasticity of sub.	0.50	macro literature
ρ	discount factor	0.02	macro literature
δ_{mm}	knowledge spillover intensity MFG to MFG	0.92	Webb et al. (2005), authors calculations
δ_{rm}	knowledge spillover intensity MFG to RI-S	0.57	Webb et al. (2005), authors calculations
δ_{nm}	knowledge spillover intensity MFG to NRI-S	0.72	Webb et al. (2005), authors calculations
δ_{mr}	knowledge spillover intensity RI-S to MFG	0.04	Webb et al. (2005), authors calculations
δ_{rr}	knowledge spillover intensity RI-S to RI-S	0.27	Webb et al. (2005), authors calculations
δ_{nr}	knowledge spillover intensity RI-S to NRI-S	0.10	Webb et al. (2005), authors calculations
δ_{mn}	knowledge spillover intensity NRI-S to MFG	0.05	Webb et al. (2005), authors calculations
δ_{rn}	knowledge spillover intensity NRI-S to RI-S	0.16	Webb et al. (2005), authors calculations
δ_{nn}	knowledge spillover intensity NRI-S to NRI-S	0.18	Webb et al. (2005), authors calculations
σ	elasticity of sub. b/w MFG and SERV	0.10	see Appendix for robustness checks
γ	spillover elasticity	0.50	see Appendix for robustness checks
ω	average final goods producer demand elasticity	2.50	see Appendix for robustness checks
υ	final goods producer demand elasticity relative to size	2.00	see Appendix for robustness checks

4.1.2 Internal Calibration

We have 14 remaining parameters $\{\epsilon, \zeta_m, \zeta_{rs}, \zeta_{ns}, \eta_m, \eta_{rs}, \eta_{ns}, \alpha, g_{b,m}, g_{b,rs}, g_{b,ns}, k_m, k_{rs}, k_{ns}\}$. For those, we employ a Simulated Method of Moments (SMM) strategy to jointly estimate them with the goal of matching US economy data moments between 1947 and 2010 with numerically simulated ones. Table 4 presents a full list of empirical data moments that we calibrate the remaining parameters to match.

Table 4: Empirical Data Moments Matched

Empirical Moment	Year	Value	Data Source
Real Consumption Growth Factor	1947-2010	2.92	Woltjer et al. (2021), Timmer et al. (2015)
MFG TFP Ind. Growth Factor	1947-2010	2.94	Jorgenson et al. (2012)
RI-S TFP Ind. Growth Factor	1947-2010	1.39	Jorgenson et al. (2012)
NRI-S TFP Ind. Growth Factor	1947-2010	1.07	Jorgenson et al. (2012)
MFG Rel. to Agg. Price Ind. Growth Factor	1947-2010	0.31	Jorgenson et al. (2012)
RI-S Rel. to Agg. Price Price Ind. Growth Factor	1947-2010	0.84	Jorgenson et al. (2012)
NRI-S Rel. to Agg. Price Price Ind. Growth Factor	1947-2010	1.21	Jorgenson et al. (2012)
MFG Expenditure Share	2010	0.13	Woltjer et al. (2021), Timmer et al. (2015)
RI-S Expenditure Share of Services	2010	0.75	Woltjer et al. (2021), Timmer et al. (2015)
MFG Scientist share	1947	0.85	NCSES (1985-2021)
RI-S Scientist share	1947	0.15	NCSES (1985-2021)
NRI-S Scientist share	1947	0.01	NCSES (1985-2021)

The vast majority of these data moments come from Section 2. We calibrate our model such that it mimics key features of the US economy's behavior between 1947 and 2010. This includes real consumption growth as well as sectoral TFP, relative prices, expenditure shares and scientist allocations. The results of the structural estimation are presented in Table 5.

Table 5: Structurally Estimated Parameters

Parameter	Interpretation	Value
ϵ	elasticity of sub. b/w RI-S and NRI-S	1.08
ζ_m	MFG income elasticity	0.91
ζ_{rs}	RI-S income elasticity	1.00
ζ_{ns}	NRI-S income elasticity	1.20
η_m	MFG arrival rate of innovation	0.46
η_{rs}	RI-S arrival rate of innovation	0.23
η_{ns}	NRI-S arrival rate of innovation	0.22
$g_{b,m}$	growth in MFG labor-augmenting technology	0.03
$g_{b,rs}$	growth in RI-S labor-augmenting technology	0.02
$g_{b,ns}$	growth in NRI-S labor-augmenting technology	0.01
$1-\alpha$	scientist elasticity	0.69
k_m	Pareto distr. parameter for MFG intermediate goods producers	18.68
k_{rs}	Pareto distr. parameter for RI-S intermediate goods producers	15.35
k_{ns}	Pareto distr. parameter for NRI-S intermediate goods producers	4.40

For the elasticity of substitution between research-intensive and non-research-intensive services, ϵ, we receive a value of 1.08 which indicates substitutability between both groups of services. This finding resonates with that of Duernecker et al. (2024) who find broad substitutability between stagnant and progressive services in post-war US. After normalising the research-intensive services income elasticity to 1.00, we get manufacturing and non-research-intensive services counterparts of 0.91 and 1.20, respectively. The generally higher income elasticities of services relative to manufacturing is also not a surprising result given that it was previously documented by Comin et al. (2021). Nevertheless, we find different income elasticities for the two services groups. For the arrival rates of innovation, we obtain 0.46, 0.23 and 0.22 for manufacturing, research-intensive and non-research-intensive services, respectively. We find a similar sectoral order for the growth rates of labor-augmenting technologies. Meanwhile, the scientist elasticity is 0.69 implying decreasing marginal returns to scale. Finally, we obtain Pareto distribution parameters of 18.68, 15.35 and 4.40 for the manufacturing, research-intensive and non-research-intensive services sectors, respectively. These parameters dictate the thickness of the Pareto tails from which the intermediate goods producers draw their productivities from. This in turn influences markups in each sector.

4.2 Simulating the Future of the US Economy

Having calibrated our model to match the evolution of the US economy between 1947 and 2010, we proceed to simulate the evolution of the economy going forward. In our first quantitative exercise, we project the behavior of the economy 65 years beyond our last in-sample, 2010. This means that the year 2010 serves as a mid-point between the first in-sample year (1947) and the last projected year (2075).

The results are presented in Table 6. The top half of Table 6 presents the sectoral expenditure, labor and scientist shares in 2010 which are all observed in the data and perfectly matched by our model. The next column shows their simulated values for year 2075 followed by the difference between both years. The bottom half of Table 6 presents the 2010 observed index value of the corresponding variable (all are normalized to 1 in year 1947) while the subsequent column shows the simulated index value for year 2075. The final column shows the share of the difference between years 1947 and 2075 that has already been covered by the mid-point year of 2010.

Starting with the top half of Table 6, the results suggest that structural change in employment and expenditure is set to persist until 2075, with the shares of expenditure and employment in manufacturing falling to 4% and 3%, respectively. Interestingly, the expenditure shares of research-intensive and non-research-intensive services in total services are predicted to remain fairly stable, with income and substitution effects roughly offsetting each other within services. However, due to structural change in production and expenditure towards services, the employment shares in both research-intensive and non-research-intensive grow in 3 p.p. each, respectively. In turn, the price of manufacturing continues exhibiting a secular decline, being in 2075 74% lower than in 2010. At the same time, the price of research-intensive services intensifies its downward trend falling 38% between 2075 and 2010, after having already fallen 26% between 2010 and 1947.

Strikingly, even though the size and price effects generate incentives to reallocate innovation activity out of manufacturing and into non-research-intensive services, the model predicts a reversal of structural change in innovation out of manufacturing. The share of scientists in manufacturing rises from 62% in 2010 to 92% in 2075, while it contracts from 4% to 2% in non-research-intensive services and from 34% to 6% in research-intensive services. Besides this predicted reallocation of innovation activity into manufacturing, a vanishing sector in terms of employment and expenditure, the economy accelerates its TFP growth from a cumulative 30% between 2010 and 1947 to a total expansion of 44.6% between 2075 and 2010. The explanation for this result comes from the quantitative importance of the economy-wide knowledge spillovers generated by manufacturing. First, knowledge spillovers within manufacturing are high enough that the increase in the flow of ideas generated by this sector more than compensates for the decline in profits induced by the sector size and the relative price effects, attracting more innovation activity. Additionally, the knowledge generated in the manufacturing sector also has a positive effect on the innovation efficiency in research-intensive and non-research-intensive services (recall that $\delta_{nm} = 0.720$ and $\delta_{rm} = 0.570$). This leads to an acceleration in TFP growth in both research-intensive and non-research-intensive services from 39% and 7% between 2010 and 1947 to 88.5% and 33.6% in the period of 2075 to 2010.

We confirm that this result is driven by our rich structure of knowledge spillovers by simulating an alternative economy with only same-sector spillovers (i.e. $\delta_{mm} = \delta_{nn} = \delta_{rr} = 1$). In this counterfactual future path, there is a full reallocation of scientists into manufacturing and TFP stagnates at its level in 2010.

Table 6: Projecting Sectoral Composition & Growth, USA 1947-2075

Variable	**1947**	**2010**	**2075**	$\Delta(2010-1947)$ **(in p.p.)**	$\Delta(2075-2010)$ **(in p.p.)**
$e_m(t)$	0.41	0.13	0.04	-0.28	-0.09
$e_{ns}(t)$	0.76	0.75	0.74	-0.01	-0.01
$e_{rs}(t)$	0.24	0.25	0.26	0.01	0.01
$S_m(t)/S(t)$	0.85	0.62	0.92	-0.23	0.30
$S_{rs}(t)/S(t)$	0.15	0.34	0.06	0.19	-0.28
$S_{ns}(t)/S(t)$	0.01	0.04	0.02	0.03	-0.02
$L_m(t)/L(t)$	0.33	0.09	0.03	-0.24	-0.06
$L_{rs}(t)/L(t)$	0.07	0.20	0.23	0.13	0.03
$L_{ns}(t)/L(t)$	0.60	0.71	0.75	0.11	0.03

Variable	**1947**	**2010**	**2075**	x_{2010}/x_{1947}	x_{2075}/x_{2010}
$c(t)$	1.00	2.92	7.34	2.92	2.51
$N_m(t)$	1.00	2.93	8.77	2.93	2.99
$N_{ns}(t)$	1.00	1.07	1.43	1.07	1.34
$N_{rs}(t)$	1.00	1.39	2.62	1.39	1.88
$p_m(t)$	1.00	0.31	0.08	0.31	0.26
$p_{ns}(t)$	1.00	1.21	1.14	1.21	0.94
$p_{rs}(t)$	1.00	0.84	0.52	0.84	0.62
$TFP(t)$	1.00	1.29	1.88	1.29	1.46

The bottom half of Table 6 reveals major gains ahead in terms of consumption growth and aggregate TFP. Indeed, we see that aggregate TFP growth factor is set to reach 1.88 by 2075, far higher than the 2010 value of 1.30. Similarly, the consumption growth factor only reached 2.92 by 2010, far below the expected factor of 7.34 projected for 2075. Aggregate TFP will mostly be driven by manufacturing. This is not due to compositional effects – the employment share of manufacturing will collapse to less than 5% by 2075 – but rather through the knowledge spillovers. The reversal of scientist allocations back to manufacturing is expected to drive major gains in manufacturing TFP which in turn will positively influence the evolution of TFP in the two services sectors. As we expect, the fast growth in manufacturing TFP will lead to its lower relative price (vis-a-vis the other two services). Taken together, this projection exercise highlights the central role spillovers will have on the US economy going forward.

4.3 Decomposing the Productivity Growth Slowdown

Our rich quantitative model is well-equipped to decompose the forces behind the observed slowdown in US productivity growth in the last few decades. We group these forces into three broad categories. The first category is structural change in production, which groups together the forces of structural change that explicitly result in shifting sectoral employment shares over time. These include biased labor-augmenting technological progress, income effects driven by non-homothetic preferences (Kongsamut et al. 2001), and substitution effects driven by relative price changes (Ngai & Pissarides 2007). The second relates to structural change in innovation, which groups together the forces that explicitly drive sectoral R&D patterns documented in Section 2. These forces include knowledge spillovers and markups – both of which rationalise the reallocation of scientists across sectors. The third category refers to demographic changes, more specifically the well-documented slowdown in the population growth rate in the US over the last few decades. The goal of this exercise is thus to quantitatively disentangle the drivers of the US productivity growth slowdown by shutting down these different channels and observing the counterfactual gains (or losses) in cumulative aggregate TFP growth between 1947 and 2010.

Table 7 presents the results from this counterfactual exercise. Each row presents the counterfactual TFP growth if we shut down the corresponding channel, keeping the channels in previous rows also muted. The cumulative growth in TFP shows the percentage total factor productivity growth between 1947 and 2010 in each scenario (i.e. $TFP_{2010}/TFP_{1947} - 1$.The final column records the share of the total change in TFP induced by the entire category driven by the force of interest.

Table 7: Decomposition of TFP Growth Slowdown, USA 1947-2010

	TFP Growth (2010-1947, %)	**Contribution to TFP Growth Slowdown (p.p. ; %)**	**Contribution to Category (p.p. ; %)**
Panel A. Benchmark Value	29.9		
Panel B. No Structural Change in Employment and Expenditure	41.9	12.0 (37.5%)	*100.0%*
B.1 Same Growth in Labor-Augmenting Techology	*35.9*		*5.9 (23.2%)*
B.2 No Substitution Effect	*29.1*		*6.8 (26.6%)*
B.3 No Income Effects	*41.9*		*12.8 (50.2%)*
Panel C. No Structural Change in Innovation	56.2	14.3 (44.7%)	*100.0%*
C.1 No Spillovers	*35.7*		*6.2 (23.3%)*
C.2 No Change in Markups	*56.2*		*20.6 (76.7%)*
Panel D. No Population Slowdown	61.9	5.6 (18.3%)	*100.0%*

An initial look at Table 7 reveals that in the absence of forces driving structural change in production, and innovation, and under no population growth slowdown, TFP would have grown 61.9% instead of 29.9% between 1947 and 2010. This implies that these forces together accounted for a 32 p.p. decline in TFP growth.

Panel B of Table 7 shows that without structural change in employment and expenditure, the US economy would have shown a TFP growth of 41.9% instead of 29.9% between 1947 and 2010. Put differently, forces driving structural change in employment and expenditure contributed to 37.5% of the TFP slowdown in this period. Diving into this channel in further detail, we find that once we apply the same growth rates of labor-augmenting technologies across our three sectors, we obtain a cumulative TFP growth rate of 36%. We next shut down the relative price effects by assigning the elasticities of substitution σ and ϵ a value of 1 (hence, a Cobb-Douglas aggregator in both the consumption of the final good and services), to find that cumulative TFP growth falls to 29.1%. This shows that the change in relative prices in this period led to a reallocation of economic activity towards services, generating higher incentives to innovate in research-intensive and non-research-intensive services via both the sector size and the relative price effect. In turn, in the absence of income effects that shifted economic activity out of manufacturing and into non-research-intensive services, TFP would have grown by 42%. once income elasticities ζ are equalised across the three sectors, the TFP growth factor jumps to 1.42, suggesting a cumulative 12 percentage point increase in the TFP index between 1947 and 2010 relative to the benchmark. This is mostly a compositional effect, as in this alternative world the US economy would have exhibited a higher share of employment in manufacturing, the most dynamic sector in terms of TFP growth.

Panel C of Table 7 shows that knowledge spillovers and heterogeneous-time-varying markups, contributors to structural change in innovation, contributed to 44.7% of the slowdown in TFP growth. If this channel had been muted, TFP would have grown 56.2% instead of 29.9%, a 14.3 percentage point increase effect relative to the result in Panel B. Decomposing this into the spillover and markup forces shows that similar to the substitution effect, spillovers have been partially reversing the US productivity growth slowdown. This is evident from the 6.2 percentage point decline in the cumulative 2010 TFP growth observed once we assign a spillover elasticity γ of 0 after already having shut down the structural change in the production category. Finally, once we keep the sectoral markup levels unchanged from their 1947 levels while still allowing for heterogeneity across sectors, we observe a counterfactual TFP growth of 56.2%, implying a 20.6 percentage-point difference to the case of no knowledge spillovers. This is because in the US during this period, markups operated in favor of slowing down the reallocation of innovation activity out of manufacturing, while biasing this reallocation towards research-intensive services instead of non-research-intensive services, being the later the biggest sector in terms of economic activity. In other words, our findings show that heterogenous, time-varying markups have been a major force behind the divergent transformation paths we observe in the data.

Panel D shows the impact of shutting down population growth slowdown on TFP growth. If the growth rate of the population had stayed at the same level as in 1947, US TFP would have accumulated 5.7 additional percentage points in TFP growth, leading to a total of 61.9% between 1947 and 2010. This suggests that only 17.7% of the productivity growth slowdown observed in the US is driven by the demographic channel, compared to 82.2% driven by structural change, of which more than half is driven by contributors of structural change in innovation.

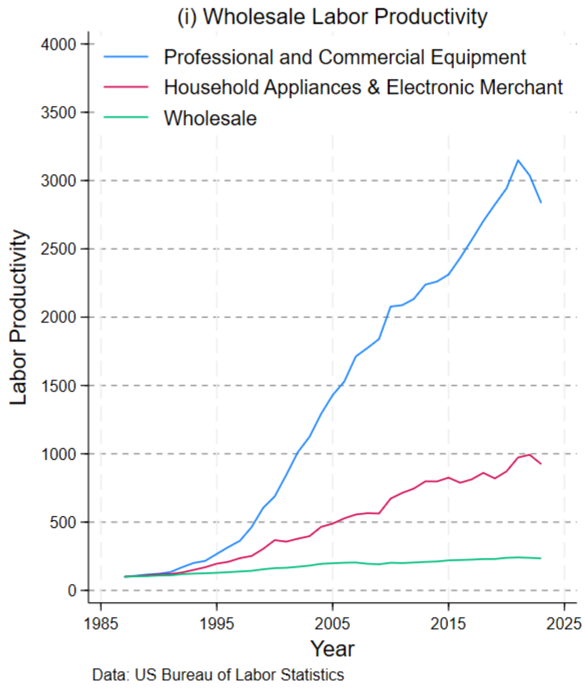
5 Conclusion

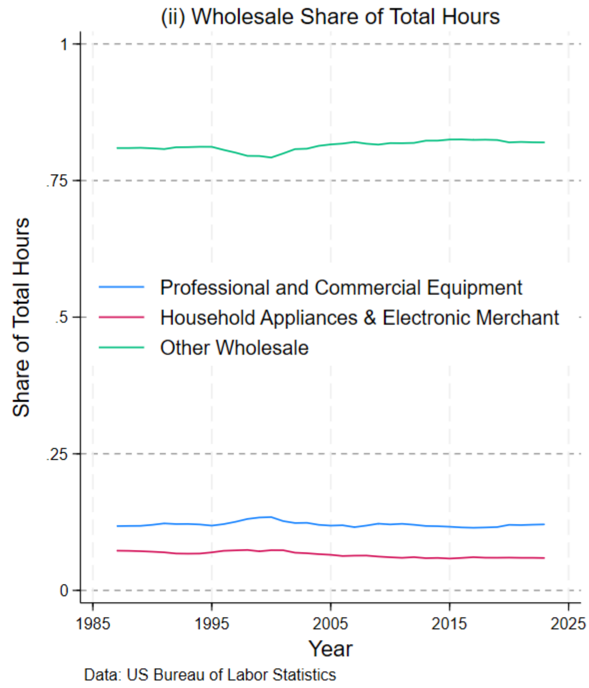
We document new evidence on the process of structural change in innovation observed in the US. Using multiple data sources, We show that like consumption and employment, innovation activity – proxied by R&D employment and patent production – moves away from manufacturing and into services over time. After splitting services into research-intensive and non-research-intensive industries, we find that most of this relocation is concentrated in research-intensive services. In contrast, we find using the same split production employment relocates away from manufacturing and into non-research-intensive services. This observation motivates our divergent transformation paths hypothesis: production employment relocates to non-research-intensive services while innovation activity relocates to research-intensive services.

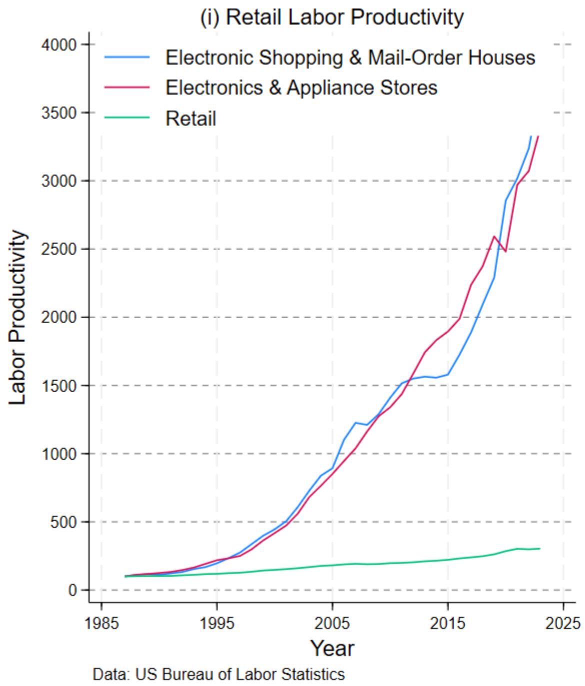
Next, we build a rich 3-sector general equilibrium model to rationalise these facts. In essence, our model combines key features from the benchmark structural change and directed technical change frameworks. The latter allows us to explicitly model R&D dynamics across sectors to endogenise the differential sectoral productivity growth rates. Embedding this into the benchmark structural change model allows us to relate differential productivity growth rates with the reallocation of consumption and labour across sectors. We enrich this framework by allowing for time-varying markups that are heterogeneous across sectors, generating incentives to innovate that are not accounted for by the traditional mechanisms of sector size and relative price. This rich structure allows us to perfectly match key trends of the US economy, including the evolution of sectoral relative prices, expenditure shares, TFP, employment and scientist allocations between 1947 and 2010.

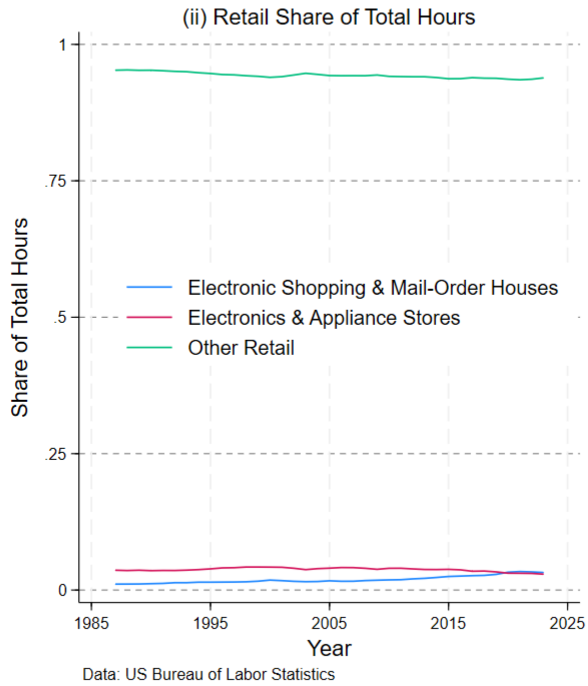
Our model is well-equipped to run quantitative exercises. Perhaps fundamentally, our goal is to decompose the sources of the observed productivity growth slowdown in the US. As it stands, our model has three potential explanations for the slowdown (i) structural change in employment and expenditure, (ii) structural change in innovation and (iii) demographic sources. We find that in the absence of structural change in both production and innovation as well as no population growth slowdown, aggregate TFP would have grown by 61.9% between 1947 and 2010 compared to the observed 29.9%. A further decomposition shows that just 18.3% of this difference can be accounted for by the demographic channel; 81.7% of the growth slowdown is due to structural change, and over half of this is driven by structural change in innovation. This counterfactual exercise highlights the major losses in TFP growth that result from forces of structural change, particularly structural change in innovation.

6 Appendix


(i) Wholesale Labor Productivity
Professional and Commercial Equipment
Household Appliances & Electronic Merchant
Wholesale
Labor Productivity
Year
Data: US Bureau of Labor Statistics


(ii) Wholesale Share of Total Hours
Professional and Commercial Equipment
Household Appliances & Electronic Merchant
Other Wholesale
Share of Total Hours
Year
Data: US Bureau of Labor Statistics


(i) Retail Labor Productivity
Electronic Shopping & Mail-Order Houses
Electronics & Appliance Stores
Retail
Labor Productivity
Year
Data: US Bureau of Labor Statistics


(ii) Retail Share of Total Hours
Electronic Shopping & Mail-Order Houses
Electronics & Appliance Stores
Other Retail
Share of Total Hours
Year
Data: US Bureau of Labor Statistics

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